Cities of Workers, Children or Seniors? Stylized Facts and Possible Implications for Growth in a Global Sample of Cities

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Abstract

A large literature documents how cities vary in their skill structure and how this has implications for their economic growth. By contrast, how cities vary in their age structure and the potential implications of this for their economic growth has been a hitherto largely neglected research area. Using novel data from a variety of historical and contemporary sources, we first show that there is 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 and find that mega-cities with higher dependency ratios - i.e. with more children and/or seniors per working-age adult - grow slower. Overall, and despite the many data and econometric challenges posed by this type of analysis, we advocate for more research on the subject given its importance.

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.

To put this into context, Shanghai has ten working-age adults (i.e. adults aged 15-64) per child and New York four per child, making them *cities of workers*. By contrast, Dhaka and Bamako, with 1.5 and one working-age adult per child respectively, are *cities of children*. Likewise, some cities have high numbers of seniors (aged 65 or more) per working-age adult. Tokyo, for example, has three working-age adults per senior, making it, and other cities with large numbers of seniors per working-age adult, *cities of seniors*.

Having high shares of children and/or seniors could impact a city's economic growth through a variety of channels. Cities of children and seniors have, by definition, relatively fewer working-age adults who can generate output, which, in turn, leads to fewer resources for investment in both physical and human capital. 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. At a city-wide level, a relatively greater number of children and/or seniors may, for example, lead to fewer knowledge spillovers and contribute to the crowding of schools and hospitals and skew the allocation of public finance in ways that may 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 may exhibit slower economic growth.

Our analysis has three steps. First, we use historical and contemporary sources to construct a new data set on the age structure of the world's largest cities for multiple time points over the past 200 years. We use this data set to document 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 sample of about 350 mega-cities. By choosing to work with a broad global sample of cities rather than a single country we are able to capture all three types of cities – cities of workers, cities of children, and cities of seniors. We find that cities whose age structures are relatively skewed towards either more children or more seniors tend to experience slower economic growth. To obtain more robust estimates, we control for core city characteristics that could explain both age structure and economic growth. As expected, the negative effects of age structure on city economic growth are driven by younger children (age 0-9) and older seniors (age 75 plus). By contrast, older children (age 10-14) and younger seniors (age 65-74) have either no significant or even a positive effect on a city's subsequent economic growth. For older children, this is consistent with the timing of their entry into the workforce, while, for younger seniors, it could be consistent with increased consumption expenditure on leisure activities in the years immediately following retirement.

Third, 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 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 some evidence for indirect effects at the household and city levels. Finally, we find possibly stronger effects for larger cities than for secondary cities or rural areas, and the largest cities among the larger cities, as well as for finance and business services compared to other urban sectors such as public services. This suggests that a higher share of children and/or seniors in a city might potentially impact a city's sectors and economic trajectory through specific "urban" mechanisms, for example human capital externalities.

Finally, despite our best efforts, we cannot be entirely sure that our results on the effect of a city's age structure on its economic growth are causal. Data scarcity issues also constrain our analysis. As such, our findings should be treated with caution. More generally, we view the role of this study as being to raise the, not previously addressed, question of whether age structure could be placed alongside agglomeration effects and human capital in terms of its importance as a driver of urban economic growth.

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 and city productivity or city growth (Ciccone and Hall, 1996; Duranton and Puga, 2004; Glaeser and Gottlieb, 2009; Combes et al., 2012; Duranton and Puga, 2014; Combes and Gobillon, 2015; De La 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; De La Roca and Puga, 2017).[1] The papers on agglomeration economies find that productivity, whether measured by nominal wages or total factor productivity, not to mention measures of firm creation and innovation, improve with city population size and/or density. They intentionally ignore the composition of a city's population, since their interest is in identifying a pure scale effect. Papers on human capital spillovers, 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.

There are far fewer studies of the role of working age adults, who are more likely to be workers, versus children and seniors, who are less likely to be workers. If children have less human capital and seniors have human capital that goes unused, our focus on age structure refines the analysis of the nexus between human capital and growth in cities.

The second literature to which our paper contributes is the "urbanization without growth" literature. Historically, urbanization has gone hand in hand with economic growth. 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, after the Second World War, the world's most rapidly growing cities, in terms of population, have been in developing countries (Fay and Opal, 2000; Glaeser, 2014; Jedwab and Vollrath, 2015; Jedwab et al., 2019). Explanations for this phenomenon 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 openness (Glaeser, 2014; Gollin et al., 2015), and institutions (Henderson et al., 2016b).

A third strand in the literature provides a demographic explanation by focusing on

[1] There is also a literature for developing countries only (Duranton, 2016; Chauvin et al., 2017; Combes et al., 2017; Quintero and Roberts, 2018; Henderson et al., 2018; Dingel et al., 2019; Bosker et al., 2020).

the role of natural population growth in driving poor country urbanization (e.g., Dyson, 2011; Jedwab et al., 2015; Jedwab and Vollrath, 2018; Castells-Quintana and Wenban-Smith, 2020). Studies in that strand examine the effects of higher total population levels, rather than the specific effects of the demographic composition of cities. More generally, we contribute to the literature on demographics and economic development (e.g., Srinivasan, 1988; Brander and Dowrick, 1994; Weil, 1997, 1999; Ahituv, 2001; Kelley and Schmidt, 2005; Kogel, 2005; Klasen and Nestmann, 2006; Feyrer, 2007; Bloom et al., 2007; Hock and Weil, 2012; Zhang et al., 2015; Birchenall, 2016). However, most of these studies examine the country-level effects of population growth (or fertility and mortality) on economic growth (and sometimes the population share of working-age adults) whereas we investigate the city-level effects of child and aged dependency ratios (controlling for city population growth, and thus its effects). While some of these studies also find negative effects of dependency ratios on growth (e.g., Weil, 1999; Kogel, 2005; Bloom et al., 2007; Hock and Weil, 2012; Zhang et al., 2015), their theoretical or empirical estimates capture effects for *all* locations of the economy – i.e., urban and rural areas – as well as aggregate effects across locations.[2] In addition, we find possibly stronger effects for larger cities than for other locations, which shows the importance of analyzing such relationships for cities. As such, our estimates are also not directly comparable with other studies' estimates that rely on national data.

The remainder of the paper is organized as follows. Section 1 provides a framework to help understand how a city's age structure may affect its economic development. Section 2 describes our global data set on city age structures and economic growth. Section 3 establishes novel stylized facts. Section 4 presents our main results. Section 5 includes a discussion of suggestive evidence on mechanisms. Section 6 concludes.

1. Framework: City Age Structure and Economic Growth

To understand the channels through which a city's age structure might affect its growth rate of real GDP per capita, we discuss a model adapted from Mankiw et al. (1992).

[2]Their specification is also different. Bloom et al. (2007) studies the country-level effects of the log of the working age share and do not distinguish the effects of children and seniors. Kogel (2005) examines the country-level effects of the log of the child dependency ratio on TFP growth, not growth in general. Zhang et al. (2015) study the effects of increased population shares of children and seniors for Chinese provinces, but not the dependency ratios, which directly limits comparability.

1.1. Model and Derivation of Estimating Equation

Assume a simple closed economy growth framework in which: (i) labor (L), human capital (H) and technology (A) are the three inputs into a city's production; (ii) the share of the population (P) that is of working-age is an exogenous constant (w); and (iii) due to the presence of human capital externalities, technology at the aggregate city level is a positive endogenous function of human capital, $A = \overline{A}H^{\gamma}$, where $\gamma > 0$. Further assume that a constant, exogenously determined, proportion of a city's income (s_H) is saved for investment in human capital, that human capital depreciates at the exogenous rate δ, and that population grows at the exogenous rate n.

Based on these assumptions, a city's output, Y, can be written as:

$$Y = AH^{\alpha}L^{\beta} = AH^{\alpha}(wP)^{\beta} = \overline{A}H^{\alpha+\gamma}(wP)^{\beta} \tag{1}$$

Assume $\beta = 1 - \alpha - \gamma$ so that, even in the presence of human capital externalities, constant returns to scale prevail at the level of aggregate city production.[3] This allows us to re-write a city's production function in equation (1) in per capita terms as follows:

$$y = Y/P = \overline{A}H^{\alpha+\gamma}(wP)^{1-\alpha-\gamma}P^{-1} = \overline{A}h^{\alpha+\gamma}w^{1-\alpha-\gamma} \tag{2}$$

where $h = (H/P)$ is human capital per person. In this equation, a city's output per person depends positively on both its human capital per person and the share of its population that is of working-age.

The dynamics of the city's human capital accumulation are given as follows:

$$\dot{H} = s_H Y - \delta H \tag{3}$$

While it follows from the quotient rule of differentiation that the accumulation of human capital per person is governed by:

$$\dot{h} = (\frac{\dot{H}}{P}) - nh \tag{4}$$

Substituting (3) into (4) yields:

$$\dot{h} = s_H y - (n + \delta)h \tag{5}$$

This equation implies that for a city's stock of human capital per person to increase, it must be investing more per person in human capital than is required to offset both the

[3]This makes the growth framework "semi-endogenous" (Jones, 1995). Aggregate technology accumulation is endogenously determined, but because constant returns prevail at the aggregate city level, growth in income per person ultimately grinds to a halt in the absence of an exogenous driving force.

depreciation of human capital and population growth. In this context, $(n+\delta)$ is the rate of effective depreciation of human capital per person. Using (2), (5) can be re-written as:

$$\dot{h} = s_H \overline{A} h^{\alpha+\gamma} w^{1-\alpha-\gamma} - (n+\delta)h \tag{6}$$

Equation (6) is the fundamental differential equation of the model.[4] This can be solved for the steady-state value of h (h^*):

$$h^* = w(\frac{s_H \overline{A}}{n+\delta})^{1/(1-\alpha-\gamma)} \tag{7}$$

By substituting (7) into (2), we can also solve for the city's steady-state level of income per person (y^*):

$$y^* = \overline{A}(h^*)^{(\alpha+\gamma)} w^{1-\alpha-\gamma} = w\overline{A}^{1/(1-\alpha+\gamma)}(\frac{s_H}{n+\delta})^{(\alpha+\gamma)/(1-\alpha-\gamma)} \tag{8}$$

In other words, a city's steady-state income per person is an increasing function of the share of its population that is of working-age w, the technology parameter $\overline{A}$, and its rate of savings for human capital accumulation s_H. Meanwhile, it is a negative function of the rate of effective depreciation of human capital, $(n+\delta)$. Steady-state income per capita is also increasing in γ, which measures the strength of human capital externalities.

When the city is out of steady-state, we can, following Mankiw et al. (1992) and Barro and i Martin (2003), derive the rate of convergence towards the steady-state by using a first-order Taylor series approximation of (6) around the steady-state:

$$\dot{h} = (\frac{\delta \dot{h}}{\delta h})(h - h^*) \tag{9}$$

Which, by differentiating (6) with respect to h and evaluating at h^*, can be re-written as:

$$\dot{h} = -(1-\alpha-\gamma)(n+\delta)(h-h^*) = -\lambda(h-h^*) \tag{10}$$

Where $\lambda = (1-\alpha-\gamma)(n+\delta)$ is the speed of convergence – i.e. the speed at which h approaches its steady-state value, h^*.

Following Mankiw et al. (1992), the evolution of the natural log of income per person can be written as:[5]

[4]The fact that this equation is less than linear in h implies the existence of a steady-state solution. If we assumed $\alpha+\gamma=1$, the model would yield fully endogenous, AK-style model, growth. $\alpha+\gamma>1$ would lead to explosive growth. This makes $\alpha+\gamma=1$ a knife-edge assumption. Hence, our preference for assuming $0<\alpha+\gamma<1$.

[5]This is based on taking a log-linear approximation of y around its steady-state value, y^*, making use of a Taylor series expansion.

$$ln(y_t) - ln(y^*) = [ln(y_0) - ln(y^*)]e^{-\lambda t} \tag{11}$$

where y_0 denotes the initial level of income per person.

From this it follows that the growth rate of income per person will be given by:

$$ln(y_t) - ln(y_0) = (1 - e^{-\lambda t})ln(y^*) - (1 - e^{-\lambda t})ln(y_0) \tag{12}$$

Substituting (8) into (12) for y^* then gives:

$$\begin{aligned} ln(y_t) - ln(y_0) = (1 - e^{-\lambda t})(\frac{1}{1-\alpha-\gamma})\overline{A} + (1 - e^{-\lambda t})(\frac{\alpha+\gamma}{1-\alpha-\gamma})ln(s_H) \\ -(1 - e^{-\lambda t})(\frac{\alpha+\gamma}{1-\alpha-\gamma})ln(n+\delta) + (1 - e^{-\lambda t})ln(w) - (1 - e^{-\lambda t})ln(y_0) \end{aligned} \tag{13}$$

This implies that, because of the model's transitional dynamics, the growth rate of income per person is an increasing function of the share of its population that is of working-age (w), the technology parameter $\overline{A}$, and the saving rate for human capital accumulation (s_H). Meanwhile, it is a negative function of both the population growth (n) and human capital depreciation rate (δ), which determine the rate of effective depreciation of human capital. This is despite the fact that all of these parameters only ultimately affect the steady-state level of income per person.[6]

Also, note that w, the share of a city's population that is of working-age, can be re-written as follows, where C and S denote the number of children and seniors in the city respectively:

$$\begin{aligned} w &= \frac{L}{L+C+S} \\ w &= \frac{L}{L(1+CDR+ADR)} \\ w &= \frac{1}{1+CDR+ADR}. \end{aligned} \tag{14}$$

Equation (14), taken together with (13), implies that a city's growth rate will be decreasing in both its *child dependency ratio* (CDR) and its *aged dependency ratio* (ADR). This is, in turn, because a city's steady-state level of income per person in (8) depends negatively on both its CDR and ADR. Substituting (14) into (13) gives:

[6] In essence, the model behaves similar to the Solow model. Changes in the model parameters affect the steady-state level of income per person, which leads to transitional effects on growth. How long these transitional effects last depends on λ.

$$ln(y_t) - ln(y_0) = (1 - e^{-\lambda t})[(\frac{1}{1-\alpha-\gamma})\overline{A} + 1] + (1 - e^{-\lambda t})(\frac{\alpha+\gamma}{1-\alpha-\gamma})ln(s_H)$$
$$-(1 - e^{-\lambda t})(\frac{\alpha+\gamma}{1-\alpha-\gamma})ln(n+\delta) - (1 - e^{-\lambda t})ln(1 + CDR + ADR) - (1 - e^{-\lambda t})ln(y_0), \quad (15)$$

The coefficient of $ln(1 + CDR + ADR)$ is $-(1 - e^{-\lambda t})$. The coefficient decreases convexly with both λ and t. However, t = 15 in our main analysis, so our estimated effects are specific to the length of the period studied. The speed of convergence, λ, then depends on both the importance of human capital in a city's output, α, and the strength of human capital externalities, γ.[7] Higher values of α and γ imply that diminishing marginal returns to human capital set in more slowly, which, in turn, implies a slower speed of convergence and larger effects of both the CDR and ADR on growth.

Next, given that $ln(1 + x)$ can be approximated by x for small values of x, we can make use of the fact that $0 < CDR + ADR < 1$ to rewrite (15), resulting in the possible following estimating equation for a cross-section of cities c:[8]

$$ln(\frac{y_{c,t}}{y_{c,0}}) = a + b.\, ln(s_{c,H}) + d.\, ln(n_c) + e.\, CDR_c + f.\, ADR_c + g.\, ln(y_{c,0}) + u_c \quad (16)$$

where u_c is the error term.[9] As can be seen, equation (16) allows for the CDR and the ADR to have potentially different effects on city growth, unlike what is implied by our simple theoretical model and equation (15) in particular. Various mechanisms not directly present in the current model – but discussed below – could lead to different effects.

Next, equation (16) is similar to what our estimating equation, equation (17), will be (details provided below) except growth is expressed in per capita terms on the left-hand side of the equation. Nevertheless, the equation relates a city's per capita growth rate to both its initial CDR and ADR levels, as well as to its initial level of income per person. Alternatively, we can regress the city's growth rate ($ln(Y_t/Y_0)$) on the CDR

[7]It also depends on the rate of effective depreciation of human capital, $(n + \delta)$.

[8]The $0 < CDR + ADR < 1$ condition holds for 98% of the main econometric sample of 351 city-observations. However, the 75th, mean and median values of $CDR + ADR$ in the sample are 0.61, 0.55 and 0.50, respectively. At these values, the difference between $CDR + ADR$ and $ln(1 + CDR + ADR)$ is 0.13, 0.11 and 0.10, respectively. The approximation is cruder for larger values of $CDR + ADR$. We thus verify that results hold if we (not shown, but available upon request): (i) drop observations above the aforementioned median value; (ii) give less weight to crudely approximated observations; and (iii) use $ln(1 + CDR + ADR)$ instead of CDR and ADR separately in our regressions.

[9]For simplicity, we abstract from human capital depreciation, which allows us to ignore δ.

and ADR, while simultaneously controlling for contemporanous city population growth ($ln(P_t/P_0)$), initial city income ($ln(Y_0)$) and initial city population size ($ln(P_0)$).[10]

Finally, the model takes the CDR and ADR as given. In particular, and much like the literature relating the economic growth of cities to their initial population size or human capital levels (see, for example, Glaeser et al. (1995)), we will focus on the effects of the initial CDR and ADR on growth, since initial values of the CDR and ADR are more exogenous than their values at the end of the period. Indeed, economic growth can in turn influence the CDR and the ADR, as in the Unified Growth Theory of Galor (2011).

1.2. Possible Mechanisms

The model can be used to discuss the mechanisms through which the CDR and the ADR can, possibly differently, affect the level and growth rate of income per capita.

Direct effects: It is obvious from the production function in (1) that any increase in the CDR and/or ADR will directly reduce a city's income. Indeed, if children and seniors do not work, an increase in the CDR or the ADR reduces per capita income by reducing w. Now, even if they work, an increase in the CDR or the ADR reduces per capita income if working-age residents work more hours and are more productive. These effects possibly differ for children and seniors depending on their respective labor force participation and productivity. While seniors are more experienced, they may also be less healthy.

In addition, we could 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". In that case, an increase in the CDR or ADR would increase the share of caregivers among the working-age population. Caregivers may work less hours than non-caregivers, which reduces incomes. Working-age parents with children or with elderly parents to look after may also sleep fewer hours and be more tired at work, resulting in lower cognitive performance, or sort into less demanding and lower productivity jobs. Finally, these effects may differ for children and seniors depending on the amount, and the specific nature, of the care they require.

Indirect effects through y and human capital accumulation: This, in turn, from (5), will reduce human capital accumulation per person, because the fall in income leads, with a fixed saving rate for investment in human capital, to less being saved for such

[10]In our estimating equation, equation (17), we use $ln(P_t/P_0)$ as a proxy for $ln(n)$ in equation (15). Adding $ln(n)$ as a control does not significantly alter our results (not shown, but available upon request).

accumulation. The result of this is a fall in the steady-state level of income per person, y^*, in (8), as well as a fall in the growth rate of income per person in (15).

Indirect effects through s_H: An increase in the CDR and/or ADR could also affect the overall share of income that is invested in human capital accumulation, and thus the steady state and growth. On the one hand, employed caregiving working-age residents, as part of any reduction in working hours, may allocate less time to human capital accumulation activities – e.g., to optional on-the-job training. Against this, however, we might expect an increase in the CDR to lead to greater investment by a city in schooling.

Indirect effects through γ: γ is the parameter that measures the strength of human capital externalities in the city. If an increase in the CDR and/or ADR leads to such externalities being weaker then, from (7) and (8), this will lead to lower steady-state levels of both human capital and income per person in the city. Such effects may be stronger for an increase in the CDR than for an increase in the ADR if seniors retain useful knowledge that is able to spillover to the working-age population.[11]

Indirect effects through $\overline{A}$: $\overline{A}$ is the "unexplained" technology parameter. Increased crowding of schools (by children) or health facilities (perhaps more likely by seniors than by children) and reduced spending on a city's productive infrastructure (e.g., roads or mass rapid transit at rush hours) associated with an increase in the CDR and/or ADR can be thought of as negatively impacting $\overline{A}$. From (7) and (8), this leads to lower steady-state levels of both human capital and income per person in the city. It also leads to a slower growth rate in (15) as the transition to this new lower steady state occurs.

Finally, our framework above is silent on the welfare effects of an increase in the CDR and/or ADR. These effects may not go in the same direction as those on income.

2. Data on City Age Structures and Economic Growth

2.1. Selection of Cities.

The problem is to define which cities should be included in our global sample for analysis. Indeed, since data on city age structures is not readily available online, we

[11]Human capital externalities arise from the spillover of knowledge between individuals because of inter-personal interactions. A higher dependency ratio could imply a lower probability that a working-age resident will engage in a conversation with another working-age resident. This assumes conversational congestion forces. However, the value of idea exchange in an economy may not be affected by increasing the non-idea population producing non-tradables (Dingel et al., 2019). Next, for any given conversation, the knowledge exchanged might have less impact on the working-age resident's productivity.

had to collect it individually for each city-year pair, for example using numerous non-electronic sources (e.g., original census volumes) as described below. We thus focused our data collection on large cities, since data was more likely to be found for well-known (i.e., large) cities, especially historically. While our selection process raises questions about whether our results can be generalized to smaller cities, we believe that other processes would have generated data for fewer cities.

More precisely, from United Nations (2018), we identified the 500 largest agglomerations, by population, globally in 2015. However, in this sample, the largest cities of the past are under-represented (e.g., Berlin and Manchester). We, therefore, added 24 cities that were absent from the list of 500 largest cities in 2015, but that were among the 100 largest cities in 1900 according to Chandler (1987). We also added 131 national capitals or primate cities that were not already included to obtain our final sample of 655 "mega-cities."[12] We then found historical age structure data for 410 out of these 655 cities. Our econometric analysis is then restricted to 351 cities for which we know the age structure circa 1990 (see Web Appx. Fig. A.1 for their locations).

2.2. Data on the Age Structure of Cities.

Sources. We consulted six sources: (i) *IPUMS:* The IPUMS-North Atlantic Population Project (Minnesota Population Center, 2017) provides census microdata for selected countries from the 18th century to the present. IPUMS-USA (Ruggles et al., 2017) provide U.S. decennial census microdata from 1920 to 1950. Finally, IPUMS-International Minnesota Population Center (2018) collects census data from many countries around the world from 1960 to the present; (ii) *Census reports:* We obtained city age structures from reports of the population census of individual countries. Many of these reports were not available online and had to be obtained in hard-copy from various libraries; (iii) *OECD:* The OECD Metropolitan Areas Database (OECD, 2019) reports demographic information for the main metropolitan areas of OECD countries; (iv) *DHS*: The Demographic and Health Surveys (DHS) program (USAID, 2018; Boyle et al., 2019) are representative health surveys for developing countries; (v) The International Income Distribution Database (*I2D2*) is a database consisting

[12]When we refer to cities we aim to include central areas, suburbs, and satellite towns. Note that our definition of a "mega-city" here departs from the regularly used one of a city that has a population in excess of ten million (United Nations, 2018).

of about 1,500 individual-level surveys and census samples (The World Bank, 2018);[13] and (vi) *Other sources:* For some cities and years, we rely on administrative counts or household surveys.

For each city-year-source, we identified the city, 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 agglomeration was not directly identified in the source, we constructed it by aggregating territorial subdivisions.

Sample for Descriptive Analysis. We have age structure data, i.e. population shares of various age groups, for 5,251 city-year pairs. Since some observations are duplicates within a same city-year, we use mean population shares in each city-year (N = 4,907).

Sample for Econometric Analysis. We will restrict our analysis to the age structure of 351 mega-cities circa 1990. 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. The median and mean city populations in our econometric sample were 1.42 million and 2.52 million inhabitants in 1995 (source: United Nations (2018); min and max = 227,000 and 33.59 million). 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 lights – i.e. total emitted light at night – 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. 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; and (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.

2.3. Data on City Boundaries and Economic Development

Nights Lights. We use the intensity of a city's night lights as a proxy for its economic activity (Henderson et al., 2012; Donaldson and Storeygard, 2016). We do so because consistent GDP or wage data is not available for most of the cities in our sample. The night lights data are provided by NGDC (2015), and are available at a fine spatial

[13] The data is harmonized and compiled by the World Bank's Development Economics Research Group.

resolution. We use the radiance calibrated version of this data, which is available for select years between 1996 and 2011, to avoid issues related to top-coding.[14]

City Boundaries. To obtain mean night light intensity for each agglomeration, i.e. the average night light intensity across an agglomeration's constituent pixels in a given year, 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, 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 polygons based on urban extent boundaries from other sources. We obtain 4,399 sq km on average vs. 2,315 sq km in European Commission (2019) (for Functional Urban Areas) in 2015, 844 sq km in Florczyk et al. (2019) (for Urban Centers) in 2015, and 1,442 sq km in Ferreyra and Roberts (2018) (data used in Bosker et al. (2020)). Second, the GRUMP boundaries are for a few multi-city agglomerations very large. For these cases, we modify the boundaries using our own analysis of Google Maps satellite images.

Per Capita GDP. One issue is whether night lights are a satisfactory proxy for local economic development. 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 measured 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

Historical Evolution. Historically, child dependency ratios (CDRs) were lower in developed country cities than the levels they reached in developing country cities in the late 20th century. Figure 1(a) shows the evolution of the CDR for New York City (N

[14]This data records levels of luminosity *beyond* the normal digital number upper bound of 63.

= 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).[15] 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 working-age adults per child. The CDR has decreased to around 0.25 today, about 4 adults per child. In cities like Hong Kong and Tokyo, current CDRs are even lower: there are 7 working-age adults per child. Next, cities in middle- and 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 country cities, although they remain well above those observed in high-income country cities.

Figure 1(b) shows the evolution of the aged dependency ratio (ADR) for New York City 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 continue to have low ADRs, with some cities like Kampala and Riyadh having 40 working-age adults per senior.

Instead of studying the evolution of mean CDRs and ADRs for each country income class, we can examine how the right tail of their distribution has shifted over time. Figure 2(a) shows the mean population-weighted CDRs and ADRs in each decade when only considering the 10 highest CDRs/ADRs in each decade. Looking at the period from 1850 onwards overall, high CDRs/ADRs have become even higher over time.[16]

City CDRs and ADRs and Economic Development. Patterns are not fully explained by changing incomes over time. Figure 2(b) shows the evolution of the ten highest CDRs and ADRs in each decade when conditioning them on log national per capita GDP in the

[15]Web Appx. Fig. A.2 shows, for each group-decade, the number of cities with at least one observation.

[16]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 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; and (vi) drop each continent one by one.

same decade (source: Maddison (2008), updated using World Bank (2017)).[17] It remains the case that both maximal CDRs and ADRs have trended upwards over time.

Relatedly, do cities with the same income level have different age structures? For the 351 cities in our econometric sample, Appendix Figure 3(a) plots the relationship between the CDR circa 1990 and log mean night light intensity in 1996. Likewise, Appendix Figure 3(b) plots the relationship between the ADR circa 1990 and log mean night light intensity in 1996. 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. The R^2 of these relationships are low, at 0.14 and 0.19, respectively.

City vs. Urban vs. Rural Dependency Ratios. Appendix Figures 4(a) and 4(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.

4. Econometric Specification and Results

4.1. Econometric Specification

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 (1985-96). For city c in continent r, we run the following long-difference regression inspired by our conceptual framework:[18]

$$\Delta LogNL_{c,r,96-11} = \kappa + \lambda \times CDR_{c,r,90} + \phi \times ADR_{c,r,90} + X_c\zeta + \mu_{c,96-11} \quad (17)$$

where $\Delta LogNL_{c,96-11}$ is the log difference in mean night light intensity between 1996 and 2011. As it is common in the literature, mean night light intensity is the sum of night lights divided by area (Henderson et al., 2012). There are two variables of interest, the child dependency ratio ($CDR_{c,r,90}$) and the aged dependency ratio ($ADR_{c,r,90}$) circa

[17] 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.

[18] Similar regressions have been used in studies on city characteristics and growth (Glaeser et al., 1995).

1990. λ and ϕ measure the effects of age structure. X_c are controls at the city level.

As suggested by the conceptual framework, we must control for initial economic development and population growth.[19] Also, not controlling for initial population size and economic development and population growth could create a spurious correlation between age structure and economic growth. We therefore add three core controls: (i) *Log population size in 1995*: Because of sorting, larger cities are likely to receive more 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. Higher housing costs 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 population size, but captured by economic size, wealthier cities grow faster. Light intensity in 1996 controls for these possibilities; and (iii) *Log population growth 1995-2010*: The dependent variable is the log change in mean night light intensity per sq km. As such, for a given area, its growth could be driven by income per capita and/or population changing. Once we control for population growth, λ and ϕ capture the effects on night light growth in *per capita* terms.[20]

Finally, since labor mobility *within* countries 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 disproportionately sort into high growth cities), we will also try *between* regressions, where we restrict our sample to consist of only the largest city from each country, between which mobility is likely limited on average.

4.2. Econometric Results

Table 1 shows the results with the core controls and six continent fixed effects (col. (2)), 97 country fixed effects (col. (3)), and the "largest city only" sample (col. (4)). For completeness, col. (1) shows the results with the core controls only.

[19] Unfortunately, data on savings rates does not exist for our global sample of cities.

[20] Furthermore, 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 income per capita growth. By controlling for population growth, we aim to capture the specific effects of the demographic composition of cities, rather than total population levels.

The CDR and the ADR both have strong negative effects, except with 97 country fixed effects (col. (3)). Note that a household with two working-age 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 which we discuss in detail below, 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%.[21] 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%. Finally, consistent with our simple theoretical model, the estimated effects are not significantly different for the CDR and the ADR.[22]

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, in col. (2), belonging to the same continent. However, there could be unobservable factors correlated with both initial age structure and future economic growth, and/or reverse causality.[23] Although not significant in col. (2), we do find that the CDR and ADR are also significant in the country fixed effects regressions when we implement additional tests, as follows.

Exploiting the Granularity of the Age Structure Data. First of all, older children (10-14) may work in developing countries, and they require less parental time than younger children (0-9). Likewise, younger seniors (65-74) may keep working (or consume more, before consuming less), and they are less likely to require care from their children. Columns (1)-(3) of Table 2 show that the negative effect of the CDR is driven by 0-9 year-olds (we lose 17 cities for which detailed age structure data is not available). Similarly, the negative effect of the ADR is driven by seniors aged 75 or older.

Exploiting Demographic Cycles. So far, we have only studied the long-run growth effects over a period of 15 years of city age structures. However, children eventually

[21]To obtain 0.28 or 0.50, we multiply -0.63 (col. (4)) or -1.12 (col. (1)) by 0.45.

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

[23]For example, expectations of future economic growth, or decline, may lead working-age adults to have more, or fewer, children. Likewise, individuals may retire earlier, or later, and retirees may disproportionately move out.

become adults. Seniors may also be more prone to illness as they age. Thus, long-run effects combine different medium-run effects. In Table 2, we re-run the same regression as before but study log night light growth between 1996 and 2003 (col. (4)-(6)) or between 2003 and 2011 (col. (7)-(9)). The controls are adjusted accordingly.[24]

Columns (4)-(6) show negative and significant effects of 0-9 year-olds on growth in the first subperiod, including when controlling for country fixed effects (col. (5)). The effects are much less negative, and mostly insignificant, in the second subperiod (col. (7)-(9)), 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. It could be that 10-14 year-olds have positive effects in the first subperiod of seven years, because that is precisely when they enter labor markets (our sample includes many developing countries). Next, 75+ year-olds, but not 65-74 year-olds, have strong, and typically statistically significant, negative effects in both periods.

Past Age Structures as IVs. Age structures are somewhat mechanically determined years before. Historical census documents rarely report city age structures and few demographic surveys took place before the 1990s. Nevertheless, for one third of the cities, we managed to find data on their age structure before our circa 1990 base year.[25]

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 growth it is. However, the instrument may be weak if age structures have changed dramatically over time. The exclusion restriction is that factors explaining age structure circa 1960 do not cause economic growth in 1996-2011, conditional on population size in 1995, economic development in 1996, population growth in 1995-2010, and continent or country fixed effects. As can be seen in col. (1)-(3) of Web Appx. Table A3, all effects are strong and significant at 10% or 15%.

Next, and in order to better capture the mechanical nature of the evolution of 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 are aged 55-74 circa 1980 and 35-54 circa 1960. Col. (4)-(6)

[24] In columns (7)-(9), 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.

[25] Also, 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 independent variables of interest.

of Web Appx. Table A3 show that the effects are relatively unchanged. The instruments are weaker than when using the dependency ratios close to 1960. Indeed, we now have 17 instruments.[26] Now, even if we restrict the instrument set to selected 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 (col. (7)-(8)). Obviously, the reported effects are not causal if the exclusion restriction is not satisfied.[27]

Overall, the regressions based on the granularity of the age structure data, demographic cycles, and instruments also suggest negative correlations between city economic growth and initial dependency ratios. Even if estimates are stronger 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.

4.3. Robustness Checks

Controls. Age structure affects city population growth, which may in turn impact city economic growth. As shown in columns (1)-(4) of Panel A in Table 3, the effects of seniors are even more negative if we do not control for population growth.

Next, for most cities, we calculate the college share circa 1990 (1985-96) using the educational attainment variables in IPUMS and the DHS.[28] Col. (5)-(8) of Panel A in Table 3 show that the results of Table 1 hold when we add this extra control.

Per Capita GDP. Log growth of city per capita GDP between 2000-2016 is calculated for 1,194 agglomerations using Oxford Economics (2019) and OECD (2019) data.[29]

Col. (1)-(4) of Panel B in Table 3 show that the effects of CDRs remain negative and significant. ADRs have negative effects, except in the "largest city only" sample (col. (4)).

[26]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 population shares of older individuals in 1960 cannot explain the CDR circa 1990.

[27]Web Appx. Table A4 shows that our IV results tend to hold when we control for past economic growth, family planning or religiosity (see table notes for details on sources): (i) national per capita GDP (constant 1990 dollars and PPP terms) in 1960, 1980 and 1996; (ii) the strength of family planning policies during the period, which could also be correlated with a country's ability to implement certain policies; and (iii) the religious mix during the period, which could be correlated with a country's evolution.

[28]In IPUMS, we use the share of individuals aged 25 or above that are classified as "university completed". In the DHS, we categorize as college graduates individuals that they classify as having reached a "Higher" educational level than "Complete Secondary". For 110 other cities, we use various data sets to reconstruct the *urban college share* as a proxy for a city's college share (see table notes).

[29]We did not use this as our main economic measure, nor Oxford Economics' or OECD's reported dependency ratios, because they do not provide information on how each estimate was obtained. For example, we do not know how many of these estimates were temporally/spatially interpolated/extrapolated.

Col. (5)-(8) of Panel B show the results with country fixed effects hold if we restrict the analysis to countries with at least 15, 25, 50 or 100 cities in the sample, respectively.[30]

Panel. Since Oxford Economics (2019) and OECD (2019) provide city CDRs and ADRs for the whole period 2000-2016, we partition the combined data set into four periods – 2000-04, 2004-08, 2008-12 and 2012-16 – and run panel regressions. The sample consists of 1,047 cities with data throughout the period (N = 1,047 $\times$ 4 = 4,188). 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 fixed effects, time-period fixed effects, and the core controls adjusted accordingly. Standard errors are clustered at the city level. As can be seen in col. (1) of Table 4, 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) and/or they increase their consumption as they retire. However, the long-run effect is negative as they may consume less as they keep getting older and become more likely to require care. Results tend to hold when adding continent- or country-specific trends (col. (3)-(4)) or continent-year fixed effects (col. (5)). In the latter case, which is the most stringent specification, the only significant effects are negative, including for the ADR.

Specification. Dependency ratios may have also changed during the period, modifying a city's steady state, and thus its growth trajectory. Web Appx. Table A5 shows for 289 cities for which dependency ratios are also available circa 2010 (2005-2016) that the effects of the CDR circa 1990 remain unchanged and that an increase in the CDR between 1990 and 2010 also has a negative effect. For the ADR, the effect of the initial ratio (1990) remains negative but loses significance. The effect of the change in the ADR then becomes positive, plausibly because cities where the ADR increases see an increase in their number of younger seniors who still work and/or consume more.

Boundaries. Results hold when we use three alternative sets of urban agglomeration

[30]The effect of going from the 10th to the 90th percentile in the CDR – which is equivalent to one extra child per household – reduces the growth rate of per capita GDP by 20-50%. We found 28-50% for night lights. For the ADR, going from the 10th to the 90th percentile, which is equivalent to an increase of 0.16, the corresponding decrease in the growth rate is between -6% and -9% in col. (1)-(3) (but +10% in col. (4)).

boundaries (see Web Appendix Table A6): (i) From European Commission (2019) (for Functional Urban Areas, defined circa 2015); (ii) From Florczyk et al. (2019) (for Urban Centers, 2015); and (iii) From Ferreyra and Roberts (2018) (for Urban Clusters, 2015).[31]

Other Locations. For 340 cities, 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. We also obtained the mean night light intensities in 1996 and 2011 for both the rural and the secondary city sectors. 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 in Table 1, using similarly defined controls, except we now include dummies for whether the observations belong to the secondary city or the rural sector. As columns (1)-(4) of Table 5 show, the effects are relatively unchanged.

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 col. (5)-(6). The interacted effects are then sufficiently large that they make the effects of age structure for secondary cities and rural areas insignificant in most cases (not shown), unlike what can be observed for megacities.

5. Heterogeneity and Possible Mechanisms

In order to shed light on the potential mechanisms by which the CDRs and ADRs could impact city economic growth, we now use our data to explore how the effect of city age structure varies spatially or sectorally within cities, between richer and poorer countries, and between larger and smaller cities. We then use the I2D2 data and data from US Time Use surveys to provide separate evidence about the channels.

5.1. Heterogeneity of the Effects of the Dependency Ratios

Central vs. Peripheral Areas. If children/seniors reduce night light intensity, does this reduction occur in more core or more sub-urban areas of the cities? Given that night lights are available at the pixel level for each city, 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

[31] This data has also been used in Bosker et al. (2020).

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. As seen in Table 6, the effects are not significantly different between central (col. (1)-(4)) and peripheral areas (col. (5)-(8)).

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 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.[32]

Developed vs. Developing Countries. The effects of age structure may depend on various factors such as whether children and seniors are 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 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 6 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 and/or because there are more flexible options for working. Conversely, the negative effects of seniors are mostly observed in developed countries, possibly because seniors work in poorer countries.[33]

Larger vs. Smaller Mega-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

[32]We also examine effects at the intensive margin vs. the extensive margin. Panel E of Web Appendix Table A6 shows that no significant difference is observed when we use the 75th percentile in initial (1996) night light intensity to distinguish the two margins.

[33]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 of 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 whereas older children may do.

children/parents, the effects on growth could be magnified. Second, the human capital externality and other effects might be stronger in large cities. In columns (5)-(8) of Panel A in Table 6, 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. 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 permit workers less flexibility in their work schedules and/or disproportionately rely on human capital. The Oxford Economics (2019) database shows the sectoral structure of GDP in 2000 and in 2015 for a sufficiently high number of cities. 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.

Next, in Columns (1)-(4) of Panel B in Table 6, 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 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.

5.2. Dependency Ratios, Labor Supply, Productivity and Earnings

In our conceptual framework section, city age structure impacts growth through their impact on income and thus human capital accumulation. In Web Appendix Section A, we describe in detail how we use the I2D2 and data from US Time Use surveys to examine how city age structure impacts labor supply, productivity, and earnings.

The full sample consists of 835 household surveys in 122 countries. Since many surveys do not allow us to identify specific cities and/or may not be representative at the city level, and since many countries do not have a survey both circa 1996 and circa 2011, we cannot use the same long-difference specification as before. Instead, we examine the cross-sectional effects of the CDRs and ADRs on incomes in urban areas.

Direct effects. 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. We add country-year sample fixed effects and Mincerian controls (gender, marriage status and education). In some cases, we also interact the sample fixed effects with third-level administrative units fixed effects, so as to limit the comparison to individuals in the same "urban area". Overall, results in Panel A of Web Appx. Table A7 show that 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. On average, children (seniors) bring 87-88% (60-64%) less income than working-age adults.[34] These effects are substantial. In our sample of 351 cities, going from the 10th to the 90th percentile in the CDR (ADR) increases the share of children (seniors) in the city from 18% to 40% (3% to 14%). If each child (senior) brings 87-88% (60-64%) less income than a working-age adult, total income decreases by 19% (7%).

Intra-household 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. Overall (Panel B of Web Appx. Table A7), 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%. 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.

[34] For children, the formulas are 0.32*(-100) + 0.68*(-82) = -88% and 0.37*(-100) + 0.63*(-80) = -87%.

In our sample of 351 cities, 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 respectively. This implies that total earnings are reduced by 3-5% and 1-2%, respectively.

City-wide effects. We study city-wide effects by adding to the previous regressions the mean CDR and ADR for the urban area in which an individual is located. Depending on how we define the urban area, we find that total earnings are reduced by 21-58% (45-67%) for each point of the CDR (ADR). Going from the 10th 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 to the 90th percentiles in the CDRs (ADRs) reduces total city income by 19% + 1-3% + 10-29% = 30-51% (7% + 1-2% + 7-11% = 15-20%).

Rural vs. Urban Areas. If we study the direct and indirect intra-household effects in rural areas, we find significantly less negative effects (see Web Appx. Table A8 which is structured like Web Appx. Table A7). In other words, children and seniors do not reduce rural labor supply and earnings as much as in urban areas, plausibly because urban sectors, unlike rural sectors, particularly rely on full-time prime-age workers.

Time Use. Probing deeper, the question arises of how the presence of children and/or seniors affects the time allocation decisions of working age adults at a more detailed level. To answer this question we turn to time use surveys for the U.S., which are available annually for 2003-2015 (Hofferth et al., 2018). 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 (the lack of which impacts productivity; and (iv) enjoying leisure time and other activities.[35]

Overall (Panel A of Web Appx. Table A9), for a household of two working-age adults, one more 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

[35] In addition to year-month of interview and day of the week fixed effects, we add Mincerian controls (gender, marriage status, education and experience). In some regressions, we also include city fixed effects to only compare relatively "similar" individuals in the same city.

that leisure time includes spending quality time with ageing parents.

In addition (Panel B of Web Appx. Table A9), 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 (16 hours per month) per household. It could be that parents wake up earlier to bring their children to school. Likewise, more seniors in the city are associated with more care time. 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 city-wide ADR effect, if all households get one extra senior, the care time cost per working-age adult is 20 mins a day (14 hours per month) per household.

6. 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.

We are hesitant to claim that our results have major policy implications. Our results are not necessarily causal and we have limited data on the mechanisms through which a city's age structure may influence its economic growth. In addition, our analysis is silent on the welfare effects for a city's residents of an increase in the CDR and/or ADR.

Were our results causal and ignoring the other welfare effects, they might imply that local governments should: (i) Track and forecast the evolution of their city's age structure in order to better adapt infrastructure investments to the needs of their current as well as future populations. In particular, cities with more children, workers or seniors have different needs (e.g., schools vs. a reliable transportation system vs. health facilities); and (ii) Consider demographic cycles in their budgetary policy decisions. Cities with more young children may grow relatively slower right now. However, the same cities should grow faster later on when such children enter labor markets.

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.

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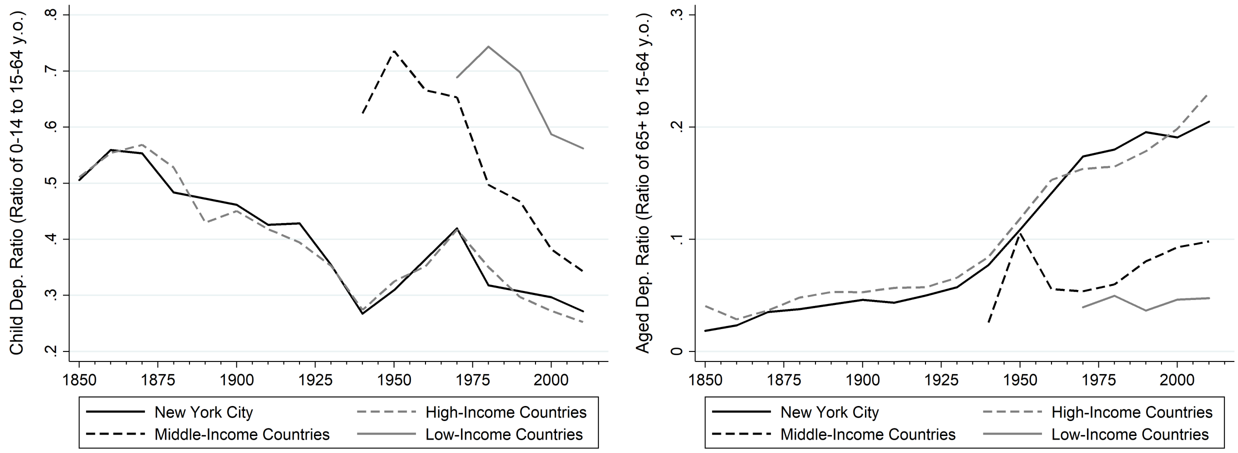
Figure 1: **Evolution of Mean City Child and Aged Dependency Ratios, 1850-2015**

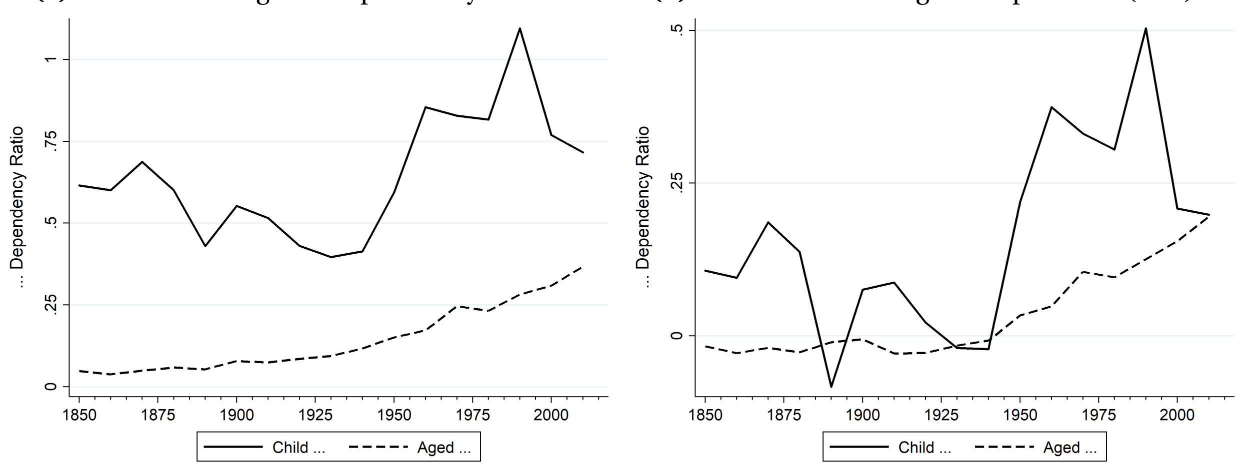
(a) City Child Dependency Ratios **(b)** City Aged Dependency Ratios



Notes: Figure 1(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 1(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 the main text for data sources.

Figure 2: **Evolution of Maximal City Child and Aged Dependency Ratios, 1850-2015**

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



Notes: Figure 2(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 2(b) shows the same evolutions when the dependency ratios are first regressed on log national per capita GDP (cst 1990 intl dol., PPP) in the same year and the residuals of that regression are used instead of the dependency ratios. See the main text for data sources.

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

Dependent Variable: Δ Log Mean Night Light (NL) Intensity 1996-2011				
	(1)	(2)	(3)	(4)
Child Dep. Ratio 1990	-1.12***	-0.87***	-0.13	-0.63**
	[0.13]	[0.14]	[0.24]	[0.28]
Aged Dep. Ratio 1990	-1.21***	-1.14***	0.10	-1.04*
	[0.35]	[0.38]	[0.57]	[0.57]
Log Pop. 1995	0.07***	0.05**	0.04	0.06*
	[0.02]	[0.02]	[0.03]	[0.03]
Log Mean NL 1996	-0.37***	-0.33***	-0.22***	-0.25***
	[0.04]	[0.04]	[0.05]	[0.05]
Δ Log Pop. 1995-2010	0.66***	0.63***	0.37***	0.28*
	[0.09]	[0.09]	[0.11]	[0.16]
Observations	351	351	351	97
Adjusted R2	0.55	0.58	0.76	0.27
Fixed Effects	N	Continent	Country	N
Largest Only	N	N	N	Y

Notes: Regressions for 351 urban agglomerations. The 351 agglomerations belong to 97 countries on 6 continents. Col. (2)-(3): 6 continent FE and 97 country FE are included, respectively. Col. (4): 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.:	ΔLogMeanNL 1996-2011			ΔLogMeanNL 1996-2003			ΔLogMeanNL 2003-2011		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CDR 0-9 90	-1.26**	-0.84	-1.99**	-1.28***	-1.30***	-1.31***	-0.12	0.17	-0.74*
	[0.61]	[0.73]	[0.82]	[0.19]	[0.11]	[0.15]	[0.19]	[0.19]	[0.37]
CDR 10-14 90	-0.02	2.41	2.75	0.49	2.89***	1.54	-0.37	0.16	1.28
	[1.31]	[1.56]	[1.92]	[1.39]	[0.45]	[0.87]	[0.64]	[0.65]	[0.74]
ADR 65-74 90	5.28**	4.27*	2.36	4.32**	1.63	2.77	1.37	3.00	-0.26
	[2.05]	[2.30]	[1.87]	[1.43]	[2.30]	[1.46]	[0.91]	[1.89]	[0.61]
ADR 75+ 90	-8.35***	-4.55**	-3.69	-5.88***	-1.57	-3.32***	-2.96**	-3.32*	-0.57
	[2.24]	[2.06]	[2.27]	[1.37]	[2.59]	[0.80]	[1.02]	[1.53]	[0.39]
Observations	334	334	92	334	334	92	334	334	92
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	Cont.	Cntry	N	Cont.	Cntry	N	Cont.	Cntry	N
Largest Only	N	N	Y	N	N	Y	N	N	Y

Notes: Regressions for 334 agglomerations. Robust SEs. * p<0.10, ** p<0.05, *** p<0.01.

Table 3: **City Dependency Ratios & Economic Growth, Controls & 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:	w/o Control for City Pop. Growth				Control: College Share ca. 1990 (1985-1996)			
CDR	-1.21***	-0.96***	-0.23	-0.51**	-1.13***	-0.90***	0.04	-0.60*
	[0.15]	[0.16]	[0.26]	[0.25]	[0.31]	[0.32]	[0.55]	[0.35]
ADR	-2.45***	-1.62***	-0.02	-1.41**	-0.87*	-0.94*	0.14	-0.73
	[0.35]	[0.39]	[0.58]	[0.57]	[0.47]	[0.54]	[0.60]	[0.70]
Obs.	351	351	351	97	334	334	334	87
Fixed Effects	N	Cont.	Cntry	N	N	Cont.	Cntry	N
Dep. Var.:	Δ Log City Per Capita GDP 2000-2016				Δ Log City Per Capita GDP 2000-2016			
Panel B:	CDRs & ADRs ca. 2000				CDRs & ADRs ca. 2000			
CDR	-1.12***	-1.02***	-0.44***	-0.61***	-0.42***	-0.39***	-0.40***	-0.40**
	[0.15]	[0.15]	[0.10]	[0.20]	[0.11]	[0.12]	[0.13]	[0.18]
ADR	-0.35**	-0.23	-0.54***	0.63	-0.44***	-0.51***	-0.53***	-0.82***
	[0.18]	[0.17]	[0.13]	[0.46]	[0.13]	[0.13]	[0.14]	[0.15]
Obs.	1,194	1,194	1,194	159	846	760	587	324
Fixed Effects	N	Cont. (6)	Cntry (159)	N	Cntry (16)	Cntry (11)	Cntry (6)	Cntry (2)
Cntry ≥ ... Cities	1	1	1	1	15	25	50	100
Core Ctrls	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Panel A: Regressions for our main sample of 351 agglomerations. *Panel A* Col. (5)-(8): For 110 other cities for which city-level information on the college share is missing, we obtain from Barro and Lee (2013) and for the year 1990 the national college share for individuals age 25 or above. 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. 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, we reconstruct the total number of urban residents age 25 or over. Assuming all college graduates live in urban areas, we obtain an urban college share, which we use as a proxy. *Panel B:* We combine the data from Oxford Economics (2019) and OECD (2019) to obtain for a sample of 1,194 agglomerations in 159 countries the log growth of city per capita GDP (cst 2012 U.S. dollars) between 2000-2016 and child and aged dependency ratios defined circa 2000. Controls include log city pop. in 2000, log city per cap. GDP in 2000 and the change in log city pop. between 2000 and 2016. Robust SEs. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 4: 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	-0.54***	-0.82***	-0.80***	-1.23***	-0.52**
	[0.11]	[0.24]	[0.25]	[0.28]	[0.24]
CDR t-8		0.37*	0.46**	0.79***	0.32
		[0.20]	[0.20]	[0.24]	[0.20]
ADR t-4	0.57***	0.95***	0.54**	0.67**	0.32
	[0.11]	[0.21]	[0.23]	[0.29]	[0.22]
ADR t-8		-0.89***	-0.69***	0.33	-0.54**
		[0.24]	[0.26]	[0.30]	[0.23]
Observations	4,188	3141	3141	3141	3141
Year FE, 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 1,047 cities in Oxford Economics (2019)-OECD (2019) for which we know city per capita GDP and the CDR and ADR ca. 2000, 2004, 2008, 2012 and 2016. Using ratios in t-4 (t-4 & t-8) we lose 1 (2) round(s) of data, hence N = 1,047 × 4 = 4,188 (1,047 × 4 = 3,141). Year and city FE 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 5: City Dep. Ratios and Growth, Including 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***	-0.74***	0.02	-0.35*	-1.08***	-0.83***	0.06	-0.49*
	[0.13]	[0.13]	[0.15]	[0.18]	[0.14]	[0.15]	[0.19]	[0.26]
ADR	-1.66***	-1.25***	-0.04	-0.91**	-2.15***	-1.66***	-0.06	-1.29**
	[0.29]	[0.33]	[0.33]	[0.41]	[0.34]	[0.37]	[0.37]	[0.59]
CDR*Rural					0.23	0.31	-0.10	0.22
					[0.35]	[0.33]	[0.27]	[0.37]
CDR*Second.					0.44*	0.54**	-0.05	0.16
					[0.26]	[0.25]	[0.16]	[0.31]
ADR*Rural					1.57	1.31	0.01	0.65
					[0.97]	[0.95]	[0.69]	[0.98]
ADR*Second.					2.16***	1.89***	0.22	0.50
					[0.73]	[0.70]	[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 6: **City Dependency Ratios and City Growth, Other Mechanisms**

Dep. Var.:	Δ Log Mean Night Light (NL) Intensity 1996-2011							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A:	*Central:* < 25th Pctile Dist. CBD				*Peripheral:* ≥ 25th Pctile Dist. CBD			
CDR	-1.14***	-0.83***	0.10	-0.65**	-1.02***	-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***	-1.38***	0.18	-0.94*	-1.19***	-1.27***	-0.10	-1.15*
	[0.35]	[0.39]	[0.62]	[0.55]	[0.38]	[0.43]	[0.60]	[0.68]
Panel B:	By Development Status (devD) 1995				By Country-Specific Minus Log Rank 1995			
CDR	-1.09**	-0.96**	-0.20**	-0.45**	-1.22***	-0.85***	0.06	-0.65**
	[0.28]	[0.37]	[0.07]	[0.17]	[0.13]	[0.16]	[0.32]	[0.29]
ADR	1.91	1.23	0.53	1.09**	-1.33***	-2.32***	-1.13*	-1.07*
	[1.49]	[1.52]	[1.31]	[0.33]	[0.38]	[0.45]	[0.62]	[0.57]
CDR*devD | -Rank	1.25**	1.49***	0.93**	0.44**	-0.15***	-0.06	0.07	0.25
	[0.34]	[0.31]	[0.34]	[0.15]	[0.04]	[0.05]	[0.11]	[0.16]
ADR*devD | -Rank	-3.09*	-2.09	-0.25	-2.88***	0.05	-0.55***	-0.52**	-9.20***
	[1.52]	[1.51]	[1.41]	[0.36]	[0.13]	[0.15]	[0.20]	[2.24]
Obs.	351	351	351	97	351	351	351	97
Panel C:	Δ Log City Consumer Serv. GDP PC				Δ Log City Fin. & Bus. Serv. GDP PC			
CDR 00	-0.16	-0.11	-0.24	-0.03	-0.53***	-0.55***	0.16	-0.47**
	[0.12]	[0.13]	[0.23]	[0.18]	[0.15]	[0.16]	[0.28]	[0.21]
ADR 00	-0.03	-0.17	0.46	0.14	-0.54**	-0.80***	-0.02	-0.81
	[0.19]	[0.20]	[0.30]	[0.43]	[0.24]	[0.24]	[0.40]	[0.51]
Obs.	278	278	278	95	278	278	278	95
Panel D:	Δ Log City Industry GDP PC				Δ Log City Public Serv. GDP PC			
CDR 00	0.08	0.06	0.30	0.43**	0.18	0.04	-0.14	0.17
	[0.13]	[0.14]	[0.23]	[0.17]	[0.17]	[0.17]	[0.25]	[0.34]
ADR 00	-0.07	-0.06	-0.50	0.36	0.77***	0.87***	0.73*	0.25
	[0.24]	[0.27]	[0.45]	[0.44]	[0.25]	[0.25]	[0.44]	[0.56]
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*: 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. *Panel B* 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 B* 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 C-D*: The dependent variable is the change in log city GDP per capita for each sector. Robust SEs.