Cities of Workers, Children or Seniors? Age Structure and Economic Growth in a Global Cross-Section of Cities

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Abstract

A large literature documents the positive influence of a city's skill structure on its rate of economic growth. By contrast, the effect of a city's age structure on its economic growth has been a hitherto largely neglected area of research. We hypothesize that cities with more working-age adults are likely to grow faster than cities with more children or seniors and set-out the potential channels through which such differential growth may occur. Using data from a variety of historical and contemporary sources, we show that there exists marked variation in the age structure of the world's largest cities, both across cities and over time. We then study how age structure affects economic growth for a global cross-section of mega-cities. Using various identification strategies, we find that mega-cities with higher dependency ratios - i.e. with more children and/or seniors per working-age adult - grow significantly slower. Such effects are particularly pronounced for cities with high shares of children. This result appears to be mainly driven by the direct negative effects of a higher dependency ratio on the size of the working-age population and the indirect effects on work hours and productivity for working age adults within a city.

JEL: R10; R11; R19; J11; J13; J14; O11; N30

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Cities can develop by increasing productivity, the share of people working, or both. Most research on the growth of cities, however, has focused on the role of productivity, ignoring the role of the share of people working. Yet, globally, cities vary markedly in their age structures and, hence, in the shares of their populations that work. When cities have high shares of children or seniors, they have low shares of people working. The question then is whether such high shares can impact a city's economic growth.

To put this into context, Figure 1(a) shows the distribution of the child dependency ratio – defined as the ratio of the number of children (aged zero to 14) to the number of working-age adults (aged 15 to 64) – for a global sample of 4,907 city-year observations. While New York City had an average of two adults per child in 1850, it now has four adults per child – increasingly making it a *city of workers.* An extreme example of a city of workers is Shanghai, with 10 adults per child. At the opposite extreme, cities such as Dhaka (1.5 adults per child) and Bamako (one adult per child) are *cities of children.* Likewise, some cities have high aged dependency ratios, defined as the ratio of the number of seniors (aged 65 or more) to the number of working-age adults (aged 15 to 64). Tokyo, for example, has three working-age adults per senior, making it and other cities with high aged dependency ratios *cities of seniors* (see Figure 1(b)).

Having high shares of children and/or seniors could impact a city's economic growth through a variety of, mainly negative, channels. Cities of children and seniors have, by definition, relatively fewer working-age adults who can generate output. More indirectly, more children and/or seniors in a city's households may lead working-age adults in those same households to allocate more time to "caring" and less time to working, and/or negatively affect their hourly productivity – for example, by experiencing less, and/or more interrupted, sleep, resulting in reduced cognitive performance at work. At a city-wide level, a relatively greater number of children and/or seniors may, for example, contribute to the crowding of schools and hospitals; undermine the likelihood of knowledge spillovers; and skew the allocation of public finance in ways that negatively affect worker productivity and growth.

In this paper, we compile and use a novel data set to show that, globally, cities vary considerably in their age structure. We then study the effects of age structure on economic growth for a global sample of mega-cities. Our results suggest that cities with higher child and aged dependency ratios exhibit significantly slower economic growth.

Our analysis has three steps. First, we use historical and contemporary sources to construct a new and unique data set on the age structure of the world's largest cities for multiple years over the past 200 years. While other data sets on the age structure of cities do exist, ours is, to the best of our knowledge, unprecedented in both the number of cities and the length of the time-period that it covers. We show how some cities, including cities in both developed countries and developing countries, are increasingly becoming cities of workers. We also show that many cities in developing countries have disproportionately more children than did cities in developed countries before the 20th century. By contrast, many developed country cities are ageing.

Second, we study how age structure circa 1990 affected economic growth over the period 1996-2011 for a restricted sample of about 350 mega-cities. We find that cities whose age structures are relatively skewed towards either more children or more seniors tend to experience slower economic growth.[1] To obtain more causal estimates, we control for core city characteristics – including a city's initial level of development and both its initial level and subsequent growth rate of population – that could explain both age structure and economic growth. As expected, younger children (aged 0-9) and older seniors (ages 75 and over) have relatively more negative effects than older children (aged 10-14) and younger seniors (aged 65-74), respectively. Likewise, the relatively negative economic effects of having a high share of children disappear in the longer run, when the same children reach working age. We also find our results to be robust to using historical (pre-1990) age structures as an instrument for contemporary age structures (circa 1990). Despite our efforts to control for the likely major sources of endogeneity, however, we cannot be entirely sure that our results on the effect of a city's age structure on its economic growth are causal. As such, our findings should be treated with caution and, thus, we refrain from making policy recommendations. More generally, we view the role of this paper as being to raise the question of whether age structure can be a fundamental driver of city economic growth rather than answering it fully.

Third, and finally, we use our main data set, as well as household survey data for a large global sample of households and time-use survey data for the United States, to provide suggestive evidence on the importance of the different mechanisms which may be driving our results. We find, as expected, that children and seniors tend to work less

[1] In the absence of better data on incomes, we use night lights data, much like Henderson et al. (2012).

than working-age adults. Even when they do work, children and seniors get paid lower wages than working-age adults, which is indicative of lower productivity. We also find evidence for indirect effects at the household or city level.

Our paper contributes to three inter-related literatures. The first is the literature on the local determinants of a city's economic performance and growth, which includes both papers on agglomeration economies (Henderson et al., 1995; Ciccone and Hall, 1996; Duranton and Puga, 2004; Glaeser and Gottlieb, 2009; Combes et al., 2012; Combes and Gobillon, 2015; Roca and Puga, 2017), and on human capital spillovers and learning effects (Rauch, 1993; Glaeser et al., 1995, 2004; Moretti, 2004b,a; Glaeser, 1999; Glaeser and Maré, 2001; Glaeser et al., 2014; Gennaioli et al., 2014; Roca and Puga, 2017).[2] The papers on agglomeration economies find that productivity, whether measured by nominal wages or TFP, not to mention measures of firm creation and innovation, tend to improve with city population size. As such, they intentionally ignore the composition of a city's population, since what they try to identify is a pure scale effect. Papers on human capital spillovers and learning effects, by contrast, focus on the skill structure of a city's population. They suggest that the spread of ideas and knowledge is facilitated by face-to-face interactions with the result that people who live in more educated cities become more productive over time. Typically, these studies regress measures of the college share, i.e. the share of workers with a college degree, on measures of wages, TFP, innovation, employment or population, whether in levels or in changes.

To our knowledge, there are far fewer studies of the role of working age adults – i.e., potential workers – versus children and seniors – i.e., potential non-workers. If children have less human capital and seniors have human capital that goes largely unused, our focus on age structure refines the analysis of the nexus between human capital and growth in cities. There are also various channels by which the presence of dependents can affect the productivity of workers, whether they are skilled or not.

The second literature to which our paper contributes is the "urbanization without growth" literature. Historically, the growth of cities, and, more generally, the occurrence of urbanization, has gone hand in hand with economic growth (Henderson, 2010;

[2]The median country in our data is Brazil, which transitioned from lower- to upper-middle income status during our period of study. There is a literature on agglomeration economies and human capital spillovers for developing countries only (Henderson, 1986; Au and Henderson, 2006; da Mata et al., 2007; Duranton, 2008, 2016; Chauvin et al., 2017; Combes et al., 2017; Quintero and Roberts, 2018).

Duranton, 2014). Prior to the two world wars, the list of the world's largest cities was dominated by cities that were in the most advanced countries of the time. However, following the end of the Second World War, the world's most rapidly growing cities, in terms of population, have been in the developing world (Fay and Opal, 2000; Glaeser, 2014; Jedwab and Vollrath, 2015; Glaeser and Henderson, 2017). Dhaka, Karachi, Kinshasa, Lagos, and Manila are some of the largest cities on the planet today, while only six of the currently largest 30 cities (e.g., London, New York and Paris) are in high income countries. Explanations for the growth of poor developing world mega-cities include urban-biased policies (Ades and Glaeser, 1995; Davis and Henderson, 2003; Castells-Quintana, 2017), natural disasters (Kocornik-Mina et al., 2015; Henderson et al., 2016a), trade (Glaeser, 2014; Gollin et al., 2015; Venables, 2016), and institutions (Glaeser, 2014; Henderson et al., 2016b). Jedwab et al. (2015) and Jedwab and Vollrath (2018) provide a demographic explanation but focus on the role of faster natural population growth in driving urbanization. They study the effects of higher total population levels, rather than the specific effects of the demographic composition of cities.

Finally, the paper contributes to the more macro literature on age structure and economic growth. By definition, GDP per capita is equal to the product of labor productivity and the share of people working. By and large, the growth literature has focused on the role of labor productivity in explaining GDP per capita and growth differences across countries. But the labor force participation rate is potentially as important. In the textbook neoclassical growth model, population growth leads to capital dilution (see Jones, Schoonbroodt and Tertilt (2010) and Galor (2012) for surveys on the relationship between population and economic growth). But population growth can also skew an economy's age structure, thus influencing dependency ratios as well as the age composition of the non-dependent population, with various macroeconomic consequences. So far, the literature has focused on the effects of countries' age structure on savings rates (Weil, 1997; Modigliani and Cao, 2004; Chamon and Prasad, 2010; Curtis et al., 2015a,b), the number of hours worked and hourly productivity (Ríos-Rull, 1996; Weil, 1997; Shimer, 2001; Feyrer, 2007; Jaimovich and Siu, 2009; Lugauer, 2012; Jaimovich et al., 2013; Lagakos et al., 2018; Islam et al., 2019b), income and consumption (Weil, 1999; Hock and Weil, 2012; Ashraf et al., 2013; Zhang et al., 2015; Maestas et al., 2016; Islam et al., 2019a), and the environment (Liddle, 2014; Casey and Galor, 2016). To our knowledge, there are no studies on how age structure affects economic growth via its economic effects on cities. Studying this question is important because cities represent a large share of overall economic activity. Thus, to better understand long-run economic growth, there is an increasing need to open the black box of cities.[3]

The remainder of the paper is organized as follows. Section 1. describes our newly assembled global data set on city age structures. Section 2. highlights some key stylized facts regarding the age structure of cities across the world. Section 3. provides a framework to help understand how a city's age structure may affect its economic development. Section 5. presents our main econometric results. Section 6. includes a discussion of suggestive evidence on mechanisms. Section 7. concludes.

1. Framework: City Age Structure and Economic Growth

To understand the channels through which a city's age structure might affect its level and growth rate of GDP per capita, assume that there are three types of residents: (i) children, who are below working-age; (ii) working-age residents; and (iii) seniors, who are above working-age. We can further divide working-age residents into "caregivers" – i.e. working-age residents who provide care either to their own children or to their retired parents – and "non-caregivers". Per capita GDP is given by:[4]

$$y = \omega_C h_C r_C + \omega_{(W,H)} h_{(W,H)} r_{(W,H)} + \omega_{(W,NH)} h_{(W,NH)} r_{(W,NH)} + \omega_S h_S r_S \tag{1}$$

where the subscripts C, W and S denote children, working-age residents and seniors respectively, while the subscripts H and NH denote caregivers ("helpers") and non-caregivers ("non-helpers") respectively. ω denotes the share of a city's population of a given type; h hours worked per person; and r output per hour.

Using equation 1, we can distinguish between two sets of effects through which a city's age structure can influence its level and/or growth rate of GDP per capita. The first is a *direct effect* of children and/or seniors earning relatively less than working-age residents. There are then *indirect effects* that work through either time allocation decisions or worker productivity. The indirect effects may be further divided into intra-household effects, where children and/or seniors in a household affect time allocation

[3]Agriculture accounts for 3% of the world's GDP (World Bank, 2017). If two thirds of non-agricultural activities take place in cities, as shown for various countries by Gollin et al. (2015), about 65% of the world's GDP possibly comes from cities. McKinsey (2011) also shows that just 600 mega-cities might generate as much as 65% of the world's economic growth.

[4]For simplicity, we abstract from income accruing to either capital or land.

and productivity of the working-age members of that same household, and city-wide effects, where time allocation and productivity of working-age residents are influenced by the *city*'s age structure. The city-wide effects are externalities.

i. Direct effect (negative). An increase in ω_C and/or ω_S reduces the share of a city's residents who are of working-age. Assuming that working-age residents work more hours than either children or seniors and that they are also more productive then an increase in the total dependency ratio $((\omega_C + \omega_S)/(\omega_{(W,H)} + \omega_{(W,NH)}))$ reduces a city's GDP per capita. As such, a shift towards a higher dependency ratio involves a slowdown in GDP per capita growth relative to any pre-existing growth path.

ii. Indirect effects: Intra-household (ambiguous). The increase in ω_C and/or ω_S will change the composition of the working-age population, raising $\omega_{(W,H)}$ relative to $\omega_{(W,NH)}$. This will negatively impact GDP per capita if $h_{(W,H)}r_{(W,H)} < h_{(W,NH)}r_{(W,NH)}$.

ii(a). Indirect effects through time-allocation (ambiguous). We can think of residents as allocating their time between four types of activity: "care", which includes time directly caring for other household members and time spent doing household chores; work and education; sleep; and leisure. Assuming, for the time being, $r_{(W,H)} = r_{(W,NH)}$, we might expect caregiving working-age residents to work less hours than non-caregiving working-age residents (i.e. $h_{(W,H)} < h_{(W,NH)}$). They may also place a higher value on their leisure time — as may, for example, be the case if parents place a high value on time spent with their children. In this case, an increase in ω_C and/or ω_S will, unless it is exactly offset by less time sleeping, reduce GDP per capita. This effect will be greater the higher is the cost of accessing outside caregiving help.

Shorter working hours may involve complete withdrawal from the workforce. Such effects may be particularly pronounced for residents who have either very young children or very elderly parents. The effects may be less pronounced in cities where childcare is subsidized; the healthcare system is strong; or where employers provide more flexible working options. Against the above, it is, however, also possible that caregiving working-age residents work more hours than their non-caregiving counterparts (i.e. $h_{(W,H)} > h_{(W,NH)}$). This may be the case if the addition of a child or a senior to a household increases its aggregate required subsistence expenditure level.

ii(b). Indirect effects through hourly productivity (ambiguous). Even if $h_{(W,H)} = h_{(W,NH)}$, a change in the composition of a city's working-age population between non-caregivers and caregivers will reduce GDP per capita if $r_{(W,H)} < r_{(W,NH)}$. For example, working-age parents with children, especially young children, or with elderly parents to look after, may sleep fewer hours and/or have more interrupted sleep and, therefore, be more tired at work, resulting in lower cognitive performance. Related to this, caregiving working-age residents may sort into less demanding and lower productivity jobs. It may further be the case that employed caregiving working-age residents, as part of any reduction in working hours, allocate less time to human capital accumulation activities – e.g., to optional on-the-job training. Thus, it may not only be the level of GDP per capita that is negatively impacted, but also the longer-run growth rate of a city's GDP per capita. Finally, if a caregiving working-age resident is made unemployed, she may be more likely to accept an ill-matching job if she must "feed the family".

Acting against the above effects, caregiving working-age residents may be more focused at work. Given a higher value of leisure time and a higher opportunity cost of working longer hours, caregiving working-age residents may work more intensively.

iii. Indirect effects: city-wide (negative for ω_C; ambiguous for ω_S):

iii(a). Human capital externality effects (negative). Human capital externalities arise from the spillover of knowledge between individuals within cities because of interpersonal interactions. For a given population, we might expect these externalities to be weaker the higher is a city's dependency ratio. This is so for two reasons. First, a higher dependency ratio implies a lower probability that a working-age resident will engage in a conversation with another working-age resident. Second, for any given conversation, the knowledge exchanged is likely to have less impact on the working-age resident's productivity. This is because the knowledge exchanged is more likely to be non-work related (e.g. knowledge exchange with a child) or, if work related, is more likely to be out-of-date (e.g. knowledge exchanged with a retiree). Weaker human capital externalities could then reduce the city's long-run GDP per capita growth rate.

iii(b). Crowding effects (negative for ω_C; ambiguous for ω_S). Cities with higher dependency ratios may suffer more from certain types of crowding effects. This is particularly so for cities in which ω_C is high, in which case we can hypothesize more traffic congestion during "school run" hours. A high value of ω_C will also translate into more crowded classrooms and pediatrician clinics, which could result in worse long-run human capital outcomes for children once they become adults. This, in turn, could have lasting negative effects on a city's long-run rate of GDP per capita growth.

For cities with high values of ω_S, we might similarly expect more crowding of health services. This could negatively impact the productivity of working-age residents. Against this, however, cities with high ω_S might experience less traffic congestion. This is because the share of the population that needs to commute to work will be lower.

Related to crowding effects, cities with higher dependency ratios may also have, on average, larger household sizes, resulting in relatively more demand for larger residential properties. This could help drive suburbanization and sprawl, with negative effects for worker productivity if this undermines knowledge spillovers.

iii(c). Public expenditure effects (negative). Cities with higher age dependency ratios may exhibit a systematic difference in the structure of public expenditure with relatively less allocated to public goods that immediately contribute to the productivity of a city's workers. Hence, cities with high values of ω_C may spend relatively more on schools and playgrounds and relatively less on, for example, roads. Similarly, cities with high values of ω_S may allocate more public expenditure to facilities and services that support the needs of seniors as opposed to more "productive" infrastructure.

Finally, if cities have different sectors and types of workers than rural areas, and given that city populations are much more spatially concentrated than rural populations, one should expect the effects described above to be particularly relevant for cities.

2. Data on City Age Structures and Economic Growth

2.1. Selection of Cities.

Data Collection Methodology. We use historical and contemporary sources to calculate measures of the age structure—and the dependency ratios—of the world's largest cities for multiple years over the past 50-200 years. We focus on *megacities*—i.e. the largest cities in the world. The problem is to define which cities should be included in the analysis. Indeed, since data on city age structures is not readily available, we had to collect it city by city and year by year. We thus limited our analysis to a restricted list of large cities for which data was more likely to be found, especially historically.

From United Nations (2018), we identified the 500 largest urban agglomerations in 2015. However, in this sample, the largest cities of the past are under-represented (e.g., Berlin, Liverpool, Manchester and St.-Louis at the time of the Industrial Revolution). We added 24 cities not among the original 500 largest cities in 2015, but among the 100 largest cities in 1900 according to Chandler (1987). We also added 131 capital or largest city for each country not previously in the sample, to account for the fact that the largest cities of smaller countries were previously under-represented as well. In total, we obtain a list of 655 mega-cities on which we focus our data collection effort. Finally, note that when we refer to cities we aim to include central areas, suburbs, and satellite towns.[5]

Sample for Descriptive Analysis. We were able to find age structure data for 424 out of these 655 cities (see the black hollow circles in Figure 2). These cities belong to 139 countries in 79 years from 1787 to 2016 (N = 4,907). We will use this data set to document how the age structure of cities has varied across space and over time.

Sample for Econometric Analysis. We will restrict our analysis to 351 out of these 424 cities for which we know the age structure circa 1990 (see the black circles in Fig. 2). We will use this data set to study the effects of age structure on economic growth, as measured using night lights data, over the period 1996-2011.[6]

2.2. Data on the Age Structure of Cities.

Sources. We collected data on the age structure of the cities for each year we could find. We consulted six main sources: (i) *IPUMS:* The IPUMS-North Atlantic Population Project (Minnesota Population Center, 2017) provides census microdata for selected developed countries from the late 18th century to the early 20th century. In addition, IPUMS-USA (Ruggles et al., 2017) provide harmonized U.S. decennial census microdata from 1920 to 1950. Finally, IPUMS-International Minnesota Population Center (2018) collects census data from other countries around the world from 1960 to date; (ii) *Census reports:* For city-years for which we could not calculte the age structure using IPUMS data, we obtain it from reports of the population census; (iii) *OECD:* The OECD Metropolitan Areas Database (OECD, 2016) reports demographic information for the main metropolitan areas of OECD countries; (iv) *DHS*: The Demographic and Health Surveys (DHS) program (USAID, 2018) are representative health surveys for developing countries; (v) *I2D2*: The International Income Distribution Database (I2D2, 2018)

[5]We followed as much as possible the definitions of urban agglomerations by United Nations (2018). They explain that urban agglomerations refer to "the population contained within the contours of a contiguous territory inhabited at urban density levels without regard to administrative boundaries. It usually incorporates the population in a city or town plus that in the suburban areas lying outside of, but being adjacent to, the city boundaries." These correspond to metropolitan statistical areas in the United States. The agglomeration of New York thus includes New Jersey and Newark.

[6]Radiance-calibrated night lights data is only available from 1996 onwards, while we measure age structure using dependency ratios that are averaged over all available years between 1985-1996.

is a database consisting of about 1,500 individual-level surveys and census samples. The surveys include nationally representative household surveys, labor force surveys and budget surveys from both developing countries and developed countries;[7] and (vi) *Other sources:* For a few observations, we rely on administrative counts or other household surveys that are neither DHS nor belonging to I2D2. In terms of data quality, census data (i.e. (i) and (ii)) should be more reliable than other data.

For each city-year-source, we identified the urban agglomeration, and obtained population by age in 5-years age buckets. For some observations however, we only know the population shares of 0-14, 15-64 and 65+ year olds. When the urban agglomeration was not directly identified in the source, we constructed it by aggregating territorial subdivisions (i.e. municipalities, cantons, parishes, etc.), based on our own analysis of which subdivisions should be included. Note that we interchangeably use the terms "urban agglomerations", "metropolitan areas", and "cities" in the rest of the paper.

Sample for Descriptive Analysis. In total, we have age structure data, i.e. population shares of various age groups, for 5,251 city-year pairs, with the following breakdown of sources: IPUMS (1,227 observations), census reports (141), OECD (3,107), the DHS 9198), I2D2 (537), and other sources (28). Since some observations are duplicates within a same city-year, we use mean population shares in each city-year. Doing so, our sample size decreases to 4,907 city-years. We will use this sample for our descriptive analysis.

Sample for Econometric Analysis. In our econometric framework, we will restrict our analysis to the age structure of 351 mega-cities circa 1990. To make sure that we have enough observations, and since censuses and surveys do not take place every year but every few years or decades, we will include any observation in the broader period 1985-1996 and then compute the "average" age structure, i.e. the mean population shares, during that period. We will also use alternative age structures based on the closest observation to the year 1990 or the closest higher-quality observation (using the following ranking: (1) IPUMS/census; (2) OECD; (3) DHS; (4) I2D2; and (5) other). Next, the median and mean populations in our sample were 1,416 and 2,517 thousand inhabitants in 1995 (source: United Nations (2018); min and max = 227 and 33,587 (000s)). Finally, the 351 agglomerations account for one third of the world's urban population according to United Nations (2018) but one quarter of the world's night

[7] The data was initially compiled by the World Bank's World Development Report (WDR) unit. The data is now harmonized and compiled by the World Bank's Development Economics Research Group.

lights in 2011 using agglomeration boundary data from CIESIN (2017) and (radiance calibrated) night lights data from NGDC (2015). If we use city GDP from Oxford Economics (2019) instead, they account for as much as 50% of the world's GDP in 2015.

Age Structure Measures. As is standard in demography, our main measures will be: (i) The *child dependency ratio*, the ratio of the number of "children", aged zero to 14, to the number of "non-dependents", aged 15 to 64; (ii) The *aged dependency ratio*, the ratio between the number of "seniors", over the age of 65, to the number of "non-dependents", aged 15 to 64; and (iii) The *total dependency ratio*, the ratio of the number of children and seniors to the number of "non-dependents". By construction, the total dependency ratio is equal to the sum of the child and aged dependency ratios.

2.3. Data on City Boundaries and City Economic Development

Nights Lights. We use the intensity of a city's night lights as a proxy for its economic activity, as is now standard in the literature (Henderson et al., 2012; Donaldson and Storeygard, 2016). We do so because consistent GDP, productivity or wage data is not available for most of the cities in our sample. Satellite images are provided by NGDC (2015), and are available at a fine spatial resolution, annually from 1996-2011.[8] We use the radiance calibrated version of this data, to avoid issues related to top-coding.[9]

City Boundaries. To obtain mean night light intensity for each agglomeration, i.e. the average night light intensity across an agglomeration's constituent pixels, we need to determine the pixels that belong to each agglomeration. The Global Rural-Urban Mapping Project (GRUMP) provides geocoded polygons of urban extent boundaries (CIESIN, 2017). For each agglomeration in our age structure data set, we find the corresponding geocoded polygon and extract mean night light intensity. There are two potential problems with using the GRUMP boundaries. First, polygons may be too small. Boundaries are from 1995, and cities have been sprawling since. However, for our main econometric sample of 351 cities, GRUMP polygons are large in comparison with other sources: 4,399 sq km on average vs. 1,613 sq km in Schneider et al. (2010) in 2002, 1,062 sq km in Demographia (2014) in 2013, and 703 sq km in European Commission (2018) in 2015.[10] Our interpretation is that GRUMP boundaries captured commuting

[8]The resolution of the night lights data is 30 arc seconds, which is approximately 1 Km^2 at the equator.

[9]This data records levels of luminosity beyond the normal digital number upper bound of 63. Such data is only available from 1996 onwards, which explains our sample-period of 1996-2011.

[10]The coefficient of correlation between log area in GRUMP and log area in these data sets is 0.52-0.64.

zones circa 1995, and thus already included areas of the agglomeration that sprawled later on. Second, the GRUMP boundaries are, in some cases, very large, in particular for multi-city agglomerations. An example is Tokyo, represented as covering a large share of Japan. While Tokyo's workers may commute from far with high-speed trains, Tokyo's boundary may not capture just Tokyo's growth. We thus manually modify GRUMP boundaries using our own analysis of Google Maps which shows boundaries for the cities in our study but does not allow users to download the corresponding GIS files.

Per Capita GDP. One issue is whether night lights are a satisfactory proxy for local economic development. However, various studies have shown that, for a variety of countries, there is a strong positive correlation between night light intensity and per capita GDP, especially for growth rates over long periods of time (Donaldson and Storeygard, 2016). The issue is that there is limited consistent GDP data for cities of different countries. Nevertheless, from Oxford Economics (2019), we obtain, for a sufficiently high number of cities, per capita GDP data (constant 2012 U.S. dollars) covering 2000-2017. Since there is limited information on how the GDP of each city was obtained and whether GDP estimates are consistent across cities, we do not use this variable as our main outcome. Still, it is reassuring that, for a common sample of 341 cities out of our main sample of 351 cities, the coefficient of correlation between log night light growth (1996-2011) and log per capita GDP growth (2000-2017) is 0.75.

3. Stylized Facts: Children, Workers and Seniors in Cities

Evolution of Child Dependency Ratios (CDRs). Historically, CDRs were lower in developed country cities than the levels they reached in developing country cities in the late 20th century. Figure 3(a) shows the evolution of the CDR for New York City, for which we have data in 37 years, and the weighted mean CDR for all mega-cities in high-, middle- and low-income countries in our descriptive sample (N = 4,907 city-years; based on the income classification of the World Bank in 2016).[11] Note that we use as weights the populations of each city in each decade. Patterns are relatively similar for New York City and other cities in high-income countries. In 1850, in today's high-income countries, the CDR was close to 0.5. There were 2 adults per child. The CDR has decreased to 0.25 today, about 4 adults per child. In cities like Hong Kong and Tokyo, the difference is even stronger: there are 7 adults per child. Next, cities in middle- and

[11] Web Appx. Fig. A1 shows, for each group-decade, the number of cities with at least one observation.

low-income countries reached CDRs of 0.75 at one point (1.3 working-age adults per child), well above the maximal CDRs observed in high-income countries (0.55, so 1.8 working-age adults per child). CDRs have recently decreased in developing countries, but CDRs still vary dramatically across countries today.

Evolution of Aged Dependency Ratios (ADRs). Figure 3(b) shows the evolution of the ADR for New York and the population-weighted mean ADR for all mega-cities in high-, middle- and low-income countries (N = 4,907). While ADRs were close to 0 in 1850, they have continuously increased in both New York and today's high-income countries. They are now close to 0.2, equivalent to about four working-age adults per senior. In cities like Tokyo or Milan, the difference is starker: there are only three working age adults per senior. Cities in richer countries are thus increasingly becoming cities of seniors. On the contrary, cities in middle- and low-income countries have low ADRs, with some cities like Kampala and Riyadh having 40 working-age adults per senior.

Robustness. Instead of studying the evolution of mean CDRs and ADRs for each income group, we can examine how the right tail of their distribution has shifted over time. In particular, Figure 4(a) shows the mean population-weighted CDRs and ADRs for the whole sample in each decade when only considering the 10 highest CDRs/ADRs in each decade. As can be seen, high dependency ratios have become even higher over time.

In Web Appx. Table A1, we verify that these patterns hold if we: (i) control for log city population size, to only compare city-year observations of the same population size; (ii) restrict our sample to only census-based observations; (iii) drop cities that appear in a few decades only, to reduce compositional biases; (iv) do not use population weights; (v) remove outliers, i.e. city-years in the top or bottom 5% of the dependency ratios; and (vi) drop each continent one by one. We find high coefficients of correlation between the baseline numbers and the numbers obtained when implementing these tests.

City CDRs and ADRs and Economic Development Today. The graphs above imply significant differences across the world, hence the need to study their economic consequences. Interestingly, these patterns are not fully explained by changing incomes over time. Figure 4(b) shows the evolution of the ten highest CDRs and ADRs in each decade when conditioning them on log national per capita GDP (in constant PPP terms) in the same decade (source: Maddison (2008), updated using World Bank (2017)).[12] As

[12] We regress the dependency ratios on log national per capita GDP (in constant 1990 international dollars and PPP terms) in the same year and obtain the mean of the 10 highest residuals.

can be seen, both maximal CDRs and ADRs have trended upwards over time.

A related question is whether two cities with the same income level can have different age structures. For the 351 cities in our main econometric sample, Figure 5(a) plots the relationship between the CDR circa 1990 (1985-1996) and log mean night light intensity in 1996, our income level measure. Likewise, Figure 5(b) plots the relationship between the ADR circa 1990 (1985-1996) and log mean night light intensity in 1996. As can be seen, city CDRs decrease, and city ADRs increase, with city economic development. However, at any given level of mean night light intensity, both CDRs and ADRs vary dramatically across cities. Likewise, the R2 of these relationships are low, at 0.14 and 0.19, respectively. Income is not the only determinant of age structures, and we exploit these idiosyncrasies in our econometric analysis below.

City vs. Urban vs. Rural Dependency Ratios. Figure 6(a) and 6(b) show the respective evolutions of the "maximal" CDRs and ADRs for mega-cities only, urban areas as a whole, and rural areas as a whole, i.e. the mean population-weighted ratios when only considering the ten highest values in each type of location in each decade. CDRs and ADRs tend to be lower in urban areas than in rural areas, which is consistent with the sorting of working-age adults into urban areas. In addition, CDRs and ADRs have increased over time in *all* types of location, so sorting must not have been sufficiently important to prevent large cities from also being affected by these patterns. Next, in our analysis, we study how dependency ratios affect the economic growth of large cities. We will nonetheless verify that results hold when also considering other types of location.

4. Econometric Specification

Long-Difference Specification. As explained in Section 1., we could expect a city's age structure to affect both its level and its growth rate of per capita GDP. However, estimating the causal effect of a city's age structure is less difficult when the outcome is the city's per capita GDP growth rate rather than its level of per capita GDP. Indeed, when growth is the dependent variable, we can control for the initial level of per capita GDP, thus comparing cities with different age structures *but* similar income levels and exploiting the idiosyncrasies highlighted in Figures 5(a)-5(b). This framework is also similar to studies on city characteristics and urban growth (e.g. Glaeser et al., 1995).

More precisely, we focus on our restricted sample of 351 mega-cities for which we have night lights data from 1996-2011 and age structure data circa 1990 (1985-1996).

For city c in continent r, we run the following long-difference regression.

$$\Delta LogNL_{c,r,96-11} = \alpha + \beta \times CDR_{c,r,90} + \gamma \times ADR_{c,r,90} + X_c\zeta + \mu_{c,96-11} \qquad (2)$$

where $\Delta LogNL_{c,96-11}$ is the log difference in mean night light intensity between 1996 and 2011. There are two main variables of interest, the child dependency ratio circa 1990 ($CDR_{c,r,90}$) and the aged dependency ratio, also circa 1990 ($ADR_{c,r,90}$). For each city, we use mean dependency ratios in the window 1985-1996. β and γ measure the effects of age structure. In some specifications, we replace CDR and ADR with TDR, the total dependency ratio. Lastly, X_c are controls at the city level or higher.[13]

Core Controls: Not controlling for initial population size and economic development and population growth could create a spurious correlation between age structure and economic growth, hence the need to add three controls: (i) *Log population size in 1995*: Larger cities receive more migrants, i.e. working-age adults. Larger cities may in turn grow faster due to agglomeration effects or slower due to congestion effects; (ii) *Log mean night light intensity in 1996*: Wealthier cities in 1996 could be wealthier due to their age structure being skewed towards working-age adults. Conversely, wealthier cities could have fewer children because the opportunity cost of having children is higher in more productive cities. Higher housing costs in wealthier cities also imply fewer people having children and seniors leaving for cheaper locations. Given mean reversion, we could then expect poorer cities to grow faster. But if there are agglomeration effects not captured by initial population size, but captured by initial economic size, wealthier cities grow faster. Light intensity in 1996 controls for these possibilities; and (iii) *Log population growth between 1995 and 2010*: Cities with a specific age structure may see their population grow faster or slower, which could then affect night light growth if population growth has economic effects. For example, cities with a large share of reproductive-age adults are likely to have higher fertility rates and experience faster population growth. Conversely, cities with a large share of seniors have higher mortality rates and experience slower population growth. Faster or slower city population growth could then accelerate or reduce GDP per capita growth. Since we aim to capture the specific effects of the demographic composition of cities,

[13] Equation 2 is consistent with a neo-classical growth framework in which a city's steady-state level of income per capita depends on its age structure. In such a framework, a change in a city's age structure which influences its steady-state will generate transitional growth dynamics, which may last many years.

rather than total population levels, we include this control in our baseline regression. However, since population growth might be a mechanism by which age structure affects economic growth, we will also study the effects when not including this control. Finally, another advantage of controlling for population growth is that β and γ now capture the effects on night light growth in per capita terms.

Continent vs. Country Fixed Effects: In some specifications, we add continent fixed effects, in order to compare cities belonging to the same continent only.[14] Therefore, causal identification is coming from comparing cities with the same initial population sizes and levels of economic development, experiencing the same population growth, and belonging to the same region of the world. We also try including country fixed effects. However, most cities within any given country have very similar age structures, leaving us with little variation to study the effects of age structure on economic growth.[15] We then miss important effects that only appear when comparing cities from different countries. With country fixed effects, the within(-country) component accounts for only 12% and 11% of the variation in child and aged dependency ratios, respectively. With continent fixed effects, the contributions of the within(-continent) component increase to 57% and 44%, respectively. In addition, with country fixed effects, variation comes only from comparing cities of the same country. Given free mobility, we expect a country's urban system to gravitate towards a spatial equilibrium in which wages across cities are equalized at the margin. In such an equilibrium, any increase (decrease) in the relative wage offered in one location will induce in-migration (out-migration) that should offset the initial increase (decrease) in the wage. Thus, in the long-run, city economic growth will be measured by population growth only (see, e.g., Glaeser et al. (1995)). However, we cannot use population growth as an outcome since city age structure may have direct effects on population growth. Since we control for population growth, we measure the effect of city age structure on the growth of night lights per capita. As such, *within* regressions will only provide significant effects if population adjusts slowly enough to changes in per capita incomes. Lastly, since free mobility encourages sorting across cities in ways that are likely to influence the age structure of cities (e.g. the fact that young, highly employable, working age adults may

[14] The six continents are: Africa, Asia, Europe, North America, Oceania and South America.
[15] That is why we use a global sample of cities, as opposed to cities taken from a single country.

disproportionately sort into high growth cities), this *within* regression creates different potential biases. We thus also try *between* regressions, where we restrict our sample to consist of only the largest city from each country, between which mobility is limited.

Other Limitations. Note that we cannot run panel regressions because we would need to have age structure data for several years within the 1996-2011 period. However, for many cities, we have data for one or two years only. The age structure data comes from censuses that take place every 10-15 years or surveys that were only conducted recently. Besides, the age structure of cities does not vary much over time, so including city fixed effects would leave little variation to exploit in the data.[16]

5. Results

5.1. Baseline Results

Results. Table 1 shows the results with: (i) the core controls (col. (1) & col. (5)); (ii) six continent fixed effects (col. (2) & col. (6)); (iii) 97 country fixed effects (col. (3) & col. (7)); and (iv) the restricted "largest city only" sample (col. (4) & col. (8)). In columns (1)-(4), we use the total dependency ratio (TDR). In columns (5)-(8), we use both the child dependency ratio (CDR) and the aged dependency ratio (ADR).

The coefficient of log city population is about 0.04-0.07. Given that the elasticity of the log change in city per capita GDP with respect to the log change in city mean night light intensity is 0.64 when we use city per capita GDP from Oxford Economics (2019) (N = 341, not shown), the implied dynamic agglomeration elasticity is about 0.03-0.05. Typical values for the elasticity are between 0.04 and 0.07 for high-income countries (Combes and Gobillon, 2015), sometimes similar or higher in middle-income countries, e.g. 0.05 in Colombia (Duranton, 2016), 0.07 in Indonesia (Bosker et al., 2018), and 0.09-0.12 in China and India (Chauvin et al., 2017; Combes et al., 2017). Our elasticity could be smaller because we focus on mega-cities or include low-income countries for which the elasticity might be lower. The coefficients on population growth (positive) and night light intensity at baseline (negative) are also consistent with our expectations.

The TDR (col. (1)-(4)), the CDR and the ADR (col. (5)-(8)) all have strong negative effects, except when 97 country fixed effects are included (col. (3) & (7)), possibly due to the reasons mentioned in Section 4.. Note that a household with two working-age

[16] When using all available years in 1985-2016 and including city fixed effects, the within(-city) component accounts for only 8-10% of the variation in the dependency ratios in our data.

adults and one child (senior) corresponds to a CDR (ADR) of 0.5. If it has two children (seniors), the ratio increases to 1. If it has three children, the ratio increases to 1.5, etc. The CDR (ADR) thus increase by 0.5 for each extra child (senior). Abstracting from the country fixed effects regressions, we find that going from the 10th percentile to the 90th percentile in the CDR – which is equivalent to an increase of about 0.5 (0.45), so one extra child – reduces the growth rate of night lights by 0.28-0.50, hence 28-50%.[17] For the ADR, going from the 10th percentile to the 90th percentile is equivalent to an increase of 0.16. Thus, the corresponding decrease in the growth rate is 17-20%. These are meaningful effects, given a mean growth rate in the sample of 28%.[18]

5.2. Investigation of Causality

We now attempt to investigate causality. Given the controls, identification is coming from comparing cities with the same initial population sizes and levels of economic development, experiencing the same population growth, and belonging to the same continent. However, there could still be unobservable factors that are correlated with both initial age structure and future economic growth, and/or reverse causality.

Exploiting the Granularity of the Age Structure Data. Age structure is more endogenous when using broad age categories than when using detailed age categories, for example whether cities have more young children (0-9) or more older children (10-14) or whether cities have more young seniors (65-74) or more older seniors (75+). Older children may work in developing countries, and they require less parental time than younger children. Likewise, younger seniors may keep working, and they require less time from their children. However, for the same CDR, whether a city has younger or older children is coming from a lag of only a few years in the number of births (and deaths) one or two decades ago. Likewise, for the same ADR, whether a city has more young or more older seniors is coming from a lag of only a few years in the number of births six or seven decades ago (and deaths in previous decades). Columns (1)-(4) of Table 2 show that the negative effect of the CDR is driven by 0-9 year-olds. Similarly, the negative effect of the ADR is driven by seniors aged 75 or older. All effects of both the 0-9 CDR and the 75+ ADR are significant except those in column (3) for the 0-9 CDR.

Exploiting Demographic Cycles. So far, we have only studied the long-run growth effects over a period of 15 years (1996-2011) of city age structures circa 1990 (1985-1996).

[17] To obtain 0.28 or 0.50, we multiply -0.62 (col. (8)) or -1.12 (col. (5)) by 0.45.

[18] Web Appendix Table A2 contains descriptive statistics for this main sample.

However, children eventually become adults. Seniors may become increasingly ill as they age and they eventually die. Thus, these long-run effects may combine different medium-run effects. In Table 2, we re-run the same regression as before, but instead of using log night light growth between 1996 and 2011 as the dependent variable, we use log night light growth between 1996 and 2003 (col. (5)-(8)) or between 2003 and 2011 (col. (9)-(16)). The core controls are adjusted accordingly. We control for log night lights in the initial year, log population in the closest year to the initial year (we have population every 5 years), and log population growth based on the closest years to the initial and final years. In columns (13)-(16) where we focus on the 2003-2011 period, we also control for log night light growth between 1996 and 2003, to capture the direct effects of dependency on growth rather than its indirect effects via past growth.

Columns (5)-(8) show negative and significant effects of 0-9 year-olds on night light growth in the first subperiod, even with country fixed effects (col. (7)). The effects are much less negative, and mostly insignificant, in the second subperiod (col. (9)-(16)), possibly due to the fact that this cohort becomes productive. The positive effects observed in some specifications for 10-14 year-olds are significantly reduced in the longer run too (col. (5)-(8) vs. col. (13)-(16)). It could be that 10-14 year-olds have positive effects in the first subperiod of seven years (2003 - 1996), because that is precisely when they enter labor markets (remember that our sample includes many developing countries). Next, 65-74 year-olds have positive medium-run effects in some specifications (col. (5)-(8)) that disappear in the longer run (col. (9)-(16)), possibly as they become too old to work or become sick. Finally, 75+ year-olds tend to have strong negative effects in the medium-run that tend to be reduced in the longer run, plausibly because some of them die, thus reducing their impact on growth.

Past City Age Structures as Instruments. Age structures are somewhat mechanically determined years before. For some of the 351 cities, we have data on their age structure before our circa 1990 base year. We thus construct instruments that either exploit the slow moving nature of age structures or the mechanical nature of their evolution over time. For these exercises, and to better understand how the instruments work, we use the CDRs and ADRs for the closest year to 1990 in the 1985-1996 period.

As our first set of IVs, we use the CDRs and ADRs for the closest year to 1960 in the 1960-1980 period. We select 1960 because the more historic the age structure used as an IV, the more exogenous to future city growth it is. However, the instrument may be weak if city age structures change dramatically over time. The instruments thus rely on factors that make some cities have disproportionately high, or low, CDRs and/or ADRs over time. The implied exclusion restriction is that these factors do not cause city economic growth in 1996-2011, conditional on the three core controls (including city economic development in 1996) and continent fixed effects. As can be seen in columns (1)-(3) of Table 3 , the number of observations drops to 142, due to lack of data on past city age structures. Yet, all effects are both strong and significant at 10% or 15%, even when including country fixed effects (the p-value for the ADR is 0.146).

To ensure city age structure in 1960-1980 is not explained by factors that explain future city growth, and given that night light intensity in 1996 does not control for economic development before 1996, we show that our IV results hold when we control for log national per capita GDP (constant 1990 dollars and PPP terms) in 1960, 1980 and 1996 (see col. (1)-(2) in Panel A of Table 4). Given that these are country level controls, we do not repeat the within-country regression.[19] Even for cities at the same income level, the dependency ratios in 1960-1980 could be a function of the strength of family planning policies during the period, which could then be correlated with a country's ability to implement certain policies. Columns (3)-(4) in Panel A of Table 4 show results hold if we add four dummies for whether family planning was "very weak", "weak", "moderate" or "strong" in 1972-1982 based on the World Bank (2007) family planning index.[20] In addition, and, again, even for cities at the same income level, the dependency ratios in 1960-1980 could depend on the religious mix during the period, which could then be correlated with a country's evolution, with potential implications for future city growth. Columns (5)-(6) show results hold if we add the national population shares in 1970 of ten different religions (source: Barro and McCleary (2003)). We control for all these factors simultaneously in columns (7)-(8).

Next, and in order to better capture the exogenous mechanical nature of the evolution of city age structures, we instrument the CDRs and the ADRs close to 1990 by the 5-year population shares for the closest year to the year 1960 during the 1960-1980 period. For example, people aged 65-84 circa 1990 should be aged 55-74 circa 1980

[19]The source for national per capita GDP is Maddison (2008), which we update using World Bank (2017).
[20]We use their 1972 index. When it is not available for 1972 but it is for 1982, we use 1982.

and 35-54 circa 1960. Columns (4)-(6) of Table 3 shows that the effects are relatively unchanged. The instruments are weaker than when using the dependency ratios close to 1960 (2.6-5.4 vs. 8.8-22.2). Indeed, we now have 17 instruments instead of two. When multiple instruments are included, they are mechanically weaker, because some of the instruments do not explain some of the endogenous variables (Angrist and Pischke, 2009). For example, the child dependency ratio (0-14) circa 1990 cannot be explained by the population shares of older individuals in 1960. In such cases, the threshold for a "high" IV F-statistic needs to be adjusted down, but there is no guide as to by how much. Now, even if we restrict the instrument set to selected 5-year population shares that are more likely to explain dependency ratios circa 1990 – 0-4, 5-9, 50-54, 55-59 and 60-64 –, the effects and the IV F-statistics remain similar. Lastly, they also remain somewhat similar if we control for historical per capita GDP, family planning and/or religious shares (Panels B and C of Table 4). Some effects lose significance though.

Overall, the strategies exploiting the granularity of the age structure data, demographic cycles, and instruments suggest that there may be negative causal growth effects of children and seniors. Even if estimates are higher than baseline estimates, they are not significantly so (not shown, but available upon request). We thus privilege the more conservative OLS specification in the rest of the analysis. In addition, these results should be taken with caution, given the lack of a definitive identification strategy explaining why cities that are similar in many other respects differ in their age structure.

5.3. Robustness Checks

College Share. Human capital per worker tends to rise with city size. Now, even if we control for city population size and initial city economic development, we do not directly control for the college share, i.e. the fraction of the population age 25 or higher that completed a BA-equivalent university degree or higher (see, e.g., Chauvin et al. (2017)). For 224 and 42 cities respectively, we calculate the college share circa 1990 (1985-1996) using the educational attainment variables in IPUMS and the DHS. One issue is that the educational attainment variables are not consistent across samples and countries. In IPUMS, we use the share of individuals aged 25 or above that are classified as "university completed". However, IPUMS explains that "university degrees are not distinguished in all samples" and that they use the number of years of university study to infer whether a BA-equivalent degree was obtained. The DHS has even more limited information. We categorize as college graduates individuals that they classify as having reached a "Higher" educational level than "Complete Secondary". For 110 other cities for which city-level information is missing, we: (i) obtain from Barro and Lee (2013) and for the year 1990 the national college share for individuals age 25 or above; (ii) we combine this information with the total population of individuals age 25 or above in 1990 (source: United Nations (2019)) to estimate the total number of college graduates age 25 or over in the country; (iii) using data on total urban population in 1990 (source: United Nations (2018)) and our own data on the age structure of urban areas circa 1990 (see details below), we reconstruct the total number of urban residents age 25 or over; and (iv) assuming all college graduates live in urban areas, we reconstruct the *urban college share*, which we use as proxy for the college share of the city. We then re-run the same regression as before but with this imperfectly measured college share as an extra control. We cluster standard errors at the country level since we use as a proxy for a large number of cities the urban college share of their respective country. Columns (1)-(4) of Panel A in Table 5 show that the baseline results of Table 1 hold.[21]

City Per Capita GDP Growth. So far, we have used night lights as our measure of city economic growth. Another measure is the log growth of city per capita GDP between 2000-2017, calculated using Oxford Economics (2019) data. We did not use this as our main growth measure because Oxford Economics (2019) provide neither details on how each estimate was obtained nor on their reliability.[22] Nonetheless, columns (5)-(8) of Panel A in Table 5 show that the effects of CDRs are even more negative, even with country fixed effects (col. (7)). This can be seen by comparing these results with columns (5)-(8) of Table 1 which show our baseline results using night lights to measure growth. On the contrary, the negative effects of seniors have disappeared. This is if we use dependency ratios defined circa 1990 (1985-1996). If we instead use ratios defined circa 2000 (1995-2006), we find stronger and always significant effects of children, and negative but insignificant effects of seniors (see Col. (1)-(4) of Panel B).

If we were to take these results and our baseline results at face value, the fact that

[21] Once country fixed effects are included, we find small, insignificant effects of the college share on city economic growth. Our sample includes both developed and developing countries. While positive effects are typically found for developed countries, evidence is mixed for developing countries (Duranton, 2016; Chauvin et al., 2017). Besides, we do not have an instrument for the college share.

[22] We do not known how many of these estimates were temporally/spatially interpolated/extrapolated. For example, we suspect some GDP estimates may come from coarse first-level administrative divisions.

seniors have strong effects on night lights but no, or weak, effects on per capita GDP growth, could suggest that the effects on night lights come from reduced consumption at night. In other words, seniors do not impact output, possibly because they still work in developing countries or have saved for their retirement in developed countries, but their consumption takes place before night time. By contrast, the fact that the negative effects of children appear stronger for per capita GDP than for night lights could be taken as suggesting that the effects on night lights come from increased consumption at night. While this may be counter-intuitive, if parents stay home in the evening instead of going out, the inside and outside lights of many housing units will be turned on, instead of only the lights at a few entertainment venues. In other words, the entertainment industry might generate less night lights per capita because of returns-to-scale in light consumption. While this is plausible, we cannot answer this question with our data, especially given the lack of reliability of Oxford Economics (2019) GDP data.[23]

Not Controlling for City Population Growth. Since age structure affects city population growth, which may in turn impact city economic growth, we examine how the effects of the dependency ratios change if we do not use population growth during the period of study as a control. As can be seen in columns (5)-(8) of Panel B in Table 5, the effects of seniors are now even more negative (except for the within-country regressions in column (7)). Indeed, cities with more seniors have lower population growth rates, which reduces night light intensity growth when one does not control for population growth.

Panel. Since Oxford Economics (2019) provide city CDRs and ADRs for the whole period 2000-2017, and assuming that Oxford Economics (2019)'s city per capita GDP data and CDR and ADR data are reliable, we partition their full data set into four periods – 2000-2004, 2004-2008, 2008-2012 and 2012-2016 – and run panel regressions.[24] The sample consists of 675 cities with data throughout the period (N = 675 $\times$ 4 = 2,700). We regress the change in log city per capita GDP in each period (t-4; t) on the initial CDR and ADR (t-4), while adding city and year fixed effects and the core controls, thus log city per capita GDP in t-4, log city population in t-4, and the change in log city population between t-4 and t. Standard errors are clustered at the city level. As can

[23] Night light intensity is measured around 8pm globally. The question is how the consumption patterns of seniors, caregivers and non-caregivers change within a day, and how this impact night lights.

[24] For the year 2000, we verify that Oxford Economics (2019)'s CDRs and ADRs are correlated with ours for the year 2000 (coefficients of correlation of 0.90-0.94). Unfortunately, no details are provided on how these estimates were obtained, including how many were temporally/spatially interpolated/extrapolated.

be seen in column (1) of Table 6, children have negative medium-run effects whereas seniors have positive medium-run effects. However, if we add the CDRs and ADRs in t-8, to distinguish medium- and long-run effects, we find stronger negative effects in the medium-run for 0-14 year-olds, positive effects in the longer run four to eight years later, when some of them enter labor markets (col. (2)). For 65+ year-olds, we find positive medium-run effects, possibly as these are experienced workers (provided they are still working). However, the long-run effect is negative as they retire and/or become sick. Results for children hold when adding continent- or country-specific trends (col. (3)-(4)) or continent-year fixed effects (col. (5)). The results on seniors are less stable.[25]

Composition of the Non-Dependent Population. If most women as well as their partners have children between the ages 15 and 35, a high share of 0-14 year-olds in the population circa 1990 could be correlated with a high share of 15-49 year-olds in the population circa 1990. Likewise, a high population share of 65-80 year-olds could be correlated with a high population share of 30-65 year-olds. Table 7 shows most results hold when we simultaneously control for: (i) the respective shares of 15-29 year-olds and 30-49 year-olds in the population of 15-64 year-olds (col.(1)-(4)); and (ii) the respective shares of 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54 and 55-59 year-olds in the population of 15-64 year-olds (col.(5)-(8)).[26] We lose significance for the CDR in col. (4) and the CDR has a positive and significant effect for the country fixed effects regression (col. (7)). The effects of seniors, by contrast, become more negative.

Other Locations. So far, we have ignored the impact on mega-cities of the age structure of surrounding secondary cities and rural areas - for example, megacities with high CDRs could be surrounded by secondary cities and/or rural areas with similarly high CDRs, which could then affect the economic growth of the megacities. [27] For 340 cities, and using the same sources as for the megacity data set, we were able to construct the CDRs and ADRs circa 1990 (1985-1996) of the urban areas and the rural areas of the 86 countries they belong to. Next, knowing the urban dependency ratios and the total urban population of each country, we calculated the CDRs, the ADRs and the population of the secondary city sector, i.e. the urban areas that do not correspond to

[25] Note that we do not have enough cities, and thus enough variation, to include country-year fixed effects. We also do not have enough periods to include a second lag of both the CDR and the ADR.

[26] By construction, we cannot include the share of 50-64 year-olds for (i) and 60-64 year-olds for (ii).

[27] Changes in city population growth due to migration are already captured by the core controls.

our megacities. We also obtained the mean night light intensities in 1996 and 2011 for both the rural and the secondary city sectors, where the secondary city sector corresponds to all GRUMP polygons that are not megacities. Next, we add these 86 (secondary city) + 86 (rural) = 172 observations to the 340 (megacity) observations (N = 512). We then re-run the same regressions as before, using similarly defined core controls, except we now include dummies for whether the observations belong to the secondary city or the rural sector (the megacities are the omitted group). As columns (1)-(4) of Table 8 show, the effects are relatively unchanged compared to the baseline.

Now, if we interact the secondary city sector and rural sector dummies with the CDRs and ADRs, we tend to obtain positive interacted effects (col. (5)-(8)). These effects are significant for secondary cities in columns (5)-(6). The interacted effects are then sufficiently large that they make the effects of age structure on secondary cities and rural areas insignificant in most cases (not shown), unlike what can be observed for megacities. This suggests that the effects of age structure on cities are stronger for larger cities than for rural areas, as well as for smaller cities. This also confirms that our econometric analysis does not only capture a purely country story.

Robustness. Results hold when we (not shown, but available upon request): (i) we use the standard uncorrected version of the night lights data (NGDC, 2015) or the differently corrected night lights data from Bluhm and Krause (2018);[28] (ii) drop cities for which we adjusted GRUMP polygons because they were implausibly large to obtain their mean night light intensity; (iii) only use census-based observations when calculating the mean dependency ratios circa 1990 (1985-96); (iv) use CDRs that include 15-19 year-olds or ADRs that include 60-64 year-olds; (v) use weights that make the per capita income distribution of the 351 cities in our sample representative of all 655 megacities in the world[29]; and (vi) cluster standard errors at the country or continental level.

6. Mechanisms

As explained in Section 1., children and seniors have direct effects on city economic growth mostly because they do not work or work fewer hours for a lower wage. They

[28] These data sets are available for the period 1992-2013, so we adjust the core controls accordingly. Bluhm and Krause (2018) document that top lights can be characterized by a Pareto distribution and thus design a correction procedure aimed at recovering the full distribution of city lights.

[29] We create and use weights so that the in-sample shares of each income group of countries (low, lower middle, upper middle and high) are equal to the same shares for the 655 megacities.

have indirect effects on the labor supply and productivity of other household members, especially caregivers. Finally, there are city-wide effects related to human capital externalities, crowding, and public expenditure. In this section, we use the I2D2 and data from US Time Use surveys to probe the plausibility and magnitude of these channels. Following this, we return to our core data set to explore how the effect of city age structure may, or may not, vary spatially or sectorally within cities, between developed and developing countries, and between larger and smaller mega-cities.

6.1. Dependency Ratios, Labor Supply, Productivity and Earnings

Direct Effects. I2D2 (2018) is a database consisting of about 1,500 individual-level surveys and census samples. We use these surveys to examine the possible direct effects and indirect intra-household or city-wide effects of the presence of children and seniors on labor supply, productivity and earnings. We only use about half of the 1,500 samples because we restrict the analysis to samples between 1990 and 2016 and for which the number of hours worked and the monthly wage are available.

We first study the direct effects of children and seniors on their own earnings. More precisely, for all "urban" individuals in the surveys, we regress a dummy equal to one if the individual works on dummies equal to one if the individual is aged 14 or lower or if the individual is aged 65 or above. In column (1) of Panel A in Table 9, we include country-year sample fixed effects and the following Mincerian controls: a male dummy, a married dummy and its interaction with the male dummy, and the number of years of education and its square. In column (2), we also add, for a smaller sample of country-years for which information is available, fixed effects corresponding to third-level administrative units (if not available, we use second-level units). This corresponds to counties in the U.S. Doing so, we limit the comparison to individuals in the same "urban area". Finally, standard errors are clustered at the household level.[30]

The effects are -0.32*** (col. 1)/-0.37*** (col. 2) for children and -0.37***/-0.42*** for seniors. Note that the numbers of samples and countries used are indicated in separate rows in the table. In columns (3)-(4), (5)-(6) and (7)-(8), we use the same two specifications and study for those who work the effects of being below 14 or above 65 on the log number of hours worked, the log hourly wage – i.e., labor productivity –, and the

[30] We use the weights from the samples. Note that the I2D2 data is not panelized.

log monthly wage.[31] As expected, children work far fewer hours, for a much lower wage, thus generating much lower earnings than working-age adults. The productivity and earnings effects are milder, but still strong and significant, for seniors. Overall, children (seniors) work 32-37% (37-42%) less than working-age adults, and when they work, they generate an income that is 80-82% (36-38%) lower. Thus, on average, children (seniors) bring 87-88% (60-64%) less income than working-age adults.[32] These effects are substantial. In our sample of 351 agglomerations, going from the 100th percentile to the 90th percentile in the CDR (ADR) increases the share of children (seniors) in the city from about 18% to 40% (3% to 14%). If each child (senior) brings 87-88% (60-64%) less income than a working-age adult, city total income decreases by 19% (7%).

Intra-household effects. To explore such effects, we examine if high household-level CDRs and ADRs affect earnings for (15-64 year-old) working-age adults, again using the same two specifications. Since we drop children and seniors to focus on working-age adults, controls now include age and age squared. Since city CDRs and ADRs are, by construction, the household size-weighted mean CDRs and ADRs of all households in the city, we use as weights the sample weights multiplied by the individual's household size. Standard errors are clustered at the household level. As can be seen in columns (1)-(2) of Panel B, the likelihood of working decreases with the CDR and the ADR. Next, for workers, the number of hours worked decreases (col. (3)-(4)), while the hourly wage either decreases or increases (col. (5)-(6)) when children are present depending on whether we add "district" (i.e. admin-3 level) fixed effects. However, on net, monthly earnings decrease (col. (7)-(8)) irrespective of specification. When seniors are present, we find no effect on hours (col. (3)-(4)) but a negative effect on the hourly wage (col. (5)-(6)) and earnings (col. (7)-(8)). Overall, each point of CDR decreases labor force participation by 2-4% but also reduces monthly earnings for workers by 2-9%, thus reducing total earnings by 6-11% (footnote 32 shows the formula used). Each point of ADR, meanwhile, reduces the probability of working by 3-5% and monthly earnings for workers by 6-7%, thus reducing total earnings by 9-12%. These effects are meaningful. In our sample of 351 agglomerations, going from the 10th to the 90th percentile in the CDR and the ADR raises the mean household CDR and ADR by about 0.5 and 0.16

[31] Since we use logs and sample fixed effects, we do not need to convert wages to a single currency.
[32] For children, the formulas are 0.32*(-100) + 0.68*(-82) = -88% and 0.37*(-100) + 0.63*(-80) = -87%.

respectively. This implies that total earnings are reduced by 3-5% and 1-2%, respectively.

City-wide effects. We study city-wide indirect effects by adding to the previous regressions the mean CDR and ADR for the entire urban area in which an individual is located. In columns (1), (3), (5) and (7) of Panel C, we use the mean CDR and ADR for the "district" of the individual.[33] In columns (2), (4), (6) and (8), we use the mean CDR and ADR for the primary sampling unit (PSU) of the individual, which we interpret as being the "neighborhood" where she lives. We cluster standard errors at the district level. Comparing Panels B and C, we see that the indirect intra-household effects are not dramatically altered by including the city-wide effects. Total earnings are now reduced by 1-3% and 1-2% for children and seniors, respectively (see footnote 32 for the formula used). Panel C then shows negative city-wide effects on labor participation (col. (1)-(2)) and earnings for those who work (col. (7)-(8)) when the city CDRs and ADRs are defined at the district level. If we use measures based on PSUs, we lose observations, because the PSU is not available for all surveys, and some effects lose significance. If we focus on point estimates only, total earnings are reduced by 21-58% (45-67%) for each point of the CDR (ADR). Going from the 10th percentiles to the 90th percentiles in the mean household CDRs (ADRs) then reduces total city income by 10-29% (7-11%).

Overall, going from the 10th percentiles to the 90th percentiles in the CDRs and the ADRs reduces total city income by 19% + 1-3% + 10-29% = 30-51% and 7% + 1-2% + 7-11% = 15-20%. If we believe the district-level effects, the direct and intra-household effects altogether account for 45% of the total effects. If we believe the more conservative PSU-level effects, the direct and intra-household effects account for 55-65% of total effects. City-wide effects are thus large. However, in our main analysis, we do not explore the instantaneous effects of age structure on city economic development. Instead, we study the dynamic 15 year-long effects of age structure on city economic development because this allows us to control for initial city economic development, an important source of endogeneity. Now, if lower incomes translate into less private and public investments, these cities' growth trajectories could be permanently affected.[34]

The effects shown so far are for urban areas only. If we study the direct and indirect

[33] Unfortunately, we do not know for enough countries the cities that the individuals belong to.

[34] If we distinguish 0-9 and 10-14 year-olds and also distinguish 65-74 and 75+ year-olds, we find that younger children (0-9) and older seniors (75+) work and earn significantly less, as well as the working-age adults in their household and their city (not shown, but available upon request).

intra-household effects in rural areas, we find significantly less negative effects (see Web Appendix Table A3 which is structured like Table 9). In other words, children and seniors do not reduce labor supply and earnings as much as in urban areas.[35]

Time Use. Children and seniors reduce labor supply and productivity. Probing deeper, the question arises of how the presence of children and/or seniors, either in the household or in the city more widely speaking, affects the time allocation decisions of working age adults at a more detailed level - i.e. how does their presence influences the allocation of time between working, providing care, sleeping (the lack of which may have detrimental effects on productivity) and leisure?[36] To answer this question we turn to time use surveys for the United States, which are available annually for 2003-2015 (Hofferth et al., 2018).[37] For these samples, we restrict our analysis to "urban" residents and study how household- and city-level CDRs and ADRs affect the number of minutes spent: (i) taking care of relatives ("care time"); (ii) working or investing in education or job training ("work time"); (iii) sleeping; and (iv) enjoying leisure time and other activities. In addition to year-month of interview and day of the week fixed effects, we add the following Mincerian controls: a male dummy, a married dummy, their interaction, the number of years of education and its square, and age and its square. We use as weights the sample weights multiplied by the size of the individual's household. Standard errors are clustered at the household level. Table 10 shows the results. In columns (2), (4), (6) and (8), we add city fixed effects to compare individuals in the same city. Note that, in this case, the city is the metropolitan statistical area (MSA) in which the individual lives. If this is not identifiable, it is the county.

In Panel A, we only include the household-level CDR and ADR measures. As can be seen, the household CDR increases care time mostly at the expense of work and leisure time, with the effect on sleeping time, although significant, only being small. An increase in the household ADR, meanwhile, increases leisure time (including the time

[35] More precisely, the labor force participation effects of columns (1)-(2) are much less negative. For those who work (Col. (7)-(8)), the direct effect of being a child on earnings and the indirect intra-household effect of seniors on the earnings of working-age adults are less negative in rural areas. We do not investigate spillovers in this table since rural populations are not spatially concentrated.

[36] Fatigue has effects on health (Kochanek et al., 2014-12), safety in the workplace (Gold et al., 1992; Lemke et al., 2016) and productivity and cognitive performance (Nuckols et al., 2009). According to Hafner et al. (2017), compared to a worker sleeping between seven and nine hours a day, workers sleeping less than six hours on average lose six working days a year, while those sleeping 6-7 hours lose 3.7 days.

[37] Ideally, we would have liked to have examined time use data for a variety of countries. Unfortunately, however, reliable time use data is difficult to come by, especially for developing countries.

used for other activities) at the expense of work time. These effects are meaningful. For a household of two working-age adults, one more 0-14 year-old child raises the CDR by 0.5, causing reductions of work, leisure and sleep time of 18 minutes, 13 minutes and 3 minutes per day per working-age adult, respectively. Assuming 22 work days per month, this corresponds to 14, 10 and 2 hours per month per household. By contrast, one more senior in a household reduces work time by 9 mins per day per working-age adult (i.e., 7 hours per month per household), whereas care time, somewhat surprisingly, decreases and leisure time increases. However, it could be that leisure time includes spending quality time with ageing parents, another form of "care time".[38]

Next, we find that the direct effects of children are mostly driven by 0-9 year-olds (not shown, but available upon request). Meanwhile, the effects of seniors are driven by 65-74 year-olds. Seniors aged 75 or more do not have measurable effects, possibly because there are private or public facilities targeted at providing care for them.[39]

In Panel B, we add city-level CDR and ADR measures, whether measured at the MSA-county level (col. (1), (3), (5) and (7)) or at the county level (col. (2), (4), (6) and (8)). County-level measures may better capture the effects of children/seniors external to the household. Also note that we add state fixed effects and cluster standard errors at the MSA-county level. Comparing Panels A and B, the intra-household effects are unchanged when adding city-level measures. The city CDR is then associated with more care time and less sleep, but the latter effect is only significant at 15% when the city CDR is defined at the MSA-county level. If all households get one extra child, the city CDR increases by 0.5, and the sleep time cost per working-age adult is 21 mins a day and 16 hours per month per household. It could be that parents wake up earlier to drive their children to school. Likewise, more seniors in the county are associated with more care time, possibly at the expense of work. This latter effect is not significant, although the point estimate is high. Indeed, if seniors have their own housing unit, the city CDR may capture the effect of taking care of one's parents rather than city-wide effects. No matter the source of the area-wide ADR effect, if all households get one extra senior, the care

[38]The effects on work and education/job training are almost driven in their entirety by "work" (not shown, but available upon request). Note that work includes commutes to the workplace. The effects on leisure and other activities are driven by "socializing, relaxing and leisure" (not shown).

[39]Each extra 0-9 year-old child reduce daily work, leisure and sleep time 22, 20, and 4 minutes per day per working-age adult, respectively (not shown, but available upon request). 10-14 year-old children have an effect on work time that is half as large and no effect on sleep or leisure (not shown).

time cost per working-age adult is 20 mins a day and 14 hours per month per household.

6.2. Heterogeneity of the Effects of the Dependency Ratios

Central vs. Peripheral Areas. We study if age structure has intra-city spatial effects. If children/seniors reduce night light intensity, does this reduction occur in more developed, or less developed, areas of the cities? Given that night lights are available at the pixel level for each city (resolution = 30 arc seconds, ≈ 1 km^2), we can re-run our baseline regressions when mean light intensity is obtained using only *central* pixels or *peripheral* pixels. More precisely, for each city, we use the fact that Google Maps reports the central point of each city (e.g., Times Square in New York and the Zocalo in Mexico City). We then classify pixels as central if they are within the bottom 25th percentile in terms of Euclidean distance to that point. Conversely, peripheral areas are pixels beyond (or at) the 25th percentile. As can be seen in Table 11, the effects are not significantly different between central areas (col. (1)-(4)) and peripheral areas (col. (5)-(8)).[40] We also examine effects at the intensive margin vs. the extensive margin, by comparing the effects when mean light intensity is computed using only bright pixels, or dark pixels, in 1996. Web Appendix Table A5 shows that no significant difference is observed when we use the 75th percentile in initial night light intensity to distinguish the two margins.[41]

These results suggest that age structure has across-the-board effects for the whole city. We might have expected children and seniors to disproportionately impact productivity, and thus night lights in the central areas, while increasing the demand for larger houses and retirement communities, which are often found in peripheral areas. However, if residents, and working-age adults in particular, are poorer as a result of the high dependency ratios, both housing and non-housing consumption will be lower on a per capita basis, and peripheral areas may end up as impacted as central areas.

A related question is whether fixing city boundaries to consistently extract mean night light intensity for the whole period may bias our results. This would be the case if city land area was expanding differentially fast when dependency is high. To answer this question, we use European Commission (2018) Global Human Settlement Layer data to obtain land area in 1990 and 2015 for 316 cities in our sample. We then re-run the same

[40] This is true as well if we: (i) Use other percentiles to distinguish central areas and peripheral areas (10, 50, 75, 90); (ii) Use the centroid of the brightest block of 5 x 5 pixels in 1996 or 2011 as an alternative location for the central business district. These results are available on request.

[41] Results are similar if we use other percentiles to distinguish the two margins (10, 25, 50, 90).

regression as before except that the dependent variable is the change in log city land area between 1990 and 2015 and the controls include log city land area in 1990. Web Appendix Table A4 shows that city land area did not vary with the dependency ratios.

Developed vs. Developing Countries. Our framework in Section 1. suggests that the effects of age structure, through the different mechanisms that we have probed above, may depend on various factors such as whether children and seniors are, to some extent, active in the workforce, the availability and cost of caregiving help from outside the household, and the quality of local health systems. This suggests that the effects of children and seniors could differ between developed countries – high-income countries in 1995 according to the World Bank's classification – and developing countries. We interact the CDRs and the ADRs with a dummy equal to one if the city belonged to a developed country in 1995. Columns (1)-(4) in Panel A of Table 12 show that the negative effects of CDRs in developing countries are mitigated in developed countries. This could be because richer countries have public and private facilities that help parents take care of their children. Conversely, the negative effects of seniors are mostly observed in developed countries, possibly because seniors work in poorer countries.

If we use the detailed CDRs and ADRs instead, we find that 65-74 year-olds have relatively more negative effects in developed countries, precisely when the retirement effect matters (not shown, but available upon request). The 75+ year-olds then have relatively more negative effects in developing countries, possibly due to the lack public and private facilities that help working-age adults take care of their old age parents (not shown). Likewise, the negative effects of children in developing countries are driven by young (0-9) children (not shown), for which public/private facilities are essential and since young children almost never work in cities whereas older children may do.[42]

The importance of care systems for parents is also investigated in Web Appendix Table A4. When we interact the CDR and the ADR, the interacted effect tends to be positive. It may be that seniors help working-age adults take care of their children.

Larger vs. Smaller Cities. There are several reasons to expect the effects of children / seniors to be relatively stronger for larger mega-cities. First, workers may work more hours and for a higher wage in larger cities. If they must take care of children/parents, the effects on growth could be magnified. Second, the human capital externality,

[42] Young children are more likely to work in the rural-based agricultural sector.

crowding and public infrastructure effects are likely to be stronger in large cities, because their economies rely on public capital and human capital whereas congestion effects increase with city size. In columns (5)-(8) of Panel A, we interact the dependency ratios with the inverse of the log rank of each city in its respective country's city-size distribution in 1995, so that the interacted effect should be interpreted as the effect of dependency for relatively larger mega-cities. Some of the interacted effects are negative and significant, which could be consistent with age structure being more consequential for larger mega-cities. This would also be consistent with our earlier results for the secondary city sector vs. the mega-city sector. However, these results are not stable across the different specifications, and should thus be taken with caution.

Sectors. Mega-cities could be disproportionately affected by dependency because the sectors that form their economies may be more demanding on workers and permit them less flexibility in their work schedules. The Oxford Economics (2019) database shows the sectoral structure of GDP in 2000 and in 2015 for a sufficiently high number of cities in our sample. While the reliability of this data can be questioned, we use it to examine whether dependency is associated with differential sectoral growth patterns.

We first regress the city GDP share of each sector on log city population in 2000 and find that larger cities rely more on financial and business services (1.78***; N = 341; not shown) while a negative effect is observed for public services (-1.65***; not shown) and agriculture (-0.66***; not shown). The shares of the three other sectors – consumer services, industry, and transportation & communications – do not vary with city size.[43]

Next, in Columns (1)-(4) of Panel B in Table 12, we regress the change in log city GDP per capita for consumer services in 2000-2015 on the CDRs and ADRs in our data circa 2000 (1995-2006). Note that the controls now include log city GDP per capita for consumer services in 2000. As can be seen, the dependency ratios tend to have no effects. Thus, the negative effects of CDRs and ADRs may not be coming from parents and seniors consuming less recreational services than other adults, especially at night. We find, as expected, negative effects for finance and business services (see col. (5)-(8)), while there are mostly no effects for industry (see col. (1)-(4) of Panel C). ADRs are positively correlated with public services (see col. (5)-(8)), which is not surprising

[43] According to the methodology note provided by Oxford Economics (2019), *consumer services* include "wholesaling; retail, hotels & catering, and arts, entertainment, recreation & other services", and *public services* consist of public administration, health and education. The other sectors are self-explanatory.

since it includes health broadly defined. This result could be in line with our proposed channel that cities with seniors invest in less productive public infrastructure.[44]

Summary. The evidence points to the following facts: (i) Direct effects are large, mostly because children and seniors do not work, or when they do, they work fewer hours for a lower wage; (ii) Indirect effects are large too, especially at the city level. However, we do not have the data to distinguish between the three classes of city-wide effects; (iii) These effects affect cities as a whole rather than specific areas; (iv) The effects appear more important for younger children and older seniors and for some sectors.

7. Conclusion

We hypothesized that cities with more working-age adults are likely to grow faster than cities with more children or seniors. Using data from a variety of historical and contemporary sources, we have shown that there exists marked variation in the age structure of the world's largest cities, and that, for a global cross-section of such cities, this variation may matter for economic growth. Hence, our results suggest that mega-cities with more children and/or seniors per working-age adult grow slower. Both direct effects coming from the low earnings of children and seniors, as well as indirect effects at the household and city level, may account for this relationship.

While we adopt several strategies to control for possible sources of endogeneity, we hesitate to claim that our results are truly causal. The effects are also not stable across all specifications, although there may be good reasons for that in some cases. Lastly, while our results on the mechanisms through which a city's age structure may influence its economic growth are suggestive, we are clearly unable to provide a full account and a quantified decomposition of the role of these different mechanisms.

Despite these limitations, our results are suggestive of the importance of a city's age structure for its economic growth. Future research should focus on addressing the limitations of this paper. Such research will help determine whether age structure should be placed alongside agglomeration effects and human capital in terms of its importance as a driver of urban economic growth. Given the markedly young population of many developing country cities and the ageing population of many developed country cities, we believe this constitutes an important research agenda.

[44] For each sector, the controls include log city sectoral GDP per capita in 2000.

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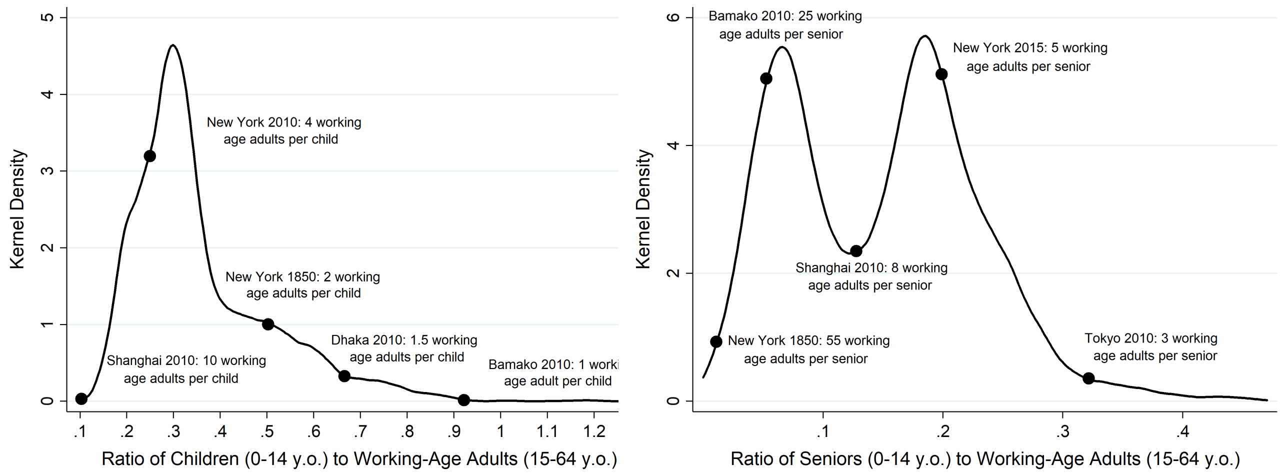
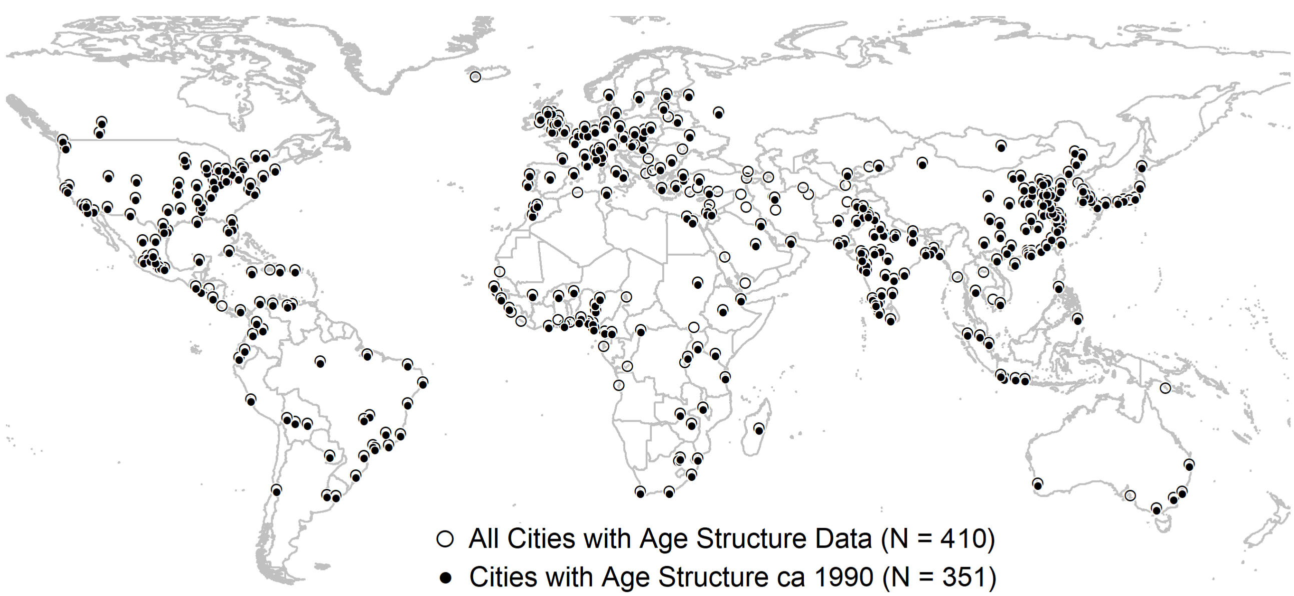
Figure 1: **Kernel Distribution of City Child and Aged Dependency Ratios, 1787-2016**

(a) Child Dependency Ratios **(b)** Aged Dependency Ratios



Notes: Figure 1(a) shows the kernel distribution of city child dependency ratios, the ratio of the number of children (aged 0-14) to the number of working-age adults (aged 15-64), for 4,907 city-years for which data is available (1787-2016). Figure 1(b) shows the kernel distribution of aged child dependency ratios, the ratio of the number of seniors (aged 65+) to the number of working-age adults (aged 15-64), for 4,907 city-years for which data is available (1787-2016). See *Web Appendix* for data sources.

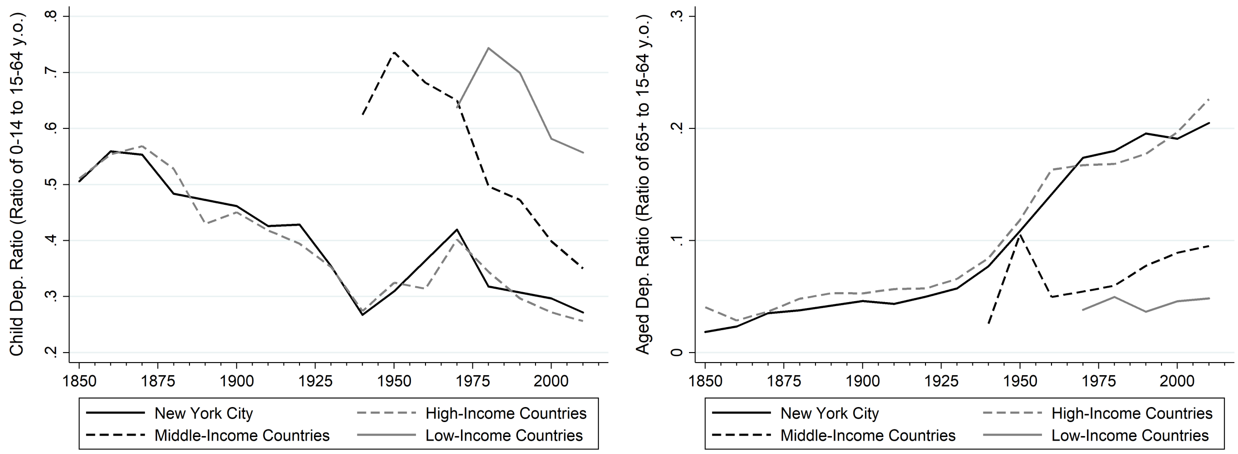
Figure 2: **Sample of Mega-Cities with Age Structure Data, 1787-2016**



Notes: This figure shows as black hollow circles 410 mega-cities for which we have age structure data at any point (1787-2016). The figure also shows as black circles 351 out of these 410 mega-cities for which we have age structure data circa 1990 (1985-1996). "Mega-cities" in our analysis are cities that were among the 500 largest urban agglomerations in 2015 or the 100 largest urban agglomerations in 1900, or capital cities or primate cities in 2015. See *Web Appendix* for data sources.

Figure 3: **Evolution of Mean City Child and Aged Dependency Ratios, 1850-2015**

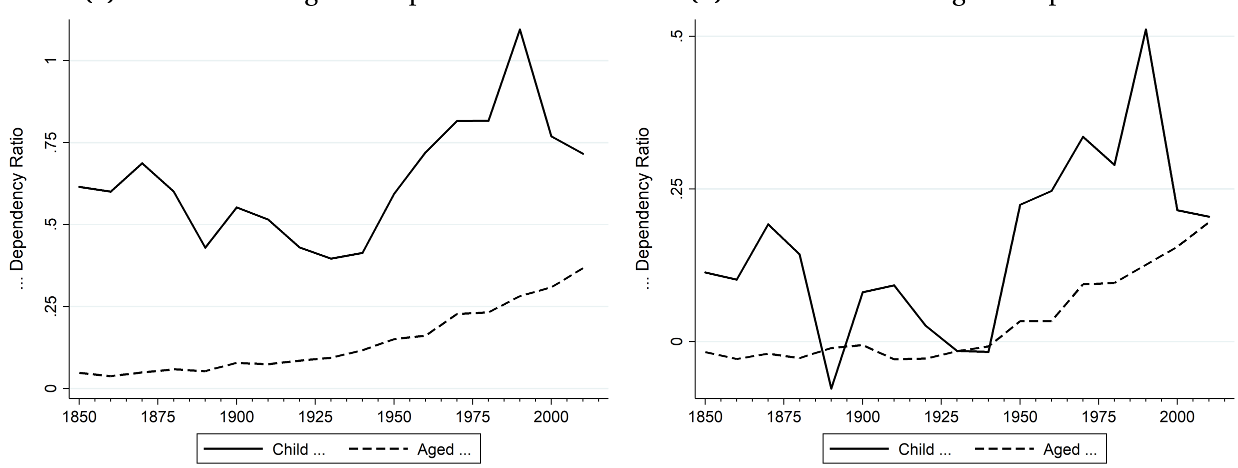
(a) City Child Dependency Ratios **(b)** City Aged Dependency Ratios



Notes: Figure 3(a) shows the evolution of the mean population-weighted child dependency ratios for each income group and decade from 1850 to 2010. The child dependency ratio is the ratio of the number of children (aged 0-14) to the number of working-age adults (aged 15-64). Figure 3(b) shows the evolution of the mean population-weighted aged dependency ratios for each income group and decade from 1850 to 2010. The aged dependency ratio is the ratio of the number of children (aged 65+) to the number of working-age adults (aged 15-64). We use as weights the population of each city in each year. The income groups are based on the classification of the World Bank in 2016. See *Web Appendix* for data sources.

Figure 4: **Evolution of Maximal City Child and Aged Dependency Ratios, 1850-2015**

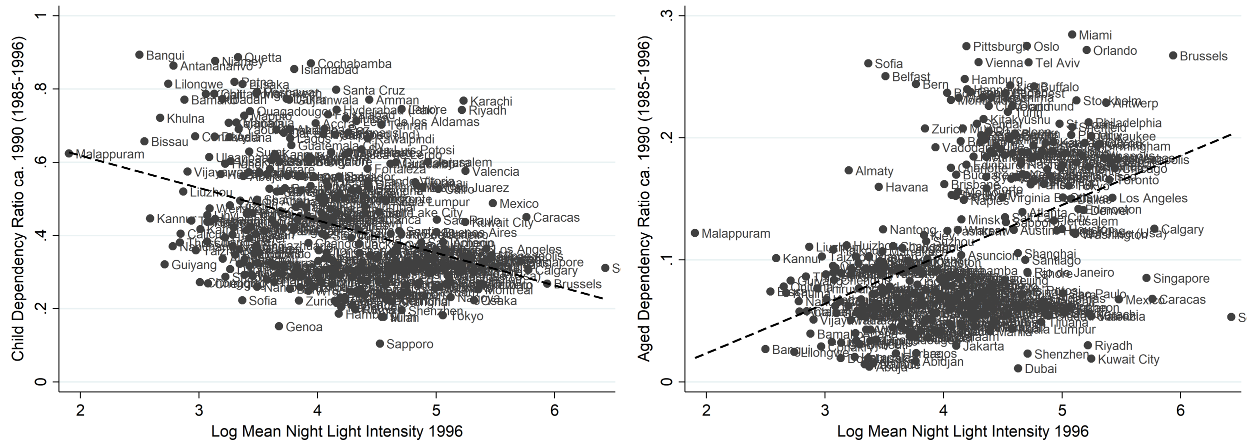
(a) Mean for 10 Highest Dep. Ratios **(b)** Conditional on Log Per Capita GDP



Notes: Figure 4(a) shows the evolution of the mean population-weighted child and aged dependency ratios when only considering the 10 highest ratios for each decade from 1850 to 2010. The child dependency ratio is the ratio of the number of children (aged 0-14) to the number of working-age adults (aged 15-64). The aged dependency ratio is the ratio of the number of children (aged 65+) to the number of working-age adults (aged 15-64). Figure 4(b) shows the same evolutions when the dependency ratios are first regressed on log national per capita GDP (cst 1990 intl dol.) in the same year and the residuals of that regression are used instead of the dependency ratios. See *Web Appendix* for data sources.

Figure 5: City Dependency Ratios and City Economic Development, ca 1990

(a) City Child Dependency Ratios **(b)** City Aged Dependency Ratios



Notes: Figure 5(a) plots for our main econometric sample of 351 cities the relationship between the child dependency ratio, the ratio of the number of children (aged 0-14) to the number of working-age adults (aged 15-64), circa 1990 (1985-1996), and log mean night light intensity, i.e. the sum of night lights per area, in 1996. Figure 5(b) plots for the same sample the relationship between aged dependency ratios circa 1990 (1985-1996), the ratio of the number of seniors (aged 65+) to the number of working-age adults (aged 15-64), and log mean night light intensity in 1996. See *Web Appendix* for data sources.

Figure 6: Evolution of Maximal City Child and Aged Dependency Ratios, All Areas

(a) Child Dependency Ratios **(b)** Aged Dependency Ratios

Notes: Figure 6(a) shows for mega-cities, urban areas and rural areas the evolution of the mean pop.-weighted child dependency ratios when only considering the 10 highest ratios for each decade from 1850 to 2010. The child dependency ratio is the ratio of the number of children (aged 0-14) to the number of working-age adults (aged 15-64). Figure 6(b) shows for mega-cities, urban areas and rural areas the evolution of the mean pop.-weighted aged dependency ratios when only considering the 10 highest ratios for each decade from 1850 to 2010. The aged dependency ratio is the ratio of the number of children (65+) to the number of working-age adults (15-64). See *Web Appendix* for data sources.

Table 1: **City Population Size, Dependency Ratios and Economic Growth**

Dep. Var.:	Δ Log Mean Night Light (NL) Intensity 1996-2011							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total Dep. Ratio 90	-1.11***	-0.86***	-0.09	-0.57*				
	[0.13]	[0.14]	[0.22]	[0.29]				
Child Dep. Ratio 90					-1.12***	-0.86***	-0.12	-0.62**
					[0.13]	[0.14]	[0.24]	[0.28]
Aged Dep. Ratio 90					-1.21***	-1.13***	0.12	-1.03*
					[0.35]	[0.38]	[0.57]	[0.57]
Log Pop. 95	0.07***	0.05**	0.04	0.07**	0.07***	0.05**	0.04	0.06*
	[0.02]	[0.02]	[0.03]	[0.03]	[0.02]	[0.02]	[0.03]	[0.03]
Log Mean NL 96	-0.38***	-0.34***	-0.22***	-0.25***	-0.37***	-0.33***	-0.22***	-0.25***
	[0.03]	[0.04]	[0.05]	[0.05]	[0.04]	[0.04]	[0.05]	[0.05]
Δ Log Pop. 95-10	0.66***	0.64***	0.37***	0.33**	0.66***	0.63***	0.37***	0.28*
	[0.08]	[0.09]	[0.11]	[0.13]	[0.09]	[0.09]	[0.11]	[0.16]
Observations	351	351	351	97	351	351	351	97
Adjusted R2	0.55	0.58	0.76	0.27	0.55	0.58	0.76	0.27
Fixed Effects	N	Cont.	Cntry	N	N	Cont.	Cntry	N
Largest Only	N	N	N	Y	N	N	N	Y

Notes: Regressions for our main sample of 351 agglomerations. The agglomerations belong to 97 countries on 6 continents. Col. (2)-(3) & (6)-(7): Continent and country FE are included, respectively. Col. (4) & (8): We restrict the sample to the largest city of each country. Robust SEs. * p<0.10, ** p<0.05, *** p<0.01.

Table 2: **City Detailed Dependency Ratios and Medium- and Long-Run Growth**

Dep. Var.:	Δ Log Mean NL 1996-2011				Δ Log Mean NL 1996-2003			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CDR 0-9 90	-1.58**	-1.25**	-0.82	-1.97**	-1.53***	-1.29***	-1.29***	-1.35***
	[0.61]	[0.61]	[0.73]	[0.82]	[0.25]	[0.20]	[0.11]	[0.18]
CDR 10-14 90	0.20	-0.03	2.39	2.71	0.63	0.50	2.89***	1.62*
	[1.35]	[1.31]	[1.57]	[1.93]	[1.20]	[1.41]	[0.44]	[0.78]
ADR 65-74 90	6.28***	5.28***	4.39*	2.45	5.05**	4.25**	1.70	2.60
	[2.03]	[2.04]	[2.27]	[1.84]	[1.81]	[1.43]	[2.21]	[1.47]
ADR 75+ 90	-9.46***	-8.34***	-4.67**	-3.82*	-6.60***	-5.79***	-1.64	-3.09**
	[2.23]	[2.22]	[2.04]	[2.19]	[1.62]	[1.36]	[2.50]	[0.82]
Dep. Var.:	Δ Log Mean NL 2003-2011				Δ Log Mean NL 2003-2011			
					Control for Δ Log Mean NL 1996-2003			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
CDR 0-9 90	-0.24	-0.13	0.27	-0.73**	-0.17	-0.11	0.19	-0.69*
	[0.21]	[0.19]	[0.15]	[0.24]	[0.19]	[0.18]	[0.18]	[0.34]
CDR 10-14 90	-0.31	-0.42	-0.12	1.25*	-0.30	-0.39	0.14	1.16
	[0.67]	[0.71]	[0.69]	[0.53]	[0.59]	[0.64]	[0.66]	[0.67]
ADR 65-74 90	2.00	1.64	2.94	0.15	1.61	1.44	3.07	0.00
	[1.09]	[1.11]	[1.88]	[0.88]	[0.80]	[0.85]	[1.80]	[0.60]
ADR 75+ 90	-3.98**	-3.38**	-3.40	-1.12	-3.26**	-3.04**	-3.40*	-0.92*
	[1.19]	[1.24]	[1.70]	[0.69]	[0.84]	[0.99]	[1.48]	[0.38]
Observations	334	334	334	92	334	334	334	92
Core Ctrls	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	N	Cont.	Cntry	N	N	Cont.	Cntry	N
Largest Only	N	N	N	Y	N	N	N	Y

Notes: Regressions for our main sample of 351 agglomerations. The specifications are the same as in Table 1 (see notes for details) except we use population in 2005, mean night light intensity in 2003 and population growth in 2005-2010 as controls in col. (9)-(16). Robust SEs. * p<0.10, ** p<0.05, *** p<0.01.

Table 3: **City Dependency Ratios and Economic Growth, Past Age Structure IVs**

Dep. Var.:	Δ Log Mean Night Light (NL) Intensity 1996-2011								
	IV1: CDR & ADR 60-80			IV2: 5-Yr Pop. Sh. 60-80			IV3: Select 5-Yr Pop. Sh. 60-80		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CDR 90	-1.26**	-1.18**	-1.57*	-0.99***	-0.84**	-1.36*	-1.41**	-1.39**	-3.13**
	[0.50]	[0.53]	[0.96]	[0.37]	[0.35]	[0.73]	[0.56]	[0.63]	[1.40]
ADR 90	-2.36**	-2.12**	-1.49	-1.97**	-1.82**	-0.94	-2.51**	-2.46**	-3.20*
	[0.94]	[0.90]	[1.03]	[0.82]	[0.75]	[0.87]	[1.09]	[1.06]	[1.85]
Obs.	142	142	142	130	130	130	130	130	130
Ctrls	Y	Y	Y	Y	Y	Y	Y	Y	Y
FE	N	Cont.	Cntry	N	Cont.	Cntry	N	Cont.	Cntry
IV F-St.	22.2	20.1	8.8	5.4	5.9	2.6	6.6	4.8	2.4

Notes: Regressions for our main sample of 351 agglomerations. Col. (2), (5) & (8): 6 continent FE are included. Col. (3), (6) & (9): 97 country FE are included. The variables of interest are not the mean CDRs and ADRs in 1985-1996 but the CDRs and ADRs for the closest year to the year 1990 in the 1985-1996 period. IV1: We use the available CDRs and ADRs for the closest year to the year 1960 in the 1960-1980 period. IV2: We use the available 5-year population shares of the city for the closest year to the year 1960 in the 1960-1980 period. IV3: Among the instruments used for IV2, we only keep the population shares for the 5-9, 10-14, 50-54, 55-59 and 60-64 year-olds. Robust SEs. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 4: **City Dependency Ratios and Economic Growth, Conditional IVs**

Dep. Var.:	Δ Log Mean Night Light (NL) Intensity 1996-2011							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A:	IV1: CDR & ADR 60-80 (N = 142)							
CDR	-1.48**	-1.77**	-1.26***	-1.40**	-1.76**	-2.49*	-1.54**	-1.29
	[0.64]	[0.81]	[0.45]	[0.57]	[0.71]	[1.28]	[0.63]	[0.86]
ADR	-1.38*	-1.13*	-1.23**	-1.30**	-2.81**	-2.51**	-1.47*	-1.57*
	[0.71]	[0.61]	[0.63]	[0.65]	[1.29]	[1.25]	[0.85]	[0.85]
IV F-St.	18.2	13.6	33.7	26.0	15.5	7.8	28.0	13.6
Panel B:	IV2: 5-Year Pop. Sh. 60-80 (N = 130)							
CDR	-1.14**	-1.20**	-1.16***	-1.07**	-1.36**	-1.37*	-1.21**	-1.09
	[0.46]	[0.51]	[0.41]	[0.48]	[0.66]	[0.77]	[0.58]	[0.72]
ADR	-1.04	-1.20**	-1.17*	-1.19*	-2.24*	-1.93*	-1.48	-1.53
	[0.69]	[0.60]	[0.67]	[0.62]	[1.17]	[1.09]	[0.94]	[0.97]
IV F-St.	6.4	7.0	8.5	6.3	3.4	3.9	5.7	3.5
Panel C:	IV3: Selected 5-Year Pop. Sh. 60-80 (N = 130)							
CDR	-1.55**	-1.87**	-1.43***	-1.70**	-2.60***	-3.97**	-2.05***	-2.48*
	[0.69]	[0.92]	[0.54]	[0.72]	[1.00]	[1.91]	[0.77]	[1.39]
ADR	-1.32	-1.44*	-1.40*	-1.68**	-4.24**	-4.73**	-3.01**	-3.20*
	[0.88]	[0.76]	[0.84]	[0.84]	[1.71]	[2.20]	[1.42]	[1.67]
IV F-St.	6.011	3.997	7.525	5.151	5.081	3.143	5.193	2.371
Core Ctrls	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	N	Cont.	N	Cont.	N	Cont.	N	Cont.
Controls	pcgdp 60,80,96		fam. plan. 72-82		shares 10 relig. 70		all simultaneously	

Notes: Regressions for our main sample of 351 agglomerations. The IV specifications are the same as in Table 3 (see notes for details). We add as controls log national per capita GDP in 1960, 1980 and 1996 and/or the national family planning index in 1972-1982 and/or the national population shares in 1970 of the 10 main religions in the world (see text for details). Robust SEs. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 5: **City Dep. Ratios & Economic Growth, City College Share & Per Capita GDP**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	Δ Log Mean Light Intensity 1996-2011				Δ Log City Per Capita GDP 1996-2011			
Panel A:	Control: College Share ca. 1990 (1985-1996)				CDRs & ADRs ca. 1990 (1985-1996)			
CDR	-1.12***	-0.90***	0.05	-0.59*	-1.72***	-1.46***	-0.30*	-0.99***
	[0.31]	[0.32]	[0.55]	[0.35]	[0.25]	[0.27]	[0.15]	[0.32]
ADR	-0.86*	-0.93*	0.16	-0.71	0.54	0.62	-0.26	0.09
	[0.48]	[0.54]	[0.60]	[0.71]	[0.44]	[0.45]	[0.34]	[0.55]
Obs.	334	334	334	87	341	341	341	97
Dep. Var.:	Δ Log City Per Capita GDP 1996-2011				Δ Log Mean Light Intensity 1996-2011			
Panel B:	CDRs & ADRs ca. 2000 (1995-2006)				w/o Control for City Pop. Growth			
CDR	-1.44***	-1.43***	-0.68***	-1.46***	-1.21***	-0.96***	-0.22	-0.50**
	[0.18]	[0.18]	[0.25]	[0.32]	[0.15]	[0.16]	[0.26]	[0.25]
ADR	-0.3	-0.27	-0.42	-0.05	-2.45***	-1.62***	-0.01	-1.41**
	[0.30]	[0.28]	[0.37]	[0.57]	[0.35]	[0.39]	[0.58]	[0.58]
	278	278	278	95	351	351	351	97
Core Ctrls	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	N	Cont.	N	Cont.	N	Cont.	N	Cont.

Notes: Panel A & Panel B Col. (1)-(4): Regressions for our main sample of 351 agglomerations. Panel A Col. (5)-(8) & Panel B Col. (1)-(4): Controls include log city pop. in 2000, log city per cap. GDP in 2000 and the change in log city pop. between 2000 and 2015. Robust SEs. * p<0.10, ** p<0.05, *** p<0.01.

Table 6: **City Dependency Ratios and Economic Growth, Panel Regressions**

Dep. Var.:	Δ Log City Per Capita GDP (t-4, t)				
	(1)	(2)	(3)	(4)	(5)
CDR t-4	-0.36***	-0.82***	-0.80***	-1.62***	-0.52**
	[0.10]	[0.25]	[0.25]	[0.36]	[0.24]
CDR t-8		0.45**	0.60***	0.88***	0.44**
		[0.20]	[0.20]	[0.29]	[0.20]
ADR t-4	0.51***	1.09***	0.83**	1.42***	0.21
	[0.19]	[0.36]	[0.33]	[0.51]	[0.27]
ADR t-8		-0.96***	-1.02***	0.21	-0.51*
		[0.33]	[0.37]	[0.62]	[0.29]
Observations	2,700	2,025	2,025	2,025	2,025
Year & City FE, Core Ctrls	yes	yes	yes	yes	yes
Extra Controls	none	none	cont.*year	cntry*year	cont.-year FE

Notes: The sample consists of 675 cities in Oxford Economics (2019) for which we know city per capita GDP and the CDR and ADR ca. 2000, 2004, 2008, 2012 and 2016. If we consider ratios in t-4 (t-4 & t-8), we lose 1 (2) round(s) of data, hence N = 675 × 4 = 2,700 (675 × 3 = 2,205). Year and city FE are always included. Col. (1): The controls include log city pop. in t-4, log city per cap. GDP in t-4 and the change in log city pop. between t-4 and t. Col. (2)-(5): We add log city pop. in t-8, log city per cap. GDP in t-8 and the change in log city pop. between t-8 and t. Robust SEs clustered at the city level. * p<0.10, ** p<0.05, *** p<0.01.

Table 7: **Dependency Ratios, Non-Dependent Population and Economic Growth**

Dep. Var.:	Δ Log Mean Night Light (NL) Intensity 1996-2011							
Controls:	Pop. Sh. of 15-29 & 30-49 ca. 1990				Pop. Sh. of 15-19 , 20-24, 25-29 ... ca. 1990			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Child Dep. Ratio 90	-0.98***	-0.82***	0.06	-0.39	-0.64***	-0.57**	0.68*	-0.76*
	[0.21]	[0.21]	[0.32]	[0.36]	[0.24]	[0.24]	[0.37]	[0.41]
Aged Dep. Ratio 90	-3.15***	-2.31***	0.40	-3.25***	-2.82***	-2.11***	-0.84	-1.82*
	[0.50]	[0.53]	[0.77]	[0.75]	[0.58]	[0.61]	[0.80]	[1.02]
Observations	339	339	339	95	339	339	339	95
Adjusted R2	0.57	0.59	0.77	0.34	0.62	0.63	0.79	0.43
Fixed Effects	N	Cont.	Cntry	N	N	Cont.	Cntry	N
Largest Only	N	N	N	Y	N	N	N	Y

Notes: Regressions for our main sample of 351 agglomerations. Col. (1)-(4): We control for the population shares ca. 1990 (1985-1996) of 15-29 year-olds and 30-49 year-olds among the 15-64 year-olds. Col. (5)-(8): We control for the population shares ca. 1990 of 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54 and 55-59 year-olds among the 15-64 year-olds. Robust SEs. * p<0.10, ** p<0.05, *** p<0.01.

Table 8: **City Dep. Ratios and Growth, Incl. Rural Areas and Secondary Towns**

Dep. Var.:	Δ Log Mean Night Light (NL) Intensity 1996-2011							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CDR	-1.02***	-0.73***	0.03	-0.35*	-1.08***	-0.83***	0.07	-0.48*
	[0.12]	[0.13]	[0.15]	[0.18]	[0.14]	[0.15]	[0.19]	[0.26]
ADR	-1.67***	-1.25***	-0.03	-0.91**	-2.15***	-1.66***	-0.05	-1.28**
	[0.29]	[0.33]	[0.33]	[0.41]	[0.34]	[0.37]	[0.37]	[0.59]
CDR*Rural					0.23	0.30	-0.10	0.21
					[0.35]	[0.33]	[0.27]	[0.37]
CDR*Second.					0.43*	0.54**	-0.06	0.15
					[0.26]	[0.25]	[0.16]	[0.31]
ADR*Rural					1.56	1.30	0.00	0.64
					[0.97]	[0.95]	[0.69]	[0.98]
ADR*Second.					2.11***	1.84***	0.17	0.46
					[0.74]	[0.71]	[0.44]	[0.87]
Obs.	512	512	512	258	512	512	512	258
Core Ctrls	Y	Y	Y	Y	Y	Y	Y	Y
Sect. Dummies	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	N	Cont.	Cntry	N	N	Cont.	Cntry	N
Largest Only	N	N	N	Y	N	N	N	Y

Notes: The sample includes 340 agglomerations of the main sample and as extra observations the secondary city sector and the rural sector of the 86 countries that the 340 agglomerations belong to (N = 340 + 86 + 86 = 512). We always include two dummy variables for whether the observation corresponds to the secondary city sector or the rural sector, and interact them with the child and aged dependency ratios. The effects of the individual sector dummies are not shown. Robust SEs. * p<0.10, ** p<0.05, *** p<0.01.

Table 9: **Direct and Indirect Effects of Children and Seniors on Earnings, I2D2**

Dep. Var.:	Dummy if Works		Log Work Hours		Log Hourly Wage		Log Monthly Wage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A:	Direct Effects (Including All Urban Individuals in the Samples)							
0-14 y.o.	-0.32***	-0.37***	-0.16***	-0.18***	-0.58***	-0.53***	-0.82***	-0.80***
	[0.00]	[0.00]	[0.05]	[0.04]	[0.09]	[0.04]	[0.07]	[0.05]
65+ y.o.	-0.37***	-0.42***	-0.26***	-0.28***	-0.09***	-0.09***	-0.36***	-0.38***
	[0.00]	[0.00]	[0.01]	[0.00]	[0.01]	[0.01]	[0.01]	[0.00]
Obs. (000s)	38,076	15,549	15,625	6,846	12,875	6,335	13,139	6,392
Adj. R2	0.30	0.34	0.14	0.16	0.91	0.85	0.91	0.83
Num. Country	122	52	122	52	122	52	122	52
Num. Sample	835	222	835	222	835	222	835	222
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Core Controls	Y	Y	Y	Y	Y	Y	Y	Y
Cntry-Dist. FE	N	Y	N	Y	N	Y	N	Y
Panel B:	Indirect Intra-Household Effects (Restricting to Urban Work.-Age Adults (15-64 y.o.))							
HH CDR	-0.02**	-0.04***	-0.04***	-0.04***	-0.05***	0.01**	-0.09***	-0.02***
	[0.01]	[0.00]	[0.01]	[0.00]	[0.02]	[0.01]	[0.01]	[0.00]
HH ADR	-0.05***	-0.03***	-0.01	-0.01	-0.06***	-0.05***	-0.07***	-0.06***
	[0.01]	[0.00]	[0.01]	[0.01]	[0.02]	[0.01]	[0.01]	[0.01]
Obs. (000s)	27,530	10,790	12,435	6,093	12,435	6,093	12,691	6,148
Adj. R2	0.17	0.25	0.2	0.08	0.96	0.86	0.95	0.85
Num. Country	121	52	121	52	121	52	121	52
Num. Sample	829	222	829	222	829	222	829	222
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Core Controls	Y	Y	Y	Y	Y	Y	Y	Y
Cntry-Dist. FE	N	Y	N	Y	N	Y	N	Y
Panel C:	Indirect City-Wide Effects (Restricting to Urban Work.-Age Adults (15-64 y.o.))							
HH CDR	-0.05***	-0.01***	-0.03***	-0.05**	0.00	0.03	-0.02***	-0.02
	[0.00]	[0.00]	[0.00]	[0.02]	[0.00]	[0.03]	[0.00]	[0.01]
HH ADR	-0.06***	0.01	-0.02***	-0.00	-0.08***	-0.02	-0.10***	-0.02
	[0.00]	[0.02]	[0.00]	[0.02]	[0.01]	[0.03]	[0.01]	[0.03]
Local CDR	-0.07***	-0.08***	-0.11***	-0.16*	-0.44***	0.02	-0.55***	-0.14
	[0.02]	[0.02]	[0.04]	[0.09]	[0.10]	[0.18]	[0.10]	[0.11]
Local ADR	-0.02	-0.31***	-0.09**	-0.22	-0.56***	0.01	-0.66***	-0.20
	[0.03]	[0.05]	[0.04]	[0.32]	[0.11]	[0.76]	[0.12]	[0.45]
"Local" Level	Dist.	PSU	Dist.	PSU	Dist.	PSU	Dist.	PSU
Obs. (000s)	6,818	1,590	4,183	599	4,183	599	4,222	639
Adj. R2	0.24	0.20	0.14	0.16	0.85	0.82	0.83	0.87
Num. Country	24	34	24	34	24	34	24	34
Num. Sample	68	116	68	116	68	116	68	116
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Core Controls	Y	Y	Y	Y	Y	Y	Y	Y

Notes: We restrict the analysis to individuals classified as "urban" in the samples. We include country-year sample FE in all regressions. The core controls in Panel A include a male dummy, a married dummy, their interaction, and the number of years of education and its square. In Panels B and C, we also add age and age squared. Col. (2), (4), (5) and (8) in Panels A and B: We include sample-district FE. We call "districts" the third-level administrative unit of the country (when not available, we use second-level administrative units). Panel A: We use as weights the weights provided by each sample. Panels B and C: We use as weights the sample weights multiplied by the size of the individual's household. Robust SEs clustered at the household level in Panels A and B and at the district level in Panel C. * p<0.10, ** p<0.05, *** p<0.01.

Table 10: **Direct and Indirect Effects of Children and Seniors on Time Use for the U.S.**

Dep. Var.:	Number of Minutes Spent Per Day on ... During the Week (Monday-Friday)							
	Personal Care of Relatives		Work, Education or Job Training		Sleep		Leisure & Other Activ.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A:	Indirect Intra-Household Effects (Restricting to Urban Work.-Age Adults (15-64 y.o.))							
HH CDR	67.8***	67.8***	-35.4***	-35.9***	-5.5***	-5.3***	-26.9***	-26.7***
	[1.9]	[1.9]	[2.4]	[2.4]	[1.4]	[1.4]	[2.1]	[2.0]
HH ADR	-10.9**	-10.1**	-18.5**	-17.0**	7.3	6.8	22.1***	20.3***
	[4.5]	[4.3]	[7.9]	[7.7]	[4.6]	[4.6]	[6.8]	[6.4]
Core Ctrls	Y	Y	Y	Y	Y	Y	Y	Y
MSA-County FE	N	Y	N	Y	N	Y	N	Y
Obs.	57,956	57,956	57,956	57,956	57,956	57,956	57,956	57,956
Adj. R2	0.26	0.26	0.20	0.21	0.10	0.11	0.12	0.13
Panel B:	Indirect City-Wide Effects (Restricting to Urban Work.-Age Adults (15-64 y.o.))							
HH CDR	67.7***	67.7***	-36.0***	-36.1***	-5.2***	-5.2***	-26.5***	-26.4***
	[2.1]	[2.1]	[2.5]	[2.5]	[1.2]	[1.2]	[2.3]	[2.3]
HH ADR	-10.6**	-10.7**	-18.0**	-18.1**	7.2	7.2	21.5***	21.5***
	[4.5]	[4.5]	[7.4]	[7.4]	[4.9]	[4.8]	[6.7]	[6.7]
Local CDR	41.8*	38.8*	-0.9	33.2	-29.3	-42.8*	-11.6	-29.3
	[24.0]	[20.6]	[39.3]	[38.2]	[19.1]	[21.8]	[31.6]	[26.9]
Local ADR	14.3	39.3*	-31.6	-45.6	-8.6	-17.6	25.9	24.0
	[20.3]	[22.5]	[36.1]	[41.4]	[19.7]	[21.7]	[30.3]	[36.0]
Core Ctrls	Y	Y	Y	Y	Y	Y	Y	Y
"Local" Level	MSA	county	MSA	county	MSA	county	MSA	county
Obs.	57,956	57,956	57,956	57,956	57,956	57,956	57,956	57,956
Adj. R2	0.26	0.26	0.20	0.20	0.10	0.10	0.13	0.13

Notes: We restrict the analysis to individuals belonging to any MSA in the samples. We include year-month of interview FE in all regressions. The core controls include a male dummy, a married dummy, their interaction, the number of years of education and its square, age and its square, and day of the week FE. We use as weights the sample weights multiplied by the size of the individual's household. Robust SEs clustered at the household level in Panel A and at the MSA or county level in Panel B. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 11: **City Dep. Ratios and Growth, Central vs. Peripheral Areas**

Dep. Var.:	Δ Log Mean Night Light (NL) Intensity 1996-2011							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Central: < 25th Pctile Dist. CBD				*Peripheral:* ≥ 25th Pctile Dist. CBD			
CDR	-1.13***	-0.83***	0.11	-0.64**	-1.01***	-0.80***	-0.35	-0.52
	[0.14]	[0.15]	[0.26]	[0.25]	[0.15]	[0.16]	[0.27]	[0.36]
ADR	-1.57***	-1.37***	0.20	-0.93*	-1.19***	-1.26***	-0.09	-1.14*
	[0.35]	[0.39]	[0.62]	[0.55]	[0.38]	[0.43]	[0.60]	[0.68]
Observations	351	351	351	97	351	351	351	97
Core Ctrls	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	N	Cont.	Cntry	N	N	Cont.	Cntry	N
Largest Only	N	N	N	Y	N	N	N	Y

Notes: Regressions for our main sample of 351 cities. We study how mean night light intensity varies if we only consider pixels that correspond to the cities' central areas vs. their peripheral areas, based on the Euclidean distance of the pixels to the central point of the cities. Robust SEs. * p<0.10, ** p<0.05, *** p<0.01.

Table 12: **City Dep. Ratios and Growth, Other Mechanisms**

Dep. Var.:	Δ Log Mean Night Light (NL) Intensity 1996-2011							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A:	By Development Status (devD) 1995				By Country-Specific Minus Log Rank 1995			
CDR	-1.09**	-0.96**	-0.20**	-0.45**	-1.21***	-0.85***	0.13	-0.64**
	[0.28]	[0.37]	[0.07]	[0.17]	[0.13]	[0.16]	[0.33]	[0.29]
ADR	1.92	1.23	0.53	1.09**	-1.42***	-2.31***	-0.96	-1.07*
	[1.49]	[1.52]	[1.31]	[0.33]	[0.37]	[0.44]	[0.61]	[0.57]
CDR*devD | -Rank	1.25**	1.50***	1.00**	0.46**	-0.13***	-0.05	0.09	0.24
	[0.34]	[0.31]	[0.29]	[0.16]	[0.04]	[0.05]	[0.10]	[0.18]
ADR*devD | -Rank	-3.09*	-2.08	-0.2	-2.87***	0.00	-0.53***	-0.44**	-9.06***
	[1.51]	[1.51]	[1.39]	[0.35]	[0.12]	[0.14]	[0.19]	[2.63]
Obs.	351	351	351	97	351	351	351	97
Panel B:	Δ Log City Consumer Serv. GDP PC				Δ Log City Fin. & Bus. Serv. GDP PC			
CDR 00	-0.16	-0.11	-0.20	-0.01	-0.53***	-0.55***	0.17	-0.48**
	[0.12]	[0.13]	[0.23]	[0.18]	[0.15]	[0.16]	[0.29]	[0.21]
ADR 00	-0.02	-0.16	0.52*	0.17	-0.54**	-0.80***	0.00	-0.83
	[0.19]	[0.20]	[0.31]	[0.43]	[0.25]	[0.24]	[0.40]	[0.52]
Obs.	278	278	278	95	278	278	278	95
Panel C:	Δ Log City Industry GDP PC				Δ Log City Public Serv. GDP PC			
CDR 00	0.08	0.06	0.26	0.44**	0.18	0.04	-0.13	0.18
	[0.12]	[0.14]	[0.23]	[0.17]	[0.17]	[0.17]	[0.25]	[0.34]
ADR 00	-0.06	-0.06	-0.55	0.38	0.78***	0.86***	0.74*	0.27
	[0.24]	[0.27]	[0.45]	[0.45]	[0.25]	[0.25]	[0.44]	[0.57]
Obs.	278	278	278	95	278	278	278	95
Core Ctrls	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	N	Cont.	Cntry	N	N	Cont.	Cntry	N
Largest Only	N	N	N	Y	N	N	N	Y

Notes: Main sample of 351 cities. Panel A Col. (1)-(4): We interact the ratios with a dummy if the country was a "high-income" country in 1995 (we interact the controls with the dummy). Panel A Col. (5)-(8): We interact the ratios with the inverse of the sample-specific rank of each city in their own country in 1995. Panels B-C: Dep. var. = change in log city GDP per cap. for each sector. Robust SEs. * p<0.10, ** p<0.05, *** p<0.01.

WEB APPENDIX: NOT FOR PUBLICATION

Figure A1: **Number of City-Decade Observations with Available Dependency Ratios**

Notes: This figure shows for each income group of countries (defined ca. 2015) the evolution of the total number of city-decade observations for which we have data on the child and aged dependency ratios. See *Web Appendix* for data sources.

WEB APPENDIX: NOT FOR PUBLICATION

Table A1: **Evolution of City Child and Aged Dependency Ratios, Robustness**

	Coefficient of Correlation with the Baseline Evolution			
Evolution:	Means for Each Income Group		Mean of 10 Highest Ratios	
	(1)	(2)	(3)	(4)
Dependency Ratio:	Child	Aged	Child	Aged
1. Conditional on Log City Pop.	0.99	0.98	0.98	0.98
2. Keep Census-Based	0.99	0.98	0.94	0.97
3. Drop if Appears 1x Only	1.00	1.00	0.97	1.00
4. Drop if Appears 2x or Less	1.00	1.00	0.93	1.00
5. Drop if Appears 3x or Less	0.99	0.99	0.83	0.99
6. No Pop. Weights	0.97	1.00	0.98	1.00
7. w/o Top Bottom 5% in Ratios	0.86	0.99	0.82	0.99
8. Drop if Africa	0.91	0.99	0.92	1.00
9. Drop if Asia	1.00	0.99	1.00	1.00
10. Drop if Europe	0.97	0.97	0.99	0.97
11. Drop if North America	0.97	0.99	0.85	0.98
12. Drop if South America	1.00	1.00	0.96	1.00
13. Drop if Oceania	1.00	1.00	1.00	1.00
Observations	20-26	20-26	15	15

Notes: Columns (1)-(2) show the population-weighted mean child and aged dependency ratios for each income group-decade. We restrict the analysis to decade with at least five city-decade observations. Columns (3)-(4) show for each decade the population-weighted mean child and aged dependency ratios when considering the 10 highest ratios in the decade. The mean population of each city in each decade is used as weights. In row 1, we first regress the dependency ratios on log city populations and then use the means of the residuals in each decade. In row 2, we only keep census-based city observations. In rows 3-5, we drop the cities for which we have data in 1, 2 or 3 or fewer decades. In row 6, population weights are not used. In row 7, we drop the top and bottom 5% in dependency ratios in the full sample of city-years. In rows 8-13, we drop each continent one by one.

Table A2: **Descriptive Statistics for the Main Econometric Sample**

Main Variable:	Obs	Mean	Std. Dev.	Min	Max
Δ Log Mean NL 95-10	351	0.28	0.51	-0.74	2.03
Log Pop. 95	351	14.32	0.84	12.33	17.33
Log Mean NL 96	351	4.11	0.72	1.90	6.43
Δ Log Pop. 95-10	351	0.36	0.30	-0.22	1.61
TDR 90	351	0.55	0.16	0.22	1.37
CDR 90	351	0.44	0.19	0.10	1.29
ADR 90	351	0.11	0.07	0.01	0.35
CDR 0-9 90	341	0.29	0.12	0.10	0.73
CDR 10-14 90	341	0.14	0.05	0.05	0.29
ADR 65-74 90	340	0.07	0.04	0.01	0.19
ADR 75+ 90	335	0.04	0.03	0.00	0.16

WEB APPENDIX: NOT FOR PUBLICATION

Table A3: **Effects of Children and Seniors on Earnings, I2D2, Rural Obs. Only**

Dep. Var.:	Dummy if Works		Log Work Hours		Log Hourly Wage		Log Monthly Wage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A:	Direct Effects (Including Only Rural Individuals in the Samples)							
0-14 y.o.	-0.16***	-0.21***	-0.07	-0.31***	-0.28**	-0.10	-0.61***	-0.69***
	[0.00]	[0.00]	[0.07]	[0.10]	[0.11]	[0.14]	[0.08]	[0.10]
65+ y.o.	-0.19***	-0.26***	-0.17***	-0.25***	-0.17***	-0.17***	-0.38***	-0.45***
	[0.00]	[0.00]	[0.02]	[0.01]	[0.02]	[0.02]	[0.02]	[0.02]
Obs. (000s)	21,178	8,294	10,863	3,414	5,874	2,584	6,048	2,621
Adj. R2	0.23	0.27	0.18	0.17	0.85	0.78	0.86	0.80
Num. Country	119	51	118	51	118	51	118	51
Num. Sample	772	177	771	177	771	177	771	177
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Core Controls	Y	Y	Y	Y	Y	Y	Y	Y
Cntry-Dist. FE	N	Y	N	Y	N	Y	N	Y
Panel B:	Indirect Intra-Household Effects (Restricting to Rural Work.-Age Adults (15-64 y.o.))							
HH CDR	-0.01	-0.02***	-0.04***	-0.05***	-0.02	0.01	-0.08***	-0.04**
	[0.01]	[0.04]	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]	[0.02]
HH ADR	-0.02**	-0.02	-0.02	-0.04	0.01	0.01	0.02	-0.02
	[0.01]	[0.01]	[0.02]	[0.03]	[0.03]	[0.05]	[0.03]	[0.04]
Obs. (000s)	18,624	5,389	5,579	2,434	5,579	2,434	5,745	2,469
Adj. R2	0.19	0.26	0.21	0.09	0.95	0.71	0.97	0.73
Num. Country	119	51	118	51	118	51	118	51
Num. Sample	767	177	766	177	766	177	766	177

Notes: We restrict the analysis to individuals classified as "rural" in the samples. We include country-year sample fixed effects in all regressions. The core controls in Panel A include a male dummy, a married dummy, their interaction, and the number of years of education and its square. In Panel B, we also add age and age squared. Col. (2), (4), (5) and (8) in Panels A and B: We also include sample-district fixed effects. We call "districts" the third-level administrative unit of the country (when not available, we use second-level administrative units of the countryu). Panel A: We use as weights the weights provided by each sample. Panel B: We use as weights the sample weights multiplied by the size of the individual's household. Robust SEs clustered at the household level in Panels A and B. * p<0.10, ** p<0.05, *** p<0.01.

WEB APPENDIX: NOT FOR PUBLICATION

Table A4: **City Dependency Ratios and Growth, Other Mechanisms**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	Dep. Var.: Δ Log Area 1990-2015				Δ Log Mean Night Lights 1996-2011			
					Complementarities btw CDR & ADR			
CDR	0.15	0.11	-0.19	-0.04	-1.63***	-1.52***	-0.05	-0.79**
	[0.10]	[0.10]	[0.24]	[0.28]	[0.18]	[0.22]	[0.43]	[0.38]
ADR	0.37	0.29	-0.6	-0.3	-3.66***	-4.25***	0.42	-1.94*
	[0.26]	[0.27]	[0.54]	[0.50]	[0.66]	[0.83]	[1.36]	[1.14]
CDR*ADR					7.86***	9.69***	-0.89	3.39
					[2.26]	[2.74]	[3.89]	[4.01]
Obs.	316	316	316	95	351	351	351	97
Core Ctrls	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	N	Cont.	Cntry	N	N	Cont.	Cntry	N
Largest Only	N	N	N	Y	N	N	N	Y

Notes: Regressions for our main sample of 351 cities. Col. (1)-(4): The dependent variable is the change in log city area between 1990 and 2015. We always control for log city area in 1990. Col. (5)-(8): We interact the child and aged dependency ratios ca. 1990. Robust SEs. * p<0.10, ** p<0.05, *** p<0.01.

Table A5: **City Dep. Ratios and Growth, Developed vs. Less Developed Areas**

Dep. Var.:	Δ Log Mean Night Light (NL) Intensity 1996-2011							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Brighter: ≥ 75th Pctile Lights 1996				*Darker:* < 75th Pctile Lights 1996			
CDR	-1.01***	-0.74***	-0.12	-0.48	-1.10***	-0.85***	-0.04	-0.44*
	[0.14]	[0.15]	[0.25]	[0.35]	[0.15]	[0.16]	[0.30]	[0.26]
ADR	-1.43***	-1.44***	0.10	-0.97	-1.72***	-1.54***	-0.24	-0.72
	[0.39]	[0.45]	[0.62]	[0.68]	[0.33]	[0.35]	[0.47]	[0.60]
	350	350	350	97	323	323	323	97
Core Ctrls	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	N	Cont.	Cntry	N	N	Cont.	Cntry	N
Largest Only	N	N	N	Y	N	N	N	Y

Notes: Regressions for our main sample of 351 agglomerations. We study how city mean night light intensity varies if we only consider pixels that correspond to the cities' developed areas vs. their less developed areas, based on the initial level of pixel night lights in 1996. Robust SEs. * p<0.10, ** p<0.05, *** p<0.01.