Demography, growth and robots in advanced and emerging economies

Matteo Lanzafame[§][ξ]

Abstract

This paper provides estimates of the impact of demographic change on labor productivity growth, relying on annual data over 1961-2018 for a panel of 90 advanced and emerging economies. We find that increases in both the young and old population shares have significantly negative effects on labor productivity growth, working via various channels—including physical and human capital accumulation. Splitting the analysis for advanced and emerging economies shows that population ageing has a greater effect on emerging economies than on advanced economies. Extending the benchmark model to include a proxy for the robotization of production, we find evidence indicating that automation reduces the negative effects of unfavorable demographic change—in particular, population aging—on labor productivity growth.

Keywords Demographic change; labor productivity; robots.

JEL Classifications C33, J11, O40.

[§] Economic Research and Regional Cooperation Department, Macroeconomic Division, Asian Development Bank, 6 ADB Avenue, Mandaluyong City 1550, Metro Manila, Philippines (email: mlanzafame@adb.org).

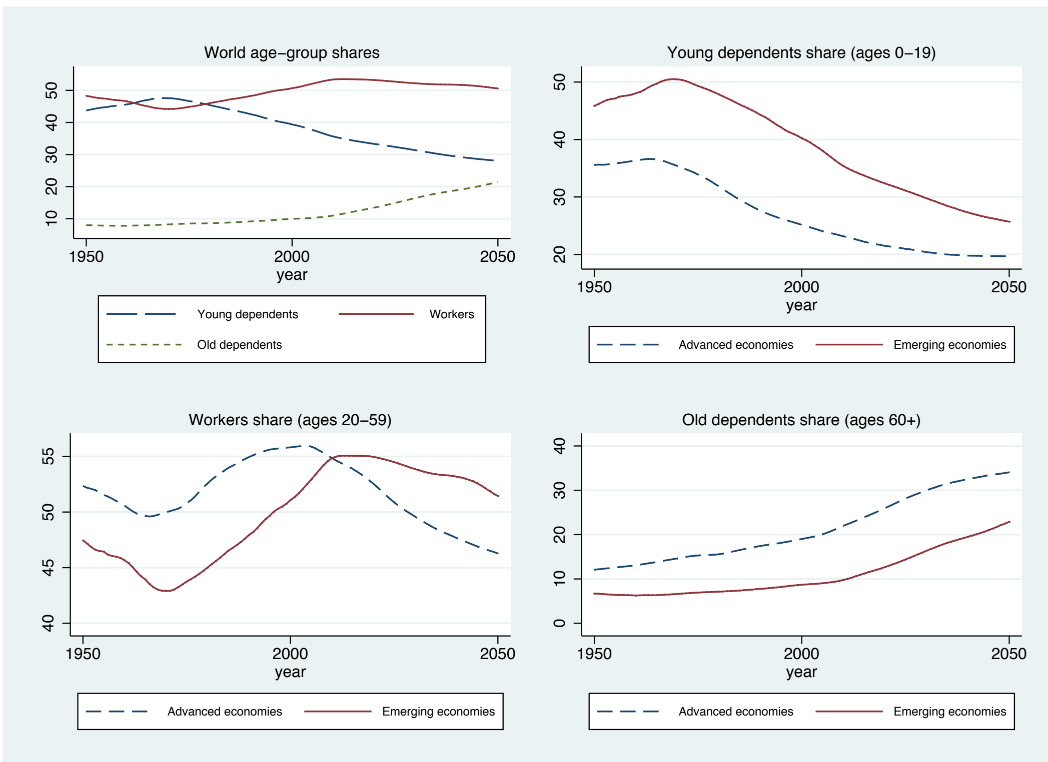
[ξ] This paper represents the views of the author and not necessarily those of the Asian Development Bank, its member countries, or its Executive Directors.

Demography, growth and robots in advanced and emerging economies

1. Introduction

This paper investigates the effects of demographic change on labor productivity growth. Demographic trends have often been highlighted in the literature as one of the main drivers of long-run growth and development. Focusing on emerging economies, several studies have illustrated how the positive effects of the demographic transition—particularly in terms of boosting population growth while reducing dependency ratios—have played a major role in Asia's remarkable growth performance over the last three decades (e.g. Bloom and Williamson, 1998). Similarly, predictions of a forthcoming African growth miracle are usually based on population projections indicating that many African countries could soon be enjoying a substantial demographic dividend, with high fertility rates and declining mortality leading to significant increases in working-age population and labor force growth (Bloom et al., 2017). Conversely, a number of contributions (e.g. Aksoy et al., 2019; Favero and Galasso, 2016) focus on the increasing 'demographic drag' affecting advanced economies, by exploring how and to what extent current demographic trends—and, in particular, population ageing—may be ushering in a new era of slow growth consistent with the so-called 'Secular Stagnation' hypothesis. Furthermore, this switch from growth-boosting factor to drag on the economy may also soon shape the economic impact of demographic change in many emerging economies, increasingly characterized by a gradual decline in fertility rates and rising life expectancy. Indeed, demographic projections from the United Nations (2019) are consistent with a scenario in which emerging economies follow the advanced along the path towards ageing and shrinking populations (Figure 1).

Figure 1. Demographic evolution in advanced and emerging economies



Notes: Data from United Nations (2019). Shares for advanced and emerging economies are weighted averages. Countries included in the advanced and emerging economies groups are reported in Table A.1 in the Appendix.

The economic challenges arising from population ageing are typically associated to increasing elderly dependency ratios, which jeopardize the sustainability of pension systems, put additional stress on the welfare state and social safety nets, and damage economic growth by reducing the number of people available for work.[1] The impact of this direct channel linking demography and growth can be conveniently illustrated by decomposing per-capita GDP (Y/P) through the following identity:

$$\frac{Y}{P} = \frac{Y}{E} \cdot \frac{E}{WAP} \cdot \frac{WAP}{P} \tag{1}$$

where Y is income, population is indicated with P, employment with E, and working-age population with WAP. Thus, per-capita GDP is expressed as the product of labor productivity (Y/E), the employment to working-age population ratio (E/WAP), and the share of working-age population (WAP/P). In growth-rate form, (1) can be specified as:

$$g_{pcy} = g_{lp} + g_{ew} + g_{wsh} \tag{2}$$

which shows that the growth rate of per-capita GDP (g_{pcy}) is equal to the sum of the growth rates of labor productivity (g_{lp}), the employment to working-age population ratio (g_{ew}) and the share of working-age population (g_{wsh}). Thus, for any given g_{lp} and g_{ew}, per-capita GDP growth will be faster the higher the growth rate of the share of working-age population. This is the direct channel via which the demographic transition, causing the growth rate of working-age population to outpace that of overall population, provided a boost to living standards first

[1] Several studies provide projections for the potential macroeconomic and fiscal effects of population aging (e.g., Cutler et al., 1990; Borsch-Supan, 2003; Vogel, Ludwig, and Börsch-Supan, 2013; National Research Council, 2012; Sheiner, 2014).

in advanced and then in emerging economies. As the demographic dividend gradually turns into a drag, this mechanism starts working in reverse: population ageing is reflected in a declining g_{wsh} and, all else constant, a falling g_{pcy}.

Demographic change, however, can affect growth performance in more ways than the rather mechanical direct effects working via g_{wsh}. Specifically, this impact may be exacerbated by a further negative effect generated by unfavorable demographics: namely, slower productivity growth. A shrinking working-age population can reduce productivity growth via various channels—including slower accumulation of physical capital, human capital and knowledge. Meanwhile, an increasing share of old workers can be expected to have a negative impact too as, beyond a certain age, workers' capabilities start decreasing. Similarly, to the extent that significant learning-by-doing and on-the-job experience are critical complements to education (e.g. Marconi, 2018), an increase in the share of young workers can also be expected to reduce aggregate productivity growth. While most of the early literature on the topic focuses on the direct channel linking demographics to output growth, the indirect channel working via labor productivity growth is arguably more important. Indeed, since productivity growth is the ultimate engine of economic growth in the long-run, the indirect-channel effects of demographic change can have a long-lasting impact in shaping the enhancement of living standards in advanced and emerging economies.

Policy reforms can help cushion the negative impact of an ageing population on g_{wsh}—for instance, by raising the normal retirement age, incentivizing greater labor force participation (e.g. by women), and relaxing constraints on migrant inflows. However, the key contribution to weakening the link between demographics and labor productivity growth can only come from the latter's main driver—that is, technological progress. In this respect, the increasing adoption of automation technologies in firms' production processes is particularly relevant. Robots can substitute for manual labor in specific tasks where automated machines are more productive than humans, thus complementing workers' skills in a variety of jobs and making workers more productive. As a result, greater robotization should be associated with a lower impact of ageing on labor productivity growth.

All of this raises several policy-relevant questions regarding the strength of the relationship between demographic change and the growth of living standards, the main channels underpinning it, and the role of automation technologies in offsetting the effects of unfavorable demographics on productivity growth.

This paper aims at exploring these issues, carrying out an empirical investigation of the relationship between demographic change and labor productivity growth. We rely on annual data over 1961-2018 for an unbalanced panel of 90 advanced and emerging economies. To control for endogeneity and capture the feedback effects between demographic change, labor productivity growth and its other determinants, we follow Aksoy et al. (2019) and adopt an estimation framework based on a Panel Vector Autoregressive model with exogenous regressors (PVARX). We find that labor productivity growth is significantly affected by demographic change, with increases in both young and old population shares having a negative impact. Splitting the analysis for advanced and emerging economies shows that population ageing has a smaller effect on the former than the latter—an outcome consistent with the view that advanced economies, which are further ahead in the demographic transition, have progressively adopted technologies to cushion the negative effects from ageing. Extending the benchmark model to consider whether automation—arguably the most important technological innovation in this context—is playing such a role supports this hypothesis. We find robust evidence that robots adoption reduces the negative impact of unfavorable demographic change—in particular, population aging—on labor productivity growth.

The remaining part of the paper is organized as follows. Section 2 provides a review of the literature on the relationship between demography and growth. Section 3 describes the data and the empirical approach adopted in the paper, while Section 4 presents and discusses the estimation results. Finally, Section 5 concludes.

2. Literature review

The impact of demographic change on economic growth and standards of living is the subject of a large empirical literature. Typically, studies select output growth or per-capita output growth as the dependent variable in a growth regression framework, aiming to isolate the demographic effects while controlling for other growth determinants (e.g. Aksoy et al. 2019; Bloom and Williamson, 1998; Bloom et al., 2000; Wei and Hao, 2010). These contributions provide fairly consistent evidence of statistically and economically significant effects of demographic change on economic growth. However, they also share a common drawback—that is, as the decomposition in (1) shows, focusing on output or per-capita output makes it difficult to disentangle the direct impact of demographic change on growth from its indirect effects working via labor productivity growth.

As mentioned, the indirect-channel demographic impact on productivity is arguably more significant, but its effects are also more complex. To the extent that different age groups are characterized by different productivity levels (e.g. because effort, physical and mental capabilities vary with age), the evolving demographic features of a population will influence aggregate labor productivity growth via compositional effects on the workforce. Additional forces can also work via various feedback channels. Standard life-cycle theory suggests that demographic change can affect labor productivity growth through a changing consumption-saving pattern. As consumption expenditure normally takes up a larger share of income after retirement, ageing populations can be expected to experience a declining private saving rate. Similarly, there is a large agreement on the negative effects of ageing on public savings, due to pensions and healthcare gradually taking up a larger share of government expenditure. All else constant, these adjustments will bring about lower investment and slower physical capital accumulation, with negative repercussions on productivity growth. Similarly, the economy-wide accumulation of human capital is likely to decline with population ageing, as a result of a shrinking share of individuals involved in acquiring education and/or updating their skills via training and learning-by-doing with on-the-job experience. Further negative feedback effects of ageing on productivity growth may be associated to slower knowledge production and innovation.

Overall, the empirical evidence on the relevance of these mechanisms is so far mixed. Lindh and Malmberg (1999) consider the impact of age structure on transitional growth in a convergence framework, using 5-year averaged panel data for OECD countries over 1950-1990. Their results point to robust demographic effects on the growth rate of GDP per worker, with a positive impact associated to the share of 50-64 year olds and negative effects for the 65-plus age-group. Relying on a panel dataset including 87 advanced and emerging economies, Feyrer (2007) finds that changes in the age structure of the workforce are significantly correlated with productivity growth. In particular, his estimates suggest that a 5% fall in the share of workers between the ages of 40 and 49 over a ten-year period is associated with an annual decline of l-2% in productivity. More recently, Maestas et al. (2016) study the relationship between aging and growth across US states, finding that a 10% growth in the share of population ages 60 and over decreases per-capita GDP growth by 5.5%—with two-thirds of the fall determined by a reduction in labor productivity growth, and only one-third by slowing labor force growth. In relation to the production of new ideas and the accumulation of knowledge in the economy, Jones's (2010) findings indicate that young and middle-aged cohorts boost innovation and, conversely, older cohorts slow it down. Similarly, relying on patent application data, Aksoy et al. (2019) show that population ageing has significantly negative effects on the rate of innovation. Focusing on the United States, Feyrer (2008) finds that the median age of innovators and managers who adopt new ideas (respectively, at about 48 and 40) remained fairly stable over 1975-95. Meanwhile, Karahan et al. (2019) link the continued decline in the US startup rate to demographic change. They note that this 'startup deficit' has significantly shifted the US firms' age distribution, which is a key determinant of aggregate productivity.

Contrasting results and evidence are provided, among others, by Cruz and Ahmed (2018). Based on five-year averaged data over 1950–2010 for a large country panel, estimations in this study fail to provide significant evidence that demographic change affects labor productivity—while indicating that the large impact of demographics on per-capita GDP growth is mostly due to changes in the child-dependency ratio. In line with Jones (2010) and

Feyrer (2008), Acemoglu et al. (2014) provide cross-country evidence of a causal impact of manager age on creative innovations—but find that this influence turns out to be small, once the effect of the sorting of young managers to firms that are more open to disruption is factored in.

Meanwhile, assessing the cross-country evidence of a negative link between population ageing and per-capita GDP growth, Acemoglu and Restrepo (2017) conclude that this relation is not statistically significant—suggesting that this outcome may be due to technological change, spurred by incentives to develop and adopt labor-saving innovations in aging societies. In a more recent contribution (Acemoglu and Restrepo, 2021), the same authors provide support for the hypothesis that population aging leads to greater (industrial) automation, as it creates a shortage of middle-aged workers specializing in manual production tasks. As a result, countries subject to more rapid population aging are also characterized by faster adoption of automation technologies. One implication of this is that the impact of demographic change may be different in advanced and emerging economies, since the former are typically further ahead in the transition towards older societies than the latter. As recognized by Acemoglu and Restrepo (2017), however, this evidence is not sufficient to establish a causal relationship between the adoption of robots and the absence of significant negative effects of population aging on economic growth.

In what follows, the possible differences between advanced and emerging economies, as well as the role played by automation, are investigated within the context of a comprehensive analysis of the relationship between demographic change and labor productivity growth.

3. Data and empirical methodology

Building on the empirical methodology adopted by Aksoy et al. (2019), this paper relies on annual data over 1961-2018 for a panel of 90 countries (35 advanced and 55 emerging economies) to investigate the effects of demographic change on labor productivity growth.[2] Our focus on labor productivity growth is a key departure from studies investigating the effects of changes in the population age structure on output growth. As mentioned, though providing valuable insights, studying empirically the link between demographics and GDP (or per-capita GDP) growth does not allow distinguishing properly between the effects of demographic change on working-age population growth and labor productivity growth. This blurs the picture of the link between demographics and growth performance.

The large panel dataset considered in our study provides several benefits. In particular, the time-series and cross-sectional dimension of the data helps in identifying the effects of the low-frequency demographic variation, as it allows exploiting the within-variation resulting from countries being in and progressing through different stages of the demographic transition over time (Aksoy et al., 2019). Moreover, the large dimension of the panel improves estimation efficiency and allows an assessment of the different impact of demographic change even when considering the subpanels of advanced and emerging economies.

We adopt a simple growth specification whereby, as well as demographic change, labor productivity growth (g_{lp}) depends on the growth of physical capital (k) and human capital (h) per worker, and the degree of knowledge intensity in the economy. To capture the latter, we rely on the Economic Complexity Index (eci) constructed by Hidalgo and Hausmann

[2] The list of countries included in our empirical analysis is reported in Table A.1 in the Appendix.

(2009), which measures the relative knowledge intensity of an economy by considering the knowledge intensity of the products it exports. As such, eci is a suitable proxy for countries' relative endowments of knowledge and, thus, their potential for technological innovation. Since it is available for a large number of emerging economies, relying on the eci index has the additional benefit of extending significantly the time-series dimension of our panel with respect to possible alternatives such as patent applications data. A similar advantage is granted by the expected human capital index (EHCI) constructed by Lim et al. (2018), which is employed to obtain h. The EHCI is defined for each birth cohort as the expected years lived from age 20 to 64 years and adjusted for educational attainment, learning or education quality, and functional health status, using rates specific to each time period, age, and sex. Lim et al. (2018) provide annual EHCI series for 195 countries over 1990-2016. The complete set of variable definitions and data sources is reported in Table A.2 in the Appendix.

Following Aksoy et al. (2019), demographic features are modeled relying on the shares (denoted d_{jit}) of the following age-groups: the young dependents aged 0-19 (d_{0-19}); the workers aged 20-59 (d_{20-59}); the old dependents aged 60 and over (d_{60+}). Population data were obtained from the World Population Prospects, the 2019 Revision (United Nations, 2019). Being largely determined by past fertility decisions, the demographic variables are characterized by very low frequency variation with respect to labor productivity growth and its other annual determinants. As such, the $d_{ijt}'s$ are assumed to be exogenous. To avoid perfect collinearity due to $\sum_{j=1}^{3} d_{jit} = 1$, the 20-59 age-group is excluded from the model. In such a setup, significant coefficients on the two included $d'_{ijt}s$ indicate that they are significantly different from the imposed zero coefficient on the 20-59 age group.

The PVARX model is, thus, specified as follows:

$$Y_{it} = Y_{it-1}A_1 + Y_{it-2}A_2 + \ldots Y_{it-p+1}A_{p-1} + Y_{it-p}A_p + D_{it}B + \mu_i + \varepsilon_{it} \tag{3}$$

where $i \in \{1,2,\ldots N\}$ indicates countries, $t \in \{1,2,\ldots T\}$ indicates time, Y_{it} is the (1×4) vector of endogenous variables (g_{lp}, k, h, eci), D_{it} indicates the (1×2) vector of exogenous age-group population shares (d_{0-19}, d_{60+}), μ_i and ε_{it} are (1×4) vectors of country fixed effects and idiosyncratic error terms, respectively. The (4×4) matrices $A_1 + A_2 + \ldots A_{p-1} + A_p$ and the (2×4) matrix B are the parameters to be estimated. The long-run equilibrium of the system is defined as follows:

$$Y_{it}^* = (I - A)^{-1}\mu_i + (I - A)^{-1}D_{it}B \tag{4}$$

and the long-run impact of the demographic variables is given by

$$B_{LR} = (I - A)^{-1}B \tag{5}$$

The long-run coefficients $b'_{ij}s$ in the matrix B_{LR} reflect both the direct influence of demographics on each variable in the system and their indirect impact, working via the feedback effects between the endogenous variables in the PVARX. The statistical significance of the $b'_{ij}s$ can be ascertained via non-linear Wald tests. Finally, the long-run impact of demographics on each variable in the system can be expressed as

$$Y_{it}^{B} = (I - A)^{-1} D_{it} B = D_{it} B_{LR} \tag{6}$$

Setting $p = 2$ to save degrees of freedom, optimal lag order selection in the PVARX model is carried out relying on the consistent model and moment selection criteria (MMSC) proposed by Andrews and Lu (2001), which are based on Hansen's (1982) J statistic of overidentifying restrictions.[3] Further, to avoid undue influence from outliers, we exclude from the analysis annual observations in which g_{lp} and/or k are higher than 20% in absolute value.[4]

We implement the PRVAX approach using the full panel of 90 countries as well as the subpanels of advanced and emerging economies, to explore the possible presence of heterogeneity between country groups. The latter may arise, for instance, if demographic trends have a smaller impact in emerging than in advanced economies, which are further ahead in the demographic transition towards ageing societies. However, to the extent that technological change and policy responses are endogenous, the opposite may also be true. That is, in line with the arguments proposed by Acemoglu and Restrepo (2017, 2021), the economic downsides of ageing may be less significant in advanced economies since these have

[3] Setting the lag order to 3 produces qualitatively equivalent results for the variables capturing demographics in the full-sample model. We also considered the inclusion of time effects in the model, but the MMSC selected the one-way fixed-effect specification as more appropriate.
[4] Estimations performed including the outliers provide qualitatively equivalent results, and are available upon request.

already adopted appropriate policy measures and technological innovations to cushion their impact. Moreover, independently of which view may be correct, it is also possible that the significant results produced by the full-panel estimates may be entirely driven by strong demographic effects in only one group of countries—thus producing misleading evidence.

4. Full-panel fixed effects and PVARX estimations

This section presents and discusses the empirical evidence on the effects of demographic change on labor productivity growth. For comparison purposes, relying on the bias-corrected least squares dummy variables (LSDVc) estimator developed by Kiviet (1995, 1999) and extended to unbalanced panels by Bruno (2005), we start by running fixed-effects regressions of the following dynamic panel data model:

$$g_{lp(i,t)} = \rho g_{lp(i,t-1)} + \beta_1 k_{(i,t-1)} + \beta_2 h_{(i,t-1)} + \beta_3 eci_{(i,t-1)} + \theta_1 d_{0-19(i,t)} + \theta_2 d_{60+(i,t)} + \mu_i + \varepsilon_{(i,t)} \tag{7}$$

where the variables treated as endogenous in the PVARX setup are lagged one period.

In line with expectations, the results in Table 1 indicate that a decline in the workers share of the population reduces labor productivity growth: both the 0-19 and the 60+ age-group shares enter with a negative sign in all specifications, with one exception for the young-dependents share in the advanced-economies estimation. However, the results provide evidence of only weak (in the full-panel specification) or no statistical significance for the 0-

19 age-group share, while the coefficient on the old-dependents share is not significant for the emerging-economies subpanel.

Table 1. LSDVc estimations: dependent variable $g_{lp(i,t)}$

	Full panel	Advanced Economies	Emerging Economies
Short-run coefficients			
$g_{lp(i,t-1)}$	0.420**	0.214**	0.464**
$k_{(i,t-1)}$	-0.249**	0.109**	-0.351**
$h_{(i,t-1)}$	0.211*	0.303	0.183
$eci_{(i,t-1)}$	-0.345	-0.613	-0.285
$d_{0-19(i,t)}$	-0.068^	0.075	-0.074
$d_{60+(i,t)}$	-0.214**	-0.115*	-0.135
Long-run coefficients			
	Full panel	Advanced Economies	Emerging Economies
$k_{(i,t-1)}$	-0.429**	0.139**	-0.655**
$h_{(i,t-1)}$	0.363*	0.385	0.341
$eci_{(i,t-1)}$	-0.595	-0.780	-0.532
$d_{0-19(i,t)}$	-0.117^	0.096	-0.138
$d_{60+(i,t)}$	-0.369**	-0.146*	-0.251
No. of observations	1914	746	1168
No. of countries	78	30	48
Average T	24.50	24.9	24.3

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level. Bootstrapped standard errors.

Though correcting for the well-known Nickel-bias (Nickel, 1981), the LSDVc approach does not take account of endogeneity issues and, relying on single-equation estimation, cannot capture the feedback effects between demographics, labor productivity growth and its other determinants. As such, the LSDVc estimator may not be well-suited for an assessment of the dynamic effects of demographics. Indeed, when the feedback channels stemming from demographic change are appropriately modeled in a PVARX framework, estimation results turn out to be substantially different.

Table 2 reports the full-panel results from estimation of the PVARX model. The main finding from the analysis is that the estimates are consistent with significant short- and long-term impacts of demographic change on labor productivity growth. In particular, the full-panel estimations indicate that for each percentage point increase in the share of the 0-19 age-group labor productivity growth falls by 0.255 percentage points in the long-run, while the same change in the 60+ age-group share has a negative long-run impact of -0.672 percentage points. These effects are larger than those associated with the corresponding short-run coefficients, owing to the significant feedback channels linking demographics to productivity growth. More specifically, the results indicate that both physical and human capital accumulation are significantly and negatively affected by a decline in the share of workers, while this is not the case for the Economic Complexity Index. Overall, the PVARX estimates appear to capture properly the long-term impact of demographic change—in particular, despite each element of the long-run coefficient matrix B_{LR} being a function of 18 parameters (matrix A and a column of matrix B), 6 out of 8 long-run demographic structure parameters turn out to be significant.

Table 2. PVARX estimations: full panel

	Short-run coefficients			
	g_{lp}	k	h	eci
$g_{lp(i,t-1)}$	0.376**	-0.082**	0.001	-0.003**
$k_{(i,t-1)}$	-0.282**	0.280**	-0.014*	0.002
$h_{(i,t-1)}$	0.255*	-0.047	0.875**	0.009*
$eci_{(i,t-1)}$	-3.092*	-3.904**	-0.052	0.941**
$d_{0-19(i,t)}$	-0.159**	-0.273**	-0.031**	0.001
$d_{60+(i,t)}$	-0.419**	-0.550**	-0.049**	0.004
	Long-run coefficients			
	g_{lp}	k	h	eci
$g_{lp(i,t-1)}$	-	-0.064**	0.002	-0.001*
$k_{(i,t-1)}$	-0.452**	-	-0.019*	0.000
$h_{(i,t-1)}$	0.408*	-0.037	-	0.002^
$eci_{(i,t-1)}$	-4.951*	-3.045**	-0.070	-
$d_{0-19(i,t)}$	-0.255**	-0.379**	-0.249*	0.014
$d_{60+(i,t)}$	-0.672**	-0.764**	-0.391**	0.063
No. of observations	1747	Lags	1	
No. of countries	76	GMM instruments	1/5	
Average T	22.99			

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level.

As for the remaining variables, human capital accumulation is found to have a significantly positive impact on labor productivity growth while, capturing cross-sectional variation in the panel, eci enters with a significantly negative coefficient—in line with the hypothesis that emerging economies, typically characterized by a lower level of economic complexity, tend to converge toward the labor productivity levels of advanced economies over time. The one puzzling result, consistent with the full-panel LSDVc estimates in Table 1, is that physical capital accumulation enters with a significantly negative sign in the g_{lp} equation. This is, however, in accordance with results in Aksoy et al. (2016) which provide evidence of a significantly negative impact of lagged investment on output growth.[5]

To sum up, the full-panel PVARX estimations provide robust support to the hypothesis that demographic change exerts significant effects on labor productivity growth and, more specifically, indicate that the impact of population ageing is strongly negative. As mentioned, however, these results may hide some heterogeneity between country groups which may affect the robustness of the estimates presented in Table 2. This issue is addressed in what follows, by carrying out separate PVARX estimations for advanced and emerging economies.

4.1 PVARX estimations for advanced and emerging economies

Table 3 and Table 4 report the PVARX estimates for, respectively, the subpanels of advanced and emerging economies.[6] The main outcome is that, as is the case for the full-panel results in Table 2, the 0-19 and 60+ age-group shares enter with a negative sign and turn out to have a

[5] As in Aksoy et al. (2016), we find a strong positive contemporaneous correlation between the g_{lp} and k residuals.

[6] The advanced-economies estimation includes the oil price as an additional exogenous regressor, since this turns out to be significant in the labor productivity growth equation.

statistically significant impact on labor productivity growth both for advanced and emerging economies.

Table 3. PVARX model: Advanced Economies

	Short-run coefficients			
	g_{lp}	k	h	eci
$g_{lp(i,t-1)}$	0.199*	-0.184**	-0.003	0.007**
$k_{(i,t-1)}$	0.100*	0.509**	0.002*	0.005**
$h_{(i,t-1)}$	0.937*	-0.803*	0.617**	0.058**
$eci_{(i,t-1)}$	-5.411*	-3.847^	-0.388	0.978**
$d_{0-19(i,t)}$	-0.584*	-0.269	-0.013	-0.017
$d_{60+(i,t)}$	-0.475*	-0.476*	-0.045	0.012
	Long-run coefficients			
	g_{lp}	k	h	eci
$g_{lp(i,t-1)}$	-	-0.204**	-0.053	0.001*
$k_{(i,t-1)}$	0.124^	-	0.034	0.001*
$h_{(i,t-1)}$	1.169*	-0.892*	-	0.009*
$eci_{(i,t-1)}$	-6.752*	-4.273^	-6.128	-
$d_{0-19(i,t)}$	-0.729*	-0.548	-0.034	-0.742
$d_{60+(i,t)}$	-0.593*	-0.969*	-0.118^	0.542
No. of observations	682	Lags	1	
No. of countries	30	GMM instruments	1/3	
Average T	22.73			

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level.

Table 4. PVARX model: Emerging Economies

	Short-run coefficients			
	g_{lp}	k	h	eci
$g_{lp(i,t-1)}$	0.461**	-0.043^	0.000	-0.004**
$k_{(i,t-1)}$	-0.466**	0.164**	-0.010	0.004^
$h_{(i,t-1)}$	0.027	0.173^	0.857**	0.009*
$eci_{(i,t-1)}$	-3.044^	-4.273**	-0.095	0.954**
$d_{0-19(i,t)}$	-0.256**	-0.361**	-0.039*	0.002
$d_{60+(i,t)}$	-0.733*	-0.920**	-0.125*	0.007
	Long-run coefficients			
	g_{lp}	k	h	eci
$g_{lp(i,t-1)}$	-	-0.029	0.000	-0.001*
$k_{(i,t-1)}$	-0.863**	-	-0.011	0.001
$h_{(i,t-1)}$	0.051	-0.117^	-	0.002
$eci_{(i,t-1)}$	-5.643	-2.915**	-0.098	-
$d_{0-19(i,t)}$	-0.475**	-0.432**	-0.276*	0.043
$d_{60+(i,t)}$	-1.358*	-1.102**	-0.870*	0.160
No. of observations	1062	Lags	1	
No. of countries	46	GMM instruments	1/4	
Average T	23.09			

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level.

Interestingly, the long-run coefficient on d_{60+} turns out to be appreciably smaller for the advanced-economies subpanel than in the case of emerging economies. This finding is consistent with the hypothesis put forward by Acemoglu and Restrepo (2017) and suggests that in advanced economies, which lie further ahead in the demographic transition, the adoption of automation technologies may have reduced the economic impact of aging—we explore this hypothesis more formally in the next section. Comparison of the results for the human capital equation in the PVARX model suggests that this is the main channel explaining the different impact of population ageing in the two country groups. Specifically, while in advanced economies a one percentage point increase in the old-dependents share lowers h by 0.12 percentage points in the long-run (and the relevant coefficient is significant only at the 10% level), the associated effect is a fall of 0.87 percentage points in the case of emerging economies. Meanwhile, the impact of d_{60+} on physical capital accumulation turns out to be of a similar magnitude in advanced and emerging economies and, as for the full panel results, there is no evidence of a statistically significant effect on eci. Taken at face value, these results suggest that economies where population ageing is more advanced appear to have dealt with the associated negative effects on productivity primarily by softening the impact on human capital accumulation.

Contrary to d_{60+}, the long-run coefficient estimate on d_{0-19} is smaller in the emerging-economies regression than it is for advanced economies—and in this case, differently-sized feedback effects on both physical and human capital accumulation appear to play a role. This result is consistent with employment rates for the population in ages 0-19 being higher in emerging economies than in advanced economies, where a larger share of young dependents are involved in education and, as a result, either do not work or have occupations with lower productivity than the average employee in the workers age-group. As such, a one percent rise in d_{0-19} has a larger impact on aggregate labor productivity in advanced economies.

Focusing on the labor productivity growth equation, it can also be noted that the coefficient on physical capital turns out to be significant and positive for the advanced-economies subpanel, while it remains negative in the case of emerging economies—thus suggesting that the puzzling finding noted for the full-panel estimations is entirely driven by the emerging-economies subpanel. Moreover, while entering with the expected signs in both estimations, eci and h turn out to be significant only for advanced economies—an outcome in line with the hypothesis that knowledge and human capital accumulation play a more prominent role as engines of growth in the latter group of countries than in emerging economies.

Overall, while reinforcing the view that demographic change has significant effects on labor productivity growth, the PVARX estimations for the subpanels of advanced and emerging economies also suggest that the relative importance of the various channels underpinning this relationship is different across these two country groups.

4.2 The role of robots

In this section, we explore formally the hypothesis that the adoption of automation technologies reduces the negative impact of aging and, more generally, unfavorable demographic change on labor productivity growth. Our approach relies on the use of a proxy for the degree of automation, based on the number of industrial robots per one thousand employees and denoted $robs_{(i,t)}$, which we use to extend the benchmark PVARX model specification.[7] To construct $robs_{(i,t)}$ for 63 economies in our panel over 1993-2015, we rely on annual data on industrial robots obtained from the International Federation of Robotics (IFR). The IFR's estimates of robot stocks are based on the somewhat unconventional assumption that the service life of a robot is exactly 12 years.[8] Thus, following Graetz and Michaels (2018), we make use of an alternative measure of annual robot stocks. This is constructed using IRF data on robot deliveries and the perpetual inventory method, assuming an annual depreciation rate of 10% and setting the initial robot stock measure as equal to the corresponding estimate provided by the IFR. We conduct robustness checks on our estimates assuming a depreciation rate of 5%, as well as relying on the measure of robot stocks based on the IRF method—the results, reported in tables A.3 and A.4 in the Appendix, remain robust.

The PVARX model is extended by introducing the following additional regressors: $robs_{(i,t)}$, which is treated as endogenous; the interaction terms between $robs_{(i,t-1)}$ and the two demographic shares, denoted $robs_{(i,t-1)}\_d_{0-19(i,t)}$ and $robs_{(i,t-1)}\_d_{60+(i,t)}$. The interaction terms are treated as exogenous in the PVARX setup, since they result from the product of a predetermined variable and an exogenous variable, while $robs_{(i,t-1)}$, $d_{0-19(i,t)}$ and $d_{60+(i,t)}$ are all controlled for in the PVARX model specification. This ensures that $d_{0-19(i,t)}$ and $d_{60+(i,t)}$ are independent of $robs_{(i,t-1)}$ as well as potentially omitted variables,

[7] The methodology follows Graetz and Michaels (2018), who indicate that this quantity-based approach is more reliable than attempting to measure "robot services", owing to the high level of aggregation of the robot price data.
[8] This implies that the depreciation rate goes from 0 over the first 12 years of service use to 100% on the first day of the 13th year.

so that estimates of the coefficients on the interaction terms will be consistent (Nizalova and Murtazashvili, 2016).

To illustrate how this model extension changes the interpretation of the results, consider the PVARX specification for the $g_{lp(i,t)}$ equation with a lag order of 1:

$$g_{lp(i,t)} = \rho g_{lp(i,t-1)} + \beta_1 k_{(i,t-1)} + \beta_2 h_{(i,t-1)} + \beta_3 eci_{(i,t-1)} + \beta_4 robs_{(i,t-1)} +$$

$$\theta_1 d_{0-19(i,t)} + \theta_2 d_{60+(i,t)} + \varphi_1 robs_{(i,t-1)_{d_{0-19(i,t)}}} + \varphi_2 robs_{(i,t-1)_{d_{60+(i,t)}}} + \mu_i + \varepsilon_{(i,t)} \quad (8)$$

The overall impact of demographic change now depends on the degree of automation. Specifically, the short-run effects on $g_{lp(i,t)}$ of changes in the young and old population shares are given by, respectively, $\theta_1 + \varphi_1 \cdot robs_{(i,t-1)}$ and $\theta_2 + \varphi_2 \cdot robs_{(i,t-1)}$. That is, for given estimates of the relevant parameters, the impact of demographics will change with a varying degree of automation, as proxied by $robs_{(i,t-1)}$. The long-run coefficients can be obtained as usual, relying on estimates of the autoregressive parameter ρ. That is, the long-run impact of changes in the young and old population shares are given by, respectively: $\theta_1^{LR} + \varphi_1^{LR} \cdot robs_{(i,t-1)}$, where $\theta_1^{LR} = \theta_1/(1-\rho)$ and $\varphi_1^{LR} = \varphi_1/(1-\rho)$; $\theta_2^{LR} + \varphi_2^{LR} \cdot robs_{(i,t-1)}$, where $\theta_2^{LR} = \theta_2/(1-\rho)$ and $\varphi_2^{LR} = \varphi_2/(1-\rho)$.

Estimates from the extended PVARX model are reported in Tables 5.A and 5.B, where we focus solely on the short- and long-run effects of demographic change and automation.[9]

[9] A full set of results is available upon request. For ease of exposition, rather than variable names as in the previous tables, the first column on the left in Table 5 refers to the relevant parameter definitions.

Table 5.A. PVARX estimations, extended model: full panel, short-run estimates

	Short-run estimates				
	g_{lp}	k	h	eci	$robs$
θ_1	-0.607**	-0.701**	0.016	0.050	-0.008^
φ_1	0.064	0.035	0.001	-0.009*	-0.016
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN}$	-0.486*	-0.635**	0.018	-0.012	-0.038^
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_ADV}$	-0.405	-0.590*	0.019	-0.023^	-0.059^
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_EME}$	-0.586**	-0.690**	0.016	0.002	-0.013^
$robs_{(i,t)}^{5\%\,CUTOFF}$	2.02	3.75	-	6.05	-
θ_2	-1.669**	-1.772**	0.018	0.029	-0.019
φ_2	0.097^	0.064	-0.001	-0.005*	-0.004
$\theta_2 + \varphi_2 \cdot robs_{(i,t)}^{MEAN}$	-1.486**	-1.650**	0.015	0.019	-0.026
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_ADV}$	-1.364**	-1.570**	0.014	0.012	-0.030
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_EME}$	-1.638**	-1.752**	0.017	0.028^	-0.020
$robs_{(i,t)}^{5\%\,CUTOFF}$	7.80	12.96	-	16.21	-

No. of observations	1173	Lags	1
No. of countries	58	GMM instruments	2/3
Average T	20.22		

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level; $robs_{(i,t)}^{MEAN}$ is the mean value of $robs_{(i,t)}$ in 2015, equal to 1.89; $robs_{(i,t)}^{MEAN\_ADV}$ is the mean value of $robs_{(i,t)}$ in 2015 for advanced economies, equal to 3.16; $robs_{(i,t)}^{MEAN\_EME}$ is the mean value of $robs_{(i,t)}$ in 2015 for emerging economies, equal to 0.32; $robs_{(i,t)}^{5\%\,CUTOFF}$ indicates the cutoff level of $robs_{(i,t)}$ for which the relevant estimates become not significant at the 5% level; $robs_{(i,t)}$ constructed assuming a 10% depreciation rate for the stock of robots.

Table 5.B. PVARX estimations, extended model: full panel, long-run estimates

Long-run estimates					
	g_{lp}	k	h	eci	$robs$
θ_1^{LR}	-0.596**	-0.505**	0.155	0.018	0.014^
φ_1^{LR}	0.063	0.025	0.010	-0.031*	0.029**
$\theta_1^{LR} + \varphi_1^{LR} \cdot robs_{(i,t)}^{MEAN}$	-0.477*	-0.457**	0.174	-0.041^	0.070**
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_ADV}$	-0.398	-0.425*	0.187	-0.080*	0.107**
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_EME}$	-0.576**	-0.497**	0.158	0.008	0.023**
$robs_{(i,t)}^{5\%\,CUTOFF}$	2.38	3.93	-	-	0.05
θ_2^{LR}	-1.638**	-1.276**	0.170	0.104	0.034
φ_2^{LR}	0.095*	0.046	-0.012	-0.019*	0.007
$\theta_2^{LR} + \varphi_2^{LR} \cdot robs_{(i,t)}^{MEAN}$	-1.459**	-1.189**	0.148	0.068	0.047*
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_ADV}$	-1.339**	-1.130**	0.133	0.044	0.055**
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_EME}$	-1.609**	-1.261**	0.166	0.098	0.036
$robs_{(i,t)}^{5\%\,CUTOFF}$	8.63	13.60	-	-	1.00
No. of observations	1173	Lags	1		
No. of countries	58	GMM instruments	2/3		
Average T	20.22				

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level; $robs_{(i,t)}^{MEAN}$ is the mean value of $robs_{(i,t)}$ in 2015, equal to 1.89; $robs_{(i,t)}^{MEAN\_ADV}$ is the mean value of $robs_{(i,t)}$ in 2015 for advanced economies, equal to 3.16; $robs_{(i,t)}^{MEAN\_EME}$ is the mean value of $robs_{(i,t)}$ in 2015 for emerging economies, equal to 0.32; $robs_{(i,t)}^{5\%\,CUTOFF}$ indicates the cutoff level of $robs_{(i,t)}$ for which the relevant estimates become not significant at the 5% level; $robs_{(i,t)}$ constructed assuming a 10% depreciation rate for the stock of robots.

Starting with the g_{lp} equation, we can see that the short- and long-run coefficient estimates on $d_{0-19(i,t)}$ and $d_{60+(i,t)}$ (i.e. $\theta_1, \theta_2, \theta_1^{LR}, \theta_2^{LR}$) are all negative and significant, as usual. However, the coefficient estimates on the interaction terms (i.e. $\varphi_1, \varphi_2, \varphi_1^{LR}, \varphi_2^{LR}$) turn out to be positive. This outcome is in line with the expectation that robot adoption reduces the impact of unfavorable demographic change on labor productivity growth. In particular, considering the effects of automation in relation to population ageing, the coefficient φ_2^{LR} indicates that each additional robot per one thousand employees boosts g_{lp} by about 0.1 percentage points in the long-run.

Table 6. Descriptive statistics for $\boldsymbol{robs_{(i,t)}}$ in 2015

	No. of observations	Mean	SD	P5	P50	P95
All economies	63	1.895	3.207	0.002	0.477	7.144
Advanced economies	35	3.157	3.857	0.023	2.274	13.883
Emerging economies	28	0.318	0.501	0.000	0.088	1.049

Notes: SD is the standard deviation; P5 is the 5th percentile; P50 is 50th percentile (median); P95 is the 95th percentile.

Since the impact of demographics changes with a varying degree of automation, it is useful to consider some examples. One convenient benchmark is given by the average degree of automation in our panel, which we measure as the mean number of industrial robots per one thousand employees in 2015—the last year with available data—which is defined as $robs_{(i,t)}^{MEAN}$ and equal to 1.89 (Table 6). As such, the estimate $\theta_1^{LR} + \varphi_1^{LR} \cdot robs_{(i,t)}^{MEAN}$ indicates that, for the average economy in our panel, a one percentage point increase in the share of the young population is associated with a 0.48 percentage-point fall in labor productivity growth in the long-run. At about -1.46 percentage points, the impact of ageing—measured by $\theta_2^{LR} + \varphi_2^{LR} \cdot robs_{(i,t)}^{MEAN}$—is about three times bigger, as well as strongly statistically significant. Note that the corresponding estimates are larger for emerging economies than for advanced economies. This is due to a significantly lower degree of automation characterizing the former: for emerging economies, the mean value of $robs_{(i,t)}$ in 2015—denoted $robs_{(i,t)}^{MEAN\_EME}$—was 0.32, and thus about one tenth of the equivalent statistic for advanced economies ($robs_{(i,t)}^{MEAN\_ADV} = 3.16$).

Given the above, a second example which provides useful insights addresses the following question: Since greater automation appears to reduce the negative effects of unfavorable demographic change on labor productivity growth, what is the value of $robs_{(i,t)}$ for which this impact becomes not statistically significant? In Table 5, this value is indicated by $robs_{(i,t)}^{5\%\,CUTOFF}$, where the level of statistical significance selected is 5%. Our findings suggest that, for the impact of ageing on g_{lp} to be not statistically significant, the number of robots per thousand employees must be 8.63 or higher—a threshold achieved by only 3 countries in our panel in 2015, i.e. Germany, Japan and Republic of Korea. For the share of young workers, the estimated $robs_{(i,t)}^{5\%\,CUTOFF}$ is equal to a much lower 2.38, a mark reached by 17 out of 63 economies in our panel in 2015. This is in line with the view that automation is substantially more valuable to ageing societies than to younger ones. One possible explanation is that robots are typically characterized by higher complementarity (substitutability) with older (younger) workers (Battisti and Gravina, 2021).

To sum up, the empirical analysis in this section provides qualified support to the hypothesis that automation reduces the negative impact of unfavorable demographic change—in particular, population aging—on labor productivity growth.

5. Conclusions

The relationship between demography and growth has for a long time been a topic of interest for economists. Departing from much of the literature, which focuses primarily of the direct channel linking demographic change to GDP or per-capita GDP growth via its effects on working-age population and labor force growth, this paper investigates the link between demographics and labor productivity growth.

The empirical analysis relies on a PVARX estimation framework, and data for a large panel of advanced and emerging economies over 1961-2018. We find robust evidence of demographic effects, with increases in both the young- and old population shares affecting negatively labor productivity growth. Disaggregating the analysis by country groups reveals interesting differences between advanced and emerging economies. In particular, the impact of ageing is lower in advanced economies, which are further along in the demographic transition towards older societies. This is in line with the view put forward by Acemoglu and Restrepo (2017, 2021), which suggests that the impact of population ageing in advanced economies may be less significant due to endogenous technological change leading to the adoption of labor-saving innovations. We further investigate this hypothesis, by extending the benchmark model to assess whether automation plays a role in cushioning the effects of demographic change. Our findings indicate that robot adoption significantly reduces the negative impact of aging and, more generally, unfavorable demographic change on labor productivity growth.

The evidence uncovered in this paper on the link between demographic change and productivity brings strong support to the notion that ageing societies will find it increasingly harder to improve living standards. In economies where demographic change is (or is projected to become) a drag on growth, policy should focus on how to boost the productivity of an ageing labor force, as this will be crucial to support living standards in the future. Our findings show that one way to achieve this objective is via greater automation of production processes, which can compensate for the negative impact of ageing on productivity growth.

References

Acemoglu D., Akcigitz, U., Celik, M.A. (2014). Young, Restless and Creative: Openness to Disruption and Creative Innovations. NBER Working Paper No. 19894

Acemoglu, D., Restrepo, P. (2017). Secular stagnation? The effect of ageing on economic growth in the age of automation. *American Economic Review: Papers & Proceedings*, 107, 174-179

Acemoglu, D., Restrepo, P. (2021). Demographics and automation. *Review of Economic Studies*, rdab031, https://doi.org/10.1093/restud/rdab031

Aksoy, Y., Basso, H.S., Smith, R.P., Grasl, T. (2016). Demographic structure and macroeconomic trends. CESifo Working Paper No. 5872

Aksoy, Y., Basso, H.S., Smith, R.P., Grasl, T. (2019). Demographic structure and macroeconomic trends. *American Economic Journal: Macroeconomics*, 11, 193-222

Andrews, D., Lu, B. (2001). Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models. *Journal of Econometrics*, 101, 123-164

Battisti, M., Gravina, A.F. (2021). Do robots complement or substitute for older workers? *Economics Letters*, 208, 110064

Bloom, D. E., Canning, D., Malaney, P. (2000). Population dynamics and economic growth in Asia. *Population and Development Review*, 26 (Supplement), 257– 90

Bloom, D. E., Kuhn, M., Prettner, K. (2017). Africa's prospects for enjoying a demographic dividend. *Journal of Demographic Economics*, 83, 63-76

Bloom, D. E., Williamson, J.G. (1998). Demographic transitions and economic miracles in emerging Asia. *The World Bank Economic Review*, 12, 419-455

Börsch-Supan, A. (2003). Labor market effects of population aging. *Labour*, 17, 5-44

Bruno, G.S.F. (2005). Approximating the bias of the LSDV estimator for dynamic unbalanced panel data models. *Economics Letters*, 87, 361-366

Cruz, M., Ahmed, S. (2018). On the impact of demographic change on economic growth and poverty. *World Development*, 105, 95-106

Cutler, D. M., Poterba, J. M., Sheiner, L. M., Summers, L. H., Akerlof, G. A. (1990). An aging society: opportunity or challenge? *Brookings Papers on Economic Activity*, 1-73

Favero, C.A., Galasso, V. (2016). Demographics and the Secular Stagnation Hypothesis in Europe. In *After the Crisis: Reform, Recovery, and Growth in Europe*, edited by F. Caselli, M. Centeno, J. Tavares, Oxford University Press

Feenstra, R.C., Inklaar, R., Timmer, M. P. (2015). The Next Generation of the Penn World Table. *American Economic Review*, 105, 3150-3182. Available for download at www.ggdc.net/pwt

Feyrer, J. (2007). Demographics and productivity. *The Review of Economics and Statistics*, 89, 100-109

Feyrer, J. (2008). Aggregate Evidence on the Link between Age Structure and Productivity. *Population and Development Review*, 34, 78-99

Graetz, G., Michaels, G. (2018). Robots at Work. *The Review of Economics and* Statistics, 100, 753–768

Hansen, L.P. (1982). Large Sample Properties of Generalized Method of Moments Estimators. *Econometrica*, 50, 1029-1054

Hidalgo, C., Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences of the United States of America*, 106, 10570-10575

International Monetary Fund (2021). *World Economic Outlook: Recovery during a Pandemic—Health Concerns, Supply Disruptions, Price Pressures*. Washington, DC, October.

Jones, B. (2010). Age and Great Invention. *The Review of Economics and Statistics*, 92, 1–14

Karahan, F., Pugsley, B., Sahin, A. (2019). Demographic Origins of the Startup Deficit. NBER Working Paper No. 25874

Kiviet, J.F. (1995). On Bias, Inconsistency and Efficiency of Various Estimators in Dynamic Panel Data Models. *Journal of Econometrics*, 68, 53-78

Kiviet, J.F. (1999). Expectation of Expansions for Estimators in a Dynamic Panel Data Model; Some Results for Weakly Exogenous Regressors. In: Hsiao, C., Lahiri, K., Lee, L.-F., Pesaran, M.H. (Eds.), *Analysis of Panel Data and Limited Dependent Variables*. Cambridge University Press, Cambridge.

Lim, S.S., Updike, R.L., Kaldjian, A.S., Barber, R.M., Cowling, K., York, H., Friedman, J., Xu, R., Whisnant, J.L., Taylor, H.J., Leever, A.T., Roman, Y., Bryant, M.F., Dieleman, J., Gakidou, E., Murray, C.J.L. (2018). Measuring human capital: a systematic analysis of 195 countries and territories, 1990–2016. *Lancet*, 392, 1217–34

Lindh, T., Malmberg, B. (1999). Age structure effects and growth in the OECD, 1950-1990. *Journal of Population Economics*, 12, 431-449

Maestas, N., Mullen, K.J., Powell, D. (2016). The effect of population ageing on economic growth, the labor force and productivity. NBER Working Paper No. 22452

Marconi, G. (2018). Education as a long-term investment: The decisive role of age in the education-growth relationship. *KYKLOS*, 71, 132-161

National Research Council of the National Academies (2012). *Aging and the Macroeconomy: Long-Term Implications of an Older Population*. Washington, D.C.: The National Academies Press

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, 49, 1417–1426

Nizalova, O., Murtazashvili, I. (2016). Exogenous treatment and endogenous factors: vanishing of omitted variable bias on the interaction term. *Journal of Econometric Methods*, 5, 71-77

Sheiner, L. (2014). The Determinants of the Macroeconomic Implications of Aging. *American Economic Review*, 104, 218-223

United Nations, Department of Economic and Social Affairs, Population Division (2019). *World Population Prospects 2019: Data Booket*. ST/ESA/SER. A/424.

Vogel, E., Ludwig, A., & Börsch-Supan, A. (2013). Aging and pension reform: extending the retirement age and human capital formation. NBER Working Paper No. 18856

Wei, Z., Hao, R. (2010). Demographic structure and economic growth: Evidence from China. *Journal of Comparative Economics*, 38, 472-491

Appendix

Table A.1. Country groups

Advanced Economies

Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, China, Iceland, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxembourg, Macao, China, Malta, Netherlands, New Zealand, Norway, Portugal, Puerto Rico, Republic of Korea, San Marino, Singapore, Slovenia, Slovakia, Spain, Sweden, Switzerland, Taipei,China, United Kingdom, United States.

Emerging Economies

Afghanistan, Algeria, Argentina, Armenia, Azerbaijan, Bangladesh, Bhutan, Brazil, Brunei, Bulgaria, Cambodia, Chile, Colombia, Côte d'Ivoire, Croatia, Dominican Republic, Ecuador, Egypt, El Salvador, Georgia, Hungary, India, Indonesia, Kazakhstan, Kyrgyz Republic, Laos, Lebanon, Malaysia, Maldives, Mexico, Mongolia, Morocco, Myanmar, Nepal, Nigeria, Pakistan, Panama, Peru, Philippines, People's Republic of China, Poland, Romania, Russia, South Africa, Sri Lanka, Tajikistan, Thailand, Tunisia, Turkey, Turkmenistan, Ukraine, Uruguay, Uzbekistan, Venezuela, Viet Nam.

Notes: Economies are defined as Advanced or Emerging following the World Economic Outlook classification (International Monetary Fund, 2021)

Table A.2. Variables and data sources

Variable	Definition	Source
g_{lp}	Percentage growth rate of labor productivity, constructed as real GDP per employee.	CEIC; Penn World Table 9.0, Feenstra *et al.* (2015).
k	Percentage growth rate of capital stock at current PPPs (in mil. 2011US$) per employee.	Penn World Table 9.0, Feenstra *et al.* (2015).
h	Percentage growth rate of the effective human capital index (EHCI).	Lim et al. (2018).
eci	Economic Complexity Index.	Observatory of Economic Complexity (https://oec.world).
d_{0-19}	Percentage of the population aged 0-19.	United Nations (2019).
d_{60+}	Percentage of the population aged 60 and over.	United Nations (2019).
$robs$	Number of industrial robots per one thousand employees.	International Federation of Robotics. World Robotics Statistics Database (accessed 23 March 2018).

Table A.3.A. PVARX estimations, extended model: full panel, short-run estimates. $\boldsymbol{robs_{(i,t)}}$ constructed assuming a 5% depreciation rate for robot stocks

	Short-run estimates				
	g_{lp}	k	h	eci	$robs$
θ_1	-0.586**	-0.695**	0.020	0.004	-0.003
φ_1	0.029	0.019	0.005	-0.008*	-0.004
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN}$	-0.511^	-0.646**	0.031	-0.018^	-0.014
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_ADV}$	-0.461	-0.613^	0.040	-0.033*	-0.021
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_EME}$	-0.575**	-0.688**	0.021	0.001	-0.004
$robs_{(i,t)}^{5\%\ CUTOFF}$	2.51	4.32	-	4.18	-
θ_2	-1.555**	-1.704**	0.018	0.029^	-0.008
φ_2	0.044	0.032	-0.001	-0.003*	-0.005^
$\theta_2 + \varphi_2 \cdot robs_{(i,t)}^{MEAN}$	-1.441**	-1.621**	0.016	0.022	-0.022
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_ADV}$	-1.363**	-1.564**	0.015	0.017	-0.031
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_EME}$	-1.538**	-1.692**	0.018	0.028^	-0.010
$robs_{(i,t)}^{5\%\ CUTOFF}$	12.98	21.41	-	-	-

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level; $robs_{(i,t)}^{MEAN}$ is the mean value of $robs_{(i,t)}$ in 2015, equal to 2.59; $robs_{(i,t)}^{MEAN\_ADV}$ is the mean value of $robs_{(i,t)}$ in 2015 for advanced economies, equal to 4.36; $robs_{(i,t)}^{MEAN\_EME}$ is the mean value of $robs_{(i,t)}$ in 2015 for emerging economies, equal to 0.38; $robs_{(i,t)}^{5\%\ CUTOFF}$ indicates the cutoff level of $robs_{(i,t)}$ for which the relevant estimates become not significant at the 5% level; $robs_{(i,t)}$ constructed assuming a 5% depreciation rate for the stock of robots.

Table A.3.B. PVARX estimations, extended model: full panel, long-run estimates. $\boldsymbol{robs_{(i,t)}}$ constructed assuming a 5% depreciation rate for robot stocks

Long-run estimates					
	g_{lp}	k	h	eci	$robs$
θ_1^{LR}	-0.581**	-0.481**	0.197	0.015	0.009
φ_1^{LR}	0.028	0.013	0.046	-0.029*	0.013
$\theta_1^{LR} + \varphi_1^{LR} \cdot robs_{(i,t)}^{MEAN}$	-0.507*	-0.448**	0.317	-0.061*	0.043
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_ADV}$	-0.457	-0.425*	0.399	-0.113*	0.067
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_EME}$	-0.570**	-0.476**	0.214	0.004	0.014
$robs_{(i,t)}^{5\%\ CUTOFF}$	2.95	4.67	-	1.85	-
θ_2^{LR}	-1.542**	-1.180**	0.184	0.102	0.026
φ_2^{LR}	0.044	0.022	-0.008	-0.010^	0.017**
$\theta_2^{LR} + \varphi_2^{LR} \cdot robs_{(i,t)}^{MEAN}$	-1.429**	-1.123**	0.162	0.077	0.070^
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_ADV}$	-1.351**	-1.084**	0.147	0.060	0.099**
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_EME}$	-1.525**	-1.172**	0.181	0.098	0.032
$robs_{(i,t)}^{5\%\ CUTOFF}$	14.81	22.71	-	-	2.69
No. of observations	1173	Lags	1		
No. of countries	58	GMM instruments	2/3		
Average T	20.22				

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level; $robs_{(i,t)}^{MEAN}$ is the mean value of $robs_{(i,t)}$ in 2015, equal to 2.59; $robs_{(i,t)}^{MEAN\_ADV}$ is the mean value of $robs_{(i,t)}$ in 2015 for advanced economies, equal to 4.36; $robs_{(i,t)}^{MEAN\_EME}$ is the mean value of $robs_{(i,t)}$ in 2015 for emerging economies, equal to 0.38; $robs_{(i,t)}^{5\%\ CUTOFF}$ indicates the cutoff level of $robs_{(i,t)}$ for which the relevant estimates become not significant at the 5% level; $robs_{(i,t)}$ constructed assuming a 5% depreciation rate for the stock of robots.

Table A.4.A. PVARX estimations, extended model: full panel, short-run estimates. $\boldsymbol{robs_{(i,t)}}$ constructed using IRF robot stock series

	Short-run estimates				
	g_{lp}	k	h	eci	$robs$
θ_1	-0.573**	-0.654**	0.021	0.005	0.004
φ_1	0.023	-0.008	0.015	-0.011*	0.003
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN}$	-0.514^	-0.674**	0.060	-0.023^	0.011
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_ADV}$	-0.475	-0.687^	0.085	-0.041*	0.016
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_EME}$	-0.562**	-0.657**	0.028	0.000	0.005
$robs_{(i,t)}^{5\%\,CUTOFF}$	2.06	3.62	-	3.52	-
θ_2	-1.454*	-1.544**	0.013	0.034^	0.009
φ_2	0.062	0.023	0.008	-0.007*	-0.005
$\theta_2 + \varphi_2 \cdot robs_{(i,t)}^{MEAN}$	-1.295**	-1.486**	0.034	0.017	-0.003
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_ADV}$	-1.190**	-1.448**	0.048	0.006	-0.011
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_EME}$	-1.426*	-1.534**	0.016	0.031^	0.007
$robs_{(i,t)}^{5\%\,CUTOFF}$	7.88	12.90	-	-	-
No. of observations	1173	Lags	1		
No. of countries	58	GMM instruments	2/3		
Average T	20.22				

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level; $robs_{(i,t)}^{MEAN}$ is the mean value of $robs_{(i,t)}$ in 2015, equal to 2.54; $robs_{(i,t)}^{MEAN\_ADV}$ is the mean value of $robs_{(i,t)}$ in 2015 for advanced economies, equal to 4.22; $robs_{(i,t)}^{MEAN\_EME}$ is the mean value of $robs_{(i,t)}$ in 2015 for emerging economies, equal to 0.44; $robs_{(i,t)}^{5\%\,CUTOFF}$ indicates the cutoff level of $robs_{(i,t)}$ for which the relevant estimates become not significant at the 5% level; $robs_{(i,t)}$ is constructed using the series for robot stocks provided by the IRF.

Table A.4.B. PVARX estimations, extended model: full panel, long-run estimates. $\boldsymbol{robs_{(i,t)}}$ constructed using IRF robot stock series

	Long-run estimates				
	g_{lp}	k	h	eci	$robs$
θ_1^{LR}	-0.584**	-0.452**	0.230	0.014	-0.023
φ_1^{LR}	0.024	-0.005	0.168	-0.031*	-0.018
$\theta_1^{LR} + \varphi_1^{LR} \cdot robs_{(i,t)}^{MEAN}$	-0.524^	-0.466**	0.657	-0.065**	-0.070
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_ADV}$	-0.485	-0.475^	0.940	-0.117**	-0.101
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_EME}$	-0.574**	-0.455**	0.305	0.000	-0.032
$robs_{(i,t)}^{5\%\,CUTOFF}$	2.26	4.19	-	1.57	-
θ_2^{LR}	-1.484**	-1.068**	0.141	0.096	-0.059
φ_2^{LR}	0.064	0.016	0.091	-0.019*	0.030
$\theta_2^{LR} + \varphi_2^{LR} \cdot robs_{(i,t)}^{MEAN}$	-1.322**	-1.028**	0.372	0.048	0.018
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_ADV}$	-1.215**	-1.002**	0.524	0.017	0.068
$\theta_1 + \varphi_1 \cdot robs_{(i,t)}^{MEAN\_EME}$	-1.456**	-1.061**	0.181	0.088	-0.046
$robs_{(i,t)}^{5\%\,CUTOFF}$	8.47	14.28	-	-	-
No. of observations	1173	Lags	1		
No. of countries	58	GMM instruments	2/3		
Average T	20.22				

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level; $robs_{(i,t)}^{MEAN}$ is the mean value of $robs_{(i,t)}$ in 2015, equal to 2.54; $robs_{(i,t)}^{MEAN\_ADV}$ is the mean value of $robs_{(i,t)}$ in 2015 for advanced economies, equal to 4.22; $robs_{(i,t)}^{MEAN\_EME}$ is the mean value of $robs_{(i,t)}$ in 2015 for emerging economies, equal to 0.44; $robs_{(i,t)}^{5\%\,CUTOFF}$ indicates the cutoff level of $robs_{(i,t)}$ for which the relevant estimates become not significant at the 5% level; $robs_{(i,t)}$ is constructed using the series for robot stocks provided by the IRF.