Workforce Ageing and Labour Productivity Dynamics

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Abstract

This paper adopts a neoclassical framework to study the effect of age composition of the working-age population on labour productivity and its determinants, based on an unbalanced panel of 64 non-oil-producing countries, over the period 1950-2017. Our first contribution comes from testing whether a shock in age structure has the ability to permanently shift labour productivity dynamics. From methodological standpoint, we try to reduce the risk of model mispecification in the existing literature, that has often overlooked the possibility of cross-sectional dependence in the data and heterogeneity in slope coefficients. We also note the importance of time series properties of the data for valid statistical inference. Our results indicate, that ageing of the working-age population depresses labour productivity growth; negative impact of individuals aged between 55 and 64 on total factor productivity growth is only partially offset by its positive impact on human and physical capital accumulation. For sustaining the current level of living standards, adoption of policies, which forestall the negative impact of older workers on innovation process and promote their positive impact on the supply of production factors, is of crucial importance. We do not find evidence, that higher public spending on education in% of GDP has such an effect.

Keywords: labour productivity, demographics, neoclassical production function, panel data

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Introduction

This paper adopts neoclassical framework to study the effect of age composition of the working age population on labour productivity and its determinants, based on a sample of 64 non-oil-producing countries, for the period between 1950 and 2017. Recent empirical work (Ayiar et al., 2016; Freyer, 2007) has focused on examining the effect of workforce age structure on either level or growth rate of labour productivity. To the best of our knowledge, no study has inspected the dynamic impact of the age structure on labour productivity dynamics. Our first contribution comes from testing whether a shock in age structure shifts labour productivity growth permanently or temporarily. From a methodological standpoint, we try to reduce the risk of model mispecification in the existing literature that has often overlooked the possibility of cross-sectional dependence in the data and heterogeneity in slope coefficients. We also note the importance of time series properties of the data for valid statistical inference and therefore carried out stationarity and cointegration tests. Our results indicate that a growing share of individuals in the working-age population between ages 55 and 64 depresses labour productivity growth;

thenegative impact of older workers on total factor productivity growth is only partially offset by their positive effect on the speed of accumulation of production factors. Younger individuals, especially those between 25 and 34, seem to be the driving force of innovation and have the most positive effect on labour productivity growth.

In recent decades, advanced economies have experienced slowdown in per capita output growth. Some macroeconomic literature has associated this phenomenon with deficiencies on the demand side, resulting in a persistent output gap (Hansen, 1938). Gordon (2014), on the other hand, considers the long-term slowdown to be mainly a supply-side problem, with demographic change being one of the main »headwinds«; productivity growth may be impaired due to a reduced labour supply and future opportunities for technological innovations. Global labour productivity growth has dropped from an average annual rate of 2.9% between 2000-2007 to 2.3% between 2010-2017 (The Conference Board, 2019). Fertility rates have been declining through twentieth century, with the post WWII baby boom period as an exception, and life expectancy increased considerably in the 1990s and 2000s. Consequently, a natural increase in population has declined and the median age of global population increased from 24 to 30 between 1990 and 2015. The reduced size of the more recent generations and ageing of the baby-boom generation implies a larger share of older individuals in the workforce and a growing number of dependents in the future. Without behavioral adjustments of economic subjects to structural changes which would stimulate aggregate demand or supply, the already impaired output per capita growth may continue to decline. In this paper we focus on the effect of workforce ageing on aggregate supply. The paper is structured as follows: Section 2 discusses implications of the neoclassical and endogenous growth paradigm on interaction between demographic structure and output dynamics and reviews empirical work. Section 3 presents estimation framework and data. In Section 4, we discuss our results, from which we draw policy implications in Section 5. Section 6 concludes.

Theoretical Background and Literature Review

Aggregate labour productivity in country i in year t $\left(\frac{Y_{it}}{L_{it}}\right)$ depends on physical capital intensity $\left(\frac{K_{it}}{L_{it}}\right)$, human capital per unit of labour $\left(\frac{H_{it}}{L_{it}}\right)$ and the level of technology A (Mankiw Romer And Weil, 1992),

$$\frac{Y_{it}}{L_{it}} = \left(\frac{K_{it}}{L_{it}}\right)^{\alpha} \left(\frac{H_{it}}{L_{it}}\right)^{\beta} A^{1-\alpha-\beta}; \quad 0 < \alpha; 0 < \beta; \alpha + \beta < 1. \quad (1)$$

Labour productivity growth (g_y) is the sum of growth rates of physical capital intensity (g_k), human capital per unit of labour (g_h) and total factor productivity (g_A),

$$g_y = \alpha g_k + \beta g_h + (1 - \alpha - \beta) g_A . \quad (2)$$

The neoclassical framework postulates that short-term labour productivity growth depends largely on savings rate and human capital accumulation, provided their increase results in the net increase of aggregate savings, level of education, and experience within an economy. Long-term growth, however, is due to decreasing marginal returns of production factors, determined exogenously by technical progress. Under endogenous growth paradigm, increase in supply of production factors permanently shifts growth. Knowledge externalities from production process (Romer, 1986) and human capital accumulation (Lucas, 1988) may eliminate decreasing returns on capital at aggregate level. Productive government spending on research and development (R&D), generated by additional output, may foster innovation and thus ensure continued growth in total factor productivity (Romer, 1990).

Neoclassical and endogenous growth models assume representative agents and thus a constant age distribution. Under this assumption, age composition only affects the level of labour productivity. Countries with more favourable demographic structure may have a higher output per unit of labour. Changing the relative sizes of different age groups, however, implies a growth effect. Age structure is correlated with a permanent shift in labour productivity growth if it impacts total factor productivity growth and if growth is endogenous to output dynamics via its effect on the supply of production factors. The first aim of this paper is to determine whether age structure affects labour productivity growth or level.

We also aim to identify the channels through which age structure operates. Age structure may be correlated with labour productivity dynamics due to age-related saving and investment decisions, determining the supply of physical and human capital. Younger households have a lower propensity to save than middle-aged ones, on average. Individuals' wealth peaks just before retirement (Modigliani, 1966), implying that an increasing proportion of middle- and old-aged workers encourages national savings. In response to longer life expectancy and weakened pension systems, older workers may also decide to increase their savings to remain consumption possibilities in retirement (Mason, 2005). Falling fertility rates and the subsequent reduced burden of childrearing may hamper household consumption and contribute to an increase in savings at the aggregate. Given that international capital markets are imperfect (meaning national savings roughly equate national investment), a larger share of older individuals in the workforce may be positively correlated with physical capital formation. Additionally, consumption smoothing and perceived higher budget constraint in the future may encourage active population to increase labour supply on intensive and extensive margin, raising the return on investment, which may in turn push down the real interest rate and foster investment activity. Age structure may as well be correlated with the accumulation of human capital, which according to Mankiw Romer and Weil (1992) largely comes from schooling. Increased life expectancy and thus longer working period increases the return on education (Ben-Porath, 1967). Ageing of the workforce may therefore increase the number of years spent in education, provided young individuals have the ability to invest in it. Behrman et al. (1999) find a positive correlation between life expectancy, school enrolment rates and human capital. Moreover, Ahlorth et al. (1997) link the peak in labour income around the age of 50 with a peak of per capita human capital supply at that age. On the other hand, Dixon (2003) associates ageing with a rise in the incidence of poor health and disability within the workforce.

Age composition may also interact with the evolution of total factor productivity. Cooley and Henricksen (2018) find that individuals' internal productivity describes an inverted U-shape over the life cycle and peaks at the age of 40. Lehman (1953) points out that researchers' innovative activity rises steeply in their 20s and 30s and peaks in the late 30s or early 40s. Acemoglu and Restrepo (2017) find a positive relationship between older populations and production automatization. Ackum-Agell (1994) also suggests that people in their 50s work more intensively than younger workers. Older workers may also be more productive thanks to their accumulated experience.

Technological absorption is also affected by age structure. A highly educated young population is believed to be the driver of absorption process, while the mature segment of the population drives technological diffusion. Studies based on microeconomic data suggest a positive correlation between a young workforce and growing enterprises, whereas stagnant firms tend to have older workforces (Prskawetz et al., 2007). Age structure is also found to be correlated with the adoption of reforms in labour and product markets. Structural reforms, which raise productivity, are generally supported by younger generations and opposed by older ones (Favero & Galasso, 2015).

A large proportion of empirical work studying the interaction between demographic structure and output dynamics has focused on the effect of the growing number of dependents in population on per capita growth (Prskawetz et al., 2007). The emphasis was thus on the effect of age composition on the supply of labour and capital dillution. Recent studies have shifted the attention to changing internal age composition of the workforce population, as dependency ratios have been commonly found insignificant in growth regressions (Prskawetz et al., 2007). Aiyar et al. (2016) link a higher share of workers aged 56-64 with lower labour productivity growth. Freyer (2007) attributes different demographic structures to almost one-quarter of the persistent productivity gap between the OECD and low-income nations and highlights the positive effect of the 40-49-year-old age group on the level of aggregate productivity. Aiyar et al. (2016) and Freyer (2007) all emphasize the importance of total factor productivity channel, through which an increasing share of older workers negatively impacts labour productivity. We try to improve upon this body of literature in several ways. First, we impose less restrictions in modelling cross-country labour productivity dynamics and its response to age structure shocks. Second, we closely examine time and cross-sectional properties of the data. Third, we do not restrict the effect of age composition to the workforce alone, but rather draw from the entire working-age population. We also limit high correlation between explanatory variables by including larger age groups than Freyer (2007) and Ayiar et al. (2016), while still controlling for the entire age distribution.

Methodology

Estimation

Labour productivity in a country i at time t, y_{it}, is assumed to follow AR(1) process and to be a function of a time invariant country fixed effects, capturing factors such as institutional quality, openness of the economy, and flexibility of the labor markets (Bloom et al., 2003), a vector of common time specific factors F_t, predominantly induced by cyclical movements and technological progress, with country specific loadings λ_i, a vector of demographic variables x_{it} and its lagged values x_{it-1} with heterogeneous slopes,

$$y_{it} = \gamma_i y_{it} + \beta_i x_{it} + \theta_i x_{it-1} + \alpha_i + \lambda_i F_t{}^k. \tag{3}$$

We proxy labour productivity with output per hour worked, which, in comparison to output per worker, eliminates the differences in full time/part time employment across countries and time. Our explanatory variables of interest are the proportion of young (aged 15-34), middle-aged (35-54) and old (55-64) individuals in the working-age population. Age shares sum to one. To avoid perfect multicollinearity, we exclude the 55-64 age group, because this group generally has the highest coefficient in regressions of human and physical capital when included. The coefficient on a specific age group is interpreted as the impact on labour productivity when the population share shifts from an excluded group into that particular group. Significant coefficients indicate they are significantly different from the implied zero coefficient on the excluded age group.

Countries are assumed to react differently to age structure shock, as country-specific features may limit the extent of labour productivity response. For instance, if national savings are positively correlated with the share of older workers, the extent to which a growing proportion of older workers also correlates with higher national capital stock, which importantly and negatively depends on the openness of the economy. A potentially positive correlation between the ageing of the population and human capital formation also depends on country-specific factors. If, in certain countries, the return on investment in education in response to longer lifespan increases relatively less than in others, a growing share of older workers will have a less positive effect on human capital formation from schooling. This may be the case in Anglo-Saxon countries, where the costs of education are higher already. Moreover, the slope coefficient may also be different in less-developed countries, where young individuals may be unable to get the funding to stay in education longer. The quality of the healthcare system, the productiveness of government spending, and the efficiency of labour and product markets may also mitigate the presumably negative effect an older population has on labour productivity.

Modelling time-specific effects with cross-section specific factor loadings is attractive, because common unobserved shocks may affect the productivity of various countries to different extents. For instance, output per hour worked may increase more in response to positive technological shock in countries closer to the technological frontier. Moreover, the response of output per hour worked to global business-cycle fluctuations may be heterogeneous in sign and magnitude. Spillover effects between neighboring or more economically integrated countries may also be larger. Omitted heterogeneous factor loadings induce cross-sectionally dependent residuals. Standard fixed effects panel data estimators become inefficient and estimated standard errors biased and inconsistent. Failure to properly capture unobserved common factors may even lead to inconsistent estimates of parameters if they are correlated with age shares (Pesaran, 2006) and to a spurious result if they are non-stationary (Everaert & Vierke, 2016).

The structure of the workforce may be endogenous to output per hour worked, as it is in addition to fertility rates and migration, which are also determined by labour participation rate. If nominal wage adapts to changes in real wage fairly quickly, and if the labour supply of certain age groups is more elastic to changes in compensation rate, there may be contemporaneous reverse causality running from labour productivity to the workforce structure. Ayiar et al. (2016) find changes in the labour-force participation rate of older workers (55-64) to be much more responsive to productivity shocks than other age groups. Han (2018) finds that young workers are more easily affected by business cycle fluctuations than prime-age workers. By using age proportions of the working-age population rather than the workforce, we avoid obtaining inconsistent estimates because of endogenous regressors. Another reason for choosing the structure of the working-age population is its capability to capture the behavioral effects of age composition on labour productivity and its components more fully. By limiting the data to only workers, we would fail to capture the effect of those productive young individuals between the ages of 15-34, who are still in school and whose contribution to productivity may be significant. A possible remaining source of endogeneity in our models is immigration. If positive shock in productivity causes certain age groups to immigrate much more than the others, age composition is endogenous. Ayiar et al. (2016), however, find that this is unlikely to be the case.

Labour productivity level follows a unit root process (Table 2, row 3). Autoregressive coefficient γ_i, from equation 3, is thus equal to unity. Our least restrictive model in equation 4 is estimated with Pesaran‘s (2006) common correlated effects mean group estimator (CCEMG),

$$\Delta y_{it} = \beta_i x_{it} + \theta_i x_{it-1} + \alpha_i + \lambda_i {F_t}^k . \quad (4)$$

is unobserved and proxied by averaging the equation 4 by cross-sections. Substituting it back to the equation 4 gives the regression in equation 5, from which parameters are estimated cross-section by cross-section with OLS. Panel coefficients are averages of individual CCE estimators,

$$y_{it} = \alpha_i^+ + \lambda_{ki}\bar{y}_t + \overline{x'_{\iota t}}\lambda_{ki} + x'_{it}\beta_i + {\varepsilon_{it}}^+ . \quad (5)$$

CCEMG allows for individual specific errors to be serially correlated, heteroskedastic and cross-sectionally dependent. To get consistent estimates, regressors need to be exogenous (Kapetanois et al. 2011). Even though the heterogenous formulation seems to be more realistic, it generally lacks any explanatory power. Provided the panel is homogeneous, efficiency gain may be achieved by pooling observations. Thus, we also estimate the model with Pesaran’s (2006) common correlated effects pooled estimator (CCEP),

$$\Delta y_{it} = \beta x_{it} + \theta x_{it-1} + \alpha_i + \lambda_i {F_t}^k . \quad (6)$$

Tranformations on data of CCEP may not leave enough variation in the panel. We therefore restrict the model to common time fixed effect and estimate the regression in equation 7 with two ways fixed effects estimator (2WFE),

$$\Delta y_{it} = \beta x_{it} + \theta x_{it-1} + \alpha_i + F_t. \tag{7}$$

Least squares estimation is applied after within cross-section and within time variation are substracted from overall variation,

$$(\Delta y_{it} - \overline{\Delta y_\iota} - \overline{\Delta y_t} + \overline{\Delta y_{\iota t}}) = \beta(x_{it} - \overline{x_\iota} - \overline{x_t} + \overline{x_{\iota t}}) + \\ + \theta(x_{it-1} - \overline{x_\iota} - \overline{x_t} + \overline{x_{\iota t-1}}). \tag{8}$$

Estimated coefficients express how one country‘s output per hour worked and age share, relative to itself, compares to another country‘s output per hour worked and age share relative to itself (Kropko and Kubinec, 2018). 2WFE does not eliminate cross-sectional and time variance of the data and assumes residuals to be serially uncorrelated within and across cross-sections with homoscedastic variance. Thus, we carry out Breuch – Pagan, Breuch – Godfrey, and Pesaran‘s CD test and if necessary report Driscoll and Kraay’s (1998) standard errors, which are robust to all forms of non-spherical residuals. If the heterogeneity of slope coefficients is omitted, the pattern will remain in residuals and 2WFE will produce biased estimates. If the source of the pattern is correlated with age shares evolution, estimates will be inconsistent. We therefore relax the assumptions of $\beta_i = \beta$, $\theta_i = \theta$ and also estimate our model with mean group estimator (MG) of Pesaran and Smith (1995), which fits the model cross-section by cross-section and computes panel coefficient as an average of country specific ones. We include trend component,

$$\Delta y_{it} = \beta_i x_{it} + \theta_i x_{it-1} + \alpha_i + F_t. \tag{9}$$

The goal of the above presented estimation framework is to choose the most appropriate method for modelling labour productivity dynamics across countries. Moreover, we are interested in whether changing age composition has an impact on labour productivity growth, as noted in Ayiar et al. (2016) or level, as proposed by Freyer (2007). Econometrically speaking we are testing whether coefficient is statistically significantly different from 0 (implying growth effect) or whether $\beta = -\theta$ (implying level effect).

We also explore the channels through which age structure operates. Labour productivity $\left(\frac{Y}{H}\right)$ is assumed to be a function of physical capital per hour worked $\left(\frac{K}{H}\right)$, total factor productivity (TFP) and human capital from schooling per hour worked $\left(\frac{HC}{H}\right)$,

$$\frac{Y}{H}_{it} = \left(\frac{K}{H}\right)_{it}^{\alpha} \left(TFP_{it} \left(\frac{HC}{H}\right)_{it}\right)^{1-\alpha}. \tag{10}$$

Alpha is set to one third. The steady-state level of capital is an increasing function of the total factor productivity level, whereas the capital-output ratio is not; thus, we express labour productivity as a function of capital-output ratio,

$$\frac{Y}{H}_{it} = \left(\frac{K}{Y}\right)_{it}^{\frac{\alpha}{1-\alpha}} TFP_{it} \left(\frac{HC}{H}\right)_{it}. \tag{11}$$

Human capital production function is assumed to be of Mincer form,

$$\frac{HC}{H}_{it} = e^{\phi(s_{it})}. \tag{12}$$

where s_{it} is the average years of schooling and $\phi(s_{it})$ is an increasing function piecewise linear with decreasing returns to scale.

We take the natural logarithms of equation 10. TFP is defined as output per bundle of production factors,

$$\ln TFP_{it} = \ln\left(\frac{Y}{H_{it}}\right) - \frac{\alpha}{1-\alpha}\ln\left(\frac{K}{Y}\right)_{it} - \ln\left(\frac{HC}{H}_{it}\right). \tag{13}$$

We estimate auxiliary regressions, in which $\ln TFP_{it}$, $\frac{\alpha}{1-\alpha}\ln\left(\frac{K}{Y}\right)_{it}$, $\ln\left(\frac{HC}{H}_{it}\right)$ are taken as a dependent variable. This produces a set of coefficients that sum to the coefficients in labour productivity models. The relative magnitude of the coefficients indicates the importance of each channel for determining the impact of age composition on labour productivity.

Data

Our primary sample is an unbalanced panel of 64 non-oil-exporting countries for the period between 1950 and 2017. Data for calculation of age shares are taken from the United Nation’s World Population Prospects database. Data for human capital index, average annual hours worked by persons engaged, real GDP, and real capital stock at constant 2011 dollar prices are taken from the Penn World table (PWT) 9.1.

Global cyclical movements may induce cross-sectional dependece of first differences of the logarithm of labour productivity (in Table 1 noted as ΔlnY/H), physical capital per hour worked (ΔlnK/Y (α/1-α)), and the residual of production function (ΔlnTFP). Time series of differenced logarithm of human capital per hour worked (ΔlnHCH/H) may be less correlated across cross-sections, as common factors driving the increasing trend of years spent in education may be eliminated. We also expect the age proportion of individuals aged 15-34 (A1) and 35-54 (A2) to be highly correlated due to common drivers of ageing population, such as global improvement in access to healthcare and greater inclusion of women in the workforce. Pesaran's CD test (2004) detects cross-sectional dependence amongst all variables. CD statistics is under the null hypothesis of weak cross-sectional independence normally distributed and boils down to verifying whether the sum of pairwise cross-sectional correlation coefficients is statistically significantly different from zero. For unbalanced panel the statistics is calculated for the common sample as following,

$$CD = \sqrt{\frac{2}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \sqrt{T_{ij}} \widehat{\rho_{ij}}\right), \tag{14}$$

where $\left(\frac{2}{N(N-1)}\right) \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \widehat{\rho_{ij}}$ is average cross-sectional coefficient $\bar{\hat{\rho}}$ reported in Table 1 along with absolute coefficient $|\bar{\hat{\rho}}|$.

Table 1. Pesaran's CD test

Variable	CD-test statistics	p-value	$\bar{\hat{\rho}}$	$\lvert\bar{\hat{\rho}}\rvert$
ΔlnY/H	45.44	0.000	0.165	0.237
ΔlnHCH/H	17.41	0.000	0.059	0.175
ΔlnK/Y (α/1-α)	47.06	0.000	0.160	0.234
ΔlnTFP	42.96	0.000	0.152	0.236
A1	245.70	0.000	0.643	0.680
A2	172.91	0.000	0.453	0.540

Cross-sectional dependence detected in data supports choice of using CCE type estimators and also has an implication for stationarity testing. For valid standard inference, variables need to be stationary or cointegrated. First-generation panel unit root tests tend to over-reject the null hypothesis of a unit root in the presence cross-sectional dependence, if the panel serie consists of common and cross-section specific component, of which one is strongly stationary (Bai and Ng, 2004). Thus, we employ Bai and Ng's (2004) panel analysis of non-stationarity in idiosynchratic and common components (PANIC). PANIC assumes panel variable (X_{it}) to be a sum of deterministic component (D_{it}), common component $\lambda_i F_t^k$ and a laregly idiosynchratic error e_{it},

$$X_{it} = D_{it} + \lambda_i{}^k F_t{}^k + e_{it}. \tag{15}$$

F_t^k is a $k \times 1$ vector of common factors and λ_i^k a vector of factor loadings. D_{it} can be $c_i + \beta_i t$ or intercept only. F_t^k and e_{it} are unobserved and estimated on the first difference model by method of principal components. An augmented Dickey and Fuller (1979) test is carried out on e_t for each cross-sectional unit. P-values of respective tests reported in table 2 are combined by Fisher method to test the null hypothesis of a unit root, which has a Chi Squared distribution with 2N degrees of freedom. The test requires us to first establish the number of common factors needed to represent the cross-sectional dependence in data. More factors better fit the factor model at the expense of efficiency loss, as more factor loadings have to be estimated. We follow selection procedure proposed by Bai and Ng (2002), who suggest to use information criterion »BIC3« and set the maximum number of common factors to 6. In the case of a single estimated factor, Bai and Ng recommend ADF for testing the presence of a unit root. Test statistics are reported in Table 2 and compared to ADF critical values with constant. If several factors are estimated, ADF tends to overstatimate the number of common trends.

PANIC shows that series of age shares in levels are non-stationary due to more common stochastic trends. The unit root in the natural logarithm of output per hour worked cannot be rejected due to non-stationary idiosynchratic and common

Table 2. PANIC test

Variable	Pooled ADF on $\hat{e}_{it}$	ADF on $\widehat{F}_t^k$					
		k1	k2	K3	k4	k5	k6
A1	531.417**	-1.574	-3.303	-1.655	-1.831	-1.922	1.342
A2	395.339**	-3.864**	-3.193*	-3.552**	0.060	-3.083*	-1.513
lnY/H	65.376	-1.610	/	/	/	/	/
ΔlnY/H	283.082**	/	/	/	/	/	/
ΔlnHC/H	272.475**	/	/	/	/	/	/
ΔlnKY α/(1- α)	295.657**	/	/	/	/	/	/
ΔlnTFP	302.282**	-1.731	/	/	/	/	/

Notes: / indicates there are 0 estimated common components. ** indicates that the unit root is rejected at 1% level. ADF critical values for no deterministic terms (for N=25) is for 1% significance level -2.661; for 5% -1.955 and for 10% -1.609. Critical values for ADF with intercept (for N=25) is at 1% level -3.724; at 5% -2.986 and at 10% -2.633. For this test we balanced our panel for macro variables, time dimension is 23. Maximum number of lags in ADF test is set to and rounded to the nearest whole number.

component. The unit root in the growth rate of total factor productivity cannot be rejected due to one non-stationary common factor. Growth rates of output per hour worked, human capital per hour worked, and physical capital per output are stationary. Standard inference in our models is applicable if residuals are stationary.

Results

Results of the models in equations 4, 6, 7, and 9 are reported together with PANIC and Pesaran's CD tests on residuals in Table 3. Cross-sectional dependence is reduced but present in the residuals of both CCEP and CCEMG, implying cross-sectional means of explanatory and dependent variables do not fully account for dependence between units. The remaining pattern, however, seems to be stationary. Results of CCE estimators imply that the age composition of the working-age population does not have a statistically significant impact on the growth rate of labour productivity and its components. The reason for this statistical insignificance may also be the lack of variation of explanatory data after transformation, making it difficult to detect any meaningful relationship. This is especially in the case of CCEMG estimator, which estimates regression cross-section by cross-section. In 2WFE model PANIC rejects unit root in the error terms, fixed effects estimator offers meaningful results,

Table 3. Growth regressions, with contemporaneous and lagged regressors, for the sample of 64 countries, over the period 1950-2017

	Homogeneous panel				Heterogenous panel			
	ΔY/H	ΔHCH/H	ΔK/Y (α/1-α)	ΔTFP	ΔY/H	ΔHCH/H	ΔK/Y (α/1-α)	ΔTFP
CCEP					CCEMG			
A1	-1.818 (5.330)	-0.237 (1.150)	0.164 (0.124)	-2.165 (4.952)	-4.571 (2.948)	**1.261‘** (0.669)	-0.580 (1.215)	**-7.375*** (3.707)
lA1	2.144 (4.752)	0.220 (1.068)	-0.323 (1.096)	2.574 (4.282)	3.547 (2.694)	-1.028 (0.744)	-0.663 (1.456)	**6.336‘** (3.586)
A2	-2.148 (4.671)	-0.279 (1.298)	-0.005 (0.153)	-2.612 (4.488)	-4.514 (2.612)	1.669 (1.232)	0.327 (1.409)	**-7.463*** (3.368)
lA2	2.319 (4.591)	0.283 (1.239)	-0.170 (1.133)	2.771 (4.148)	4.353 (2.664)	-1.483 (1.195)	-0.438 (1.379)	**6.293‘** (3.446)
$\hat{\bar{\rho}}_e$ (CD p-value)	-0.018 (0.000)	-0.011 (0.001)	-0.018 (0.000)	-0.020 (0.000)	-0.015 (0.000)	0.008 (0.015)	-0.017 (0.000)	-0.016 (0.000)
Pooled ADF on $\hat{e}_{it}$	292.463	280.801	323.781	274.357	279.069	291.501	346.265	275.759
ADF on $\hat{e}_{it}$ $(\widehat{F}_t^k)$	/	/	/	/	/	/	/	/
	2WFE				MG with trend			
A1	0.194 (0.426) (0.591)	-0.317 (0.135) (0.171)	-0.338 (0.235) (0.310)	0.693 (0.597) (0.772)	0.958 (2.326)	-0.051 (0.609)	0.774 (0.677)	1.718 (0.545)
lA1	0.173 (0.426) (0.586)	0.285 (0.135) (0.172)	0.254 (0.236) (0.310)	-0.219 (0.598) (0.791)	-0.192 (2.279)	-0.068 (0.637)	-0.470 (0.649)	-1.237 (3.098)
A2	-0.153 (0.403) (0.636)	-0.301 (0.128) (0.163)	0.170 (0.226) (0.289)	-0.112 (0.565) (0.775)	0.711 (2.004)	-0.271 (0.638)	0.098 (0.675)	1.332 (2.782)
lA2	0.418 (0.403) (0.636)	0.270 (0.128) (0.172)	-0.259 (0.225) (0.305)	0.491 (0.565) (0.806)	0.503 (1.824)	0.172 (0.637)	-0.431 (0.659)	0.148 (2.589)
$\hat{\bar{\rho}}_e$ (CD p-value)	-0.020 (0.000)	-0.010 (0.005)	-0.022 (0.000)	-0.021 (0.000)	0.155 (0.000)	0.048 (0.000)	0.135 (0.000)	0.170 (0.000)
Pooled ADF on $\hat{e}_{it}$	298.357	268.906	306.595	294.989	325.543	286.523	349.415	301.319
ADF on $\hat{e}_{it}$ $(\widehat{F}_t^k)$	-2.722	/	/	/	/	/	/	-3.668

Notes: All dependent variables are in natural logarithms. A1 = share of 15-34 year olds, A2 = share of 35-54 year olds, A3 = share of 55-64 year olds (excluded). lA denotes lagged shares. Standard errors in parentheses. , significant at 10%; * significant at 5%; ** significant at 1%; *** significant at 0%. Driscoll Kraay standard errors are in the second row below coefficients in 2WFE, maximum lag considered in autocorrelation is 4. Last two rows of each model report results from PANIC on residuals. / indicates no common trends. is average correlation coefficient between cross-country errors, reported together with CD statistics‘ p-value.

even though errors are cross-sectionally dependent (Han, 2018). Breusch–Godfrey test detects serial correlation in time dimension of residuals and Breuch-Pagan test that they have heteroskedastic variance. Provided factors inducing cross-sectional dependence of residuals are not correlated with age shares, estimated parameters are consistent but not efficient and standard error-biased. We thus adjust standard errors with Driscoll and Kraay (1998) method, which guards against all three cases of non-spherical residuals. After this adjustment, partial elasticities of age shares in all models estimated with 2WFE turn insignificant.

Insignificant results may be driven by strong collinearity between explanatory variables. Variance inflation factor (VIF) shows that a large proportion of the variance of the estimated coefficients is inflated by existence of correlation among age shares and its lagged values. VIFs for all age variables largely exceed 200. To deal with this problem, we also estimate regressions in which only the contemporaneous values of age shares are included (Table 4). VIF of explanatory variables drops to 6. Coefficients are of expected sign and their size is in all models reduced. CCEMG and CCEP again report no significant correlation between age composition and productivity growth, coefficients in CCEMG seem to be particularly biased. Estimates in the 2WFE model are significant and are also of the same sign as in CCEP model. Residuals are stationary. Coefficients in our 2WFE model represent how the shift from an excluded age group to a particular age group affects labour productivity growth, across countries, relative to its mean value. Increasing the share of individuals aged 55-64 seems to be correlated with lower labour productivity growth (Table 4). A 1 p.p. shift from age group 55-64 to 15-34 is a associated with an increase of labour productivity growth for 0.35 p.p., whereas a 1 p.p. shift from 55-64 to 35-54 age group increases labour productivity growth for 0.25 p.p. TFP channel dominates. The youngest share promotes TFP growth to the largest extent. A 1 p.p. shift from 55-64 to 15-34 age group is associated with 0.45 p.p. higher TFP growth, whereas shifting from 55-64 to 35-54 group increases TFP growth for 0.34 p.p. The negative effect of 55-64 age share on TFP growth is, to a very limited extent, offset by its positive effect on the growth rate of physical capital per output and human capital per hour worked. Moving from the 55-64 age group into the 15-34 age group is associated with a 0.037 p.p. drop in the growth rate of human capital per hour worked, whereas no

Table 4. Growth regressions, with contemporaneous regressors, for the sample of 64 countries, over the period 1950-2017

	Homogeneous panel				Heterogeneous panel			
	ΔY/H	ΔHCH/H	ΔK/Y (α/1-α)	ΔTFP	ΔY/H	ΔHCH/H	ΔK/Y (α/1-α)	ΔTFP
	CCEP				CCEMG			
A1	0.190 (0.647)	-0.047 (0.078)	-0.105 (0.212)	0.328 (0.396)	-0.071 (0.986)	-0.083 (0.117)	-0.390 (0.241)	-0.390 (0.241)
A2	0.073 (0.603)	-0.049 (0.100)	-0.114 (0.176)	0.229 (0.775)	1.021 (0.747)	-0.192 (0.167)	-0.267 (0.185)	-0.267 (0.185)
$\bar{\bar{\rho}}_e$ (CD p-value)	-0.017 (0.000)	-0.012 (0.000)	-0.017 (0.000)	-0.020 (0.000)	-0.013 (0.001)	-0.011 (0.002)	-0.017 (0.000)	-0.017 (0.000)
Pooled ADF on $\hat{e}_{it}$	290.486	262.682	302.743	292.741	295.774	291.804	359.775	359.775
ADF on $\hat{e}_{it}$ $(\widehat{F}_t^k)$	/	/	/	/	/	/	/	/
	2WFE				MG with trend			
A1	**0.354***** (0.045) (0.072)	**-0.037*** (0.014) (0.017)	**-0.070*** (0.026) (0.033)	**0.451***** (0.063) (0.094)	0.498 (0.342)	0.024 (0.068)	0.255 (0.157)	0.088 (0.371)
A2	**0.253*** (0.058) (0.103)	-0.032 (0.018) (0.025)	-0.062 (0.033) (0.042)	**0.344*** (0.081) (0.134)	**1.048**** (0.402)	**-0.132*** (0.055)	**-0.310*** (0.157)	**1.463**** (0.502)
$\bar{\bar{\rho}}_e$ (CD p-value)	-0.020 (0.000)	-0.010 (0.006)	-0.022 (0.000)	-0.021 (0.000)	0.154 (0.000)	0.044 (0.000)	0.133 (0.000)	0.160 (0.000)
Pooled ADF on $\hat{e}_{it}$	300 ***	269***	304***	298***	330***	293***	334***	341***
ADF on $\hat{e}_{it}$ $(\widehat{F}_t^k)$	/	/	/	/	/	/	/	-3.211***

Notes: All dependent variables are in natural logarithms. A1 = share of 15-34 year olds, A2 = share of 35-54 year olds, A3 = share of 55-64 year olds. Standard errors in parentheses. , significant at 10%; * significant at 5%; ** significant at 1%; *** significant at 0%. Driscoll Kraay standard errors are in the second row below coefficients in 2WFE, maximum lag considered in autocorrelation is set to 4. Last two rows of each model report results from PANIC on residuals. / indicates no common trends. is average correlation coefficient between cross-country errors, reported together with CD statistics' p-value.

significant relationship is detected when moving to the 35-54 age group. Moving from the 55-64 to the 14-34 age group depresses physical capital deepening about twice as much as human capital deepening, whereas the effect of moving from the 55-64 to the 35-54 group is also insignificant.

To reduce heterogeneity of the panel, we also estimate growth regressions with 2WFE for the sample of OECD countries (Table 5). The TFP channel remains dominant, whereas human capital becomes insignificant. Error cross-sectional dependence is stronger in those models, indicating stronger spillover effects across OECD countries. For this sample we also report estimates with age proportions by 10-year age groups (Table 6). Individuals aged 55-64 are again found to be negatively correlated with labour productivity growth. Moving from this age group

Table 5. Growth regressions, with contemporaneous regressors, for the sample of OECD countries, over the period 1950-2017

	2WFE			
	ΔY/H	ΔHCH/H	ΔK/Y (α/1-α)	ΔTFP
A1	**0.223***** (0.047)	-0.028 (0.018)	**-0.092***** (0.025)	**0.296***** (0.064)
A2	**0.121*** (0.056)	-0.016 (0.021)	-0.031 (0.029)	0.119 (0.077)
$\bar{\hat{\rho}}_e$ (CD p-value)	-0.052 (0.000)	-0.032 (0.000)	-0.065 (0.000)	-0.053 (0.000)
Pooled ADF on $\hat{e}_{it}$	177.879	143.830	144.780	162.856
ADF on $\hat{e}_{it}$ $(\widehat{F}_t^k)$	-2.680	-3.827	-1.773	-2.120

Notes: All dependent variables are in natural logarithms. A1 = share of 15-34 year olds, A2 = share of 35-54 year olds, A3 = share of 55-64 year olds (excluded). Standard errors in parentheses. , significant at 10%; * significant at 5%; ** significant at 1%; *** significant at 0%. Last two rows of each model report results from PANIC on residuals. is average correlation coefficient between cross-country errors, reported together with CD statistics‘ p-value.

Table 6. Growth regressions, with contemporaneous regressors, narrower definition of age shares, for the sample of OECD countries, over the period 1950-2017

	2WFE			
	ΔY/H	ΔHCH/H	ΔK/Y (α/1-α)	ΔTFP
W0	**0.215***** (0.050) (0.050)	-0.036 (0.019) (0.023)	**-0.107*** (0.022) (0.058)	**-0.324***** (0.019) (0.077)
W1	**0.267***** (0.060) (0.073)	0.015 (0.023) (0.028)	-0.012 (0.027) (0.043)	**0.251*** (0.023) (0.114)
W2	0.104 (0.059) (0.093)	-0.032 (0.022) (0.035)	-0.027 (0.026) (0.053)	0.114 (0.023) (0.141)
W3	**0.171*** (0.073) (0.074)	0.033 (0.028) (0.035)	-0.001 (0.032) (0.045)	0.119 (0.028) (0.112)
$\bar{\hat{\rho}}_e$ (CD p-value)	-0.052 (0.000)	-0.032 (0.000)	-0.066 (0.000)	-0.066 (0.000)
Pooled ADF on $\hat{e}_{it}$	175.430	134.619	146.486	146.487
ADF on $\hat{e}_{it}$ $(\widehat{F}_t^k)$	/	/	/	/

Notes: All dependent variables are in natural logarithms. W0 = share of 15-24 year olds, W1 = share of 25-34 year olds, W2 = share of 35-44 year olds, W3 = share of 45-54 year olds, W4= share of 55-64 yea olds (excluded). Standard errors in parentheses. , significant at 10%; * significant at 5%; ** significant at 1%; *** significant at 0%. Driscoll Kraay standard errors are in second row below coefficients in 2WFE, maximum lag considered in autocorrelation is set to 4. Last two rows of each model report results from PANIC on residuals. / indicates no common trends. is average correlation coefficient between cross-country errors, reported together with CD statistics‘ p-value.

Table 7. Level regressions, for the sample of 64 countries, over the period 1950-2017

	Homogeneous panel				Heterogeneous panel			
	ΔY/H	ΔHCH/H	ΔK/Y (α/1-α)	ΔTFP	ΔY/H	ΔHCH/H	ΔK/Y (α/1-α)	ΔTFP
	CCEP				CCEMG			
ΔA1	0.084	-0.183	-0.183	0.348	-1.570	0.216	0.919	-2.538
	(2.225)	(0.633)	(1.016)	(3.099)	(1.195)	(0.545)	(0.577)	(1.910)
ΔA2	-0.758	-0.283	0.153	-0.786	**-2.262‘**	0.766	1.355	**-5.420***
	(1.931)	(0.661)	(1.026)	(3.125)	(1.306)	(0.957)	(0.738)	(2.131)
	-0.014	-0.013	-0.020	-0.015	-0.015	-0.010	-0.017	-0.017
CD p-value	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)
	2WFE				MG with trend			
ΔA1	0.361	-0.309	-0.296	0.817	-0.610	**0.932***	0.388	-2.228
	(0.419)	(0.168)	(0.227)	(0.586)	(1.604)	(0.427)	(0.540)	(2.507)
ΔA2	0.338	-0.323	0.122	0.439	-1.369	0.300	0.137	**-3.176‘**
	(0.397)	(0.160)	(0.212)	(0.555)	(1.216)	(0.390)	(0.519)	(1.838)
$\bar{\bar{\rho}}_e$	-0.021	-0.011	-0.022	-0.022	0.154	0.048	0.136	0.153
CD p-value	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: All dependent variables are in natural logarithms. A1 = share of 15-34 year olds, A2 = share of 35-54 year olds, A3 = share of 55-64 year olds (excluded). Standard errors in parentheses. , significant at 10%; * significant at 5%; ** significant at 1%; *** significant at 0%. is average correlation coefficient between cross-country errors, CD statistics‘ p-value is reported in last row.

to the 25-34 age group seems to have the most positive effect on labour productivity growth; a shift by 1 p.p. is correlated with 0.27 p.p. higher growth. Shifting from the 55-64 to the 25-34 group has the most positive effect on TFP growth, whereas shifting to the 15-24 age group depresses it by about 0.32 p.p. In this setting, age composition seems to have an insignificant effect on human capital accumulation and only has a significantly positive effect on physical capital formation when shifting from age group 55-64 to 15-24.

Our results suggest that the age structure indeed has a growth and not a level effect. Table 7 reports results from level regressions for the sample of 64 countries, in which we restrict β from equation 4 to be equal to – θ and thus estimate,

$$\Delta y_{it} = \Delta\beta x_{it} + \alpha_i + \lambda_i {F_t}^k \, . \qquad (16)$$

Slope coefficients on the first differences of young and middle-aged groups are insignificant.

Our results speak in favour of the life-cycle theory, hypotheses of adaptation of individuals’ behavior to population ageing, and endogenous growth theory. Our findings are also in line with Cooley and Henricksen (2018), whose growth accounting exercise shows that the fastest-ageing G7 countries had a positive growth contribution from higher capital accumulation and negative growth contribution from TFP.

Policy Implications

The share of older individuals in the working-age population will continue to increase in the coming decades. Policy measures, which forestall the negative effect of individuals aged 55-64 on TFP or promote their positive effect on supply of production factors, will be of crucial importance for sustaining the current level of living standards. The extent to which higher domestic savings result in higher domestic investment depends on the relative return on capital at home versus abroad and on openness of the economy. The possible effect of demographic structure on savings thus adds to the importance of ensuring the stability of domestic financial markets and implies that more autonomous economies will be able to deal with ageing in the future. Higher public investment into capital-intensive technologies may also be a plausible reform. Buyse et al. (2017) find that tax incentives, moderately large public R&D subsidies, and investment in tertiary education promote business R&D investment, and thus total factor productivity growth, to the greatest extent. Aiyar et al. (2016) find that higher public R&D spending (but not also private), lower employment protection regulation, and active labour-market policies also forestall the negative impact of workforce ageing on TFP growth. Investment in education may, in addition to promoting TFP growth, also stimulate number of years spent in education, higher spending feeds through easier access to funding or raises the quality of education, and thus increases the return of investment in it. Larger public spending on education may therefore promote a positive impact of the growing share of older workers on human capital formation. We note that the net effect of public spending on education depends significantly on how it is financed (Agenor and Neanidis, 2011), which not taken into account is in this setting. We introduce a policy measure: government spending on education as a% of GDP (P_{it-1}) as a mediating variable for the impact of 55-64 age share () on human capital per hour growth, $\Delta\frac{HC}{H}_{it}$,

$$\Delta\frac{HC}{H}_{it} = \beta_1 A3_t + \beta_2 P_{it-1} + \beta_3 (A3_t P_{it-1}) + \alpha_i + F_t\,. \qquad (17)$$

Following Ayiar et al. (2016) we include lagged policy variable to reduce endogeneity risk. The partial elasticity of moving from the 15-54 to the 55-64 age group $\beta_1+\beta_3\,P_{it-1}$ is . The difference between this partial elasticity and the coefficient on age share in regression without interaction term (Table 8, column 2) indicates the mediation effect of a policy variable. This estimation is based on an unbalanced panel of 62 countries for the period between 1970 and 2017. Data for general government spending on education as% of GDP, which covers current, capital, and transfers from international sources to government, is calculated using data from the UNESCO Institute for Statistics and is available at World Bank's World Development Indicators.

Table 8. The effect of age share 55-64 on the growth rate of human capital per hour worked, for the sample of 62 countries, over the period 1970-2017

Dependent variable	ΔHCH/H	ΔHCH/H
A3	**0.051** (0.019)** (0.022)*	**0.113** (0.042)*** (0.065)*
lP	/	0.003 (0.001)' (0.002)
lP*A3	/	-0.012 (0.007)' (0.010)
R squared	0.003	0.006
CD p-value	**0.050***	**0.090***

Notes: A3= share of 55-64 year olds. Standard errors in parentheses. ' significant at 10%; * significant at 5%; ** significant at 1%; *** significant at 0%. Last row is CD statistics' p-value, * indicates rejection of weak cross-sectional dependence between resiudals at 5% level. In regression in column 2 Breusch-Godfrey test rejects serial correlation at 1% level, whereas Breuch-Pagan detects heteroskedasticity; White corrected standard errors are reported in the second row below coefficients. In regression in column 1, we detect autocorrelation and heteroskedasticity; Newey West adjusted standard errors are reported in the second row below coefficients, maximum lag is set to $T^{0,25}$.

The results in Table 8 highlight the positive correlation between public spending and human capital formation. However, interaction term is statistically insignificant after White correction, implying that public spending on education does not have a statistically significant mediating effect on the impact of age composition on human capital growth. $\beta_1+\beta_3\,P_{it-1}$ is equal to -0.282. It seems that if anything, higher government spending on education in% of GDP reduces the positive impact of increasing share of individuals aged 55-64 in working age population on human capital growth, implying public spending on education has a relatively larger positive effect on formation of human capital amongst younger generations.

Conclusion

The results of our analysis highlight a negative correlation between the increasing share of individuals aged 54 to 65 and labour productivity growth, due to their negative impact on total factor productivity growth. The younger generations, particularly those between the ages of 25 and 34 are most positively correlated with TFP growth. This result is robust to different samples and alternative formulation of age proportions. The negative effect of individuals aged between 55 and 64 on TFP growth is offset by their positive impact on the speed of accumulation of physical and human capital, but only to a very limited extent. This effect is, however, less robust. For modelling labour productivity dynamics and its response to changing age composition two ways fixed effects estimator already employed by Ayiar et al. (2016) and Freyer (2007) seems to be the most appropriate, provided slope coefficients are poolable. A cross-sectional dependence of age and macroeconomic variables is a possible source of biased estimates. A significantly reduced variation of the data, from which parameters in two ways fixed effects are estimated, requires careful interpretation of slope coefficients. Considering the rapid ageing of developed economies' workforce, projected for the future, and the already impaired trend of labour productivity growth, policies that forestall the negative impact of older workers on innovation process and promote their positive impact on physical and human capital formation will be of crucial importance for sustaining the current level of living standards. We do not find evidence that higher public spending on education in% of GDP has such an effect. The next step is to identify policy measures, which will mitigate the negative contribution of older workers to labour productivity growth.

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Staranje delovno sposobnega prebivalstva in dinamika produktivnosti dela

Izvleček

Pričujoči članek v okviru neoklasične teorije rasti preučuje vpliv starostne strukture delovno sposobnega prebivalstva na produktivnost dela ter na njene determinante. Ekonometrična analiza temelji na podlagi panelnih podatkov 64 držav med leti 1950 in 2017. Naš prvi prispevek izvira iz testiranja ali šok v starostni strukturi permanentno spremeni dinamiko produktivnosti dela. Iz metodološkega vidika se prispevek navezuje na zmanjšanje tveganja napačne določitve funkcijske oblike regresijskega modela. Obstoječa literatura namreč zanemarja možnost presečne odvisnosti podatkov in heterogenost regresijskih koeficientov. Opozorimo tudi na pomembnost analiziranja lastnosti časovnih vrst za korektno statistično sklepanje. Rezultati nakazujejo, da staranje delovno sposobnega prebivalstva zavira rast produktivnosti dela; negativen prispevek posameznikov, starih med 55 in 64 let, k rasti skupne faktorske produktivnosti pa je le delno kompenziran s strani njihovega pozitivnega prispevka k formaciji fizičnega in človeškega kapitala. Za ohranjanje trenutnega življenjskega standarda je ključnega pomena sprejetje ekonomskih politik, ki zavirajo negativen vpliv starejših delavcev na inovacijski proces in spodbujajo njihov pozitiven vpliv na ponudbo proizvodnih dejavnikov. Ne najdemo dokazov, da ima višja javna poraba za izobraževanje v % BDP takšen učinek.

Ključne besede: produktivnost dela, demografija, neoklasična produkcijska funkcija, panelni podatki