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How demography shapes the macroeconomic returns to automation

Izabella Kuncz *, Petra Németh, Eszter Szabó-Bakos

Institute of Economics, Corvinus University of Budapest, Fővám Square 8., Budapest, 1093, Hungary

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ABSTRACT

This paper investigates how demographic change interacts with automation to shape long-term macroeconomic outcomes. Using a calibrated general equilibrium model with heterogeneous labor and capital, we simulate five OECD countries with diverse demographic and technological profiles: Republic of Korea, Australia, Italy, Hungary, and Türkiye. Our model replicates key findings from the literature, including the positive relationship between aging and robot accumulation, as well as the growing capital income share at the expense of the labor income share. Beyond these, we uncover several novel insights. First, robot accumulation is driven more by the share of high-skilled labor and production technology than by declining interest rates. Second, while aging initially boosts robotization, this growth is ultimately constrained by the shrinking pool of high-income contributors. Third, only countries with low initial consumption and production relying on low-skilled labor avoid declines in per capita income. Fourth, robotization often replaces rather than expands capital. Fifth, wage convergence between high- and low-skilled workers emerges as a consequence of automation. Finally, increasing general educational attainment does not necessarily raise per capita GDP growth in aging societies undergoing automation. These findings highlight the importance of labor market structure and technological composition in mediating the macroeconomic effects of automation during demographic transitions.

1. Introduction

The long-term economic outlook of many countries is increasingly shaped by two fundamental processes: demographic aging and rapid technological progress in automation. While these phenomena often unfold simultaneously, their relative intensity varies across countries. Within the OECD, considerable heterogeneity in aging patterns can be observed, accompanied by differing levels of automation development. The Republic of Korea represents an extreme case, characterized by both the fastest rate of population aging and the highest industrial robot density worldwide. Although both aging and automation have profound implications for economic growth, an important open question is whether their joint evolution amplifies or mitigates long-run growth dynamics. Ultimately, this depends on whether automation attenuates or exacerbates the economic costs of aging, typically measured in terms of output losses. More broadly, a country's long-run economic trajectory is contingent on its initial conditions and the complex interaction between these processes over time. Against this background, the present study reviews the literature on the aggregate macroeconomic implications of demographic aging and automation.

Demographic aging affects economic growth through multiple channels. A substantial body of literature shows that shifts in age structure toward older cohorts are associated with adverse macroeconomic outcomes (see, for example, Choi and Shin, 2015; Jones, 2022; Kim et al., 2016; Maestas et al., 2023). In particular, aging societies are likely to experience a persistent slowdown in economic growth and a decline in output per capita in the long run (Aksoy et al., 2019; Maestas et al., 2023; OECD, 2025; Stähler, 2021). A key direct mechanism is the contraction of the working-age population, which reduces labor input, generates lower output, and has become an obstacle to economic growth (Basso & Jimeno, 2021; Maestas et al., 2023; OECD, 2025; Stähler, 2021). At the same time, demographic aging may generate countervailing forces. An increase in the share of elderly individuals is often associated with higher aggregate savings, which exert downward pressure on interest rates. Lower interest rates, in turn, can stimulate investment in capital accumulation, innovation, and automation (e.g. Basso and Jimeno, 2021; Kopecky and Taylor, 2022). Nonetheless, aging may also depress labor productivity growth, as a shrinking pool of workers reduces both human capital accumulation and innovative capacity, thereby lowering the efficiency of research and development (Basso & Jimeno, 2021; Maestas et al., 2023).

In parallel, the economic consequences of automation have become a central topic in recent research. There is broad consensus that automation contributes to labor market polarization: while it enhances

* Corresponding author.
E-mail addresses: izabella.kuncz@uni-corvinus.hu (I. Kuncz), petra.nemeth@uni-corvinus.hu (P. Németh), eszter.szabobakos@uni-corvinus.hu (E. Szabó-Bakos).

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productivity, it simultaneously displaces workers (displacement effect Acemoglu and Restrepo, 2018; Acemoglu and Restrepo, 2019; Acemoglu and Restrepo, 2020). Technological unemployment is therefore a salient concern, particularly as advanced automation technologies – most notably industrial robots – can substitute for human labor at a substantial scale (Frey & Osborne, 2017). In theoretical terms, automation is often modeled as a near-perfect substitute for labor (Acemoglu & Restrepo, 2018; Prettner, 2019; Prettner & Strulik, 2020; Stähler, 2021). The relevant literature indicates that low-skilled workers and those engaged in routine-intensive tasks are especially vulnerable to displacement (Frey & Osborne, 2017; Lassébie & Quintini, 2022; Prettner, 2019). Survey-based evidence conducted in several European countries further suggests that younger, lower-educated, and lower-income workers exhibit higher levels of anxiety regarding automation, particularly when exposed to new technologies in the workplace (Włoch et al., 2025). A distinguishing feature of contemporary automation, relative to earlier technological waves, is its capacity to replace rather than augment labor input (Prettner & Bloom, 2020). Across OECD countries, occupations at high risk of automation account for approximately 28 percent of total employment (Lassébie & Quintini, 2022). However, the displacement effect appears to be concentrated in specific manufacturing subsectors where the elasticity of substitution between robots and labor exceeds unity (Du et al., 2026).

Automation also has important distributional implications. Declining demand for low-skilled labor exerts downward pressure on their wages (Acemoglu & Restrepo, 2018, 2020), whereas high-skilled workers may experience wage gains (contrary to the findings of Acemoglu and Restrepo, 2020), thereby widening wage inequality (Prettner and Bloom, 2020; Prettner and Strulik, 2020; Stähler, 2021). This dynamic is likely to contribute to rising income inequality. Moreover, automation compels low-skilled workers to transition into occupations requiring higher levels of education, creativity, and social skills (Frey & Osborne, 2017). While there is substantial evidence that automation enhances aggregate productivity (Cette et al., 2021; Eder et al., 2024), several studies argue that it may reduce employment and the labor income share. Recent technological advances – such as robotics and machine learning – have shifted income from labor to capital, increasing the capital-to-income ratio while decreasing labor's share (Acemoglu and Restrepo, 2022a; Basso and Jimeno, 2021; Prettner, 2019; Prettner and Strulik, 2020). Empirical evidence from past decades supports this trend (Bergholt et al., 2022). Given that labor income is more evenly distributed than capital income, this shift further exacerbates inequality (Acemoglu & Restrepo, 2022b; Stähler, 2021).

Importantly, automation itself is often driven by demographic change (Abeliansky et al., 2020; Acemoglu & Restrepo, 2017, 2022a; Stähler, 2021), aging populations and shrinking workforces incentivize firms to substitute labor with automation capital (Basso & Jimeno, 2021). This substitution may partially offset the negative growth effects of aging. Empirical evidence indicates that aging economies – such as the Republic of Korea – exhibit a stronger propensity to adopt robotics technologies than countries with more stable demographic structures (Acemoglu & Restrepo, 2022a; Prettner & Bloom, 2020). Conversely, countries with relatively stable working-age populations and abundant labor supply over the next decades, such as Türkiye and China, tend to display lower levels of robot density (Prettner & Bloom, 2020).

The present study focuses on the macroeconomic effects of automation in the context of aging societies. The existing literature suggests, that the overall impact of automation on economic growth depends critically on the composition of the labor force, particularly the share of low-skilled workers, due to the displacement effect. Using concrete examples of OECD countries and a general equilibrium model with infinitely optimizing agents, we simulate that the aging pattern of an economy and in addition the skill composition of the labor force also are key determinants of the macroeconomic consequences of the rapid automation.

While a growing literature examines the macroeconomic implications of demographic aging and automation theoretically and empirically (e.g., Abeliansky and Prettner, 2023 Acemoglu and Restrepo, 2022a, Basso and Jimeno, 2021), existing studies typically abstract from cross-country heterogeneity in the level of aging, automation and skill composition or do not provide a quantified analysis across different types of OECD economies. This paper contributes to the literature by integrating demographic dynamics, robot capital accumulation, and labor skill heterogeneity within a unified general equilibrium framework calibrated to OECD countries. Our model successfully replicates key findings established in the existing literature: robot accumulation increases with aging and the capital income share rises at the expense of the labor income share. Moreover, the results of the model-based simulation present several new insights that significantly enrich and refine the current understanding of the relationship between demographic aging and automation: the proportion of low-skilled workers matters in terms of the effects of automation in aging societies.

This study is guided by a set of interrelated research questions. First, to what extent does demographic aging stimulate the accumulation of robots across economies, and through which underlying mechanisms does this relationship operate? Second, under what conditions can automation mitigate or even offset the adverse effects of demographic aging on per capita income growth? Third, how does the diffusion of automation influence the wage differential between high-skilled and low-skilled workers, and how does this effect vary with country-specific structural characteristics? Finally, does the advancement of automation systematically reallocate income from labor to capital across different types of economies? To this end, we identify OECD countries that differ in terms of their aging population structure, current level of automation, and proportion of people with higher education.

The structure of this paper is as follows. Following the introduction, Section 2 outlines the demographic trajectories of the countries under study. Section 3 presents the general equilibrium model, while Section 4 details the calibration process. Section 5 discusses the results of the model, and Section 6 concludes with a summary of the main findings and limitations of the analysis.

2. Motivation for country selection and comparative features

The selection of OECD countries for model-based simulation is driven by the objective of capturing cross-country heterogeneity in demographic aging trajectories. Accordingly, the analysis focuses on the expected evolution of the relative proportion of key age cohorts within the population. Across many OECD economies, the working-age population is declining – a trend projected to persist through 2060 – albeit with substantial variation in both pace and magnitude across countries. This demographic shift has already contributed to labor shortages and increasingly tight labor market conditions in a number of these economies (OECD, 2025).

For the model, the evolution of the age structure is quantified using median population estimates by age from the United Nations World Population Prospects (United Nations, Department of Economic and Social Affairs, Population Division, 2024). The model calibration relies on observed data for 2024 and projected demographic trends up to 2075. In our model, the proportions of young individuals, the working-age population, and the elderly are treated as exogenous variables. Individuals aged 0–18 are classified as ”young”, while those aged 65 and above are categorized as ”old”. Across the selected OECD countries, the pace, magnitude, and trajectory of population aging differ substantially, suggesting that the macroeconomic effects of automation may also vary across national contexts. The evolution of these demographic ratios constitutes a central input into the model framework.

To capture this heterogeneity, the analysis distinguishes several representative demographic patterns. First, some countries exhibit relatively slow population aging, characterized by a low initial share of elderly individuals (18 percent) and only a moderate increase –

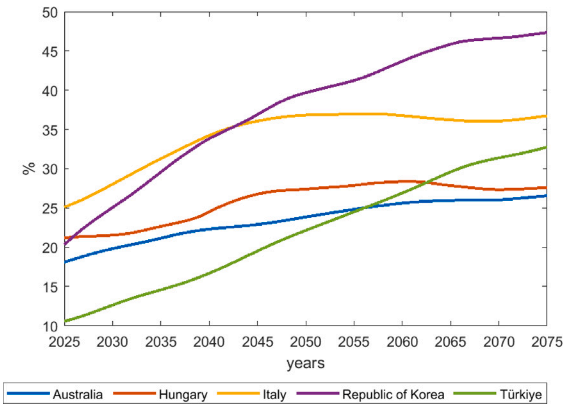

Fig. 1. The projected proportion of people over 64 in the population, 2025–2075.
Source: Own calculation based on data of population's median estimates by United Nations, Department of Economic and Social Affairs, Population Division (2024).

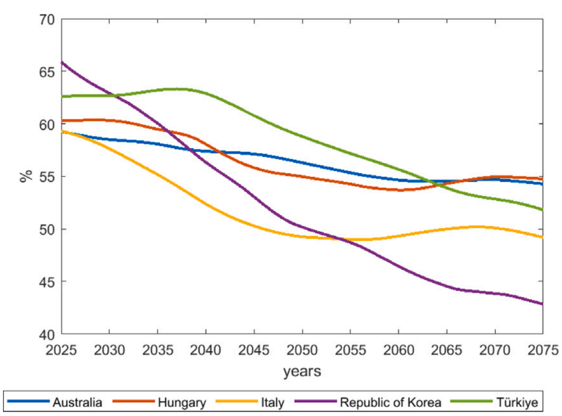

Fig. 2. The projected proportion of people aged 19–64 in the population, 2025–2075.
Source: Own calculation based on data of population's median estimates by United Nations, Department of Economic and Social Affairs, Population Division (2024).

approximately 10 percentage points – over the next half century. In such cases, the working-age population remains relatively large and declines only gradually. Australia represents a prominent example of this pattern among OECD economies (see Figs. 1 and 2).

A second group includes countries where the aging process is somewhat more pronounced but still moderate in its trajectory. Hungary, for instance, is projected to experience an increase in the share of elderly individuals from approximately 22 percent to 28 percent over the next 50 years. However, the proportion of the working-age population is expected to remain broadly stable in the near term, with more substantial declines occurring only after 2040 (see Figs. 1 and 2). A third pattern is exemplified by countries such as Italy, where population aging is already advanced and is expected to intensify in the coming decades. In this case, the share of the working-age population is projected to decline markedly by 2050 – from around 60 percent to 50 percent – before the aging process begins to moderate (see Fig. 2).

Finally, the analysis considers economies experiencing rapid and sustained demographic aging, most notably the Republic of Korea. In this case, the share of elderly individuals is projected to rise sharply, accompanied by a continuous and substantial decline in the working-age population. In contrast, Türkiye represents a relatively young economy within the sample, exhibiting the lowest share of elderly individuals. Nevertheless, demographic aging is expected to accelerate in the coming decades. Notably, Türkiye stands out as the only country in the sample where the working-age population is projected to remain broadly stable over the next 15 years (see Figs. 1 and 2).

Furthermore, a notable disparity is evident among the sample countries in terms of the distribution of working-age population's educational attainment, in the relative earnings of the high-skilled, in the GDP per capita as well as the initial robot density. This data is presented and discussed later in Section 4, namely in the Calibration.

3. The structure of the model

To examine the impact of aging and certain labor market characteristics on automation and the functioning of the economy, we divide the workers to low- and high-skilled, and construct a simple three-agent model. The representative agents – a representative consumer working in the high-skilled labor market segment, a representative consumer engaged in low-skilled labor activities, and a representative firm – make decisions over an infinite time horizon. Both high-skilled and low-skilled consumers earn income from labor and asset accumulation, which is allocated to consumption, tax obligations, and further savings.

The firm produces goods offered to consumers using three inputs: capital, labor, and robots. In the production process, robots and low-skilled labor are perfect substitutes (as in Prettner, 2019; Prettner and Strulik, 2020; Acemoglu and Restrepo, 2018; Stähler, 2021). Therefore, an increase in the quantity of robots, ceteris paribus, displaces low-skilled labor from the market. At the same time, the accumulation of both robots and capital, ceteris paribus, enhances the productivity of high-skilled labor.

We deliberately adopt this specification in the production function rather than modeling low-skilled labor and robots as (imperfect) substitutes. This choice reflects our intent to capture a qualitatively different phase of technological change. In earlier periods, technological progress – such as the introduction of computers, spreadsheets, email, and mechanized equipment – primarily complemented labor by raising its marginal product: workers could produce more output with the same effort.

By contrast, the current wave of digitalization and automation appears to operate differently for a subset of workers. As emphasized by Acemoglu and Restrepo (Acemoglu and Restrepo, 2018), certain groups – particularly among the low-skilled – face a heightened risk of displacement by digital technologies and robots. For these workers, technological progress may reduce rather than increase their marginal product, fundamentally altering the relationship between labor and technology compared with earlier episodes of innovation.

Agents interact in several markets, namely, the markets for goods and services, labor, capital, robots, and assets. Through these interactions, equilibrium prices are determined for all relevant factors: the real rental rate of capital, the real rental rate of robots, the real wages of both low- and high-skilled workers, and the real interest rate.

Formally, the decisions of each type of representative consumer – both the high-skilled and the low-skilled – are guided by the maximization of lifetime utility, as defined below.

$$U_i = \sum_{t=1}^{\infty} \beta^{t-1} \left(\frac{c_{i,t}^{1-\sigma}}{1-\sigma} - \Psi_i \frac{l_{i,t}^{1+\eta}}{1+\eta} \right),$$

where $i = H, L$ represents the type of the consumer – H for high-skilled, L for low-skilled – $c_{i,t}$ and $l_{i,t}$ denote the consumption and labor supply, respectively, while σ, Ψ and η are positive parameters, and β represents the personal discount factor. The individual's budget constraint is given by the time series of the following formula

$$(1-\tau)\, w_{i,t} l_{i,t} + \left(1 + r_t\right) s_{i,t} = \left(1 + nch_t x\right) c_{i,t} + s_{i,t+1}, \tag{1}$$

where $w_{i,t}$ represents the wage of the worker, τ is the tax rate, $s_{i,t+1}$ is the savings accumulated in period t, and r_t is the interest rate announced in period $t-1$, that yields a return to the economic agent in period t. We assume that the number of children raised by a high-skilled economic agent does not differ from the proportion of children in the population, which is represented by the exogenous variable nch_t. Parameter x indicates the consumption of children relative to that of active economic agents.

Under the above assumptions, the economic agent chooses the path of consumption, labor supply, and savings that satisfies the following sequence of first-order conditions over time

$$\frac{c_{i,t}^{-\sigma}}{1+nch_t x} = \beta\left(1+r_{t+1}\right)\frac{c_{i,t+1}^{-\sigma}}{1+nch_{t+1}x} \tag{2}$$

$$\Psi_i l_{i,t}^{\eta} = (1-\tau)\, w_{i,t}\frac{c_{i,t}^{-\sigma}}{1+nch_t x}. \tag{3}$$

From the equations above, one might conclude that there is no significant difference in outcomes between low-skilled and high-skilled workers. To keep the model focused on the questions raised in the introduction, we assume that both groups share identical preference structures: they choose to raise the same number (or fraction) of children, participate in the labor market, earn income, consume, and save.

The key distinction in their economic status arises from the production side rather than from preferences. In particular, an increase in the number of robots benefits high-skilled workers, while low-skilled workers are adversely affected. To account for the observed differences in real wages between the two groups, we allow the parameter Ψ_i in the utility function to be type-specific.

Another important difference concerns savings behavior. It is reasonable to assume that low-skilled workers save significantly less than high-skilled workers.[1] We maintain this assumption during the calibration process.

The firm transforms production factors into output using the technology described by the function

$$Y_t = a_t K_t^{\alpha} L_{H,t}^{\mu}\left(\zeta M_t + L_{L,t}\right)^{1-\alpha-\mu}, \tag{4}$$

where Y_t is output, a_t is the total factor productivity, K_t is the aggregate of traditional physical capital inputs (machines, assembly lines) used, M_t is the automation capital (for simplicity, from now on, the use of robots), $L_{H,t}$ and $L_{L,t}$ are the aggregate quantities of high-skilled and low-skilled labor, respectively. The parameter ζ reflects the efficiency of robots and their relative weight compared to low-skilled labor, while α and μ are positive parameters.

In this production function, robots and low-skilled labor are perfect substitutes. Therefore, an increase in the number of robots, ceteris paribus, reduces the marginal product – and thus the wage – of low-skilled labor (see Prettner and Bloom, 2020 and Prettner, 2023). At the same time, the same increase in robot quantity, ceteris paribus, supports high-skilled labor by increasing its marginal product and wage (as in Prettner and Bloom, 2020; Prettner and Strulik, 2020; Stähler, 2021).

Given the prices, the firm aims to determine the input demand and output level that maximizes its profit. The behavioral equations consistent with the above assumptions can be expressed as follows:

$$r_t^K = \alpha\frac{Y_t}{K_t} \tag{5}$$

$$w_{H,t} = (1-\mu)\frac{Y_t}{L_{H,t}} \tag{6}$$

$$w_{L,t} = (1-\alpha-\mu)\frac{Y_t}{\zeta M_t + L_{L,t}} \tag{7}$$

$$r_t^M = (1-\alpha-\mu)\frac{Y_t}{\zeta M_t + L_{L,t}}\zeta, \tag{8}$$

where r_t^K, r_t^M, $w_{H,t}$, and $w_{L,t}$ denote the rental prices paid for capital, robots, and the two types of labor, respectively.

[1] In a previous version of the model, their savings were even set to zero.

The fiscal policy decision maker finances pensions (tr_t) from the taxes paid by consumers. If the total amount of taxes collected does not match the value of the pensions, the state incurs debt (D_t). The budget constraint can be expressed in the following form

$$N_{H,t}\tau w_{H,t} l_{H,t} + N_{L,t}\tau w_{L,t} l_{L,t} + D_{t+1} = N_{O,t} tr_t + \left(1+r_t\right) D_t, \tag{9}$$

where $N_{H,t}$, $N_{L,t}$ and $N_{O,t}$ denote the number of high-skilled workers, low-skilled workers and older people in the population.

Prices ensure equilibrium in the markets. Equilibrium in the goods market is achieved when all products are utilized either for consumption, capital accumulation, or robot accumulation.

$$Y_t = \left(1+nch_t\right)\left(N_{H,t}c_{H,t} + N_{L,t}c_{L,t}\right) + K_{t+1} - \left(1-\delta_K\right)K_t + M_{t+1} - \left(1-\delta_M\right)M_t + N_{O,t}tr_t \tag{10}$$

For simplicity, we assume that all pension income of the elderly is devoted to consumption.

In the two labor markets, wages bring the firms' labor demand into equilibrium with the labor supply, which is given by $L_{H,t} = N_{H,t} l_{H,t}$ and $L_{L,t} = N_{L,t} l_{L,t}$.

In the asset market, the aggregate savings of consumers, $N_{H,t}s_{t+1} + N_{L,t}s_{L,t+1}$, finance the newly acquired capital and robot stock, as well as the debt of the fiscal policymaker. Formally

$$N_{H,t}s_{H,t+1} + N_{L,t}s_{L,t+1} = D_{t+1} + K_{t+1} + M_{t+1}.$$

Moreover, the returns on the two investment assets must be equal to each other, as well as to the return on savings

$$1 + r_{t+1} = r_{t+1}^K + \left(1-\delta_K\right) \tag{11}$$

$$r_{t+1}^K + \left(1-\delta_K\right) = r_{t+1}^M + \left(1-\delta_M\right). \tag{12}$$

At a given path for the exogenous variables (the number of old – in the model pensioner – agents, the number of children per active population, the pension benefit and the ratio of high-skilled workers relative to the active population) the equations and the first-order conditions (Eqs. (1)–(12)) determine the optimal path of the endogenous variables.

4. Calibration

The primary objective of this paper is to assess the expected impact of specific demographic and labor market characteristics on economic output in the context of automation. We treat the future evolution of demographic structures in the selected countries as exogenous, using the United Nations' medium-variant projections. The remaining parameters are calibrated to ensure that the model closely matches key observed data in the selected countries, such as the proportions of high- and low-skilled workers, the high-skill wage premium, and average GDP relative to the Korean GDP. Table 1 and the subsequent discussion report the data that the model replicates in steady state for each economy, while Table 2 presents the calibrated parameter values that allow the model to match these data.

In the model, the population weights, i.e. the ratio of children to the total population (namely nch_t), the ratio of the working-age population to the total population (namely $n_t = \frac{N_{H,t}+N_{L,t}}{N_t}$), and the ratio of the elderly to the total population (namely $n_{O,t} = \frac{N_{O,t}}{N_t}$) are projected based on the UN World Population Prospects 2024 (United Nations, Department of Economic and Social Affairs, Population Division, 2024), as already presented in Section 2. As with the data, in the model we considered dependent children to be those aged 0–18, working-age people to be those aged 19–64, and elderly people to be those over 64.

The distinction between high-skilled and low-skilled labor within the working-age population is fundamental to the model in two respects. First, only high-skilled labor has sufficient income to finance the accumulation of capital factors, the accumulation of robots, and the

Table 1
Exogenous data about the educational attainment distribution, earnings, relative average per capita GDP in Republic of Korea, Italy, Australia, Hungary and Türkiye.
Source: Educational attainment distribution (OECD Dataset, 2025a), relative earnings (OECD Dataset, 2025b), relative average per capita GDP (World Bank, Data Catalogue, 2023).

Economy	Distribution of adults with tertiary educational attainment (%, from 25 to 65 years, 2023)	Distribution of 25-35 year old with tertiary educational attainment (%, from 25 to 35 years, 2023)	Earnings of workers with tertiary educational attainment relative to the earnings of workers with upper secondary educational attainment or below (%, 2022)	Relative average per capita GDP for the 2003–2023 period (Korea = 100) manufacturing industry (2023)
Republic of Korea	54.5	69.7	34.25	100.00
Italy	21.6	30.6	53.8[1]	118.62
Australia	51.4	56.3	31.86	186.34
Hungary	29.8	29.4	86.44	71.62
Türkiye	25.9	42.7	76.84	48.23

[1] In 2021.

Table 2
Parameter values of the model.
Source: Authors' calculation.

Parameter	Name	Korea	Australia	Italy	Hungary	Türkiye	Source
a	total factor productivity	5.58	9.92	5.46	4.67	3.05	calibrated
α	capital intensity of the production function	0.23	0.23	0.23	0.23	0.23	set
μ	high-skilled labor intensity of the production function	0.44	0.41	0.06	0.18	0.12	calibrated
ζ	the weight of robots in the low skilled industry	0.0054	0.0025	0.0032	0.0059	0.0086	calibrated
σ	the parameter that determines the exponent of the consumption in the utility function	1	1	1	1	1	set
η	the parameter that determines the exponent of the labor supply in the utility function	0.76	0.76	0.76	0.76	0.76	set
Ψ_H	weight parameter for labor in the utility function of the high-skilled worker	6.27	6.30	21.39	15.65	18.16	calibrated
Ψ_L	weight parameter for labor in the utility function of the low skilled worker	8.32	8.32	8.32	8.32	8.32	calibrated
δ_M	depreciation rate for robots	0.01	0.01	0.01	0.01	0.01	set
δ_K	depreciation rate for capital	0.01	0.01	0.01	0.01	0.01	set
β	personal discount factor	0.98	0.98	0.98	0.98	0.98	set

government debt. In steady state we assume that low-skilled workers can only finance their own consumption and that of their children from their disposable income in a given period. Therefore, the development of robots capable of replacing low-skilled workers is strongly influenced by the number of high-skilled workers on the market, their income, and their desired spending structure.

Another factor that makes the distinction between high-skilled and low-skilled labor particularly important in terms of results in the model is that, based on the technology described by the production function. An increase in the number of robots, ceteris paribus, helps high-skilled labor and displaces low-skilled labor in accordance with the relevant literature review. Assuming that all other factors remain unchanged, the perfect substitutability between robots and low-skilled labor makes the marginal product of low-skilled labor – and thus the real wages – a negative function of the available number of robots. Thus, an increase in the number of robots leads to a decrease in real wages of low-skilled workers, which results in a decline in their labor supply.

The marginal product of high-skilled labor – and thus its real wage – is a positive function of the number of robots, according to the chosen function form, meaning that the use of more robots tends to help the productivity of high-skilled labor (instead of displacing them in the labor market). Therefore, ceteris paribus, the more robots high-skilled workers accumulate, the higher their real wages will be, the more motivated they will be to work harder, and the higher their income will be, which will enable them to finance even more robots.

Although we know that not all tertiary-educated individuals are high-skilled in practice, and some workers with lower formal education may have high skills, moreover some vocational programs below tertiary level can lead to high-skill jobs, we still used educational attainment level as a proxy for workers' skills. We define high-skill workers as those with at least a college degree (as Jaimovich et al., 2021), and all other workers as low-skilled.

The second column of Table 1, which presents the first quantitative indicator, shows these data for the five countries we examined, based on data from OECD Dataset (2025a). Korea and Australia have relatively high proportions of high-skilled workers – 54.5 and 51.4 percent, respectively –, while in Italy, Türkiye, and Hungary, this proportion is extremely low, at 21.6, 25.9, and 29.8 percent, respectively (see Table 1 second column). It is worth noting that if we compare the proportions of the total working-age population by educational attainment with the educational attainment of the 25–34 age group (see Table 1 third column), then, based on data of OECD Dataset (2025a), we experience that the proportion of high-skilled workers in this age group is higher everywhere except Hungary, where it is slightly lower. Based on these data, it merits examination to consider a scenario in the model simulations that takes into account not only aging but also an increase in the proportion of high-skilled workers in the future.

During the calibration process, we incorporated not only the ratio of high-skilled to low-skilled workers but also the relative wage differential between these two categories. The relevant data are provided by OECD Dataset (2025b), from which the pertinent elements are presented in the fourth column of Table 1. Unsurprisingly, significant wage disparities were observed in countries with a lower proportion of high-skilled workers. In Italy, high-skilled workers earn 53.8% more than their low-skilled counterparts, while in Hungary this wage gap reaches 86.44%, and in Türkiye 76.84%. In contrast, in Korea and Australia – countries with a high proportion of high-skilled workers – the premium associated with tertiary education is lower, amounting to 34.25% and 31.86%, respectively.

The robot density, which can be quantified by the number of industrial robots per 10,000 employees in the manufacturing industry, reflects the degree of automation in a country. The most automated country in the world today is the Republic of Korea, where the robot density was 1012 robots per 10,000 employees in 2023 according to the data of International Federation of Robotics (2025), which is an outstanding achievement. In comparison, in Italy, according to the same metric, there are only 228 robots per 10,000 employees which is still above average compared to the EU, Asia or North America (International Federation of Robotics, 2025). Although Australia has a high GDP per capita, the level of robotization still lags behind the levels measured in many developed economies (it was around 80 in 2022 International Federation of Robotics, 2023). In Hungary, the robot density is showing an increasing trend, it was estimated only around 100 robots per 10,000 employees in 2022, but according to estimates, Türkiye is even further behind (International Federation of Robotics, 2023).

To ensure that our model accurately reflects the key elements of the actual economic processes of each economy, we also incorporated per capita GDP into the calibration. Since the model is best suited to approximating ratios, all values were normalized relative to Korea's average per capita GDP, based on World Bank data (World Bank, Data Catalogue, 2023). The average was calculated over the 2003–2023 period, and the results are presented in the last column of Table 1. Australia and Italy recorded higher average per capita GDP than Korea during the examined period (Australia reached 186.37% of Korea's per capita GDP, while Italy reached 118.62%). In contrast, Hungary and Türkiye lagged significantly behind the other three countries, with per capita GDP at 71.62% and 48.23% of Korea's level, respectively.

The differences observed in demographic data, the varying ratio of high-skilled to low-skilled workers, the income disparities between these two groups, and the differences in economic performance across the five countries examined all lead to significantly different technologies, preferences – particularly attitudes toward work – and levels of robot utilization. The parameters used in the calculations consist of values calibrated based on the data presented in this chapter and values set by the authors are summarized in Table 2.

5. Quantitative analysis

5.1. Results for the baseline model

A central insight of the model is that demographic aging functions not only as a drag on economic growth through the contraction of the working-age population, but also as a catalyst for automation. As the labor force shrinks, firms substitute labor – particularly low-skilled labor – with robot capital. This mechanism is consistent with existing empirical and theoretical work; however, the present framework extends this insight by demonstrating that the magnitude and sustainability of robot accumulation depend critically on the share of high-skilled workers. In economies where high-skilled labor is relatively abundant, automation can expand more rapidly, as these workers both complement automation technologies and provide the savings necessary to finance capital accumulation. By contrast, in economies with a declining base of high-skilled workers, the expansion of robot capital is constrained, suggesting that automation is not an unlimited substitute for demographic decline. As a result, some of the quantitative simulation results derived from the model align with findings emphasized in the existing literature, while others extend beyond the current body of knowledge.

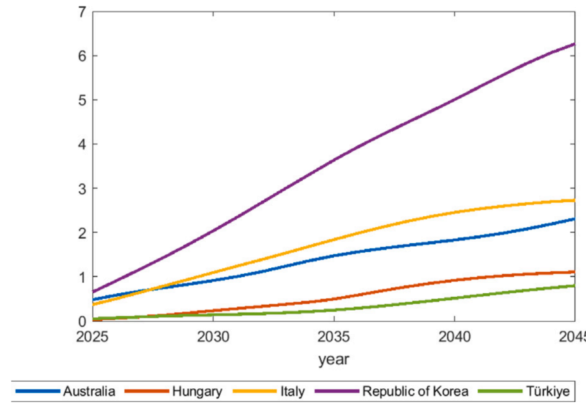

Fig. 3. The evolution of robots over time.
Source: Authors' contribution based on the model results.

The accumulation of robots increases in every economy solely as a consequence of demographic changes, specifically population aging (see Fig. 3). This general feature has appeared in various model versions (see Prettner, 2023; Prettner, 2019 and Basso and Jimeno, 2021). However, our findings offer novel insights: (i) the increase in robot stock is substantial, and (ii) beyond the general conclusion that aging boosts robot accumulation, it can be further established that the pace and timing of robot growth vary significantly across economies. These differences depend on the demographic aging trajectory and the share of high-skilled labor within the total population and the role of high-skilled workers in the production process. Republic of Korea has the highest initial robot stock, while Türkiye and Hungary have the lowest. Italy and Australia are positioned in the middle range (see Fig. 3). From these initial conditions, aging sets the robot stock on a trajectory with a positive slope. According to the literature (e.g., Basso and Jimeno, 2021), this is primarily due to the increasing propensity to save in aging societies, which lowers interest rates and, consequently, the rental cost of robots, thus incentivizing firms to accumulate more robots. However, our model-based results suggest that this mechanism is not necessarily the primary driver of robot stock growth.

In addition to interest rates, two other factors influence the temporal evolution of robot stock. First, the number of economic agents capable of purchasing robots, and their income levels are crucial. Second, the nature of the technology and the intensity of the composite input – which includes robots – also play a significant role.

In Republic of Korea, the proportion of high-skilled workers is exceptionally high (see Table 1), and the production technology heavily relies on this segment of the labor force (see the value of μ in Table 2). As a result, the rapidly aging society – which would already be inclined to accumulate robots – receives two additional incentives: first, the large group of high-skilled workers possesses substantial income that can be allocated toward purchasing robots; second, firms' demand for robots increases, as robots enhance the productivity of high-skilled labor.

The rise in robot stock in Hungary – starting from a similar low level than Türkiye – is also not driven by declining interest rates. Hungary has a higher proportion of high-skilled workers than Türkiye (29.8% vs. 25.9% see Table 1), and the production function exhibits greater intensity with respect to high-skilled labor (0.18 vs. 0.12 see the value of μ in Table 2). The first characteristic facilitates greater robot accumulation from a financing perspective, while the second

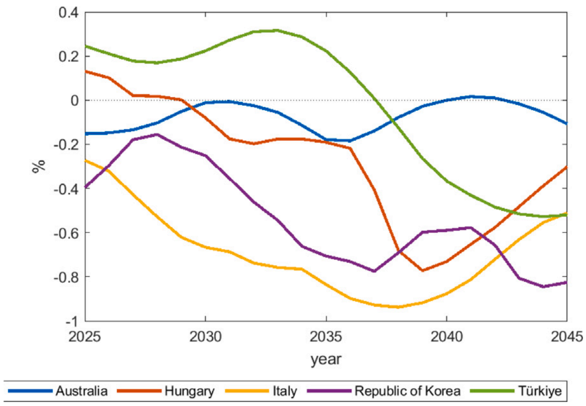

Fig. 4. Growth rate of GDP per capita, %.
Source: Authors' contribution based on the model results.

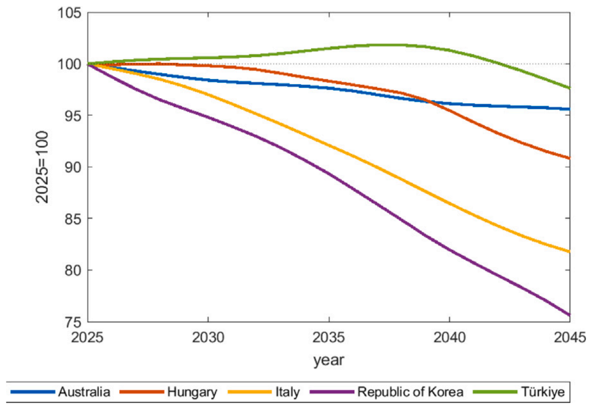

Fig. 5. The evolution of the aggregate labor input, 2025=100.
Source: Authors' contribution based on the model results.

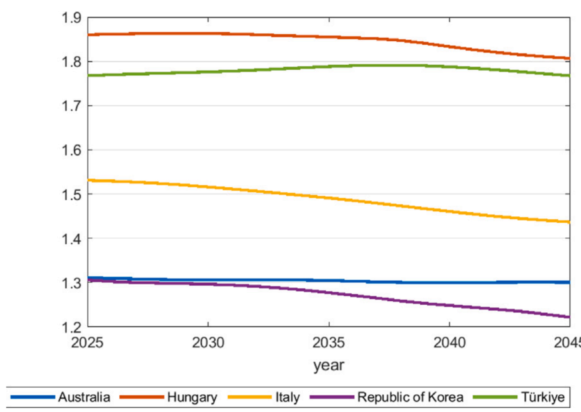

Fig. 6. High-skilled wage premium (high-skilled to low-skilled wage ratio).
Source: Authors' contribution based on the model results.

incentivizes firms to increase the quantity of robots that enhance the productivity of intensively utilized high-skilled workers.

Another important finding concerns the heterogeneous growth effects of automation across countries. While aging generally exerts downward pressure on per capita income, the results indicate that automation can partially mitigate – or in specific cases even reverse – this effect. Despite the striking increase in robot utilization, demographic changes lead to a rise in per capita GDP only in Türkiye and Hungary – and even in these countries – the growth is temporary. In Republic of Korea, Australia, and Italy, per capita GDP declines (see Fig. 4).

Türkiye and Hungary differ from the other economies examined in two key respects. First, both countries have a very low stock of high-skilled labor (see Table 1), and their production technologies tend to rely more heavily on low-skilled workers (see Table 2), which allows for effective substitution between labor and robots. Second, they start from a very low level of per capita consumption. The first factor contributes to the initial positive change in per capita output from the supply side while the second allows demand for goods and services to remain high despite population aging.

A further insight is that automation often entails the replacement of traditional capital with robotic capital, rather than an expansion of the total capital stock. This substitution alters the structure of production, with important implications for productivity, investment behavior, and long-term growth trajectories. This implies that observed increases in robot density may coincide with stagnation or even declines in total capital accumulation, reflecting a qualitative shift in production rather than a quantitative expansion.

Based on the projected changes in GDP, the response of total labor utilization to demographic transformation is unsurprising (see Fig. 5). According to our calculations, labor utilization is expected to show some growth only in Türkiye, where per capita GDP continues to rise for a longer period; in all other countries, it is projected to decline. This result is consistent with the main literature. This decline is driven by both the extensive margin – aging reduces the number of economically active participants in the labor market – and the intensive margin – a significant drop in demand – and the technological structure that affects real wages, which in turn discourages economic actors from offering greater labor input.

It is therefore not surprising that the largest decline is observed in Korea, where aging is most rapid – both factors are present, but the extensive margin dominates – and in Italy, where the intensive margin is more prominent. In Italy, the proportion of high-skilled labor in the labor market is relatively low (see Table 1), and the economy relies on technologies that make limited use of high-skilled labor (see Table 2). As a result, the decline in demand leads to a more pronounced drop in real wages within the high-skilled category. Moreover, high-skilled economic actors – whose labor supply is significantly influenced by preferences – are highly sensitive to changes in real wages. In contrast, the total labor force declines much less in Australia, due to a slower aging process, a large pool of high-skilled labor, and technologies that intensively utilize high-skilled workers. Similarly, the decline in total labor force is modest in Hungary, where demand for goods and services does not fall as sharply with aging (see Fig. 5).

As demand declines, wages also fall (as in Acemoglu and Restrepo 2020), most notably affecting workers in the high-skilled sector. This downward pressure on wages leads to a narrowing of wage differentials between high-skilled and low-skilled labor groups (see Fig. 6). This convergence in wages should not be interpreted as a sign of decreasing economic inequality by itself. But in this case the difference between the overall income of the two groups – which encompasses not only labor earnings but also traditional capital income and revenues derived from supplying robots – are projected to decrease (see Fig. 7). This result contrasts with much of the literature emphasizing polarization and rising inequality (see Prettner and Bloom, 2020; Prettner and Strulik, 2020; Stähler, 2021), and highlights the importance of accounting for general equilibrium effects and the endogenous response of automation. It also suggests that the distributional consequences of automation may be more nuanced and context-dependent than often assumed.

In aging societies, the accumulation of robots is accelerating. As the demand for robots rises, so too does the return on investment associated with their use. This trend contributes to a growing concentration of income among those economic actors who are able to finance, acquire, and lease such advanced inputs. In our model, these actors are both the

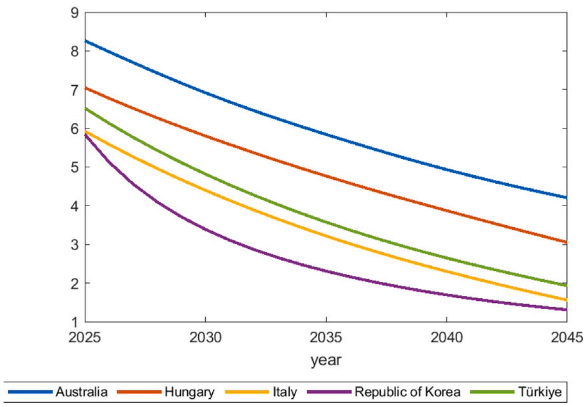

Fig. 7. Relative income of high- and low-skilled workers.
Source: Authors' contribution based on the model results.

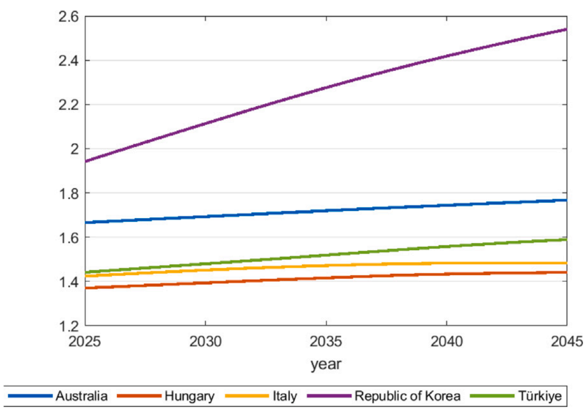

Fig. 8. Capital–labor income share ratio.
Source: Authors' contribution based on the model results.

high-skilled and low skilled workers, who possess both the financial capacity and the strategic positioning to benefit from the expanding role of robots in production.

This dynamic introduces a new dimension of inequality: while wage gaps between labor groups may shrink, the distribution of non-labor income becomes increasingly skewed. All individuals, by virtue of their access to traditional capital and automation capital, are able to accumulate substantial income streams that are decoupled from traditional labor market participation. As a result, the overall structure of inequality shifts from wage-based disparities to differences rooted in capital ownership and technological leverage. This is illustrated in Fig. 8, which shows the growing (traditional plus automation) capital income to labor income, highlighting a key structural shift in income composition.

To summarize our baseline results, the model offers several novel insights that significantly deepen the understanding of the complex relationship between demographic aging, automation technological progress, and labor market composition. These outcomes emerge from the dynamic interaction between shifting demographic structures, the nature of production technologies, and the relative proportions of high-skilled and low-skilled workers. Alongside replicating key findings from the existing literature, the model reveals new mechanisms that have received limited attention, contributing to a more comprehensive view of the economic transformations driven by aging and automation.

Our analysis shows that robot accumulation is not primarily driven by declining interest rates, as suggested in earlier models. Instead, it is closely tied to the share of high-skilled workers and the technological characteristics of production. In economies where technology is designed to capitalize on high-skilled labor, the growth of robot stock is both faster and more substantial.

At the same time, the expansion of robot capital in aging societies faces inherent constraints. As the number of high-skilled contributors declines, the financial resources available for robot investment become increasingly limited. These resources must be distributed across multiple competing needs, which naturally curbs the scale of robot deployment over time.

The baseline model also demonstrates that per capita GDP tends to decline as societies age. However, this trend is not universal. In economies with low initial consumption levels and production technologies that effectively utilize low-skilled labor, robots can substitute for the shrinking workforce. In such contexts, demand remains relatively stable, helping to mitigate the decline in income.

Moreover, demographic aging leads to a narrowing of the wage gap between high-skilled and low-skilled workers when robots are also included in the production function. As the relative wage income of high-skilled workers declines, it converges toward that of low-skilled workers. This shift challenges conventional assumptions about skill-based wage hierarchies and reshapes labor market dynamics in fundamental ways.

In addition to these new findings, the baseline version of the model successfully reproduces several well-established results from the literature. It confirms that demographic aging is associated with increased robot accumulation across economies and that the share of capital income decreases relative to labor income as automation progresses.

Taken together, these results highlight the importance of incorporating demographic structure, technological design, and labor skill composition into models of automation and economic transformation. They provide a robust framework for understanding the evolving nature of production, income distribution, and inequality in aging societies.

To determine whether our results are driven by parameter selection or by the behavior of economic agents and demographic changes, we conducted a sensitivity analysis. Partial results of this analysis, along with their interpretation, are presented in Appendix. Based on this, we found no justification for modifying the baseline model parameters.

5.2. The impact of the increase in the proportion of high-skilled workers

Based on the data shown in Table 1, with the exception of Hungary, all countries included in our study are expected to see an increase in the proportion of high-skilled workers within the adult population in the future. We can conclude this by comparing the proportion of high-skilled workers among young employees (aged 25–34) with the proportion within the entire working-age group. It is hypothesized that this trend will persist in the long term, and that the current educational attainment of young people provides a good approximation for the educational attainment of the adult population in 30 years' time.

Since we have already established in the previous subsection that the proportion of this group of workers is key to the development of macroeconomic aggregates, in this subsection we extend the baseline scenario by introducing a continuous increase in the proportion of high-skilled workers. In this scenario, the previously constant nh_t indicator increases continuously and evenly for the entire working-age population until it reaches the ratio specified in Table 1 for 25–35-year-olds over a period of 30 periods. As no relevant change in the proportion of high-skilled workers is expected in Hungary, we do not deal with the analysis of this country further here.

Our results show that the effect of the increase in the proportion of high-skilled workers on economic growth is not clear-cut. This highlights the fact that the structure of production, the initial level of educational attainment, and its rate of increase also strongly influence the consequences of automation in aging societies. Therefore, the aging pattern is not the only decisive factor that we need to pay attention to when assessing the economic consequences of automation.

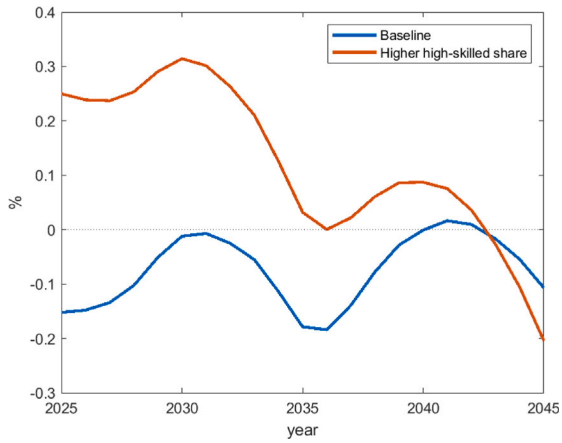

Fig. 9. Growth rate of GDP per capita in Australia.
Notes: Growth rate of GDP per capita in the baseline scenario (blus line) and with a continuously increasing share of high-skilled workers (red line).
Source: Authors' contribution based on the model results.

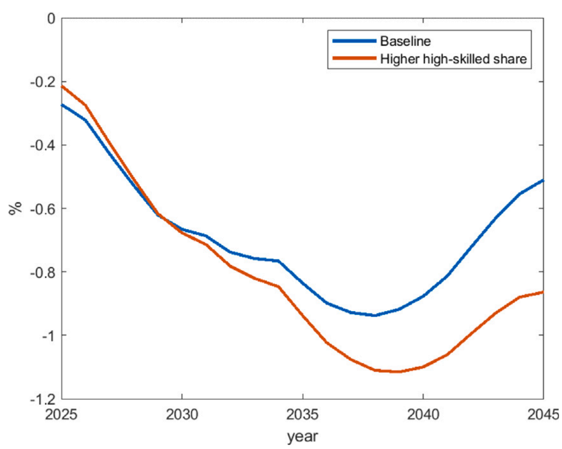

Fig. 10. Growth rate of GDP per capita in Italy.
Notes: Growth rate of GDP per capita in the baseline scenario (blus line) and with a continuously increasing share of high-skilled workers (red line).
Source: Authors' contribution based on the model results.

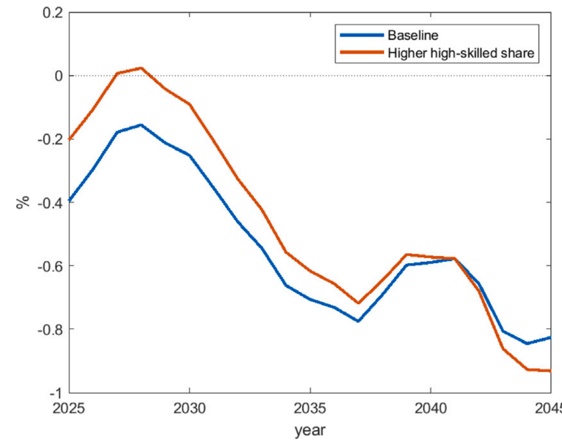

Fig. 11. Growth rate of GDP per capita in Republic of Korea.
Notes: Growth rate of GDP per capita in the baseline scenario (blus line) and with a continuously increasing share of high-skilled workers (red line).
Source: Authors' contribution based on the model results.

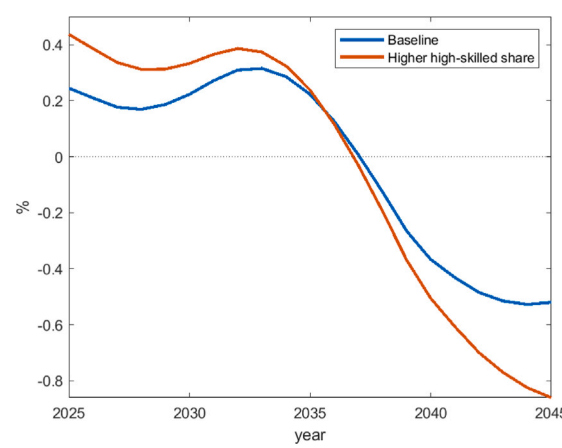

Fig. 12. Growth rate of GDP per capita in Türkiye.
Notes: Growth rate of GDP per capita in the baseline scenario (blus line) and with a continuously increasing share of high-skilled workers (red line).
Source: Authors' contribution based on the model results.

The continuous increase in the proportion of high-skilled workers may have an endogenous effect on per capita GDP growth in the countries included in the sample: in some cases, it increases the growth rate of GDP per capita, and there are examples of it turning a negative growth rate into a positive one, while in other countries it worsens it compared to the baseline. Figs. 9–12 shows that the this shock is unable to fully offset the negative impact of population aging on per capita GDP growth in Italy and Republic Korea (see Figs. 10 and 11).

In both Italy and South Korea, the quantity of robots increases more rapidly relative to the baseline scenario (see Figs. A2 and A3). At the same time, the dynamics of aggregate labor remain broadly similar to the baseline in both economies, however, when the proportion of high-skilled workers rises, aggregate labor is consistently lower (see Figs. A6 and A7). The negative impact of these structural changes in the labor market dominates per capita GDP growth.

In contrast, in Australia, the decline due to demographic transformation can be successfully compensated for over 10 years (see Fig. 9) by an appropriate increase in the high-skilled worker share, as this process significantly boosts robotization (see Fig. A1). Türkiye – as shown in the previous subsection – differs from the other countries by generating positive growth already under the baseline scenario. Initially, the dynamics are similar in both cases, but after a few years, the baseline one places the economy in a more favorable position (see Fig. 12). The reason is that while an increase in the share of high-skilled workers leads to faster growth in the stock of robots (see Fig. A4), aggregate labor input shows a continuous decline instead of the increase observed in the baseline (see Fig. A8). Hence, both the extensive and the intensive margins induce a decline when accelerated automation coincides with population aging.

The findings of the model underscore that it is not possible to draw general conclusions about the consequences of this shock: an increase in the proportion of high-skilled workers over an extended period does not necessarily exert a favorable influence on per capita GDP growth within the context of an aging society and automation. Consequently, the aging pattern must not be considered the sole decisive factor in assessing the economic consequences of automation.

6. Conclusion

This study explores the complex interplay between demographic aging and automation, and how these forces jointly shape macroeconomic outcomes across different national contexts. By employing a calibrated general equilibrium model and analyzing five OECD countries – Republic of Korea, Australia, Italy, Hungary, and Türkiye – we provide a

Table A1
Effects of parameter changes on GDP per capita, physical capital inputs and robots: mean and standard deviation of percentage deviations from baseline scenario over the next 20 periods (%).
Source: Authors' calculation.

		10% increase in α		10% decrease in α		10% increase in δ_K		10% decrease in δ_K		10% increase in δ_M		10% decrease in δ_M		1% increase in β		1% decrease in β	
		Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Australia	Y	−0.08	0.02	0.08	0.02	0.02	0.01	−0.02	0.01	0.01	0.02	−0.01	0.02	0.09	0.09	−0.16	0.06
	M	−1.13	0.23	1.32	0.22	−0.49	0.08	0.54	0.09	−1.72	0.15	1.87	0.22	15.56	3.70	−13.36	1.83
	K	9.93	0.02	−9.94	0.01	−3.16	0.01	3.37	0.01	0.01	0.02	−0.01	0.02	49.71	0.20	−25.38	0.06
Republic of Korea	Y	−0.41	0.11	0.41	0.11	0.11	0.03	−0.11	0.03	−0.00	0.08	−0.00	0.08	1.05	0.57	−1.20	0.40
	M	−2.31	1.41	2.55	1.63	−0.27	0.30	0.31	0.30	−1.61	0.05	1.69	0.02	14.68	12.59	−14.75	4.47
	K	9.60	0.10	−9.66	0.08	−3.03	0.04	3.23	0.05	0.01	0.10	−0.01	0.11	50.21	1.23	−25.89	0.36
Italy	Y	−0.26	0.07	0.23	0.06	0.06	0.02	−0.07	0.02	0.07	0.05	−0.07	0.05	−0.36	0.12	0.17	0.13
	M	0.66	0.51	−0.74	0.92	−0.90	0.22	0.95	0.20	−1.10	0.46	1.23	0.56	22.65	4.96	−12.32	2.89
	K	9.76	0.06	−9.83	0.05	−3.13	0.01	3.33	0.02	0.07	0.05	−0.07	0.05	49.06	0.25	−25.14	0.12
Hungary	Y	−0.10	0.03	0.11	0.03	0.03	0.01	−0.03	0.01	0.02	0.02	−0.02	0.02	−0.19	0.14	0.01	0.11
	M	−3.98	6.14	4.53	6.88	0.35	1.68	−0.33	1.74	−1.21	0.74	1.33	0.91	−1.61	29.32	−3.95	13.38
	K	9.89	0.03	−9.91	0.03	−3.15	0.01	3.37	0.01	0.03	0.03	−0.03	0.03	49.36	0.26	−25.28	0.10
Türkiye	Y	−0.15	0.05	0.14	0.05	0.05	0.02	−0.05	0.02	0.02	0.02	−0.02	0.02	−0.48	0.32	−0.03	0.18
	M	−13.52	7.37	14.16	7.94	3.29	2.16	−3.44	2.26	−4.22	2.83	5.05	3.50	−49.91	35.46	14.87	16.82
	K	9.81	0.07	−9.85	0.05	−3.13	0.02	3.34	0.02	0.02	0.02	−0.02	0.02	48.94	0.50	−25.31	0.15

nuanced understanding of how structural differences in labor markets and production technologies mediate the economic consequences of aging.

Our model-based simulations successfully reproduce key findings from the existing literature, notably that aging leads to increased robot accumulation and that capital income increasingly diverges from labor income. These results confirm the broader trend of automation being used as a compensatory mechanism in response to shrinking labor forces. However, our research goes further by identifying several novel dynamics that challenge conventional assumptions.

First, we find that the share of high-skilled labor and the structure of production technology are more influential in determining robot accumulation than interest rate dynamics. This insight shifts the focus from macro-financial conditions to labor market composition and technological design. Second, while aging does stimulate automation, this process is inherently limited by the declining number of high-income contributors who can finance such investments. The growth in robot stock is therefore substantial but ultimately finite.

Third, we show that aging does not uniformly lead to a decline in per capita income. Countries with low initial consumption levels and production technologies that rely heavily on low-skilled labor – such as Türkiye and Hungary – can temporarily avoid this decline, as robots effectively substitute for displaced workers while the relatively modest reduction in consumption when transitioning from a low level of consumption to slightly lower levels during retirement helps sustain the overall demand for goods and services.

Fourth, automation often involves the replacement of existing capital rather than its expansion, indicating a shift in the composition of productive assets rather than a net increase. This has implications for investment strategies and capital formation in aging economies.

Fifth, we observe a narrowing of the wage gap between high-skilled and low-skilled workers, driven by the productivity-enhancing effects of robots across skill levels.

Finally, an increase in the proportion of high-skilled workers over an extended period does not necessarily exert a favorable influence on per capita GDP growth within the context of an aging society and automation.

The results of the model are sensitive to key structural assumptions, particularly the trajectory of demographic aging and the relative composition of high-skilled and low-skilled workers. Deviations from the assumed demographic paths – such as faster or slower aging, abrupt changes in cohort shares, or shifts in the distribution of educational attainment – may alter the simulated macroeconomic effects of automation. Moreover, a potential source of measurement bias arises from the operational definition of "high-skilled" workers as individuals with tertiary education, which may not fully capture skill heterogeneity in practice.

Taken together, these findings underscore the importance of considering demographic structure, labor market segmentation, and technological characteristics when evaluating the macroeconomic impact of automation. Policymakers should be aware that the benefits of automation are not evenly distributed and that its effectiveness in mitigating the costs of aging depends heavily on country-specific factors. Future applied research could extend this framework to include endogenous skill formation, migration, and policy interventions aimed at balancing equity and efficiency in aging societies.

CRediT authorship contribution statement

Izabella Kuncz: Writing – original draft, Software, Conceptualization, Visualization. **Petra Németh:** Writing – original draft, Data Curation, Conceptualization, Investigation. **Eszter Szabó-Bakos:** Writing – original draft, Software, Conceptualization, Methodology, Formal Analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

The model includes four parameters that are fixed based on the literature: β, δ_M, δ_K, and α. All other parameters are calibrated; thus, any change in these four parameters also affects the values of the remaining parameters. In the sensitivity analysis, we increased and decreased δ_M, δ_K, and α by 10% relative to their baseline values. For β, such large variations were not feasible, so we applied a $\pm 1\%$ change instead.

Table A1 presents, for a selected set of variables, the average percentage deviation from their baseline model values caused by the parameter change, calculated over a 20-period horizon from the initial period.

Although we computed these statistics for all endogenous variables in the model, we deliberately chose to present results for per capita income, per capita capital stock, and per capita robot stock, as these variables capture two clearly distinguishable groups of outcomes. For one group of variables, the average deviation from the baseline model is negligible under any parameter variation, providing no justification for modifying the baseline parameters. In cases where the deviations are relatively large, both their direction and magnitude are of a similar order across all countries; consequently, neither the overall trends nor the relative proportions change, which likewise does not warrant any adjustment of the baseline specification.

An exception to the general grouping pattern described above is the effect of changes in the β parameter. In the baseline model, β is set to 0.98, which corresponds to an approximate long-run natural interest rate of 2%. A $\pm 1\%$ change in β would imply a long-run interest rate

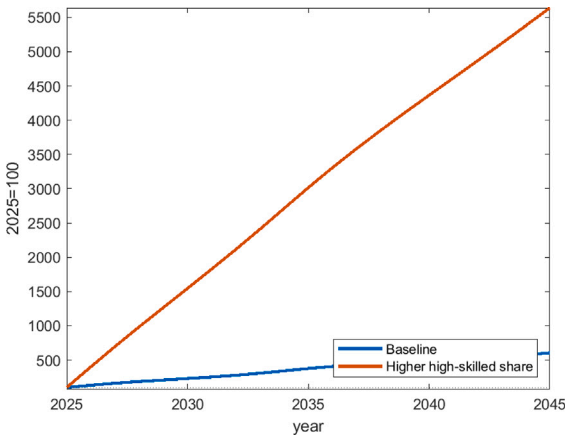

Fig. A1. Robots in Australia.
Note: The evolution of robots over time in the baseline scenario (blue line) and with a continuously increasing share of high-skilled workers, 2025=100 (red line).
Source: Authors' contribution based on the model results.

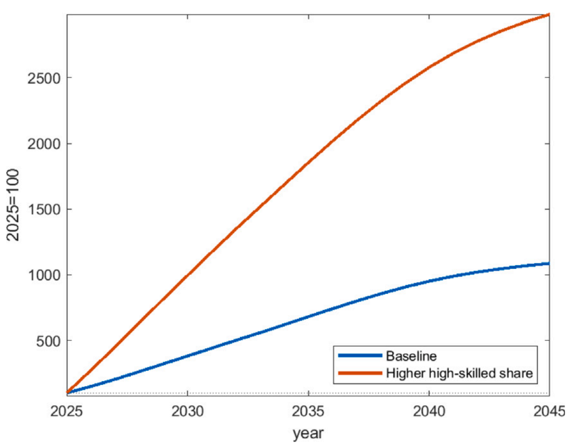

Fig. A2. Robots in Italy.
Note: The evolution of robots over time in the baseline scenario (blue line) and with a continuously increasing share of high-skilled workers, 2025=100 (red line).
Source: Authors' contribution based on the model results.

of approximately 1% and 3%, respectively. As shown in the table, this leads to substantial changes in the capital and robot stock, and in the case of an increase, even produces deviations in opposite directions for two countries (Hungary and Türkiye) (see Fig. A5). However, even these changes do not alter the key results established under the baseline model: the intensification of robot accumulation, the existence of an upper bound to this accumulation, the eventual decline in per capita GDP in all countries, and the convergence of low- and high-skilled wages. Accordingly, this did not require any modification of the baseline parameter structure.

Data availability

Data will be made available on request.

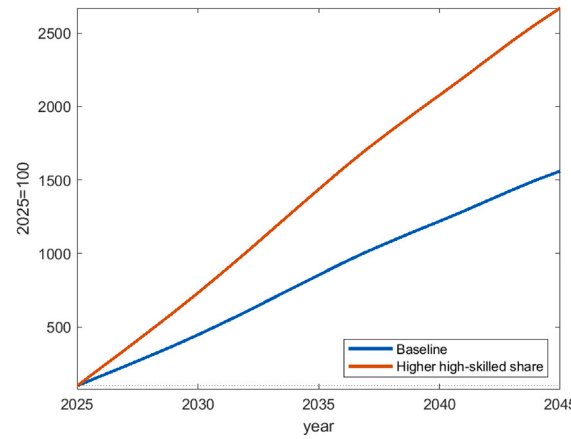

Fig. A3. Robots in Republic of Korea.
Note: The evolution of robots over time in the baseline scenario (blue line) and with a continuously increasing share of high-skilled workers, 2025=100 (red line).
Source: Authors' contribution based on the model results.

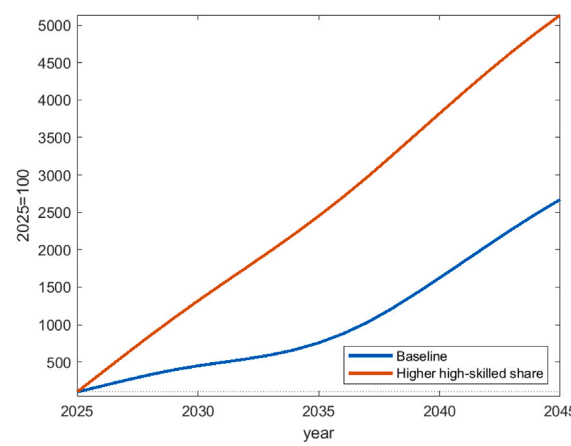

Fig. A4. Robots in Türkiye.
Note: The evolution of robots over time in the baseline scenario (blue line) and with a continuously increasing share of high-skilled workers, 2025=100 (red line).
Source: Authors' contribution based on the model results.

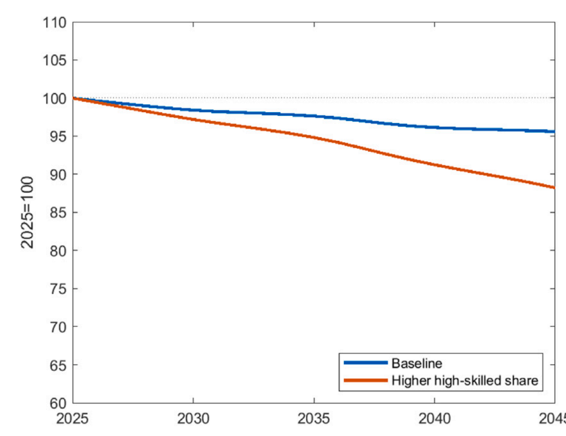

Fig. A5. Aggregate labor in Australia.
Note: The evolution of the aggregate labor input in the baseline scenario (blue line) and with a continuously increasing share of high-skilled workers, 2025=100 (red line).
Source: Authors' contribution based on the model results.

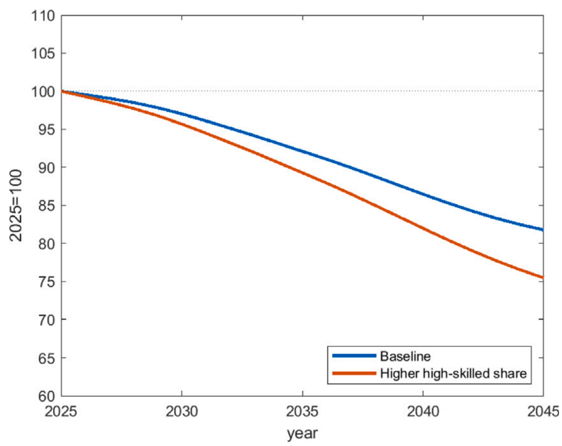

Fig. A6. Aggregate labor in Italy.
Note: The evolution of the aggregate labor input in the baseline scenario (blue line) and with a continuously increasing share of high-skilled workers, 2025=100 (red line).
Source: Authors' contribution based on the model results.

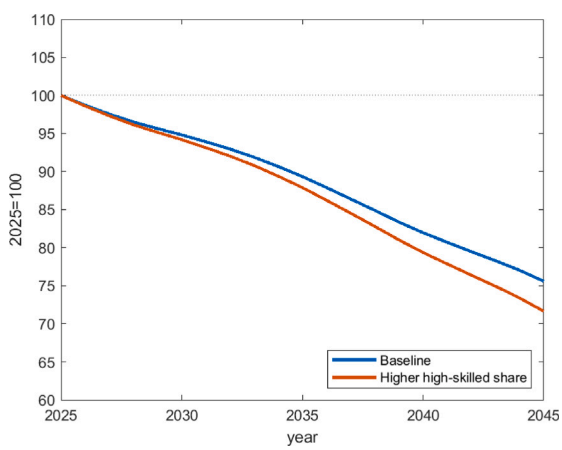

Fig. A7. Aggregate labor in Republic of Korea.
Note: The evolution of the aggregate labor input in the baseline scenario (blue line) and with a continuously increasing share of high-skilled workers, 2025=100 (red line).
Source: Authors' contribution based on the model results.

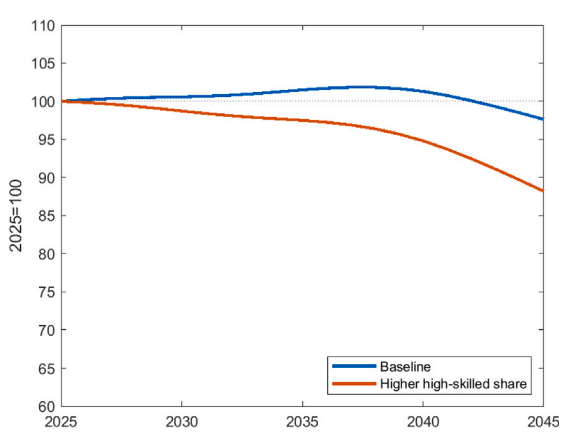

Fig. A8. Aggregate labor in Türkiye.
Note: The evolution of the aggregate labor input in the baseline scenario (blue line) and with a continuously increasing share of high-skilled workers, 2025=100 (red line).
Source: Authors' contribution based on the model results.

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