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DEMOGRAPHY, GROWTH, AND ROBOTS IN ADVANCED AND EMERGING ECONOMIES

Antonio Francesco Gravina and Matteo Lanzafame

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Antonio Francesco Gravina
and Matteo Lanzafame

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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 significant 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

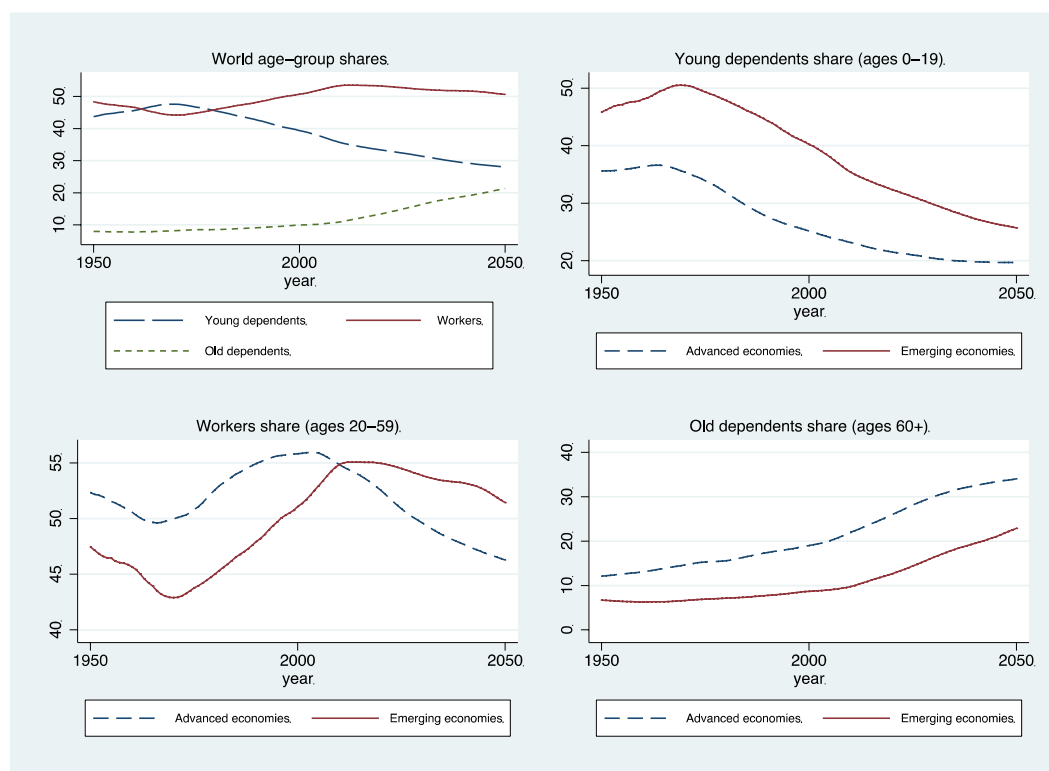
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INTRODUCTION

This paper investigates the effects of demographic change on labor productivity growth. Together with structural change, demographic trends are often highlighted as one of the main drivers of long-run growth and development. To a significant extent, demographic trends and productivity growth are related. For instance, the life-cycle hypothesis suggests that raising aggregate savings and investment rates is one way that the “demographic dividend” can boost an economy’s growth rate, as a growing young labor force tries 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, as populations age, the changes in consumption and investment patterns are bound to affect the sectoral allocation of productive resources, which typically shift toward less productive services such as health care and elderly care. These structural change channels are some of the reasons demographic forces are believed to exert powerful effects on economic growth. However, the empirical evidence is still mixed, partly because the link between demographic change and growth is rather complex.

Several studies focusing on emerging economies illustrate 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).

Figure 1: Demographic Evolution in Advanced and Emerging Economies



Note: Shares for advanced and emerging economies are weighted averages. Appendix Table A.1 shows the list of advanced and emerging economies.

Source: United Nations (2019).

Conversely, some contributions (e.g., Aksoy et al. 2019; Favero and Galasso 2016) focus on the increasing “demographic drag” affecting advanced economies. They explore how population aging may be ushering in a new era of slow growth consistent with the secular stagnation hypothesis. This switch from being a growth-boosting factor to a drag on the economy may also soon shape the economic impact of demographic change in many emerging economies, characterized by a gradual decline in fertility rates and an increase in life expectancy.¹ Demographic projections from the United Nations (2019) are consistent with a scenario in which emerging economies follow advanced economies along the path toward aging populations and shrinking populations (Figure 1).

¹ On the link between population aging and growth in Asia, see, among others, Asian Development Bank (2011), Lee and Shin (2019), Lee et al. (2017), and Park et al. (2012).

Economic challenges arising from population aging are typically associated with increasing elderly 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 illustrated by decomposing per capita gross domestic product or GDP (Y/P) through the following identity:

$$\frac{Y}{P} = \frac{Y}{E} \cdot \frac{E}{WAP} \cdot \frac{WAP}{P} \quad (1)$$

where Y indicates income, P population, E employment, and WAP working-age population. 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:

$$g_{pcy} = g_{lp} + g_{ew} + g_{wsh} \quad (2)$$

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 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} , the higher the working-age population growth rate, the faster per capita GDP grows. This is the direct channel through which the demographic transition—causing the working-age population growth rate to outpace the overall population growth rate—provided a boost to living standards, first in advanced economies 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, holding all else constant, a falling g_{pcy} .

Unfavorable demographics, however, can affect growth in more ways than the rather mechanical direct effects working via g_{wsh} . A shrinking working-age population can reduce productivity growth through various channels, including slower accumulation of physical capital, human capital, and knowledge. Meanwhile, an increasing share of older workers can also be expected to have a negative impact, with workers' capabilities decreasing as they age. Similarly,

² 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 Borsch-Supan 2013; National Research Council 2012; Sheiner 2014).

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. 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 on 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 mitigating the negative effects of aging can only come from technological progress, the main driver of labor productivity growth.³ In this respect, the increasing adoption of automation technologies in production processes is particularly relevant. Robots can substitute for manual labor in tasks where automated machines are more productive than humans, thus complementing workers' skills and increasing workers' productivity. As a result, greater robotization should be associated with a lower impact of aging on labor productivity growth.

All these matters raise 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 which allows us to capture the causal effects of demographic change. We start by empirically investigating the relationship between demographic change and labor productivity growth, relying on annual data over 1961–2018 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 and labor productivity growth (including its other determinants). To do so, we follow Aksoy et al. (2019) and use a Panel Vector Autoregressive model with exogenous

³ Examples of the emerging literature examining the link between technology and population aging include ADB (2019) and Park et al. (2022).

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 young and old population shares having a negative impact.

Next, we split the analysis to consider advanced and emerging economies separately as economies in these two groups are, on average, at significantly different stages of the demographic transition. Results show that population aging has a smaller effect in advanced economies, which are ahead in the demographic transition and have progressively adopted technologies to cushion the negative effects of population 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 robotization 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 2 provides a review of the literature on the relationship between demography and growth; Section 3 describes the data and empirical approach; Section 4 reports and discusses the estimation results; and Section 5 presents our conclusions.

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 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 via labor productivity growth.

The indirect-channel demographic impact on productivity is arguably more significant, but its effects are also more complex. To the extent that different productivity levels characterize different age groups (e.g., because effort and 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. Holding all else constant, these adjustments will bring about lower investment and slower physical capital accumulation, with negative repercussions on productivity growth. The economy-wide accumulation of human capital is also likely to decline with population aging as a result of fewer individuals involved in acquiring education and/or updating their skills through training and learning-by-doing with on-the-job experience. Other negative feedback effects of aging on productivity growth may be associated with slower knowledge production and innovation.

Overall, the empirical evidence on the relevance of these mechanisms is mixed. Lindh and Malmberg (1999) considered the impact of age structure on transitional growth in a convergence framework, using 5-year averaged panel data for Organisation for Economic Co-operation and Development (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 with the share of people aged 50–64 years and negative effects for the 65-plus age group. Relying on a panel dataset including 87 advanced and emerging economies, Feyrer (2007) found that changes in the age structure of the workforce are significantly correlated with productivity growth. 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 1%–2% in productivity. More recently, Maestas et al. (2016) studied the relationship between aging and growth across the United States and found 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' (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) found that population aging has significantly negative effects on the rate of innovation. Focusing on the United States, Feyrer (2008) found that the median age of innovators and managers who adopt new ideas remained fairly stable at 48 years for innovators and 40 years for managers over 1975–1995. Meanwhile, Karahan et al. (2019) linked the continued decline in the United States (US) startup rate to demographic change. They noted that the “startup deficit” has significantly shifted 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 5-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; instead, they indicate 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.

Assessing the cross-country evidence of a negative link between population aging and per-capita GDP growth, Acemoglu and Restrepo (2017) concluded that this relation is not statistically significant. They suggest that this outcome may be due to technological change, spurred by incentives to develop and adopt labor-saving innovations in aging societies. Acemoglu and Restrepo (2021) also provided 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, economies 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 advanced economies are typically further ahead of emerging economies in the transition toward older societies. Acemoglu and Restrepo (2017) acknowledged that 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.

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

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 economies (35 advanced economies 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. While it provides valuable insights, empirically studying the link between demographics and GDP (or per capita GDP) growth does not allow the effects of demographic change on working-age population growth to be properly distinguished from its effects on 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 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 degree of knowledge intensity, 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 has the additional benefit of significantly extending the time-series dimension of our panel with respect to possible alternatives such as patent applications data. The expected human capital index (EHCI) constructed by Lim et al. (2018), which is employed to obtain h , gives a similar advantage. 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,

⁴ The list of economies included in our empirical analysis is reported in Table A.1 in the Appendix.

using rates specific to each period, age, and sex. Lim et al. (2018) provide annual EHCI series for 195 economies over 1990–2016.⁵

Following Aksoy et al. (2019), demographic features are modeled relying on the shares (denoted d_{jit}) of the following age-groups: young dependents aged 0–19 (d_{0-19}); workers aged 20–59 (d_{20-59}); and old dependents aged 60 and over (d_{60+}). Population data were obtained from the 2019 revision of the *World Population Prospects* (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, 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 as follows:

$$Y_{it} = Y_{it-1}A_1 + Y_{it-2}A_2 + \dots + Y_{it-p+1}A_{p-1} + Y_{it-p}A_p + D_{it}B + \mu_i + \varepsilon_{it} \quad (3)$$

where $i \in \{1, 2, \dots, N\}$ indicates economies, $t \in \{1, 2, \dots, T\}$ 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 is (1×4) vectors of economy fixed effects, and ε_{it} is (1×4) vector of idiosyncratic error terms. The (4×4) matrixes $A_1 + A_2 + \dots + A_{p-1} + A_p$ and the (2×4) matrix B are the parameters to be estimated. The long-run equilibrium of the system is defined as follows:

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

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

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

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

⁵ The complete set of variable definitions and data sources is reported in Table A.2 in the Appendix.

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:

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

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.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. Heterogeneous effects of demographic change may arise, for instance, if demographic trends have a smaller impact in emerging economies than in advanced economies, as the latter are ahead in the demographic transition toward aging societies. However, to the extent that technological changes 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 aging may be less significant in advanced economies since these have already adopted appropriate policy measures and technological innovations to cushion their impact. 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 economies—thus producing misleading evidence.

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 MMSC selected the one-way fixed-effect specification as more appropriate.

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

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 which Kiviet (1995, 1999) developed and Bruno (2005) extended to unbalanced panels, we start by running fixed-effects regressions of the following dynamic panel data model:

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

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 $g_{lp(i,t)}$

| | Short-Run Coefficients | | |
|---------------------|-------------------------------|--------------------|--------------------|
| | Full panel | Advanced Economies | Emerging Economies |
| $g_{lp(i,t-1)}$ | 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 economies | 78 | 30 | 48 |
| Average T | 24.50 | 24.9 | 24.3 |

LSDVc = least squares dummy variables.

Note: **, * and [^] indicate significance at the 1%, 5%, and 10% levels, respectively. Bootstrapped standard errors.

Source: Authors' calculations.

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 and labor productivity growth (including 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 estimates are consistent with significant short- and long-term impacts of demographic change on labor productivity growth. 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. The results indicate that both physical and human capital accumulation are significantly and negatively affected by a decline in the share of workers, which is not the case for the Economic Complexity Index. Overall, the PVARX estimates appear to capture well 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 economies | 76 | GMM instruments | 1/5 | |
| Average T | 22.99 | | | |

GMM = generalized method of moments, PVARX = panel vector autoregressive model with exogenous regressors.

Note: **, * and ^ indicate significance at the 1%, 5%, and 10% levels, respectively. Bootstrapped standard errors.

Source: Authors' calculations.

As for the remaining variables, human capital accumulation is found to have a significantly positive impact on labor productivity growth. 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. (2019) which provide evidence of a significantly negative impact of lagged investment on output growth.⁸

To sum up, the full-panel PVARX estimations support the hypothesis that demographic change exerts significant effects on labor productivity growth and, more specifically, indicate that the impact of population aging is strongly negative. 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 by carrying out separate PVARX estimations for advanced and emerging economies.

PVARX ESTIMATIONS FOR ADVANCED AND EMERGING ECONOMIES

Table 3 shows the PVARX estimates for the subpanels of advanced economies, while Table 4 shows the PVARX estimates for emerging economies.⁹ 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 statistically significant impact on labor productivity growth both for advanced and emerging economies.

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 the oil price as an additional exogenous regressor since this turns out to be significant in the labor productivity growth equation.

Table 3: PVARX Model for 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 economies | 30 | GMM instruments | 1/3 | |
| Average T | 22.73 | | | |

GMM = generalized method of moments, PVARX = panel vector autoregressive model with exogenous regressors.

Note: **, * and ^ indicate significance at the 1%, 5%, and 10% levels, respectively. Bootstrapped standard errors.

Source: Authors' calculations.

Table 4: PVARX Model for 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 economies | 46 | GMM instruments | 1/4 | |
| Average T | 23.09 | | | |

GMM = generalized method of moments, PVARX = panel vector autoregressive model with exogenous regressors.

Note: **, * and [^] indicate significance at the 1%, 5%, and 10% levels, respectively. Bootstrapped standard errors.

Source: Authors' calculations.

Interestingly, the long-run coefficient on d_{60+} turns out to be smaller for the advanced-economies subpanel than for emerging economies. This is consistent with the hypothesis that Acemoglu and Restrepo (2017) put forward: In advanced economies, which lie further ahead in the demographic transition, the adoption of automation technologies may have reduced the economic impact of aging (as we explore 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 impacts of population aging in the two economy 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 similar in advanced

and emerging economies. 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 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—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 is 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 1% rise in d_{0-19} has a larger impact on aggregate labor productivity in advanced economies.

On the labor productivity growth equation, it can also be noted that the coefficient on physical capital is significant and positive for the advanced-economies subpanel while it remains negative in emerging economies. This suggests 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 advanced economies 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.

THE ROLE OF ROBOTS

In this section, we explore 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 $robs_{(i,t)}$, which we use to extend the benchmark PVARX model specification.¹⁰ 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). While the time-series for this extended-model analysis is shorter, 35 out the 63 economies included are advanced economies and 28 are emerging economies so that the panel used remains balanced between, and representative of, the two economy groups (Table 6). 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.¹¹ 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. We assume an annual depreciation rate of 10% and set 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% and relying on the measure of robot stocks based on the IFR method. The results remain robust.¹²

The PVARX model is extended by introducing these additional regressors: $robs_{(i,t)}$, which is treated as endogenous, and 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, so that estimates of the coefficients on the interaction terms will be consistent (Nizalova and Murtazashvili 2016).

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 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.

¹² These results are not included in this paper but are available upon request.

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:

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

The impact of demographic change now depends on the degree of automation. 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 . 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 $\varphi_2^{LR} = \varphi_2 / (1 - \rho)$.

Table 5A: Full Panel Short-Run PVARX Estimates, Extended Model

| | 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 [^] |
| $robs_{(i,t)}^{5\% \text{ CUTOFF}}$ | 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 |
| $\theta_2 + \varphi_2 \cdot robs_{(i,t)}^{MEAN_ADV}$ | -1.364** | -1.570** | 0.014 | 0.012 | -0.030 |
| $\theta_2 + \varphi_2 \cdot robs_{(i,t)}^{MEAN_EME}$ | -1.638** | -1.752** | 0.017 | 0.028 [^] | -0.020 |
| $robs_{(i,t)}^{5\% \text{ CUTOFF}}$ | 7.80 | 12.96 | - | 16.21 | - |
| No. of observations | 1173 | Lags | 1 | | |
| No. of economies | 58 | GMM instruments | 2/3 | | |
| Average T | 20.22 | | | | |

GMM = generalized method of moments, PVARX = panel vector autoregressive model with exogenous regressors.

Notes:

** , * and [^] indicate significance at the 1%, 5%, and 10% levels, respectively;

$robs_{(i,t)}^{MEAN}$ 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;

$robs_{(i,t)}^{5\% \text{ CUTOFF}}$ 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.

Source: Authors' calculations.

Table 5B: Full Panel Long-Run PVARX Estimates, Extended Model

| | 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** |
| $robs_{(i,t)}^{5\% \text{ CUTOFF}}$ | 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* |
| $\theta_2 + \varphi_2 \cdot robs_{(i,t)}^{MEAN_ADV}$ | -1.339** | -1.130** | 0.133 | 0.044 | 0.055** |
| $\theta_2 + \varphi_2 \cdot robs_{(i,t)}^{MEAN_EME}$ | -1.609** | -1.261** | 0.166 | 0.098 | 0.036 |
| $robs_{(i,t)}^{5\% \text{ CUTOFF}}$ | 8.63 | 13.60 | - | - | 1.00 |
| No. of observations | 1173 | Lags | 1 | | |
| No. of economies | 58 | GMM instruments | 2/3 | | |
| Average T | 20.22 | | | | |

GMM = generalized method of moments, PVARX = panel vector autoregressive model with exogenous regressors.

Notes:

** , * and [^] indicate significance at the 1%, 5%, and 10% levels, respectively;

$robs_{(i,t)}^{MEAN}$ 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;

$robs_{(i,t)}^{5\% \text{ CUTOFF}}$ 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.

Source: Authors' calculations.

Estimates from the extended PVARX model are reported in Table 5A and Table 5B, where we focus solely on the short- and long-run effects of demographic change and automation.¹³

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

¹³ 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.

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. 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.

Table 6: Descriptive Statistics for $robs_{(i,t)}$, 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 |

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

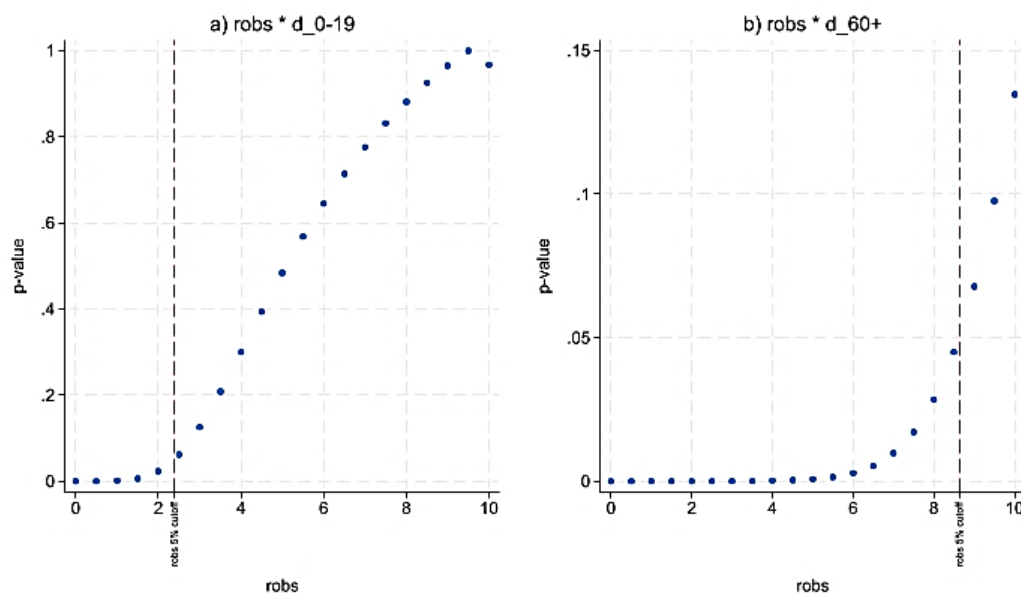
Source: Authors' calculations.

Since the impact of demographics changes with varying degrees 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 1,000 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 aging—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 this 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 Tables 5A and 5B, 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 aging on g_{lp} to be not statistically significant in the long run, the number of robots per 1,000 employees must be 8.63 or higher—a threshold achieved by only three economies in our panel in 2015, i.e., Germany, Japan, and the Republic of Korea. For the share of young workers, the estimated $robs_{(i,t)}^{5\% CUTOFF}$ is equal to 2.38, a mark reached by 17 out of 63 economies in our panel in 2015. Figure 2 also shows that the impact of aging on g_{lp} starts becoming 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 more valuable to aging societies than to younger ones. One possible explanation is that robots are typically characterized by higher complementarity with older workers and higher substitutability with younger workers (Battisti and Gravina 2021).

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



Source: Authors' calculations.

The empirical analysis in this section supports the hypothesis that automation reduces the negative impact of unfavorable demographic change—in particular, population aging—on labor productivity growth.

CONCLUSIONS

Economists have long been interested in the relationship between demography and growth. 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 over 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 older populations. This is in line with the view put forward by Acemoglu and Restrepo (2017, 2021), which suggests that the impact of population aging in advanced economies may be less significant due to the adoption of labor-saving innovations. We investigated this hypothesis by extending the benchmark model to assess whether automation plays a role in cushioning the effects of demographic change. We found that robot adoption significantly reduces the negative impact of aging—and, more generally, unfavorable demographic change—on labor productivity growth.

Evidence uncovered in this paper of the link between demographic change and productivity supports 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, policy should focus on how to boost an aging labor force's productivity, which will be crucial to supporting living standards in the future. Our findings show that this can be achieved through greater automation of production processes, which can compensate for the negative impact of aging on productivity growth.

APPENDIX

Table A.1: Economy Groups

| Advanced Economies | | |
|---------------------------|--------------------------------------|--------------------------------|
| 1. Australia | 14. Iceland | 27. Portugal |
| 2. Austria | 15. Ireland | 28. Puerto Rico |
| 3. Belgium | 16. Israel | 29. Republic of Korea |
| 4. Canada | 17. Italy | 30. San Marino |
| 5. Cyprus | 18. Japan | 31. Singapore |
| 6. Czech Republic | 19. Latvia | 32. Slovenia |
| 7. Denmark | 20. Lithuania | 33. Slovakia |
| 8. Estonia | 21. Luxembourg | 34. Spain |
| 9. Finland | 22. Macau, China | 35. Sweden |
| 10. France | 23. Malta | 36. Switzerland |
| 11. Germany | 24. The Netherlands | 37. Taipei, China |
| 12. Greece | 25. New Zealand | 38. United Kingdom |
| 13. Hong Kong, China | 26. Norway | 39. United States |
| Emerging Economies | | |
| 1. Afghanistan* | 20. Georgia | 38. Peru |
| 2. Algeria | 21. Hungary | 39. Philippines |
| 3. Argentina | 22. India | 40. People's Republic of China |
| 4. Armenia | 23. Indonesia | 41. Poland |
| 5. Azerbaijan | 24. Kazakhstan | 42. Romania |
| 6. Bangladesh | 25. Kyrgyz Republic | 43. Russian Federation |
| 7. Bhutan | 26. Lao People's Democratic Republic | 44. South Africa |
| 8. Brazil | 27. Lebanon | 45. Sri Lanka |
| 9. Brunei Darussalam | 28. Malaysia | 46. Tajikistan |
| 10. Bulgaria | 29. Maldives | 47. Thailand |
| 11. Cambodia | 30. Mexico | 48. Tunisia |
| 12. Chile | 31. Mongolia | 49. Türkiye |
| 13. Colombia | 32. Morocco | 50. Turkmenistan |
| 14. Côte d'Ivoire | 33. Myanmar** | 51. Ukraine |
| 15. Croatia | 34. Nepal | 52. Uruguay |
| 16. Dominican Republic | 35. Nigeria | 53. Uzbekistan |
| 17. Ecuador | 36. Pakistan | 54. Venezuela |
| 18. Egypt | 37. <u>Panama</u> | 55. Viet Nam |
| 19. El Salvador | | |

Notes: Economies are defined as advanced or emerging following the *World Economic Outlook* classification (International Monetary Fund 2021).

*ADB placed on hold its regular assistance in Afghanistan effective 15 August 2021. ADB Statement on Afghanistan | [Asian Development Bank](#) (published on 10 November 2021). Manila.

**ADB has placed on hold its assistance in Myanmar effective 1 February 2021. ADB Statement on Myanmar | [Asian Development Bank](#) (published on 10 March 2021). Manila.

Source: Authors.

Table A.2: Variables and Data Sources

| Variable | Definition | Source |
|-------------------------|--|--|
| <i>g_{lp}</i> | Percentage growth rate of labor productivity, constructed as real GDP per employee. | CEIC; Penn World Table 9.0, Feenstra et al. 2015. |
| <i>k</i> | Percentage growth rate of capital stock at current PPPs (in mil. 2011US\$) per employee. | Penn World Table 9.0, Feenstra et al. 2015. |
| <i>h</i> | Percentage growth rate of the effective human capital index (EHCI). | Lim et al. 2018. |
| <i>eci</i> | Economic Complexity Index. | Observatory of Economic Complexity. https://oec.world . |
| <i>d₀₋₁₉</i> | Percentage of the population aged 0–19. | United Nations. 2019. |
| <i>d₆₀₊</i> | Percentage of the population aged 60 and over. | United Nations. 2019. |
| <i>robs</i> | Number of industrial robots per 1,000 employees. | International Federation of Robotics. World Robotics Statistics Database (accessed 23 March 2018). |

Source: Authors.

REFERENCES

- Acemoglu D., U. Akcigitz, and M. A. Celik. 2014. Young, Restless and Creative: Openness to Disruption and Creative Innovations. *NBER Working Paper No. 19894*.
- Acemoglu, D. and P. Restrepo. 2017. Secular Stagnation? The Effect of Aging on Economic Growth in the Age of Automation. *American Economic Review: Papers & Proceedings*. Vol. 107, pp. 174–179.
- Acemoglu, D. and P. Restrepo. 2021. Demographics and Automation. *Review of Economic Studies*, rdab031, <https://doi.org/10.1093/restud/rdab031>.
- Aksoy, Y., H. S. Basso, R. P. Smith, and T. Grasl. 2016. Demographic Structure and Macroeconomic Trends. *CESifo Working Paper No. 5872*.
- _____. 2019. Demographic Structure and Macroeconomic Trends. *American Economic Journal: Macroeconomics*. Vol. 11, 193–222.
- Andrews, D. and B. Lu. 2001. Consistent Model and Moment Selection Procedures for GMM Estimation with Application to Dynamic Panel Data Models. *Journal of Econometrics*. Vol. 101, pp. 123–164.
- ADB. 2011. *Asian Development Outlook 2011 Update – Preparing for Demographic Transitions*. Manila: ADB.
- _____. 2019. *Asian Economic Integration Report 2019/2020 - Demographic Change, Productivity, and the Role of Technology*. Manila: ADB.
- Battisti, M. and A. F. Gravina. 2021. Do Robots Complement or Substitute for Older Workers? *Economics Letters*. Vol. 208, 110064.
- Bloom, D. E., D. Canning, and P. N. Malaney. 2000. Population Dynamics and Economic Growth in Asia. *Population and Development Review*, Vol. 26, 257–290. <http://www.jstor.org/stable/3115219>.
- Bloom, D. E., M. Kuhn., and K. Prettnner. 2017. Africa’s Prospects for Enjoying a Demographic Dividend. *Journal of Demographic Economics*. Vol. 83, pp. 63–76.
- Bloom, D. E. and J. G. Williamson. 1998. Demographic Transitions and Economic Miracles in Emerging Asia. *The World Bank Economic Review*. Vol. 12, pp. 419–455.
- Börsch-Supan, A. 2003. Labor Market Effects of Population Aging. *Labour*. Vol. 17, pp. 5–44.
- Bruno, G. S. F. 2005. Approximating the Bias of the LSDV Estimator for Dynamic Unbalanced Panel Data Models. *Economics Letters*. Vol. 87, pp. 361–366.
- Cruz, M. and S. Ahmed. 2018. On the Impact of Demographic Change on Economic Growth and Poverty. *World Development*. Vol. 105, pp. 95–106.
- Cutler, D. M., J. M. Poterba, L. M. Sheiner, L. H. Summers, and G. A. Akerlof. 1990. An Aging Society: Opportunity or Challenge? *Brookings Papers on Economic Activity*. pp. 1-73.

- Favero, C. A. and V. Galasso. 2016. Demographics and the Secular Stagnation Hypothesis in Europe. In F. Caselli, M. Centeno, J. Tavares, eds. *After the Crisis: Reform, Recovery, and Growth in Europe*. Oxford University Press.
- Feenstra, R. C., R. Inklaar, and M. P. Timmer. 2015. The Next Generation of the Penn World Table. *American Economic Review*, Vol. 105, pp. 3150–3182. www.ggdc.net/pwt.
- Feyrer, J. 2007. Demographics and Productivity. *The Review of Economics and Statistics*. Vol. 89, pp. 100–109.
- _____. 2008. Aggregate Evidence on the Link between Age Structure and Productivity. *Population and Development Review*. Vol. 34, pp. 78–99.
- Graetz, G. and G. Michaels. 2018. Robots at Work. *The Review of Economics and Statistics*. Vol. 100, pp. 753–768.
- Hansen, L. P. 1982. Large Sample Properties of Generalized Method of Moments Estimators. *Econometrica*. Vol. 50, pp. 1029–1054.
- Hidalgo, C. and R. Hausmann. 2009. The Building Blocks of Economic Complexity. *Proceedings of the National Academy of Sciences of the United States of America*. Vol. 106, 10570–10575.
- International Monetary Fund. 2021. *World Economic Outlook: Recovery during a Pandemic—Health Concerns, Supply Disruptions, Price Pressures*. Washington, DC: IMF
- Jones, B. 2010. Age and Great Invention. *The Review of Economics and Statistics*. Vol. 92, pp. 1–14
- Karahan, F., B. Pugsley, and A. Sahin. 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*. Vol. 68, pp. 53–78.
- _____. 1999. Expectation of Expansions for Estimators in a Dynamic Panel Data Model; Some Results for Weakly Exogenous Regressors. In: C. Hsiao, K. Lahiri, L. F. Lee, and M. H. Pesaran, eds. *Analysis of Panel Data and Limited Dependent Variables*. Cambridge: Cambridge University Press.
- Lee, H. H. and K. Shin. 2019. Nonlinear Effects of Population Aging on Economic Growth. *Japan and the World Economy*. Vol. 51, 100963.
- Lee, S. H., J. Kim, and D. Park. 2017. Demographic change and fiscal sustainability in Asia. *Social Indicators Research*, 134, 287-322.
- Lim, S. S., R. L. Updike, A. S. Kaldjian, R. M. Barber, K. Cowling, H. York, et al. 2018. Measuring human capital: a systematic analysis of 195 countries and territories, 1990–2016. *The Lancet*, 392(10154), 1217-1234.

- Lindh, T. and B. Malmberg. 1999. Age Structure Effects and Growth in the OECD, 1950-1990. *Journal of Population Economics*. Vol. 12, pp. 431–449.
- Maestas, N., K. J. Mullen, and D. Powell. 2016. The Effect of Population Aging 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*. Vol. 71, pp.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*. Vol. 49, pp. 1417–1426.
- Nizalova, O. and I. Murtazashvili. 2016. Exogenous Treatment and Endogenous Factors: Vanishing of Omitted Variable Bias on the Interaction Term. *Journal of Econometric Methods*. Vol. 5, pp. 71–77.
- Park, C. Y., K. Shin, and A. Kikkawa. 2022. Demographic Change, Technological Advance, and Growth: A Cross-Country Analysis. *Economic Modelling*. Vol. 108, 105742.
- Park, D., S. H. Lee, and A. Mason, eds. 2012. *Aging, Economic Growth, and Old-Age Security in Asia*. Manila: ADB / UK, US: Edward Elgar Publishing.
- Sheiner, L. 2014. The Determinants of the Macroeconomic Implications of Aging. *American Economic Review*. Vol. 104, pp. 218–223.
- United Nations, Department of Economic and Social Affairs, Population Division. 2019. *World Population Prospects 2019: Data Booklet*. ST/ESA/SER. A/424.
- Vogel, E., A. Ludwig, and A. Börsch-Supan. 2013. Aging and Pension Reform: Extending the Retirement Age and Human Capital Formation. *NBER Working Paper* No. 18856.
- Wei, Z. and R. Hao. 2010. Demographic Structure and Economic Growth: Evidence from China. *Journal of Comparative Economics*. Vol. 38, pp. 472–491.

Demography, Growth, and Robots in Advanced and Emerging Economies

This paper estimates the impact of demographic change on labor productivity growth. The analysis covers a panel of 90 advanced and emerging economies over 1961–2018 and produces three main findings. First, increases in the young and old population shares exert significantly negative effects on labor productivity growth, working via various channels. Second, population aging has a greater negative impact on emerging economies than on advanced economies. Third, automation reduces the negative effects of unfavorable demographic change—in particular, population aging.

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