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Population aging and economic growth: A semiparametric panel data analysis

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Abstract

Using panel data of 71 countries for the period 1991-2015, this paper examines how population aging affects the marginal effects of the factors that determine growth. Sub-sample comparisons between the OECD member countries and low and lower-middle income countries are also performed. The analysis is based on a fixed effects panel data varying coefficient model, which assumes that aging affects growth through the slope coefficients on the other explanatory variables. Thus, by construction, the model allows for multiple channels through which aging can influence growth. I estimate the model by a consistent estimator, proposed in the literature, that removes fixed effects using kernel-based weights. Three main findings emerge. First, the marginal effect of total years of schooling on growth is significantly positive and stays somewhat linear as aging increases for both the OECD and low and lower-middle income countries. Second, the marginal effect of investment on growth increases with aging for the OECD countries, while it is characterized by an inverse-U shaped pattern for low and lower-middle income countries. Finally, the marginal effect of population growth on economic growth is always negative and it increases in magnitude with aging for the OECD countries, while it is characterized by a U-shaped pattern for low and lower-middle income countries.

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1. Introduction

According to the UN forecasts, at the global level, the number of people above 60 years old is projected to increase from just under 800 million in 2011 to just over 2 billion in 2050 (see Bloom et al. 2011). Moreover, world population is projected to increase 3.7 times from 1950 to 2050; however, the number of people aged 60 and above will increase by a factor of almost 10. Changes in population age structure can affect macroeconomic outcomes since different age groups differ in their (i) consumption and saving patterns; (ii) productivity levels; (iii) labor supply; (iv) contribution to innovation; and (v) investment opportunities (see Aksoy et al. 2019). While there exist numerous empirical studies—often based on a parametric estimation framework—examining the effect of population aging on growth, the results are mixed and the debate on the topic is continuing. For example, recent studies by Lindh and Malmberg (1999), Eggertsson et al. (2019), Aksoy et al. (2019), and Maestas et al. (2023) find a negative effect of aging on growth. On the other hand, Bloom et al. (2010b), Lee et al. (2013), and Acemoglu and Restrepo (2017) find either a positive or an insignificant effect of aging on growth. In another study, Teixeira et al. (2017) find different results for different regions. Specifically, their results suggest that aging negatively affects the growth of developed countries, while, in the case of emerging economies, the negative impact of aging is not contemporaneous but rather it takes time to occur. For less developed countries, in contrast, past (10-years lagged) aging is found to have a weakly positive effect on growth. Still, using panel data for 25 OECD countries, An and Jeon (2006) find that growth rates initially increase and then decrease with population aging. It is worth noting that most of the aforementioned studies focus on the OECD countries. However, as documented in Teixeira et al. (2017), although population aging was initially visible only in developed countries, recent demographic studies have highlighted that less developed countries and emerging economies are transitioning to "aging society" at a faster rate than developed countries.

The objective of the current paper is to provide new empirical evidence on the relationship between aging and the growth of GDP per capita, considering both the OECD countries and low and lower-middle income countries[1]. Specifically, using a semiparametric estimation technique proposed by Sun et al. (2009), this paper contributes to the literature by exploring how changes in population age structure may influence the marginal effects of the main variables used in the empirical growth literature[2] that potentially determine economic growth. I base my analysis on a varying coefficient panel data model with fixed effects and assume the regression coefficients to be a function of a variable that captures population age structure. The task is to estimate those functional coefficients of the explanatory variables. Most of the existing literature uses a parametric specification in which aging affects growth directly and linearly. However, in these studies, often some indirect channels[3] are provided to account for the estimated relationship between aging and growth. This discrepancy motivates me to use the semiparametric specification which assumes that aging affects growth through the slope

[1]According to the World Bank, for the current 2022 fiscal year, low-income economies are defined as those with a GNI per capita, calculated using the World Bank Atlas method, of $1,045 or less in 2020; lower middle-income economies are those with a GNI per capita between $1,046 and $4,095.

[2]As in Mankiw et al. (1992) among many others.

[3]Examples include physical capital and human capital investment channels.

coefficients on the other explanatory variables. Thus, by construction, the model allows for multiple channels through which aging can influence growth. The rest of the paper is organized as follows. Section 2 explains the data and variables used in the empirical analysis. Section 3 introduces the econometric model. Section 4 reports the estimation results and relates them to the findings from the existing literature. Section 5 concludes.

2. Data and variables

In my baseline full-sample analysis, I exploit a balanced panel dataset of 71 countries for the period 1991-2015. In the sub-sample analysis, I consider 28 OECD member countries and 20 low and lower-middle income countries. Given that the focus of this study is on long-run growth, all the variables are measured as five-year averages[4] so that all short term business cycle fluctuations can be averaged out. This yields five chronological observations, corresponding to five sub-periods namely 1991-1995, 1996-2000, 2001-2005, 2006-2010, and 2011-2015, for each country. Note that the canonical approach to address cyclical fluctuations in cross-country or time-series studies is to average data over fixed-length intervals of five years. Following this standard, in the current study, 5-year averaging has been used. That said, a recent paper by Sturn and Epstein (2021) suggest that 5-year averaging may not be sufficient because business cycles can last longer than 5 years. However, there are examples of authors who have used shorter intervals. For example, Burnside and Dollar (2000) use 4-year periods. Similarly, Annen and Kosempel (2009) use 4-year averages for their main results, but do a sensitivity test to show that the main results of their empirical growth regressions are not sensitive to the period length (they consider periods of 4, 5, 6, 8, and 10 years).

The annual data on real GDP per capita growth, real GDP per capita, real GDP, and gross fixed capital formation, all in constant 2010 US dollars, are obtained from the World Bank's World Development Indicators. I divide the raw data on GDP per capita growth by 100 percent to express them in decimals and calculate the five-year averages for the five subperiods. The investment rate variable is measured by the five-year averages of the ratio of gross fixed capital formation to real GDP. The initial GDP per capita is measured by the logarithm of real GDP per capita in the start of each sub-period, namely 1990, 1995, 2000, 2005, and 2010. Following Acemoglu and Restrepo (2017), the variable for aging is defined as the ratio of the population above 50 years old to the population between 20 and 49 in the start of each sub-period. The data on population by five-year age groups in five-year intervals are provided by the United Nations. The schooling variable—a proxy for human capital stock—is measured by the logarithm of male average years of total schooling for ages above 25 in the start of each sub-period. Barro and Lee's (2016)[5] educational attainment dataset provides data on average years of total schooling for male population aged 25-64 in five-year intervals covering the period 1870-2010. The annual data on population growth rates in percentage units are obtained from the World Bank's World Development Indicators.

[4]The exceptions are the variables that are defined at the initial period.

[5]For details, visit `http://www.barrolee.com/`.

The percentage values are expressed in decimals and then the five-year averages for the subperiods are calculated. Tables I, II, and III below summarize the summary statistics for the variables used in my analysis for the full sample, the OECD sample, and the sample for low and lower-middle income countries, respectively.

Table I: Summary statistics, Full-sample (355 observations)

Variables	Mean	SD	Min	Max
Growth rate of GDP per capita	0.02	0.02	−0.046	0.091
Log of initial GDP per capita	8.975	1.465	6.019	11.561
Log of initial average total years of schooling	2.017	0.418	0.077	2.631
Investment rate	0.217	0.055	0.067	0.478
Population growth rate	0.014	0.01	−0.013	0.05
The variable for aging	0.489	0.22	0.171	1.12

Table II: Summary statistics, the OECD sample (140 observations)

Variables	Mean	SD	Min	Max
Growth rate of GDP per capita	0.017	0.017	−0.033	0.082
Log of initial GDP per capita	10.362	0.611	8.688	11.561
Log of initial average total years of schooling	2.321	0.184	1.754	2.631
Investment rate	0.217	0.04	0.126	0.412
Population growth rate	0.008	0.006	−0.005	0.035
The variable for aging	0.691	0.166	0.312	1.12

Table III: Summary statistics, Low and lower-middle income countries (100 observations)

Variables	Mean	SD	Min	Max
Growth rate of GDP per capita	0.021	0.019	−0.046	0.056
Log of initial GDP per capita	7.177	0.657	6.019	8.795
Log of initial average total years of schooling	1.615	0.453	0.077	2.312
Investment rate	0.212	0.068	0.067	0.478
Population growth rate	0.02	0.007	0.004	0.036
The variable for aging	0.309	0.055	0.192	0.522

3. Econometric model

I consider the following fixed-effects varying coefficient panel data regression model:

$$Y_{it} = X_{it}^T \theta(Z_{it}) + \mu_i + v_{it} \tag{1}$$

where

$$X_{it} = \begin{pmatrix} X_{it}^0 \\ X_{it}^1 \\ X_{it}^2 \\ X_{it}^3 \\ X_{it}^4 \end{pmatrix} = \begin{pmatrix} Constant_{it} \\ Log\ Initial\ GDP\ per\ capita_{it} \\ Log\ Initial\ Schooling\ Years_{it} \\ Investment\ Rate_{it} \\ Population\ Growth\ Rate_{it} \end{pmatrix} \tag{2}$$

$$\theta(Z_{it}) = \begin{pmatrix} \theta_0(Z_{it}) \\ \theta_1(Z_{it}) \\ \theta_2(Z_{it}) \\ \theta_3(Z_{it}) \\ \theta_4(Z_{it}) \end{pmatrix} = \begin{pmatrix} Intercept \\ Marginal\ Effect\ of\ X^1 \\ Marginal\ Effect\ of\ X^2 \\ Marginal\ Effect\ of\ X^3 \\ Marginal\ Effect\ of\ X^4 \end{pmatrix} \tag{3}$$

Model (1) can be expanded as:

$$Y_{it} = X_{it}^0\theta_0(Z_{it}) + X_{it}^1\theta_1(Z_{it}) + X_{it}^2\theta_2(Z_{it}) + X_{it}^3\theta_3(Z_{it}) + X_{it}^4\theta_4(Z_{it}) + \mu_i + v_{it} \tag{4}$$

with $i = 1, ..., n$ and $t = 1, ..., m$. n is the number of countries and m is the number of periods. Thus, in the full sample analysis $n = 71$ and $m = 5$; in the OECD sample $n = 28$ and $m = 5$; and in the sample for low and lower-income countries $n = 20$ and $m = 5$. The matrix for the explanatory variables, X_{it}, contains a constant term, X_{it}^0, and four traditional Solow regressors, namely log of initial GDP per capita, X_{it}^1, log of initial average total years of schooling, X_{it}^2, investment rate, X_{it}^3, and population growth rate X_{it}^4. μ_i are the unobserved country specific fixed effects. They are assumed to be i.i.d with a zero mean and finite variance and are allowed to be correlated with X_{it} and/or Z_{it} in an unknown way. The random errors, v_{it}, are also assumed to be i.i.d with zero mean and finite variance and are independent of μ_i, Z_{it}, and X_{it}. $\theta(\cdot)$ contains five unknown functions that depend on the covariate Z_{it}—the variable for aging. These unknown functions capture the marginal effects of the explanatory variables in X_{it} on the dependent variable Y_{it}—the growth rate of real GDP per capita. The goal is to estimate these unknown coefficient curves at every observation point $z = Z_{it}$.

To estimate model (4), I use a consistent estimator proposed by Sun et al. (2009) and follow the notations used in the paper closely. Due to the existence of the fixed effects, model (4) cannot be estimated directly. Thus, as an identification condition, the authors assume that $\sum_{i=1}^{n} \mu_i = 0$. Given this restriction, model (4) can be rewritten in a matrix format as follows:

$$Y = B\{X, \theta(Z)\} + D\mu + V \tag{5}$$

where $Y = (Y_1^T, ..., Y_n^T)^T$ and $V = (v_1^T, ..., v_n^T)^T$ are $(nm) \times 1$ vectors with $Y_i^T = (Y_{i1}, ..., Y_{im})$ and $v_i^T = (v_{i1}, ..., v_{im})$. $B\{X, \theta(Z)\}$ stacks all $X_{it}^T\theta(Z_{it})$ into an $(nm) \times 1$ vector. $\mu = (\mu_2, ..., \mu_n)^T$ is an $(n-1) \times 1$ vector, and $D = [-e_{n-1}\ I_{n-1}]^T \otimes e_m$ is an $(nm) \times (n-1)$ matrix.

In estimating the unknown functions in $\theta(\cdot)$ in model (5), based on a local linear regression approach, the authors introduce the following fixed effects estimator:

$$vec\{\hat{\beta}(z)\} = \{R(z,h)^T S_h(z) R(z,h)\}^{-1} R(z,h)^T S_h(z) Y \tag{6}$$

where $\hat{\beta}(z) = \{\hat{\beta}_0(z), ..., \hat{\beta}_4(z)\}^T$ is a 5×2 matrix with $\hat{\beta}_l(z) = \{\hat{\theta}_l(z), h\hat{\theta}_l(z)^T\}^T$ being a 2×1 column vector for $l = 0, 1, ..., 4$. $vec\{\hat{\beta}(z)\}$ is a 10×1 column vector in which the matrix $\hat{\beta}(z)$ is stacked. In other words, at each specific point $z = Z_{it}$, the first five elements of vector $vec\{\hat{\beta}(z)\}$ will give us the estimates of $\hat{\theta}_0(Z_{it})$,...,$\hat{\theta}_4(Z_{it})$ at that point. $R(z,h) = [R_1(z,h)^T, ..., R_n(z,h)^T]^T$ is an $(nm) \times 10$ matrix; $R_i(z,h) = [G_{i1}(z,h) \otimes X_{i1} ... G_{im}(z,h) \otimes X_{im}]^T$ is an $m \times 10$ matrix; and $G_{it}(z,h) = [1, \frac{Z_{it}-z}{h}]^T$ is a 2×1 vector. $S_h(z) = M_h(z)^T W_h(z) M_h(z)$; $M_h(z) = I_{nm} - D\{D^T W_h(z) D\}^{-1} D^T W_h(z)$; $W_h(z) = diag\{K_h(Z_1, z), ..., K_h(Z_n, z)\}$ is an $(nm) \times (nm)$ diagonal local weight matrix; and $K_h(Z_i, z) = diag\{K_h(\frac{Z_{i1}-z}{h}), ..., K_h(\frac{Z_{i5}-z}{h})\}$ is an $m \times m$ diagonal matrix. Finally, $K_h(\frac{Z_{it}-z}{h})$ is a Gaussian kernel function and h is the optimal bandwidth.

Under certain conditions, the asymptotic distribution of $vec\{\hat{\beta}(z)$ can be derived and is given as follows[6]:

$$\sqrt{nh}\{\hat{\theta}(z) - \theta(z) - \Delta\} \rightarrow^d N(0, \sum_{\theta(z)}) \tag{7}$$

where the term Δ is the leading term of $bias(\hat{\theta}(z))$ and can be ignored when we use the result in (7) to construct the confidence intervals of the estimates, shown in (9) below.
A consistent estimator for $\sum_{\theta(z)}$ is given by:

$$\hat{\sum}_{\theta(z)} = S_p \hat{\Omega}(z,h)^{-1} \hat{J}(z,h) \hat{\Omega}(z,h)^{-1} S_p^T \rightarrow^p \sum_{\theta(z)} \tag{8}$$

where $\hat{\Omega}(z,h) = \frac{1}{nh} R(z,h)^T S_h(z) R(z,h)$; $\hat{J}(z,h) = \frac{1}{nh} R(z,h)^T S_h(z) \hat{V} \hat{V}^T S_h(z) R(z,h)$; $\hat{V}$ is the vector of estimated residuals; and S_p is the first five rows of the 10×10 identity matrix.

The 95 percent confidence intervals for the estimation results can now be constructed as follows:

$$\hat{\theta}_{h_1}(z) \pm 1.96 * \frac{1}{\sqrt{nh}} (\hat{\sum}_{\theta(z)})^{1/2} \tag{9}$$

where $\hat{\theta}_{h_1}(z)$ are the estimates when the under-smoothing bandwidth, h_1, is used; whereas, in calculating $\hat{\sum}_{\theta(z)}$, the optimal bandwidth h—selected via a cross-validation method—is used.

4. Estimation results

4.1. Full-sample results

Figure 1 below shows the estimation results and respective confidence intervals from the full sample analysis. In each panel, the thick black curve corresponds to the estimated

[6] Refer to the reference paper for details of the derivation.

coefficient curve, while the dotted-red and -green curves capture the upper and lower bounds of the 95 percent confidence interval (CI), respectively. Panel A shows the estimates of θ_1, which captures the marginal effect of initial GDP per capita. As expected, the signs for the estimates are always negative, suggesting conditional convergence. We can see that, as population ages, the marginal effect becomes more negative. That is, with rapid aging, for the countries with high initial GDP per capita, the growth becomes even slower. In their theoretical framework, Boucekkine et al. (2002) point out that the increase in life expectancy in high-income countries is mainly reflected by the increased years at the end of life and thus may have a negative effect on economic growth. In contrast, in low-income countries, where infant mortality rates are still relatively high, the increased life expectancy is mainly driven by additional youthful years and as a result it may have a positive effect on growth. The foregoing arguments by Boucekkine et al. (2002) may help explain the more pronounced negative effect of initial GDP per capita with aging on growth found in this paper.

Panel B shows how the marginal effect of schooling on growth, θ_2, changes as population ages. As expected the marginal effect is always positive—capturing the positive effect of human capital on growth—however, there is little evidence that the marginal effect changes as the aging ratio increases. Additionally, for very old ages, the marginal effect becomes insignificant. In their theoretical framework, Lisenkova et al. (2013) show that aging affects economic growth negatively by decreasing a country's stock of human capital. Specifically, they point out that aging leads to the fall in the proportion of the current and future working group and this in turn lowers the productivity level of workers in the labor market. The lower productivity level then leads to the slower growth of the economy. Moreover, these authors also point out that, with aging population, the government is pressured to allocate more budgets to health care and social services rather than to education and skills training programs. This in turn further decreases the productivity level of workers. On the other hand, Bloom et al. (2010a) argue that, since increased life expectancy due to better health will allow individuals to work longer period of time, aging may not lead to lower productivity level. They further point out that an increase in the retirement age or immigration can offset the negative effect of the fall in proportion of working group. The points made by Bloom et al. (2010a) may explain the lack of negative effect of aging on growth through human capital channel found in the current paper. The insignificance of the marginal effect for very old ages may suggest that, at older ages, the effects provided by Lisenkova et al. (2013) start to dominate.

Next, the estimates for the marginal effect of investment on growth, θ_3, are shown in Panel C and it increases as aging deepens. We will see in the next subsection that this result is driven by the OECD group and can be explained by the arrival of labor-replacing technologies as pointed out in both Acemoglu and Restrepo (2017) and Acemoglu and Restrepo (2022).

Finally, Panel D captures the estimates for θ_4, the marginal effect of population growth on economic growth: it is always negative and overall it increases in magnitude with aging. That is, aging population further exacerbates the negative effect of population growth on the economy. A possible explanation is that aging leads to less labour force participation. The negative effect of population growth on economic growth is qualitatively in line with the predictions of the Solow Growth model and the evidence provided by Mankiw et al. (1992), among others.

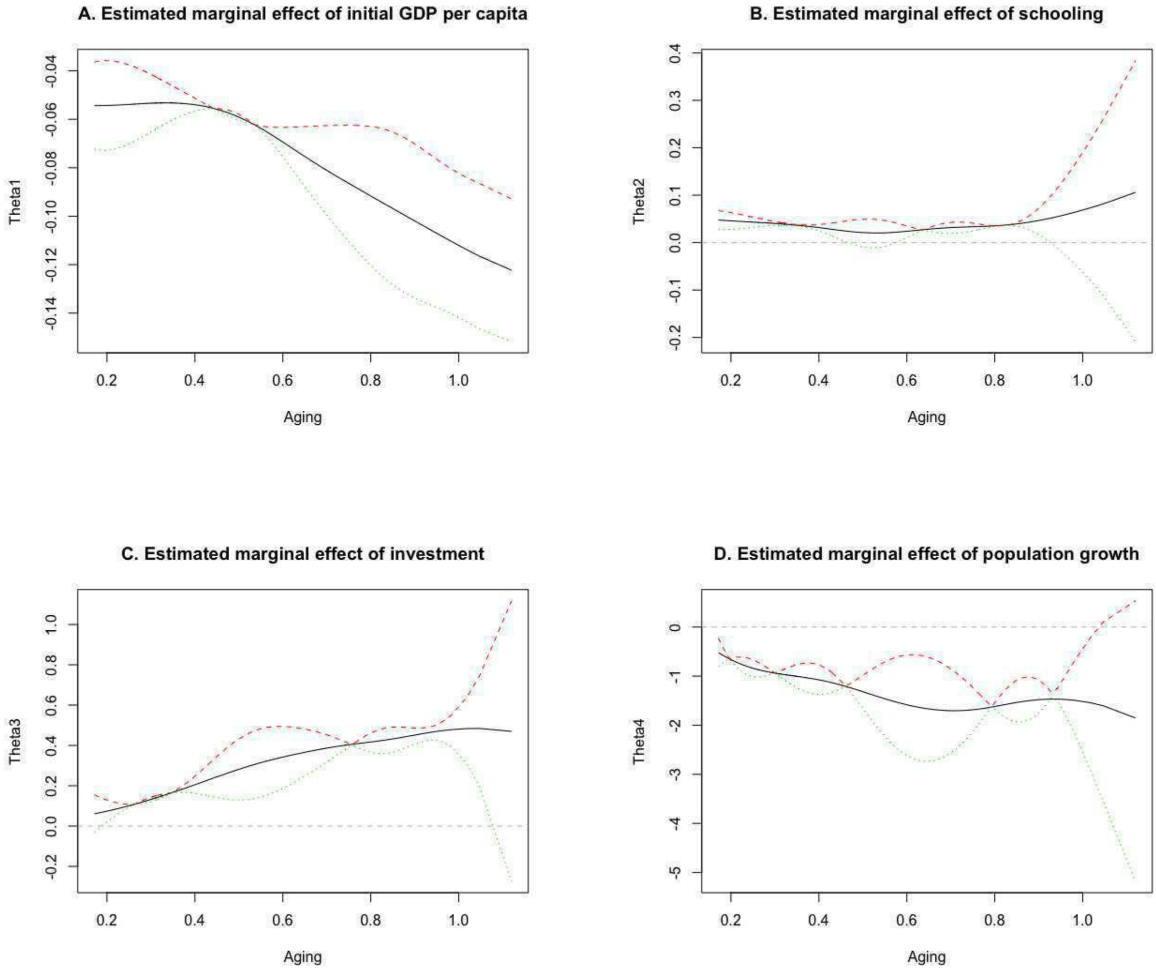

Figure 1: Estimated marginal effects and 95% CIs, Aging measured by the ratio of population above 50 to population between 20 and 49, Full-sample

4.2. Sub-sample results

Figure 2 below motivates me to repeat the same analysis we have seen so far with the two different groups, the OECD member countries and low and lower-middle middle countries, separately. The figure shows how aging trends look like across these two groups. There is an increasing trend for the OECD countries, while the trend for low and lower-middle income countries has been relatively stable over the years.

Figures 3 and 4 show the estimation results from these two sub-samples. Shown in Panel A of both figures are the coefficient curves for initial GDP per capita. For the OECD sample,

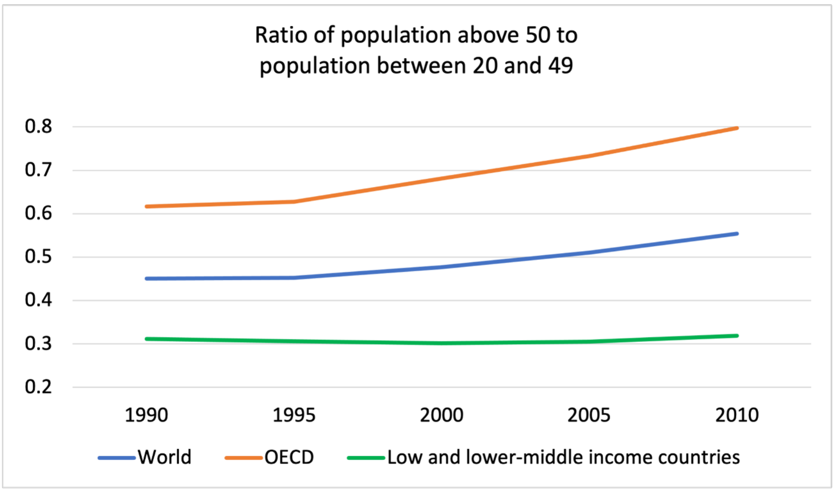

Figure 2: Aging from 1990 to 2010. Data are from the United Nations.

the coefficient curve is more or less consistent with the full sample result in Panel A of Figure 1. In contrast, for low and lower-middle income countries, as shown in Panel A of Figure 4, the coefficient curve looks somewhat linear for the most part.

Regarding the marginal effect of schooling, as shown in Panel B of both Figures 3 and 4, the results are consistent with the full-sample result shown in Panel B of Figure 1, that is, the marginal effect is always positive and stays somewhat constant as the aging ratio increases. Teixeira et al. (2017) find empirically that investment in human capital at the level of primary schooling has a positive impact on growth, especially that of least developed countries, while secondary schooling is found to be positively associated with growth of developed countries only. The analysis in the current paper adds to their results by providing evidence that human capital in the form of total years of schooling matters for the growth of both groups.

Next, shown in Panel C of both Figures 3 and 4 are the coefficient curves for investment. For the OECD case, we can see that, as aging increases, the marginal effect of investment on growth also increases. This pattern is also consistent with the result from the full sample. One possible explanation for this result is the arrival of labor-replacing technologies. As documented in both Acemoglu and Restrepo (2017) and Acemoglu and Restrepo (2022), countries undergoing more rapid demographic change are more likely to adopt robots. The authors also show that when capital is sufficiently abundant, as in the OECD countries, a shortage of younger workers can trigger so much more adoption of new automation technologies so that the negative effects of labor scarcity could be completely neutralized or even reversed. However, this is not the case for the low and lower-middle income countries. The marginal effect of investment on growth increases with aging up to a point, but after that, the effect decreases with further aging of the population. For low and lower-middle income countries, there is not sufficiently abundant capital to begin with. Thus, even when aging increases, the possibility of adoption of the latest labor-replacing technologies is not guaranteed.

Lastly, in Panel D of both Figures 3 and 4, the estimated marginal effects of population growth for the each group are shown. For the OECD group, the marginal effect is always negative and it somewhat increases in magnitude with the aging ratio. The overall pattern is consistent with the full-sample result we have seen in Panel D of Figure 1. On the other hand, as shown in Panel D of Figure 4, for the low and lower-middle income group, the marginal effect is characterized by a weakly U-shaped curve. The upward-sloping part at older ages may be explained by better health outcomes and longer life expectancy.

5. Conclusion

By allowing the coefficients that capture the marginal effects of factors—four traditional Solow regressors namely initial GDP per capita, total years of schooling, investment rate, and population growth—that determine economic growth to vary with population age structure, the present paper have studied empirically the indirect effects of aging on growth. The main findings are as follows. Regarding the marginal effect of total years of schooling, for both the OECD and the low and lower-middle income countries, the marginal effect is found to be significantly positive and stays somewhat constant as aging increases.

The marginal effect of investment is found to differ across the two groups. For the OECD case, as aging increases, the marginal effect also increases. In contrast, in the case of the low and lower-middle income countries, the marginal effect of investment on growth increases with aging up to a point, but after that, the effect decreases with further aging of the population. One possible explanation for these results is the arrival of labor-replacing technologies as pointed out both in Acemoglu and Restrepo (2017) and Acemoglu and Restrepo (2022). When capital is sufficiently abundant, as in the OECD countries, a shortage of younger workers can trigger so much more adoption of new automation technologies so that the negative effects of labor scarcity could be completely neutralized or even reversed. However, for low and lower-middle income countries, there is not sufficiently abundant capital to begin with. Thus, even when aging increases, the possibility of adoption of the latest labor-replacing technologies is not guaranteed.

Finally, the marginal effect of population growth on economic growth is also found to differ across the two groups. For the OECD group, the marginal effect is always negative and it increases in magnitude with aging. On the other hand, for the low and lower-middle income group, the marginal effect is characterized by a U-shaped curve.

While this paper provides evidence that population aging may influence growth indirectly through different factor accumulation variables and the effects may differ between the OECD countries and low and lower-middle income countries, more research is needed to understand the mechanisms behind these results.

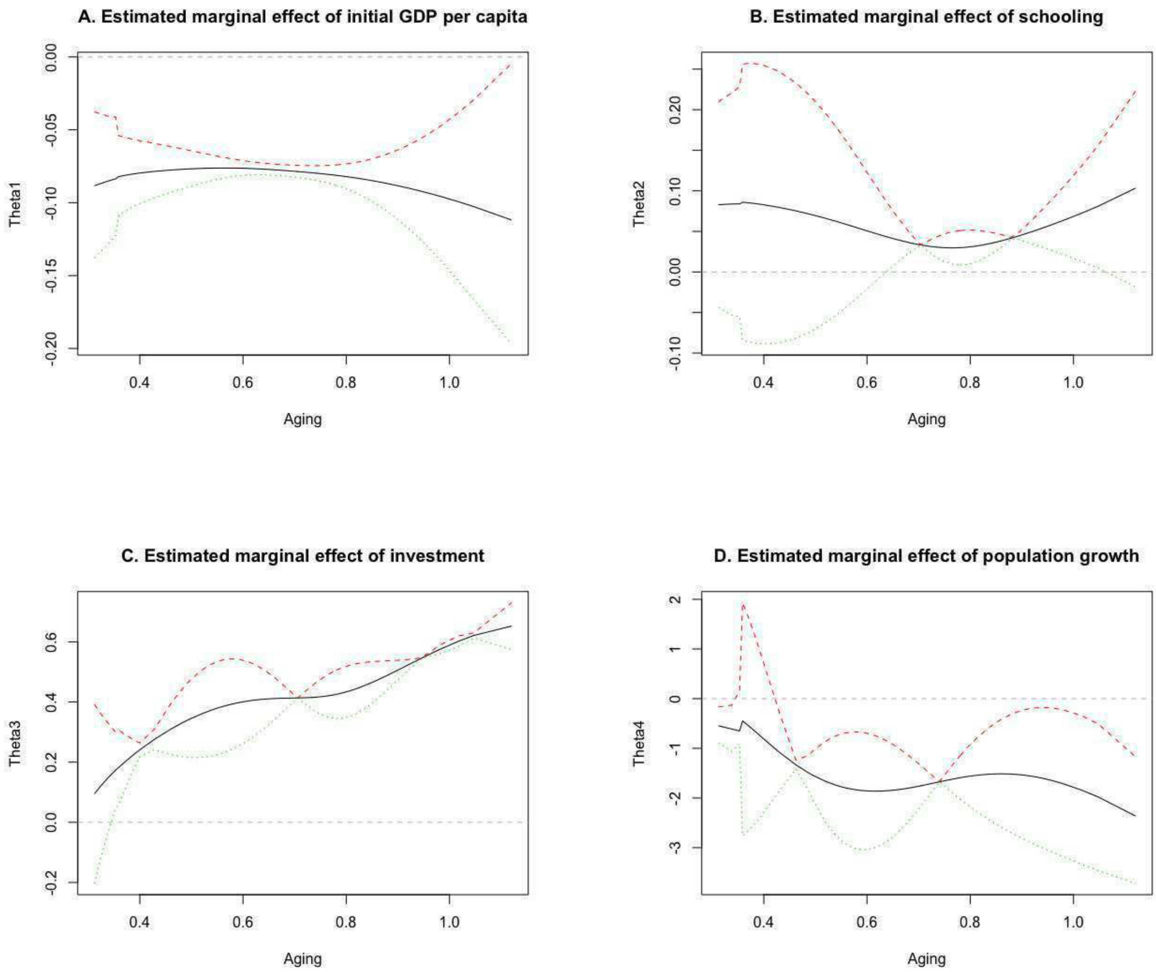

Figure 3: Estimated marginal effects and 95% CIs, Aging measured by the ratio of population above 50 to population between 20 and 49, the OECD sample

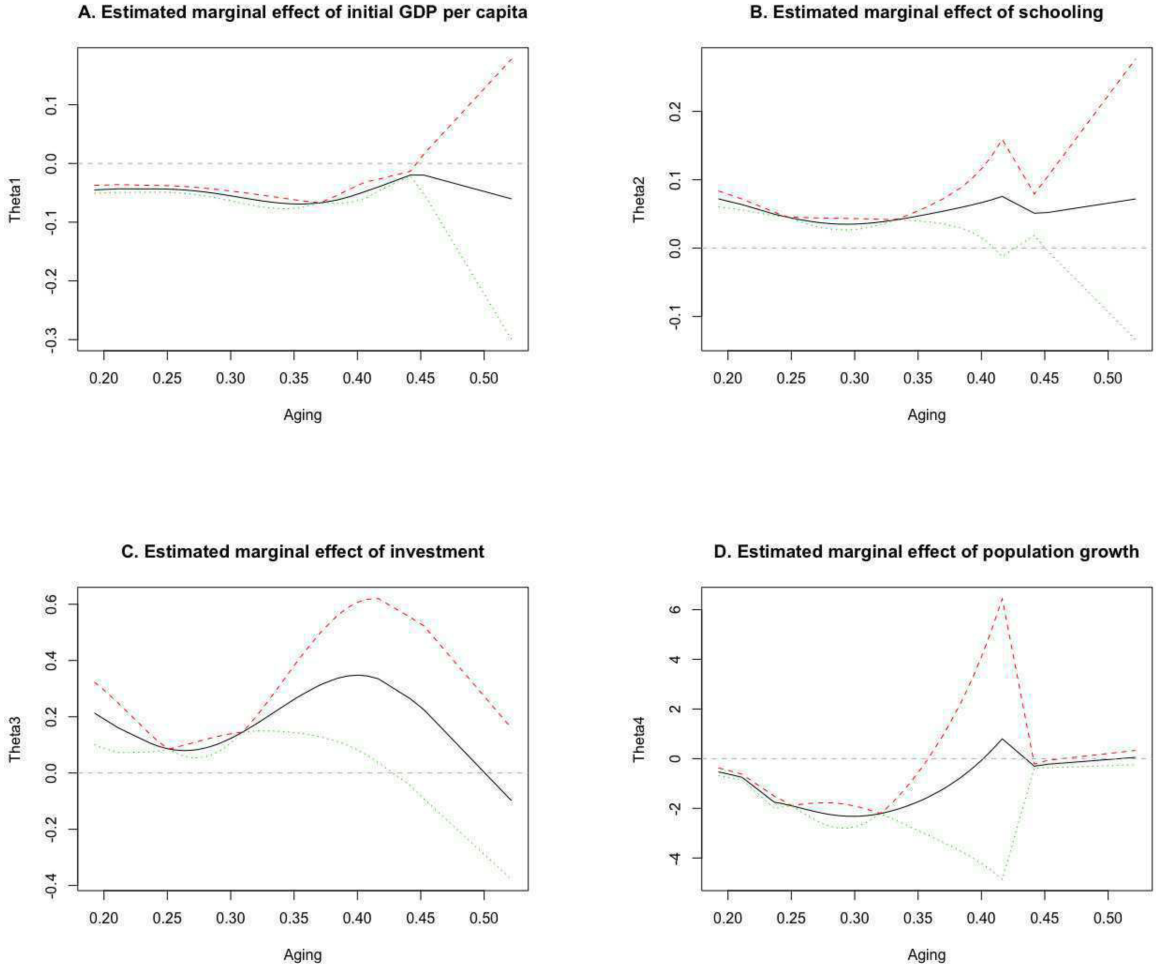

Figure 4: Estimated marginal effects and 95% CIs, Aging measured by the ratio of population above 50 to population between 20 and 49, Low and lower-middle income countries

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