Demography, Growth, and Robots in Advanced and Emerging Economies

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This paper provides estimates of the impact of demographic change on labor productivity growth, relying on annual data during 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 aging 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 codes: C33, J11, O40

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I. Introduction

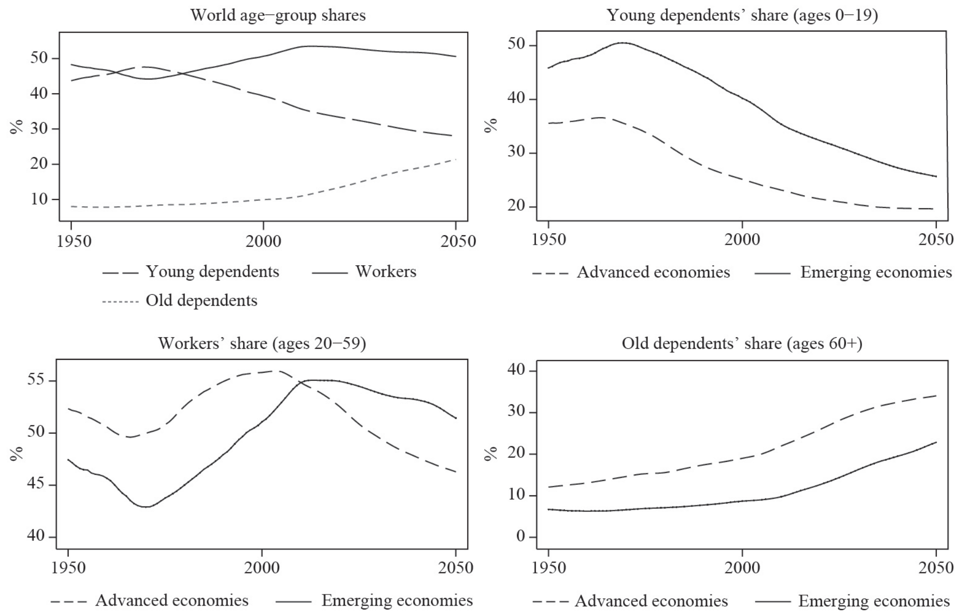
This paper investigates the effects of demographic change on labor productivity growth. Together with structural change, demographic trends have often been highlighted in the literature as one of the main drivers of long-run growth and development. Indeed, to a significant extent, the two themes are related. For instance, the life-cycle hypothesis suggests that one way the so-called "demographic dividend" can boost a country's growth rate is by raising aggregate savings and investment rates, as members of a growing and young labor force try to smooth consumption over time by saving part of their rising incomes. High savings and investment rates are key features of the "take-off" stage of structural transformation, which historically has coincided with industrialization. Similarly, changing consumption and investment patterns, as the population ages, are bound to affect the sectoral allocation of productive resources, which typically shift toward less productive services—such as health care and old-age care. Thus, these structural change channels are one of the reasons why demographic forces are believed to exert powerful effects on economic growth. The empirical evidence, however, is still mixed, partly because the link between demographic change and growth is rather complex.

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 3 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 the working-age population and labor force growth (Bloom, Kuhn, and Prettner 2017).

Conversely, a number of contributions (e.g., Favero and Galasso 2016, Aksoy et al. 2019) focus on the increasing "demographic drag" affecting advanced economies by exploring how population aging may be ushering in a new era of slow growth consistent with the so-called secular stagnation hypothesis. Furthermore, this switch from being a growth-boosting factor to a drag on the economy may soon shape the economic impact of demographic change in many emerging economies, which is increasingly characterized by a gradual decline in fertility rates and rising life expectancy.[1] Indeed, demographic projections from the United Nations, Department of

[1]On the association between population aging and growth in Asia, see, among others, ADB (2011); Park, Lee, and Mason (2012); Lee, Kim, and Park (2017); and Lee and Shin (2019).

Figure 1. **Demographic Evolution in Advanced and Emerging Economies**



Notes: Shares for advanced and emerging economies are weighted averages. Economies included in the advanced and emerging economies groups are reported in Table A1 in the Appendix.
Source: United Nations, Department of Economic and Social Affairs, Population Division (2019).

Economic and Social Affairs, Population Division (2019) are consistent with a scenario in which emerging economies follow the path toward aging and shrinking populations (Figure 1).

The economic challenges arising from population aging are typically associated with increasing old-age dependency ratios, which jeopardize the sustainability of pension systems, put additional stress on welfare states and social safety nets, and damage economic growth by reducing the number of people available for work.[2] The impact of this direct channel linking demography and growth can be conveniently illustrated by decomposing per capita gross domestic product (GDP), or (Y/P) in the following equation, through the following identity:

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

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

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

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

which shows that the growth rate of per capita GDP (g_{pcy}) equals the sum of the growth rates of labor productivity (g_{lp}), the ratio of employment to working-age population (g_{ew}), and the share of the working-age population (g_{wsh}). Thus, for any given g_{lp} and g_{ew}, per capita GDP will grow faster and the higher the growth rate of the working-age population. This is the direct channel via which the demographic transition—causing the growth rate of the working-age population to outpace that of the overall population—provided a boost to living standards, first in advanced and then in emerging economies. As the demographic dividend gradually turns into a drag, this mechanism starts working in reverse: Population aging is reflected in a declining g_{wsh} and, all else being constant, a falling g_{pcy}.

Unfavorable demographics, however, can affect growth in more ways than the rather mechanical direct effects working via g_{wsh}. Specifically, this impact may be exacerbated by a further negative effect: 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 older 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 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 aging 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 cushioning the negative effects of aging on labor productivity growth can only come from the latter's main driver—that is, technological progress.[3] 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 and making them more productive. As a result, greater robotization should be associated with a lower impact of aging 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 explores these issues. We contribute to the literature by producing novel findings based on an estimation framework that allows us to capture the causal effects of demographic change. We start by investigating empirically the relationship between demographic change and labor productivity growth, relying on annual data from 1961 to 2018 for an unbalanced panel of 90 advanced and emerging economies. The large time-series and cross-sectional dimensions of our panel allow controlling for endogeneity and capturing the feedback effects between demographic change, labor productivity growth, and its other determinants. To do so, we follow Aksoy et al. (2019) and use a panel vector autoregressive model with exogenous regressors (PVARX), which allows us to estimate the causal effects of demographics. We find that labor productivity growth is significantly affected by demographic change, with increases in both the young and old population shares having a negative impact. Next, we split the analysis to separately consider advanced and emerging economies as, on average, economies in these two groups are at significantly different stages of the demographic transition. Results show that population aging has a smaller effect in advanced economies. This outcome is consistent with the view that these economies, which are further ahead in the demographic transition, have progressively adopted technologies to cushion the negative impacts from aging. To complete the analysis, we consider whether automation—arguably the most important technological innovation in this context—is playing such a role. We find robust causal evidence that robot adoption reduces the negative impact of unfavorable demographic change—in particular, population aging—on labor productivity growth.

The remainder of the paper is organized as follows. Section II provides a review of the literature on the relationship between demography and growth. Section III describes

[3]Examples of the emerging literature examining the link between technology and population aging include ADB (2019) and Park, Shin, and Kikkawa (2022).

the data and empirical approach, while section IV presents and discusses the estimation results. Section V concludes.

II. 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., Bloom and Williamson 1998; Bloom, Canning, and Malaney 2000; Wei and Hao 2010; Aksoy et al. 2019). These contributions provide 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 equation (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, aging populations can be expected to experience a declining private savings rate. Similarly, there is a large agreement on the negative effects of aging on public savings, due to pensions and health care gradually taking up a larger share of government expenditure. All else being the same, these adjustments will reduce investment and slow physical capital accumulation, with negative repercussions on productivity growth. Similarly, the economy-wide accumulation of human capital is likely to decline with population aging, 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 effects of aging on productivity growth may be associated with a slower pace of 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 members of the Organization for Economic Co-operation and Development from 1950 to 1990. Their results point to robust demographic effects on the growth rate of GDP per worker, with a positive impact associated with the share of 50–64-year-olds and negative effects for those aged 65 and above. 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 10-year period is associated with an annual decline of l%–2% in productivity. More recently, Maestas, Mullen, and Powell (2016) studied the relationship between aging and growth across different states in the United States (US), finding that 10% growth in the share of the population aged 60 and above 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' (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 aging has significantly negative effects on the rate of innovation. Focusing on the US, Feyrer (2008) finds that the median age of innovators and managers who adopted new ideas remained fairly stable from 1975 to 1995 at about 48 years and 40 years, respectively. Meanwhile, Karahan, Pugsley, and Sahin (2019) link the continued decline in the US start-up rate to demographic change. They note that this "start-up deficit" has significantly shifted US firms' age distribution, which is a key determinant of aggregate productivity.

Contrasting results and evidence are provided by, among others, Cruz and Ahmed (2018). Based on 5-year averaged data during 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, Akcigitz, and Celik (2014) provide cross-country evidence of a causal impact of manager's 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 aging and per capita GDP growth, Acemoglu and Restrepo (2017) conclude that this relationship 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 2022), 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 a faster adoption of automation technologies. One implication of this is that the impact of demographic change may differ between advanced and emerging economies, since the former are typically further ahead in their transitions toward 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.

III. Data and Empirical Methodology

Building on the empirical methodology adopted by Aksoy et al. (2019), this paper relies on annual data during 1961–2018 for a panel of 90 economies (35 advanced and 55 emerging economies) to investigate the effects of demographic change on labor productivity growth.[4] 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 help in identifying

[4]The list of economies included in our empirical analysis is reported in Table A1 in the Appendix.

the effects of the low-frequency demographic variation, as it allows exploiting the within-variation resulting from economies 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 impacts 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 (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 economies' relative endowments of knowledge and, thus, their potential for technological innovation. Since it is available for many 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 ages 20–64 and adjusted for educational attainment, learning or education quality, and functional health status, using rates specific to each period, age, and sex. Lim et al. (2018) provide annual EHCI series for 195 economies during 1990–2016.[5]

Following Aksoy et al. (2019), demographic features are modeled relying on the shares (denoted d_{jit}) of the following age groups: (i) young dependents aged 0–19 (d_{0-19}), (ii) workers aged 20–59 (d_{20-59}), and old dependents aged 60 and over (d_{60+}). Population data were obtained from *World Population Prospects, the 2019 Revision* (United Nations, Department of Economic and Social Affairs, Population Division 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 $d'_{ijt}s$ is 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.

[5]The complete set of variable definitions and data sources is reported in Table A2 in the Appendix.

The PVARX model is, thus, specified as follows:

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

where $i \epsilon \{1, 2, \ldots, N\}$ indicates countries, $t \epsilon \{1, 2, \ldots, T\}$ indicates time, Y_{it} is the (1×4) vector of endogenous variables $(g_{\mathrm{lp}}, k, h, \mathrm{eci})$, D_{it} indicates the (1×2) vector of exogenous age-group population shares (d_{0-19}, d_{60+}), and μ_i and ε_{it} are (1×4) vectors of the country fixed effects and idiosyncratic error terms, respectively. The (4×4) matrices $A_1 + A_2 + \cdots + A_{p-1} + A_p$ 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

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

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 nonlinear Wald tests. Finally, the long-run impact of demographics on each variable in the system can be expressed as follows:

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

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 proposed by Andrews and Lu (2001), which are based on Hansen's (1982) J statistic of overidentifying restrictions.[6] 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.[7]

We implement the PVARX approach using the full panel of 90 economies, as well as the subpanels of advanced and emerging economies, to explore the possible presence of heterogeneity between economy groups. The latter may arise, for instance, if demographic trends have a smaller impact in emerging versus advanced economies,

[6]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 model and moment selection criteria identified the one-way, fixed effects specification as more appropriate.

[7]Estimations performed including the outliers provide qualitatively equivalent results and are available upon request.

which are further ahead in the demographic transition toward aging 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, 2022), the economic downsides of aging may be less significant in advanced economies since they have already adopted appropriate policy measures and technological innovations to cushion the impact. Moreover, independent 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 economies—thus producing misleading evidence.

IV. Full-Panel Fixed Effects and Panel Vector Autoregressive Model with Exogenous Regressors 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:

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

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

In line with expectations, the results in Table 1 indicate that a decline in the working-age 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.

Though correcting for the well-known Nickell bias (Nickell 1981), the LSDVc approach does not take account of endogeneity issues and, relying on a 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.

Table 1. **Least Squares Dummy Variables Estimations: Dependent Variable $g_{\mathrm{lp}(i,t)}$**

	Full Panel	**Advanced Economies**	**Emerging Economies**
		Short-Run Coefficients	
$g_{\mathrm{lp}(i,t-1)}$	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
$\mathrm{eci}_{(i,t-1)}$	−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	
$k_{(i,t-1)}$	−0.429***	0.139***	−0.655***
$h_{(i,t-1)}$	0.363**	0.385	0.341
$\mathrm{eci}_{(i,t-1)}$	−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
Number of observations	1,914	746	1,168
Number of economies	78	30	48
Average time (years)	24.50	24.90	24.30

d_{0-19} = percentage of the population aged 0–19, d_{60+} = percentage of the population aged 60 and over, eci = Economic Complexity Index, g_{lp} = percentage growth rate of labor productivity (constructed as real gross domestic product per employee), h = percentage growth rate of the Expected Human Capital Index, k = percentage growth rate of capital stock at current purchasing power parity ($ million in 2011 prices) per employee.
Notes: ***, **, and * indicate, respectively, significance at the 1%, 5%, and 10% levels. Bootstrapped standard errors.
Source: Authors' calculations.

Indeed, when the feedback channels stemming from demographic change are appropriately modeled in a PVARX framework, the estimation results turn out to be substantially different.

Table 2 reports the full-panel results from the 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 population 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. Specifically, the results indicate that both physical and human capital accumulations are significantly and negatively affected by a decline in the share of workers, while this is not the case for the eci. Overall, the PVARX estimates appear to capture properly the

Table 2. **Panel Vector Autoregressive Model with Exogenous Regressors Estimations: Full Panel**

	g_{lp}	k	h	eci
		Short-Run Coefficients		
$g_{\text{lp}(i,t-1)}$	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**
$\text{eci}_{(i,t-1)}$	−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		
$g_{\text{lp}(i,t-1)}$		−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*
$\text{eci}_{(i,t-1)}$	−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	1,747	Lags	1	
No. of economies	76	GMM instruments	1/5	
Average time (years)	22.99			

d_{0-19} = percentage of the population aged 0–19, d_{60+} = percentage of the population aged 60 and over, eci = Economic Complexity Index, g_{lp} = percentage growth rate of labor productivity (constructed as real gross domestic product per employee), GMM = generalized method of moments, h = percentage growth rate of the Expected Human Capital Index, k = percentage growth rate of the capital stock at current purchasing power parity ($ million in 2011 prices) per employee.
Notes: ***, **, and * indicate, respectively, significance at the 1%, 5%, and 10% levels. Standard errors are clustered by economy.
Source: Authors' calculations.

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), six out of eight long-run demographic structure parameters turn out to be significant.

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, which are 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 the results in Aksoy et al. (2016), which provide evidence of a significantly negative impact of lagged investment on output growth.[8]

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, specifically, indicate that the impact of population aging is strongly negative. As mentioned, however, these results may hide some heterogeneity between economy 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.

A. Panel Vector Autoregressive Model with Exogenous Regressors Estimations for Advanced and Emerging Economies

Tables 3 and 4 report the PVARX estimates for, respectively, the subpanels of advanced and emerging economies.[9] The main outcome is that, as is the case for the full-panel results in Table 2, both the 0–19 and the 60+ age-group shares enter with a negative sign and turn out to have a statistically significant impact on labor productivity growth both for advanced and emerging economies—albeit only at the 10% level for the 60+ age-group share in the case of emerging economies.

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 following section. A comparison of the results for the human capital equation in the PVARX model suggests that this is the main channel explaining the different impacts of population aging in the two economy groups. Specifically, while in advanced economies, a 1 percentage point increase in the old-dependents share lowers h by 0.12 percentage points in the long run and the relevant coefficient is not statistically significant, the associated effect is a statistically significant 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

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

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

Table 3. **Panel Vector Autoregressive Model with Exogenous Regressors Model: Advanced Economies**

	g_{lp}	k	h	eci
	Short-Run Coefficients			
$g_{lp(i,t-1)}$	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***
$\text{eci}_{(i,t-1)}$	−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			
$g_{lp(i,t-1)}$		−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**
$\text{eci}_{(i,t-1)}$	−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
Number of observations	682	Lags	1	
Number of economies	30	GMM instruments	1/3	
Average time (years)	22.73			

d_{0-19} = percentage of the population aged 0–19, d_{60+} = percentage of the population aged 60 and over, eci = Economic Complexity Index, g_{lp} = percentage growth rate of labor productivity (constructed as real gross domestic product per employee), GMM = generalized method of moments, h = percentage growth rate of the Expected Human Capital Index, k = percentage growth rate of capital stock at current purchasing power parity ($ million in 2011 prices) per employee.
Notes: ***, **, and * indicate, respectively, significance at the 1%, 5%, and 10% levels. Standard errors are clustered by economy.
Source: Authors' calculations.

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 in which population aging 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 aged 0–19 being higher in emerging economies than in advanced economies, where a larger share of young dependents is involved in education and, as a result, 0–19-year-olds either do not work or have occupations with lower productivity than the average

Table 4. **Panel Vector Autoregressive Model with Exogenous Regressors Model: Emerging Economies**

	g_{lp}	k	h	eci
		Short-Run Coefficients		
$g_{\text{lp}(i,t-1)}$	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**
$\text{eci}_{(i,t-1)}$	−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		
$g_{\text{lp}(i,t-1)}$		−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
$\text{eci}_{(i,t-1)}$	−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
Number of observations	1,062	Lags	1	
Number of economies	46	GMM instruments	1/4	
Average time (years)	23.09			

d_{0-19} = percentage of the population aged 0–19, d_{60+} = percentage of the population aged 60 and over, eci = Economic Complexity Index, g_{lp} = percentage growth rate of labor productivity (constructed as real gross domestic product per employee), GMM = generalized method of moments, h = percentage growth rate of the Expected Human Capital Index, k = percentage growth rate of capital stock at current purchasing power parity ($ million in 2011 prices) per employee.
Notes: ***, **, and * indicate, respectively, significance at the 1%, 5%, and 10% levels. Standard errors are clustered by economy.
Source: Authors' calculations.

employee in the workers' age group. As such, a 1% rise in d_{0-19} has a larger impact on aggregate labor productivity in advanced economies.

Focusing on the labor productivity growth equation, the coefficient on physical capital turns out to be positive (albeit not significant) for the advanced economies subpanel, while it remains negative and significant 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 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 economy groups.

B. 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 1,000 employees and denoted $\text{robs}_{(i,t)}$, which we use to extend the benchmark PVARX model specification.[10] To construct $\text{robs}_{(i,t)}$ for 63 economies in our panel during 1993–2015, we rely on annual data on industrial robots obtained from the International Federation of Robotics (IFR).[11] While the time-series for this extended-model analysis is shorter, 35 out of the 63 economies included are advanced economies and 28 are emerging economies, so that the panel we use remains balanced between and representative of the two economy groups. 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.[12] Thus, following Graetz and Michaels (2018), we make use of an alternative measure of annual robot stocks. This is constructed using IFR 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 IFR method—the results remain robust.[13]

The PVARX model is extended by introducing the following additional regressors: $\text{robs}_{(i,t)}$, which is treated as endogenous, and the interaction terms between $\text{robs}_{(i,t-1)}$ and the two demographic shares, denoted $\text{robs}_{(i,t-1)}\_d_{0-19(i,t)}$ and

[10]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.

[11]International Federation of Robotics. World Robotics Statistics Database. https://ifr.org/ (accessed 23 March 2018).

[12]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.

[13]To save space, these results are not included in the paper. They are available upon request.

$\text{robs}_{(i,t-1)}\_d_{60+(i,t)}$. 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 $\text{robs}_{(i,t-1)}$, $d_{0-19(i,t)}$, 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 $\text{robs}_{(i,t-1)}$, as well as potentially omitted variables, 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 $g_{\text{lp}(i,t)}$ equation with a lag order of 1:

$$\begin{aligned} g_{\text{lp}(i,t)} = {} & \rho g_{\text{lp}(i,t-1)} + \beta_1 k_{(i,t-1)} + \beta_2 h_{(i,t-1)} + \beta_3 \text{eci}_{(i,t-1)} + \beta_4 \text{robs}_{(i,t-1)} \\ & + \theta_1 d_{0-19(i,t)} + \theta_2 d_{60+(i,t)} + \varphi_1 \text{robs}_{(i,t-1)} d_{0-19(i,t)} \\ & + \varphi_2 \text{robs}_{(i,t-1)} d_{60+(i,t)} + \mu_i + \varepsilon_{(i,t)}. \end{aligned} \tag{8}$$

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

Estimates from the extended PVARX model are reported in Tables 5 and 6, where we focus solely on the short- and long-run effects of demographic change and automation, respectively.[14]

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., $\theta_1, \theta_2, \theta_1^{\text{LR}}, \theta_2^{\text{LR}}$) are all negative and significant, as usual. However, the coefficient estimates on the interaction terms (i.e., $\varphi_1, \varphi_2, \varphi_1^{\text{LR}}, \varphi_2^{\text{LR}}$) 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. Considering the effects of automation in relation to population aging, the coefficient φ_2^{LR} indicates that each additional robot per 1,000 employees boosts g_{lp} by about 0.1 percentage points in the long run.

Since the impacts of demographics change with a varying degree of automation, it is useful to consider some examples. One convenient benchmark is given by the

[14]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 Tables 5 and 6 refers to the relevant parameter definitions.

Table 5. **Panel Vector Autoregressive Model with Exogenous Regressors 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
$\theta_1 + \varphi_1 \cdot \text{robs}_{(i,t)}^{\text{MEAN}}$	−0.486	−0.635**	0.018	−0.012	−0.038*
$\theta_1 + \varphi_1 \cdot \text{robs}_{(i,t)}^{\text{MEAN\_ADV}}$	−0.405	−0.590**	0.019	−0.023*	−0.059***
$\theta_1 + \varphi_1 \cdot \text{robs}_{(i,t)}^{\text{MEAN\_EME}}$	−0.586**	−0.690***	0.016	0.002	−0.013*
$\text{robs}_{(i,t)}^{5\%\ \text{CUTOFF}}$	0.19	3.44		5.13	
θ_2	−1.669**	−1.772***	0.018	0.029	−0.019
φ_2	0.097*	0.064	−0.001	−0.005**	−0.004
$\theta_2 + \varphi_2 \cdot \text{robs}_{(i,t)}^{\text{MEAN}}$	−1.486*	−1.650***	0.015	0.019	−0.026
$\theta_2 + \varphi_2 \cdot \text{robs}_{(i,t)}^{\text{MEAN\_ADV}}$	−1.364**	−1.570***	0.014	0.012	−0.030
$\theta_2 + \varphi_2 \cdot \text{robs}_{(i,t)}^{\text{MEAN\_EME}}$	−1.638**	−1.752***	0.017	0.028	−0.020
$\text{robs}_{(i,t)}^{5\%\ \text{CUTOFF}}$	1.70	12.68		18.89	
Number of observations	1,173	Lags	1		
Number of economies	58	GMM instruments	2/3		
Average time (years)	20.22				

eci = Economic Complexity Index; g_{lp} = percentage growth rate of labor productivity, constructed as real gross domestic product per employee; GMM = generalized method of moments; h = percentage growth rate of the Expected Human Capital Index; k = percentage growth rate of capital stock at current purchasing power parity ($ million in 2011 prices) per employee; robs = number of industrial robots per 1,000 employees; $\text{robs}_{(i,t)}^{\text{MEAN}}$ = mean value of $\text{robs}_{(i,t)}$ in 2015, equal to 1.89; $\text{robs}_{(i,t)}^{\text{MEAN\_ADV}}$ = mean value of $\text{robs}_{(i,t)}$ in 2015 for advanced economies, equal to 3.16; $\text{robs}_{(i,t)}^{\text{MEAN\_EME}}$ = mean value of $\text{robs}_{(i,t)}$ in 2015 for emerging economies, equal to 0.32; $\text{robs}_{(i,t)}^{5\%\ \text{CUTOFF}}$ indicates the cutoff level of $\text{robs}_{(i,t)}$ for which the relevant estimates become not significant at the 5% level; $\text{robs}_{(i,t)}$ constructed assuming a 10% depreciation rate for the stock of robots.

Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered by economy.

Source: Authors' calculations.

average degree of automation in our panel, which we measure as the mean number of industrial robots per 1,000 employees in 2015—the last year with available data—which is defined as $\text{robs}_{(i,t)}^{\text{MEAN}}$ and equal to 1.89. As such, the estimate $\theta_1^{\text{LR}} + \varphi_1^{\text{LR}} \cdot \text{robs}_{(i,t)}^{\text{MEAN}}$ indicates that, for the average economy in our panel, a 1 percentage point increase in the share of the young population is associated with a 0.48 percentage points decline in labor productivity growth in the long run. At about −1.46 percentage points, the impact of aging—measured by $\theta_2^{\text{LR}} + \varphi_2^{\text{LR}} \cdot \text{robs}_{(i,t)}^{\text{MEAN}}$—is about three times bigger, as well as being strongly statistically significant. Note that

Table 6. **Panel Vector Autoregressive Model with Exogenous Regressors Estimations, Extended Model: Full Panel, Long-Run Estimates**

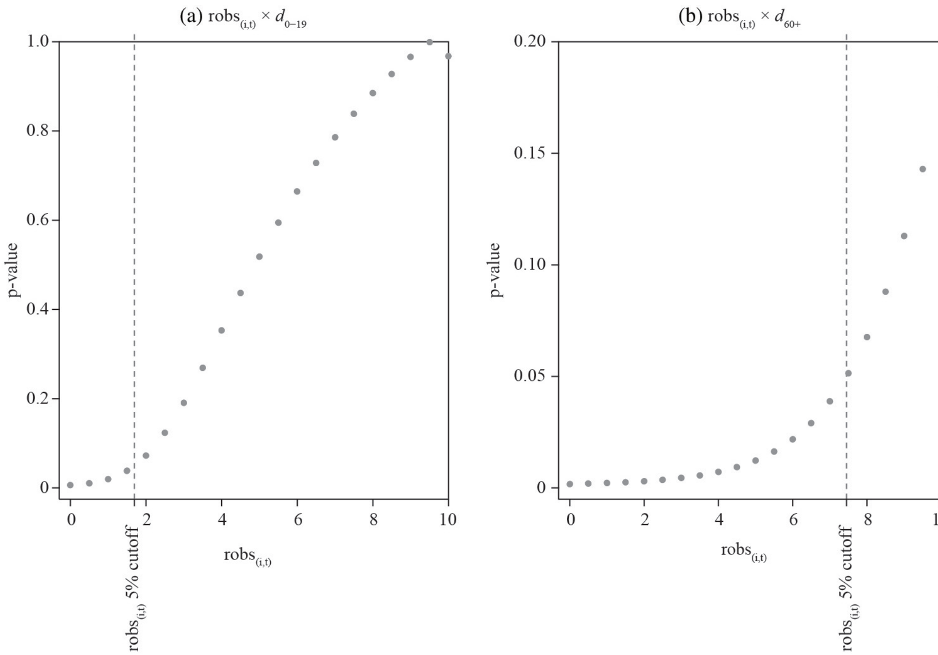
	Long-Run Estimates				
	g_{lp}	k	h	**eci**	**robs**
θ_1^{LR}	−0.596***	−0.505***	0.155	0.018	0.014
φ_1^{LR}	0.063	0.025	0.010	−0.031	0.029***
$\theta_1^{\text{LR}} + \varphi_1^{\text{LR}} \cdot \text{robs}_{(i,t)}^{\text{MEAN}}$	−0.477*	−0.457**	0.174	−0.041*	0.070***
$\theta_1 + \varphi_1 \cdot \text{robs}_{(i,t)}^{\text{MEAN\_ADV}}$	−0.398	−0.425**	0.187	−0.080**	0.107***
$\theta_1 + \varphi_1 \cdot \text{robs}_{(i,t)}^{\text{MEAN\_EME}}$	−0.576***	−0.497***	0.158	0.008	0.023*
$\text{robs}_{(i,t)}^{5\%\ \ \text{CUTOFF}}$	1.69	1.93			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*
$\theta_2^{\text{LR}} + \varphi_2^{\text{LR}} \cdot \text{robs}_{(i,t)}^{\text{MEAN}}$	−1.459***	−1.189***	0.148	0.068	0.047
$\theta_2 + \varphi_2 \cdot \text{robs}_{(i,t)}^{\text{MEAN\_ADV}}$	−1.339***	−1.130***	0.133	0.044	0.055
$\theta_2 + \varphi_2 \cdot \text{robs}_{(i,t)}^{\text{MEAN\_EME}}$	−1.609***	−1.261***	0.166	0.098	0.036
$\text{robs}_{(i,t)}^{5\%\ \ \text{CUTOFF}}$	7.45	8.20			1.00
Number of observations	1,173	Lags	1		
Number of economies	58	GMM instruments	2/3		
Average time (years)	20.22				

eci = Economic Complexity Index; g_{lp} = percentage growth rate of labor productivity, constructed as real gross domestic product per employee; GMM = generalized method of moments; h = percentage growth rate of the Expected Human Capital Index; k = percentage growth rate of capital stock at current purchasing power parity ($ million in 2011 prices) per employee; robs = number of industrial robots per 1,000 employees; $\text{robs}_{(i,t)}^{\text{MEAN}}$ = mean value of $\text{robs}_{(i,t)}$ in 2015, equal to 1.89; $\text{robs}_{(i,t)}^{\text{MEAN\_ADV}}$ = mean value of $\text{robs}_{(i,t)}$ in 2015 for advanced economies, equal to 3.16; $\text{robs}_{(i,t)}^{\text{MEAN\_EME}}$ = mean value of $\text{robs}_{(i,t)}$ in 2015 for emerging economies, equal to 0.32; $\text{robs}_{(i,t)}^{5\%\ \text{CUTOFF}}$ indicates the cutoff level of $\text{robs}_{(i,t)}$ for which the relevant estimates become not significant at the 5% level; $\text{robs}_{(i,t)}$ constructed assuming a 10% depreciation rate for the stock of robots.
Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered by economy.
Source: Authors' calculations.

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 $\text{robs}_{(i,t)}$ in 2015—denoted $\text{robs}_{(i,t)}^{\text{MEAN\_EME}}$—was 0.32, and thus about one-tenth of the equivalent statistic for advanced economies ($\text{robs}_{(i,t)}^{\text{MEAN\_ADV}}$= 3.16).

Given the above, a second example that 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

Figure 2. **Statistical Significance of the Long-Run Impact of Demographic Change on g_{lp} for Varying $robs_{(i,t)}$**



Notes: $robs_{(i,t)}$ = number of industrial robots per 1,000 employees, constructed assuming a 10% depreciation rate for the stock of robots. $robs^{5\%\ CUTOFF}_{(i,t)}$ indicates the cutoff level of $robs_{(i,t)}$ for which the relevant estimates become not significant at the 5% level.
Source: Authors' illustration.

$robs_{(i,t)}$ for which this impact is no longer statistically significant? In Tables 5 and 6, this value is indicated by $robs^{5\%\ CUTOFF}_{(i,t)}$, where the level of statistical significance selected is 5%. Our findings suggest that, for the impact of aging on g_{lp} to not be statistically significant in the long run, the number of robots per 1,000 employees must be 7.45 or higher—a threshold achieved by only three economies in our panel in 2015: Germany, Japan, and the Republic of Korea. For the share of young workers, the estimated $robs^{5\%\ CUTOFF}_{(i,t)}$ is equal to a much lower 1.69, a mark reached by 20 out of 63 economies in our panel in 2015.[15] Additionally, Figure 2 shows that the impact of aging on g_{lp} rapidly becomes less statistically significant only for values of $robs_{(i,t)}$ higher than 6. These findings are in line with the view that automation is substantially

[15]The 20 economies are Austria; Belgium; Czech Republic; Denmark; Finland; France; Germany; Hungary; Italy; Japan; the Republic of Korea; the Netherlands; Singapore; Slovakia; Spain; Sweden; Switzerland; Taipei,China; and the US.

more valuable to aging 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.

V. Conclusions

The relationship between demography and growth has long been a topic of interest for economists. Departing from much of the literature, which focuses primarily on 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 during 1961–2018. We find robust evidence of demographic effects, with increases in both the young and old population shares negatively affecting labor productivity growth. Disaggregating the analysis by economy groups reveals interesting differences between advanced and emerging economies. In particular, the impact of aging is lower in advanced economies, which are further along in the demographic transition toward having an older population. This is in line with the view put forward by Acemoglu and Restrepo (2017, 2022), which suggests that the impact of population aging in advanced economies may be less significant due to the adoption of labor-saving innovations. We 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 aging 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, policies should focus on how to boost the health capacity to work and the productivity of an aging labor force, as this will be crucial to support living standards in the future (e.g., Chen and Park 2024, Kikkawa et al. 2024). 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 aging on productivity growth.

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References

Acemoglu, Daron, Ufuk Akcigitz, and Murat Alp Celik. 2014. "Young, Restless and Creative: Openness to Disruption and Creative Innovations." NBER Working Paper No. 19894.

Acemoglu, Daron, and Pascual Restrepo. 2017. "Secular Stagnation? The Effect of Aging on Economic Growth in the Age of Automation." *American Economic Review: Papers & Proceedings* 107 (5): 174–79.

———. 2022. "Demographics and Automation." *The Review of Economic Studies* 89 (1): 1–44.

Aksoy, Yunus, Henrique S. Basso, Ron P. Smith, and Tobias Grasl. 2016. "Demographic Structure and Macroeconomic Trends." CESifo Working Paper No. 5872.

———. 2019. "Demographic Structure and Macroeconomic Trends." *American Economic Journal: Macroeconomics* 11 (1): 193–222.

Andrews, Donald W. K., and Biao Lu. 2001. "Consistent Model and Moment Selection Procedures for GMM Estimation with Application to Dynamic Panel Data Models." *Journal of Econometrics* 101 (1): 123–64.

Asian Development Bank (ADB). 2011. *Asian Development Outlook 2011 Update: Preparing for Demographic Transitions*. Manila.

———. 2019. *Asian Economic Integration Report 2019/2020: Demographic Change, Productivity, and the Role of Technology*. Manila.

Battisti, Michele, and Antonio Francesco Gravina. 2021. "Do Robots Complement or Substitute for Older Workers?" *Economics Letters* 208: 110064.

Bloom, David E., David Canning, and Pia N. Malaney. 2000. "Population Dynamics and Economic Growth in Asia." *Population and Development Review* 26: 257–90.

Bloom, David E., Michael Kuhn, and Klaus Prettner. 2017. "Africa's Prospects for Enjoying a Demographic Dividend." *Journal of Demographic Economics* 83 (1): 63–76.

Bloom, David E., and Jeffrey G. Williamson. 1998. "Demographic Transitions and Economic Miracles in Emerging Asia." *The World Bank Economic Review* 12 (3): 419–55.

Börsch-Supan, Axel. 2003. "Labor Market Effects of Population Aging." *Labour* 17: 5–44.

Bruno, Giovanni S. F. 2005. "Approximating the Bias of the LSDV Estimator for Dynamic Unbalanced Panel Data Models." *Economics Letters* 87 (3): 361–66.

CEIC. https://www.ceicdata.com/en (accessed 8 July 2019).

Chen, Zeyuan, and Albert Park. 2024. "Understanding the Health Capacity to Work among Older Persons in Rural and Urban People's Republic of China." *Asian Development Review* 41 (1): 39–67.

Cruz, Marcio, and S. Amer Ahmed. 2018. "On the Impact of Demographic Change on Economic Growth and Poverty." *World Development* 105: 95–106.

Cutler, David M., James M. Poterba, Louise M. Sheiner, and Lawrence H. Summers. 1990. "An Aging Society: Opportunity or Challenge?" *Brookings Papers on Economic Activity* 1990 (1): 1–73.

Favero, Carlo A., and Vincenzo Galasso. 2016. "Demographics and the Secular Stagnation Hypothesis in Europe." In *After the Crisis: Reform, Recovery, and Growth in Europe*, edited by Francesco Caselli, Mário Centeno, and José Tavares, 109–45. Oxford: Oxford University Press.

Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer. 2015. "The Next Generation of the Penn World Table." *American Economic Review* 105 (10): 3150–82.

Feyrer, James. 2007. "Demographics and Productivity." *The Review of Economics and Statistics* 89 (1): 100–109.

———. 2008. "Aggregate Evidence on the Link between Age Structure and Productivity." *Population and Development Review* 34: 78–99.

Graetz, Georg, and Guy Michaels. 2018. "Robots at Work." *The Review of Economics and Statistics* 100 (5): 753–68.

Hansen, Lars Peter. 1982. "Large Sample Properties of Generalized Method of Moments Estimators." *Econometrica* 50 (4): 1029–54.

Hidalgo, César, and Ricardo Hausmann. 2009. "The Building Blocks of Economic Complexity." *Proceedings of the National Academy of Sciences of the United States of America* 106 (26): 10570–75.

International Federation of Robotics. World Robotics Statistics Database. https://ifr.org/ (accessed 23 March 2018).

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

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

Karahan, Fatih, Benjamin Pugsley, and Aysegül Sahin. 2019. "Demographic Origins of the Startup Deficit." NBER Working Paper No. 25874.

Kikkawa, Aiko, Takashi Oshio, Yasuyuki Sawada, Satoshi Shimizutani, Naohiro Ogawa, Albert Park, and Tetsushi Sonobe. 2024. "Health Capacity to Work among Older Persons in Asia: Key Findings from a Regional Comparative Study." *Asian Development Review* 41 (1): 5–37.

Kiviet, Jan F. 1995. "On Bias, Inconsistency and Efficiency of Various Estimators in Dynamic Panel Data Models." *Journal of Econometrics* 68 (1): 53–78.

———. 1999. "Expectation of Expansions for Estimators in a Dynamic Panel Data Model; Some Results for Weakly Exogenous Regressors." In *Analysis of Panel Data and Limited Dependent Variables*, edited by Cheng Hsiao, Kajal Lahiri, Lung Fei Lee, and M. Hashem Pesaran, 199–225. Cambridge: Cambridge University Press.

Lee, Hyun Hoon, and Kwanho Shin. 2019. "Nonlinear Effects of Population Aging on Economic Growth." *Japan and the World Economy* 51: 100963.

Lee, Sang Hyop, Jungsuk Kim, and Donghyun Park. 2017. "Demographic Change and Fiscal Sustainability in Asia." *Social Indicators Research* 134: 287–322.

Lim, Stephen S., Rachel L. Updike, Alexander S. Kaldjian, Ryan M. Barber, Krycia Cowling, Hunter York, Joseph Friedman, R. Xu, Joanna L. Whisnant, Heather J. Taylor, Andrew T. Leever, Yesenia Roman, Miranda F. Bryant, Joseph Dieleman, Emmanuela Gakidou, and

Christopher J. L. Murray. 2018. "Measuring Human Capital: A Systematic Analysis of 195 Countries and Territories, 1990–2016." *Lancet* 392 (10154): 1217–34.

Lindh, Thomas, and Bo Malmberg. 1999. "Age Structure Effects and Growth in the OECD, 1950–1990." *Journal of Population Economics* 12 (3): 431–49

Maestas, Nicole, Kathleen J. Mullen, and David Powell. 2016. "The Effect of Population Aging on Economic Growth, the Labor Force and Productivity." NBER Working Paper No. 22452.

Marconi, Gabriele. 2018. "Education as a Long-Term Investment: The Decisive Role of Age in the Education–Growth Relationship." *KYKLOS* 71 (1): 132–61.

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

Nickell, Stephen. 1981. "Biases in Dynamic Models with Fixed Effects." *Econometrica* 49 (6): 1417–26.

Nizalova, Olena, and Irina Murtazashvili. 2016. "Exogenous Treatment and Endogenous Factors: Vanishing of Omitted Variable Bias on the Interaction Term." *Journal of Econometric Methods* 5 (1): 71–77.

Observatory of Economic Complexity. https://oec.world (accessed 8 July 2019).

Park, Cyn-Young, Kwanho Shin, and Aiko Kikkawa. 2022. "Demographic Change, Technological Advance, and Growth: A Cross-Country Analysis." *Economic Modelling* 108: 105742.

Park, Donghyun, Sang-Hyop Lee, and Andrew Mason, eds. 2012. *Aging, Economic Growth, and Old-Age Security in Asia*. Cheltenham: Edward Elgar Publishing.

Sheiner, Louise. 2014. "The Determinants of the Macroeconomic Implications of Aging." *American Economic Review* 104 (5): 218–23.

United Nations, Department of Economic and Social Affairs, Population Division. 2019. *World Population Prospects 2019, Online Edition. Rev 1*. New York.

Vogel, Edgar, Alexander Ludwig, and Axel Börsch-Supan. 2013. "Aging and Pension Reform: Extending the Retirement Age and Human Capital Formation." NBER Working Paper No. 18856.

Wei, Zheng, and Rui Hao. 2010. "Demographic Structure and Economic Growth: Evidence from China." *Journal of Comparative Economics* 38 (4): 472–91.

Appendix

Table A1. **Economy Groups**

Advanced Economies
Australia; Austria; Belgium; Canada; Cyprus; Czech Republic; Denmark; Estonia; Finland; France; Germany; Greece; Hong Kong, China; Iceland; Ireland; Israel; Italy; Japan; the Republic of Korea; Latvia; Lithuania; Luxembourg; Macau, China; Malta; Netherlands; New Zealand; Norway; Portugal; Puerto Rico; 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 Darussalam; Bulgaria; Cambodia; Chile; People's Republic of China; Colombia; Côte d'Ivoire; Croatia; Dominican Republic; Ecuador; Egypt; El Salvador; Georgia; Hungary; India; Indonesia; Kazakhstan; Kyrgyz Republic; Lao People's Democratic Republic; Lebanon; Malaysia; Maldives; Mexico; Mongolia; Morocco; Myanmar; Nepal; Nigeria; Pakistan; Panama; Peru; Philippines; Poland; Romania; Russian Federation; South Africa; Sri Lanka; Tajikistan; Thailand; Tunisia; Türkiye; Turkmenistan; Ukraine; Uruguay; Uzbekistan; Venezuela; Viet Nam.

Notes: All economies are defined as either advanced or emerging based on their classification in International Monetary Fund (2021).
Source: Authors' compilation.

Table A2. **Variable and Data Sources**

Variable	Definition	Source
g_{lp}	Percentage growth rate of labor productivity, constructed as real gross domestic product per employee	CEIC. https://www.ceicdata.com/en (accessed 8 July 2019); Penn World Table 9.0, Feenstra, Inklaar, and Timmer (2015)
k	Percentage growth rate of capital stock at current purchasing power parity ($ million in 2011 prices) per employee	Penn World Table 9.0, Feenstra, Inklaar, and Timmer (2015)
h	Percentage growth rate of the Expected Human Capital Index	Lim et al. (2018)
eci	Economic Complexity Index	Observatory of Economic Complexity. https://oec.world (accessed 8 July 2019).
d_{0-19}	Percentage of the population aged 0–19	United Nations, Department of Economic and Social Affairs, Population Division (2019)
d_{60+}	Percentage of the population aged 60 and over	United Nations, Department of Economic and Social Affairs, Population Division (2019)
robs	Number of industrial robots per 1,000 employees	International Federation of Robotics. World Robotics Statistics Database. https://ifr.org/ (accessed 23 March 2018).

Source: Authors' compilation.