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Can Education Compensate the Effect of Population Aging on Macroeconomic Performance? Evidence from Panel Data*

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Abstract

This paper investigates the consequences of population aging and of changes in the education composition of the population for macroeconomic performance. Estimation results from a theoretically founded empirical framework show that aging as well as the education composition of the population influence economic performance. The estimates and simulations based on population projections and different counterfactual scenarios show that population aging will have a substantial negative consequence for macroeconomic performance in many countries in the years to come. The results also suggest that education expansions tend to offset the negative effects, but that the extent to which they compensate the aging effects differs vastly across countries. The simulations illustrate the heterogeneity in the effects of population aging on economic performance across countries, depending on their current age and education composition. The estimates provide a method to quantify the increase in education that is required to offset the negative consequences of population aging. Counterfactual changes in labor force participation and productivity required to neutralize aging are found to be substantial.

JEL-classification: J11; O47

Keywords: Demographic Change; Demographic Structure; Distribution of Skills; Projections; Education-Aging-Elasticity

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1 Introduction

Population aging is one of the most important economic and social challenges in the twenty-first century. With increasing life expectancy and falling fertility, the populations of most countries grow older, resulting in substantial shifts in the age composition of workforce and population at large. At the same time, the demographic transition and the associated shift in the age distribution imply substantial changes in the aggregate stock of human capital as well as its age distribution, as relatively large cohorts with low or moderate levels of formal education are replaced by relatively small cohorts with high levels of formal education.

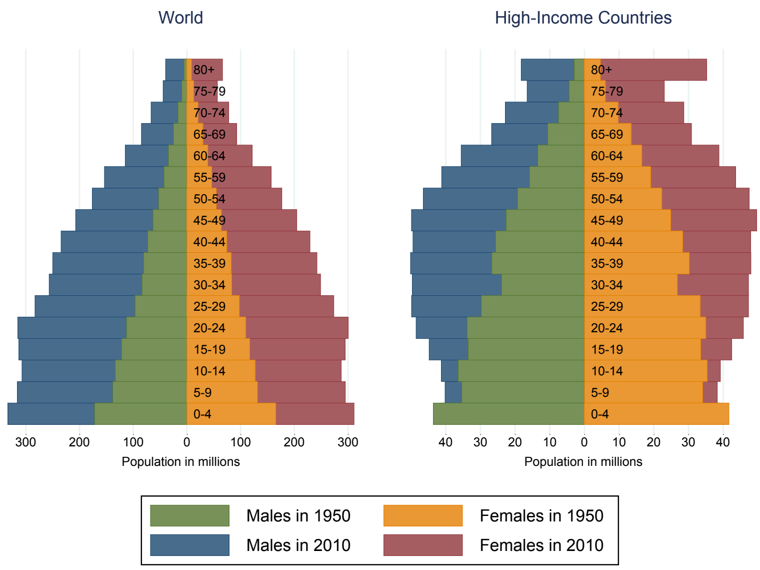
This can be illustrated by changes in the age structure of populations over long time periods. Panel (a) of Figure 1 plots the age structure in the world and in high-income (OECD) countries in 1950 and 2010. Evidently, not only the size of the world population has changed over this period but, in particular, also the age composition. Whereas in a global perspective the population has increased rather uniformly across all ages, with a slowdown only visible for the youngest cohorts below 20 years of age, aging is much more pronounced among the high-income countries. However, even within the group of high-income countries, there are substantial differences in the demographic dynamics. Panel (b) of Figure 1 plots the corresponding patterns for Germany, the United Kingdom, and France in 1950 and 2010. In Germany, the age composition of the population is most uneven, with the consequence of a stronger aging momentum than in the UK and, in particular, in France, where the age composition is fairly uniform at ages below 65.

These demographic changes have important consequences for productivity and human capital. The shift in the age composition has implications for the informal, experience-related human capital embodied in the population. This follows from the empirically well-documented age-experience profile from life cycle models of human capital (Ben-Porath, 1967). At the same time, populations differ greatly in their formal education attainment, both across age groups and across countries. Younger cohorts typically exhibit much higher levels of schooling and formal training. Figure 2 documents the secular increase in the share of high skilled over the period 1950 to 2010 for high-income (OECD) and Non–OECD countries in Panel (a), as well as for three developed countries, Germany, the UK, and France, in Panel (b).

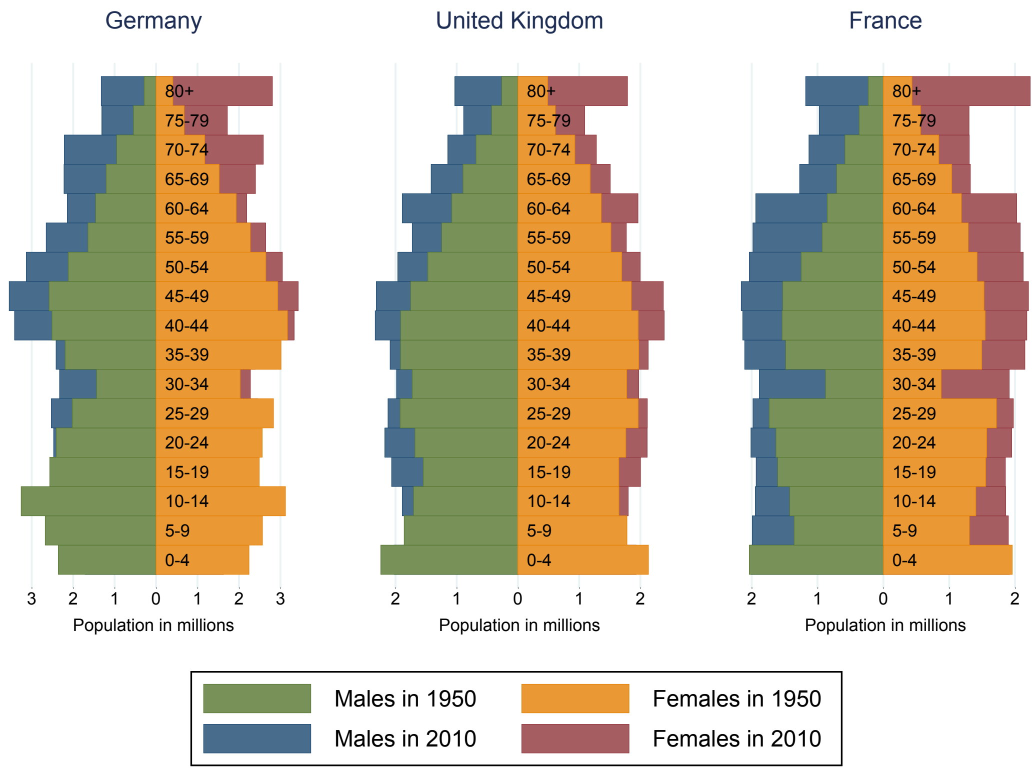
Although these forceful demographic dynamics can be expected to have major implications for macroeconomic performance, the joint effects of population aging and of changes in the human capital endowment for macroeconomic performance are still not well understood. Whereas the economic consequences of aging and of changes in human capital have been investigated in isolation, their interactions have been largely neglected in the existing literature.

This paper addresses three questions that remain open in light of the existing literature: How do population aging and the contemporaneous changes in aggregate human capital affect macroeconomic performance? Can investment in education offset the (potentially negative) effects of population aging? And, finally, what are the corresponding prospects of future economic development?

Using data from a cross-country panel of more than 130 countries for the period 1950 to 2010, we investigate empirically how changes in the age structure of the workforce and in the distribution of human capital affect macroeconomic performance in terms of levels and growth rates. The investigation is based on an extended empirical development accounting model that encompasses the empirical frameworks used in the existing literature and that allows estimating the distinct effects of aging and human capital. These estimates can be used for a detailed analysis



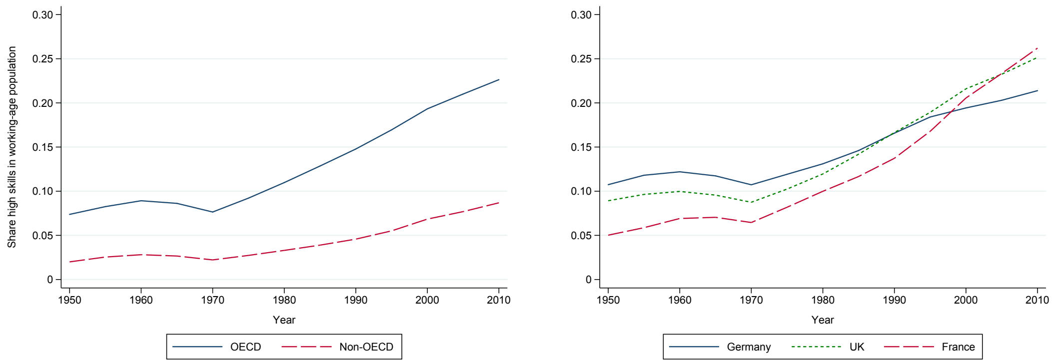
(a) World and High–Income Countries



(b) Germany, United Kingdom and France

Figure 1: Population Dynamics – Selected Regions

Data source: United Nations, Department of Economic and Social Affairs (2015). World Population Prospects: The 2015 Revision.



(a) OECD and Non–OECD Countries

(b) Germany, United Kingdom and France

Figure 2: Dynamics of Educational Attainment

of the relative importance of aging and human capital dynamics for the projected development paths of countries around the world until 2050, and for a quantitative assessment of different scenarios of aging and education acquisition.

The analysis proceeds in three steps. The first step sets the stage by restricting the analysis to the effects of population aging and of changes in the aggregate human capital endowment for macroeconomic performance in isolation from each other, thereby replicating the existing evidence in the literature. The estimation results reveal that changes in the age composition of the work force significantly affect economic performance. The estimates mirror the well-known hump-shaped individual productivity patterns from micro studies, with the largest positive effects being associated with prime working ages and smaller effects for young and old population segments. Likewise, the levels and dynamics in aggregate human capital are shown to affect economic performance independently from the demographic structure.

In the second step, the empirical analysis explicitly considers the interactions between aging and changes in the skill composition. This analysis complements and extends the existing literature, which, with few exceptions, has largely been restricted to focusing either on population aging or changes in the human capital endowment in isolation. The results reveal that population aging has substantial implications on economic performance even when accounting for changes in the education composition, and that the demographic structure of the workforce and education both jointly affect economic performance. Moreover, the demographic structure affects economic performance non-monotonically, implying heterogeneous prospective development paths conditional on the extent of demographic change. At the same time, there is little evidence for eroding productivity of human capital attained in terms of formal education in older cohorts.

In the third and final step of the analysis, the estimation results are used to conduct quantitative exercises that shed light on the relative importance of the changes in the age and in the skill composition of the workforce that occur as consequence of the ongoing process of population aging. In particular, based on the empirical estimates, macroeconomic performance is projected under several alternative scenarios that use the projected changes in age composition and education. These projections are compared to counterfactual scenarios that fix the age composition or human capital at current levels. According to these quantitative exercises, aging and a slowdown in education attainment will dampen economic performance, particularly, in developed economies where aging is especially pronounced and the population has already attained fairly high levels of education throughout all age cohorts. Investment into education turns out to be a powerful force in compensating the negative consequences of population aging. However, the results also suggest that even enhanced investments in education are unlikely to completely offset the effects of population aging in the countries that face the greatest pressure of population aging. In contrast, for economies with a relatively stable demographic structure, aging is projected to have rather neutral effects on macroeconomic performance, while the projected increase in human capital implies a positive prospective performance.

Furthermore, the results provide an estimate of the elasticity of substitution between the age composition and the human capital endowment of a country. This elasticity provides new insights into the change in the distribution of human capital that is needed in order to offset the effects of changes in the age composition of the workforce. The quantitative estimate for this elasticity suggests that aging-related shifts in the composition of the population require substantial increases in the education of young cohorts.

This paper contributes to the literature in multiple ways. Several contributions in macro-development have focused on the consequences of aging by focusing on the implications of variation in the young- and old-age dependency ratio for the demographic dividend (Bloom and Williamson, 1998; Bloom, Canning and Sevilla, 2003), and, more recently, Aiyar, Ebeke, and Shao (2016), and Acemoglu and Restrepo (2017) for productivity and technical change. Other contributions have analyzed the effects of aging and skills on growth. Feyrer (2007) finds that the age composition of the workforce affects macroeconomic performance, mainly through total factor productivity. Maestas, Mullen, and Powell (2016) use variation in aging across US states over the period 1980–2010 to estimate the growth effect of aging and find a substantial negative effect. However, these studies only indirectly account for the changes in human capital and its age composition. In contrast, Cuaresma, Lutz, and Sanderson (2014) investigate the joint effect of skills and aging. Instead of conducting a cohort-based analysis that accounts for the distribution of skills and aging as we do in this paper, they look at the role of labor force participation and dependency ratios. On the other hand, Sunde and Vischer (2015) show that human capital affects output growth through the productivity of production factors and the potential to innovate (Lucas, 1988; Aghion and Howitt, 1992), or to adopt and diffuse new technologies (Nelson and Phelps, 1966). The approach taken in this paper incorporates these different contributions into a single coherent framework. This allows investigating the relative importance of changes in the age composition and in the skill composition of the population, shedding light on the robustness of earlier results. Thereby, we provide a systematic investigation and decomposition of aging effects through shifts in the demographic composition and changes in the human capital distribution which is missing in the existing literature. The findings indeed point to interactions between population aging and changes in the human capital composition, suggesting that restricting attention to only one dimension delivers an incomplete picture.

To our knowledge, the only two papers that go in a similar direction are by Lindh and Malmberg (1999) and Cuaresma, Loichinger, and Vincelette (2016). However, the analysis by Lindh and Malmberg (1999) is confined to using cross-country data for OECD countries, whereas Cuaresma, Loichinger, and Vincelette (2016) focus on European countries. Our analysis is based on a theoretically founded empirical framework that encompasses frameworks used previously and presents estimation and projection results for a long panel data set for more than 130 countries. Moreover, the estimates presented below contribute by allowing to conduct counterfactual simulations of economic performance under alternative scenarios of aging, human capital dynamics, labor force participation and productivity. Another novelty are the estimates for an upper bound of the semi-elasticity between changes in the age structure and changes in human capital, as well as of changes in labor force participation and productivity improvements, which are required to offset the macroeconomic consequences of the changes in the age composition in the most favorable case.

The analysis is also related to, and complementing, microeconometric work on age-education decompositions of labor earnings. Work by Card and Lemieux (2001) has used models with imperfect substitution between similarly educated workers in different age groups to study the dynamics of the college wage premium. More recent work by Acemoglu and Autor (2011) and Autor and Dorn (2013) shows for census data and tasks how skill-biased technological progress and changes in the supply of skill levels across cohorts has led to wage polarization in the United States. Vandenberghe (2017) investigates whether a better educated and more experienced workforce contributes to the recent rise in total factor productivity (TFP). Our estimation and projection results complement these studies by providing novel insights in the consequences of population aging and demographic change. In analogy to the approach popularized by Card and Lemieux (2001) and applied by Fitzenberger and Kohn (2006), we develop a decomposition that allows estimating elasticities of substitution between demographic aging and changes in the education structure. Our empirical findings also complement recent evidence for the effect of aging on productivity and wages. For instance, Göbel and Zwick (2013) find that productivity among employees is highest around 50 and only find modest declines in the productivity at older ages, while Börsch-Supan and Weiss (2016) find that there are (almost) no negative aging effects on productivity for production line workers before age 60. Complementing this, Mahlberg et al. (2013) find little evidence between productivity or wages at the firm level and the share of older employees in that firm. The findings for the aggregate level presented in this paper deliver macroeconomic age profiles that are consistent with these findings.

The quantitative analysis sheds new light on the potential implications of aging and education dynamics for growth. Recent work by Acemoglu and Restrepo (2017) suggests that directed technical change and a rapid adoption of automation technologies might provide a countervailing force to the negative growth effects of population aging, particularly in countries that undergo more pronounced demographic changes. Our findings allow to quantify how large, ceteris paribus, the productivity improvements of directed technical change would have to be in different countries in order to fully offset the effects of population aging and the associated education dynamics.

The remainder of this paper is structured as follows. Section 2 presents our methodology and empirical framework. A data description is provided in Section 3. Section 4 provides estimation results and Section 5 presents the implications of these estimation results for future economic performance, using different scenarios of aging and education projections. Section 6 concludes.

2 Methodology

The analysis is based on an aggregate production framework that underlies the standard development accounting model as in Benhabib and Spiegel (1994) and Hall and Jones (1999). Output Y is produced as a function of total factor productivity A, physical capital K and human capital H of the form:

$$Y_{it} = A_{it} K_{it}^{\alpha} H_{it}^{1-\alpha} \tag{1}$$

Subscripts i and t denote cross-sectional units (countries) and time units (five-year intervals), respectively. Dividing by the labor force (working-age population), L_{it}, delivers the output per worker in intensive form

$$y_{it} = \frac{Y_{it}}{L_{it}} = A_{it} k_{it}^{\alpha} \left(\frac{H_{it}}{L_{it}} \right)^{1-\alpha}$$

with $k_{it} = \frac{K_{it}}{L_{it}}$ being capital per worker.

The aggregate stock of human capital, H_{it}, is a function of human capital per worker h_{it} and the overall quality of the labor force Q as a function of the demographic structure of the workforce and cohort-specific productivity parameters. Quality of the labor force is assumed to be a simple size-weighted average

$$H_{it} := h_{it} Q_{it} = h_{it} \left[\pi_1 L_{it}^1 + \cdots + \pi_k L_{it}^J \right], \tag{2}$$

where $L_{it}^1, \ldots, L_{it}^J$ denote the labor force of each age cohort in the workforce and $\pi_1, \ldots, \pi_J$ the respective productivity of each group. Age-related productivity differences can be related to differences in physical strength, or, more likely, correspond to differences in human capital that is acquired on the job in terms of experience. This is consistent with standard models of human capital acquisition over the life cycle (Ben-Porath, 1967). Moreoer, this specification implies that productivity-adjusted labor shares of different age groups are perfectly substitutable, and in the empirical analysis, relative productivity differences across age groups will be estimated and held fixed across countries. This allows us to study the effects of changing supplies of labor in different age (and skill) groups while fixing their relative efficiency.[1] The aggregate human capital stock per worker is thus given by

$$\frac{H_{it}}{L_{it}} = h_{it} \left[\left(\frac{1}{L_{it}} \right) \sum_{j=1}^{J} \pi_j L_{it}^j \right] = h_{it} \left[\sum_{j=1}^{J} \pi_j \frac{L_{it}^j}{L_{it}} \right] = h_{it} \left[\sum_{j=1}^{J} \pi_j S_{it}^j \right]$$

with S^j denoting the share of each age cohort in the total labor force such that $\sum_{j=1}^{J} S_{it}^j = 1$. In

[1] Analyzing the simple case with substitution elasticity of one between physical and human capital and perfect substitution across age cohorts has the advantage of a straightforward derivation of a linear estimation framework. Moreover, the case of perfect substitution appears to be conservative in the present setting; see, e.g., the discussion by Caselli and Ciccone (2017). Alternatively, one could model the quality of the labor force more flexibly using a general constant elasticity of substitution (CES) form as in similar settings applied to different contexts; see, e.g., Sato (1967), Hellerstein and Neumark (1995), Card and Lemieux (2001) or, more recently, Vandenberghe (2017). The CES specification would allow for more flexible substitution patterns between age groups. This assumption is inessential, however, and could be relaxed by working with a CES specification and conducting estimates using a non-linear estimation model.

order to avoid multicollinearity in the empirical model, a reference category S^r_{it} is chosen so that

$$\frac{H_{it}}{L_{it}} = h_{it}\pi_r\left[S^r_{it} + \sum_{j\neq r}\frac{\pi_j}{\pi_r}S^j_{it}\right] = h_{it}\pi_r\left[(1 - \sum_{j\neq r}S^j_{it}) + \sum_{j\neq r}\frac{\pi_j}{\pi_r}S^j_{it}\right].$$

The aggregate human capital stock per worker is then given by

$$\frac{H_{it}}{L_{it}} = h_{it}\pi_r\left[1 + \sum_{j\neq r}\lambda^j S^j_{it}\right], \tag{3}$$

with $\lambda^j := \frac{\pi_j}{\pi_r} - 1$ denoting the difference in relative productivity between an age cohort j and the reference category. Inserting the expression for the human capital stock per worker in (3) into the production function in (1) and taking logs yields

$$\begin{aligned}\ln(y_{it}) &= \ln(A_{it}) + \alpha\ln(k_{it}) + (1-\alpha)\ln\left(\frac{H_{it}}{L_{it}}\right)\\ &= \ln(A_{it}) + \alpha\ln(k_{it}) + (1-\alpha)\Big[\ln(h_{it}) + \ln(\pi_r)\Big] + (1-\alpha)\ln\left(1 + \sum_{j\neq r}\lambda^j S^j_{it}\right).\end{aligned}$$

The last term in parentheses can be expected to be close to unity since the term for productivity ratios λ^j and the share of each age cohort in the total workforce is close to zero for a sufficiently large number of age groups, and correspondingly also their product. Hence, the last term in logarithms can reasonably be approximated by $\ln(1+x) \approx x$, i.e.,

$$\ln\left(1 + \sum_{j\neq r}\lambda^j S^j_{it}\right) \approx \sum_{j\neq r}\lambda^j S^j_{it}. \tag{4}$$

Human capital per worker h is assumed to be a function of an individual worker's skills which can either be high or low. Correspondingly, each skill group is assigned a skill-specific productivity $\{\pi_h, \pi_l\}$. Averaging over the entire economy, human capital per worker is, thus, the weighted average of the shares of each skill group $\{S^h,\ 1 - S^h\}$ multiplied by the respective productivity, or formally

$$h_{it} = \pi_h S^h_{it} + \pi_l(1 - S^h_{it}). \tag{5}$$

Taking logs and choosing the low skill group as reference, this expression can be rearranged to

$$\ln(h_{it}) = \ln\left[\pi_l\left(1 + \left(\frac{\pi_h}{\pi_l} - 1\right)S^h_{it}\right)\right],$$

which, using the same arguments as before, can be approximated by

$$\ln(h_{it}) = \ln(\pi_l) + \ln\left(1 + \lambda^h S^h_{it}\right) \approx \ln(\pi_l) + \lambda^h S^h_{it} \tag{6}$$

with $\lambda^h := \frac{\pi_h}{\pi_l} - 1$ denoting the difference in relative productivity between high-skilled and low-skilled workers. Log output is thus given by

$$\ln(y_{it}) \approx c + \ln(A_{it}) + \alpha\ln(k_{it}) + (1-\alpha)\lambda^h S^h_{it} + (1-\alpha)\sum_{j\neq r}\lambda^j S^j_{it}, \tag{7}$$

where $c = (1-\alpha)\big[\ln(\pi_l)+\ln(\pi_r)\big]$ is a constant. By taking first differences, the model is expressed in terms of growth rates:

$$\Delta \ln(y_{it}) \approx \Delta \ln(A_{it}) + \alpha \Delta \ln(k_{it}) + (1-\alpha)\lambda^h \Delta S_{it}^h + (1-\alpha)\Bigg[\sum_{j\neq r} \lambda^j \Delta S_{it}^j\Bigg]. \tag{8}$$

Since, in practice, total factor productivity is not observed, we model a country's total factor productivity as being determined by three components: An exogenous time trend ζ_t which represents freely available technology from the world technological frontier in a given period t, allowing for a technology diffusion process across countries; the past level of output which, by definition, comprises past TFP; and an idiosyncratic error component ε_{it} which serves as the error term for the empirical framework. This modeling assumption for TFP is motivated by the strong correlation between initial productivity, reflected by output per worker, and subsequent growth rates (see, e.g., Baumol, 1986).[2] Lagged output per worker therefore introduces persistence in the availability of technology within countries into the levels specification. This persistence may for example reflect capital-embodied technology that has been accumulated over time. Consequently, we posit that

$$\ln(A_{it}) = \zeta_t + \gamma \ln(y_{it-1}) + \varepsilon_{it}. \tag{9}$$

Moreover, this specification implies a further straightforward extension of our estimation framework to long-run productivity differences across countries along other dimensions that might enter equation (9) as additional control variables (e.g., institutions).

Therefore, the empirical model which is used to estimate the effect of the demographic structure of the workforce and the distribution of skills on output is given by

$$\ln(y_{it}) = \gamma \ln(y_{it-1}) + \alpha \ln(k_{it}) + (1-\alpha)\lambda^h S_{it}^h + (1-\alpha)\Bigg[\sum_{j\neq r} \lambda^j S_{it}^j\Bigg] + c_i + \zeta_t + \varepsilon_{it}, \tag{10}$$

where c_i allows for country-specific constants. The model in levels is estimated with the within-transformation to remove the constant c and account for country-specific fixed effects.

In terms of dynamics, we assume that total factor productivity growth of a country is determined by four components: An exogenous time trend τ_t which represents growth of freely available technology at the world technological frontier in a given period t, allowing for a technology diffusion process across countries; the economy's share of high skills in period $t-1$ which may facilitate the diffusion and adoption of already existing technologies (Nelson and Phelps, 1966) or foster novel innovation (Romer, 1990; Aghion and Howitt, 1992); the past level of output which, by definition, comprises past TFP; and an idiosyncratic error component u_{it} which serves as the error term for the empirical framework.

Consequently, the growth rate of total factor productivity is assumed to take the form

$$\Delta \ln(A_{it}) = \tau_t + \theta S_{it-1}^h + \psi \ln(y_{it-1}) + u_{it}. \tag{11}$$

[2] In an earlier version of this paper, we also included lagged skills in the levels equation. However, the respective variable was always insignificant in the empirical application and did not quantitatively change the overall effect of skills on output. Hence, the variable has been dropped from the specification.

This modeling of technological progress again accommodates for the strong correlation between initial productivity and subsequent growth (Baumol, 1986) and has been widely applied in models that study economic growth in general or the demographic dividend in particular (Fagerberg, 1994; Dowrick and Rogers, 2002; Bloom, Canning, and Sevilla, 2003; Cuaresma, Lutz, and Sanderson, 2014). Specifically, this modeling assumption implies conditional convergence in productivity across countries. In contrast to other models of conditional convergence such as Mankiw, Romer, and Weil (1992), however, this modeling of TFP growth allows for long-run differences in productivity even after the diffusion process is complete. Such differences may enter the estimation model through other variables in equation (11). Correspondingly, the estimation equation in growth rates is given by

$$\begin{aligned}\Delta \ln(y_{it}) &= \psi \ln(y_{it-1}) + \alpha \Delta \ln(k_{it}) \\ &+(1-\alpha)\lambda^h \Delta S^h_{it} + \theta S^h_{it-1} + (1-\alpha)\left[\sum_{j\neq r} \lambda^j \Delta S^j_{it}\right] + \tau_t + u_{it}. \end{aligned} \tag{12}$$

Estimating the model in terms of growth rates also accommodates for the possibility of an unit root in the error term if income follows a random-walk. Correspondingly, the series will be stationary. As will become clear below, coefficient estimates do not differ substantially between both models, but, unsurprisingly, the levels model is more efficient and explains a larger fraction of the variation. Results for both versions of the model are reported in Section 4.

This specification of the estimation framework is very flexible and can be adjusted to obtain the regression models of important other contributions of the literature. For example, the estimation model of Feyrer (2007) is obtained by assuming human capital to be the exponential of a piece-wise linear function of human capital savings and imposing no further assumptions on the structure of TFP growth apart from a common time trend across. Given this set of assumptions, the effect of the demographic structure is contained by total factor productivity.

The specification of Cuaresma, Lutz, and Sanderson (2014) can be obtained under the following assumptions: human capital per worker takes an exponential form as described above; GDP is expressed in terms of per capita instead of per worker terms; and the demographic structure of the workforce is neglected. In this case, the demographic structure enters output through the labor force participation rate and the share of the working-age population in the total population.

Finally, the specification of Sunde and Vischer (2015) is derived by assuming that human capital enters both, productivity and output, in logarithms instead of shares. Further control variables can be included by extending either the TFP residual by lagged level controls or the output by additional terms as a multiplicative or exponential function.

3 Data

Data for output and physical capital are from Penn World Tables by Feenstra, Inklaar, and Timmer (2015). The main dependent variables are log output per worker and the corresponding growth rate. In robustness analysis, we also use output per capita.

Data for the demographic structure are taken from different sources. The primary source of information about the working-age population for age cohorts in five-year intervals from 15 to 69 as well as for human capital and the corresponding projections is the IIASA–VID database by Lutz et al. (2007).[3] We define age cohorts of the workforce as cohort shares of the total working-age population in brackets 15–19 (below 20), 20–24, 25–29, 30–34, 35–39, 40–44, 45–49, 55–59, 60–64, 65–69 (65+). This reflects the potential workforce of a cohort in a given period in the estimation; i.e., we refrain from an adjustment for hours worked or employment shares to avoid endogeneity problems that might bias the estimates. In some specifications, the cohorts are collapsed to ten-year intervals in order to reduce the number of parameters to be estimated. The microeconometric evidence on age-productivity profiles discussed in the introduction indicates that the cohort 50–54 represents the most productive cohort. In light of this finding, we take this cohort as the reference group. Different classifications do not affect the results qualitatively. An alternative data source for population counts and human capital by age is Barro and Lee (2013). For this data set, no population projections are available, which is the reason for using the IIASA–VID data as baseline. Alternative population counts and projections as well as young- and old-age dependency ratios are obtained from the United Nations World Population Prospects.[4] Data on life expectancy are obtained from the World Development Indicators provided by the World Bank.[5]

Human capital per worker is proxied by the share of high- and low-skilled individuals in the working-age population. The share of low-skilled workers is defined as the sum of the respective shares of individuals with either no formal education, or primary or secondary schooling only. Correspondingly, the share of high-skilled corresponds to those workers who have received formal tertiary education or equivalent vocational skills. The respective shares are taken from the IIASA–VID database by Lutz et al. (2007). As described in Section 2, the share of high-skilled human capital is chosen as reference category. Data are available for up to 139 countries in five-year intervals from 1960 to 2010 (13 time periods in total). Table A1 in the Appendix reports descriptive statistics.

In the projection analysis, we also make use of data for hours and labor market participation provided by the International Labor Organization (International Labour Organization, 2011).[6] In addition, we use projections for hours and labor market participation for 26 European countries that have been constructed recently by Fürnkranz-Prskawetz, Hammer, and Loichinger (2016).

4 Estimation Results

This section reports the estimation results regarding the effect of the age structure and the distribution of skills on economic performance. In a first step, both effects are investigated in isolation, thereby reproducing the analysis conducted in the existing literature. In a second step, we provide evidence for a model that combines both dimensions. The section ends with results from robustness checks and alternative estimation frameworks.

[3]The IIASA–VID projection data are available at `http://www.iiasa.ac.at/web/home/research/researchPrograms/WorldPopulation/Projections_2014.html`.

[4]Data from United Nations World Population Prospects are from the 2015 Revision and available at `https://esa.un.org/unpd/wpp/Download/Standard/Population/`.

[5]The data can be retrieved at `databank.worldbank.org/wdi`.

[6]The data can be obtained online at `https://www.ilo.org/ilostat`.

The empirical models are estimated either in levels as in equation (10) or first differences as proposed in equation (12). Lagged levels of output per worker and the share of high-skilled workers in the population enter all estimation models in levels to control for convergence dynamics of output and technological diffusion, respectively. If not stated otherwise, specifications are estimated for a baseline panel of 120 countries in five-year intervals for the time period 1950–2010.[7]

4.1 Demographic Structure

Estimation results for the effect of the age structure of the workforce on output are reported in Column (1) of Table 1 for the model in levels. The reference age group in the levels model is the cohort aged 50 to 54. The results are obtained from a specification of the estimation framework with country fixed effects, period fixed effects, and controls for lagged output per worker and capital per worker.

The results reveal that all coefficients for the cohort-specific workforce shares are negative and significant. Therefore, shifting population mass out of the reference cohort 50–54 into another cohort implies a negative effect on output. This effect is particularly pronounced for a relative increase of the population group aged 60–64, revealing a negative effect due to population aging. An increase in the population share of this cohort by one percentage point at the cost of the reference group of age 50–54 implies a decrease in output per worker of roughly 5.5 percent. Population shifts of such size are no exception in the data. Across all workforce shares, around 25 percent of all out-shifts of a cohort are roughly equal to a unit percentage point shift or even larger. The same pattern holds for 25 percent of all in-shifts into a cohort. Furthermore, the estimated negative point estimates are largest for the age cohorts which are either at the very beginning or at the end of their work lives. These patterns are consistent with estimates from disaggregate data mentioned in the Introduction, which suggest that productivity is highest for individuals around age 50, when they have acquired sufficient work experience and on-the-job training. In particular, the results are also in line with a hump-shaped pattern as predicted by standard human capital theory over the life cycle (Ben-Porath, 1967): For middle-aged cohorts additional productivity gains become smaller as the marginal return from more experience decreases and ultimately declines to zero as the benefits of additional education investments deteriorate with the lower amortization period. At some point, the depreciation rate of human capital outweighs additional gains by experience so that individual productivity decreases in many cases toward the end of the work-life. Taken together, the results largely confirm earlier micro-level findings on the effects of population aging (e.g., Göbel and Zwick, 2013). Moreover, the joint Wald test on the coefficients of all workforce shares confirms that the overall demographic structure plays a significant role for output.

Table 2 Column (1) contains the corresponding results for the model in (log) differences. To be consistent with the levels model, the difference model uses the change in the age cohort aged 50–54 as reference category. The results essentially replicate those obtained for the levels model, both qualitatively and quantitatively. In particular, the age pattern and the importance of heterogeneity in the effect of changes in the age composition of the workforce on output growth is very similar. The results also show that the estimated coefficient for lagged output per worker

[7] The robustness material contains results for 139 countries when using alternative data sources.

Table 1: Effects of Aging and Education on Economic Performance: Levels Model

	Demography	Skills	Demography & Skills	Bias Correction	Demography Instrumented	Skills Instrumented	Both Instrumented
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share $<$ 20	-3.84***		-3.06**	-3.05**	-3.64***	-2.09*	-2.53**
	(1.22)		(1.21)	(1.40)	(1.21)	(1.20)	(1.18)
Share 20–24	-2.37**		-1.84*	-1.82	-3.23**	-1.16	-2.58*
	(1.10)		(1.10)	(1.38)	(1.37)	(1.11)	(1.36)
Share 25–29	-3.56**		-3.12**	-3.18*	-2.77*	-2.58*	-2.30
	(1.42)		(1.39)	(1.89)	(1.47)	(1.32)	(1.41)
Share 30–34	-3.06**		-2.74**	-2.74*	-3.96***	-2.33*	-3.61**
	(1.27)		(1.25)	(1.54)	(1.43)	(1.21)	(1.41)
Share 35–39	-4.01***		-3.71**	-3.63**	-2.97*	-3.33**	-2.49*
	(1.44)		(1.43)	(1.74)	(1.57)	(1.39)	(1.51)
Share 40–44	-1.53		-1.35	-1.37	-1.87	-1.12	-1.81
	(1.32)		(1.29)	(1.62)	(1.41)	(1.26)	(1.39)
Share 45–49	-3.19**		-3.07**	-3.31*	-3.98**	-2.92**	-3.89**
	(1.43)		(1.41)	(1.95)	(1.55)	(1.37)	(1.51)
Share 55–59	-4.66**		-4.37**	-4.76**	-4.40**	-4.00**	-4.16**
	(1.85)		(1.81)	(2.18)	(1.82)	(1.74)	(1.77)
Share 60–64	-5.48***		-5.50***	-5.96***	-6.06***	-5.53***	-6.33***
	(1.37)		(1.34)	(1.76)	(1.50)	(1.30)	(1.48)
Share 65+	-3.06*		-3.24**	-3.35*	-4.21***	-3.47**	-4.22**
	(1.58)		(1.55)	(1.80)	(1.62)	(1.56)	(1.68)
Share high–skill		0.97***	1.08***	0.85***	0.84**	2.45***	2.35***
		(0.34)	(0.40)	(0.32)	(0.41)	(0.76)	(0.77)
Output p.w. (t–1)	0.50***	0.48***	0.48***	0.59***	0.48***	0.46***	0.46***
	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)
Capital p.w.	0.32***	0.33***	0.33***	0.29***	0.33***	0.35***	0.34***
	(0.05)	(0.04)	(0.05)	(0.02)	(0.05)	(0.05)	(0.05)
Cohort shares (p–value)	0.01		0.01	0.00	0.01	0.00	0.00
Skill share (p–value)		0.00	0.01	0.01	0.04	0.00	0.00
First stage F–statistic					13.3	27.9	4.5
Hansen test (p–value)					—	0.25	0.28
Countries	120	120	120	120	120	120	120
Observations	1,098	1,098	1,098	1,053	1,098	1,098	1,098
R^2	0.86	0.86	0.87		0.87	0.86	0.86

Notes: This table reports results for demographic and human capital data by IIASA–VID (Lutz et al., 2007). The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w., measured in logarithms, are included as controls in all specifications. Column (4) corrects for the dynamic–panel bias using the Bruno (2005) estimator. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) or high-skill shares are jointly different from zero are reported. Instruments are shifted age cohorts in Column (5); the lagged shares of high skills of cohorts at the edge of the working–age population in Column (6); and a combination of both in Column (7). See Figure A3 for an illustration. First stage F–statistic reports the first stage Kleibergen–Paap rk Wald F–statistic. Hansen test p–values refer to the robust overidentifying restriction test. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

is positive and smaller than one in the levels model, and negative in the model in differences, providing evidence for the usual conditional convergence patterns.[8] The estimated values for the capital income share α is 0.32 for the specification in Column (1) of Table 1 and 0.40 for the specification in Column (1) of Table 2.

The results in the differences specification closely resemble the empirical specifications estimated by Feyrer (2007) and reproduce his results for a different data set.[9]

[8] The bias in coefficient estimates in specifications with lagged dependent variable and fixed effects should be moderate in a relatively long panel with 13 time periods, see Nickell (1981) and Judson and Owen (1999); see also the discussion in Section 4.4.

[9] In particular, Feyrer (2007) also finds point estimates that are negative relative to the relatively most productive age cohort. The point estimates are qualitatively very similar to the results for empirical specification proposed in this paper and quantitatively slightly smaller. Similar results are found for regressions for each output channel are shown without and with additional fixed effects which allow for country-specific growth trends.

Table 2: Effects of Aging and Education on Economic Performance: Differences Model

	Demography	Skills	Demography & Skills	Bias Correction	Demography Instrumented	Skills Instrumented	Both Instrumented
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Share < 20	-3.68***		-2.83**	-1.24	-4.23***	-3.35***	-5.22***
	(1.16)		(1.19)	(1.13)	(1.36)	(1.26)	(1.81)
Δ Share 20–24	-3.03***		-2.05**	-1.35	-4.03***	-2.54**	-4.91***
	(1.01)		(1.02)	(0.98)	(1.27)	(1.12)	(1.48)
Δ Share 25–29	-3.47***		-2.78**	-1.70	-4.34***	-3.12***	-4.91***
	(1.15)		(1.15)	(1.13)	(1.51)	(1.20)	(1.74)
Δ Share 30–34	-3.92***		-3.41***	-2.48**	-4.10**	-3.15***	-4.20**
	(1.13)		(1.14)	(1.15)	(1.76)	(1.11)	(1.89)
Δ Share 35–39	-4.97***		-4.58***	-3.75***	-4.44***	-4.89***	-4.29***
	(1.22)		(1.23)	(1.20)	(1.50)	(1.37)	(1.56)
Δ Share 40–44	-2.56**		-2.33**	-1.12	-2.70**	-2.36**	-2.60**
	(1.10)		(1.06)	(0.94)	(1.16)	(1.11)	(1.21)
Δ Share 45–49	-3.08***		-2.93***	-1.60*	-4.09***	-2.92***	-4.21***
	(1.12)		(1.09)	(0.94)	(1.19)	(1.09)	(1.24)
Δ Share 55–59	-2.35**		-2.17**	-1.01	-2.65***	-2.28**	-3.13***
	(0.96)		(0.95)	(0.97)	(1.01)	(1.00)	(1.12)
Δ Share 60–64	-5.26***		-5.14***	-3.08***	-5.63***	-5.29***	-6.25***
	(1.20)		(1.20)	(1.06)	(1.41)	(1.29)	(1.57)
Δ Share 65+	-6.61***		-6.22***	-1.71	-6.32***	-6.49***	-6.93***
	(1.67)		(1.64)	(1.43)	(1.80)	(1.70)	(1.99)
Δ Share high–skill		2.68**	3.30***	1.21	1.87	0.64	-3.09
		(1.07)	(1.15)	(0.87)	(1.16)	(4.23)	(4.75)
Share high–skill (t–1)		0.67***	0.55**	0.42***	0.55*	0.71*	0.83**
		(0.24)	(0.25)	(0.15)	(0.33)	(0.37)	(0.41)
Output p.w. (t–1)	-0.21***	-0.24***	-0.23***	-0.02***	-0.24***	-0.24***	-0.23***
	(0.03)	(0.03)	(0.03)	(0.01)	(0.03)	(0.03)	(0.03)
Δ Capital p.w.	0.40***	0.39***	0.41***	0.43***	0.40***	0.41***	0.40***
	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)
Cohort shares (p–value)	0.01		0.01	0.01	0.00	0.00	0.00
Skills shares (p–value)		0.00	0.00	0.00	0.05	0.01	0.11
First stage F–statistic					8.5	52.1	5.9
AR(2) test (p–value)				0.65			
Hansen test (p–value)				0.33	—	0.45	0.50
Countries	120	120	120	120	120	120	120
Observations	1,098	1,098	1,098	978	1,053	1,053	1,053
R^2	0.42	0.39	0.43		0.42	0.43	0.40

Notes: This table reports results for demographic and human capital data by IIASA–VID (Lutz et al., 2007). The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w., measured in logarithms, are included as controls in all specifications. Column (4) corrects for the dynamic–panel bias using the system GMM estimator by Arellano and Bover (1995) and Blundell and Bond (1998). The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) or high-skill shares are jointly different from zero are reported. Instruments are shifted age cohorts in Column (5); the lagged shares of high skills of cohorts at the edge of the working–age population in Column (6); and a combination of both in Column (7). See Figure A3 for an illustration. First stage F–statistic reports the first stage Kleibergen–Paap rk Wald F–statistic. Hansen test p–values refer to the robust overidentifying restriction test. For system GMM, also the p–values of the AR(2) test are reported. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

4.2 Human Capital and Distribution of Skills

As a next step, the analysis focuses on the role of the effect of human capital and the distribution of skills on economic performance. Column (2) of Table 1 presents the corresponding estimates for a specification that only includes the share of high skilled in addition to lagged output and capital per worker. The point estimate of the share of individuals with high-skilled human capital is positive and highly significant. A one percentage point increase in the share of high skilled of in an economy is accompanied by an increase in output of 0.97 percent.

Column (2) of Table 2 presents the corresponding results for a specification in differences. This specification also accounts for the possibility that, conceptually, human capital influences output (growth) through two channels. First, changes in the share of skills account for composition effects of productions factors which can be accrued to the complementarity of human and physical capital in standard growth models (Solow, 1956; Lucas, 1988). Second, the accumulation of human capital may alleviate the diffusion and adoption of already existing technologies (Nelson and Phelps, 1966) or spur innovation as in the endogenous growth literature (Romer, 1990; Aghion and Howitt, 1992). Not accounting for both channels might lead to a potential bias in the estimates due to the omission of one relevant channel from the estimation, as indicated by the results of Sunde and Vischer (2015). The results provide evidence supporting the specification with both levels and changes of human capital as suggested by the work of Sunde and Vischer (2015). Both point estimates of levels and changes in the share of high-skilled human capital are positive and individually and jointly significant.[10]

Quantitatively, the results imply that a one percentage point larger share of skilled workers in the economy is accompanied by an 0.67 percent increase in growth of output per worker over a five-year period. In light of the literature, this effect works through innovation as well as diffusion and adoption of new technologies. Growth of one percentage point in the share of high-skilled implies an increase in the growth rate of 2.68 percent over five years. The coefficient for lagged output per worker takes negative values for the differences model, indicating conditional convergence, and the coefficient of the capital income share is similar to the previous results.

4.3 Considering Demographics and Skills in Combination

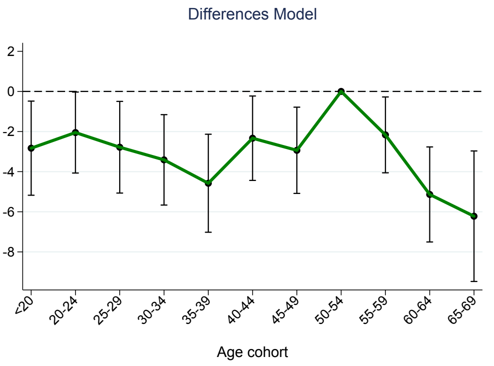
While the results so far have successfully reproduced the findings in the existing literature, the specifications have considered the demographic structure and the influence of human capital in isolation. However, in view of the possibility that the age structure and the human capital composition of the population are correlated and both influence macroeconomic performance, the estimates might suffer from omitted variables bias. In order to investigate this possibility and potential interactions, we now proceed to estimate more comprehensive models that accounts for both the demographic structure of the workforce and the distribution of skills in the population.

Columns (3) of Tables 1 and 2 present the estimation results for such an extended specification. The coefficient estimates for the age structure and human capital are qualitatively similar, indicating that both dimensions affect macroeconomic performance. In the levels model, the skill pattern appears to exhibit slightly smaller coefficient estimates than in the specification without human capital, while the human capital effect is slightly larger than in the specification without controlling for the age structure. The same is true for the differences model, with the exception of the effect of the share of high-skilled individuals in levels, whose coefficient is also slightly smaller than in Column (2).

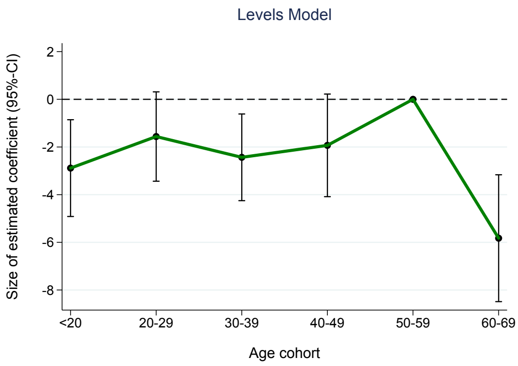
Figure 3 provides a graphical representation of the estimates of the coefficients for the

[10] The specification of the model in levels that follows from equation (10) does not contain a term involving the change in the share of skilled in the population, since this term emerges from the dynamics of TFP. In unreported estimations, we nevertheless included changes in the share of high-skilled individuals in the specification of the empirical model of the levels estimation to estimate a symmetric empirical specification in both levels and differences and obtain directly comparable estimates of the coefficients of interest. Moreover, this specification provides a natural specification test since the coefficient of the change in the skill share is hypothesized to be zero in light of the theoretical model (10). The findings suggest that the coefficient is indeed not significantly different from zero in an extended version of the specification in Column (2) of Table 1, which indirectly supports the empirical model. The estimation results are qualitatively and quantitatively almost identical when estimating a specification of the levels model that does additionally include the change in the share skilled, see Table A2 in the Appendix for details.

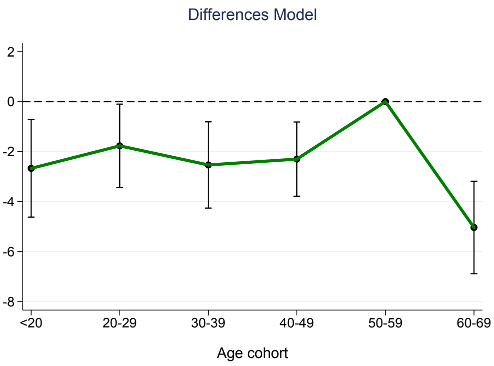
(a) Five–year cohorts (Table 1, Column 3)



(b) Five–year cohorts (Table 2, Column 3)



(c) Ten–year cohorts (Table A7, Column 3)



(d) Ten–year cohorts (Table A8, Column 3)

Figure 3: Macro Productivity Profiles

different age shares obtained with (a) the levels model and (b) the model in differences. Panels (c) and (d) reproduce the respective productivity profiles for an alternative specification using ten-year instead of five-year age cohorts. The graphs illustrate that the age-related coefficients are somewhat smaller in absolute terms for the differences model but otherwise very comparable. Hence, an increase in the share of a specific age cohort relative to the 50 to 54 year olds leads to a reduction in output. Moreover, the skill distribution positively affects macroeconomic performance through its level and change, which is consisten with the innovation and adoption of technology as well as the composition of production factors. Most importantly, demographic structure of the workforce and human capital both jointly affect output. Therefore, both channels are conceptually relevant for themselves even if they interact substantially.

4.4 Alternative Estimation and Identification Strategies

The estimation results presented so far, in particular in the levels specification, were based on a two-way fixed effects estimator with a lagged dependent variable (log output per worker) as additional regressor. Consequently, the coefficient estimates, in particular for the lagged dependent variable might be biased, see Nickell (1981). To investigate whether this might be an issue for the coefficients of interest, Columns (4) of Tables 1 and 2 present the corresponding results obtained with an estimator that corrects for the potential bias in dynamic panels.[11] The estimation results are qualitatively and quantitatively very similar for the levels model, whereas they reflect some quantitative differences in the differences specification. Alternative estimation results obtained with a levels model without lagged dependent variable also deliver qualitatively similar results.[12] The simulation results shown below will be based mainly on the levels model.

Another potential concern is identification and endogeneity. The identification of the coefficients for aging and human capital so far was based on the implicit assumption that the current workforce (in terms of age structure and skill composition) is the result of fertility and education decisions in the past. Controlling for past income, capital and country-specific intercepts related to productivity and other time-invariant factors account for country-specific differences in economic performance that might influence, or correlate with, the age and skill composition. Additionally, the results implicitly correspond to an intention-to-treat interpretation, where population shares reflect the potential size of the workforce of each age cohort, instead of accounting for the actual workforce, which might be affected by endogenous labor supply decisions at the extensive or intensive margin, and thus give rise to endogeneity concerns. The estimates thus implicitly assume changes in the workforce be arguably exogenous given the lagged dependent variable, country-fixed effects, and period fixed effects. The finding of similar results in the levels and differences models is reassuring in this regard since similar estimates for the respective coefficients are obtained despite the use of alternative variation for identification.

Nonetheless, in order to probe further into potential identification problems caused by unobserved variables that correlate with the factors of production and thus lead to problems of endogeneity bias, we present the results from three alternative identification approaches based on instrumental variables (IV).

A first alternative way to obtain identification is to exploit the fact that the demographic structure of the working-age population follows very stable and predictable dynamics. Concretely, a cohort of individuals aged 40 at a particular point in time will be of age 50 ten years later. The same is approximately true for the age composition since the relative sizes of cohorts of different ages are unlikely to change over time and thus provide valuable predictors over long periods of time. Simultaneously, however, lagged age shares satisfy the exclusion restriction of an instrument, which stipulates that they must be unrelated to unobserved factors driving macroeconomic performance some decades into the future. Hence, demographic dynamics lend themselves naturally to an instrumental variables approach in the present setting of panel data.

On the basis of these considerations, the IV strategy exploits the fact that the relative size of particular cohorts at some point in time predicts these cohorts' size in the future. At the same time, it is unaffected by economic performance in the future and, thus, exogenous for the purpose of the estimation framework applied here. For a given country-period-cohort cell, this is plausibly the case, in particular, once conditioning on the lagged dependent variable and country-fixed

[11] In the levels model the bias-correction is implemented via the corrected fixed effects estimator of Bruno (2005). To be internally consistent with the theoretical model outlined in Section 2, the bias-correction in the differences model is performed using the system GMM estimator of Arellano and Bover (1995) and Blundell and Bond (1998).

[12] See Table A3 in the Appendix. Due to the omission of the lagged dependent variable, the human capital variable picks up some of the persistence, with the consequence of slightly larger coefficient estimates for human capital obtained with this specification. In the following, we restrict attention to the model with lagged dependent variable, which delivers results for the role of human capital that are more conservative in this respect.

effects. The share of the working-age population of a particular cohort, for instance the 25–29 year old in 1990, is instrumented using the respective share of this cohort in 1985, when it was the cohort of 20–24 year olds, using the corresponding lag structure. Additional identification is obtained by the fact that this strategy exploits that the shares of the youngest cohorts of working age adults are instrumented by shares of cohorts that were not even in the labor force, and by using cohorts that have already left the labor force when the outcome variables are realized. Panels (a) and (b) of Figure A3 in the Appendix illustrate this identification strategy.[13]

Columns (5) of Tables 1 and 2 present the second stage results from two-stage least squares (2SLS) estimations using this instrumentation strategy for the age shares in the corresponding specifications (in levels or differences). The first stage is sufficiently strong, as indicated by the respective F-statistics. The coefficients in the outcome equation closely resemble those obtained from standard panel estimation techniques, however. In particular, the overall patterns remain unchanged.

A similar identification strategy can be applied to the share of high-skilled individuals (or its change). The logic here is that the formal (tertiary or vocational) education attained by a given cohort is unlikely to change over the range of five or ten years. At the same time, using the lagged shares provides variation that is less likely to be affected by (or correlated with) contemporaneous macroeconomic performance, conditional on the full set of controls. The variation in the share of high skilled over the course of five or ten years primarily depends on the education of young individuals entering the labor force and of the old individuals leaving the labor force. We therefore use the lagged skill shares in these respective age cohorts as instruments. The logic of this identification approach is illustrated in Panels (c) and (d) of Figure A3.[14] Columns (6) of Tables 1 and 2 present the corresponding results for the second stage of the 2SLS framework applied to human capital. Again, the first stage is strong as expected. The estimates for the outcome equation are qualitatively identical and quantitatively somewhat larger for human capital than those obtained with the baseline estimation approach, whereas the coefficient estimates for the age shares are somewhat smaller.[15] Again, this suggests that endogeneity bias appears not to be a serious concern for the qualitative patterns.

Columns (7) of Tables 1 and 2 present the corresponding results for the second stage of the 2SLS framework applied to both the age structure and human capital. Again, the overall pattern is very similar.

4.5 Robustness and Further Results

In order to investigate the robustness of these results, we conducted several additional checks.

[13]Moreover, the figure illustrates that this IV approach can be applied regardless of whether the data are coded in five-year or than ten-year cohorts.

[14]Notice that this additional instrumentation strategy provides the possibility of conducting overidentification tests as there are more instruments than instrumented variables.

[15]One potential caveat with the instrumentation approach of human capital could be that the education composition of the share of the young entering the labor force might reflect anticipated macroeconomic performance, and thus pose a potential problem of endogeneity, while this is unlikely for the cohort leaving the labor force. In additional robustness checks, we therefore applied an alternative identification that only uses the education composition of the cohort that exits the labor force, paralleling the approach popularized by Acemoglu and Johnson (2007) by implicitly assuming that all newly entering cohorts are high skilled. The results are qualitatively similar, see Table A4 in the Appendix.

A first robustness check concerns the estimation of the same model using an alternative data set for the age composition and human capital endowment provided by Barro and Lee (2013). The corresponding results reveal very similar estimation results.[16]

A second robustness check concerns the possibility of overfitting and multicollinearity by using data at the level of five-year age cohorts. Estimation results obtained with data for ten-year age cohorts deliver qualitatively and quantitatively similar results for the effects of the age structure of the population, and even slightly larger coefficient estimates for human capital.[17] The same holds when restricting the specification to only four or three age cohorts.[18]

As third robustness check, we considered an alternative coding of the human capital composition by considering the average years of schooling, while allowing for a more flexible specification. The results confirm the previous findings, both regarding the age profile as well as regarding the relevance of the share of high skilled individuals with at least secondary education.[19]

Another robustness check refers to the use of income (output) per capita instead of output per worker as variable of main interest. While output per worker captures the notion of productivity and macroeconomic performance from the perspective of the production process, income per capita might be seen as more relevant from a policy perspective. The results are essentially the same for income per capita.[20]

Results obtained with an extended specification that also accounts for the age-related change in skills by incorporating cohort-specific information on the share of skilled individuals are also similar. In particular, these estimates only provide weak evidence for differences in the effect of the share of high-skilled individuals across different age cohorts when controlling for cohort-specific skill shares. At the same time, the qualitative and quantitative results for the effects of the demographic age structure as such remain largely unaffected.[21]

To some extent, these findings shed new light on the results of Cuaresma, Lutz, and Sanderson (2014), who conclude, based on an analysis that uses a comparable dataset, that the demographic dividend is mostly the byproduct of increases in education. Whereas Cuaresma, Lutz, and Sanderson (2014) do not specifically control for the cohort-based demographic structure but instead for labor force participation and the relative size of the working-age population to total population (i.e., the inverse of the dependency ratio), the findings here suggest that the age structure might have an independent effect from the human capital endowment.[22]

Instead of considering the age composition of the work force, the previous literature has

[16]See Tables A5 and A6 in the Appendix for detailed estimation results and Figure A4 for the corresponding estimated age-productivity profiles.

[17]Detailed results are reported in Tables A7 and A8 in the Appendix. Panels (c) and (d) of Figure 3 show the corresponding productivity profiles obtained with ten-year panel data.

[18]See Figure A5 in the Appendix.

[19]Detailed results can be found in Table A9 in the Appendix.

[20]Notice that the estimation equation for income per capita can also be directly derived from the conceptual framework. This requires defining the sizes of the age groups as shares of the total population (rather than of the working age population) and controlling for the (young and old age) dependency ratio. The respective results are displayed in Table A10 in the Appendix. The corresponding productivity profiles are displayed in Figure A6 in the Appendix.

[21]See the results in Tables A11 and A12 in the Appendix for details.

[22]Moreover, the analysis of Cuaresma, Lutz, and Sanderson (2014) accounts for variation in labor force participation rates, which might be driven partly by cyclical phenomena instead of long-run trends, which imposes problems for identification. As indicated before, the effects of the demographic structure presented here correspond to intention to treat effects, which are likely to provide a lower bound of the actual effect under the assumption of relatively stable participation patterns.

focused on the old age dependency ratio. Additional results suggest that adding the dependency ratio as well as the size of the working age population (in logs or in absolute numbers) as further control variables leaves the results essentially unaffected.[23] This suggests that the role of aging for macroeconomic performance does not predominantly work through population size or the share of elderly but through the age composition of the work force. Consequently, a main economic implication of low fertility in the aftermath of the demographic transition appears to be population aging rather than a shrinking (or reduced growth) of the population at large. This issue will be discussed in more detail in the simulations below.

Controlling for life expectancy also leaves the main results unaffected.[24] Using average years of schooling instead of the population share with a high-skilled education delivers similar results for the role of the age structure but no significant effect for human capital in terms of average years of schooling.[25] This result potentially reflects the fact that skill shares provide a more appropriate measure of the skill endowment than the use of average years of schooling.[26]

Note that controlling for the dependency ratio, the size of the working-age population and life expectancy at birth accounts for variation in fertility, health and longevity across countries and over time, respectively. Controlling for these variables might lead to endogeneity concerns if economic development unfolds a feedback mechanism on either of these dimensions in the long run and, at the same time, the corresponding variables are correlated with the age structure or with education. If selection on observables is informative for selection on unobservables, the stability of parameter estimates across specifications with additional controls suggests that the bias is limited.[27] Hence, it is reassuring that including further control variables does not considerably affect the quantitative and qualitative results compared to our baseline specification.

4.6 Education to Counteract the Effects of Aging?

Instead of relying on qualitative assessments of the implications of population aging and education dynamics, the estimation framework and the corresponding estimates also allow to go one step further in the quantification of the increase in education that is needed to offset the effects of population on economic performance. In particular, the framework provides the possibility to estimate an elasticity of substitution between changes in the age structure and changes in the human capital structure of the economy that is needed to keep output per worker constant. An upper bound for this skills-aging-elasticity in the levels model is given by

$$\eta^j_{max} = \frac{(1-\widehat{\alpha})\widehat{\lambda}^j}{(1-\widehat{\alpha})\widehat{\lambda}^h} = \frac{\widehat{\lambda}^j}{\widehat{\lambda}^h} < 0. \tag{13}$$

[23]See Appendix Tables A13, A14 and A15 for detailed results.
[24]See Table A16 in the Appendix for details.
[25]See Table A17 in the Appendix for details.
[26]See, for example, Hanushek and Woessmann (2012).
[27]Moreover, the coefficient estimates across the different specifications are very similar while the variation explained fairly comparable, indicating that selection and endogeneity concerns should be limited, following arguments in the spirit of Altonji, Elder, and Taber (2005) and Oster (2017).

In the differences model, the elasticity takes the form

$$\eta^j_{max} = \frac{(1-\widehat{\alpha})\widehat{\lambda}^j}{(1-\widehat{\alpha})\widehat{\lambda}^h + \widehat{\theta}} < 0. \tag{14}$$

The corresponding parameters are the structural estimates of the empirical model in (10) or (12). Since the elasticity depends on the level of schooling in the previous period and changes in the current skill distribution, an increase in the share of skills in the same period can only work through the composition channel (i.e., the denominator is $(1-\widehat{\alpha})\widehat{\lambda}^h$ in this case). In the following period, the skills-aging-elasticity is given by the expression in (13) corrected for additional changes in the distribution of skills which are again weighted by $(1-\widehat{\alpha})\widehat{\lambda}^h$. Since the denominator is positive and the cohort-effects of the demographic structure are negative as long as the most productive cohort is chosen as reference group, the elasticity will always exhibit a negative sign. Hence, the elasticity is largest, when the denominator is maximized. This is the case when the share of high-skilled workers in the population increases over at least two consecutive periods and no human capital is lost due to retirement or emigration in the working-age population. Consequently, η^j cannot be greater than the expression stated in (13). In fact, it is lower whenever the gains in human capital are lost to some extent. Thus, η^j_{max} represents an upper bound for the skills-aging-elasticity. Moreover, this upper bound has a natural interpretation in that it is the most favorable scenario under which negative feedback from changes in the demographic structure on output can be compensated.

The elasticity can be computed for each age group. For example, suppose an aging society where a large fraction of the workforce (the baby boomer cohorts) shift out of the most productive group of the 50–54 year olds into the less productive group of the 60–64 year olds. Columns (3) of Tables 1 and 2 then provide upper bounds for the skills-aging elasticity of $\eta^{60-64}_{max} = -\frac{5.50}{1.08} \approx -5.09$ and $\eta^{60-64}_{max} = -\frac{5.14}{3.30+0.55} \approx -1.34$. Assuming constant returns to schooling, the share of high-skill workers would thus have to increase by 1.34 to 5.09 percentage points in order to offset a one percentage point shift out of the cohort 50–54 into the cohort 60–64. However, since schooling takes place mostly at a young age, it is unrealistic to increase the human capital of older workers by more than a small extent. Changes in the skill distribution must therefore come mostly through young cohorts. This is particularly problematic if young cohorts are small in size relative to the cohorts approaching retirement such as in the case of the baby boomer generation. Therefore, even in the presence of large human capital increases, the demographic structure unfolds a forceful effect on macroeconomic performance. This may also be one of the reasons why large-scale extensions of schooling in developing countries in the context of the demographic transition (and the decline in fertility) were not associated by a strong development boost.[28]

However, as discussed in Section 4.5, a richer specification that considers the education composition of different age cohorts of the working-age population (age 15 to 69) delivers little evidence for a strong and systematic role of the skill distribution across age groups for output. The corresponding estimates are insignificant in most cases. Also the Wald test for joint significance of the estimated parameter sets fails to reject that estimates are jointly different from zero in many

[28] Another reason may be that schooling quality is generally low. For more information see, e.g., Hanushek and Woessmann (2008).

cases.[29] Hence, we find little evidence for the obsolescence of high-skilled education embodied in older generations.

5 Implications for Future Economic Performance

By and large, the estimation results reveal a relevant role of demographic dynamics in terms of aging as well as in terms of changes in the human capital embodied in the working population, for economic development. At the same time, the heterogeneity across subsamples indicates that aging might not affect all countries in the same way. In particular, countries with a relatively old population, and with an ongoing aging process, appear to be affected most by the adverse effects of aging.

In order to obtain a more coherent picture of these patterns, and gain some understanding of the relative importance of human capital in offsetting the effects of population aging, this section presents the results of simulations of economic performance based on the baseline estimates of the previous section, and several alternative scenarios regarding aging and human capital dynamics.

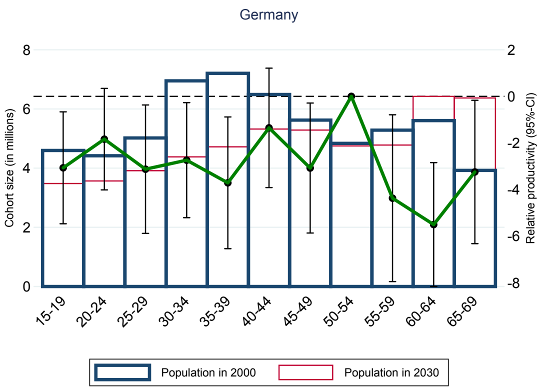
5.1 Projecting the Effects of Aging and Education on Future Performance

While aging appears to be a process that is hard if not impossible to influence in the short and medium run, the skill composition of the population is a possible dimension through which policy might try to influence the economic prospects of a country. This raises the question about the relative importance of population aging and changes in the skill composition, and about the likely scenarios faced by countries with different age and skill compositions of their populations.

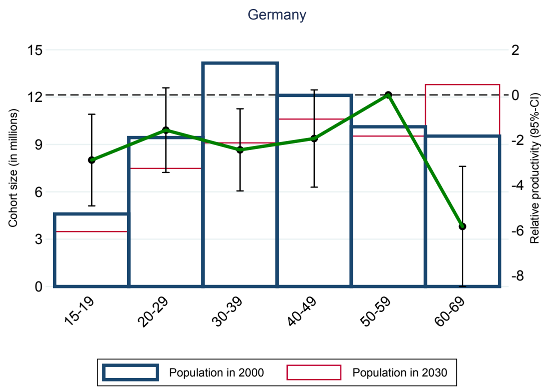
To illustrate the usefulness of the methodology developed in this paper for addressing these questions, consider Figure 4, which contrasts the coefficient estimates for the age structure obtained with specifications for five-year and ten-year age cohorts, with the projected change in the age structure for Germany, the UK, and France. Taking the age-profile of coefficients as a stable world average, the predicted economic performance will differ only because of heterogeneous aging patterns across countries. This is illustrated by the different age structures in Germany, the UK, and France. Similarly, one can use projections of the human capital composition for the two countries to compute the predicted performance due to the changes in this dimension.

In the following, we use the estimates to conduct counterfactual experiments to infer the relative importance of aging and changes in the skill composition of the population for future economic development. To this end, we use available projections of the prospective age and skill composition of the population. These projections can be conducted under several scenarios. The baseline scenario is to use the estimates to obtain an estimate of output per worker (or its growth rate) by inserting population projections in terms of age and skill structure and compute output as in equation (10) over the period over which projections for age structure and skill composition are available. This scenario uses all information about the evolution of the economy and, thus, provides a best practice projection.

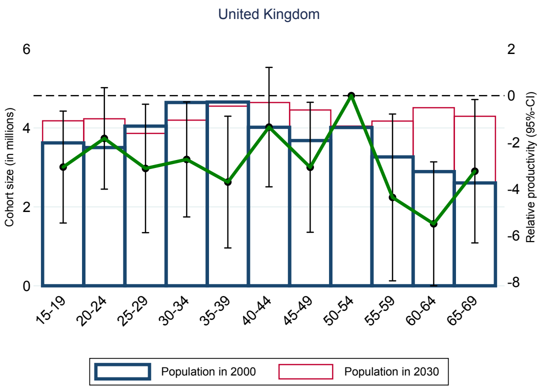
[29] In order to further test whether there might be an interplay between the demographic structure of the workforce and the distribution of skills, interacted models can be estimated. This allows to test the null hypothesis whether the effect of the demographic structure is stronger (or weaker) the larger the share of high-skilled workers in the population is. However, there is only weak evidence that this is the case (results not shown).



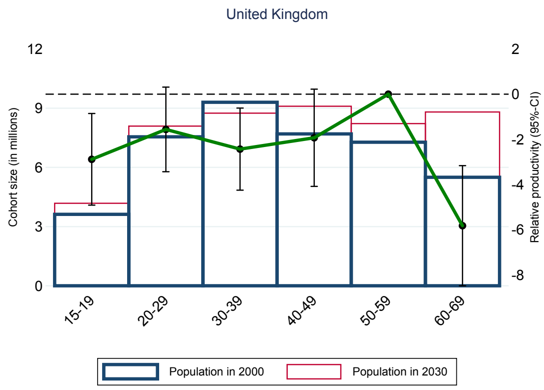
(a) Germany (five–years cohorts)



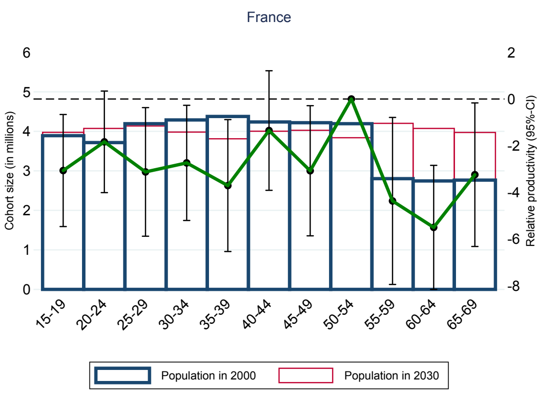
(b) Germany (ten–year cohorts)



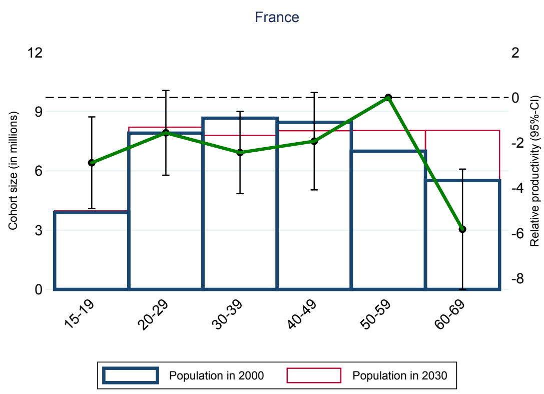
(c) United Kingdom (five–years cohorts)



(d) United Kingdom (ten–year cohorts)



(e) France (five–years cohorts)



(f) France (ten–year cohorts)

Figure 4: Macro Productivity Profiles and Demographic Change for Selected Countries

As a consistency check for this methodology, we use the estimates obtained from the sample 1950–2000 to project economic performance until 2010, based on the actual observations for the changes in the age structure and in the skill share between 2000 and 2010. The results suggest that the model is able to track development rather well, with the exception that unpredictable events such as the global financial crisis of 2007/2008 imply deviations of the model projections from the actual data.[30]

[30]See Figure A7, where the economic performance of Non–OECD countries is matched well, whereas the

As a first alternative scenario, we use only the projection for the human capital structure but keep the age composition of the population constant. In other words, this corresponds to a simulation that stops the aging process and keeps the population at its current status quo in terms of age composition. Conceptually, this corresponds to the (deliberately extreme and unrealistic) counterfactual assumption of a stable population ("constant demographic structure").

As a second alternative scenario, we simulate the model using the available population projections for the dynamics of the age structure but keep the composition of human capital in the population constant at the present levels. This corresponds to a scenario that evaluates the consequences of aging in isolation while keeping human capital constant ("constant human capital"). The reference year for both counterfactual exercises is 2010.

In the following, we use Germany, the UK, and France as prime examples of developed economies that differ in terms of the speed of population aging. All three countries have comparable income levels and experienced roughly comparable patterns of economic development in the past. As Figure 1 shows, however, the three countries have different age structures of their population and correspondingly face different dynamics of population aging in the future. Moreover, the trajectories of educational attainment differ across these two countries as shown in Figure 2.[31] Using the same set of coefficient estimates from the empirical analysis for both countries, we can therefore provide comparable simulations that allow us to identify the implications of the projected aging and human capital dynamics for future development.

Figure 5 presents the corresponding projection results for the different scenarios for Germany, the UK, and France. For all three countries, the simulated performance using the available projections for aging and human capital suggest a dampened economic performance in the decades to come. The predicted slow-down is more pronounced for Germany than for the UK and France. Obviously, these projections are based on strong assumptions and should not be confused with forecasts of output growth, since important components like capital accumulation, depreciation, etc., are not adequately modeled in these simulations but held constant at their 2010 levels.[32] Nevertheless, they are useful as a benchmark for comparing the projections to the counterfactual simulations that freeze the demographic structure or the human capital distribution at their respective current shapes. When considering a constant age structure ("constant demographic structure"), the projection of the economic performance in both countries is more positive than in the baseline projection, implying a negative effect of population aging. However, the difference between the best projection and this counterfactual projection is substantially more different in the case of Germany, which faces more pronounced population aging than the UK and France. Alternatively, keeping the human capital structure unchanged ("constant human capital") implies a moderately dampened economic development in Germany, whereas the development in the UK and France is affected more negatively by this scenario. While in Germany, freezing the skill share at its current level has relatively minor implications, in particular in the near future, a continued upskilling of the population in the UK and France seems to be a major factor for future development. Taken together, the results predict that in Germany population aging is a

projection of economic performance is too benevolent for OECD countries, which have been affected more by the global financial crisis up to 2010.

[31] The same applies for education projections, see Figure A8 in the Appendix.

[32] Below, we turn to alternative simulation scenarios that also incorporate capital projections and alternative scenarios for education attainment.

powerful dampening force for economic performance that is likely to unfold its effects in the future, whereas the effect of changes in the education composition have rather limited power because the population is already very skilled and young cohorts are small in size. In contrast, in the UK, and even more so in France, aging poses less of a problem, whereas a failure to keep pace with the projected education attainment might impose substantial negative effects on development. This relative difference between aging and education is illustrated in Panel (b) of Figure 5, which compares the predicted dynamics of output per worker using the projections for demography and human capital to the counterfactual with both distributions frozen at their current shapes: Germany is predicted to exhibit a lower performance than under the counterfactual status quo whereas the UK and France will develop faster. Part of this is due to the greater leverage for human capital implied by the different demographic (age-)structure. Greater aging pressure also limits the scope for human capital, which is embodied in the young but small cohorts, to compensate. Similarly heterogeneous results obtain for other developed economies such as the USA and Japan.[33]

One noteworthy aspect in this context is that specifications without a control for the lagged development deliver somewhat larger effect for human capital. Correspondingly, projections obtained with these specifications deliver a somewhat more benign scenario, with greater scope for human capital in compensating the effects of population aging for countries that face substantial population aging but have a rather skilled population.[34]

Figure 6 presents the corresponding results for OECD and Non–OECD countries. Again, the benchmark projections deliver a rather pessimistic outlook about economic performance in both samples. Freezing the age structure at its current level implies faster development in the OECD countries, suggesting that aging will be a major impediment for economic performance in the future. A potentially more surprising result is that aging appears to have a similar negative effect on economic development in Non–OECD countries, as evidenced by the simulation that keeps the age structure constant ("constant demographic structure"). The positive trajectory is mainly due to improvements in the skill composition of the population. Conducting the alternative scenario with constant skill structure but incorporating the demographic aging process reveals a worse performance for OECD and Non–OECD countries compared to the baseline scenario.[35] This result highlights the importance of increasing human capital in the process of the demographic transition and the corresponding aging of the population in developing countries. The results are striking in showing the potential of human capital to counteract negative implications of aging, particularly when there is substantial scope for improvements in the education attainment of the population, as in less developed countries.

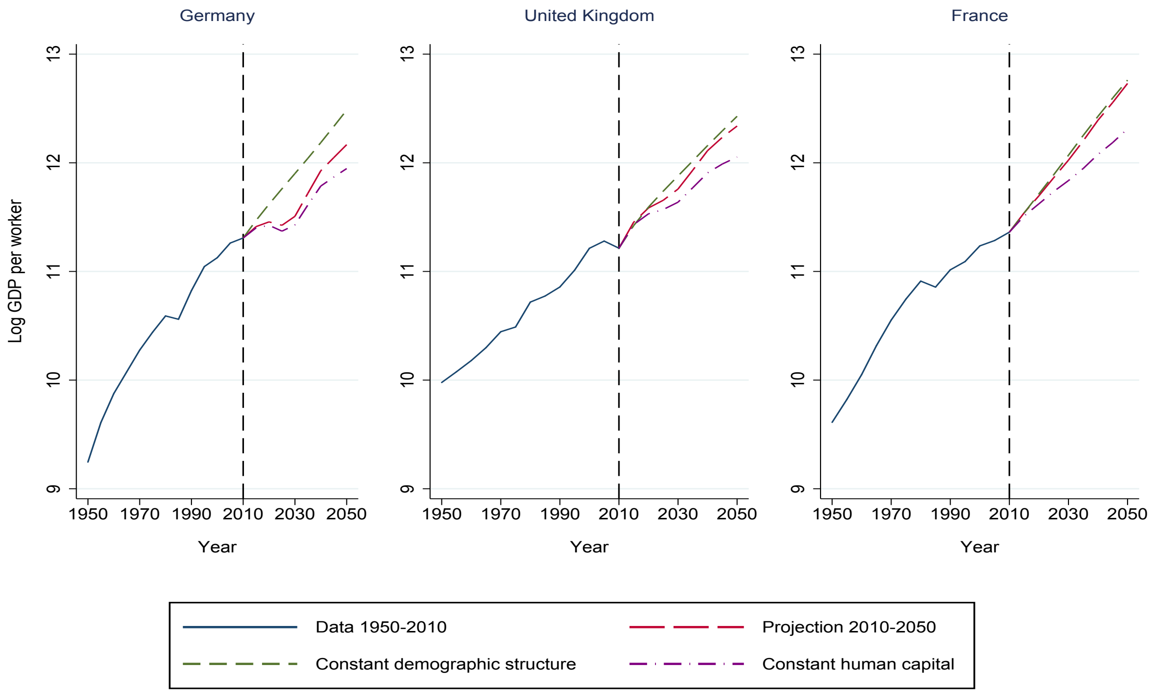
In countries with high fertility rates and a relatively young population, such as many African countries, population aging might even exert a positive effect: Since aging allows for the acquisition of more experience, it implies greater incentives to acquire more formal human capital. The key impediment for development in these countries appears to be a slow-down in the accumulation of human capital. Simulations illustrate this for Niger, Nigeria, Uganda and Mali.[36]

[33] See Figure A9 in the Appendix.

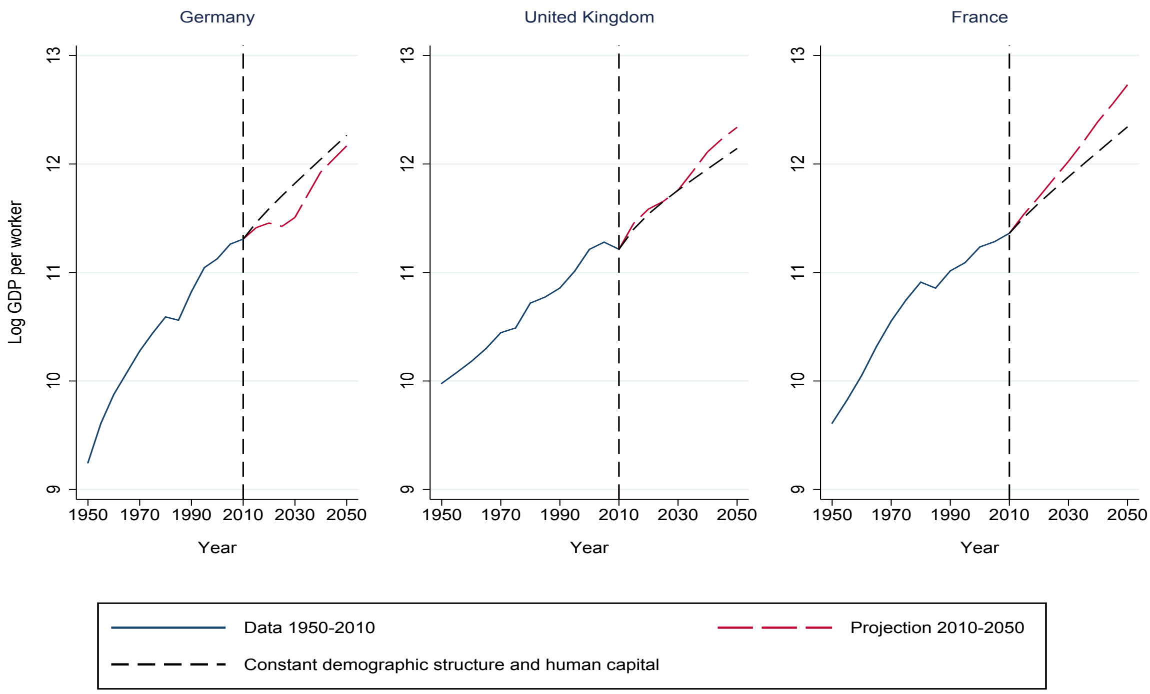
[34] See Figure A10 in the Appendix for details.

[35] Figure A8 in the Appendix illustrates the education projections that are neglected in this scenario. Alternative scenarios comprise constant enrollment rates, see the discussion below.

[36] See Figure A11 in the Appendix.

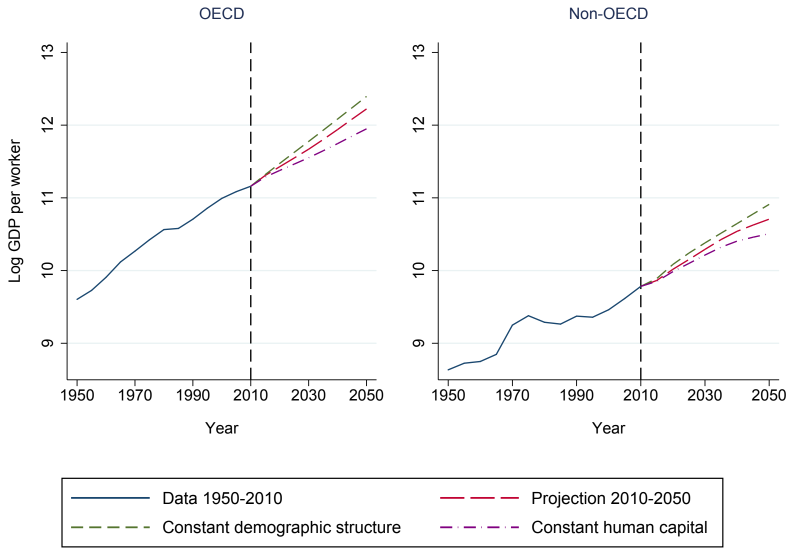


(a) Selected Countries: Germany, United Kingdom and France

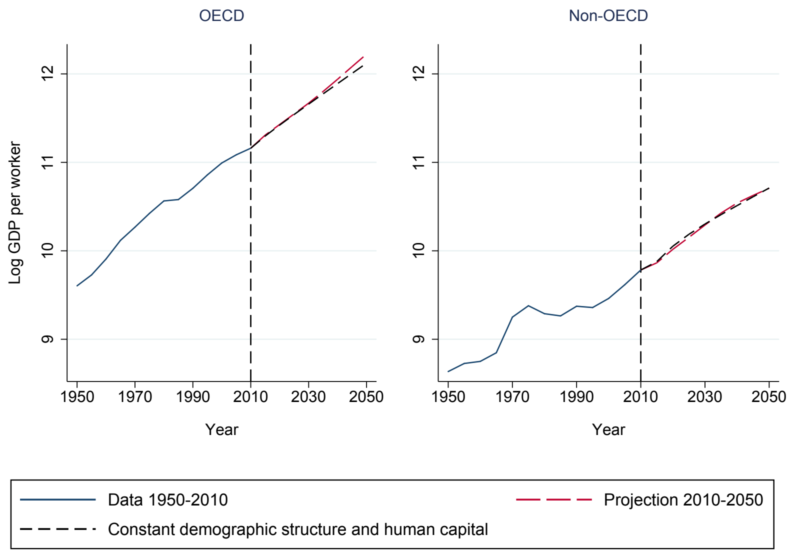


(b) Aging vs. Human Capital Accumulation

Figure 5: Projections Under Different Scenarios



(a) Developed vs. Developing Economies



(b) Aging vs. Human Capital Accumulation

Figure 6: Projections under Different Scenarios

5.2 Sensitivity and Alternative Scenarios

The projection results are robust to changes in the specification of the estimation equation or the use of income per capita rather than income per worker.[37] Moreover, if based on the empirical results of the instrumental variables approach (Table 1, Column 7), the projection results remain qualitatively unchanged with education showing a slightly more promising quantitative role for

[37]To illustrate this, Figures A12, A13 and A14 in the Appendix present the corresponding projections for a coarser specification of age groups, for income per capita instead of output per worker for selected countries and county groups. Figures A15 and A16 show the corresponding projections when accounting for the size of the working age population.

future development.[38]

Obviously, the quantitative dimension of the projections obtained with the different simulation scenarios are subject to a number of potentially restrictive and unrealistic assumptions. First, the alternative scenarios, in particular the assumption of a constant age structure as if the population were stable in its current form ("constant demographic structure"), were deliberately extreme. It should be clear that such a scenario is not only unrealistic but also inconsistent in terms of the implied demographic dynamics of non-stable populations. It should therefore be seen as an illustrative thought experiment, rather than a realistic (or even in some way implementable) possibility with normative character. A less extreme way to construct counterfactual scenarios in this context is to make alternative assumptions about vital rates. Such scenarios would fix fertility, or mortality, or both, at their 2010 levels, instead of fixing the age shares, and then compare the implied aging dynamics with the actually projected ones. The problem with these scenarios is that the resulting patterns of population aging differ only very mildly compared to the available projections.[39] This reflects the well-known difficulty for any policy aiming at vital rates to change the momentum of population aging. On the contrary, such scenarios camouflage the true extent of the consequences of aging for economic performance as they imply differences in the age structure that are too minor to provide substantially new insights. We therefore view the alternative scenarios studied here as more illustrative.

Second, the simulations are based on the assumption of physical capital following the average growth trend over the period 1950–2010. This assumption is clearly counterfactual, but it allows us to focus on the demographic aspects while remaining agnostic about the implications for savings and capital accumulation. An alternative is to specify an auxiliary equation for the accumulation of physical capital per worker as a function of past output, past levels of physical and human capital, and the age structure of the population, along the line of the estimation framework for output. Such an auxiliary equation can be estimated and the coefficient estimates can be used to predict physical capital under alternative scenarios, and in a second step output. The results from such a refined methodology leave the main results, in particular related to the relative importance of aging and human capital dynamics in different countries unaffected.[40]

Third, the simulations are obtained under the assumption of stable coefficients over time and across countries, as well as a constant growth trend. These assumptions allow for a comparable simulation across all countries, thereby providing the possibility to identify differences in economic performance that are due to projections in the demographic domain (the age structure) and projections in the domain of human capital, while holding other factors, such as structural parameters of relative productivity constant. This delivers qualitative results that are internally consistent. To investigate the robustness of the findings with respect to less restrictive assumptions

[38] Table A17 presents the corresponding projections for Germany, France, OECD and Non–OECD countries.

[39] This is illustrated in Figure A18.

[40] Figure A19 in the Appendix compares the projection scenarios for exogenous and endogenous capital. The simulation results suggest that capital accumulation is reduced in developed countries as consequence of aging, whereas the differences are less pronounced in low-income countries. This is consistent with the results from computable general equilibrium models that predict a negative effect of aging populations on capital formation, see, e.g., Sanchez-Romero (2013). However, these estimates are based on the implicit and counterfactual assumption of closed economies without access to international capital markets. See Börsch-Supan, Ludwig, and Winter (2006) and Domeij and Floden (2006) for quantitative and empirical studies on the implications of population aging for international capital flows.

about parameter stability, we also conducted the same counterfactual projections based on estimation results obtained for the sample period 1990–2010 instead of the entire sample period 1950–2010. The results of these projections are qualitatively very similar.[41]

Finally, the combination of estimation and projection analysis is subject to the criticism of not explicitly accounting for behavioral adjustments and mechanisms that underlie the population projections, and potential equilibrium effects, like fertility. In our view, the purpose of this paper is not so much about identifying point estimates but about making the point that, holding structural parameters fixed, the imminent and unrelenting demographic dynamics of the coming decades will have first-order effects on macroeconomic performance. The methodology is suited to address this issue, and the sensitivity analysis shown in this section indicates that the result are robust to various scenarios that should account for the scope of such behavioral adjustments. However, a structural analysis of behavioral adjustments is beyond the scope of this paper.

Overall, the projection results suggest that the implications of population aging on economic performance differ across countries with different age compositions and human capital projections. We therefore proceed by investigating this issue in more detail.

5.3 The Role of the Contemporaneous Age Composition

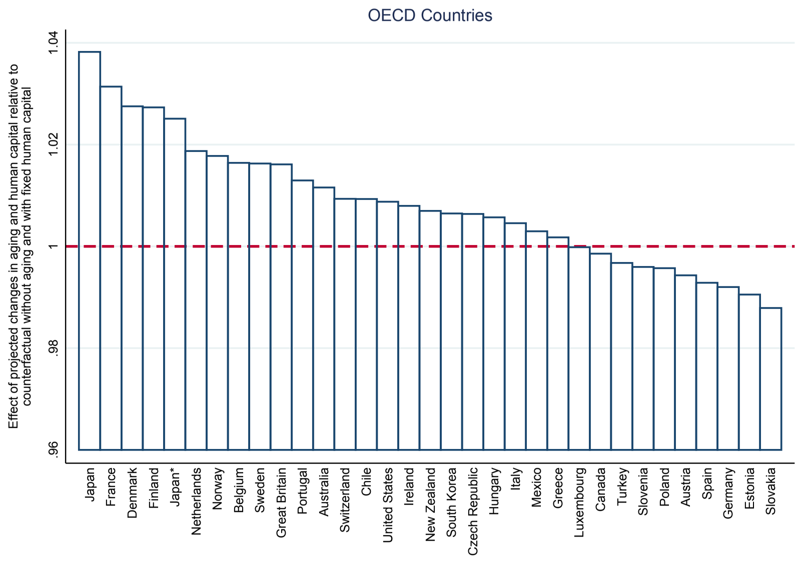
After having established how population aging and the contemporaneous changes in aggregate human capital affect macroeconomic performance and how this influences the prospects of future economic development, we return to the question whether investment in education can potentially offset the effects of population aging. Using the simulation methodology, we focus on which countries are predicted to suffer most from population aging, measured in terms of economic performance. We then contrast the positive impact of human capital acquisition to the predicted negative effect of aging, allowing us to quantify whether the former is large enough to offset the latter.

Using similar counterfactual experiments as in the previous section, one can simulate the effect of projected changes in the age and human capital structure of a country and compare it to a counterfactual scenario where both the age and human capital structures are fixed at their current (2010) levels. Figure 7 provides a plot of the predicted performance of OECD and Non–OECD countries relative to the counterfactual status quo. Countries with a young population that are projected to further increase their share of skilled individuals, such as France, are predicted to exhibit a substantially better performance than they would absent population aging and continued skill acquisition. On the other end of the spectrum, countries like Germany but also Austria, Spain, Estonia or Slovakia, that face substantial population aging with populations that do not have much scope for further upskilling, are likely to do worse than under the counterfactual status quo. Similar patterns can be observed for Non–OECD countries.

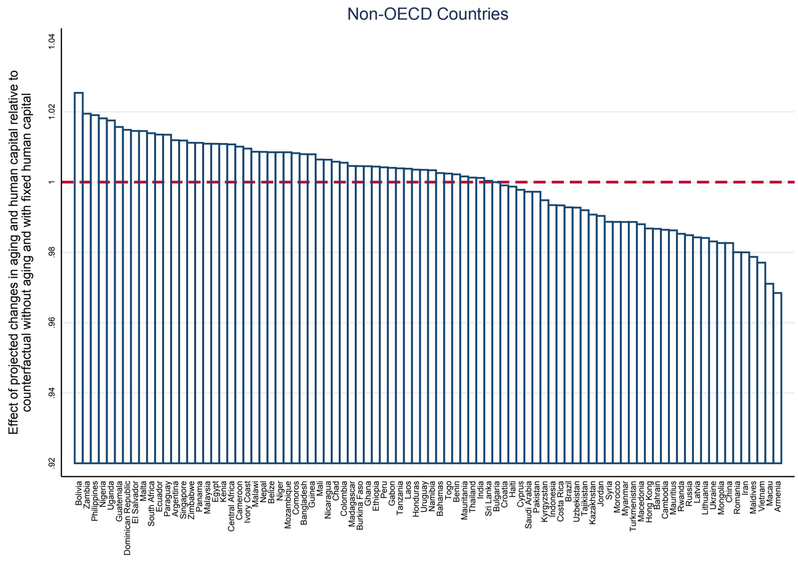
These predicted effects are mainly due to the differences in the scope for further acquisition of human capital at the aggregate level. This is illustrated by a decomposition, in which the contribution of the projected aging of the population to predicted economic performance is isolated from the contribution of the projected change in human capital.[42]

[41]See Figures A20 and A21 in the Appendix.

[42]See Figures A22 and A23 in the Appendix for the respective graphs.



(a) OECD Countries



(b) Non–OECD Countries

Figure 7: Projected Performance Relative to the Counterfactual Status Quo

Returning to the estimation framework, additional results confirm these insights by revealing heterogeneity in the effects when splitting the sample into subsamples with different levels of economic or demographic development. In particular, the results reveal stronger effects of changes in the age structure on economic performance in Non–OECD than in OECD countries.[43] This finding could indicate that the aging process is less pronounced once the demographic transition is completed. Alternatively, this finding could indicate that the adoption of technologies allows rich economies to insulate themselves from the negative effects of aging on average, as suggested by Acemoglu and Restrepo (2017). In contrast, poorer countries in which the process

[43] See Table A18 in the Appendix for details.

of population aging sets in with force might experience particularly adverse effects on their economic performance. This finding is also consistent with the finding that population aging has a more pronounced effect on societies with a large share of young people when considering a sample split.

A more direct way of testing this conjecture is by investigating the stability of coefficients for samples split in terms of the observation period, or in terms of the relative age of the population. When considering estimates separately for the period before and after 1990, the results reveal that the importance of population aging appears to have increased in recent decades. Concretely, the effects are stronger when considering a subsample for the period after 1990.[44] When splitting the sample into countries with populations that are old versus countries with young populations relative to the median of the young age dependency ratio, one obtains large and negative effects of the age structure in the "old" countries but large and positive effects of the age structure for the group of "young" countries.[45] This is consistent with the patterns obtained from the simulation shown in Figure 7. Aging is predominantly a problem for economic development in countries with an unfavorable age composition (such as Germany, and many Eastern European and Asian countries), whereas countries with a young population are standing to gain from the projected aging and education patterns (such as France, or many countries in Africa).[46]

5.4 The Scope for Adjustment

We conclude the analysis by investigating several alternative margins besides additional investments in education along which the aging effect might be counteracted. A key dimension in this respect is the intensity with which human capital, and labor in general, is supplied. To explore whether the decline in the relative supply of labor by young cohorts due to population aging could be neutralized by an increased labor force participation, in particular by women, or by longer work weeks, we proceed in three steps. First, we provide an assessment of the scope of adjustment along this dimension by comparing the effective labor supply of the different age groups in 2010 to the projected levels in 2050. The effective labor supply in 2010 is computed by using the same information about the age structure of the work force as in the estimates and combining it with data about the absolute size of the workforce and information about age-specific labor force participation at the extensive and intensive margin provided by the International Labour Organization (2011).[47] For 2050, we use the IIASA–VID projection for the working age population and assume that age-specific labor force participation and hours worked by women attain the same level as for men in the 2010 ILO data. This allows us to construct several alternative scenarios compared to the (implicit) assumption of constant female labor force participation and hours worked in the results presented so far. In particular, we compare the baseline projection as before, which assumes constant labor force participation at

[44] See Tables A19 and A20 in the Appendix for details.

[45] See Table A21 in the Appendix.

[46] Interestingly, also countries with a rather old and well educated population, such as Japan, are projected to gain from the future dynamics. This is partly due to the fact that they already underwent substantial shifts in the age distribution in the past and stand to face a "pause" in the coming decades. For this reason, we report also a scenario Japan* where the demographic structure has been fixed in the year 2000 instead of 2010. In other countries, the development is projected to be positive due to considerable immigration that is projected to stabilize the age distribution, as, e.g., in Switzerland.

[47] The data are available at `https://www.ilo.org/ilostat`.

the extensive and intensive margin, to three alternative scenarios: a projection that also accounts for changes in female labor force participation, for changes in hours, and for changes in both, until 2050. When comparing the magnitudes relative to the projected effects of aging for the size of the work force of each age group, these increases appear rather moderate. In particular, these projections indicate that the overall patterns of aging will at most be moderated but not completely neutralized.[48]

In a second step, we make use of novel age projections of labor force participation constructed by Fürnkranz-Prskawetz, Hammer, and Loichinger (2016) for 26 European countries to project the macroeconomic performance of these countries using the baseline estimates obtained from the age structure of the working age population. In particular, using the 2010 data on labor force participation, we construct an index for the labor force participation that takes value 100 for each age group in 2010, and compute the relative change up to 2050 using the projection data by Fürnkranz-Prskawetz, Hammer, and Loichinger (2016). The projection results document that aging remains a substantial impediment for economic development for most countries.[49] A drawback of this analysis is that it relies on estimates that do not incorporate information about labor force participation but that only rely on the age structure of the working age population. This reduced form approach helps avoiding endogeneity problems related to labor force participation, but it introduces a slight methodological inconsistency.

In a third step, we therefore re-estimate the model using information on the effective labor force and hence effective human capital supply, by incorporating age-specific differences in the intensive margin, for the period from 1980 to 2010 for which respective age-structured data are available from the ILO (International Labour Organization, 2011). In this context, it is worth noting that most of the respective variation is driven by female labor force participation. Based on these estimates, we then project macroeconomic performance using the workforce projections by Lutz et al. (2007) and by Fürnkranz-Prskawetz, Hammer, and Loichinger (2016). The descriptive statistics indicate that the age structure of the working age population and of the work force are rather similar.[50] Consistently, the estimation results do not differ substantially from the baseline estimates and deliver the same qualitative results.[51] Correspondingly, the projections incorporating age-specific labor force participation patterns do not deliver substantially different results. In particular, aging remains to exert a major negative effect on macroeconomic performance, whereas human capital is only able to offset this effect partially.[52] Overall, the results from these three exercises suggest that the incorporation of age-specific projections for labor force participation and hours worked does not greatly affect the conclusions regarding the effects of aging and skills for future macroeconomic performance.

Another margin of adjustment is a potential shift in the age-profile of productivity. Whether

[48]This is illustrated in Figures A24 and A25 in the Appendix, where we plot the labor supply in terms of the total weekly hours worked by the different age groups as of 2010 and the projected change under the different scenarios until 2050, for Germany and France, and OECD and Non–OECD countries, respectively. Notice that the data and projections average over men and women.

[49]See Figure A26 in the Appendix.

[50]In particular for age groups above 20 years of age, see Table A1 in the Appendix for details.

[51]Table A22 contains the corresponding estimation results.

[52]Figure A27 in the Appendix provides a direct comparison of the projections obtained with the baseline methodology and with estimates that incorporate variation in labor force participation for the 26 EU countries for which labor force projections are available. Figure A28 plots the respective projections for Germany and France.

in the future the productivity will peak at younger or older ages is an open question. Given the ongoing improvements of health status and labor force attachment of older cohorts in the workforce, and the observation of a stable experience premium that has led to the conjecture of experience-biased technical change (Caselli, 2015), one might expect that the most productive age range might shift from 50–54 to older ages.[53] To account for this possibility, we replicated the projections by shifting the estimated productivity profile by one age group (i.e., considering ages 55–59 years as the most productive group instead of 50–54 years). The corresponding results reveal a modified projection of the consequences of population aging compared to the baseline in the sense that the negative effects of population aging in countries like Germany are delayed.[54]

Finally, the methodology allows us to address the question regarding the scope for technical change or productivity improvements to offset the effects of aging. Recent work has suggested that directed technical change might provide a countervailing force to the negative growth effects of population aging (Acemoglu and Restrepo, 2017). Likewise, improvements in the quality of human capital have been shown to affect macroeconomic performance across states (Hanushek, Ruhose, and Woessmann, 2017). To investigate this issue, we conduct another counterfactual exercise and compute the extent of skill-biased technical change or quality improvement, in the form of an increase in the relative productivity of high-skilled to low-skilled workers, λ^h, that is needed to offset the effect of population aging until 2050. The results of this exercise replicate the previous findings about which countries are expected to suffer or gain from population aging, but this time the estimates provide a quantitative interpretation in terms of productivity. In particular, the relative productivity of high-skilled workers would have to increase by more than two-fold to counteract the effects of population aging in countries that are affected negatively by population aging, such as Germany.[55]

6 Conclusion

This study presents novel evidence regarding the role of the demographic structure of the workforce and the distribution of skills for aggregate economic performance. On the basis of an extended development accounting model, we derive a flexible empirical framework that can accommodate empirical models previously used in the literature. In particular, assuming that the quality of the labor force depends on the demographic structure allows incorporating workforce demographics into the production function and provides a coherent framework to evaluate the implications of population aging and education dynamics for future economic development.

The estimation results show that changes in the age structure of the working-age population have a strong effect on output, even when controlling for human capital. At the same time, the evidence suggests that the stock of human capital embodied in the population has a positive effect on economic performance, conditional on the age structure of the population. The effects of aging in terms of changing relative sizes of the different age cohorts mirror productivity

[53] Complementing this, research productivity as measured by scientific breakthroughs has shifted to older ages (Jones and Weinberg, 2011). However, there is also evidence that suggests that new technologies such as ICT might shift the productivity peak to younger years (Falck, Heimisch, and Wiederhold, 2016). In the present context, a shift to younger years would reinforce the effects of aging.

[54] See Figures A29, A30 and A31 in the Appendix for details.

[55] See Figure A32 in the Appendix for details.

profiles that have been found earlier, in terms of hump-shaped productivity patterns over the age dimension. Consequently, the results show that population aging in old societies reduces the future growth potential. The estimates suggest that human capital can help to compensate for these aging pressures and deliver an upper bound for the elasticity between the age structure and the distribution of skills. This elasticity allows gauging the change in the distribution of skills that is required to offset the negative effects of aging of the workforce. The quantitative estimates of this elasticity predict that shifts out of the most productive age cohort into older and less productive age groups can be offset by higher investment into schooling. However, these offsetting effects might not be sufficient to fully compensate for aging, particularly in developed countries. Nevertheless, the results suggest that a continued expansion of education is crucial for future macroeconomic performance.

The results are also useful to infer the relative importance of aging and human capital accumulation for macroeconomic performance by ways of projections on the basis of different scenarios of population aging and human capital dynamics. Projections of future economic development predict that aging will play an important role by slowing down economic development in developed and less developed countries. Aging is, hence, not a problem of the developed world only. There is substantial heterogeneity in the projected macroeconomic performance as result of differential population aging patterns across countries. This heterogeneity emerges through the heterogeneous productivity but also as consequence of the implications for the scope of human capital in compensating this effect. In fact, the projections reveal a central role of human capital in ameliorating the negative consequences of aging. This is particularly the case in countries that are yet underdeveloped in terms of human capital endowments and that have considerable potential for an increase in the human capital endowment of the still largely low-skilled population. The scope of human capital improvements for compensating the consequences of population aging appears more limited in economies that age faster. However, the findings make clear that without further improvements in the skill composition of the workforce in these countries, the consequences of population aging will be much more dramatic. Additional projections suggest that increased female labor force participation or longer work hours will be unlikely to neutralize these effects or replace human capital. Moreover, skill-biased technical change will have to be substantial to counteract these developments.

We would like to end with a word of caution. The main purpose of this paper is not about making accurate predictions; the future will certainly look different than in our projections. Rather, the contribution of this paper lies in providing new evidence for the close connections between aging and the supply of human capital, as well as their implications for macroeconomic performance, with the aim of raising the awareness of the profession, and of policy makers, regarding this link. Overall, the results are consistent with an important role of long-run demographic dynamics for future economic development, pointing toward the possibility of more stagnant development in the future. In this sense, the results complement recent findings by Cervellati, Sunde, and Zimmermann (2017). In our view, these issues do not receive adequate attention by researchers and policy makers.

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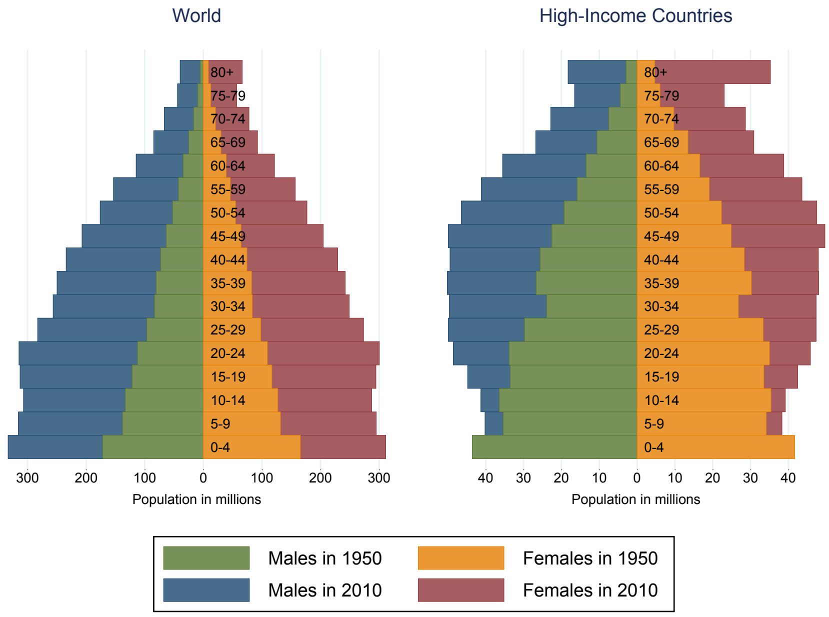
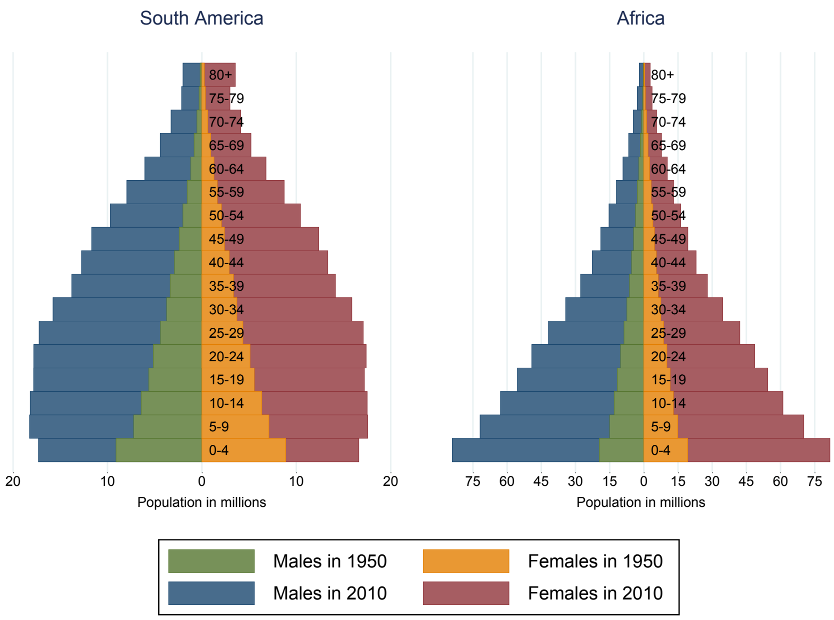
Supplementary Material for Publication as Online Appendix

Additional Figures



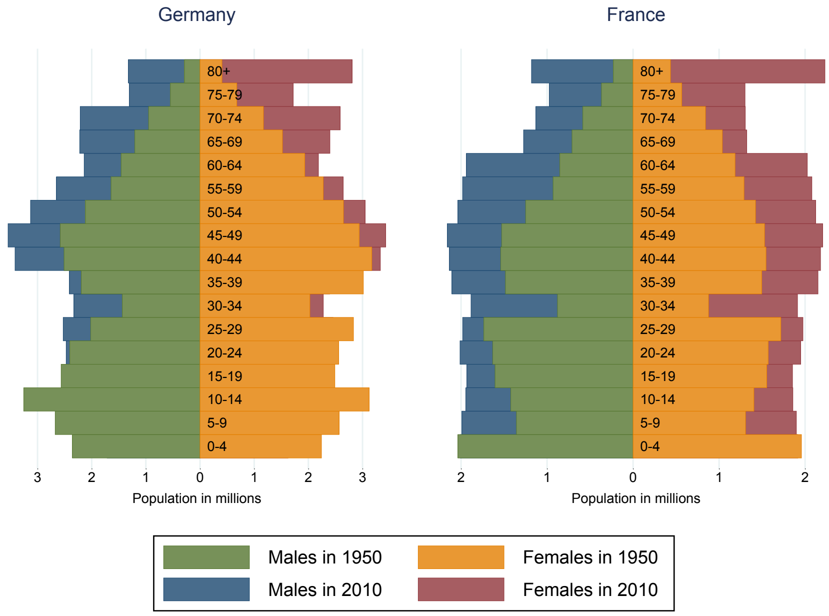
(a) World and High–Income Countries



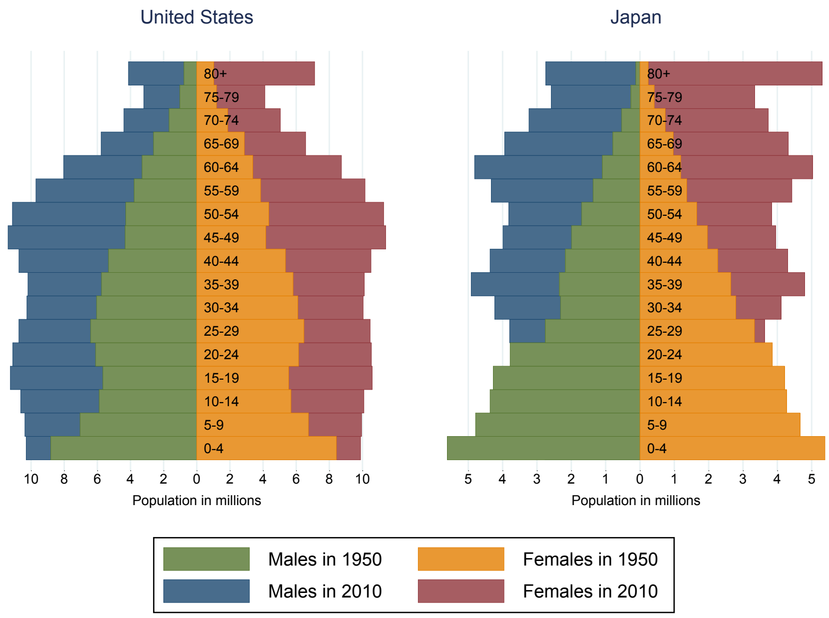
(b) South America and Africa

Figure A1: Population Dynamics – Selected Regions

Data source: United Nations, Department of Economic and Social Affairs (2015). World Population Prospects: The 2015 Revision.



(a) Germany and France



(b) United States and Japan

Figure A2: Population Dynamics – Selected Countries

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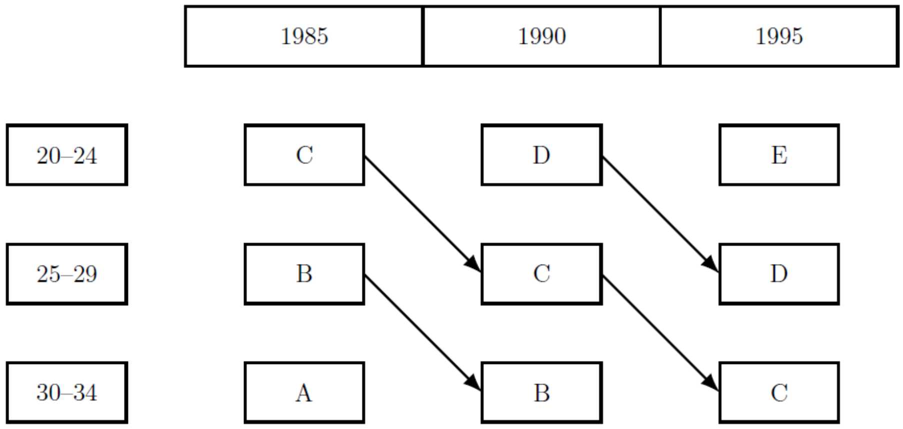
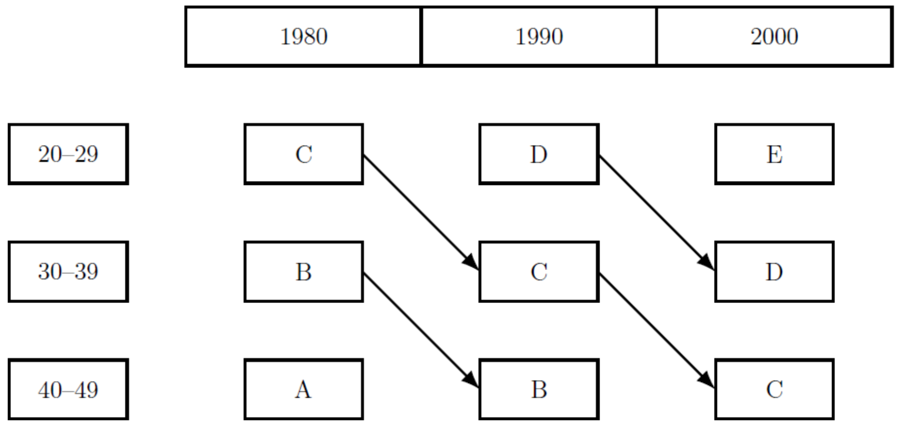
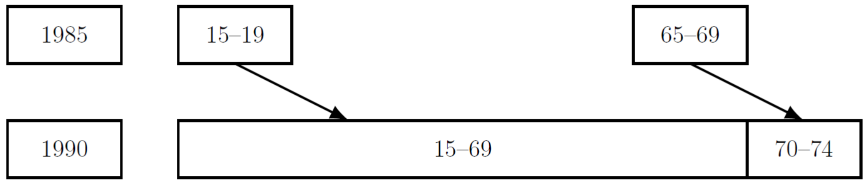


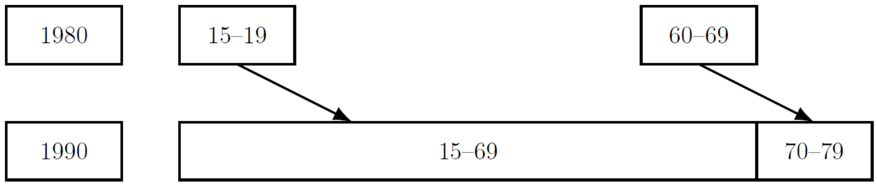
(a) Five–year cohorts



(b) Ten–year cohorts



(c) Human capital, five–year cohorts

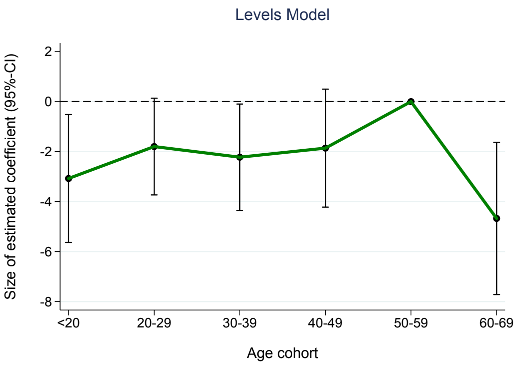


(d) Human capital, ten–year cohorts

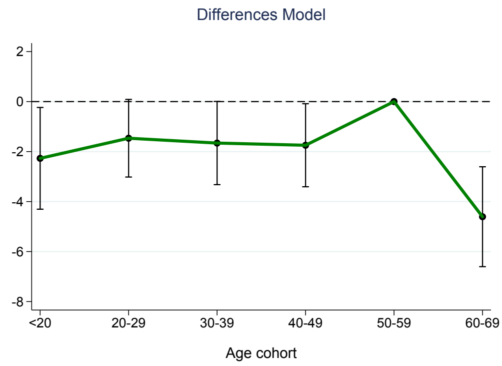
Figure A3: Illustration of Demographic Dynamics as Instrumental Variable

(a) Five–year cohorts (Table A5, Column 3)

(b) Five–year cohorts (Table A6, Column 3)



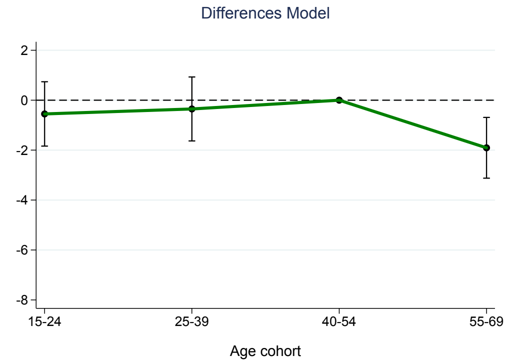
(c) Ten–year cohorts (Table A7, Column 3)



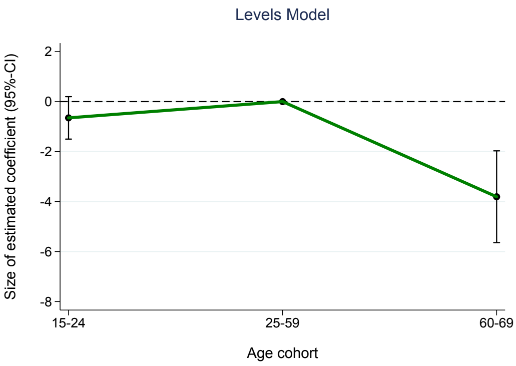
(d) Ten–year cohorts (Table A8, Column 3)

Figure A4: Macro Productivity Profiles: Barro–Lee Data

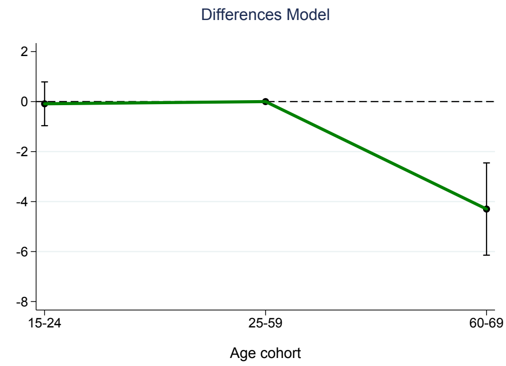
(a) Fifteen–year cohorts (estimates unreported)



(b) Fifteen–year cohorts (estimates unreported)



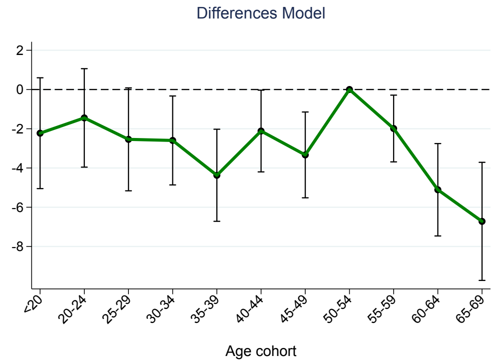
(c) Prime–age group (estimates unreported)



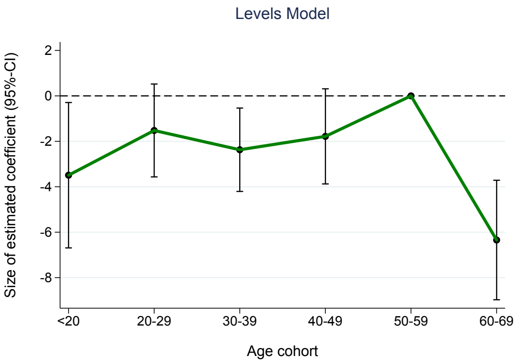
(d) Prime–age group (estimates unreported)

Figure A5: Macro Productivity Profiles (Alternative Cohort Structure)

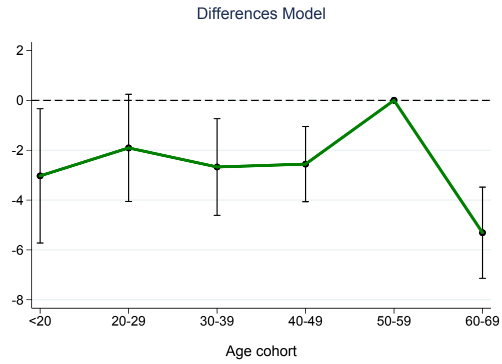
(a) Five–year cohorts (Table A10, Column 3)



(b) Five–year cohorts (estimates unreported)



(c) Ten–year cohorts (estimates unreported)



(d) Ten–year cohorts (estimates unreported)

Figure A6: Macro Productivity Profiles: Income Per Capita

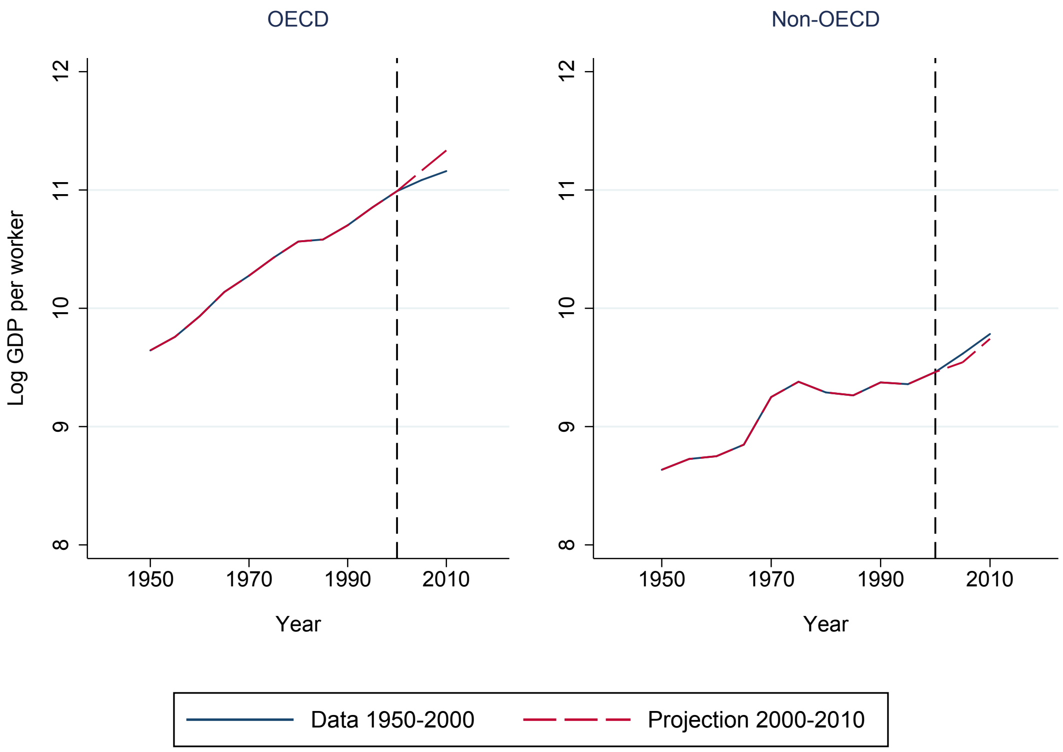
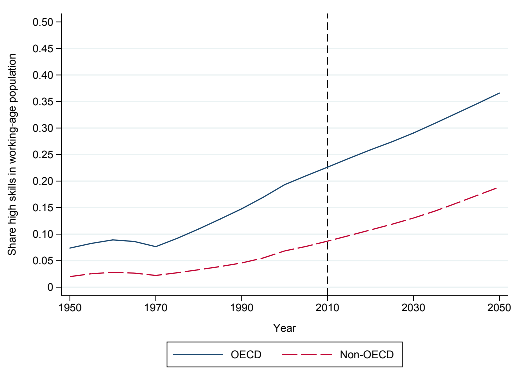
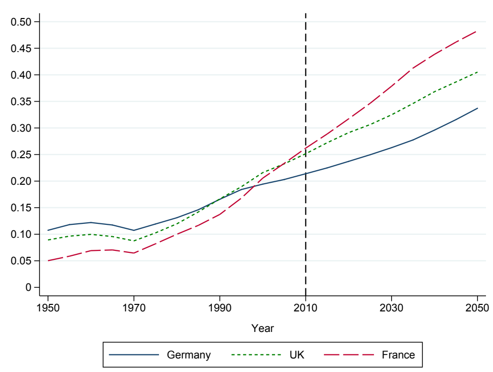


Figure A7: Within–Sample Projection (2000–2010)

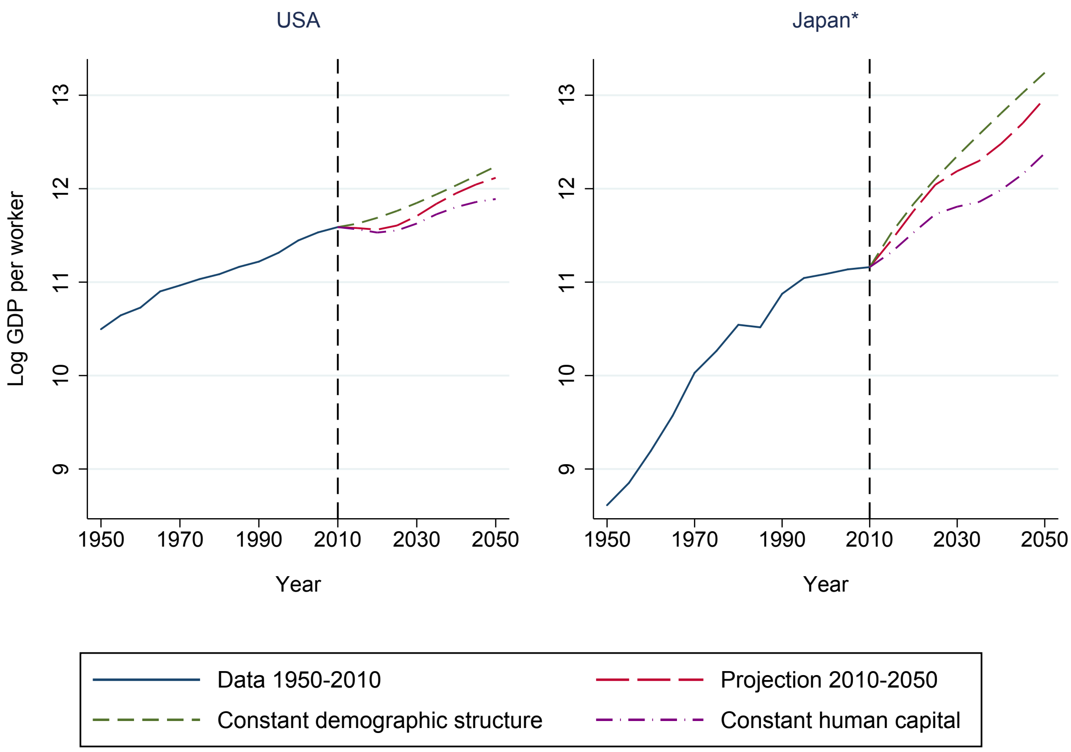


(a) OECD and Non–OECD Countries

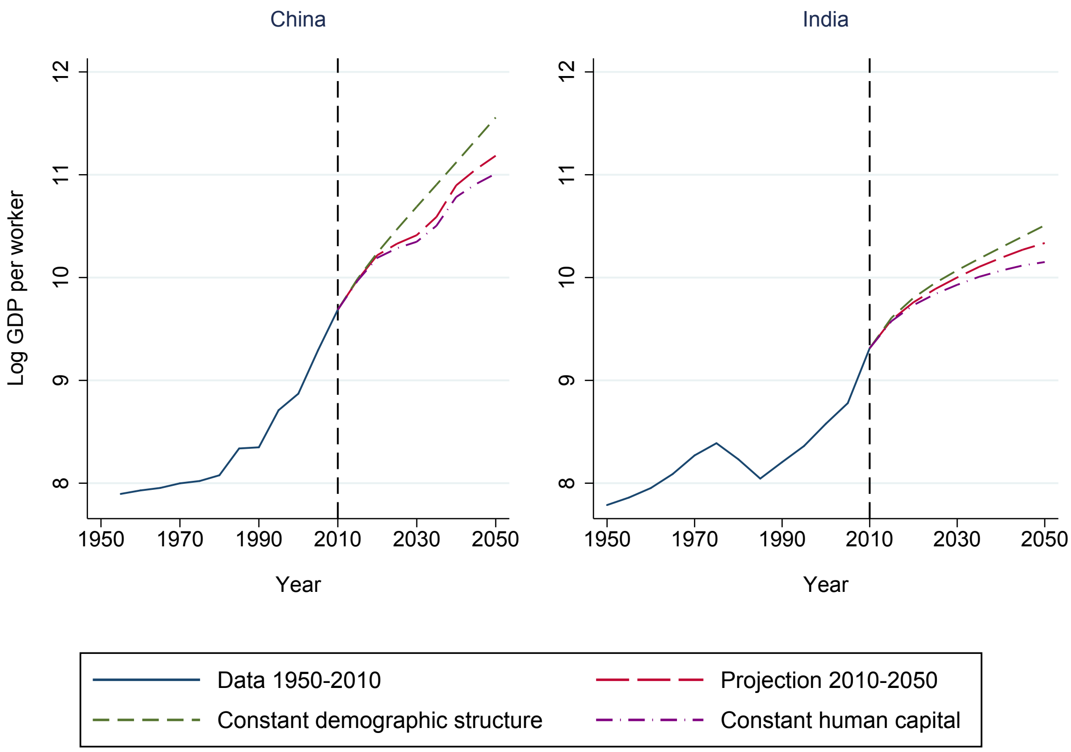


(b) Germany, United Kingdom and France

Figure A8: Actual and Projected Educational Attainment

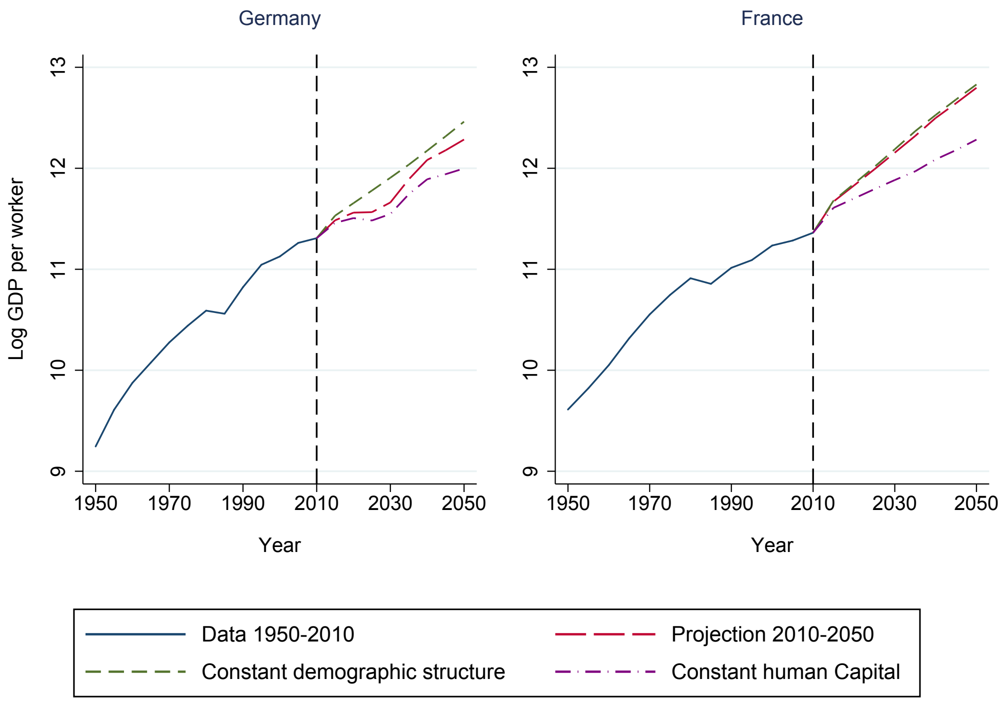


(a) Selected Countries: USA and Japan

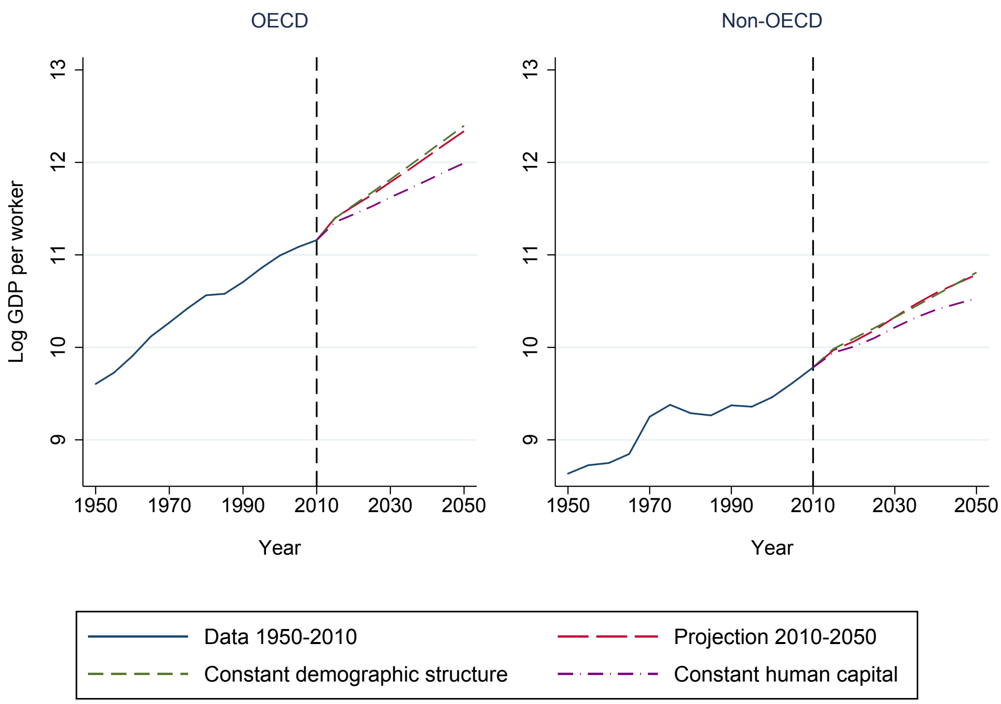


(b) Selected Countries: China and India

Figure A9: Projections under Different Scenarios

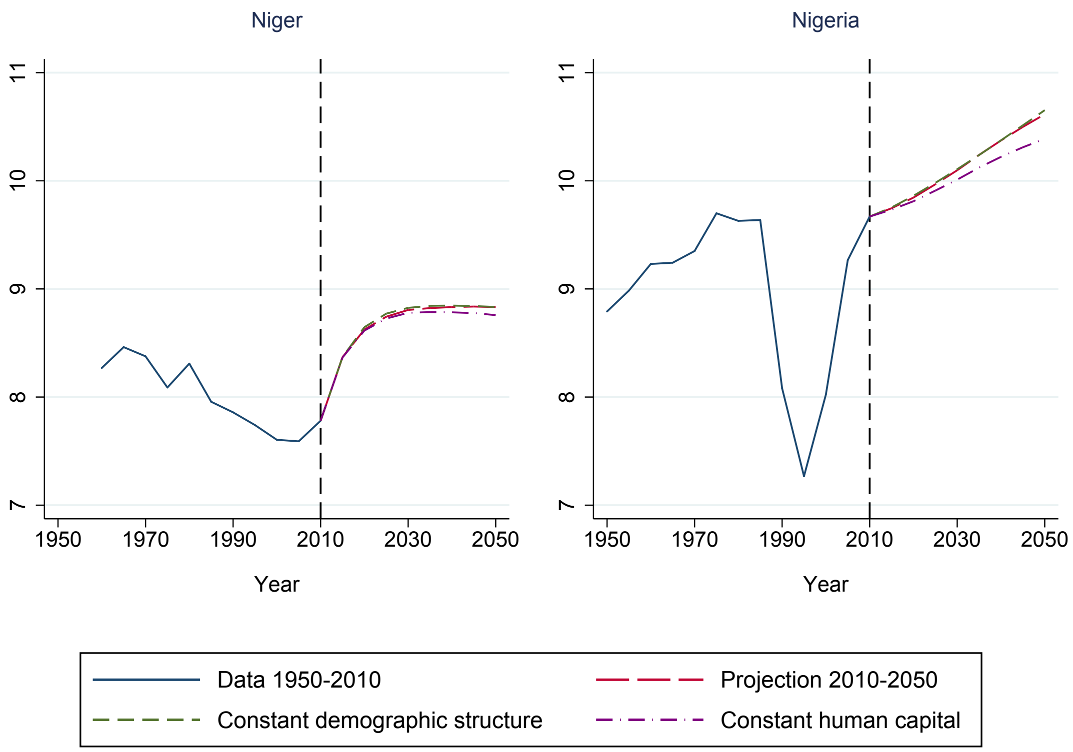


(a) Selected Countries: Germany and France

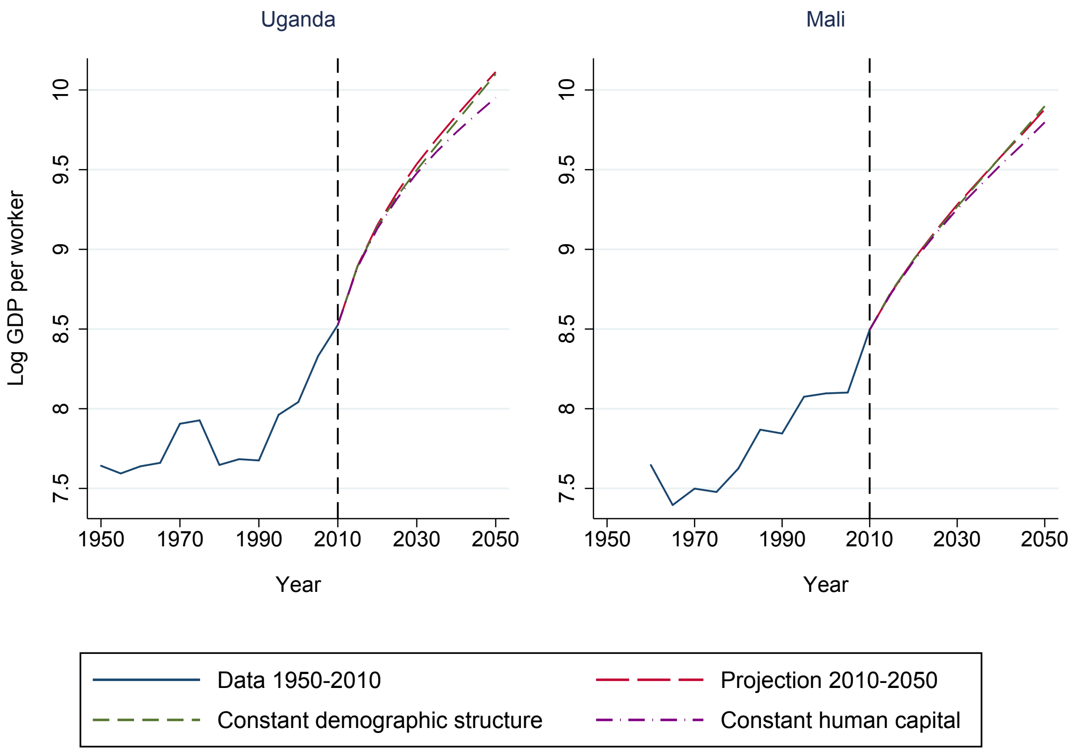


(b) Selected Regions: OECD and Non–OECD Countries

Figure A10: Projections for Model Without Lagged Dependent Variable

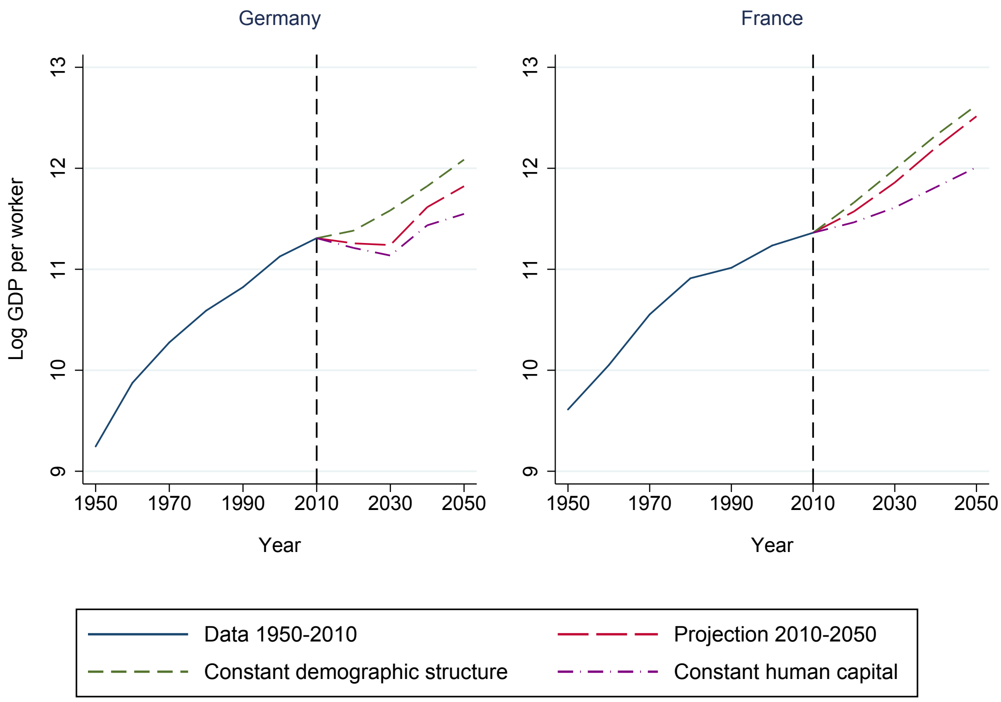


(a) Selected Countries: Niger and Nigeria

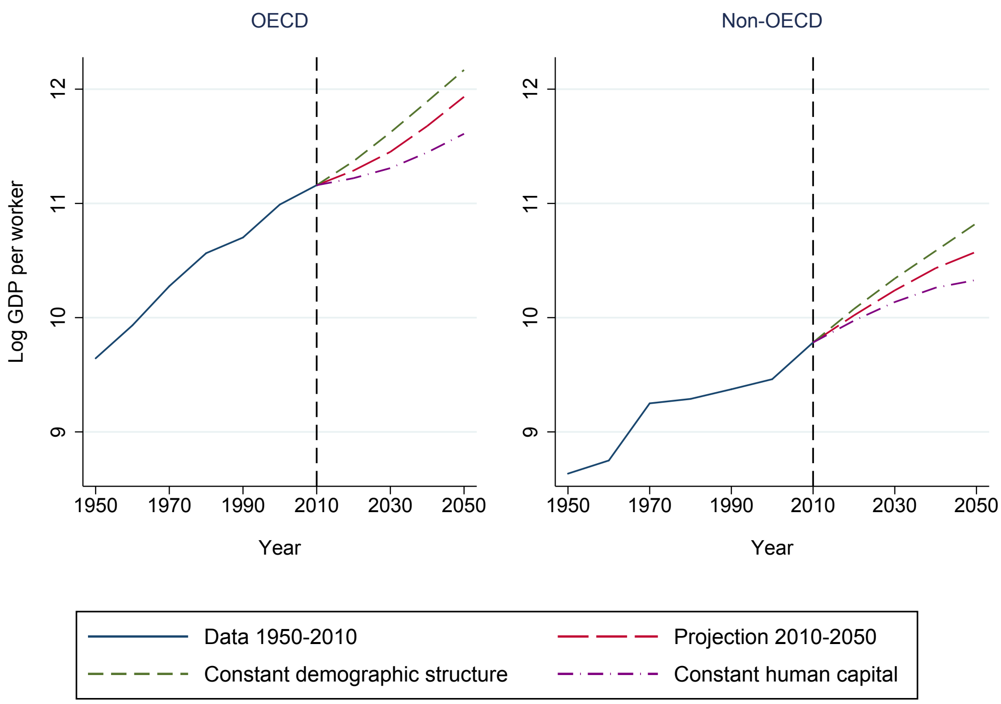


(b) Selected Countries: Uganda and Mali

Figure A11: Projections under Different Scenarios

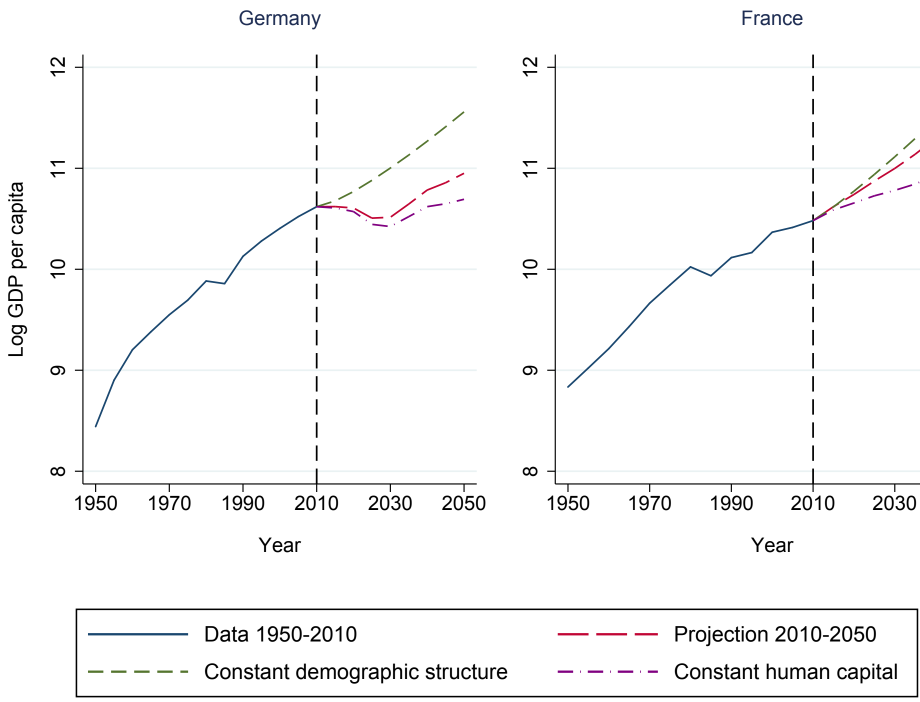


(a) Selected Countries: Germany and France

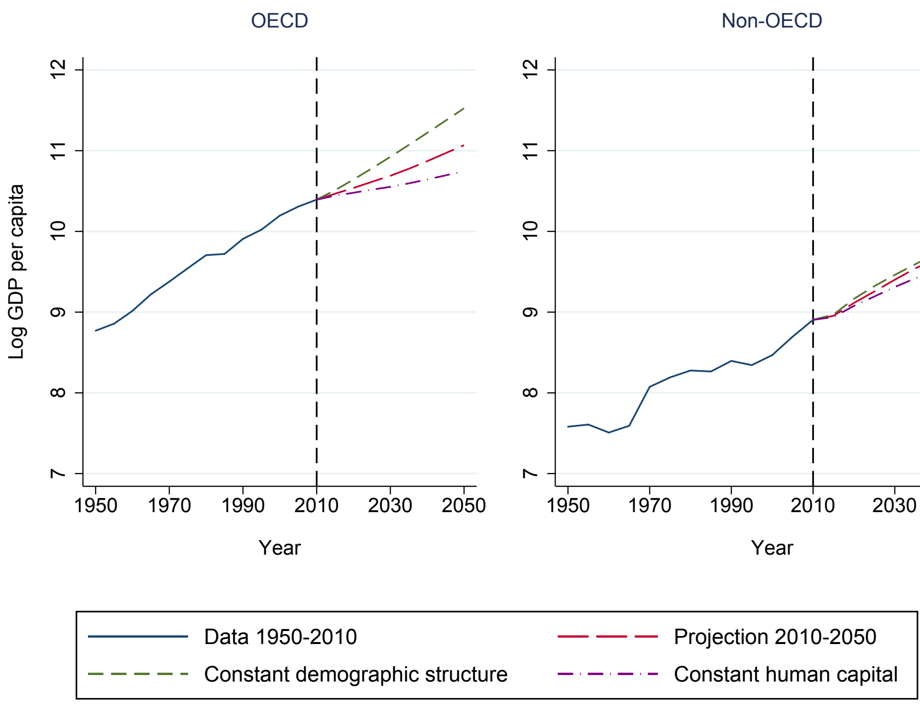


(b) Selected Regions: OECD and Non–OECD Countries

Figure A12: Projections for Model With Prime–Age Group (see Figure A5, Panel b)

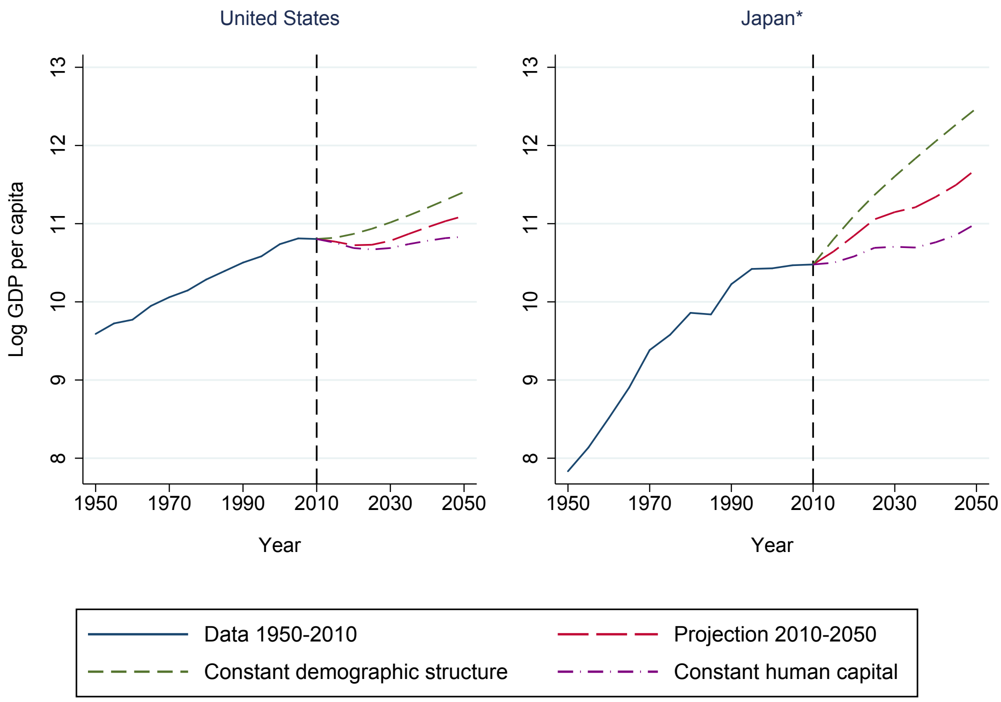


(a) Selected Countries: Germany and France

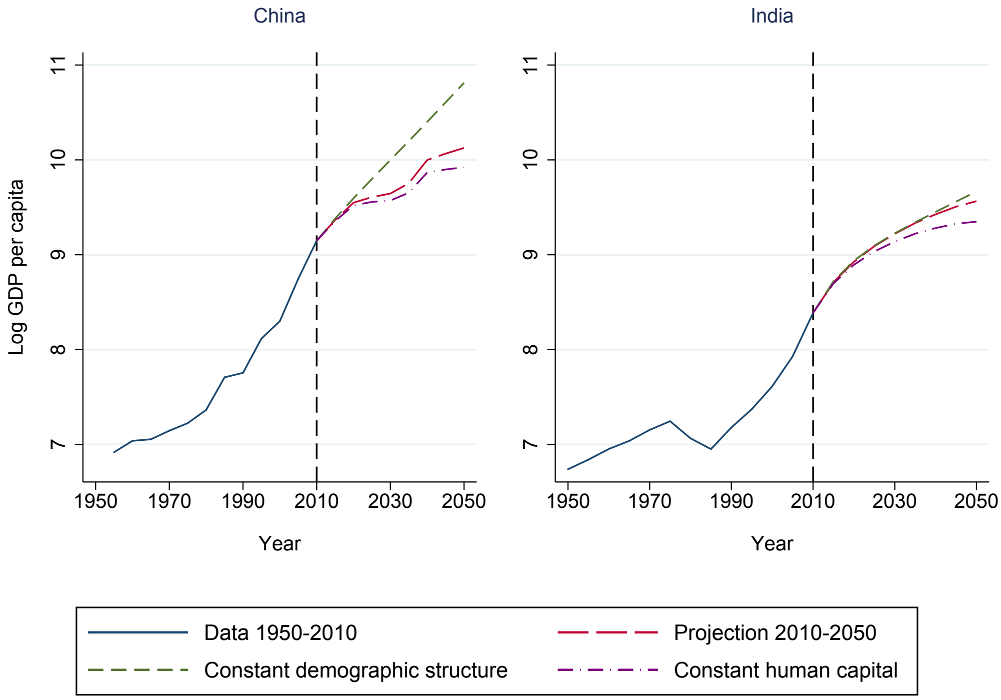


(b) Selected Regions: OECD and Non–OECD Countries

Figure A13: Projections for Income Per Capita

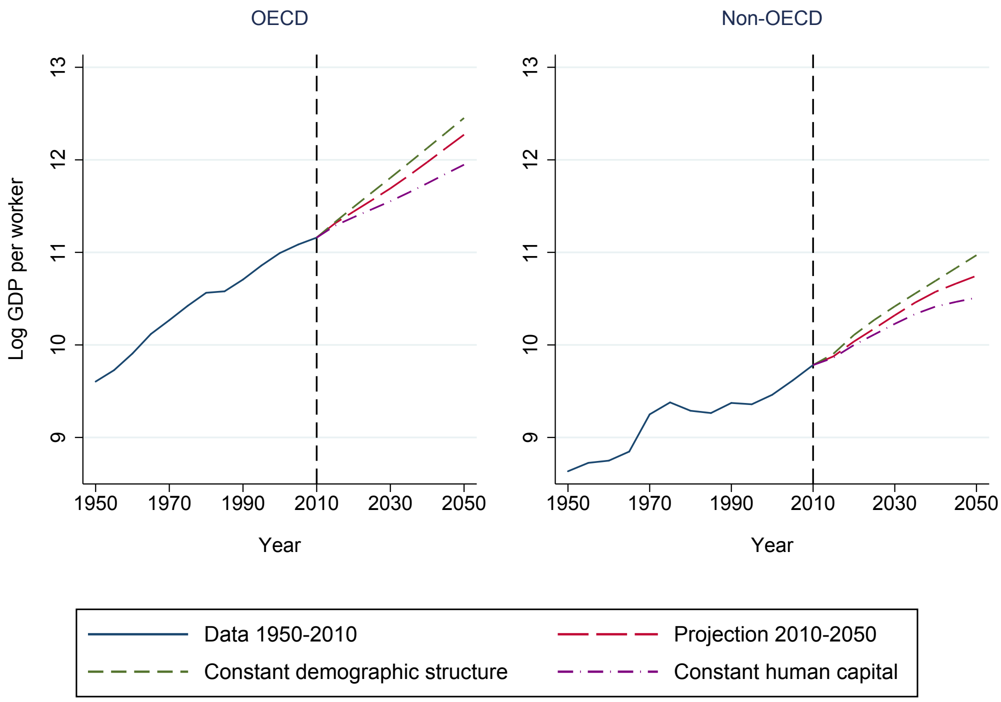


(a) Selected Countries: USA and Japan

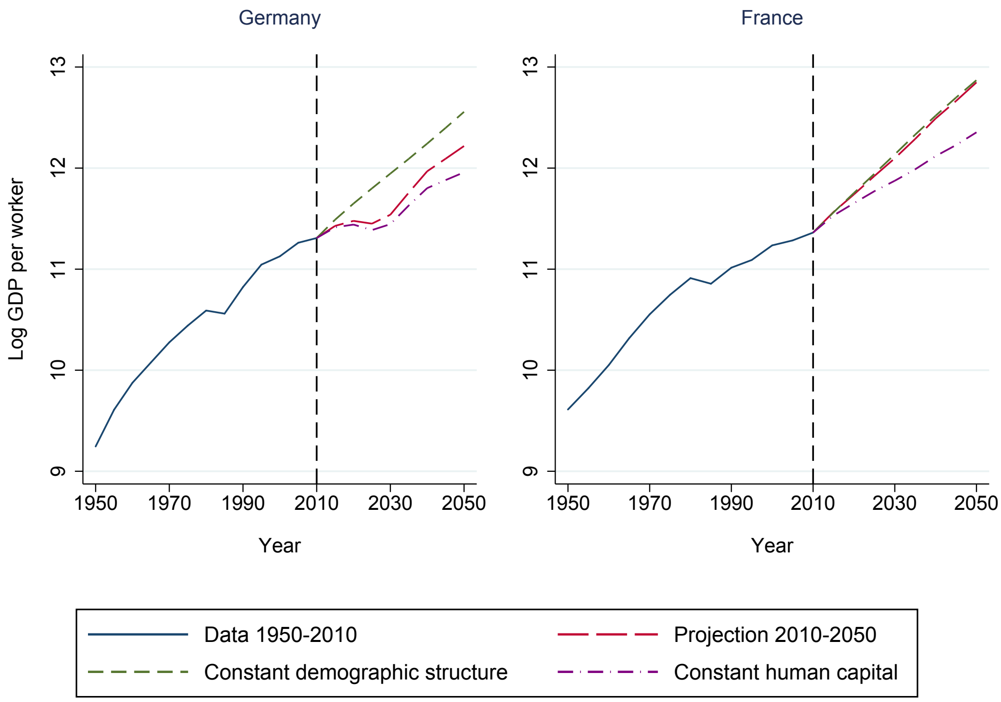


(b) Selected Countries: China and India

Figure A14: Projections for Income Per Capita

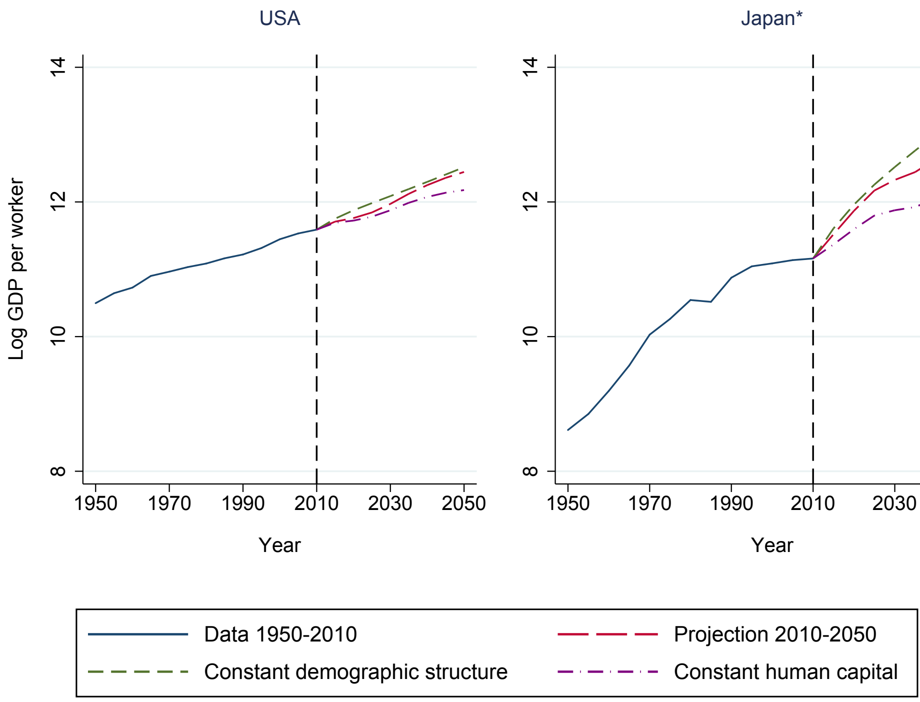


(a) Selected Regions: OECD and Non–OECD Countries

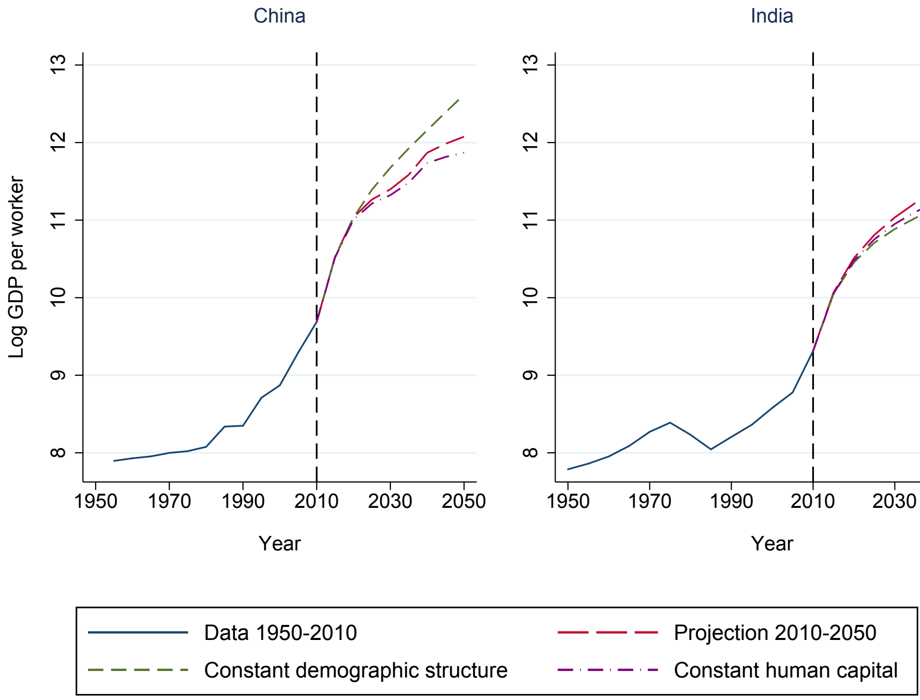


(b) Selected Countries: Germany and France

Figure A15: Projections when Controlling for the Size of the Working–Age Population

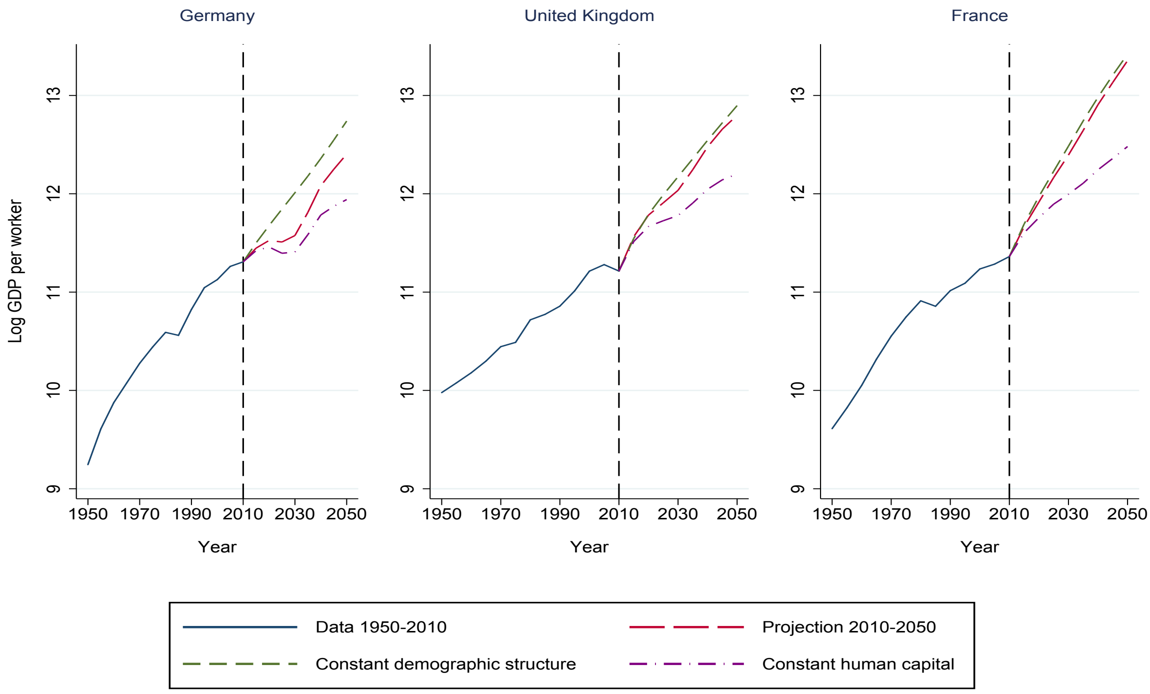


(a) Selected Countries: USA and Japan

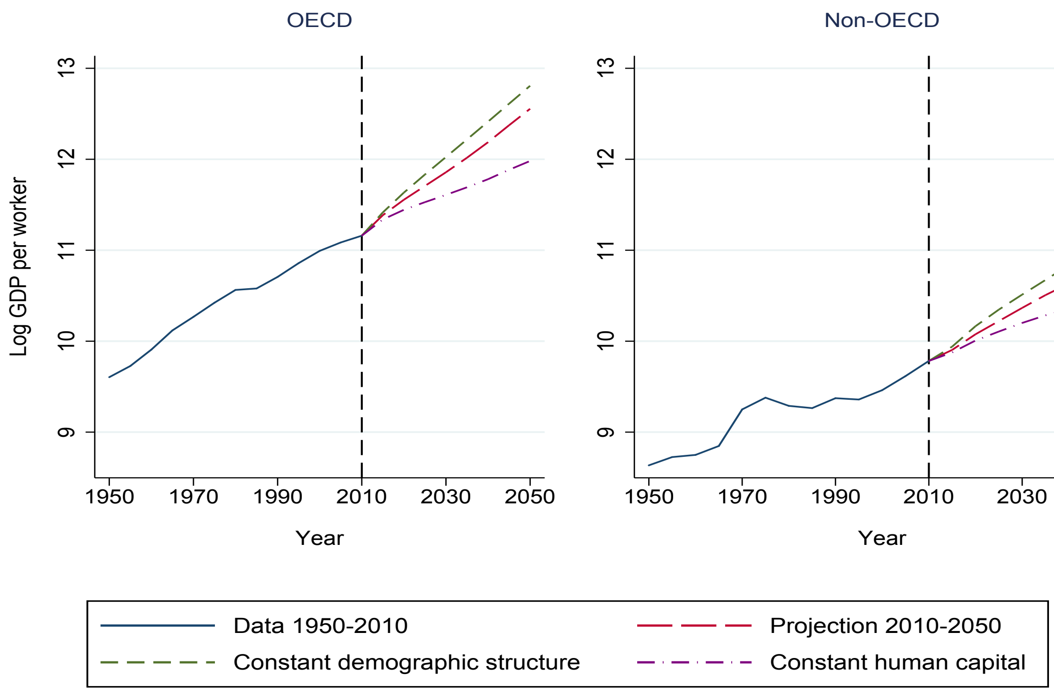


(b) Selected Countries: China and India

Figure A16: Projections when Controlling for the Size of the Working–Age Population

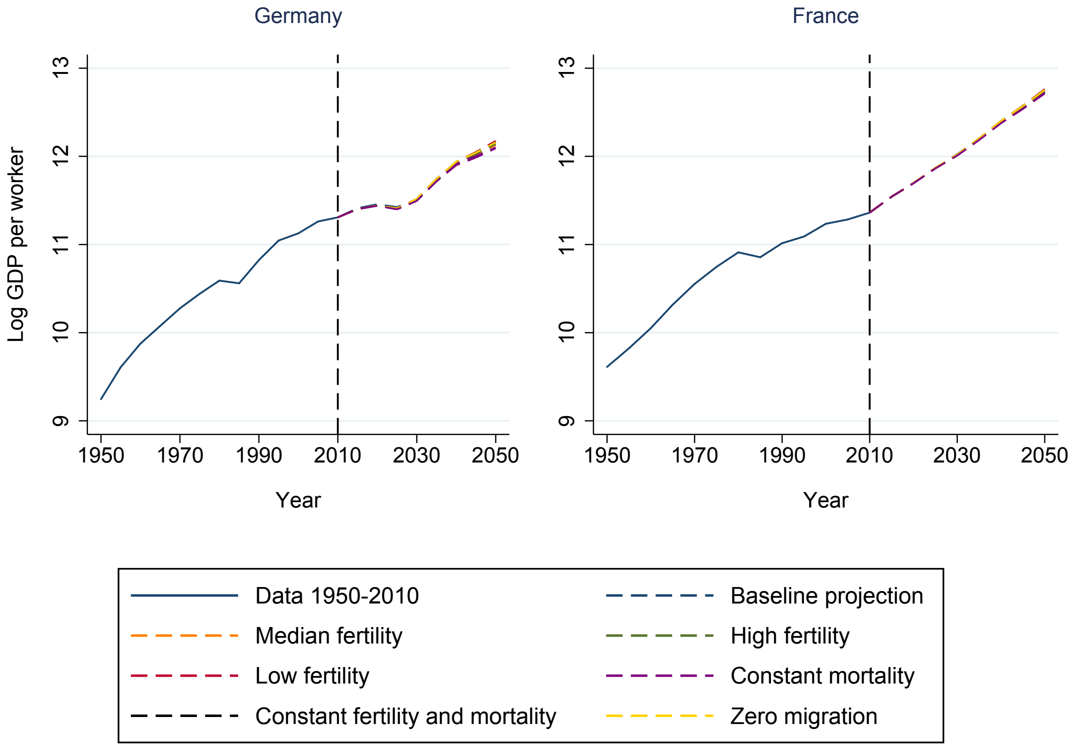


(a) Selected Countries: Germany and France

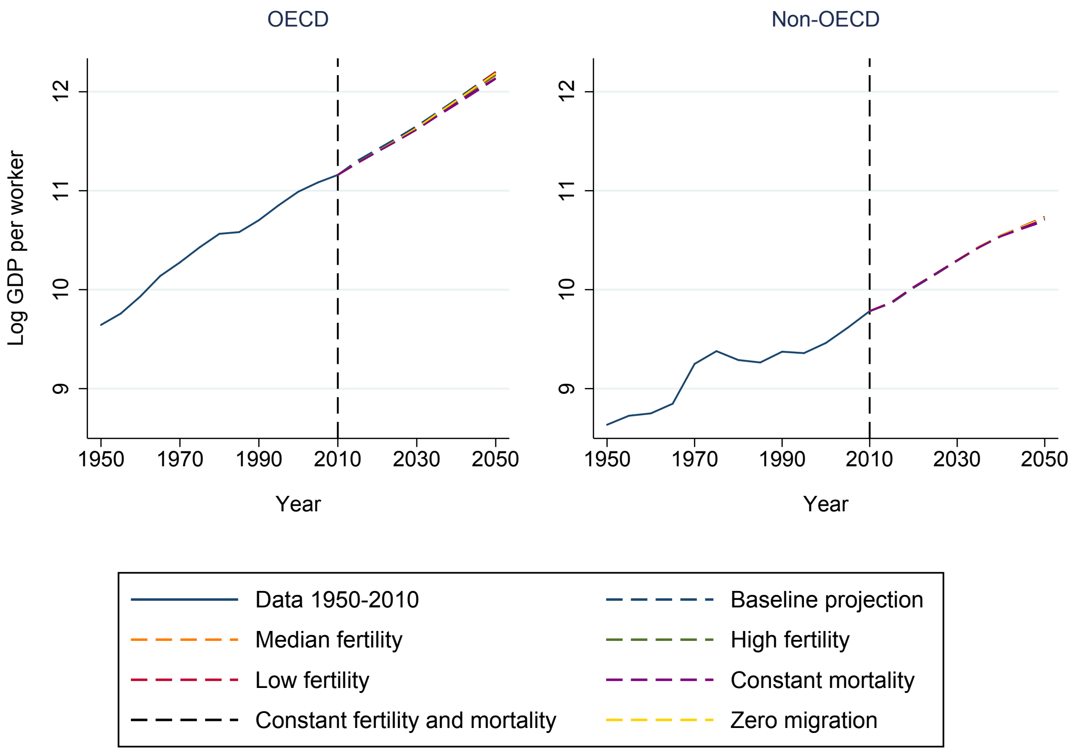


(b) Developed vs. Developing Economies

Figure A17: Projections for Instrumental Variables Model

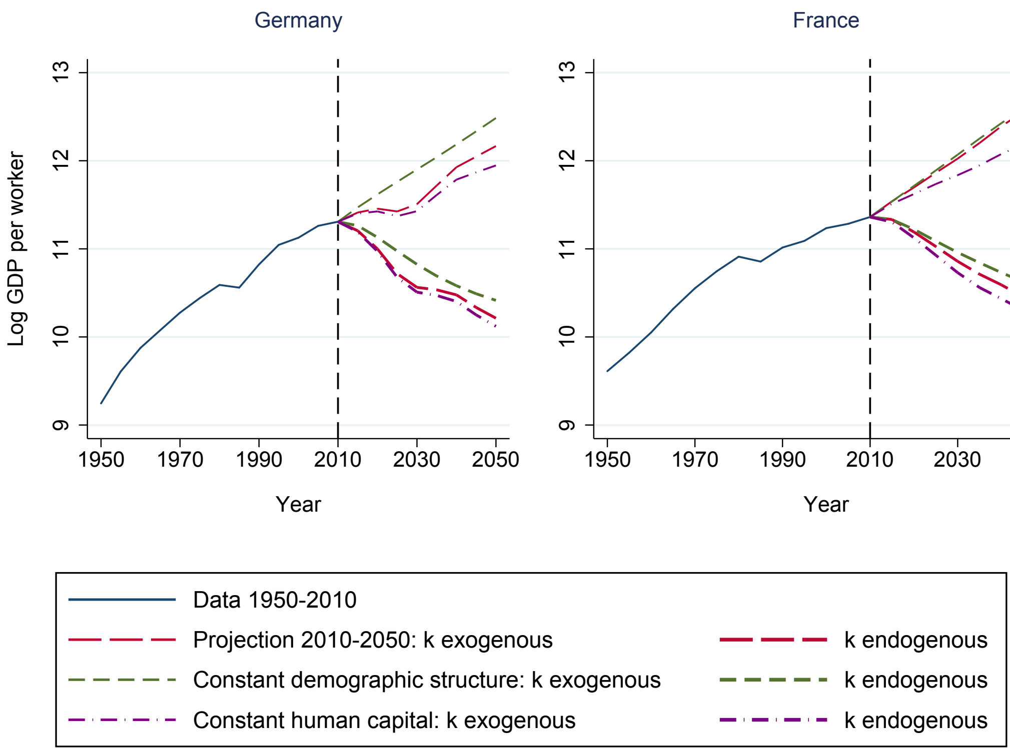


(a) Germany vs. France

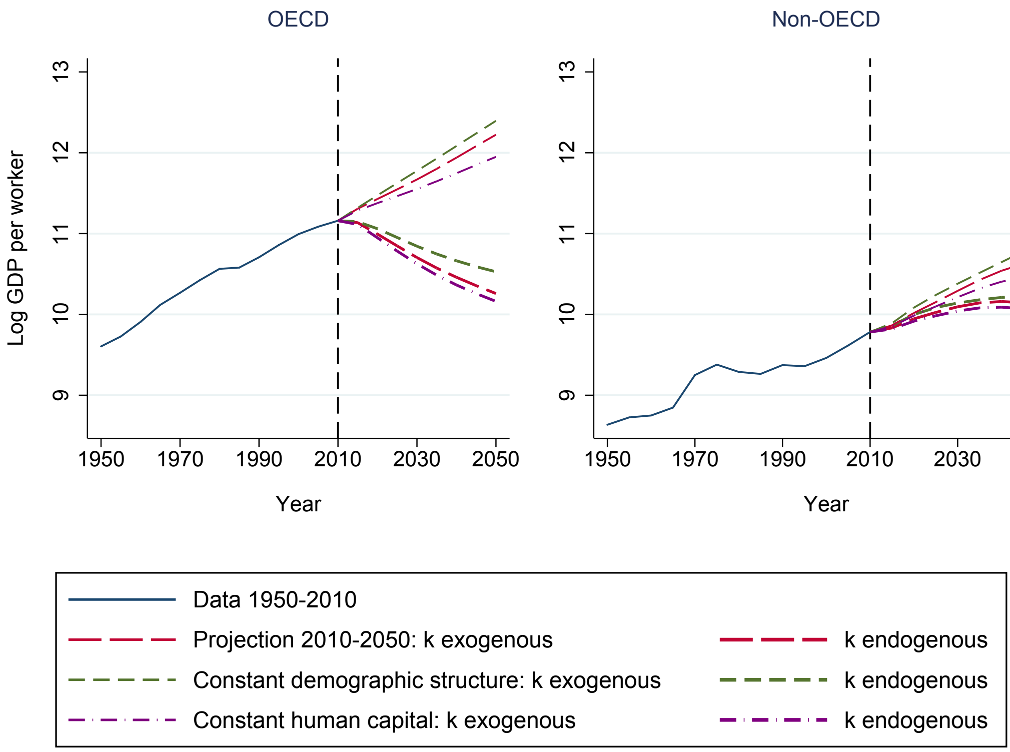


(b) OECD vs Non–OECD Countries

Figure A18: Projections with Alternative Assumptions About Fertility, Mortality and Migration

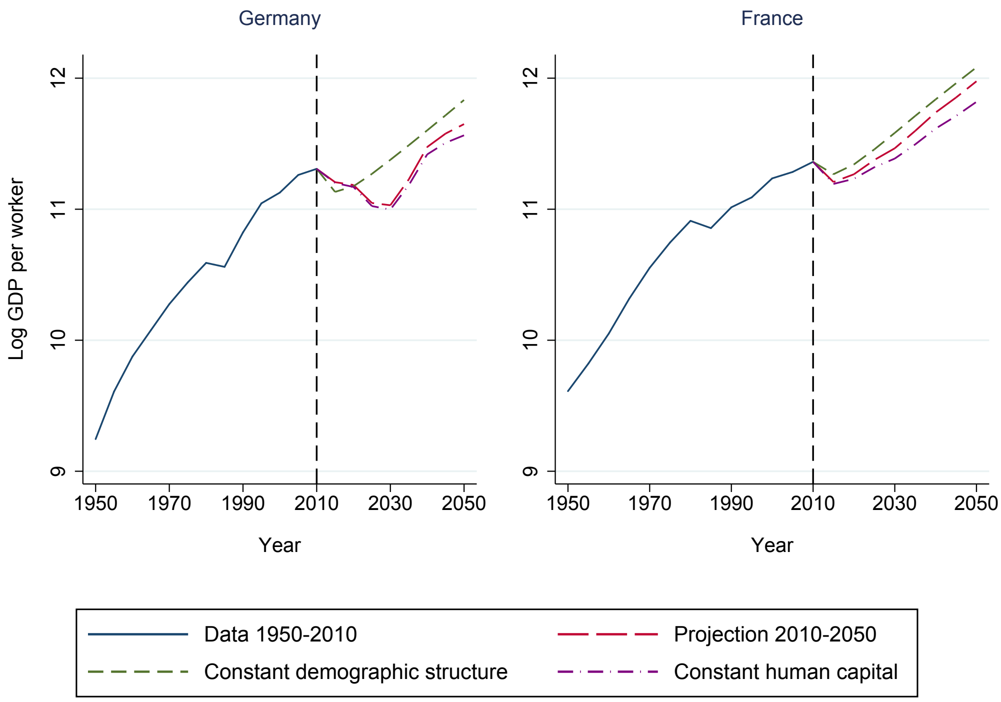


(a) Germany vs. France

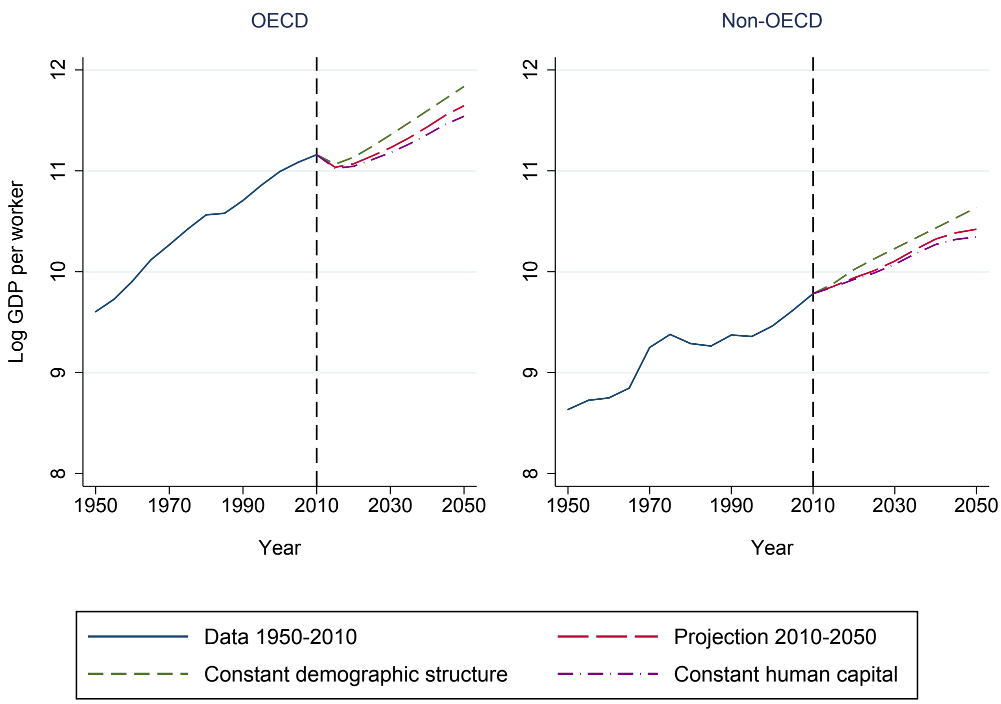


(b) OECD vs Non–OECD Countries

Figure A19: Projections with Endogenous Capital

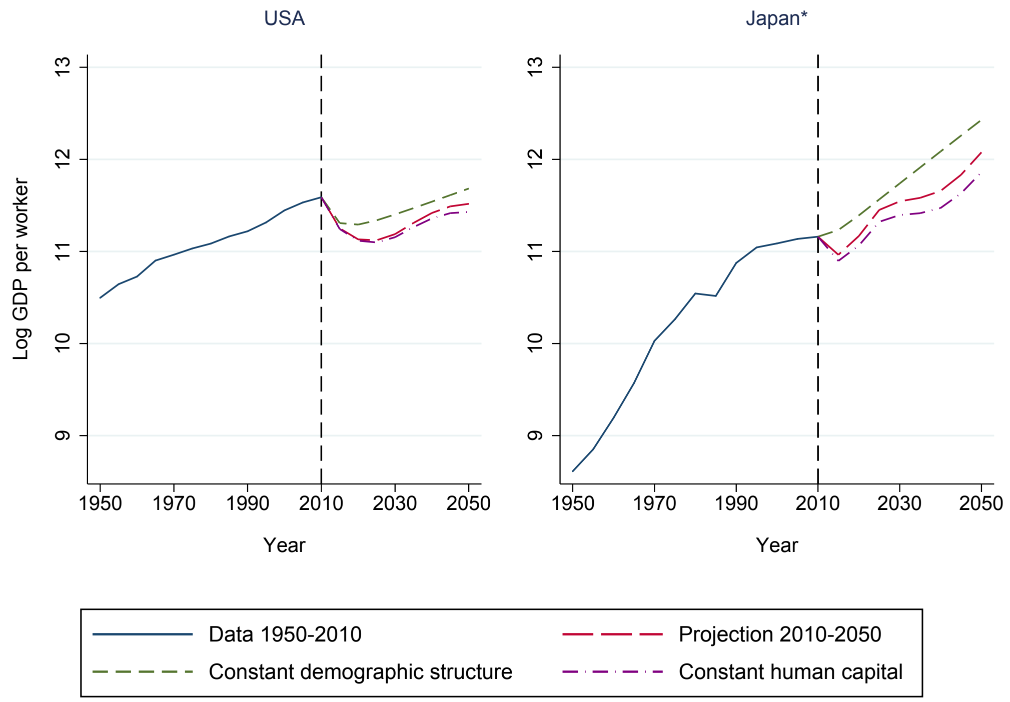


(a) Selected Countries: Germany and France

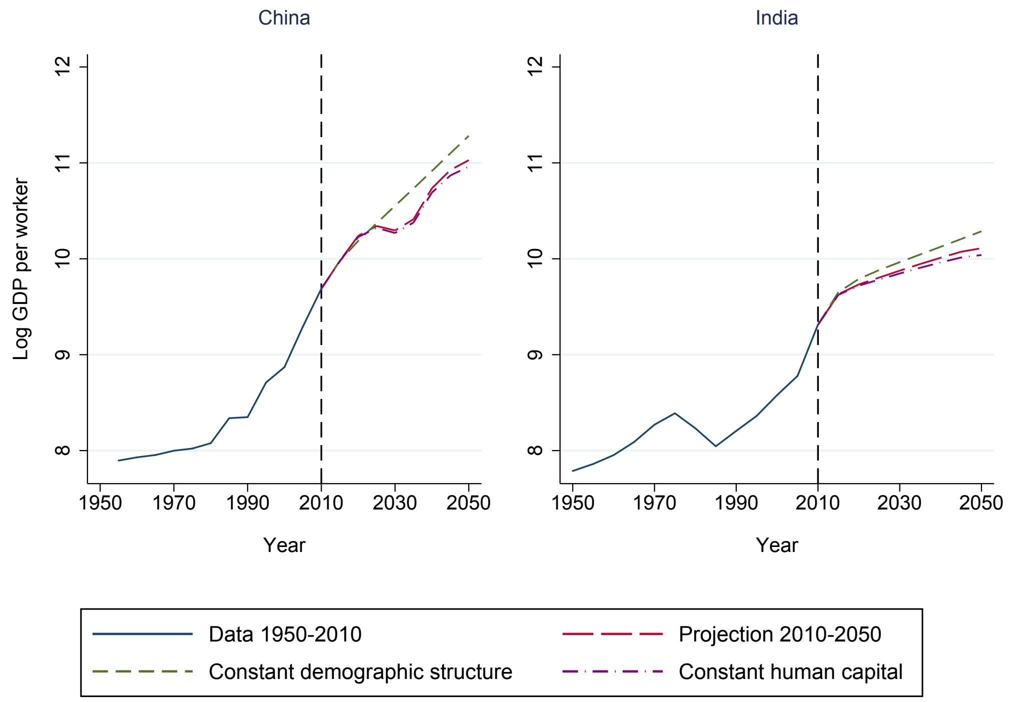


(b) Selected Regions: OECD and Non–OECD Countries

Figure A20: Projections for 1990–2010 Sample

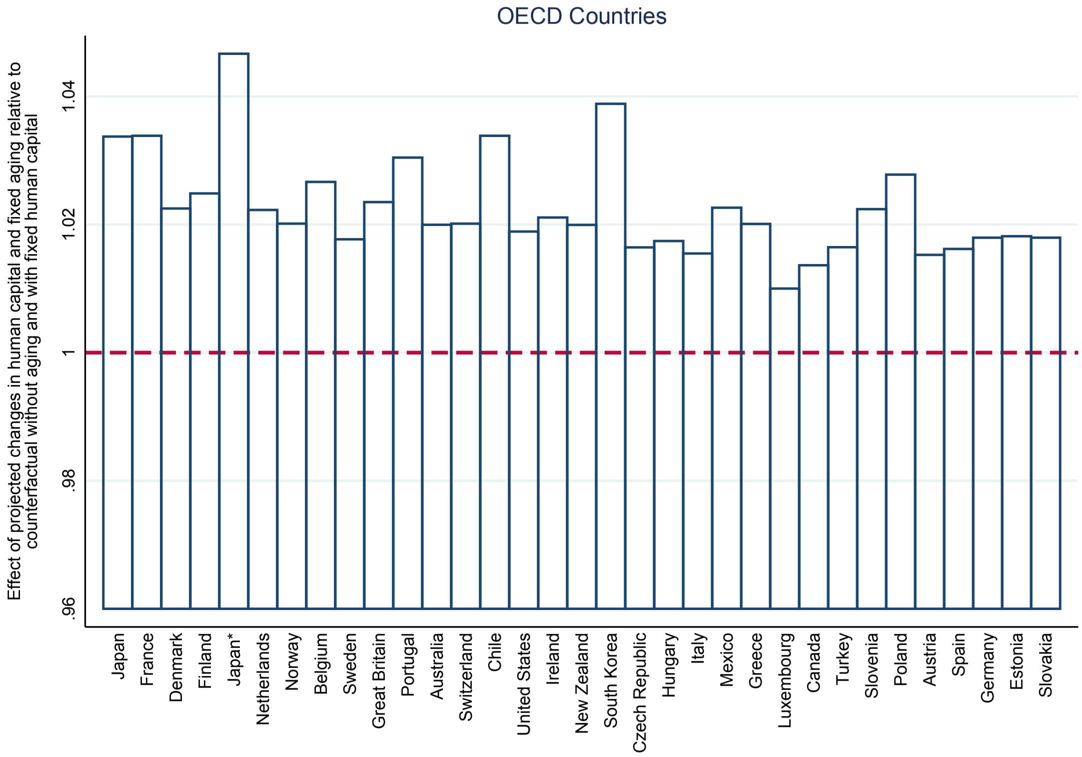


(a) Selected Countries: USA and Japan

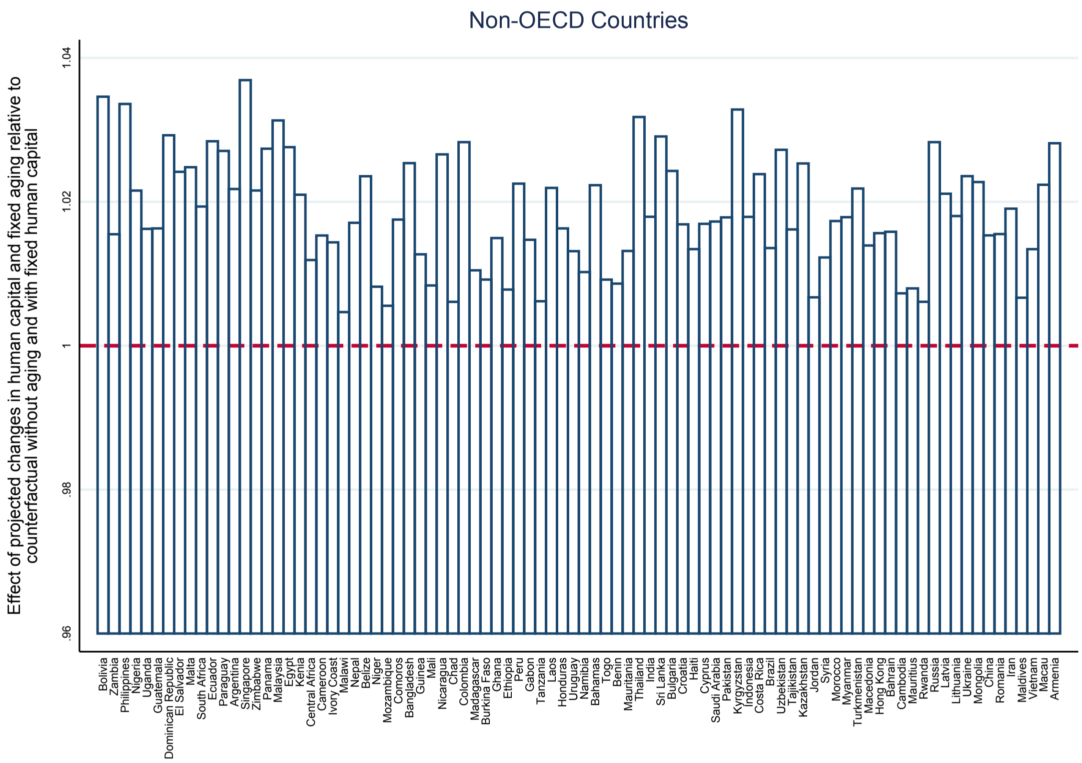


(b) Selected Countries: China and India

Figure A21: Projections for 1990–2010 Sample

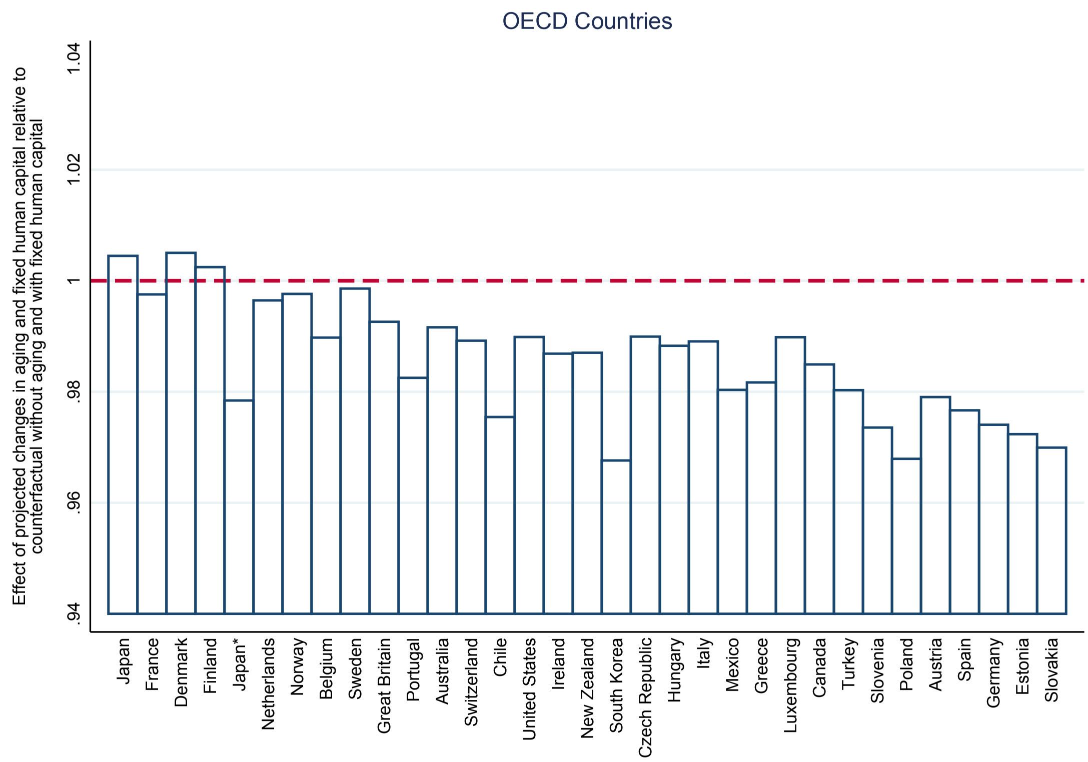


(a) OECD Countries

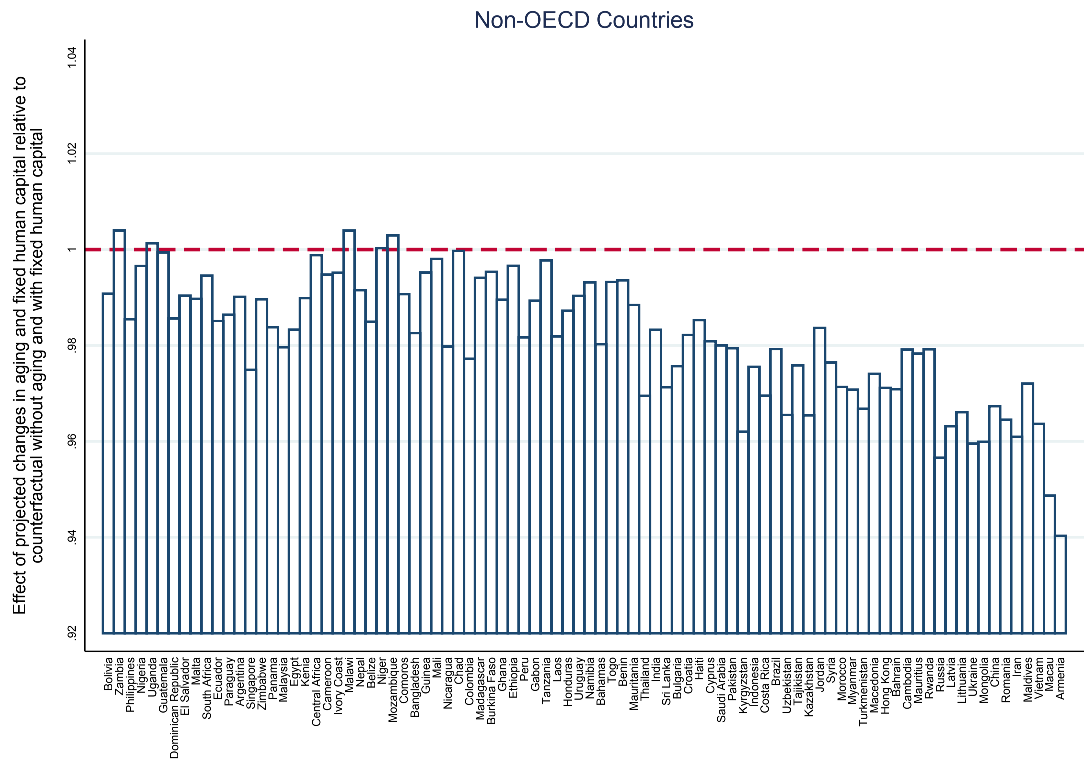


(b) Non–OECD Countries

Figure A22: Economic Performance for Constant Relative to Changing Demographic Structure

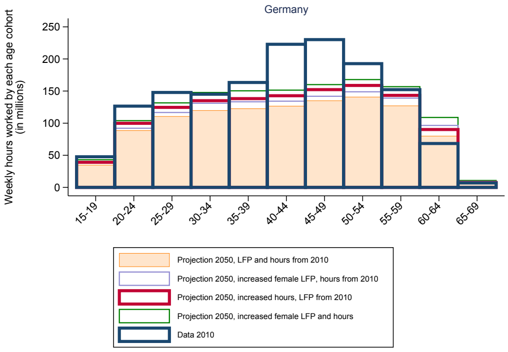


(a) OECD Countries

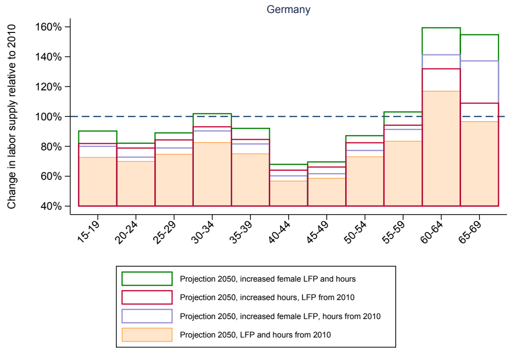


(b) Non–OECD Countries

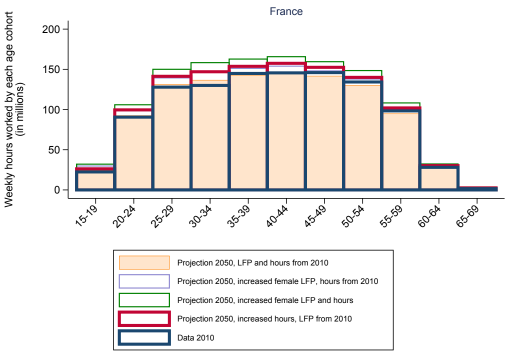
Figure A23: Economic Performance for Constant Relative to Changing Human Capital



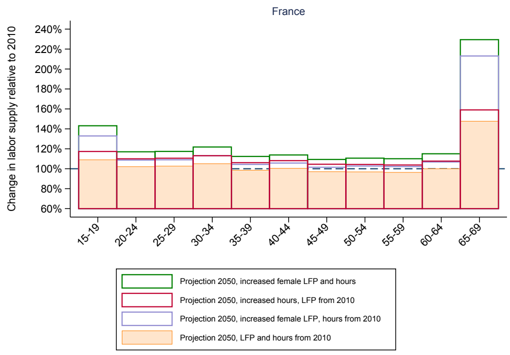
(a) Germany (in hours)



(b) Germany (in percent)

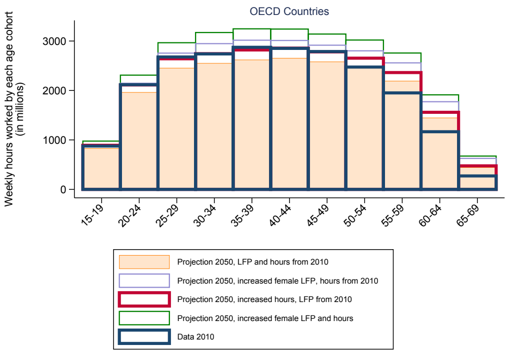


(c) France (in hours)

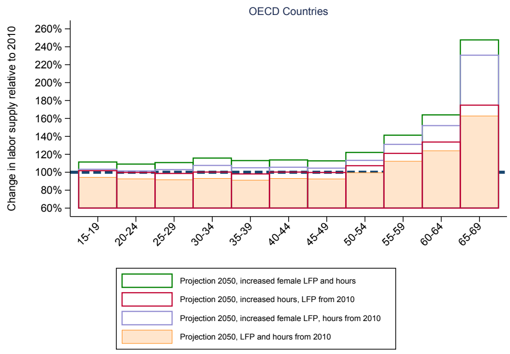


(d) France (in percent)

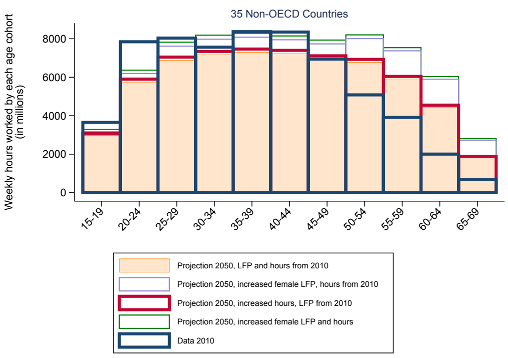
Figure A24: Projected Change in Cohort Labor Supply between 2010 and 2050



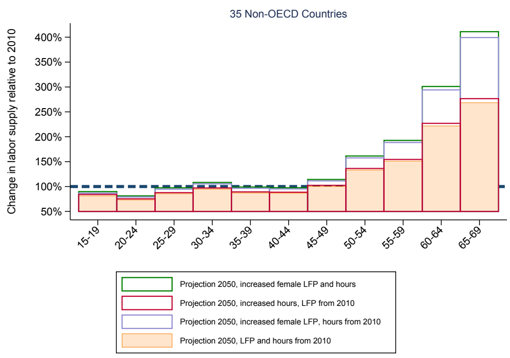
(a) OECD Countries (in hours)



(b) OECD Countries (in percent)

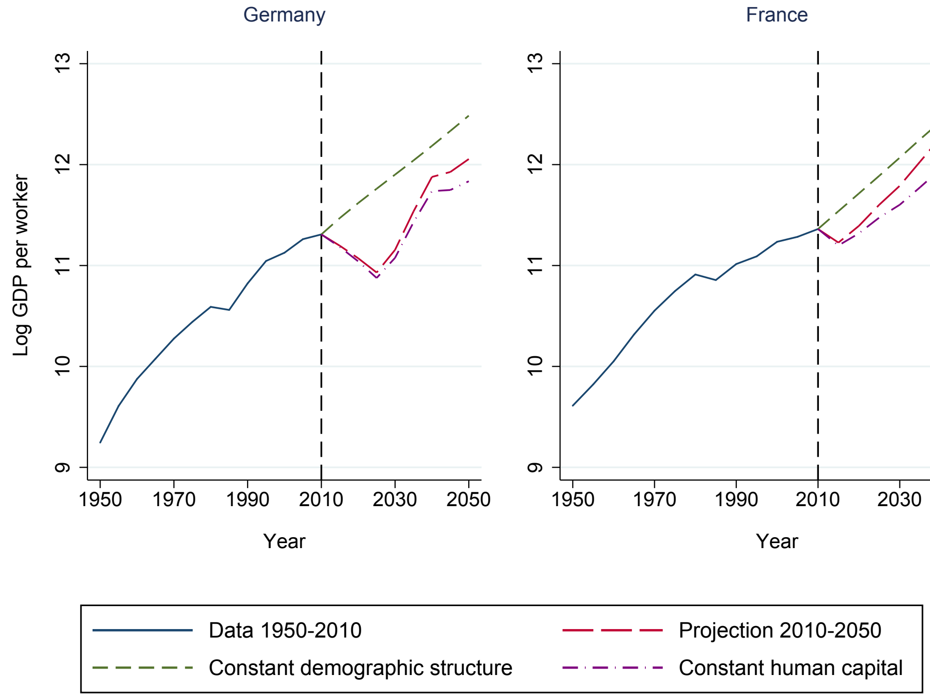


(c) 35 Non–OECD Countries (in hours)

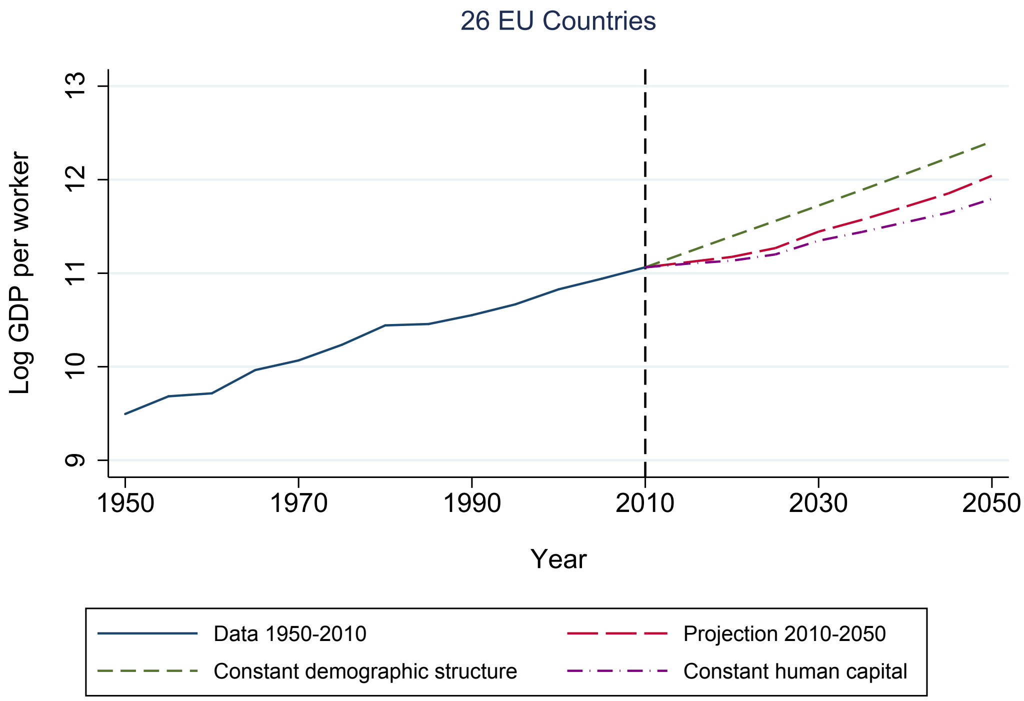


(d) 35 Non–OECD Countries (in percent)

Figure A25: Projected Change in Cohort Labor Supply between 2010 and 2050

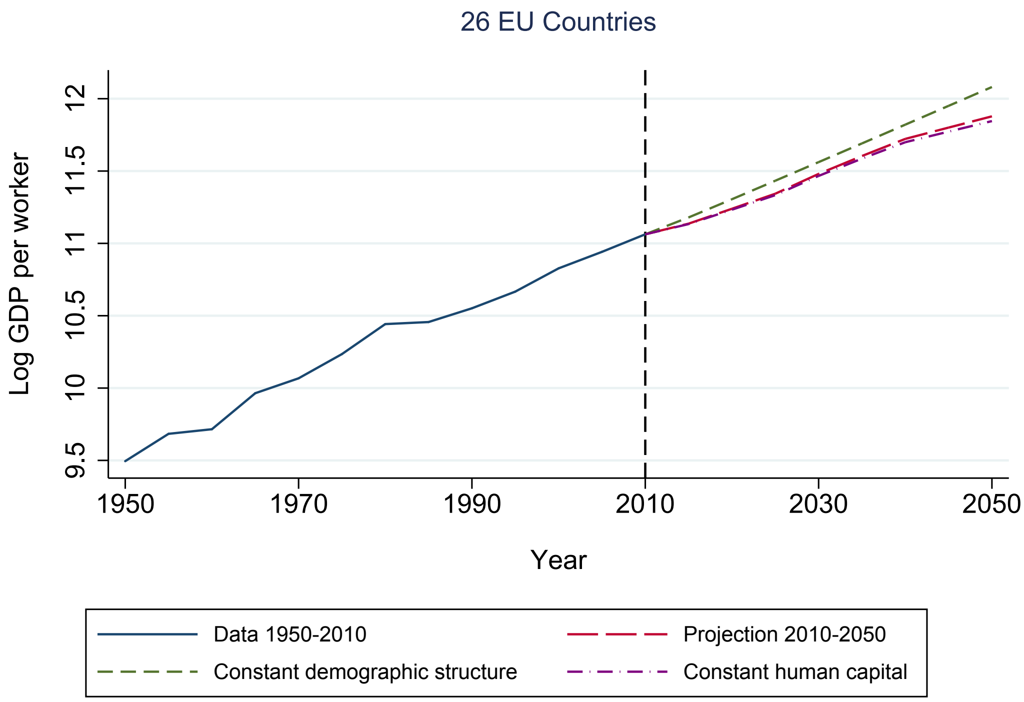


(a) Germany and France

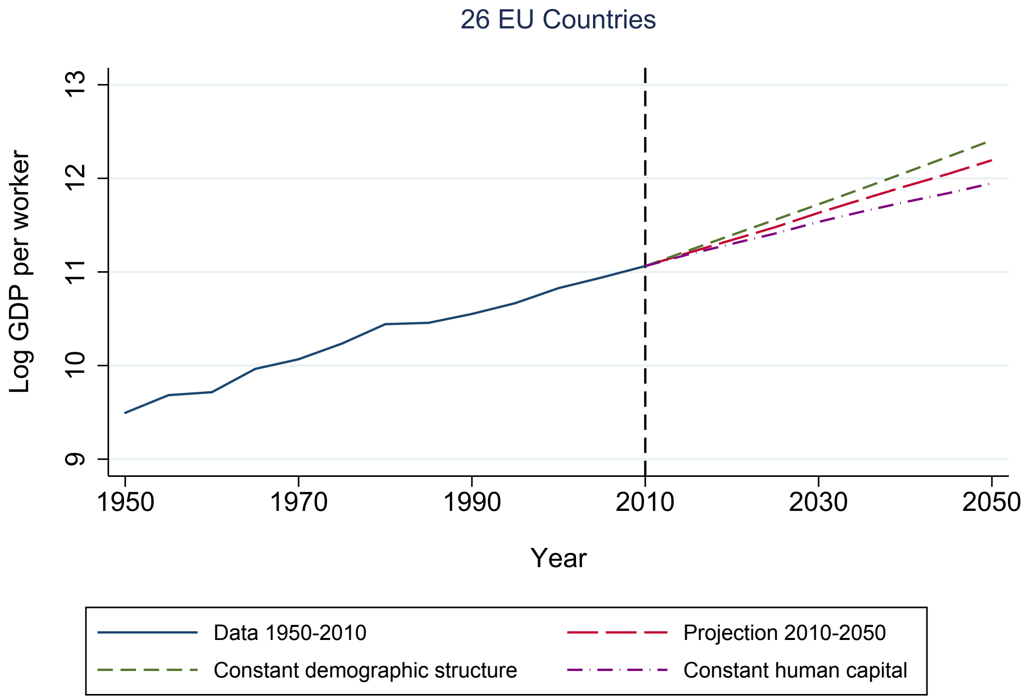


(b) 26 EU Countries

Figure A26: Reduced Form Projections: Changing Labor Force Participation based on Estimates from Working–Age Population



(a) Estimates based on Labor Force



(b) Estimates based on Working–Age Population (Baseline)

Figure A27: Projections: Labor Force Participation vs. Working–Age Population

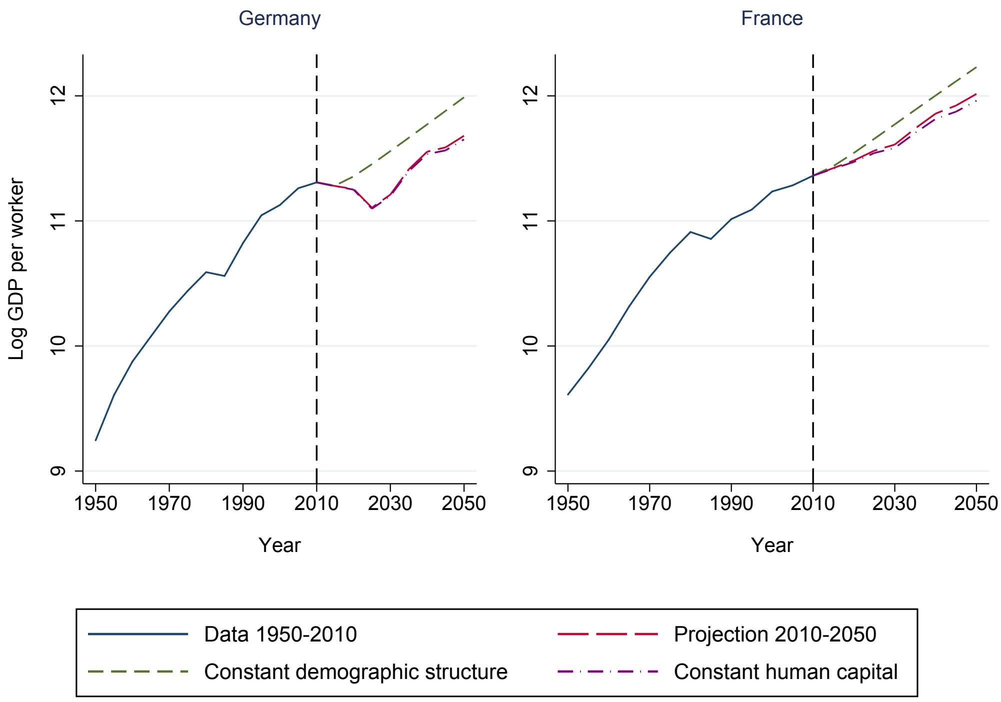
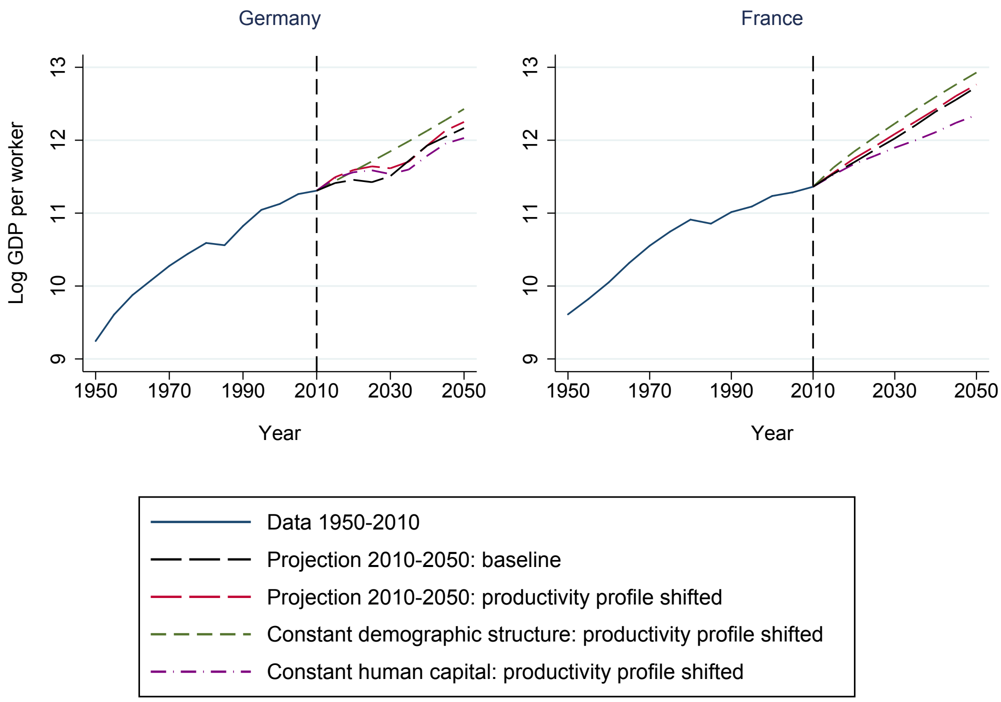
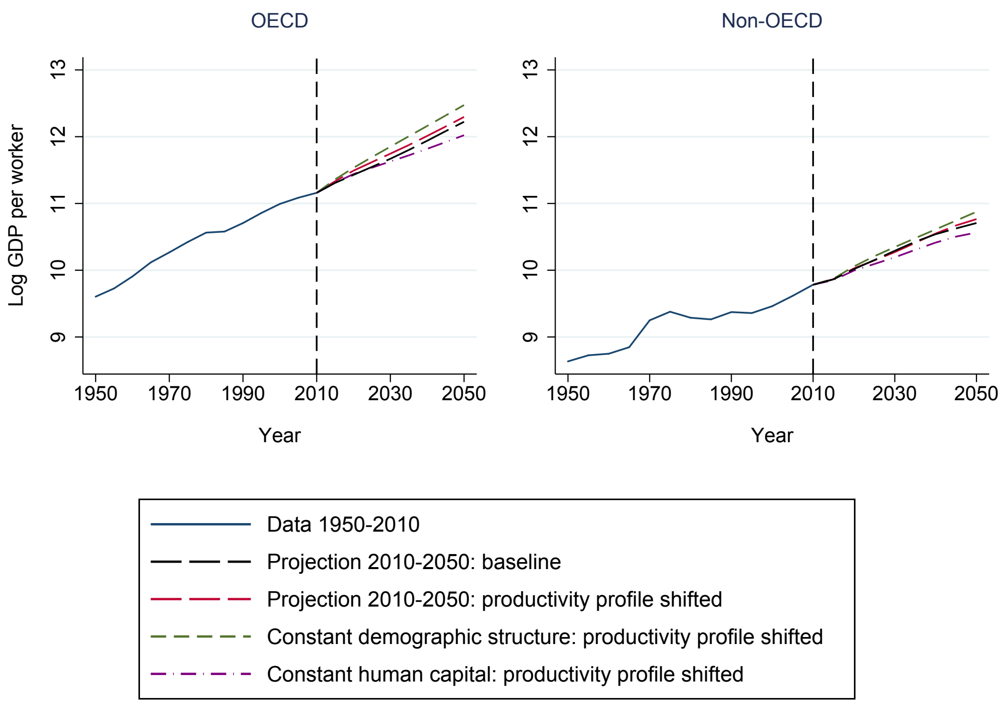


Figure A28: Projections for Changing Labor Force Participation (Germany and France)

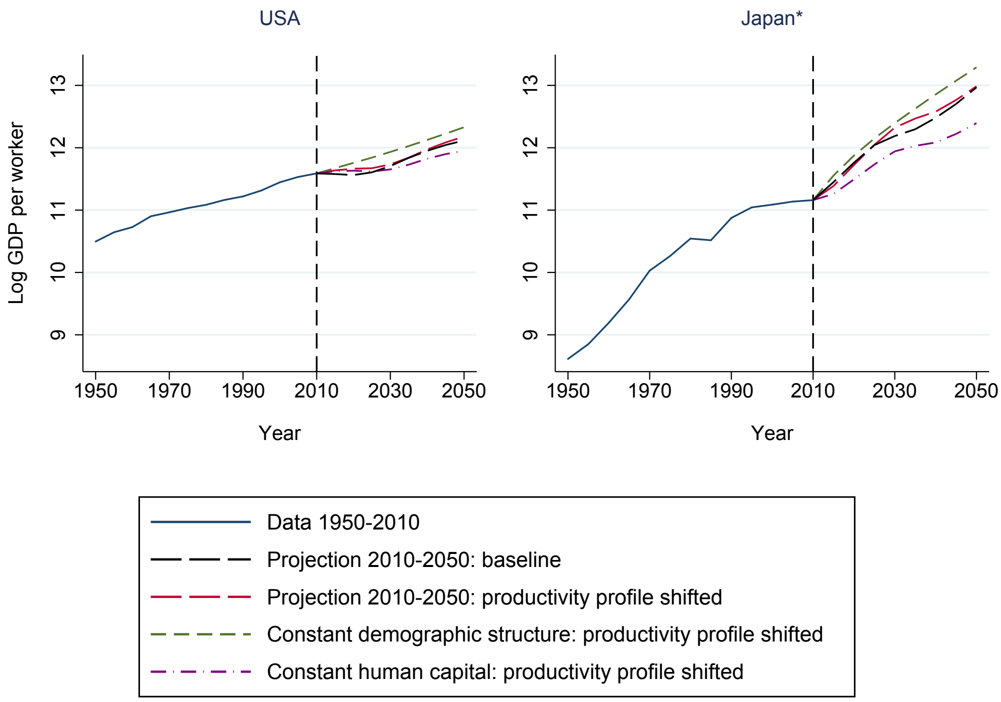


(a) Selected Countries: Germany and France

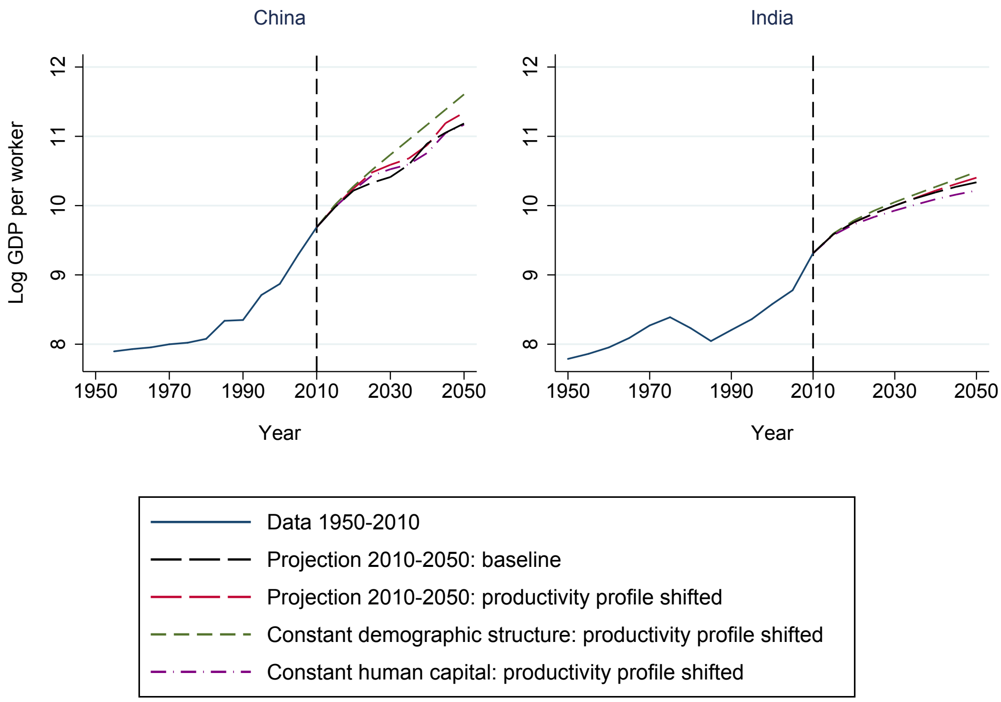


(b) Selected Regions: OECD and Non–OECD Countries

Figure A29: Projections for Shifted Productivity Profile



(a) Selected Countries: USA and Japan



(b) Selected Countries: China and India

Figure A30: Projections for Shifted Productivity Profile

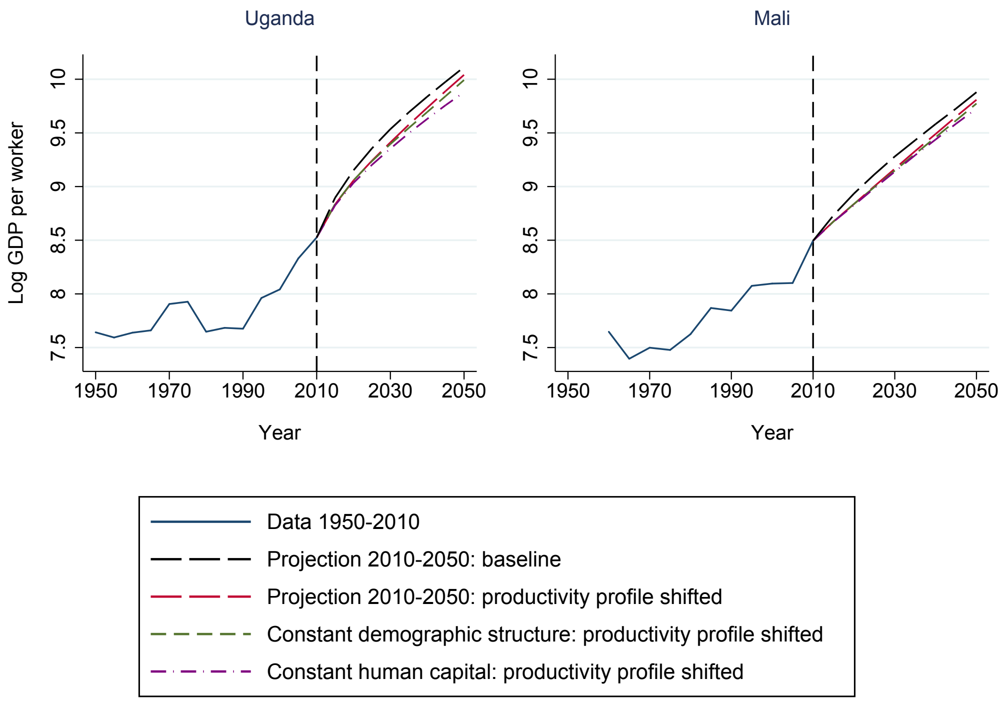
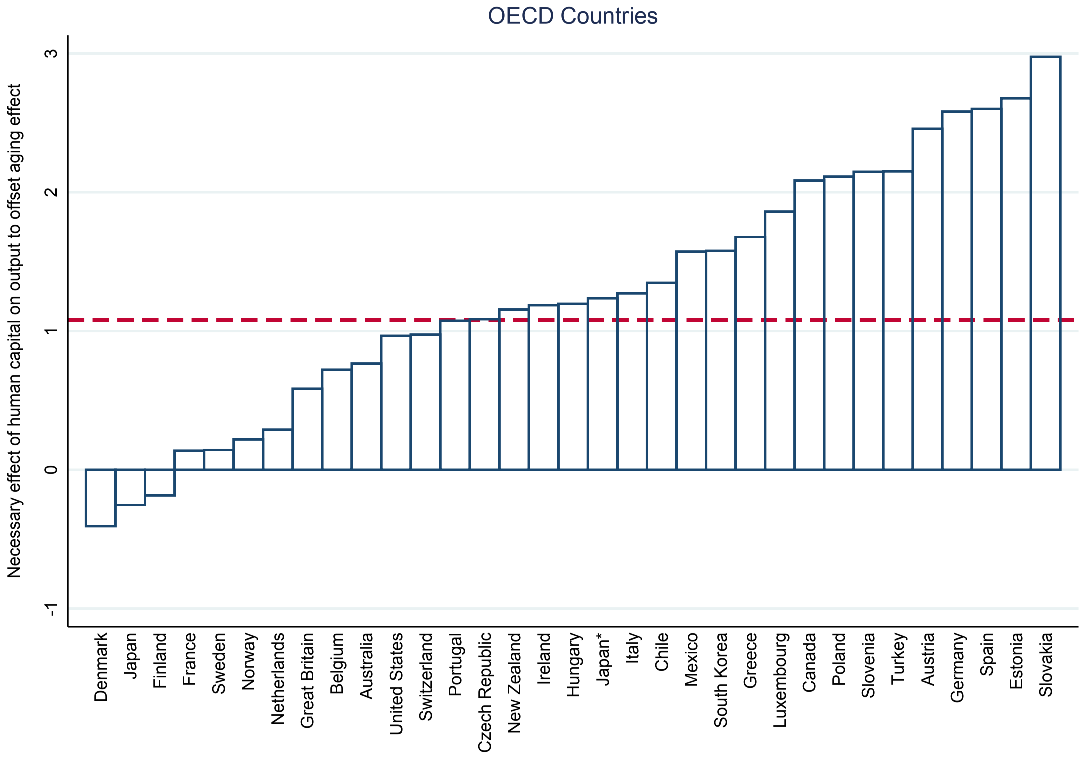
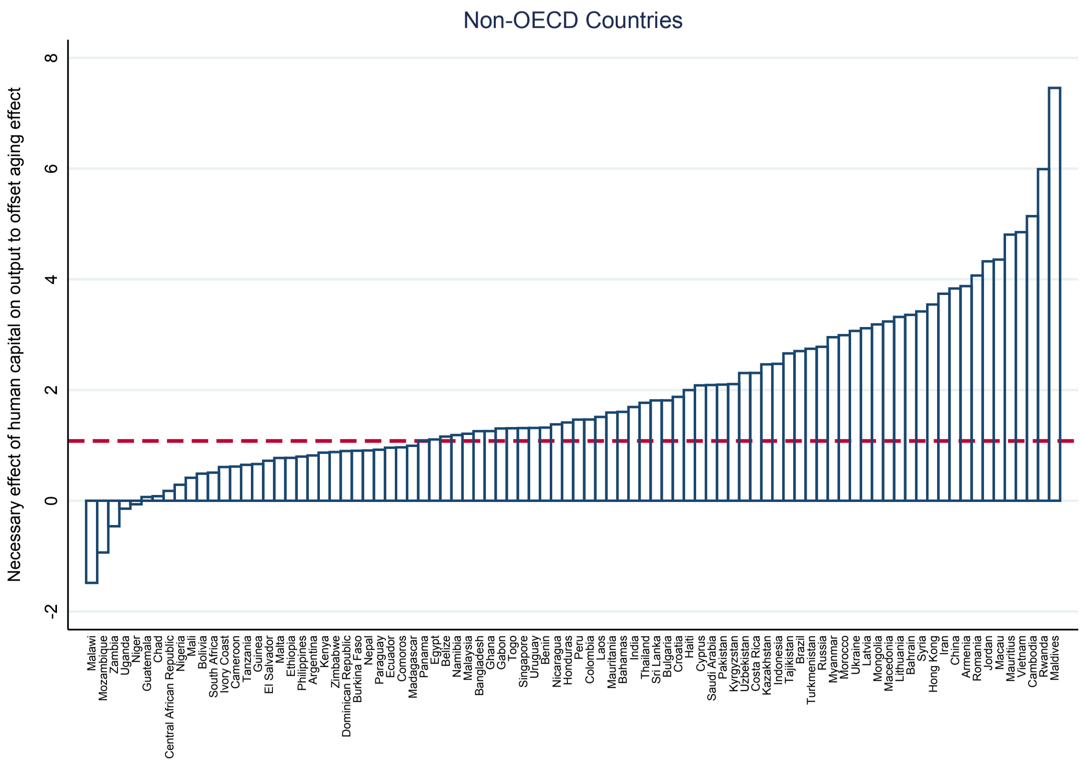


Figure A31: Projections for Shifted Productivity Profile



(a) OECD Countries



(b) Non–OECD Countries

Figure A32: How Large Must λ^h Be to Offset Aging Effect?

Additional Tables

Table A1: Descriptives Statistics

	IIASA–VID sample ($n = 120$)					Barro–Lee sample ($n = 139$)				
	Mean	Std. Dev.	Min	Max	Obs.	Mean	Std. Dev.	Min	Max	Obs.
GDP and physical capital										
Log output p.w.	9.59	1.12	6.92	12.12	1098	9.72	1.12	6.18	13.07	1259
Growth of output p.w.	0.11	0.22	-1.56	1.24	1098	0.10	0.23	-1.19	1.24	1259
Log output p.c.	8.61	1.18	5.95	11.45	1098	8.71	1.19	5.05	12.43	1259
Growth of output p.c.	0.12	0.23	-1.57	1.24	1098	0.11	0.23	-1.28	1.20	1259
Log capital p.w.	10.31	1.50	5.69	13.02	1098	10.45	1.45	5.69	13.87	1259
Growth of capital p.w.	0.17	0.25	-2.05	2.12	1098	0.17	0.25	-1.31	2.16	1259
Share of age cohort in working–age population										
Total (in millions)	28.34	90.41	0.08	1013.06	1098	25.01	85.21	0.09	1018.27	1259
Change (in millions)	2.77	9.04	-4.18	93.45	1098	2.16	7.81	-4.13	96.55	1259
Share < 20	0.16	0.04	0.07	0.25	1098	0.16	0.04	0.06	0.25	1259
Share 20–24	0.14	0.03	0.07	0.21	1098	0.14	0.03	0.07	0.24	1259
Share 25–29	0.13	0.02	0.08	0.19	1098	0.13	0.02	0.08	0.25	1259
Share 30–34	0.11	0.01	0.07	0.19	1098	0.11	0.02	0.07	0.20	1259
Share 35–39	0.10	0.01	0.07	0.15	1098	0.10	0.01	0.05	0.18	1259
Share 40–44	0.09	0.01	0.05	0.15	1098	0.09	0.01	0.04	0.15	1259
Share 45–49	0.08	0.02	0.05	0.13	1098	0.08	0.02	0.04	0.13	1259
Share 50–54	0.07	0.02	0.03	0.12	1098	0.07	0.02	0.03	0.12	1259
Share 55–59	0.06	0.02	0.02	0.11	1098	0.06	0.02	0.01	0.11	1259
Share 60–64	0.05	0.02	0.01	0.11	1098	0.05	0.02	0.01	0.11	1259
Share 65+	0.04	0.02	0.01	0.09	1098	0.04	0.02	0.01	0.09	1259
Share high–skills in working–age population										
Share high–skill	0.08	0.07	0.00	0.37	1098	0.08	0.09	0.00	0.58	1259
Change in share high–skill	0.01	0.01	-0.02	0.06	1098	0.01	0.02	-0.08	0.15	1259
Share < 20	0.01	0.03	0.00	0.25	1098	0.03	0.05	0.00	0.46	1259
Share 20–24	0.07	0.08	0.00	0.54	1098	0.12	0.13	0.00	0.93	1259
Share 25–29	0.12	0.10	0.00	0.56	1098	0.11	0.12	0.00	0.83	1259
Share 30–34	0.12	0.10	0.00	0.53	1098	0.10	0.11	0.00	0.66	1259
Share 35–39	0.11	0.09	0.00	0.50	1098	0.10	0.11	0.00	0.62	1259
Share 40–44	0.10	0.09	0.00	0.46	1098	0.09	0.10	0.00	0.62	1259
Share 45–49	0.08	0.08	0.00	0.44	1098	0.08	0.10	0.00	0.62	1259
Share 50–54	0.07	0.08	0.00	0.42	1098	0.07	0.09	0.00	0.60	1259
Share 55–59	0.06	0.07	0.00	0.39	1098	0.06	0.08	0.00	0.58	1259
Share 60–64	0.05	0.06	0.00	0.37	1098	0.05	0.07	0.00	0.57	1259
Share 65+	0.04	0.05	0.00	0.32	1098	0.04	0.06	0.00	0.54	1259
Dependency ratio and life expectancy										
Dependency ratio	0.64	0.21	0.21	1.07	1086	0.64	0.21	0.16	1.09	1236
Life expectancy	64.79	11.20	23.73	82.98	1053	65.25	10.86	23.73	82.98	1198
Share of age cohort in total labor force										
Total (in millions)	22.45	78.59	0.06	801.59	582	19.36	73.45	0.06	801.59	672
Change (in millions)	1.66	5.31	-6.22	58.49	479	1.44	4.96	-6.22	58.49	551
Share < 20	0.08	0.05	0.01	0.20	645	0.08	0.05	0.01	0.19	742
Share 20–24	0.13	0.03	0.05	0.22	645	0.13	0.03	0.05	0.22	742
Share 25–29	0.14	0.02	0.08	0.22	645	0.15	0.02	0.07	0.23	742
Share 30–34	0.13	0.02	0.09	0.23	645	0.14	0.02	0.09	0.23	742
Share 35–39	0.12	0.02	0.07	0.20	645	0.12	0.02	0.07	0.20	742
Share 40–44	0.11	0.02	0.05	0.17	645	0.11	0.02	0.05	0.17	742
Share 45–49	0.09	0.02	0.04	0.16	645	0.09	0.02	0.04	0.17	742
Share 50–54	0.07	0.02	0.03	0.14	645	0.07	0.02	0.03	0.14	742
Share 55–59	0.05	0.02	0.02	0.12	645	0.05	0.02	0.02	0.12	742
Share 60–64	0.03	0.01	0.00	0.09	645	0.03	0.01	0.00	0.09	742
Share 65+	0.03	0.02	0.00	0.10	645	0.03	0.02	0.00	0.10	742

Table A2: Robustness: Differenced and Lagged Share of High-Skills

	Demography	Skills	Demography & Skills	Bias Correction	Demography Instrumented	Skills Instrumented	Both Instrumented
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				(a) IIASA–VID sample			
Share < 20	-3.84***		-2.97**	-2.96**	-3.54***	-2.01	-2.73**
	(1.22)		(1.21)	(1.40)	(1.21)	(1.27)	(1.26)
Share 20–24	-2.37**		-1.87*	-1.86	-3.27**	-0.96	-2.40*
	(1.10)		(1.10)	(1.39)	(1.36)	(1.13)	(1.39)
Share 25–29	-3.56**		-3.25**	-3.28*	-2.88**	-2.22*	-1.80
	(1.42)		(1.39)	(1.90)	(1.47)	(1.34)	(1.41)
Share 30–34	-3.06**		-2.80**	-2.79*	-4.03***	-1.84	-3.35**
	(1.27)		(1.25)	(1.54)	(1.43)	(1.22)	(1.49)
Share 35–39	-4.01***		-3.72**	-3.64**	-2.99*	-3.84**	-2.58
	(1.44)		(1.43)	(1.75)	(1.57)	(1.55)	(1.68)
Share 40–44	-1.53		-1.32	-1.34	-1.81	-0.79	-1.82
	(1.32)		(1.30)	(1.62)	(1.42)	(1.30)	(1.44)
Share 45–49	-3.19**		-3.01**	-3.24*	-3.93**	-2.81**	-3.80**
	(1.43)		(1.40)	(1.94)	(1.55)	(1.40)	(1.53)
Share 55–59	-4.66**		-4.28**	-4.68**	-4.30**	-3.94**	-4.15**
	(1.85)		(1.81)	(2.17)	(1.83)	(1.81)	(1.83)
Share 60–64	-5.48***		-5.45***	-5.90***	-6.01***	-5.64***	-6.46***
	(1.37)		(1.35)	(1.76)	(1.51)	(1.30)	(1.48)
Share 65+	-3.06*		-3.28**	-3.39*	-4.26***	-3.31*	-3.97**
	(1.58)		(1.54)	(1.80)	(1.60)	(1.73)	(1.75)
Δ Share high–skill		1.89*	2.23*	1.80	1.82*	0.68	-0.12
		(1.07)	(1.16)	(1.23)	(1.10)	(2.31)	(2.29)
Share high–skill (t–1)		0.87**	0.94**	0.70**	0.72	2.80***	2.65***
		(0.35)	(0.43)	(0.33)	(0.45)	(0.84)	(0.86)
Cohort shares (p–value)	0.01		0.01	0.02	0.01	0.00	0.00
Skill shares (p–value)		0.01	0.02	0.03	0.06	0.00	0.01
First stage F–statistic					13.5	37.1	8.7
Hansen test (p–value)					—	0.39	0.50
				(b) Barro–Lee sample			
Share < 20	-3.64***		-3.18***	-2.88**	-3.03*	-3.26**	-3.01*
	(1.17)		(1.20)	(1.36)	(1.55)	(1.30)	(1.61)
Share 20–24	-1.55		-1.24	-1.29	-1.72	-1.08	-1.58
	(1.14)		(1.13)	(1.61)	(1.63)	(1.17)	(1.63)
Share 25–29	-3.61**		-3.39**	-3.38**	-2.88	-3.16**	-2.51
	(1.41)		(1.41)	(1.57)	(1.84)	(1.41)	(1.81)
Share 30–34	-2.39*		-2.23*	-1.95	-1.93	-1.99	-1.55
	(1.29)		(1.29)	(1.65)	(1.81)	(1.30)	(1.83)
Share 35–39	-2.53*		-2.32*	-2.01	-2.71	-2.90*	-3.15
	(1.39)		(1.40)	(1.65)	(2.01)	(1.60)	(2.24)
Share 40–44	-2.24		-2.03	-2.13	-1.08	-1.58	-0.74
	(1.44)		(1.41)	(1.63)	(1.76)	(1.41)	(1.74)
Share 45–49	-1.83		-1.82	-1.72	-2.39	-1.66	-1.97
	(1.47)		(1.46)	(2.14)	(2.15)	(1.46)	(2.09)
Share 55–59	-3.75**		-3.51*	-3.88	-2.71	-3.36*	-2.52
	(1.85)		(1.84)	(2.49)	(2.40)	(1.83)	(2.38)
Share 60–64	-4.95***		-4.92***	-5.50***	-5.40***	-5.05***	-5.40***
	(1.40)		(1.39)	(1.90)	(1.67)	(1.36)	(1.62)
Share 65+	-1.44		-1.48	-1.48	-2.28	-1.43	-2.33
	(1.65)		(1.61)	(2.06)	(2.08)	(1.67)	(2.20)
Δ Share high–skill		0.69	0.51	0.37	0.56	-1.35	-0.93
		(0.50)	(0.51)	(0.40)	(0.50)	(2.08)	(2.29)
Share high–skill (t–1)		0.68***	0.55**	0.34	0.60**	0.78*	0.83*
		(0.22)	(0.25)	(0.23)	(0.25)	(0.40)	(0.42)
Cohort shares (p–value)	0.00		0.02	0.05	0.01	0.01	0.00
Skill shares (p–value)		0.01	0.07	0.23	0.05	0.02	0.03
First stage F–statistic					12.5	4.0	1.0
Hansen test (p–value)					—	0.78	0.88

Notes: Panel (a) reports results for demographic and human capital data by IIASA–VID (Lutz et al., 2007), Panel (b) for data from Barro and Lee (2013). The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w. are measured in logarithms (coefficients unreported). Column (4) corrects for the dynamic–panel bias using the Bruno (2005) estimator. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) or high-skill shares are jointly different from zero are reported. Instruments are shifted age cohorts in Column (5); the lagged share of high skills of the edge of the working–age population in Column (6); and a combination of both in Column (7). See Figure A3 for an illustration. First stage F–statistic reports the first stage Kleibergen–Paap rk Wald F–statistic. Hansen test p–values refer to the robust overidentifying restriction test. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A3: Robustness: Levels Model Without Lagged Dependent Variable

	Demography	Skills	Demography & Skills	Demography Instrumented	Skills Instrumented	Both Instrumented
	(1)	(2)	(3)	(4)	(5)	(6)
Share < 20	-5.56***		-3.77***	-4.46***	-2.80**	-3.32**
	(1.14)		(1.22)	(1.43)	(1.32)	(1.56)
Share 20–24	-1.65		-0.56	-2.35*	0.03	-1.75
	(1.11)		(1.14)	(1.35)	(1.19)	(1.35)
Share 25–29	-4.41***		-3.41***	-2.91**	-2.87**	-2.42*
	(1.19)		(1.19)	(1.41)	(1.19)	(1.43)
Share 30–34	-3.79***		-3.04***	-4.56***	-2.63**	-4.18***
	(1.20)		(1.15)	(1.34)	(1.16)	(1.35)
Share 35–39	-3.63***		-3.02**	-2.15	-2.69**	-1.72
	(1.28)		(1.30)	(1.36)	(1.30)	(1.34)
Share 40–44	-1.87		-1.45	-1.71	-1.22	-1.66
	(1.26)		(1.23)	(1.38)	(1.21)	(1.36)
Share 45–49	-2.12*		-1.94*	-2.49*	-1.85*	-2.47*
	(1.14)		(1.12)	(1.34)	(1.10)	(1.32)
Share 55–59	-2.02		-1.60	-0.89	-1.37	-0.83
	(1.30)		(1.29)	(1.37)	(1.27)	(1.34)
Share 60–64	-5.25***		-5.32***	-5.66***	-5.35***	-5.95***
	(1.32)		(1.28)	(1.39)	(1.26)	(1.39)
Share 65+	-2.40		-2.84*	-3.97**	-3.08*	-3.95**
	(1.72)		(1.68)	(1.69)	(1.69)	(1.75)
Share high–skill		2.64***	2.32***	1.80**	3.59***	3.24***
		(0.52)	(0.70)	(0.80)	(1.09)	(1.19)
Capital p.w.	0.56***	0.57***	0.56***	0.56***	0.57***	0.56***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Cohort shares (p–value)	0.00		0.00	0.00	0.00	0.00
Skill share (p–value)		0.00	0.00	0.02	0.00	0.01
First stage F–statistic				13.2	27.4	4.5
Hansen test (p–value)				—	0.37	0.59
Countries	120	120	120	120	120	120
Observations	1,098	1,098	1,098	1,098	1,098	1,098
R^2	0.80	0.80	0.81	0.80	0.80	0.80

Notes: This table reports results for demographic and human capital data by IIASA–VID (Lutz et al., 2007). The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Capital p.w., measured in logarithms, is included as control in all specifications. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) or high-skill shares are jointly different from zero are reported. Instruments are shifted age cohorts in Column (5) (see Figure A3); the lagged shares of high skills of cohorts at the edge of the working–age population in Column (6); and a combination of both in Column (7). First stage F–statistic reports the first stage Kleibergen–Paap rk Wald F–statistic. Hansen test p–values refer to the robust overidentifying restriction test. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A4: Robustness: Alternative Instrumentation of Human Capital (Levels)

	Inflow and Outflow (Baseline)		Inflow and Outflow GMM		Outflow Only	
	(1)	(2)	(3)	(4)	(5)	(6)
Share < 20	-2.09*	-2.53**	-1.79	-2.31**	-1.87	-2.31**
	(1.20)	(1.18)	(1.18)	(1.16)	(1.18)	(1.17)
Share 20–24	-1.16	-2.58*	-0.93	-2.25*	-1.01	-2.45*
	(1.11)	(1.36)	(1.09)	(1.32)	(1.09)	(1.33)
Share 25–29	-2.58*	-2.30	-2.27*	-2.05	-2.45*	-2.16
	(1.32)	(1.41)	(1.30)	(1.39)	(1.30)	(1.39)
Share 30–34	-2.33*	-3.61**	-2.37*	-3.72***	-2.24*	-3.56**
	(1.21)	(1.41)	(1.21)	(1.40)	(1.21)	(1.41)
Share 35–39	-3.33**	-2.49*	-2.95**	-1.93	-3.24**	-2.39
	(1.39)	(1.51)	(1.35)	(1.42)	(1.37)	(1.47)
Share 40–44	-1.12	-1.81	-0.66	-1.46	-1.07	-1.80
	(1.26)	(1.39)	(1.19)	(1.35)	(1.24)	(1.39)
Share 45–49	-2.92**	-3.89**	-2.71**	-3.64**	-2.89**	-3.89**
	(1.37)	(1.51)	(1.35)	(1.50)	(1.36)	(1.51)
Share 55–59	-4.00**	-4.16**	-3.59**	-3.79**	-3.91**	-4.11**
	(1.74)	(1.77)	(1.70)	(1.73)	(1.72)	(1.75)
Share 60–64	-5.53***	-6.33***	-5.29***	-6.10***	-5.53***	-6.38***
	(1.30)	(1.48)	(1.29)	(1.47)	(1.30)	(1.48)
Share 65+	-3.47**	-4.22**	-3.28**	-3.88**	-3.52**	-4.02**
	(1.56)	(1.68)	(1.55)	(1.65)	(1.58)	(1.68)
Share high–skill	2.45***	2.35***	2.56***	2.44***	2.77***	2.64***
	(0.76)	(0.77)	(0.75)	(0.77)	(0.80)	(0.82)
Output p.w. (t–1)	0.46***	0.46***	0.46***	0.45***	0.46***	0.45***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Capital p.w.	0.35***	0.34***	0.34***	0.34***	0.35***	0.35***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Cohort shares (p–value)	0.00	0.00	0.00	0.01	0.00	0.01
Skill share (p–value)	0.00	0.00	0.00	0.00	0.00	0.00
First stage F–statistic	27.9	4.5	27.9	4.53	59.7	5.4
Hansen test (p–value)	0.25	0.28	0.25	0.28	—	—
Countries	120	120	120	120	120	120
Observations	1,098	1,098	1,098	1,098	1,098	1,098
R^2	0.86	0.86	0.86	0.86	0.86	0.86

Notes: This table reports results for demographic and human capital data by IIASA–VID (Lutz et al., 2007). The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w., measured in logarithms, are included as controls in all specifications. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) or high-skill shares are jointly different from zero are reported. Instruments are shifted shares of high skills for the 15–19 year olds (inflow) and the 65–69 year olds (outflow); and shifted age cohorts in all even columns. See Figure A3 for an illustration. First stage F–statistic reports the first stage Kleibergen–Paap rk Wald F–statistic. Hansen test p–values refer to the robust overidentifying restriction test. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A5: Robustness: Barro–Lee Data (Levels)

	Demography	Skills	Demography & Skills	Bias Correction	Demography Instrumented	Skills Instrumented	Both Instrumented
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share < 20	-3.64***		-3.18***	-2.88**	-3.03*	-2.86**	-2.60*
	(1.17)		(1.20)	(1.35)	(1.56)	(1.15)	(1.47)
Share 20–24	-1.55		-1.24	-1.29	-1.72	-1.02	-1.50
	(1.14)		(1.13)	(1.60)	(1.63)	(1.09)	(1.58)
Share 25–29	-3.61**		-3.39**	-3.37**	-2.89	-3.24**	-2.68
	(1.41)		(1.42)	(1.57)	(1.88)	(1.38)	(1.82)
Share 30–34	-2.39*		-2.23*	-1.96	-1.93	-2.11*	-1.65
	(1.29)		(1.28)	(1.64)	(1.81)	(1.25)	(1.79)
Share 35–39	-2.53*		-2.31*	-2.02	-2.71	-2.15	-2.49
	(1.39)		(1.38)	(1.64)	(2.01)	(1.35)	(1.95)
Share 40–44	-2.24		-2.04	-2.13	-1.08	-1.89	-0.92
	(1.44)		(1.42)	(1.62)	(1.78)	(1.36)	(1.75)
Share 45–49	-1.83		-1.82	-1.72	-2.40	-1.82	-2.21
	(1.47)		(1.46)	(2.13)	(2.19)	(1.43)	(2.14)
Share 55–59	-3.75**		-3.51*	-3.89	-2.71	-3.33*	-2.46
	(1.85)		(1.83)	(2.47)	(2.40)	(1.77)	(2.34)
Share 60–64	-4.95***		-4.91***	-5.49***	-5.41***	-4.89***	-5.41***
	(1.40)		(1.39)	(1.90)	(1.68)	(1.37)	(1.68)
Share 65–69	-1.44		-1.47	-1.47	-2.28	-1.50	-2.10
	(1.65)		(1.60)	(2.05)	(2.07)	(1.57)	(2.04)
Share high–skill		0.68***	0.55**	0.36*	0.60**	0.94**	0.96**
		(0.22)	(0.24)	(0.21)	(0.24)	(0.37)	(0.38)
Output p.w. (t–1)	0.53***	0.52***	0.51***	0.64***	0.51***	0.50***	0.50***
	(0.05)	(0.05)	(0.05)	(0.03)	(0.05)	(0.05)	(0.05)
Capital p.w.	0.27***	0.28***	0.28***	0.23***	0.29***	0.29***	0.29***
	(0.04)	(0.04)	(0.04)	(0.02)	(0.04)	(0.04)	(0.04)
Cohort shares (p–value)	0.00		0.02	0.05	0.00	0.02	0.00
Skill share (p–value)		0.00	0.02	0.09	0.02	0.01	0.01
First stage F–statistic					12.6	27.8	5.1
Hansen test (p–value)					—	0.30	0.45
Countries	139	139	139	139	138	139	138
Observations	1,259	1,259	1,259	1,211	1,248	1,259	1,248
R^2	0.84	0.84	0.84		0.84	0.81	0.84

Notes: This table reports results for demographic and human capital data by Barro and Lee (2013). The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w. are measured in logarithms. Column (4) corrects for the dynamic–panel bias using the Bruno (2005) estimator. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) or high-skill shares are jointly different from zero are reported. Instruments are shifted age cohorts in Column (5); the lagged shares of high skills of cohorts at the edge of the working–age population in Column (6); and a combination of both in Column (7). See Figure A3 for an illustration. First stage F–statistic reports the first stage Kleibergen–Paap rk Wald F–statistic. Hansen test p–values refer to the robust overidentifying restriction test. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A6: Robustness: Barro–Lee Data (Differences)

	Demography	Skills	Demography & Skills	Bias Correction	Demography Instrumented	Skills Instrumented	Both Instrumented
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Share < 20	-3.16***		-2.66***	-1.66*	-4.13***	-2.84**	-4.66***
	(1.01)		(1.01)	(0.98)	(1.39)	(1.12)	(1.70)
Δ Share 20–24	-2.52***		-1.92**	-1.60*	-3.14**	-2.06*	-3.63**
	(0.93)		(0.91)	(0.92)	(1.44)	(1.10)	(1.68)
Δ Share 25–29	-3.16***		-2.70***	-1.89*	-4.08***	-2.82**	-4.58**
	(1.03)		(1.01)	(1.13)	(1.57)	(1.11)	(1.87)
Δ Share 30–34	-2.99***		-2.57**	-2.44**	-3.21**	-2.40**	-3.58**
	(1.08)		(1.08)	(1.20)	(1.56)	(1.10)	(1.78)
Δ Share 35–39	-3.38***		-2.89**	-2.43**	-3.80**	-3.23**	-4.27**
	(1.14)		(1.15)	(1.20)	(1.78)	(1.32)	(2.01)
Δ Share 40–44	-2.53**		-2.12*	-1.16	-2.18	-2.17*	-2.55*
	(1.11)		(1.10)	(0.97)	(1.36)	(1.15)	(1.49)
Δ Share 45–49	-2.41**		-2.20**	-0.88	-3.12**	-2.14**	-3.26**
	(1.09)		(1.08)	(0.92)	(1.56)	(1.08)	(1.62)
Δ Share 55–59	-2.08**		-1.96*	-0.97	-1.75	-1.88*	-1.86
	(1.02)		(1.02)	(1.00)	(1.17)	(1.03)	(1.24)
Δ Share 60–64	-5.06***		-5.07***	-3.10***	-4.83***	-5.20***	-4.85***
	(1.22)		(1.24)	(1.07)	(1.44)	(1.23)	(1.46)
Δ Share 65+	-5.56***		-5.31***	-1.89	-5.19***	-5.50***	-5.38**
	(1.66)		(1.65)	(1.47)	(1.97)	(1.72)	(2.13)
Δ Share high–skill		1.07**	0.94**	0.65*	0.91*	0.34	-0.30
		(0.48)	(0.47)	(0.33)	(0.47)	(1.89)	(2.18)
Share high–skill (t–1)		0.63***	0.61***	0.37***	0.61***	0.63***	0.52**
		(0.20)	(0.20)	(0.10)	(0.23)	(0.20)	(0.24)
Output p.w. (t–1)	-0.24***	-0.26***	-0.25***	-0.03***	-0.27***	-0.26***	-0.27***
	(0.03)	(0.03)	(0.03)	(0.01)	(0.03)	(0.03)	(0.03)
Δ Capital p.w.	0.36***	0.36***	0.37***	0.39***	0.36***	0.36***	0.36***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Cohort shares (p–value)	0.01		0.02	0.14	0.00	0.00	0.01
Skills shares (p–value)		0.00	0.00	0.00	0.01	0.00	0.04
First stage F–statistic					6.8	6.5	0.8
AR(2) test (p–value)				0.35			
Hansen test (p–value)				0.25	—	0.07	0.09
Countries	139	139	139	139	138	139	138
Observations	1,259	1,259	1,259	1,120	1,200	1,211	1,200
R^2	0.37	0.36	0.38		0.39	0.39	0.38

Notes: This table reports results for demographic and human capital data by Barro and Lee (2013). The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w. are measured in logarithms. Column (4) corrects for the dynamic–panel bias using the system GMM estimator by Arellano and Bover (1995) and Blundell and Bond (1998). The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) or high-skill shares are jointly different from zero are reported. Instruments are shifted age cohorts in Column (5); the lagged shares of high skills of cohorts at the edge of the working–age population in Column (6); and a combination of both in Column (7). See Figure A3 for an illustration. First stage F–statistic reports the first stage Kleibergen–Paap rk Wald F–statistic. Hansen test p–values refer to the robust overidentifying restriction test. For system GMM, also the p–values of the AR(2) test are reported. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A7: Robustness: Ten–Year Cohorts (Levels)

	Demography	Skills	Demography & Skills	Bias Correction	Demography Instrumented	Skills Instrumented	Both Instrumented
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	(a) IIASA–VID sample						
Share < 20	-4.19***		-2.89***	-2.23	-3.30***	-1.79	-2.13*
	(1.03)		(1.02)	(1.39)	(1.13)	(1.14)	(1.28)
Share 20–29	-2.26**		-1.56	-0.93	-1.90*	-0.97	-1.20
	(0.92)		(0.95)	(1.34)	(1.08)	(1.00)	(1.12)
Share 30–39	-2.82***		-2.43***	-1.87*	-2.57**	-2.11**	-2.31**
	(0.92)		(0.92)	(1.08)	(1.01)	(0.92)	(1.01)
Share 40–49	-2.17*		-1.93*	-1.29	-2.35*	-1.73	-2.07*
	(1.11)		(1.09)	(1.68)	(1.23)	(1.08)	(1.21)
Share 60+	-5.68***		-5.83***	-6.09***	-5.84***	-5.95***	-5.89***
	(1.38)		(1.34)	(1.94)	(1.34)	(1.34)	(1.35)
Share high–skill		1.81***	1.78***	1.35**	1.65***	3.26***	3.17***
		(0.47)	(0.52)	(0.58)	(0.53)	(0.94)	(0.97)
Output p.w. (t–1)	0.22***	0.17***	0.19***	0.38***	0.19***	0.16***	0.16***
	(0.04)	(0.04)	(0.04)	(0.08)	(0.04)	(0.05)	(0.04)
Capital p.w.	0.47***	0.49***	0.48***	0.42***	0.48***	0.50***	0.50***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Cohort shares (p–value)	0.00		0.00	0.02	0.00	0.00	0.00
Skill share (p–value)		0.00	0.00	0.02	0.00	0.00	0.00
First stage F–statistic					121.8	30.0	8.0
Hansen test (p–value)					—	0.32	0.33
Countries	120	120	120	120	119	119	119
Observations	541	541	541	496	540	540	540
R^2	0.82	0.82	0.83		0.83	0.82	0.82
	(b) Barro–Lee sample						
Share < 20	-3.95***		-3.08**	-2.52*	-3.14***	-2.36*	-2.43**
	(1.24)		(1.29)	(1.51)	(1.20)	(1.33)	(1.20)
Share 20–29	-2.19**		-1.80*	-1.55	-2.01*	-1.47	-1.68
	(0.98)		(0.98)	(1.35)	(1.15)	(0.98)	(1.17)
Share 30–39	-2.51**		-2.22**	-1.75	-2.21**	-1.99*	-1.96*
	(1.07)		(1.08)	(1.28)	(1.08)	(1.09)	(1.11)
Share 40–49	-2.09*		-1.86	-1.51	-2.20	-1.68	-1.95
	(1.20)		(1.19)	(1.87)	(1.43)	(1.17)	(1.43)
Share 60+	-4.77***		-4.67***	-4.99**	-5.59***	-4.59***	-5.51***
	(1.58)		(1.54)	(2.33)	(1.46)	(1.52)	(1.44)
Share high–skill		1.20***	0.97***	0.73*	1.09***	1.76***	1.85***
		(0.32)	(0.36)	(0.42)	(0.37)	(0.65)	(0.68)
Output p.w. (t–1)	0.25***	0.21***	0.22***	0.36***	0.23***	0.19***	0.20***
	(0.05)	(0.05)	(0.05)	(0.07)	(0.05)	(0.05)	(0.05)
Capital p.w.	0.41***	0.44***	0.43***	0.38***	0.43***	0.44***	0.45***
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
Cohort shares (p–value)	0.01		0.03	0.18	0.00	0.04	0.00
Skill share (p–value)		0.00	0.01	0.08	0.00	0.01	0.01
First stage F–statistic					23.8	20.0	5.8
Hansen test (p–value)					—	0.24	0.39
Countries	139	139	139	139	137	138	137
Observations	621	621	621	573	615	620	615
R^2	0.78	0.78	0.78		0.78	0.78	0.78

Notes: Panel (a) reports results for demographic and human capital data by IIASA–VID (Lutz et al., 2007), Panel (b) for data from Barro and Lee (2013). The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w. are measured in logarithms. Column (4) corrects for the dynamic–panel bias using the Bruno (2005) estimator. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) or high-skill shares are jointly different from zero are reported. Instruments are shifted age cohorts in Column (5); the lagged share of high skills of the edge of the working–age population in Column (6); and a combination of both in Column (7). See Figure A3 for an illustration. First stage F–statistic reports the first stage Kleibergen–Paap rk Wald F–statistic. Hansen test p–values refer to the robust overidentifying restriction test. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A8: Robustness: Ten–Year Cohorts (Differences)

	Demography	Skills	Demography & Skills	Bias Correction	Demography Instrumented	Skills Instrumented	Both Instrumented
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				(a) IIASA–VID sample			
Δ Share < 20	-3.87***		-2.67***	-3.01**	-2.31**	-4.42***	-3.60***
	(0.97)		(0.99)	(1.20)	(1.08)	(1.16)	(1.26)
Δ Share 20–29	-2.68***		-1.77**	-1.92**	-2.34**	-2.70***	-2.89***
	(0.80)		(0.84)	(0.94)	(1.06)	(0.88)	(1.05)
Δ Share 30–39	-3.00***		-2.53***	-2.95***	-2.82**	-2.49**	-2.19*
	(0.82)		(0.87)	(1.04)	(1.11)	(0.97)	(1.24)
Δ Share 40–49	-2.50***		-2.30***	-2.53***	-2.95***	-2.54***	-2.37**
	(0.78)		(0.75)	(0.81)	(0.91)	(0.84)	(0.98)
Δ Share 60+	-5.28***		-5.03***	-4.47***	-4.26***	-5.26***	-5.05***
	(0.94)		(0.93)	(0.93)	(1.05)	(0.96)	(1.18)
Δ Share high–skill		4.05***	3.44***	2.35***	3.95***	-2.04	-2.46
		(0.96)	(1.07)	(0.79)	(1.06)	(3.16)	(3.30)
Share high–skill (t–1)		1.10**	1.08**	0.51*	0.90	1.58***	1.51**
		(0.46)	(0.49)	(0.28)	(0.62)	(0.61)	(0.73)
Output p.w. (t–1)	-0.41***	-0.47***	-0.45***	-0.03***	-0.49***	-0.46***	-0.46***
	(0.05)	(0.05)	(0.05)	(0.01)	(0.05)	(0.05)	(0.05)
Δ Capital p.w.	0.40***	0.40***	0.41***	0.52***	0.41***	0.40***	0.40***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Cohort shares (p–value)	0.00		0.00	0.00	0.00	0.00	0.00
Skills shares (p–value)		0.00	0.00	0.00	0.00	0.03	0.11
First stage F–statistic					49.1	31.8	8.1
AR(2) test (p–value)				0.13			
Hansen test (p–value)				0.75	—	0.14	0.11
Countries	120	120	120	119	119	119	119
Observations	541	541	541	421	495	495	495
R^2	0.58	0.56	0.60		0.60	0.60	0.60
				(b) Barro–Lee sample			
Δ Share < 20	-2.93***		-2.27**	-2.62**	-2.96**	-3.38***	-3.77**
	(1.03)		(1.03)	(1.09)	(1.38)	(1.30)	(1.67)
Δ Share 20–29	-2.02**		-1.47*	-1.31*	-2.22**	-2.15**	-2.88**
	(0.79)		(0.79)	(0.78)	(1.05)	(1.03)	(1.38)
Δ Share 30–39	-2.15**		-1.66*	-2.22**	-1.69	-2.17**	-2.39*
	(0.83)		(0.84)	(0.99)	(1.13)	(1.04)	(1.44)
Δ Share 40–49	-2.06**		-1.75**	-1.32	-1.43	-2.33**	-1.94
	(0.84)		(0.84)	(0.90)	(1.03)	(0.93)	(1.18)
Δ Share 60+	-4.74***		-4.61***	-3.64***	-4.72***	-4.72***	-4.89***
	(1.00)		(1.01)	(1.10)	(1.14)	(1.04)	(1.17)
Δ Share high–skill		1.28**	0.99*	0.88*	1.08**	-0.58	-1.05
		(0.56)	(0.53)	(0.50)	(0.54)	(1.75)	(2.07)
Share high–skill (t–1)		1.10***	1.06***	0.84***	1.15***	0.84	0.62
		(0.39)	(0.39)	(0.22)	(0.44)	(0.53)	(0.65)
Output p.w. (t–1)	-0.43***	-0.48***	-0.46***	-0.06***	-0.51***	-0.48***	-0.48***
	(0.05)	(0.05)	(0.04)	(0.01)	(0.05)	(0.05)	(0.05)
Δ Capital p.w.	0.32***	0.34***	0.34***	0.40***	0.31***	0.32***	0.31***
	(0.05)	(0.05)	(0.05)	(0.07)	(0.05)	(0.05)	(0.05)
Cohort shares (p–value)	0.00		0.00	0.01	0.00	0.00	0.00
Skills shares (p–value)		0.00	0.01	0.00	0.01	0.04	0.12
First stage F–statistic					27.5	6.1	1.5
AR(2) test (p–value)				0.13			
Hansen test (p–value)				0.15	—	0.09	0.06
Countries	139	139	139	138	137	138	137
Observations	621	621	621	482	567	572	567
R^2	0.52	0.51	0.54		0.56	0.55	0.54

Notes: Panel (a) reports results for demographic and human capital data by IIASA–VID (Lutz et al., 2007), Panel (b) for data from Barro and Lee (2013). The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w. are measured in logarithms. Column (4) corrects for the dynamic–panel bias using the system GMM estimator by Arellano and Bover (1995) and Blundell and Bond (1998). The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) or high-skill shares are jointly different from zero are reported. Instruments are shifted age cohorts in Column (5); the lagged share of high skills of the edge of the working–age population in Column (6); and a combination of both in Column (7). See Figure A3 for an illustration. First stage F–statistic reports the first stage Kleibergen–Paap rk Wald F–statistic. Hansen test p–values refer to the robust overidentifying restriction test. For system GMM, also the p–values of the AR(2) test are reported. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A9: Robustness: Human Capital Granularity (Levels)

	Demography	Skills	Demography & Skills	Bias Correction	Demography Instrumented	Skills Instrumented	Both Instrumented
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share < 20	-3.64***		-3.51***	-3.10***	-3.53**	-3.50***	-3.50**
	(1.17)		(1.21)	(1.20)	(1.54)	(1.22)	(1.52)
Share 20–24	-1.55		-1.36	-1.43	-1.93	-1.47	-2.19
	(1.14)		(1.10)	(1.40)	(1.61)	(1.11)	(1.68)
Share 25–29	-3.61**		-3.55**	-3.45**	-3.09	-3.57**	-3.14*
	(1.41)		(1.43)	(1.66)	(1.89)	(1.46)	(1.90)
Share 30–34	-2.39*		-2.42*	-2.11	-2.35	-2.66**	-2.59
	(1.29)		(1.29)	(1.39)	(1.77)	(1.28)	(1.85)
Share 35–39	-2.53*		-2.38*	-2.08	-2.75	-2.44*	-2.82
	(1.39)		(1.38)	(1.55)	(2.00)	(1.38)	(2.02)
Share 40–44	-2.24		-2.21	-2.25	-1.39	-2.32*	-1.68
	(1.44)		(1.42)	(1.51)	(1.75)	(1.39)	(1.75)
Share 45–49	-1.83		-2.01	-1.84	-2.76	-2.29	-3.03
	(1.47)		(1.45)	(2.12)	(2.20)	(1.43)	(2.27)
Share 55–59	-3.75**		-3.64**	-3.97*	-3.09	-3.76**	-3.27
	(1.85)		(1.83)	(2.11)	(2.40)	(1.82)	(2.43)
Share 60–64	-4.95***		-5.15***	-5.65***	-5.59***	-5.03***	-5.61***
	(1.40)		(1.43)	(1.74)	(1.71)	(1.48)	(1.73)
Share 65–69	-1.44		-1.77	-1.72	-2.76	-2.17	-3.08
	(1.65)		(1.60)	(1.68)	(2.09)	(1.58)	(2.15)
Years of schooling < 4		0.01	0.01	0.02	0.01	0.00	-0.00
		(0.05)	(0.05)	(0.04)	(0.05)	(0.08)	(0.08)
4–6 years of schooling		-0.00	0.01	0.02	0.01	0.01	0.00
		(0.03)	(0.04)	(0.03)	(0.03)	(0.05)	(0.05)
6–7 years of schooling		0.01	0.02	0.03	0.02	0.09	0.08
		(0.02)	(0.02)	(0.03)	(0.02)	(0.09)	(0.09)
8–10 years of schooling		0.05**	0.04*	0.03	0.04*	0.09	0.08
		(0.02)	(0.02)	(0.03)	(0.02)	(0.06)	(0.06)
Years of schooling > 10		0.13***	0.11***	0.08	0.12***	0.20**	0.20**
		(0.04)	(0.04)	(0.05)	(0.04)	(0.09)	(0.10)
Output p.w. (t–1)	0.53***	0.52***	0.51***	0.65***	0.51***	0.51***	0.51***
	(0.05)	(0.05)	(0.05)	(0.03)	(0.05)	(0.05)	(0.05)
Capital p.w.	0.27***	0.28***	0.28***	0.23***	0.28***	0.28***	0.28***
	(0.04)	(0.04)	(0.04)	(0.02)	(0.04)	(0.04)	(0.04)
Cohort shares (p–value)	0.00		0.01	0.00	0.00	0.08	0.05
Skill share (p–value)		0.00	0.01	0.49	0.01	0.07	0.07
First stage F–statistic					12.7	10.5	3.4
Countries	139	139	139	139	138	139	138
Observations	1,259	1,259	1,259	1,211	1,248	1,259	1,248
R^2	0.84	0.84	0.84		0.84	0.84	0.84

Notes: This table reports results for demographic and human capital data by Barro and Lee (2013). The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w. are measured in logarithms. Column (4) corrects for the dynamic–panel bias using the Bruno (2005) estimator. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) or high-skill shares are jointly different from zero are reported. Instruments are shifted age cohorts in Column (5); the lagged years of schooling (6); and a combination of both in Column (7). See Panel (a) of Figure A3 for an illustration. First stage F–statistic reports the first stage Kleibergen–Paap rk Wald F–statistic. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A10: Robustness: Income Per Capita

	Demography	Skills	Demography & Skills	Bias Correction	Demography Instrumented	Skills Instrumented	Both Instrumented
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share < 20	-3.41**		-2.60*	-2.45	-4.56**	-1.84	-3.40*
	(1.41)		(1.40)	(1.51)	(1.89)	(1.42)	(1.84)
Share 20–24	-3.06***		-2.43**	-2.52*	-3.50**	-1.83*	-2.99**
	(1.11)		(1.09)	(1.43)	(1.49)	(1.10)	(1.47)
Share 25–29	-4.41***		-3.89***	-4.03**	-3.39**	-3.41**	-2.98*
	(1.42)		(1.39)	(1.95)	(1.59)	(1.35)	(1.54)
Share 30–34	-2.96**		-2.58**	-2.66*	-3.66***	-2.23*	-3.35**
	(1.22)		(1.19)	(1.59)	(1.41)	(1.18)	(1.40)
Share 35–39	-5.05***		-4.67***	-4.78***	-3.83**	-4.31***	-3.38**
	(1.38)		(1.38)	(1.79)	(1.58)	(1.35)	(1.53)
Share 40–44	-1.80		-1.56	-1.73	-1.91	-1.33	-1.82
	(1.31)		(1.28)	(1.67)	(1.42)	(1.25)	(1.40)
Share 45–49	-4.31***		-4.13***	-4.56**	-4.72***	-3.96***	-4.62***
	(1.50)		(1.47)	(2.01)	(1.78)	(1.43)	(1.75)
Share 55–59	-5.29***		-4.92***	-5.50**	-4.75***	-4.57***	-4.50**
	(1.70)		(1.65)	(2.25)	(1.83)	(1.59)	(1.77)
Share 60–64	-5.95***		-5.94***	-6.67***	-6.35***	-5.93***	-6.54***
	(1.41)		(1.37)	(1.83)	(1.54)	(1.33)	(1.52)
Share 65+	-3.61**		-3.80**	-4.20**	-4.47**	-3.97**	-4.54**
	(1.60)		(1.58)	(1.87)	(1.74)	(1.58)	(1.77)
Dependency Ratio	-0.79**	-1.19***	-0.80**	-0.71*	-1.32**	-0.81**	-1.25**
	(0.39)	(0.36)	(0.38)	(0.38)	(0.56)	(0.38)	(0.54)
Dependency Ratio (t–1)	-0.27	0.22	-0.25	-0.20	0.68	-0.24	0.53
	(0.51)	(0.36)	(0.51)	(0.49)	(0.81)	(0.51)	(0.77)
Share high–skill		1.03***	1.22***	0.91***	0.95**	2.37***	2.20***
		(0.39)	(0.40)	(0.34)	(0.43)	(0.74)	(0.75)
Output p.c. (t–1)	0.54***	0.50***	0.51***	0.64***	0.50***	0.49***	0.48***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Capital p.w.	0.28***	0.28***	0.29***	0.24***	0.29***	0.30***	0.30***
	(0.04)	(0.04)	(0.04)	(0.02)	(0.04)	(0.05)	(0.05)
Cohort shares (p–value)	0.00		0.00	0.00	0.00	0.00	0.00
Skill share (p–value)		0.01	0.00	0.01	0.03	0.00	0.00
First stage F–statistic					13.2	28.7	6.7
Hansen test (p–value)					—	0.19	0.22
Countries	120	120	120	120	120	120	120
Observations	1,098	1,098	1,098	1,053	1,098	1,098	1,098
R^2	0.88	0.88	0.89		0.88	0.88	0.88

Notes: This table reports results for demographic and human capital data by IIASA–VID (Lutz et al., 2007). The dependent variable is log output per capita. All regressions include country–specific fixed and time effects. Lagged output p.c., capital p.w. and the (lagged) dependency ratio, measured in logarithms, are included as controls in all specifications. Column (4) corrects for the dynamic–panel bias using the Bruno (2005) estimator. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) or high-skill shares are jointly different from zero are reported. Instruments are shifted age cohorts in Column (5); the lagged shares of high skills of cohorts at the edge of the working–age population in Column (6); and a combination of both in Column (7). See Figure A3 for an illustration. First stage F–statistic reports the first stage Kleibergen–Paap rk Wald F–statistic. Hansen test p–values refer to the robust overidentifying restriction test. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A11: Heterogeneity: Accounting for Human Capital Differences Between Cohorts

	Demography & Skills		Bias Correction		Skills Instrumented	
	IIASA–VID	Barro–Lee	IIASA–VID	Barro–Lee	IIASA–VID	Barro–Lee
	(1)	(2)	(3)	(4)	(5)	(6)
Share < 20	-2.59**	-3.16***	-2.55*	-2.64**	-1.91	-2.63
	(1.20)	(1.16)	(1.33)	(1.32)	(1.75)	(1.92)
Share 20–24	-1.04	-1.07	-1.00	-0.96	-1.99	-0.50
	(1.13)	(1.14)	(1.31)	(1.53)	(1.75)	(2.18)
Share 25–29	-2.07	-2.97**	-2.15	-2.73*	-1.53	-2.56
	(1.41)	(1.43)	(1.84)	(1.60)	(2.14)	(1.86)
Share 30–34	-2.02	-2.11*	-2.07	-1.67	-1.86	-1.80
	(1.24)	(1.26)	(1.53)	(1.59)	(1.62)	(1.46)
Share 35–39	-2.77*	-2.21	-2.72	-1.69	-2.30	-1.69
	(1.47)	(1.39)	(1.66)	(1.64)	(1.96)	(2.16)
Share 40–44	-0.58	-1.86	-0.62	-1.77	-0.33	-1.32
	(1.27)	(1.35)	(1.58)	(1.60)	(1.69)	(2.17)
Share 45–49	-2.36*	-1.77	-2.65	-1.51	-2.35	-1.74
	(1.40)	(1.50)	(1.88)	(2.09)	(2.13)	(1.65)
Share 55–59	-3.39*	-3.02*	-3.64*	-2.97	-3.07	-2.46
	(1.78)	(1.74)	(1.95)	(2.36)	(2.24)	(2.67)
Share 60–64	-4.78***	-4.49***	-5.24***	-4.85**	-4.99***	-3.94*
	(1.28)	(1.46)	(1.70)	(1.90)	(1.70)	(2.10)
Share 65+	-2.19	-1.18	-2.30	-0.97	-0.95	-0.72
	(1.56)	(1.57)	(1.80)	(2.11)	(3.18)	(1.88)
Share high–skill < 20	0.53	-0.27	0.39	-0.21	-1.76	-0.70
	(0.37)	(0.23)	(0.59)	(0.24)	(2.22)	(2.11)
Share high–skill 20–24	-0.52***	0.22*	-0.43*	0.22	-1.11	1.16
	(0.19)	(0.11)	(0.23)	(0.14)	(1.05)	(3.78)
Share high–skill 25–29	1.16***	0.07	1.01***	0.04	6.19	-0.58
	(0.35)	(0.12)	(0.37)	(0.17)	(6.92)	(2.69)
Share high–skill 30–34	0.46	0.03	0.31	-0.03	-9.38	-0.03
	(0.43)	(0.18)	(0.56)	(0.25)	(12.76)	(0.41)
Share high–skill 35–39	-1.04*	-0.31	-1.09	-0.33	6.13	-0.44
	(0.62)	(0.27)	(0.70)	(0.39)	(9.39)	(1.06)
Share high–skill 40–44	0.12	-0.17	0.25	-0.25	-1.51	-0.05
	(0.54)	(0.31)	(0.79)	(0.49)	(2.39)	(0.78)
Share high–skill 45–49	0.44	-0.39	0.40	-0.55	0.21	-0.35
	(0.59)	(0.34)	(0.82)	(0.52)	(0.74)	(0.76)
Share high–skill 50–54	-0.31	0.70	-0.39	0.77	-0.51	0.36
	(0.71)	(0.47)	(0.80)	(0.52)	(0.78)	(0.74)
Share high–skill 55–59	-0.61	0.55	-0.52	0.71	-1.64	0.74
	(0.62)	(0.56)	(0.75)	(0.61)	(1.68)	(0.97)
Share high–skill 60–64	0.86	-0.07	0.89	-0.13	1.07	0.97
	(0.59)	(0.44)	(0.84)	(0.57)	(0.84)	(3.59)
Share high–skill 65+	0.78	0.13	0.76	0.13	0.64	-0.76
	(0.55)	(0.41)	(0.75)	(0.53)	(0.86)	(2.76)
Output p.w. (t–1)	0.46***	0.52***	0.57***	0.66***	0.47***	0.52***
	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)
Capital p.w.	0.35***	0.29***	0.30***	0.23***	0.33***	0.28***
	(0.05)	(0.04)	(0.02)	(0.02)	(0.05)	(0.04)
Cohort shares (p–value)	0.01	0.04	0.02	0.24	0.04	0.22
Skill share (p–value)	0.00	0.11	0.00	0.14	0.02	0.35
First stage F–statistic					0.1	0.0
Countries	120	139	120	139	120	139
Observations	1,098	1,259	1,053	1,211	1,098	1,259
R^2	0.87	0.84			0.82	0.84

Notes: Columns (1), (3) and (5) report results for demographic and human capital data from IIASA–VID (Lutz et al., 2007), Columns (2), (4) and (6) for data by Barro and Lee (2013). The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w. are measured in logarithms. Columns (3) and (4) correct for the dynamic–panel bias using the Bruno (2005) estimator. Instruments are the lagged shares of high skills of cohorts at the edge of the working–age population in Columns (5) and (6); see Panel (c) of Figure A3 for an illustration. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) and the first stage Kleibergen–Paap rk Wald F–statistic are reported. The IV specification is just–identified. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A12: Heterogeneity: Accounting for Human Capital Differences Between Cohorts

	Demography & Skills		Bias Correction		Skills Instrumented	
	IIASA–VID	Barro–Lee	IIASA–VID	Barro–Lee	IIASA–VID	Barro–Lee
	(1)	(2)	(3)	(4)	(5)	(6)
Share < 20	-3.33***	-3.41***	-3.08**	-2.86**	-3.34***	-3.39***
	(1.21)	(1.18)	(1.36)	(1.30)	(1.19)	(1.16)
Share 20–24	-1.83	-1.13	-1.65	-1.05	-1.83*	-1.11
	(1.13)	(1.15)	(1.37)	(1.55)	(1.11)	(1.12)
Share 25–29	-3.37**	-3.43**	-3.21*	-3.23**	-3.37**	-3.42**
	(1.40)	(1.43)	(1.85)	(1.53)	(1.37)	(1.40)
Share 30–34	-3.06**	-2.26*	-2.90*	-1.81	-3.06**	-2.26*
	(1.25)	(1.29)	(1.54)	(1.62)	(1.22)	(1.27)
Share 35–39	-3.68**	-2.56*	-3.47**	-2.06	-3.68***	-2.56*
	(1.44)	(1.35)	(1.71)	(1.59)	(1.41)	(1.32)
Share 40–44	-1.67	-2.00	-1.54	-1.93	-1.67	-1.99
	(1.30)	(1.44)	(1.56)	(1.60)	(1.28)	(1.41)
Share 45–49	-3.30**	-1.94	-3.41*	-1.71	-3.30**	-1.95
	(1.40)	(1.47)	(2.01)	(2.07)	(1.37)	(1.45)
Share 55–59	-4.50**	-3.26*	-4.59**	-3.42	-4.50**	-3.23*
	(1.80)	(1.82)	(2.05)	(2.26)	(1.77)	(1.78)
Share 60–64	-5.76***	-5.10***	-6.12***	-5.52***	-5.76***	-5.11***
	(1.38)	(1.41)	(1.74)	(1.83)	(1.36)	(1.38)
Share 65+	-3.74**	-1.69	-3.75**	-1.58	-3.74**	-1.70
	(1.55)	(1.63)	(1.85)	(2.07)	(1.52)	(1.60)
Share high-skill 50–54	0.78**	0.52***	0.69***	0.40**	0.78***	0.56***
	(0.31)	(0.19)	(0.23)	(0.20)	(0.30)	(0.21)
Rel. sh. high–skill < 20	-0.0001***	0.00	-0.00	0.00	-0.0001***	0.00
	(0.0000)	(0.00)	(0.00)	(0.01)	(0.0000)	(0.00)
Rel. sh. high–skill 20–24	-0.00	0.00	-0.00	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Rel. sh. high–skill 25–29	0.00	0.00	0.00	-0.00	0.00	0.00
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Rel. sh. high–skill 30–34	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Rel. sh. high–skill 35–39	0.00	-0.01	0.00	-0.01	0.00	-0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Rel. sh. high–skill 40–44	0.00	-0.01	-0.00	-0.01	0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Rel. sh. high–skill 45–49	0.02	0.01	0.02	0.01	0.02	0.01
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
Rel. sh. high–skill 55–59	0.01	0.04	0.01	0.05	0.01	0.04
	(0.01)	(0.04)	(0.04)	(0.04)	(0.01)	(0.04)
Rel. sh. high–skill 60–64	0.01	-0.06	0.01	-0.06	0.01	-0.06
	(0.01)	(0.04)	(0.03)	(0.05)	(0.01)	(0.04)
Rel. sh. high–skill 65+	0.03**	0.03	0.03	0.04	0.03**	0.03
	(0.02)	(0.04)	(0.03)	(0.05)	(0.02)	(0.04)
Output p.w. (t–1)	0.48***	0.51***	0.59***	0.64***	0.48***	0.51***
	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
Capital p.w.	0.35***	0.29***	0.31***	0.23***	0.35***	0.29***
	(0.05)	(0.04)	(0.02)	(0.03)	(0.05)	(0.04)
Cohort shares (p–value)	0.01	0.01	0.01	0.05	0.00	0.00
Skill share (p–value)	0.00	0.00	0.37	0.81	0.00	0.00
First stage F–statistic					7.3e+5	2505.3
Countries	120	139	120	139	120	139
Observations	1,098	1,255	1,053	1,208	1,098	1,255
R^2	0.87	0.85			0.87	0.85

Notes: Columns (1), (3) and (5) report results for demographic and human capital data from IIASA–VID (Lutz et al., 2007), Columns (2), (4) and (6) for data by Barro and Lee (2013). The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w. are measured in logarithms. Columns (3) and (4) correct for the dynamic–panel bias using the Bruno (2005) estimator. Instruments are the lagged shares of high skills of cohorts at the edge of the working–age population in Columns (5) and (6); see Panel (c) of Figure A3 for an illustration. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) and the first stage Kleibergen–Paap rk Wald F–statistic are reported. The IV specification is just–identified. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A13: Robustness: Controlling for the Dependency Ratio (Levels)

	Demography	Skills	Demography & Skills	Bias Correction	Demography Instrumented	Skills Instrumented	Both Instrumented
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				(a) IIASA–VID sample			
Share < 20	-3.45***		-2.70**	-2.61*	-3.37***	-1.71	-2.21*
	(1.26)		(1.25)	(1.43)	(1.27)	(1.25)	(1.24)
Share 20–24	-2.65**		-2.10*	-2.21	-3.46**	-1.38	-2.79**
	(1.08)		(1.08)	(1.38)	(1.38)	(1.08)	(1.36)
Share 25–29	-3.56**		-3.13**	-3.22*	-2.82*	-2.56*	-2.34*
	(1.42)		(1.39)	(1.89)	(1.46)	(1.32)	(1.40)
Share 30–34	-3.03**		-2.71**	-2.74*	-3.96***	-2.29*	-3.59**
	(1.28)		(1.25)	(1.53)	(1.43)	(1.22)	(1.41)
Share 35–39	-4.07***		-3.77***	-3.72**	-3.03*	-3.37**	-2.54*
	(1.44)		(1.43)	(1.74)	(1.58)	(1.39)	(1.51)
Share 40–44	-1.66		-1.47	-1.55	-2.00	-1.22	-1.94
	(1.30)		(1.28)	(1.62)	(1.39)	(1.23)	(1.37)
Share 45–49	-3.26**		-3.14**	-3.37*	-4.02***	-2.98**	-3.93***
	(1.43)		(1.41)	(1.95)	(1.55)	(1.37)	(1.51)
Share 55–59	-4.63**		-4.35**	-4.75**	-4.39**	-3.96**	-4.14**
	(1.85)		(1.81)	(2.18)	(1.83)	(1.74)	(1.77)
Share 60–64	-5.44***		-5.46***	-5.93***	-6.04***	-5.49***	-6.32***
	(1.36)		(1.33)	(1.76)	(1.50)	(1.29)	(1.48)
Share 65+	-2.90*		-3.09*	-3.25*	-4.16**	-3.34**	-4.20**
	(1.60)		(1.57)	(1.79)	(1.64)	(1.57)	(1.69)
Dependency ratio	-0.13	-0.16	-0.12	-0.11	-0.08	-0.11	-0.09
	(0.13)	(0.11)	(0.13)	(0.10)	(0.13)	(0.13)	(0.12)
Share high–skill		0.89**	1.08***	0.85***	0.84**	2.51***	2.40***
		(0.34)	(0.40)	(0.32)	(0.41)	(0.76)	(0.77)
Cohort shares (p–value)	0.01		0.01	0.04	0.01	0.00	0.00
Skill share (p–value)		0.01	0.01	0.01	0.04	0.00	0.00
First stage F–statistic					12.6	28.6	4.7
Hansen test (p–value)					—	0.20	0.25
				(b) Barro–Lee sample			
Share < 20	-3.63***		-3.15**	-2.71**	-3.08*	-2.87**	-2.65*
	(1.22)		(1.24)	(1.36)	(1.58)	(1.20)	(1.50)
Share 20–24	-1.64		-1.32	-1.56	-1.67	-1.13	-1.46
	(1.15)		(1.12)	(1.58)	(1.67)	(1.08)	(1.63)
Share 25–29	-3.61**		-3.38**	-3.39**	-2.88	-3.24**	-2.68
	(1.42)		(1.42)	(1.59)	(1.88)	(1.38)	(1.83)
Share 30–34	-2.46*		-2.31*	-2.08	-1.93	-2.23*	-1.65
	(1.30)		(1.30)	(1.76)	(1.81)	(1.27)	(1.79)
Share 35–39	-2.63*		-2.41*	-2.18	-2.69	-2.28*	-2.49
	(1.38)		(1.38)	(1.75)	(2.00)	(1.34)	(1.95)
Share 40–44	-2.24		-2.02	-2.19	-1.06	-1.90	-0.90
	(1.43)		(1.40)	(1.63)	(1.78)	(1.34)	(1.75)
Share 45–49	-1.76		-1.77	-1.69	-2.39	-1.78	-2.21
	(1.48)		(1.46)	(2.31)	(2.19)	(1.44)	(2.15)
Share 55–59	-3.70**		-3.43*	-3.82*	-2.71	-3.27*	-2.46
	(1.84)		(1.82)	(2.23)	(2.40)	(1.76)	(2.33)
Share 60–64	-5.16***		-5.18***	-5.79***	-5.41***	-5.20***	-5.41***
	(1.39)		(1.37)	(1.58)	(1.68)	(1.34)	(1.68)
Share 65+	-1.47		-1.48	-1.53	-2.29	-1.49	-2.12
	(1.66)		(1.61)	(2.13)	(2.07)	(1.58)	(2.04)
Dependency ratio	-0.01	-0.09	-0.01	-0.01	0.02	-0.01	0.01
	(0.14)	(0.12)	(0.14)	(0.10)	(0.14)	(0.13)	(0.14)
Share high–skill		0.71***	0.61**	0.43*	0.60**	0.97**	0.96**
		(0.22)	(0.24)	(0.24)	(0.25)	(0.38)	(0.39)
Cohort shares (p–value)	0.00		0.01	0.00	0.00	0.00	0.00
Skill share (p–value)		0.00	0.01	0.07	0.02	0.01	0.01
First stage F–statistic					10.5	29.5	5.5
Hansen test (p–value)					—	0.47	0.47

Notes: Panel (a) reports results for demographic and human capital data by IIASA–VID (Lutz et al., 2007), Panel (b) for data from Barro and Lee (2013). The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w. are measured in logarithms (coefficients unreported). Column (4) corrects for the dynamic–panel bias using the Bruno (2005) estimator. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) or high-skill shares are jointly different from zero are reported. Instruments are shifted age cohorts in Column (5); the lagged share of high skills of the edge of the working–age population in Column (6); and a combination of both in Column (7). See Figure A3 for an illustration. First stage F–statistic reports the first stage Kleibergen–Paap rk Wald F–statistic. Hansen test p–values refer to the robust overidentifying restriction test. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A14: Robustness: Population Scale Effects (in Logarithms)

	Demography	Skills	Demography & Skills	Bias Correction	Demography Instrumented	Skills Instrumented	Both Instrumented
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share < 20	-3.54***		-3.06***	-3.04**	-3.62***	-2.61**	-3.06***
	(1.13)		(1.16)	(1.40)	(1.14)	(1.21)	(1.15)
Share 20–24	-1.65		-1.39	-1.45	-2.71**	-1.14	-2.47*
	(1.05)		(1.06)	(1.39)	(1.33)	(1.08)	(1.34)
Share 25–29	-3.08**		-2.86**	-2.97	-2.64*	-2.64**	-2.46*
	(1.38)		(1.37)	(1.90)	(1.44)	(1.33)	(1.40)
Share 30–34	-2.58**		-2.43**	-2.43	-3.50**	-2.28*	-3.39**
	(1.18)		(1.18)	(1.54)	(1.38)	(1.17)	(1.37)
Share 35–39	-3.60**		-3.45**	-3.48**	-2.80*	-3.31**	-2.58*
	(1.38)		(1.38)	(1.75)	(1.52)	(1.36)	(1.50)
Share 40–44	-0.95		-0.90	-0.95	-1.48	-0.86	-1.52
	(1.23)		(1.22)	(1.63)	(1.34)	(1.19)	(1.33)
Share 45–49	-2.67*		-2.66*	-2.95	-3.76**	-2.65**	-3.76**
	(1.36)		(1.35)	(1.96)	(1.48)	(1.32)	(1.47)
Share 55–59	-4.00**		-3.90**	-4.36**	-4.11**	-3.79**	-4.05**
	(1.66)		(1.66)	(2.19)	(1.69)	(1.64)	(1.68)
Share 60–64	-5.35***		-5.38***	-5.87***	-6.10***	-5.41***	-6.25***
	(1.33)		(1.32)	(1.77)	(1.47)	(1.29)	(1.47)
Share 65+	-4.52***		-4.45***	-4.41**	-4.62***	-4.37***	-4.67***
	(1.49)		(1.48)	(1.83)	(1.59)	(1.47)	(1.60)
Working-Age Population	-0.20***	-0.12**	-0.17***	-0.14***	-0.17***	-0.14***	-0.14***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Share high–skill		0.70**	0.72*	0.55	0.51	1.42*	1.34*
		(0.32)	(0.39)	(0.35)	(0.40)	(0.75)	(0.75)
Output p.w. (t–1)	0.46***	0.46***	0.46***	0.56***	0.46***	0.45***	0.45***
	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)
Capital p.w.	0.33***	0.33***	0.34***	0.29***	0.33***	0.34***	0.34***
	(0.05)	(0.05)	(0.05)	(0.02)	(0.05)	(0.05)	(0.05)
Cohort shares (p–value)	0.00		0.00	0.00	0.00	0.00	0.00
Skill share (p–value)		0.03	0.07	0.11	0.21	0.06	0.08
First stage F–statistic					13.2	26.4	4.2
Hansen test (p–value)					—	0.18	0.16
Countries	120	120	120	120	120	120	120
Observations	1,098	1,098	1,098	1,053	1,098	1,098	1,098
R^2	0.87	0.86	0.87		0.87	0.87	0.87

Notes: This table reports results for demographic and human capital data by IIASA–VID (Lutz et al., 2007). The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w., capital p.w. and the working-age population are measured in logarithms. Column (4) corrects for the dynamic–panel bias using the Bruno (2005) estimator. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) or high-skill shares are jointly different from zero are reported. Instruments are shifted age cohorts in Column (5); the lagged share of high skills of the edge of the working–age population in Column (6); and a combination of both in Column (7). See Figure A3 for an illustration. First stage F–statistic reports the first stage Kleibergen–Paap rk Wald F–statistic. Hansen test p–values refer to the robust overidentifying restriction test. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A15: Robustness: Population Scale Effects (in Absolute Values)

	Demography	Skills	Demography & Skills	Bias Correction	Demography Instrumented	Skills Instrumented	Both Instrumented
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share < 20	-3.75***		-2.80**	-2.75**	-3.41***	-1.69	-2.16*
	(1.23)		(1.22)	(1.38)	(1.22)	(1.22)	(1.20)
Share 20–24	-2.41**		-1.80	-1.78	-3.28**	-1.09	-2.61*
	(1.10)		(1.09)	(1.39)	(1.37)	(1.10)	(1.35)
Share 25–29	-3.48**		-2.94**	-2.97	-2.60*	-2.31*	-2.03
	(1.42)		(1.39)	(1.89)	(1.46)	(1.32)	(1.39)
Share 30–34	-3.04**		-2.66**	-2.64*	-3.90***	-2.21*	-3.51**
	(1.28)		(1.25)	(1.54)	(1.44)	(1.21)	(1.42)
Share 35–39	-4.01***		-3.65**	-3.58**	-2.96*	-3.24**	-2.46
	(1.45)		(1.44)	(1.75)	(1.58)	(1.40)	(1.52)
Share 40–44	-1.54		-1.33	-1.33	-1.86	-1.08	-1.80
	(1.32)		(1.29)	(1.62)	(1.41)	(1.26)	(1.40)
Share 45–49	-3.15**		-3.00**	-3.23*	-3.88**	-2.81**	-3.75**
	(1.43)		(1.40)	(1.96)	(1.55)	(1.36)	(1.51)
Share 55–59	-4.71**		-4.39**	-4.79**	-4.38**	-4.01**	-4.13**
	(1.85)		(1.81)	(2.20)	(1.83)	(1.74)	(1.77)
Share 60–64	-5.49***		-5.52***	-6.00***	-6.01***	-5.56***	-6.28***
	(1.37)		(1.34)	(1.77)	(1.50)	(1.30)	(1.48)
Share 65+	-2.95*		-3.12**	-3.22*	-4.11**	-3.32**	-4.06**
	(1.59)		(1.57)	(1.81)	(1.63)	(1.59)	(1.70)
Working-Age Population	0.04*	0.05**	0.06***	0.06***	0.05**	0.07***	0.07***
$(\widehat{\beta}, se(\widehat{\beta}) \times 100)$	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Share high–skill		1.08***	1.28***	1.06***	0.99**	2.77***	2.62***
		(0.34)	(0.41)	(0.34)	(0.43)	(0.79)	(0.81)
Output p.w. (t–1)	0.51***	0.48***	0.49***	0.59***	0.48***	0.46***	0.46***
	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)
Capital p.w.	0.32***	0.33***	0.33***	0.29***	0.33***	0.34***	0.34***
	(0.05)	(0.04)	(0.05)	(0.02)	(0.05)	(0.05)	(0.05)
Cohort shares (p–value)	0.01		0.01	0.01	0.01	0.00	0.00
Skill share (p–value)		0.00	0.00	0.00	0.02	0.00	0.00
First stage F–statistic					13.2	26.6	4.4
Hansen test (p–value)					—	0.31	0.37
Countries	120	120	120	120	120	120	120
Observations	1,098	1,098	1,098	1,053	1,098	1,098	1,098
R^2	0.87	0.86	0.87		0.87	0.86	0.86

Notes: This table reports results for demographic and human capital data by IIASA–VID (Lutz et al., 2007). The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w. are measured in logarithms. The working-age population is measured in millions. Column (4) corrects for the dynamic–panel bias using the Bruno (2005) estimator. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) or high-skill shares are jointly different from zero are reported. Instruments are shifted age cohorts in Column (5); the lagged share of high skills of the edge of the working–age population in Column (6); and a combination of both in Column (7). See Figure A3 for an illustration. First stage F–statistic reports the first stage Kleibergen–Paap rk Wald F–statistic. Hansen test p–values refer to the robust overidentifying restriction test. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A16: Robustness: Controlling for Life Expectancy (Levels)

	Demography	Skills	Demography & Skills	Bias Correction	Demography Instrumented	Skills Instrumented	Both Instrumented
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				(a) IIASA–VID sample			
Share < 20	-3.70***		-2.71**	-2.69*	-3.49***	-1.29	-1.91
	(1.23)		(1.22)	(1.38)	(1.22)	(1.26)	(1.23)
Share 20–24	-2.36**		-1.72	-1.83	-3.22**	-0.80	-2.33*
	(1.12)		(1.11)	(1.36)	(1.39)	(1.13)	(1.39)
Share 25–29	-3.51**		-2.95**	-3.06	-2.65*	-2.13	-1.82
	(1.45)		(1.41)	(1.87)	(1.49)	(1.35)	(1.42)
Share 30–34	-2.52**		-2.11*	-2.16	-3.61**	-1.52	-3.21**
	(1.25)		(1.22)	(1.53)	(1.46)	(1.19)	(1.43)
Share 35–39	-4.59***		-4.30***	-4.28**	-3.29*	-3.88**	-2.61
	(1.63)		(1.60)	(1.72)	(1.77)	(1.55)	(1.68)
Share 40–44	-1.17		-0.93	-1.03	-1.64	-0.59	-1.55
	(1.31)		(1.29)	(1.60)	(1.41)	(1.29)	(1.43)
Share 45–49	-2.95**		-2.80**	-3.07	-3.77**	-2.59*	-3.58**
	(1.43)		(1.40)	(1.93)	(1.52)	(1.37)	(1.48)
Share 55–59	-4.45**		-4.11**	-4.57**	-4.16**	-3.62**	-3.79**
	(1.87)		(1.84)	(2.16)	(1.82)	(1.78)	(1.77)
Share 60–64	-5.37***		-5.41***	-5.88***	-5.99***	-5.47***	-6.32***
	(1.35)		(1.32)	(1.75)	(1.48)	(1.27)	(1.46)
Share 65+	-2.97*		-3.04*	-3.18*	-4.22**	-3.14*	-4.11**
	(1.77)		(1.74)	(1.80)	(1.70)	(1.79)	(1.81)
Life expectancy	0.00	0.01	0.00	0.005**	0.00	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.002)	(0.00)	(0.00)	(0.00)
Share high–skill		1.14***	1.32***	1.13***	0.98**	3.21***	3.04***
		(0.35)	(0.42)	(0.32)	(0.44)	(0.86)	(0.89)
Cohort shares (p–value)	0.01		0.01	0.01	0.01	0.00	0.00
Skill share (p–value)		0.00	0.00	0.00	0.03	0.00	0.00
First stage F–statistic					12.2	30.4	5.1
Hansen test (p–value)					—	0.47	0.57
				(b) Barro–Lee sample			
Share < 20	-3.21***		-2.61**	-2.35*	-2.41	-2.24*	-1.84
	(1.21)		(1.24)	(1.31)	(1.52)	(1.20)	(1.44)
Share 20–24	-1.12		-0.66	-0.90	-1.24	-0.38	-0.99
	(1.14)		(1.11)	(1.54)	(1.61)	(1.07)	(1.56)
Share 25–29	-3.10**		-2.78*	-2.87*	-2.13	-2.57*	-1.86
	(1.42)		(1.44)	(1.54)	(1.81)	(1.40)	(1.76)
Share 30–34	-1.78		-1.62	-1.48	-0.88	-1.52	-0.52
	(1.29)		(1.27)	(1.72)	(1.84)	(1.24)	(1.83)
Share 35–39	-2.87*		-2.54*	-2.42	-2.85	-2.34	-2.59
	(1.53)		(1.51)	(1.70)	(2.23)	(1.47)	(2.16)
Share 40–44	-1.34		-1.07	-1.28	-0.08	-0.90	0.12
	(1.39)		(1.36)	(1.57)	(1.69)	(1.31)	(1.68)
Share 45–49	-1.15		-1.12	-1.08	-1.37	-1.11	-1.15
	(1.51)		(1.49)	(2.24)	(2.13)	(1.47)	(2.09)
Share 55–59	-2.87		-2.49	-3.00	-1.91	-2.26	-1.62
	(1.83)		(1.82)	(2.19)	(2.35)	(1.76)	(2.30)
Share 60–64	-4.53***		-4.50***	-5.08***	-4.52***	-4.49***	-4.57***
	(1.35)		(1.33)	(1.55)	(1.61)	(1.30)	(1.61)
Share 65+	-0.74		-0.75	-0.77	-1.65	-0.76	-1.44
	(1.72)		(1.67)	(2.08)	(2.12)	(1.64)	(2.09)
Life expectancy	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Share high–skill		0.86***	0.74***	0.60***	0.69***	1.20***	1.17***
		(0.23)	(0.26)	(0.23)	(0.26)	(0.44)	(0.44)
Cohort shares (p–value)	0.00		0.01	0.00	0.00	0.01	0.00
Skill share (p–value)		0.00	0.00	0.01	0.01	0.01	0.01
First stage F–statistic					15.5	28.1	4.9
Hansen test (p–value)					—	0.15	0.15

Notes: Panel (a) reports results for demographic and human capital data by IIASA–VID (Lutz et al., 2007), Panel (b) for data from Barro and Lee (2013). The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w. are measured in logarithms (coefficients unreported). Column (4) corrects for the dynamic–panel bias using the Bruno (2005) estimator. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) or high-skill shares are jointly different from zero are reported. Instruments are shifted age cohorts in Column (5); the lagged share of high skills of the edge of the working–age population in Column (6); and a combination of both in Column (7). See Figure A3 for an illustration. First stage F–statistic reports the first stage Kleibergen–Paap rk Wald F–statistic. Hansen test p–values refer to the robust overidentifying restriction test. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A17: Robustness: Average Years of Schooling (Levels)

	Demography	Skills	Demography & Skills	Bias Correction	Demography Instrumented	Skills Instrumented	Both Instrumented
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share $<$ 20	-3.64***		-3.66***	-3.23**	-3.70**	-3.83***	-3.97***
	(1.17)		(1.18)	(1.37)	(1.55)	(1.16)	(1.53)
Share 20–24	-1.55		-1.54	-1.53	-2.04	-1.47	-1.83
	(1.14)		(1.14)	(1.60)	(1.65)	(1.11)	(1.68)
Share 25–29	-3.61**		-3.62**	-3.52**	-3.15*	-3.65***	-3.36*
	(1.41)		(1.41)	(1.58)	(1.89)	(1.36)	(1.92)
Share 30–34	-2.39*		-2.37*	-2.05	-2.30	-2.28*	-2.24
	(1.29)		(1.28)	(1.64)	(1.77)	(1.26)	(1.69)
Share 35–39	-2.53*		-2.54*	-2.21	-3.01	-2.55*	-2.86
	(1.39)		(1.39)	(1.64)	(2.03)	(1.37)	(2.03)
Share 40–44	-2.24		-2.24	-2.29	-1.25	-2.23	-1.44
	(1.44)		(1.44)	(1.62)	(1.79)	(1.42)	(1.81)
Share 45–49	-1.83		-1.81	-1.70	-2.60	-1.70	-2.53
	(1.47)		(1.47)	(2.13)	(2.20)	(1.48)	(2.20)
Share 55–59	-3.75**		-3.78**	-4.11*	-3.05	-3.91**	-3.39
	(1.85)		(1.85)	(2.47)	(2.42)	(1.82)	(2.43)
Share 60–64	-4.95***		-4.96***	-5.53***	-5.43***	-5.07***	-5.69***
	(1.40)		(1.40)	(1.90)	(1.70)	(1.36)	(1.68)
Share 65+	-1.44		-1.40	-1.39	-2.47	-1.20	-1.95
	(1.65)		(1.63)	(2.04)	(2.10)	(1.63)	(2.07)
Years of schooling		0.00	-0.01	-0.01	-0.01	-0.04**	-0.04**
		(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Output p.w. (t–1)	0.53***	0.54***	0.53***	0.66***	0.53***	0.53***	0.53***
	(0.05)	(0.05)	(0.05)	(0.03)	(0.05)	(0.05)	(0.05)
Capital p.w.	0.27***	0.27***	0.28***	0.22***	0.28***	0.28***	0.28***
	(0.04)	(0.04)	(0.04)	(0.02)	(0.04)	(0.04)	(0.04)
Cohort shares (p–value)	0.00		0.00	0.03	0.00	0.00	0.00
Skill share (p–value)		1.00	0.68	0.26	0.67	0.04	0.04
First stage F–statistic					12.3	103.5	18.9
Hansen test (p–value)					—	0.00	0.00
Countries	139	139	139	139	138	139	138
Observations	1,259	1,259	1,259	1,211	1,248	1,259	1,248
R^2	0.84	0.84	0.84		0.84	0.84	0.83

Notes: This table reports results for demographic and human capital data by Barro and Lee (2013). Human capital is proxied by average years of schooling. The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w. are measured in logarithms. Column (4) corrects for the dynamic–panel bias using the Bruno (2005) estimator. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) or high-skill shares are jointly different from zero are reported. Instruments are shifted age cohorts in Column (5); the lagged share of high skills of the edge of the working–age population in Column (6); and a combination of both in Column (7). See Figure A3 for an illustration. First stage F–statistic reports the first stage Kleibergen–Paap rk Wald F–statistic. Hansen test p–values refer to the robust overidentifying restriction test. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A18: Heterogeneity: Sample Split OECD and Non–OECD Countries (Levels)

	Demography	Skills	Demography & Skills	Bias Correction	Demography Instrumented	Skills Instrumented	Both Instrumented
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				(a) OECD Countries			
Share < 20	0.35		0.60	0.44	0.72	1.28	1.43
	(0.99)		(1.07)	(1.23)	(1.05)	(1.09)	(1.16)
Share 20–24	-0.98		-0.89	-0.66	-1.89*	-0.63	-1.73*
	(0.89)		(0.89)	(1.35)	(0.97)	(0.82)	(0.98)
Share 25–29	-0.40		-0.26	-0.15	1.05	0.12	1.16
	(1.22)		(1.24)	(1.56)	(1.24)	(1.21)	(1.29)
Share 30–34	-0.41		-0.32	-0.04	-1.18	-0.07	-1.02
	(1.12)		(1.12)	(1.33)	(1.32)	(1.03)	(1.26)
Share 35–39	0.49		0.62	0.87	1.01	1.00	1.25
	(0.97)		(0.98)	(1.54)	(0.98)	(0.94)	(1.05)
Share 40–44	-0.77		-0.74	-0.70	-0.55	-0.66	-0.62
	(1.10)		(1.10)	(1.31)	(1.01)	(1.08)	(1.02)
Share 45–49	-0.54		-0.52	-0.47	-0.78	-0.47	-0.90
	(1.12)		(1.13)	(1.84)	(0.99)	(1.10)	(1.01)
Share 55–59	0.02		0.04	-0.04	-0.00	0.09	-0.08
	(1.59)		(1.62)	(1.69)	(1.47)	(1.59)	(1.52)
Share 60–64	-1.57		-1.65	-1.75	-1.79	-1.87*	-2.18**
	(1.14)		(1.12)	(1.52)	(1.11)	(1.02)	(1.06)
Share 65+	-1.76		-1.71	-1.87	-2.22	-1.60	-2.14
	(1.29)		(1.34)	(1.53)	(1.41)	(1.45)	(1.61)
Share high–skill		0.21	0.41	0.51*	0.42	1.51**	1.60***
		(0.34)	(0.32)	(0.29)	(0.28)	(0.61)	(0.59)
Cohort shares (p–value)	0.45		0.24	0.03	0.01	0.02	0.00
Skill share (p–value)		0.54	0.21	0.09	0.14	0.01	0.01
First stage F–statistic					22.8	9.9	1.8
Hansen test (p–value)					—	0.33	0.31
Countries	32	32	32	32	32	32	32
Observations	341	341	341	318	341	341	341
				(b) Non–OECD countries			
Share < 20	-5.44***		-4.88***	-5.15**	-6.88***	-3.03*	-4.47**
	(1.85)		(1.84)	(2.54)	(2.07)	(1.78)	(1.89)
Share 20–24	-3.14*		-2.85	-3.24	-5.58**	-1.88	-4.42*
	(1.77)		(1.77)	(2.88)	(2.40)	(1.76)	(2.27)
Share 25–29	-4.35*		-4.11*	-4.57*	-5.80**	-3.29*	-4.54**
	(2.23)		(2.18)	(2.77)	(2.54)	(1.99)	(2.24)
Share 30–34	-4.48**		-4.30**	-4.70*	-6.55**	-3.67**	-6.21**
	(1.88)		(1.85)	(2.84)	(2.67)	(1.78)	(2.59)
Share 35–39	-7.06***		-6.89***	-7.04**	-6.87**	-6.30***	-5.29*
	(2.48)		(2.47)	(2.96)	(3.19)	(2.32)	(3.01)
Share 40–44	-1.71		-1.66	-1.86	-3.80	-1.48	-3.88
	(2.46)		(2.42)	(3.09)	(3.06)	(2.26)	(2.98)
Share 45–49	-4.12		-4.18	-5.02	-8.14**	-4.37*	-7.74**
	(2.55)		(2.53)	(3.98)	(3.54)	(2.43)	(3.25)
Share 55–59	-7.70***		-7.56***	-8.24*	-9.02***	-7.11***	-8.37***
	(2.83)		(2.78)	(4.58)	(3.16)	(2.61)	(3.02)
Share 60–64	-7.66***		-7.67***	-8.96***	-9.60***	-7.73***	-10.11***
	(2.34)		(2.27)	(2.97)	(2.92)	(2.04)	(2.67)
Share 65+	-4.47		-4.41	-4.92	-6.23*	-4.21	-5.95*
	(2.81)		(2.76)	(3.58)	(3.21)	(2.63)	(3.12)
Share high–skill		0.96*	0.92	0.60	0.50	4.03***	3.98***
		(0.50)	(0.68)	(0.67)	(0.73)	(1.45)	(1.49)
Cohort shares (p–value)	0.01		0.01	0.00	0.00	0.00	0.03
Skill share (p–value)		0.06	0.18	0.37	0.49	0.01	0.01
First stage F–statistic					6.3	28.2	4.6
Hansen test (p–value)					—	0.83	0.90
Countries	88	88	88	88	88	88	88
Observations	757	757	757	735	757	757	757

Notes: This table reports results for demographic and human capital data by IIASA–VID (Lutz et al., 2007). Panel (a) reports results for OECD countries, Panel (b) for Non–OECD countries. The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w. are measured in logarithms (coefficients unreported). Column (4) corrects for the dynamic–panel bias using the Bruno (2005) estimator. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) or high-skill shares are jointly different from zero are reported. Instruments are shifted age cohorts in Column (5); the lagged shares of high skills of cohorts at the edge of the working–age population in Column (6); and a combination of both in Column (7). See Figure A3 for an illustration. First stage F–statistic reports the first stage Kleibergen–Paap rk Wald F–statistic. Hansen test p–values refer to the robust overidentifying restriction test. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A19: Heterogeneity: Sample Split Before and After 1990 (Levels)

	Demography & Skills		Bias Correction		Skills Instrumented	
	–1990	1990+	–1990	1990+	–1990	1990+
	(1)	(2)	(3)	(4)	(5)	(6)
Share < 20	2.49	-5.21***	2.83	-4.40**	2.50*	-1.38
	(1.51)	(1.68)	(2.15)	(1.96)	(1.50)	(2.19)
Share 20–24	1.64	-3.60**	1.60	-2.92	1.63	-0.27
	(1.30)	(1.58)	(2.08)	(2.32)	(1.27)	(1.89)
Share 25–29	0.76	-5.05***	0.88	-4.65**	0.76	-2.82
	(1.82)	(1.79)	(2.64)	(2.35)	(1.78)	(1.82)
Share 30–34	1.30	-4.72***	1.59	-4.40	1.29	-1.72
	(1.68)	(1.64)	(2.15)	(2.70)	(1.69)	(2.16)
Share 35–39	0.66	-5.31***	1.44	-5.00*	0.65	-3.89**
	(1.60)	(1.74)	(2.69)	(3.02)	(1.61)	(1.76)
Share 40–44	2.83**	-5.45***	3.20	-5.47**	2.83**	-1.95
	(1.37)	(1.76)	(2.49)	(2.65)	(1.34)	(2.11)
Share 45–49	1.36	-5.56***	0.52	-4.85	1.38	-4.61**
	(1.52)	(1.87)	(2.95)	(3.34)	(1.49)	(1.99)
Share 55–59	1.49	-5.60***	1.68	-5.80**	1.49	-4.18**
	(1.85)	(2.10)	(3.30)	(2.88)	(1.81)	(2.02)
Share 60–64	-1.56	-7.34***	-1.56	-8.29***	-1.55	-8.21***
	(1.62)	(1.89)	(2.57)	(2.22)	(1.57)	(1.84)
Share 65+	1.66	-7.56***	3.00	-7.53**	1.65	-8.40***
	(1.67)	(2.12)	(2.97)	(3.25)	(1.60)	(2.54)
Share high–skill	1.10	0.56	0.28	0.42	1.17	6.36**
	(1.01)	(0.81)	(0.90)	(0.92)	(2.03)	(2.53)
Output p.w. (t–1)	0.54***	0.23***	0.80***	0.42***	0.54***	0.20***
	(0.10)	(0.06)	(0.07)	(0.08)	(0.10)	(0.06)
Capital p.w.	0.28***	0.46***	0.19***	0.41***	0.28***	0.46***
	(0.07)	(0.06)	(0.04)	(0.04)	(0.07)	(0.06)
Cohort shares (p–value)	0.15	0.02	0.27	0.00	0.27	0.00
Skill share (p–value)	0.28	0.49	0.75	0.65	0.56	0.01
First stage F–statistic					19.0	14.3
Hansen test (p–value)					0.29	0.52
Countries	103	120	103	120	85	120
Observations	516	582	471	479	498	582
R^2	0.82	0.74			0.82	0.70

Notes: This table reports results for demographic and human capital data by IIASA–VID (Lutz et al., 2007). The sample is split in periods before 1990 (1955–1985) and after 1990 (1990–2010). The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w. are measured in logarithms. Columns (3) and (4) correct for the dynamic–panel bias using the Bruno (2005) estimator. Instruments are the lagged shares of high skills of cohorts at the edge of the working–age population in Columns (5) and (6); see Panel (c) of Figure A3 for an illustration. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) and the first stage Kleibergen–Paap rk Wald F–statistic are reported. Hansen test p–values refer to the robust overidentifying restriction test. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A20: Heterogeneity: Sample Split Before and After 1990 (Levels, Barro–Lee Data)

	Demography & Skills		Bias Correction		Skills Instrumented	
	–1990	1990+	–1990	1990+	–1990	1990+
	(1)	(2)	(3)	(4)	(5)	(6)
Share < 20	0.05	-3.78*	0.74	-2.74	0.05	-2.56
	(1.38)	(2.15)	(2.31)	(1.70)	(1.35)	(2.20)
Share 20–24	1.76	-2.24	1.01	-1.23	1.77	-0.74
	(1.31)	(1.78)	(2.36)	(1.92)	(1.30)	(1.89)
Share 25–29	-1.84	-4.49**	-1.52	-3.68*	-1.83	-4.05*
	(1.61)	(2.03)	(2.74)	(2.08)	(1.57)	(2.08)
Share 30–34	-0.49	-2.52	-0.14	-1.75	-0.47	-1.40
	(1.54)	(2.21)	(2.28)	(2.31)	(1.56)	(2.28)
Share 35–39	-0.13	-1.95	0.13	-1.43	-0.12	-1.14
	(1.27)	(2.17)	(2.50)	(2.46)	(1.24)	(2.19)
Share 40–44	1.01	-5.42**	1.57	-5.32**	1.00	-4.26**
	(1.33)	(2.19)	(2.45)	(2.60)	(1.30)	(2.17)
Share 45–49	-0.14	-2.58	-0.45	-0.99	-0.14	-2.33
	(1.34)	(2.72)	(3.30)	(2.86)	(1.32)	(2.71)
Share 55–59	1.61	-4.39	1.34	-4.22	1.61	-3.56
	(1.54)	(2.73)	(3.51)	(2.67)	(1.51)	(2.78)
Share 60–64	-1.12	-7.16***	-1.76	-7.98***	-1.10	-6.92***
	(1.60)	(1.81)	(2.79)	(1.83)	(1.56)	(1.81)
Share 65+	0.54	-3.98	1.76	-3.68	0.56	-3.38
	(1.89)	(2.54)	(3.14)	(3.03)	(1.83)	(2.68)
Share high–skill	0.18	0.69	-0.01	0.59	0.13	2.11**
	(0.38)	(0.55)	(0.44)	(0.46)	(0.51)	(1.05)
Output p.w. (t–1)	0.54***	0.23***	0.84***	0.48***	0.54***	0.21***
	(0.08)	(0.06)	(0.06)	(0.06)	(0.08)	(0.05)
Capital p.w.	0.31***	0.35***	0.18***	0.29***	0.31***	0.36***
	(0.06)	(0.05)	(0.04)	(0.03)	(0.06)	(0.05)
Cohort shares (p–value)	0.36	0.01	0.32	0.00	0.36	0.01
Skill share (p–value)	0.64	0.21	0.99	0.20	0.80	0.04
First stage F–statistic					8.3	15.6
Hansen test (p–value)					0.31	0.18
Countries	122	139	122	139	97	139
Observations	582	677	534	555	557	677
R^2	0.81	0.67			0.81	0.66

Notes: This table reports results for demographic and human capital data by Barro and Lee (2013). The sample is split in periods before 1990 (1955–1985) and after 1990 (1990–2010). The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w. are measured in logarithms. Columns (3) and (4) correct for the dynamic–panel bias using the Bruno (2005) estimator. Instruments are the lagged shares of high skills of cohorts at the edge of the working–age population in Columns (5) and (6); see Panel (c) of Figure A3 for an illustration. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) and the first stage Kleibergen–Paap rk Wald F–statistic are reported. Hansen test p–values refer to the robust overidentifying restriction test. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A21: Robustness: Old Versus Young Populations (Levels)

	Demography	Skills	Demography & Skills	Bias Correction	Demography Instrumented	Skills Instrumented	Both Instrumented
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	(a) Old populations (above median of the young–age dependency ratio)						
Share < 20	-4.26***		-3.92**	-4.12***	-3.35**	-3.57**	-2.86*
	(1.54)		(1.55)	(1.58)	(1.38)	(1.60)	(1.47)
Share 20–24	-1.93		-1.76	-1.97	-3.62**	-1.58	-3.51**
	(1.27)		(1.28)	(1.91)	(1.47)	(1.27)	(1.51)
Share 25–29	-4.79**		-4.64**	-5.08***	-2.24	-4.48***	-2.03
	(1.82)		(1.79)	(1.82)	(1.53)	(1.74)	(1.54)
Share 30–34	-3.32**		-3.22**	-3.23*	-5.28***	-3.12**	-5.18***
	(1.32)		(1.31)	(1.72)	(1.72)	(1.28)	(1.72)
Share 35–39	-4.51**		-4.39**	-4.54**	-2.27	-4.27**	-2.11
	(1.81)		(1.80)	(2.16)	(1.78)	(1.75)	(1.75)
Share 40–44	-3.27**		-3.23**	-3.59**	-3.85***	-3.19**	-3.86***
	(1.32)		(1.31)	(1.53)	(1.28)	(1.27)	(1.29)
Share 45–49	-5.28***		-5.25***	-5.65**	-4.43***	-5.22***	-4.43***
	(1.80)		(1.80)	(2.33)	(1.65)	(1.74)	(1.64)
Share 55–59	-5.47**		-5.38**	-6.19**	-5.38***	-5.29***	-5.32***
	(2.10)		(2.09)	(2.42)	(1.92)	(2.02)	(1.91)
Share 60–64	-6.22***		-6.29***	-7.11***	-6.32***	-6.37***	-6.54***
	(1.59)		(1.57)	(1.63)	(1.67)	(1.51)	(1.68)
Share 65+	-6.13***		-6.13***	-6.29***	-5.90***	-6.13***	-5.95***
	(1.54)		(1.54)	(1.83)	(1.54)	(1.52)	(1.56)
Share high–skill		0.15	0.54	0.47	0.41	1.10	1.13
		(0.38)	(0.42)	(0.43)	(0.42)	(0.95)	(0.92)
Cohort shares (p–value)	0.02		0.01	0.00	0.00	0.00	0.00
Skill share (p–value)		0.69	0.21	0.28	0.33	0.25	0.22
First stage F–statistic					6.5	16.2	2.6
Hansen test (p–value)					—	0.24	0.18
Observations	549	549	549	525	543	543	543
R^2	0.93	0.92	0.93		0.93	0.93	0.93
	(b) Young populations (below median of the young–age dependency ratio)						
Share < 20	3.42		3.67	2.88	-0.49	4.45	0.65
	(3.11)		(3.18)	(3.80)	(5.27)	(3.01)	(5.35)
Share 20–24	3.42		3.46	2.80	-1.90	3.58	-1.47
	(3.09)		(3.09)	(4.01)	(5.33)	(3.02)	(5.41)
Share 25–29	5.23		5.24	4.24	1.70	5.26*	1.88
	(3.26)		(3.25)	(3.99)	(6.07)	(3.13)	(6.14)
Share 30–34	0.50		0.53	-0.20	-2.22	0.63	-1.88
	(3.94)		(3.96)	(4.62)	(5.29)	(3.93)	(5.41)
Share 35–39	4.45		4.45	4.25	1.23	4.46	1.41
	(2.84)		(2.84)	(4.24)	(6.31)	(2.80)	(6.41)
Share 40–44	7.66*		7.60*	6.65	4.25	7.39*	3.99
	(3.90)		(3.89)	(4.54)	(6.70)	(3.77)	(6.71)
Share 45–49	3.66		3.55	2.95	-6.74	3.22	-6.71
	(3.94)		(3.95)	(5.89)	(7.94)	(3.91)	(8.04)
Share 55–59	-0.84		-0.67	-1.37	-7.54	-0.17	-7.34
	(5.22)		(5.19)	(7.04)	(10.07)	(4.95)	(10.20)
Share 60–64	1.76		2.04	1.21	-2.17	2.87	-1.75
	(6.15)		(6.13)	(7.46)	(11.31)	(5.81)	(11.26)
Share 65+	9.94		9.91	9.45	14.80	9.84*	17.70
	(6.26)		(6.22)	(6.43)	(13.30)	(5.97)	(13.16)
Share high–skill		0.88	0.77	0.48	0.63	3.09**	3.05*
		(0.92)	(1.07)	(1.11)	(1.11)	(1.44)	(1.61)
Cohort shares (p–value)	0.07		0.07	0.24	0.66	0.11	0.66
Skill share (p–value)		0.34	0.47	0.66	0.57	0.03	0.06
First stage F–statistic					0.9	32.2	0.9
Hansen test (p–value)					—	0.50	0.53
Observations	549	549	549	528	545	545	545
R^2	0.70	0.69	0.70		0.69	0.70	0.69

Notes: This table reports results for demographic and human capital data by IIASA–VID (Lutz et al., 2007). The sample has been split with respect to the young–age dependency ratio. Panel (a) reports results for observations for which the young–age dependency ratio is above the median, Panel (b) for observations below the median. The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w. are measured in logarithms (coefficients unreported). Column (4) corrects for the dynamic–panel bias using the Bruno (2005) estimator. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) or high-skill shares are jointly different from zero are reported. Instruments are shifted age cohorts in Column (5); the lagged share of high skills of the edge of the working–age population in Column (6); and a combination of both in Column (7). See Figure A3 for an illustration. First stage F–statistic reports the first stage Kleibergen–Paap rk Wald F–statistic. Hansen test p–values refer to the robust overidentifying restriction test. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A22: Robustness: Labor Force Shares

	Demography	Skills	Demography & Skills	Bias Correction	Demography Instrumented	Skills Instrumented	Both Instrumented
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Labor Force Share < 20	-4.96***		-4.91***	-4.53***	-5.64***	-3.14*	-1.85
	(1.34)		(1.37)	(1.44)	(1.74)	(1.63)	(2.39)
Labor Force Share 20–24	-4.16***		-4.07***	-3.76***	-6.00***	-0.85	-3.96**
	(1.27)		(1.32)	(1.43)	(1.41)	(1.77)	(1.66)
Labor Force Share 25–29	-4.03***		-3.96***	-4.25**	-4.67***	-1.45	-2.10
	(1.34)		(1.38)	(1.70)	(1.60)	(1.65)	(2.10)
Labor Force Share 30–34	-4.28***		-4.21***	-4.05**	-7.13***	-1.79	-5.36**
	(1.51)		(1.52)	(1.69)	(1.83)	(1.81)	(2.31)
Labor Force Share 35–39	-5.54***		-5.48***	-5.49***	-5.68***	-3.50**	-4.43**
	(1.49)		(1.48)	(1.89)	(1.90)	(1.65)	(2.15)
Labor Force Share 40–44	-4.25***		-4.22***	-4.30**	-5.63***	-3.01**	-5.01***
	(1.38)		(1.39)	(1.67)	(1.64)	(1.42)	(1.93)
Labor Force Share 45–49	-4.60**		-4.57**	-4.62*	-6.59***	-3.70*	-5.49**
	(1.77)		(1.77)	(2.40)	(1.81)	(1.94)	(2.14)
Labor Force Share 55–59	-5.78***		-5.77***	-5.79**	-6.27***	-5.35***	-6.78***
	(1.88)		(1.89)	(2.52)	(1.92)	(2.01)	(2.11)
Labor Force Share 60–64	-6.93***		-6.92***	-7.68***	-9.28***	-6.71**	-10.16***
	(2.43)		(2.44)	(2.24)	(2.71)	(3.04)	(3.41)
Labor Force Share 65+	-2.00		-1.98	-1.28	-6.80	-1.57	-11.76*
	(2.12)		(2.13)	(1.98)	(4.74)	(3.16)	(6.69)
Share high–skill		0.85**	0.19	-0.29	0.08	6.99***	6.29**
		(0.33)	(0.66)	(0.59)	(0.69)	(2.54)	(2.93)
Output p.w. (t–1)	0.25***	0.50***	0.25***	0.41***	0.23***	0.18***	0.19***
	(0.05)	(0.05)	(0.05)	(0.04)	(0.06)	(0.06)	(0.07)
Capital p.w.	0.46***	0.33***	0.46***	0.42***	0.47***	0.46***	0.48***
	(0.06)	(0.04)	(0.06)	(0.03)	(0.06)	(0.06)	(0.06)
Cohort shares (p–value)	0.03		0.04	0.00	0.00	0.12	0.02
Skill share (p–value)		0.01	0.77	0.62	0.91	0.01	0.03
First stage F–statistic					2.8	10.9	1.1
Hansen test (p–value)					—	0.60	0.73
Countries	120	120	120	120	120	120	120
Observations	645	1,098	645	645	645	645	645
R^2	0.76	0.86	0.76		0.75	0.68	0.65

Notes: This table reports results for demographic data by International Labour Organization (2011) and human capital data by IIASA–VID (Lutz et al., 2007). The dependent variable is log output per worker. All regressions include country–specific fixed and time effects. Lagged output p.w. and capital p.w., measured in logarithms, are included as controls in all specifications. Column (4) corrects for the dynamic–panel bias using the Bruno (2005) estimator. The p–value for a Wald test whether coefficients of workforce shares (proxied by the working–age population) or high-skill shares are jointly different from zero are reported. Instruments are shifted age cohorts in Column (5); the lagged shares of high skills of cohorts at the edge of the working–age population in Column (6); and a combination of both in Column (7). See Figure A3 for an illustration. First stage F–statistic reports the first stage Kleibergen–Paap rk Wald F–statistic. Hansen test p–values refer to the robust overidentifying restriction test. Standard errors are clustered at the country–level. Asterisks indicate significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.