Age diversity and economic growth

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Abstract

This research explores the impact of age diversity on economic growth. First, we build a model with skill complementarity between young and old workers, which gives rise to positive returns to age diversity. The model also suggests that returns to age diversity are lower in economies whose sectoral composition is biased towards a given age group's skills. Second, we take our two testable predictions to the data. Using country-level panel data with a novel instrument, regional data from Europe, and grid cell-level data, we find support for both of our hypotheses. Our results suggest that a one standard deviation increase in age diversity is associated with a 47% increase in GDP per capita. Third, using age-specific population projections for 2015-2100, we estimate the impact of future changes in age diversity on income per capita around the world. We find that middle-income countries will be the biggest beneficiaries of future changes in age diversity.

Keywords: age diversity, economic growth, innovation, skill complementarity, demographics.

JEL classification: J11, O15, O32, J24.

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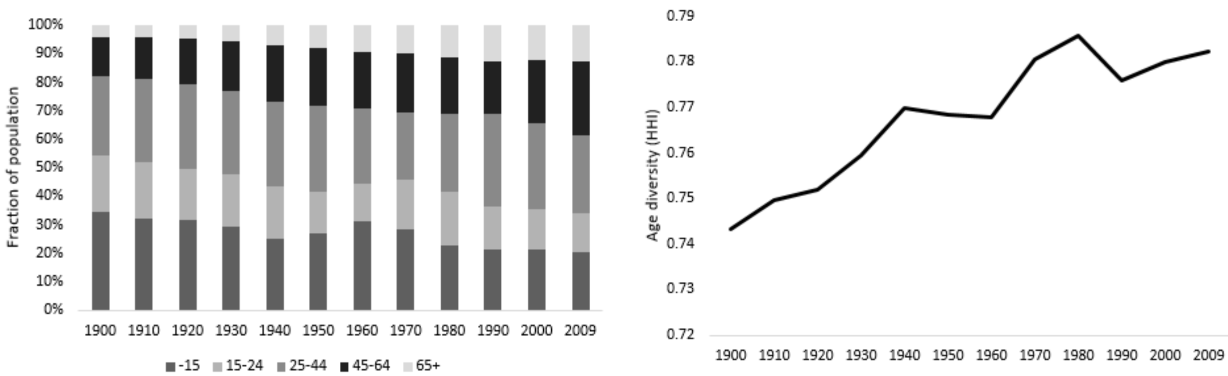
1 Introduction

Rising life expectancy and falling fertility have been the features of advanced economies for the past few decades. While of course these trends lead to population ageing, their other often overlooked consequence is that the populations of advanced economies have been becoming more age diverse. As Figure 4a illustrates, in 1900 82% of the US population was under the age of 45. In 2009, the same figure was 61%. This, of course, means that the population is ageing, but it also means that it is becoming more age diverse as shown in Figure 1b. Many studies have looked at the effect of population ageing in advanced economies,[1] but the macroeconomic effects of increasing age diversity have been much more underexplored.



(a) Population by age

(b) Age diversity over time

Figure 1: Recent demographic trends in the US

By creating a workforce where all age groups are more equally represented, age diversity can foster an environment where complementarities between different age groups can be harnessed. This could allow economies to potentially increase their productivity. In fact, a 2010 survey of 80 employers from a variety of industries showed that roughly 40% of respondents consider age diversity an imperative (Roundtree (2011)). In a world where companies aim to maximize shareholder value, one would interpret this as an endorsement of age diversity as a driver of productivity.[2] Therefore, the recent trends of falling fertility and increasing life expectancy in advanced economies may have positive macroeconomic effects as well by increasing workforce diversity.

This paper asks whether these hypothesized macroeconomic benefits of age diversity are real by investigating whether age diversity has an effect on economic output. Further, we also ask under what conditions the potential benefits of age diversity are higher.

[1] For a survey, see Lee and Mason (2011).

[2] The firm-level empirical study of Backes-Gellner and Veen (2013) backs up this claim.

To answer these questions, we begin by considering a simple model of age diversity. In the model, skill complementarities between young and old workers give rise to an economy where output is increasing in age diversity. A crucial ingredient of the model, and of positive returns to diversity, is, therefore, that the skill sets of young and old workers are on average different and complementary.[3] An important assumption for this result to hold is that the economy's sectoral composition is not "age-biased". By this, we mean that on average, the sectoral composition of the economy does not rely more heavily on the skills that young people have more of than on the skills old people have more of, and vice versa. We find that if this situation doesn't hold, that is if on average an economy's sectoral composition is age-biased, then increasing diversity is not always beneficial. This is intuitive: if young people are twice as productive in the tech sector, and the tech sector produces 70% of the economy's output, then the economy is better off if it has more young people than old people. The model can, however, tell us more than this. In particular, we show that in a sample of countries with varying degrees of age bias, we should expect that the more age-biased a country is, the lower its returns to diversity are on average. This is also intuitive, as more age-biased economies are effectively more likely to fall into the region of the parameter space where returns to diversity are negative for them, simply because this region is larger for them.

In sum, we derive two testable predictions from our model: that age diversity should have a positive effect on output, and that these returns to age diversity should be lower in more age-biased economies. We find evidence for these predictions empirically. We consider three levels of analysis: country-level, European regional-level, and grid cell-level. The country and regional analyses are conducted on panel data, while the grid cell-level analysis is a cross section for the year 2010. In all analyses, we regress a measure of economic output (GDP per capita and night lights) on a measure of age diversity. To identify the effect of age diversity on output, we do three things. First, we include country, region, and year fixed effects in all our panel data specifications. This allows us to control for all time-invariant country- and region-specific characteristics, and for all common global shocks. Second, we directly control for a variety of measures of demographic structure that may be correlated with age diversity. These include, for instance, the old and young age dependency ratios. Third, we instrument for age diversity in our country-level analysis using the volatility of past fertility rates. This instrument has a mechanical relationship with age diversity to some extent.

We find that age diversity indeed has a significant positive effect on economic output. Our results suggest that a one standard deviation increase in age diversity leads to a 47% increase in GDP per capita. In order to estimate potential heterogeneity in this effect depending on

[3] Appendix B provides some empirical discussion of this statement.

the age bias of an economy, we interact age diversity with measures of sectoral composition. We find that economies that are more reliant on age-biased sectors such as innovation and R&D[4] stand less to gain from increased age diversity. Quantitatively, moving from the 25th percentile of age bias to the 75th percentile can cut the benefits of age diversity in half.

As a final exercise, using population projections by age group for 2015-2100, we calculate projected age diversity by country for the remainder of the 21st century. Using these estimates, we then explore how different regions of the world will be impacted by changing age diversity in the future. Future patterns of age diversity suggest that middle-income countries will gain the most, opening up their lead in income per capita over low-income countries, and narrowing their deficit with high-income countries. Low- and middle-income countries will both benefit from changing age diversity, while high-income countries will not be majorly impacted by it.

There are two strands of literature that are directly related to our paper. First, there is a nascent literature on the effects of age diversity and closely related concepts on economic activity. Backes-Gellner and Veen (2013) find evidence on the firm-level that age diversity is beneficial for firm productivity in creative industries in Germany. Our paper, in turn, takes this insight to a global macroeconomic level, and attempts to provide better identification. Furthermore, we also propose the concept of age bias to explain heterogeneous returns to diversity. Gregory and Patuelli (2015) and Arntz and Gregory (2014) meanwhile focus on the effect of age structure on regional development within Germany. While they acknowledge the potential importance of age diversity, it is not their main focus, and identification for age diversity is tricky in a within-country context where migration can be an important confounder. Finally, Gu and Stoyanov (2018) find that the changing age structure of advanced economies has changed what industries these countries have comparative advantage in, and has thus shifted their trade patterns.

Second, there is a literature on the effects of various facets of diversity on economic outcomes. Broadly speaking, this literature has found that, on the one hand, diversity may positively affect productivity by bringing together people with different perspectives and thus sparking innovation (Alesina et al. (2016)). On the other hand, diversity can decrease productivity by fractionalizing societies (Alesina et al. (2003)) and making people less cooperative (Hjort (2014)). It is not surprising that these opposing forces have also been found to give rise to a hump-shaped pattern between diversity and economic growth (Ashraf and Galor (2013)). Our paper contributes to this literature in two ways. First, we consider a previously ignored facet of diversity. Second, age diversity is perhaps the first

[4] A discussion of age bias in these industries can be found in Appendix B.

aspect of diversity that appears less beneficial in an innovative environment. This finding suggests that returns to diversity exhibit more heterogeneity and context-dependence than previously thought.

2 Model

In this section, we present a model of age diversity and economic growth. The main purpose here is to present a simple framework showcasing the economic mechanisms via which age diversity can affect economic growth. The key driving force in our model is skill complementarity: workers of different age have different skills that complement each other in the production process. In addition, if the economy values the skills of a given age group more, then returns to diversity are lower. These are the two key elements of our model.

2.1 Set up

Consider an economy with a representative firm that employs young and old workers. Young and old workers are complementary in producing output, but they have different levels of productivity. The productivity of each age group depends on the economy's sectoral composition: young people are more productive in economies that produce more of their output in industries where young people have a comparative advantage (young bias), and vice versa for old people (old bias).

2.1.1 Firms

The firm's profit-maximization problem is

$$\max_{L_y, L_o \geq 0} L_y^{b(z)} L_o^{b(1-z)} - w_y L_y - w_o L_o, \tag{1}$$

where L_y and L_o are young and old labor, w_y and w_o are the wages of young and old workers, $z \in (0,1)$ measures the economy's sectoral composition with higher levels corresponding to more reliance on young-biased industries, and $b : (0,1) \to (0,1)$ with $b' > 0$ represents returns to adding more workers to the production process. The price of output is normalized to 1. We may think of z as the share of young-biased industries in output. Meanwhile, $b(\cdot)$ simply maps this share to returns to scale: the more young-biased the economy's industries are, the more productive young workers are in the aggregate.

2.1.2 Consumers

Consumers maximize utility according to

$$\begin{aligned} \max_{c,L_y,L_o\geq 0} u(c) \text{ s.t.} \\ c \leq w_y L_y + w_o L_o \\ L_y \leq \delta N, L_o \leq (1-\delta)N, \end{aligned} \tag{2}$$

where $u(c)$ is utility derived from consumption (c), $N \geq 2$ is total population, and $\delta \in (0,1)$ is the share of young people in the total population. Since there is no disutility of labor, labor is supplied inelastically.

2.1.3 Equilibrium

The optimal solutions from (1) and (2) lead to the labor market clearing equations

$$\begin{aligned} (1-\delta)N &= \left(\frac{w_y}{b(z)}\right)^{\frac{1}{b(z)(1-z)}} (\delta N)^{\frac{1-b(z)}{b(1-z)}} \\ \delta N &= \left(\frac{w_o}{b(1-z)}\right)^{\frac{1}{b(z)}} [(1-\delta)N]^{\frac{1-b(1-z)}{b(z)}}, \end{aligned}$$

which imply equilibrium wages

$$\begin{aligned} w_y &= b(z)(1-\delta)^{b(1-z)}\delta^{b(z)-1}N^{b(z)+b(1-z)-1} \\ w_o &= b(1-z)\delta^{b(z)}(1-\delta)^{b(1-z)-1}N^{b(z)+b(1-z)-1}. \end{aligned}$$

2.2 The effect of diversity

We now proceed to examine the effect of age diversity on economic output. To begin, in Lemma 1, we establish what total output is in equilibrium.

Lemma 1. *The total output of the economy is*

$$GDP = N^{b(z)+b(1-z)}\delta^{b(z)}(1-\delta)^{b(1-z)}[b(z)+b(1-z)]. \tag{3}$$

Proof. This follows from the fact that GDP $= w_y L_y + w_o L_o$. □

It is straightforward now to calculate the relationship between output and the age structure as represented by δ. This is done in Lemma 2.

Lemma 2. *There exists a unique $\delta \in (0,1)$ which maximizes output.*

Proof. See Appendix A. $\square$

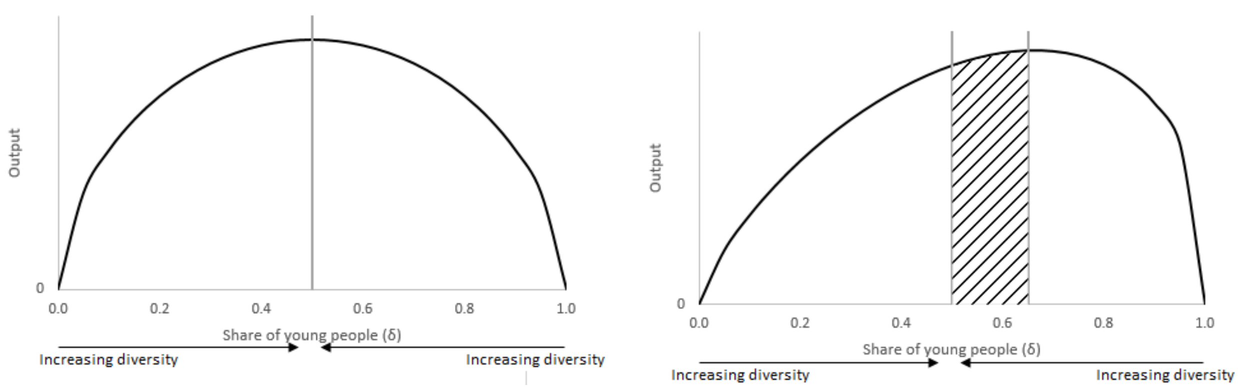
We can now establish our first result about age diversity using Assumption 1. Let us first define diversity by its conventional measure of one minus the Herfindahl-Hirschman Index (HHI): $d \equiv 1 - \delta^2 - (1-\delta)^2$. Now let us consider Proposition 1.

Assumption 1. *The economy's sectoral composition is not biased towards either age group, that is $z = \frac{1}{2}$.*

Proposition 1. *Under Assumption 1, output is increasing in diversity.*

Proof. See Appendix A. $\square$

Proposition 1 is our first testable prediction. It says that under some conditions, output is increasing in age diversity. This prediction of the model is also illustrated in Figure 2a: given that peak diversity is reached at $\delta = \frac{1}{2}$, it is apparent that output is increasing in diversity.



(a) Unbiased case ($z = 0.5$) (b) Young-biased case ($z = 0.7$)

Figure 2: Output, share of young people, and diversity

2.2.1 Age bias and returns to diversity

We now consider economies where there is some age bias in sectoral composition, or in other words Assumption 1 does not hold. For intuition, Figure 2b shows the relationship between the share of young people (δ), diversity (d), and output. We see that in the shaded region output is decreasing in diversity. This is intuitive as an economy with age bias in sectoral composition is better off having more of the age group that is more productive.

But what would we expect to see in the data? Suppose that we have a sample of countries whose demographic compositions are uniformly distributed so that $\delta \sim U(0,1)$. Then it is apparent from Figure 2a that for countries with no age bias ($z = \frac{1}{2}$), we would always see a non-negative return that would essentially vary from 0 to infinity – corresponding to the slope of the curve in Figure 2a. So in a regression involving such countries, we would identify a positive coefficient when regressing output on age diversity.

Now, when we have countries with $z \neq \frac{1}{2}$ such the one in Figure 2b, then the observed returns to diversity would depend on what the country's δ is. In particular, if it falls in the shaded region, we would see negative returns. So returns vary from finite negative numbers to positive infinity. In a regression of such countries, we would identify a coefficient that could be lower than the one in the case without age bias. This is because we are essentially averaging the returns to diversity of countries outside and inside the shaded region. Those that are inside the shaded region drag down the average. It is also apparent that the higher the age bias, the larger the shaded region, and the more potential there is for returns to diversity to be depressed. We would therefore expect that returns to diversity are dampened by the presence of age bias in an economy's sectoral composition. This intuition is formally established in Proposition 2.

Proposition 2. *If returns to additional labor are such that $b'' < 0$, then in a sample of countries with uniformly distributed δ, average returns to diversity are decreasing in age bias with returns being maximized in the case of no age bias at $z = \frac{1}{2}$.*

Proof. See Appendix A. □

Proposition 2 says that on average returns to diversity will be higher in places with less age bias. In other words, the closer an economy's z is to $\frac{1}{2}$ the higher returns to diversity it will have on average. Proposition 2 is our second testable prediction.

3 Data and empirical strategy

Our goal now is to examine whether our two testable hypotheses hold in the data. First, Proposition 1 says that age diversity should have a positive effect on output. Second, Proposition 2 refines this result by stating this relationship should be weaker in countries where the sectoral composition is biased towards either age group. In this section, we first describe how we test these two predictions, and then we proceed by describing the data sets we use.

3.1 Empirical strategy

In order to test whether there is an positive relationship between age diversity and output, we turn to two panel data sets: (1) a panel data of countries spanning the years 1948-2015, and (2) a panel data of European regions at the NUTS2 level spanning the years 2000-2016. In addition to these two data sets, we also look at a cross-sectional grid cell-level data set for the year 2010. We restrict our attention to the working age population (20-70) in all cases.

In general, we estimate regressions of the form

$$y_{ict} = \alpha_0 d_{ict} + X_{ict}\beta + \omega_i + \gamma_c + \delta_t + \epsilon_{ict}, \tag{4}$$

where y_{ict} is log GDP per capita in region i of country c in year t, d_{ict} is age diversity, X_{ict} represent various control variables, and ω_i, γ_c and δ_t are region, country and year fixed effects. Naturally, in the country-level regressions, there are no regional fixed effects. Similarly, in our cross-section of grid cells, there are no regional or year fixed effects. The prediction is that $\alpha_0 > 0$.

Further, in order to test whether the expected positive relationship between age diversity and output is dampened in economies with age-biased sectoral composition, we estimate regressions of the form

$$y_{ict} = \alpha_0 d_{ict} + \alpha_1 d_{ict} n_{ict} + X_{ict}\beta + \omega_i + \gamma_c + \delta_t + \epsilon_{ict}, \tag{5}$$

where n_{ict} is some measure of the economy's reliance on innovative and R&D activities to produce its output. We interpret the sectors represented by n_{ict} as sectors that are young-biased, that is sectors where young people are on average more productive. In other words, economies where innovative and R&D activities represent a large chunk of output have a sectoral composition that is biased towards the skillset of younger workers. In light of this interpretation, we expect $\alpha_1 < 0$: that is, returns to diversity are lower in age-biased economies. Appendix B provides some discussion of why we expect that young people are more productive in these industries.

Identification

In the country-level regressions, reverse causality is unlikely to be an issue for specifications (4) and (5), because current GDP cannot easily affect current age diversity without considerable cross-country migration. It may, however, be an issue in the regional and grid cell-level analyses. Another concern may be omitted variable bias. It could be for instance that past GDP affected fertility patterns and thus current age diversity, but it also affected current

GDP. This would, however, be a time-invariant omitted variable bias, and all such biases are effectively controlled for by our comprehensive country and region fixed effects. These fixed effects also ensure that factors such as institutions and culture are unlikely to be driving our results. In addition, our year fixed effects ensure that any common global shocks to GDP in a given year are controlled for as well.

The biggest threat to identification are, therefore, country-specific (or at least not globally common) time-varying factors that are correlated with both GDP and age diversity. Perhaps the most obvious examples here are other measures of demographic structure such as the old and young age dependency ratios, mean age, or the share of various age groups in the population. Controlling for such measures can help resolve most of these issues, but we still cannot necessarily ensure that we excluded all alternative explanations. In order to overcome this issue, we instrument for age diversity using the second and third moments (variance and skewness) of the distribution of past fertility. Mechanically, it should be the case that the more fertility varied from year to year, the more age diverse the population is.

It is easiest to illustrate how we construct our instrument with an example. Suppose we would like to construct the instrument for age diversity in Australia in 2015. Given that we focus on the population aged 20-70, we know that our target population was born between the years of 1945 and 1995. In this case therefore, we just take annual fertility data for Australia between these two years, and calculate the variance and skewness. We then use these measures as instruments.

The exclusion restriction would require that the volatility of past fertility only affects current GDP through its effect on age diversity. This seems plausible, though it may also be the case that volatility in fertility is related to economic volatility. However, to the extent that macroeconomic volatility is the property of a country's economic system, this should be picked up by our country fixed effects. Furthermore, globally present transitory periods of volatility (such as the 1970s) should be picked by our year fixed effects.

While our comprehensive country, region and year fixed effects, our controls for other measures of demographic characteristics, and our instruments go a long way in ruling out alternative hypotheses, we of course cannot ensure that there isn't something else going on. Regardless, we are able to rule out a great number of the most likely alternative explanations.

3.2 Data

We now proceed to describe the data sets we use to estimate (4) and (5). A more detailed description of all variables used can be found in Appendix E.

3.2.1 Age diversity

We measure age diversity by the mean absolute difference. This measure corresponds to the expected years of age difference between two individuals that are randomly chosen from the population. This is the natural counterpart to the HHI for non-categorical variables, where distance between any two groups can be measured. The mean absolute difference is essentially how the Gini coefficient is measured as well. Mathematically, our measure of age diversity is

$$\mathrm{AD} \equiv \sum_i \sum_j p_i p_j |\mathrm{age}_i - \mathrm{age}_j|,$$

where i and j are age groups, p_i and p_j are the share of each age group in the population, and age_i and age_j is the age of each group. The data needed to calculate this metric is population by age. For the country-level analysis, we use data from the UN Statistics Division's demographic data set. For the European regional analysis, we use data from Eurostat. And for the grid cell-level analysis, we use the Gridded Population of the World (GPW) data set (CIESIN (2017)).

3.2.2 Other variables

Innovative and R&D activities are measured by capital stock per inhabitant on the country level. On the European regional level, we use employment in various industries to look for age-bias in sectoral composition. Our primary measure of innovative and R&D activities there is employment in hi-tech manufacturing. To construct our instrument, we use data on the total fertility rate from the World Bank. Unfortunately, there is no data available to calculate our instrument on the regional or grid cell-level.

4 Empirical results

This section discusses the results of our empirical analysis. First, we explore our country-level evidence, where we are able to provide the best identification. Then, we move on to the European regional analysis, which, while more correlational in nature, reassures us of the results' consistency as well as provides additional robustness checks. We finish by showing our grid cell-level evidence, which is the most speculative, but also reaffirms consistency across data sets.

4.1 Country-level results

Table D.1 shows our main results. In Columns (1)-(3), we see three OLS specifications: (1) an unconditional relationship between age diversity and GDP per capita; (2) mean age is added as a basic control for demographic structure; and (3) we use capital per capita as a measure of the economy's age-biased sectoral composition. We see three interesting results. First, age diversity has a significant positive relationship with income per capita throughout specifications as consistent with Proposition 1. Second, returns to age diversity are lower in more age-biased economies as evidenced by the negative sign on the interaction between age diversity and capital per capita in Column (3). This is consistent with Proposition 2. And third, the magnitude of age diversity's coefficient does not go down as we add more controls suggesting that selection on unobservables is not an issue in our case.

In Columns (4) and (5) we re-estimate Columns (2) and (3) as IV specifications. As discussed in Section 3, the volatility of past fertility is used as an instrument. Our conclusions about positive returns to age diversity, and diminishing returns in the face of age bias are reinforced by the IV specifications. The first-stage relationship between the volatility of past fertility and age diversity is strong.

Finally, in Columns (6) and (7), we consider a type of falsification exercise. Instead of using the age diversity of the entire working age population, we restrict our attention to the age diversity of the population aged 20-40. We then re-estimate Columns (3) and (5): the OLS and IV specifications with interaction terms. First, we see that there are positive returns to the age diversity of young people as well indicating that it is not only the fraction of old people in the working age population that is driving our results. Second, we see that the sign of the interaction term reverses: returns to age diversity among young people are increasing in the degree of young-bias in the economy. This is very intuitive as it shows that the more young-biased the economy, the more important the composition of the young workforce is. Table D.2 reproduces these results for both the entire working age population and the 20-40 population from Columns (3) and (5)-(7) using an alternative measure of the economy's age bias: the proportion of medium- and high-tech industry value added in total value added.

To alleviate remaining concerns about age diversity being correlated with other demographic indicators, in Table D.3 we directly control for the old-age dependency ratio, young-age dependency ratio, and the fraction of the population in various age brackets. The specifications estimated in this table are our most complete ones with age diversity being instrumented and an interaction term with innovation included, corresponding to Column (5) in Table D.1. Our results stay intact: age diversity is robustly positively associated with income per capita, but returns are lower in age-biased economies. The magnitude of the coefficient on age diversity does not diminish upon the inclusion of these additional controls.

Our results are economically significant. The coefficient in Column (4) of Table D.1 implies that a one standard deviation increase (1.81) in age diversity is associated with a 47% increase in GDP per capita. In other words, moving from the 25th percentile of age diversity (corresponding to Colombia in 2005) to the 75th percentile (corresponding to Germany in 2014) can increase GDP per capita by 62%. This is 12% of the gap between Colombia's 2005 GDP per capita and Germany's 2014 GDP per capita.

The coefficients in Column (5) refine these results by taking the economy's sectoral composition into account. While the effective coefficient on age diversity is 0.316 at the 25th percentile of capital per capita (low age bias), it is roughly half that (0.166) at the 75th percentile (high age bias).

4.2 European regional results

Table D.4 corroborates our findings at the European regional level. Unfortunately, our instrument cannot be calculated at this level due to a lack of data. We nevertheless use lagged values of age diversity as instruments in some specifications following Backes-Gellner and Veen (2013), even though the exclusion restriction is most likely violated. The insights from Table D.4 are consistent with those gained in the country-level analysis. In Columns (1)-(3), we reproduce the same analysis as in Columns (1)-(3) of Table D.1. The same pattern of results emerges: consistently positive returns to age diversity, and lower returns in regions that are more age-biased. Our measure age bias now is the fraction of employment in the hi-tech manufacturing sector. In Columns (4)-(5), we instrument for age diversity with its two lagged values. Column (5) also instruments for hi-tech employment using its two lagged values.

Finally, Columns (6)-(7) reproduce Columns (3)-(5) but swapping working age population age diversity with the age diversity of the population aged 20-40. This is done in the same spirit as in the country-level analysis, and these columns therefore largely correspond to Columns (6)-(7) in Table D.1. The insights are unchanged: young age diversity has a positive sign, while the negative interaction between innovation and age diversity disappears when we restrict our attention to people aged 20-40.

Once more, to alleviate concerns about correlation with other demographic measures, in Table D.6 we control for the old-age dependency ratio, young-age dependency ratio, and the fraction of various age groups in the population. Our insights are unchanged.

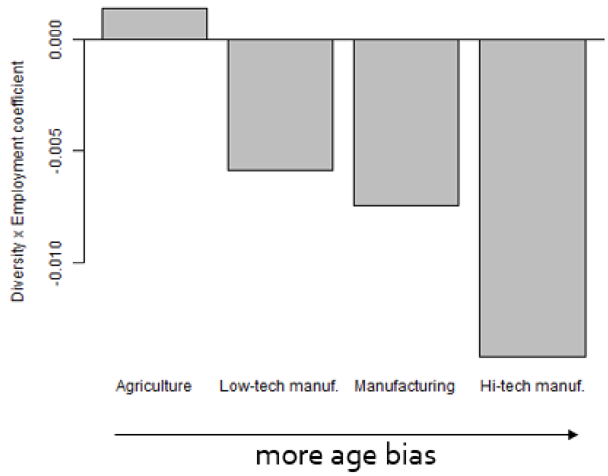


Figure 3: The effect of age bias on returns to diversity

An additional piece of analysis we can do in our regional data set is summarized in Figure 3. Namely, instead of interacting age diversity with hi-tech manufacturing employment, we interact it with employment in various other industries and then compare across industries. We pick industries that we can conceivably rank by their potential age bias. From low age bias to high, the industries we consider are: agriculture, low-tech manufacturing, manufacturing, and hi-tech manufacturing. We see in Figure 3 that the coefficient on the interaction term between age diversity and employment in various industries is lower the more age-biased an industry is. In other words, this lends credence to Proposition 2: the more age-biased an economy is, the lower the returns to age diversity are. The regressions results underlying the figure can be found in Table D.5.

At the European regional level, our results remain economically significant. Using the coefficient from Column (3) of Table D.4, we find that a one standard deviation (0.51) increase in age diversity is associated with a 4% higher income per capita. Moving from the 25th percentile of age diversity (corresponding to Alsace, France in 2000) to the 75th percentile (corresponding to Andalucia, Spain in 2003) is also associated with a 4% increase in GDP per capita.

The coefficient in Column (5), meanwhile, refines this result by saying that the coefficient of age diversity is 0.077 at the 25th percentile of hi-tech employment, but only about half that (0.041) at the 75th percentile of hi-tech employment.

4.3 Grid cell-level analysis

As a final step in our analysis, we examine our two testable predictions using grid cell-level data. This is a cross-sectional data set for 2010, which uses night lights to proxy for income per capita. Our analysis is done with 30 arcminute grid cells, which are roughly 50×50 kilometres at the equator. While identification is problematic in a grid cell-level analysis due to the fact that we only have cross-sectional data, which prevents us from adding grid cell fixed effects, we nevertheless see in Tables D.7-D.8 that lights per square kilometre and lights per worker are both significantly positively associated with age diversity.

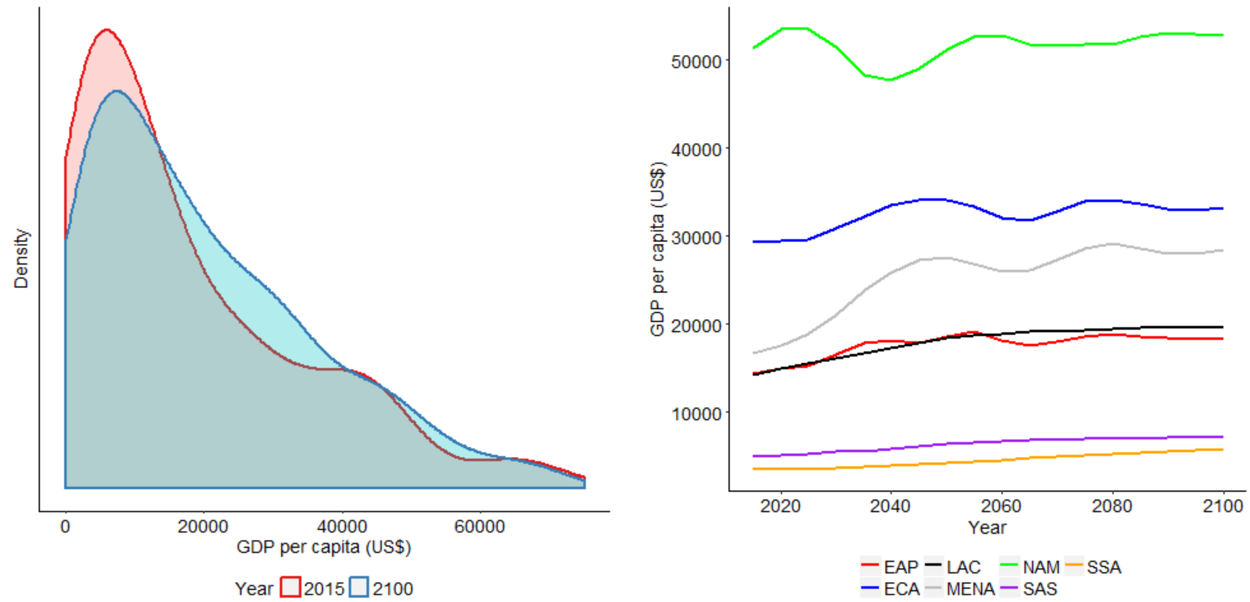
In both tables, Column (1) shows the unconditional relationship between age diversity and night lights. Column (2) includes mean age as a control. Column (3) includes a battery of geographical controls following Henderson et al. (2018). Column (4) uses the proportion of land area used as cropland from Ramankutty et al. (2008) as a proxy for age bias. Similarly to our employment in agriculture variable in the European regional analysis, we interpret this as a measure of how age-biased a grid cell is with higher reliance on cropland corresponding to less age bias. Both tables suggest that returns to age diversity are not lower in less age-biased areas lending credence to Proposition 2 and staying consistent with our country-level and regional results.

5 Age diversity in the future

Given our results in Section 4, we now estimate the economic impact of changing age diversity over the 21st century. Using population projections by age group for the period 2015-2100 from the United Nations (2017), we calculate projected age diversity by country for the remainder of the 21st century. Then, given our specification in (4), it is clear that holding everything else constant, the effect of age diversity in any year $t > 2015$ on income per capita relative to 2015 is

$$\frac{GDP_t}{GDP_{2015}} = e^{\alpha_0(d_t - d_{2015})}.$$

Figure 4a shows how the global distribution of income per capita will change in response to changes in age diversity. The figure compares the distribution in 2015 to the projected distribution in 2100 holding everything but age diversity constant. We see that age diversity will be an important force driving low-income countries out of poverty: the mass of countries with an income per capita under US\$20,000 is predicted to be considerably lower in 2100 than in 2015. More countries will fall between an income per capita of US\$20,000 and US\$60,000



(a) Distribution of income per capita

(b) Income per capita by region, 2015-2100

Figure 4: The effect of age diversity over the 21st century

as well. Nevertheless, global inequalities in income per capita are left vastly unchanged by changes in age diversity.

This message, however, conceals the regional differences in the effects of age diversity. This is shown in Figure 4b, which plots projected GDP per capita (as predicted by changes in age diversity alone) for 2015-2100 by World Bank region. We see that age diversity will have no significant effect aside from some fluctuations in North America (NAM) and Europe and Central Asia (ECA). Other regions see more positive effects. The Middle East and North Africa (MENA) in particular will receive a considerable economic boost from increasing age diversity. This would theoretically allow this region to overtake Latin America and the Caribbean (LAC) and East Asia Pacific (EAP), which both see only more modest effects. Meanwhile, the poorest economies of South Asia (SAS) and Sub-Saharan Africa (SSA) will both experience moderate upward pressure on income per capita due to increasing age diversity. The shift to higher age diversity will be more pronounced in South Asia first, widening the gap between the two poorest regions, but then by the end of the century Sub-Saharan Africa will catch up.

Figure C.1 plots GDP per capita over 2015-2100 by income status. We see that, most likely driven by improvements in the Middle East and North Africa and Latin America, it is middle-income countries that stand the most to gain from the projected changes in age diversity. Middle-income countries will open up their gap over low-income countries via the channel of age diversity, but they will shrink their gap with high-income countries leaving global inequalities by and large unchanged.

6 Discussion

Our paper identifies a new dimension via which demographics affect economics. Our two key findings are that age diversity can have a positive effect on income per capita, and that the magnitude of this effect depends on the economy's sectoral composition. Our paper underlines the importance of demographic factors in the growth process, and suggests several factors policymakers should pay attention to.

First, it pays to have a good demographic balance or, in other words, high age diversity in the population. This suggests that policymakers should ensure that fertility rates stay fairly stable over long periods of times, and that any transition in fertility is smooth rather than abrupt. Of course, it is rather difficult to manage fertility through policy. A perhaps easier avenue via which age diversity can be impacted is migration. This is especially relevant at the regional level, where our findings reinforce those of Gregory and Patuelli (2015) and Arntz and Gregory (2014).

Second, while returns to age diversity are important, not all is doomed if a government's hands are tied in managing age diversity. On the contrary, our findings suggest that ensuring that the sectoral composition of an economy is consistent with its demographic structure can make up for a lack of age diversity. This implies that regional and national policymakers should both pay attention to demographic projections, and incentivize the emergence of industries that can thrive in their particular demographic environment in the long run. In other words, similarly to Gu and Stoyanov (2018), we emphasize the connection between the comparative advantage of an economy and its age structure.

Third, while our paper doesn't directly tackle this question, it is conceivable that schemes that keep older workers' skills up-to-date in a rapidly changing environment can mitigate the costs of low age diversity. Things such as continuous education schemes can ensure that the skill gap between young and old workers are not as large as they would be in the absence of such interventions, and thus that old workers are better substitutes for young workers than they otherwise would be.

A variety of questions about age diversity remain open to future research. One such question is how age diversity and its economic impacts interact with changes in other demographic indicators. This is especially important, because if age diversity is used as a policy tool, policymakers will inadvertently impact other demographic characteristics as well when they try to manage age diversity. Another interesting question is the effect of more specific policy prescriptions on managing age diversity. While we provide some broad policy recommendations above, more specific prescriptions are necessary for potential practical implementation and policy evaluation.

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A Proofs

A.1 Proof of Lemma 2

The derivative of output with respect to the share of young people is

$$\frac{\partial \text{GDP}}{\partial \delta} = N^{b(z)+b(1-z)}[b(z)+b(1-z)]\left[b(z)\delta^{b(z)-1}(1-\delta)^{b(1-z)} - b(1-z)\delta^{b(z)}(1-\delta)^{b(1-z)-1}\right].$$

This is a continuous function of δ with the properties

$$\lim_{\delta\to 0}\frac{\partial \text{GDP}}{\partial \delta} = \infty$$
$$\lim_{\delta\to 1}\frac{\partial \text{GDP}}{\partial \delta} = -\infty.$$

Therefore, this function must reach its maximum somewhere on the open interval $(0,1)$. The maximum indeed exists, and it's unique at $\delta^* = \frac{b(z)}{b(z)+b(1-z)}$.

A.2 Proof of Proposition 1

Diversity, d, is maximized at $\delta = \frac{1}{2}$. Furthermore, at $z = \frac{1}{2}$, we also have that the share of young people that maximizes output is $\delta^* = \frac{1}{2}$. Therefore, output is maximized at peak diversity. Finally, it is clear from (3) that output is increasing in diversity at any given δ.

A.3 Proof of Proposition 2

In a regression of output on age diversity, the coefficient we would see is

$$\beta(z) \equiv \frac{\int_0^{\frac{1}{2}} \frac{\partial \text{GDP}}{\partial \delta} dF(\delta)}{F(1/2)} - \frac{\int_{\frac{1}{2}}^1 \frac{\partial \text{GDP}}{\partial \delta} dF(\delta)}{1-F(1/2)},$$

where $F(\cdot)$ is the CDF of the uniform distribution. In other words, we would see the expected returns to diversity given the distribution of δ. It is straightforward to show that

$$\beta(z) = 4\text{GDP}|_{\delta=\frac{1}{2}} = \underbrace{\left(\frac{N}{2}\right)^{b(z)+b(1-z)}}_{\equiv A(z)}[b(z)+b(1-z)].$$

Taking the derivative with respect to z, we have

$$\begin{aligned}\frac{\partial \beta}{\partial z} &= A(z)[b'(z)-b'(1-z)] + A'(z)[b(z)+b(1-z)] \\ &= A(z)[b'(z)-b'(1-z)]\left(1+\ln\frac{N}{2}[b(z)+b(1-z)]\right),\end{aligned}$$

since $A'(z) = A(z)[b'(z) - b'(1-z)] \ln \frac{N}{2}$. Note now that this is a continuous function in z with the properties

$$\lim_{z \to 0} \frac{\partial \beta}{\partial z} > 0$$
$$\lim_{z \to 1} \frac{\partial \beta}{\partial z} < 0,$$

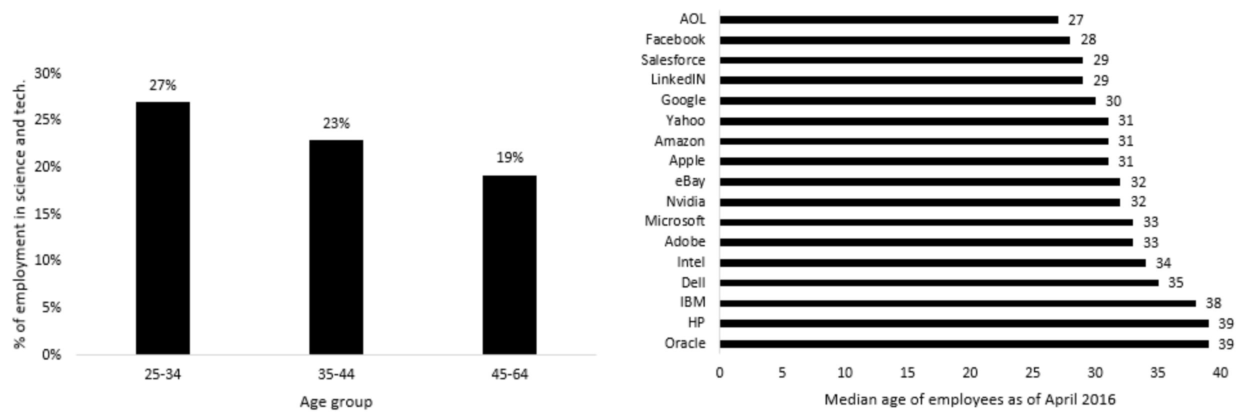
which follow from the facts that $b' > 0$ and $b'' < 0$. Therefore, this function must reach its maximum somewhere on the open interval $(0, 1)$. The maximum indeed exists, and it's unique at $z^* = \frac{1}{2}$. This follows by setting $\frac{\partial \beta}{\partial z}$ equal to zero, and noting that $A(z) > 0$ and $\left(1 + \ln \frac{N}{2}[b(z) + b(1-z)]\right) > 0$, so it must be that at the optimum

$$b'(z) - b'(1-z) = 0,$$

which can only happen at $z = \frac{1}{2}$ because $b' > 0$.

B Young people and innovation-heavy industries

Throughout our analysis, we use innovative and R&D-heavy industries as a proxy for a sector of the economy that is young-biased: that is, a sector where young people are more productive. Intuitively, it is straightforward why this may be the case. The human capital stock of young people is likely to be more up-to-date and thus relevant in industries with rapid progress. In addition, Gu and Stoyanov (2018) emphasize that younger workers are more adaptable, which is another key skill for succeeding in a rapidly changing environment. Finally, there is also evidence that some cognitive skills such as working memory or reaction time decline with age (Mattay et al. (2006)).



(a) % of age group employed in science and technology

(b) Median age of employees at US tech companies

Figure B.5: The young-bias of innovative and R&D-heavy industries

In addition to these intuitive reasons, we show in Figure B.5a that young people are considerably more likely to be employed in science and technology in the European Union. The numbers in Figure B.5a represent the fraction of all employed people in a given age group that works in science and technology with tertiary qualifications. It is apparent that young people are overrepresented in these industries.

Figure B.5b further shows that the median age at top US tech companies is incredibly low. This figure says that half of all workers at Facebook for instance are 28 years old or younger (Pelisson and Hartmans (2017)). This data is backed up by reports in the popular press. For instance, a survey of 1,011 US tech workers showed that 43% of tech workers are worried about losing their jobs due to their age, and that millennials are five times more likely than baby boomers to click on job advertisements looking for web developers or Android developers, and four times more likely to click on ads looking for Java developers or data scientists (Mukherjee (2017)). Anecdotal reports also confirm that older tech workers find it hard to remain employed in the industry. A market research firm found that salaries in the tech sector begin to fall around age 45 with people in their fifties asking for the same salaries as millennials with a mere two years of experience (Kuchler (2017)).

C Figures

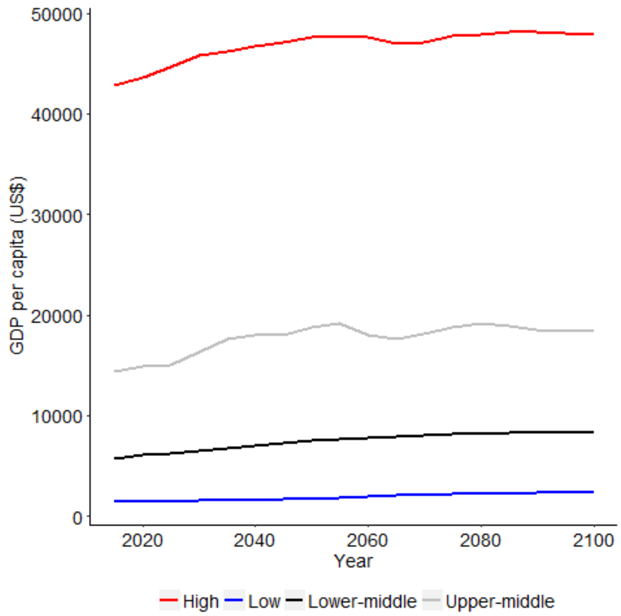


Figure C.1: The effect of age diversity on income per capita by income status, 2015-2100

D Tables

D.1 Cross-country tables

Table D.1: Main results of cross-country analysis

	Dependent variable:						
	Log GDP per capita (PPP)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	IV	IV	OLS	IV
Age diversity	0.097***	0.136***	0.186***	0.259***	0.343***		
	(0.009)	(0.011)	(0.013)	(0.044)	(0.042)		
Age diversity (young)						0.253***	0.641***
						(0.066)	(0.167)
Capital per capita			0.094***		0.187***	0.009**	-0.009
			(0.013)		(0.030)	(0.004)	(0.007)
Mean age		−0.021***	−0.029***	−0.053***	−0.066***	0.007**	−0.001
		(0.004)	(0.004)	(0.011)	(0.011)	(0.003)	(0.005)
Age diversity × Capital p.c.			−0.010***		−0.022***		
			(0.002)		(0.004)		
Age diversity (young) × Capital p.c.						0.012***	0.035***
						(0.004)	(0.007)
First stage F-statistic	-	-	-	55.81	35.24	-	59.03
No. of countries	168	168	166	155	155	166	155
Observations	1,823	1,823	1,819	1,471	1,471	1,818	1,471
R^2	0.958	0.959	0.961	0.969	0.969	0.957	0.965
Adjusted R^2	0.952	0.953	0.956	0.964	0.965	0.951	0.959

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows the positive relationship between age diversity and GDP per capita in panel data of countries (1960-2015). The table also shows that this relationship is weaker for regions with higher capital per capita. All columns include region, country, and year fixed effects. "Age diversity (young)" refers to the age diversity of 20-40 year-olds. Capital per capita is measured as the real capital stock per 10,000 inhabitants. The IV columns instrument for age diversity using the standard deviation and skewness of past fertility.

Table D.2: Main results with an alternative measure of innovation

	Dependent variable:			
	Log GDP per capita (PPP)			
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Age diversity	0.322***	0.493***		
	(0.023)	(0.091)		
Age diversity (young)			1.043***	2.953***
			(0.241)	(0.576)
Hi-tech employment	0.565***	1.599***	−0.285***	−0.350***
	(0.119)	(0.360)	(0.075)	(0.130)
Mean age	−0.109***	−0.088***	−0.018	0.164***
	(0.016)	(0.020)	(0.023)	(0.043)
Age diversity × Hi-tech	−0.084***	−0.223***		
	(0.016)	(0.049)		
Age diversity (young) × Hi-tech			0.355***	0.563***
			(0.122)	(0.215)
First stage F-statistic	-	18.48	-	25.99
No. of countries	93	91	93	91
Observations	804	779	804	779
R^2	0.978	0.976	0.974	0.970
Adjusted R^2	0.974	0.972	0.970	0.963

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows that the positive relationship between age diversity and GDP per capita in our panel data of countries (1960-2015) is robust to an alternative measure of innovation: hi-tech employment. All columns include region, country, and year fixed effects. "Age diversity (young)" refers to the age diversity of 20-40 year-olds. The IV columns instrument for age diversity using the standard deviation and skewness of past fertility.

Table D.3: Alternative measures of age structure in the cross-country analysis

	Dependent variable:		
	Log GDP per capita (PPP)		
	(1)	(2)	(3)
Age diversity	0.334***	0.639***	0.504***
	(0.041)	(0.098)	(0.097)
Age diversity × Capital p.c.	−0.021***	−0.024***	−0.037***
	(0.004)	(0.004)	(0.005)
Capital per capita	0.179***	0.208***	0.299***
	(0.029)	(0.034)	(0.040)
Old age dependency ratio	1.300**		
	(0.516)		
Young age dependency ratio		4.971***	
		(1.198)	
Fraction 20-29			−3.777***
			(1.105)
Fraction 30-39			−2.854*
			(1.470)
Fraction 40-49			−4.627**
			(1.942)
Fraction 50-59			2.028
			(2.607)
Fraction 60-69			−3.793
			(3.694)
First-stage F-statistic	36.89	22.88	67.28
No. of countries	155	155	155
Observations	1,471	1,471	1,471
R^2	0.970	0.964	0.968
Adjusted R^2	0.965	0.958	0.964
Note:			*p<0.1; **p<0.05; ***p<0.01

This table shows that the positive relationship between age diversity and GDP per capita in our panel data of countries (1960-2015) is robust to an alternative measures of age structure. All columns include region, country, and year fixed effects. All columns instrument for age diversity using the standard deviation and skewness of past fertility.

D.2 Regional tables

Table D.4: Main results of European regional analysis

	Dependent variable:							
	Log GDP per capita, PPS							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	IV1	IV2	OLS	IV1	IV2
Age diversity	0.034***	0.034***	0.073***	0.094***	0.108***			
	(0.006)	(0.006)	(0.012)	(0.013)	(0.015)			
Age diversity (young)						0.944***	0.976***	0.889***
						(0.041)	(0.046)	(0.051)
Hi-tech employment			0.231***	0.275***	0.291***	0.011*	0.016**	0.035***
			(0.050)	(0.052)	(0.061)	(0.007)	(0.007)	(0.009)
Mean age		−0.007	−0.006	0.009	0.005	0.132***	0.142***	0.121***
		(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.008)
Age div. × Hi-tech			−0.012***	−0.015***	−0.014***			
			(0.003)	(0.003)	(0.004)			
Age div. (young) × Hi-tech						0.016**	0.004	−0.001
						(0.006)	(0.007)	(0.009)
Observations	4,316	4,316	3,765	3,369	3,185	3,765	3,369	3,185
R^2	0.963	0.963	0.965	0.971	0.970	0.971	0.975	0.975
Adjusted R^2	0.960	0.960	0.962	0.968	0.967	0.968	0.973	0.972

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows the positive relationship between age diversity and GDP per capita in panel data of European regions (1995-2015). The table also shows that this relationship is weaker for regions with higher hi-tech employment. All columns include region, country, and year fixed effects. "Age diversity (young)" refers to the age diversity of 20-40 year-olds. The IV1 specifications instrument for age diversity using its two lagged values. The IV2 specifications instrument, in addition, for hi-tech employment using its two lagged values.

Table D.5: Age diversity and GDP per capita, interaction with industry composition

	Dependent variable:								
	Log GDP per capita, PPS								
	Agriculture			Low-tech manufacturing			Manufacturing		
	(1) OLS	(2) IV1	(3) IV2	(4) OLS	(5) IV1	(6) IV2	(7) OLS	(8) IV1	(9) IV2
Age diversity	0.064***	0.075***	0.082***	0.054***	0.086***	0.083***	0.114***	0.138***	0.164***
	(0.007)	(0.008)	(0.009)	(0.014)	(0.015)	(0.016)	(0.016)	(0.017)	(0.018)
Employment	−0.054***	−0.033***	−0.070***	0.055*	0.091**	0.076*	0.099***	0.109***	0.144***
	(0.010)	(0.012)	(0.013)	(0.033)	(0.036)	(0.041)	(0.016)	(0.018)	(0.020)
Mean age	0.003	0.015***	0.013**	0.005	0.019***	0.022***	−0.002	0.017***	0.016***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age diversity × Employment	0.001**	0.0002	0.001*	−0.004**	−0.007***	−0.006**	−0.005***	−0.006***	−0.007***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	3,845	3,441	3,257	3,993	3,564	3,447	4,027	3,593	3,500
R^2	0.969	0.972	0.969	0.961	0.968	0.968	0.962	0.967	0.965
Adjusted R^2	0.966	0.970	0.965	0.958	0.965	0.965	0.958	0.964	0.962

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows how age diversity interacts with a region's dependence on various industries. "Employment" refers to the fraction of people employed in the given sector (agriculture, low-tech manufacturing, or manufacturing). The less innovative industries a region is dependent on, the higher the returns to age diversity. The IV1 specifications instrument for age diversity using its two lagged values. The IV2 specifications instrument, in addition, for employment using its two lagged values.

Table D.6: Alternative measures of age structure in the European regional analysis

	Dependent variable:		
	Log GDP per capita, PPS		
	(1)	(2)	(3)
Age diversity	0.098***	0.054***	0.182***
	(0.015)	(0.012)	(0.016)
Hi-tech employment	0.286***	0.274***	0.239***
	(0.061)	(0.051)	(0.054)
Age diversity × Hi-tech	−0.014***	−0.014***	−0.012***
	(0.004)	(0.003)	(0.003)
Old age dependency ratio	0.708***		
	(0.269)		
Young age dependency ratio		−6.392***	
		(0.196)	
Fraction 20-29			0.792***
			(0.303)
Fraction 30-39			4.873***
			(0.258)
Fraction 40-49			1.307***
			(0.338)
Fraction 50-59			4.797***
			(0.300)
Fraction 60-69			0.736***
			(0.273)
Observations	3,185	3,185	3,185
R^2	0.970	0.979	0.978
Adjusted R^2	0.967	0.977	0.975
Note:	*p<0.1; **p<0.05; ***p<0.01		

This table shows that the positive relationship between age diversity and GDP per capita in our panel data of European regions (1995-2015) is robust to alternative measures of age structure. All columns include region, country, and year fixed effects. All columns are IV specifications that instrument for age diversity using its lagged values from the previous two years. In addition to this, hi-tech employment is also instrumented with its two lagged values.

D.3 Grid cell-level tables

Table D.7: Age diversity and lights per square km at the grid cell-level

	Dependent variable:			
	Log lights per sq. km			
	(1)	(2)	(3)	(4)
Age diversity	0.470***	0.237***	0.267***	0.217***
	(0.006)	(0.015)	(0.013)	(0.013)
Cropland				−6.073***
				(0.657)
Mean age		−0.150***	0.004	−0.008
		(0.008)	(0.007)	(0.007)
Age diversity × Cropland				1.064***
				(0.067)
Country fixed effects	Yes	Yes	Yes	Yes
Geographical controls	No	No	Yes	Yes
Observations	62,292	56,532	56,532	55,674
R^2	0.388	0.342	0.561	0.584
Adjusted R^2	0.386	0.340	0.559	0.583

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows the positive relationship between age diversity and log lights per square km in a cross section of 30 arc minute grid cells for the year 2010. All columns include country fixed effects. Geographical controls include ruggedness, malaria ecology, temperature, precipitation, growing days, land suitability, absolute latitude, elevation, coastal dummy, distance to coast, nearby harbor, river or lake dummy, and fourteen biome dummies. Lights per sq. km is radiance-corrected, and therefore not top coded.

Table D.8: Age diversity and lights per worker at the grid cell-level

	Dependent variable:			
	Log lights per worker			
	(1)	(2)	(3)	(4)
Age diversity	0.162***	0.170***	0.191***	0.177***
	(0.020)	(0.021)	(0.019)	(0.019)
Cropland				2.706***
				(1.012)
Mean age		−0.196***	−0.035***	−0.036***
		(0.011)	(0.011)	(0.011)
Age diversity × Cropland				−0.013
				(0.103)
Country fixed effects	Yes	Yes	Yes	Yes
Geographical controls	No	No	Yes	Yes
Observations	56,550	56,532	56,532	55,674
R^2	0.232	0.236	0.379	0.385
Adjusted R^2	0.230	0.234	0.376	0.383

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows the positive relationship between age diversity and log lights per worker in a cross section of 30 arc minute grid cells for the year 2010. All columns include country fixed effects. Geographical controls include ruggedness, malaria ecology, temperature, precipitation, growing days, land suitability, absolute latitude, elevation, coastal dummy, distance to coast, nearby harbor, river or lake dummy, and fourteen biome dummies. Lights per worker is radiance-corrected, and therefore not top coded.

E Data description

E.1 Country-level data

GDP per capita. This is the main dependent variable. It refers to expenditure-side real GDP per capita from the Penn World Table 9.0.

Age diversity. This is the main explanatory variable. It is the age diversity of the population aged 20-70 measured as a mean absolute difference. The source is the UN Statistics Division's population by age data.

Age diversity (20-40). The age diversity of the population aged 20-40 measured as a mean absolute difference. The source is the UN Statistics Division's population by age data.

Mean age. The mean age in a given country. The source is the UN Statistics Division's population by age data.

Capital per capita. The real capital stock per 10,000 inhabitants from the Penn World Table 9.0.

Fertility standard deviation and skewness. These are the main instrumental variables. They refer to the standard deviation and skewness of past fertility corresponding to the years when 20-70 year-olds were born. This is further explained in Section 3.1. The source is the World Bank's fertility data.

Hi-tech value added. This refers to the proportion of medium and high-tech industry value added in total value added. The source is the UN Statistics Division's Sustainable Development Goals database.

Old age dependency ratio. The fraction of the population aged 65 and older. The source is the UN Statistics Division's population by age data.

Young age dependency ratio. The fraction of the population aged 15 and younger. The source is the UN Statistics Division's population by age data.

Fractions of various age groups. The fraction of the population in a given age group. The source is the UN Statistics Division's population by age data.

E.1.1 Regional data

GDP per capita. This is the main dependent variable. It refers to real GDP per capita from Eurostat.

Age diversity. This is the main explanatory variable. It is the age diversity of the population aged 20-70 measured as a mean absolute difference. The source is Eurostat's population by age data.

Age diversity (20-40). The age diversity of the population aged 20-40 measured as a mean absolute difference. The source is Eurostat's population by age data.

Mean age. The mean age in a given country. The source is Eurostat's population by age data.

Employment in various industries. Employment in a given industry as a percentage of total employment in the region. The source is Eurostat.

Old age dependency ratio. The fraction of the population aged 65 and older. The source is Eurostat's population by age data.

Young age dependency ratio. The fraction of the population aged 15 and younger. The source is Eurostat's population by age data.

Fractions of various age groups. The fraction of the population in a given age group. The source is Eurostat's population by age data.

E.1.2 Grid cell-level data

Lights per square kilometer. Night light intensity per square kilometer as observed from space in 2010 in 30 arc minute grid cells. Radiance-corrected data is used, which is not top coded. This follows Henderson et al. (2018).

Lights per worker. Night light intensity per worker as observed from space in 2010 in 30 arc minute grid cells. Radiance-corrected data is used, which is not top coded. This follows Henderson et al. (2018).

Age diversity. This is the main explanatory variable. It is the age diversity of the population aged 20-70 measured as a mean absolute difference. The source is the GPW population by age data from CIESIN (2017).

Cropland. This represents the proportion of land areas used as cropland (land used for the cultivation of food) in the year 2000. The source is Ramankutty et al. (2008).