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Automation and aging: The impact on older workers in the workforce

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ABSTRACT

Developed countries are seeing advances in automation and, at the same time, their populations are aging. In this paper we examine both phenomena using the delay in retirement age as a nexus. Although automation is freeing workers from repetitive, hard work, older workers feel threatened by new automation advances which generate skill mismatches. Two links are highlighted: First, since skill mismatches affect low-skilled older workers more than those who are highly skilled, the latter will remain active for a longer period of time while the former will be pushed to retire. Second, the highly skilled workers who decide to prolong their working lives are a valuable resource for further automation advances because this technology continues to need human-assisted solutions. Our analysis establishes an important role for adult training to fill the gap between initial education and the demands of a rapidly changing labor market in order to encourage individuals to postpone their retirement and, hence, to ensure the sustainability of the social insurance system.

Introduction

Today there is an ongoing and multifaceted process of automation and digitalization which has been called the Fourth Industrial Revolution. Schwab (2017) characterizes the fourth industrial revolution as physical (autonomous vehicles, 3D printing, robotics), digital (the Internet of Things, Artificial Intelligence (AI), block chain), and biological (synthetic biology, gene editing). Although automation has extended to all industrialized countries, significant inroads have been made in countries with more rapidly aging populations. In this regard, some empirical research supports a positive relationship between aging and automation. By using data over the period 1993–2013 for 60 countries, Abeliansky and Prettner (2023) find that a 1 % increase in population growth is associated with an approximately 2 % reduction in the growth rate of automation density. In other words, those countries with a slowdown of population growth – corresponding to a faster population aging - invest more in the adoption of automation technologies. Their reasoning is that the older the demographic structure the stronger the incentive to invest in automation capital since automation acts as a substitute for the relatively scarce labor input. However, they also admit as a possible explanation that aging countries are richer and, hence, more able to invest in automation. Acemoglu and Restrepo (2022) also find that aging, proxied by the higher ratio of older to middle-aged workers, is positively related to the intensive use of robots and other industrial automation technologies. This effect is more noticeable in industries which depend mostly on middle-aged workers and those which have greater opportunities for automation. Interestingly, they provide evidence that aging also boosts innovation in automation technologies. Making use of data from 103 countries, aging appears positively associated with greater exports of automation technologies and, analyzing data from 69 countries, we can also see that aging populations show a strong positive relationship with robotics-related patents.

Most of the theoretical literature about the link between aging and automation points to money saving as the key factor. Irmen (2021) establishes that aging encourages automation in the long run because longer lifespans demand a more cautious approach to spending. Greater saving allows for a higher accumulation of fixed capital which, in turn, increases wages, and hence, the incentives for automation. Stähler (2021) also connects aging to a higher level of savings. The higher saving surplus linked to a longer life augments traditional and automation capital stocks which have a positive impact on the output. They provide a caveat to this positive effect, since the share of active workers in the economy falls, which harms production. If productivity increases from automation overcompensates for the reduction of the labor force, automation, aging and production evolve positively all together. In the same line, Zhang et al. (2022) establish that an increase in longevity leads to more savings and, hence, more investment in automation

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capital. However, ambiguity about the effect of automation on output in their analysis lies in the decline in employment of low-skilled workers and, at the same time, the rise of both physical and automation capital stocks and the employment of highly-skilled workers.

These analyses do not introduce the role of the current increase in participation by older workers in the labor force, although population aging is progressing hand in hand with a rise of labor force participation among older adults. While it is true that there is a growing literature over the effects of automation on labor market,[2] the evidence about the impact of automation advances on the labor supply of older workers is scant. Autor and Dorn (2009) claim that contractions in routine employment as result of automation disproportionately increase the share of workers employed in nonroutine jobs and only the youngest highly educated workers exhibit upward occupational reallocation. However, Nedelkoska and Quintini (2018) establish that those more threatened by automation are precisely the youngest workers because their occupational pattern relies mostly on elementary jobs most susceptible to automation. Anyway, there exists a consensus in literature that educational attainment attenuates the link between automation and workforce detachment (Brandes and Wattenhofer, 2016; Frey and Osborne, 2017; Grigoli et al., 2020). In this paper we build a theoretical framework that embraces automation, aging, a labor market whose workers exhibit different skill levels and the decision of older workers to prolong their working life or not. In particular, our model highlights two mechanisms. First, automation has an unequal effect on the retirement decision across different groups of workers. While one can surmise that the advance of automation acts as a force that pushes all older workers into retirement because of the obsolescence of jobs or skills, the most affected workers will be the less-skilled. The idea behind our approach is that automation moves those older workers who are less qualified quickly toward retirement. The second mechanism is that those more highly skilled older workers, whose jobs are less exposed to the risk of automation and consequently, decide to prolong their working lives and increase the amount of highly-qualified labor. This extra resource might have a positive effect on technological advances, in particular automation. Innovation in automation requires prior knowledge but also necessitates human participation. For example, so-called hybrid intelligence, which combines the complementary capabilities of humans and artificial intelligence, has contributed to further advancements in the robotics field, such as the management of multi-component robotic systems (Duro et al. 2010). Automation allows for a wide range of tasks to be performed with very little human intervention, especially routine tasks, but innovation advances require creativity, intuition, judgment and adaptability, which are intrinsic to human nature (Autor, 2015). For this reason, an increase in the labor participation of highly-qualified senior workers might provide additional resources for the research sector, making future advances in automation more feasible. In this scenario, we can appreciate that the links between aging and automation are bidirectional, acting as a channel of transmission on the retirement decision of older workers.

The remainder of the paper is organized as follows. Section 2 presents the basic model and its equilibrium. Section 3 analyzes the implications of longer life expectancy and a higher mismatch between skills and automation advances on both the rate of participation of older workers and the economic growth rate in the long term. Section 4 summarizes the main results and suggests some avenues for future research.

[2] See, among others, Graetz and Michaels (2018), Autor and Salomons (2018), Acemoglu and Restrepo (2020).

The model

Households

We make use of the household aspect of the model of Aisa et al. (2012). Consider an overlapping generations economy. The population of the economy is made up of individuals that live for two periods, namely young and older age. The lifetime of an individual is uncertain. Everyone lives during the first period, but ultimately dies with a probability p. Thus, survival to old age is not assured, with $1-p$ being the probability of remaining alive in the second period of life. We normalize the size of each new generation to 1. Every individual of each generation is identified with a different value of the sub index i, continuously distributed along the interval $[0,1]$. Each individual is born with a different skill level θ_i, also uniformly distributed along the interval $[0,1]$. The assumption of a uniform distribution of the skills along the interval $[0,1]$ allows us to identify $\theta_i = i$.

Each individual belonging to generation t earns a wage income equal to $w_t\theta_i$. A part of this income is consumed, $c^y_{i,t}$, and the rest is saved, $s_{i,t} = w_t\theta_i - c^y_{i,t}$. The surviving older workers obtain a capital income $R_{t+1}s_{i,t}$ in period $t+1$, where R_{t+1} is the rate of return on savings. Any (surviving) older individuals may supplement their capital income by remaining in the labor market and, thus, earning a wage $w_{t+1}\delta_{i,t+1}\theta_i e_{i,t+1}$, where $e_{i,t+1}$ denotes their labor force participation and $\delta_{i,t+1}\theta_i$ measures their effective skill level when older. That is to say, $\delta_{i,t+1}$ captures the fraction of youthful skill maintained in the second period of life, with $0 \leq \delta_{i,t+1} < 1$. Thus, the older-age consumption of an individual i is given by $c^o_{i,t+1} = R_{t+1}s_{i,t} + w_{t+1}\delta_{i,t+1}\theta_i e_{i,t+1}$. We assume that the older worker's labor force participation is a zero-one decision: $e_{i,t+1} = 0$ if he or she decides to retire or $e_{i,t+1} = 1$ if he or she decides to work during his or her second period of life.

Every individual derives utility from youthful consumption $c^y_{i,t}$, older-age consumption $c^o_{i,t+1}$ and amount of leisure time if the individual retires when older λ. The expected utility of an individual i born in t is given by:

$$EU\left(c^y_{i,t}, c^o_{i,t+1}, e_{i,t+1}\right) = \left[1+\lambda\left(1-e_{i,t+1}\right)\right]^{1-p}\left[\left(\frac{c^y_{i,t}}{1-\beta}\right)^{1-\beta}\left(\frac{c^o_{i,t+1}}{\beta}\right)^{\beta(1-p)}\right]. \tag{1}$$

Given the uncertainty about surviving the second period of life, the expected utility derived from consumption and leisure when older appears multiplied by the life expectancy, 1-p. Parameter $\beta \in (0,1)$ is related to the intertemporal discount rate of consumption. A positive discount rate for the future consumption requires $\frac{\beta}{(1-\beta)} < 1$.

Therefore, the representative individual i of the cohort born in t faces the following optimization problem:

$$\underset{e_i,\{c_i\}}{Max} \quad EU\left(c^y_{i,t}, c^o_{i,t+1}, e_{i,t+1}\right) = \left[1+\lambda\left(1-e_{i,t+1}\right)\right]^{1-p}\left[\left(\frac{c^y_{i,t}}{1-\beta}\right)^{1-\beta}\left(\frac{c^o_{i,t+1}}{\beta}\right)^{\beta(1-p)}\right],$$

$$\text{s.t.}: s_{i,t} = w_t\theta_i - c^y_{i,t} \tag{2}$$

$$c^o_{i,t+1} = R_{t+1}s_{i,t} + w_{t+1}\delta_{i,t+1}\theta_i e_{i,t+1}$$

$$e_{i,t+1} \in 0\{0,1\}; c^y_{i,t}, c^o_{i,t+1} > 0$$

The problem can be solved in two stages. In the first one, individuals decide about their levels of consumption when young and older, $\{c_i\} = \left\{c^y_{i,t} > 0, c^o_{i,t+1} > 0\right\}$, which will depend on their decision about retirement in later life. In the second stage of life, they decide whether to retire $\left(e_{i,t+1} = 0\right)$ or not $\left(e_{i,t+1} = 1\right)$ by comparing welfare in the two situations. The optimal consumption profile, conditional on the retirement decision, is characterized by the following values of consumption when young and older, respectively:

$$c_{i,t}^{y}=\frac{1-\beta}{1-\beta p}\left(w_t\theta_i+\frac{w_{t+1}\delta_{i,t+1}\theta_i}{R_{t+1}}e_{i,t+1}\right) \tag{3}$$

$$c_{i,t+1}^{o}=\frac{\beta(1-p)}{1-\beta p}R_{t+1}\left(w_t\theta_i+\frac{w_{t+1}\delta_{i,t+1}\theta_i}{R_{t+1}}e_{i,t+1}\right) \tag{4}$$

which imply an associate individual savings function given by:

$$s_{i,t}=\frac{1-p}{1-\beta p}\left[\beta w_t\theta_i-(1-\beta)\frac{w_{t+1}\delta_{i,t+1}\theta_i}{(1-p)R_{t+1}}e_{i,t+1}\right] \tag{5}$$

As observed in previous literature about savings and aging, a longer life expectancy increases individual savings, *ceteris paribus*. The reason is that a higher probability of surviving into the second period implies a higher probability of enjoying the consumption derived from savings in the second period, which makes individuals reserve more income (Reinhart 1999). Logically, the individuals who remain in the labor market in the second period of life have saved less than those who decide to retire: the former will earn an additional income w_{t+1} per unit of effective labor supplied in the second period, while retired individuals will receive no income in this period.

The second stage corresponds to the decision about retirement in the second period. Individuals compare the welfare derived from the two scenarios, given the optimal consumption decisions taken in the first stage. By introducing these optimal values into the utility function, we surmise that the level of welfare achieved by worker i who decides to remain in the labor market when older is given by:

$$EU(e_{i,t+1}=1)=[R_{t+1}(1-p)]^{\beta(1-p)}\left(\frac{w_t\theta_i+\frac{w_{t+1}\delta_{i,t+1}\theta_i}{R_{t+1}}}{1-\beta p}\right)^{1-\beta p} \tag{6}$$

whereas the welfare if he/she retires is:

$$EU(e_{i,t+1}=0)=(1+\lambda)^{1-p}[R_{t+1}(1-p)]^{\beta(1-p)}\left(\frac{w_t\theta_i}{1-\beta p}\right)^{1-\beta p} \tag{7}$$

An individual will be willing to participate in the labor market when older only if the value of his or her utility in (6) is not lower than that in (7), that is to say, if the following condition holds:

$$\left(w_t\theta_i+\frac{w_{t+1}\delta_{i,t+1}\theta_i}{R_{t+1}}\right)^{1-\beta p}\geq(1+\lambda)^{1-p}(w_t\theta_i)^{1-\beta p} \tag{8}$$

At this point, we diverge from the work of Aisa et al. (2012) by assuming a different skill-profile when older, in which the combination of automation and aging plays a relevant role regarding productivity loss in later years. This combination has recently received the name of *aging-and-tech job vulnerability*, a term which represents the reduction in job quality that older workers face because of both their own biological aging and the automation of their job tasks (Alcover et al., 2021). The skill-profile of individual i born in t when older takes the following functional form:

$$\delta_{i,t+1}=\frac{(1-p)^{\gamma}\theta_i^{\sigma}}{\left(\frac{A_{t+1}}{A_t}\right)^{\psi}} \tag{9}$$

with $\psi>0$, $\gamma>0$ and $\sigma>0$. A_t denotes the automation level in period t and $\frac{A_{t+1}}{A_t}$ represents the automation advances between t and $t+1$. Eq. (9) captures three ideas:

1. The expected individual skill loss from aging depends on the advances in automation in the economy in which this individual lives. The Fourth Revolution is a locomotive that enables the economic advancement of economies at an aggregate level, but it also causes negative external effects such as the mismatch between the new skills required and the skills possessed by workers. Those senior workers who live in countries in which automation and digitalization are advancing at a very rapid pace will suffer from a process of marked skill obsolescence or skill misalignment. This negative externality does not emerge in countries when automation and digitalization advances hardly affect their productive structure. Empirical evidence gives support to this idea highlighting that the current changes in the labor market, mostly tied to automation and digitalization, have increased the perception of job insecurity of older workers who feel intimidated by new technologies (Burgard and Seelye, 2016). The parameter ψ is the automation elasticity of the decline in skills and gives the percentage change in the skill decline with age when there is a one percent increase in automation progress, holding everything else constant.
2. Aging decreases the physical, cognitive, and socio-emotional abilities of individuals per se, but this decline resulting from aging is lower when life expectancy increases. Even in a context without automation advances ($A_{t+1}=A_t$), each individual suffers an unavoidable decline in skills in old age (Rizzuto et al. 2012). However, the decline is slower when longevity improves because of what is known as the compression of morbidity (Costa, 2002). The compression of morbidity means that the burden of lifetime illness is compressed into a shorter period before the time of death and, hence, both physical and cognitive abilities are extended into old age. The parameter γ gives the percentage change in the fraction of youthful skill maintained in the old age when the life expectancy level rises in a one percent, maintaining everything else constant.
3. The combined effect of automation and aging threaten older workers in a nonhomogeneous way, in such a way that low-skilled senior workers are more adversely affected by the mixture of aging and automation than highly-skilled workers. Low-skilled individuals are working in jobs threaten by a higher risk of automation[3] (Brandes and Wattenhofer, 2016; Frey and Osborne, 2017; Nedelkoska and Quintini, 2018, Grigoli et al, 2020) and, hence, automation will displace them more straightforwardly into retirement, if they are eligible for it, than highly-skilled workers. Additionally, empirical evidence also establishes that low-skilled workers participate in fewer retraining activities since they face limited opportunities for on-the-job learning and thus are more affected by skill misalignments derived from the advances in automation and digitalization (Fouarge et al., 2013; Ruhose et al., 2019). The parameter σ measures how sensitive the skill decline as consequence of the aging is to the skill level of each individual, keeping everything else constant.

Incorporating (9) into (8), individuals' decision about retirement is determined by their skill level, which is the element that introduces heterogeneity across workers in our model. In particular, there is a critical skill level $\theta_{i^*,t+1}$ such that workers whose skill level exceeds this critical value, that is to say, those from i_{t+1}^{*} to 1, obtain more utility remaining in the labor market in the second period of life, while those with a lower skill level (those from 0 to i_{t+1}^{*}) decide to retire:

$$\frac{w_{t+1}(1-p)^{\gamma}\theta_{i^*,t+1}^{\sigma}}{R_{t+1}\left(\frac{A_{t+1}}{A_t}\right)^{\psi}}\geq\Lambda w_t \tag{10}$$

where $\Lambda=(1+\lambda)^{\frac{1-p}{1-\beta p}}-1>0$. On the one hand, a higher relative wage in the second period of life, a higher expectancy level and a higher skill level act as stimulus for remaining in the labor market. On the other hand, the leisure associated with retirement captured by the term Λ, a higher skill misalignment as consequence of automation advances, and higher savings returns act as incentives for retirement. By putting together these factors, we surmise that highly-skilled individuals have

[3] Nedelkoska and Quintini (2018) point out an exception: some relatively low-skilled workers such as personal care workers.

more incentive to remain working while low-skilled individuals choose to retire. This outcome conforms to the bulk of the empirical evidence, that the more skilled individuals or, in other words, those with the highest levels of education, tend to retire later (Taylor et al., 2014; Virtanen et al., 2017; Carlstedt et al., 2018), even in environments highly automated (Casas and Román, 2023). We can rewrite (10) in terms of the participation rate of older people in labor market z_{t+1} as:

$$z_{t+1} = 1 - \left[\Lambda \frac{w_t R_{t+1} \left(\frac{A_{t+1}}{A_t} \right)^{\psi}}{w_{t+1} (1-p)^{\gamma}} \right]^{\frac{1}{\sigma}} \tag{11}$$

with $z_{t+1} = 1 - \theta_{i^*_{t+1}}$ and $0 < z_{t+1} < 1$.

Once we have characterized the optimal consumption and retirement of people, the characterization of individuals' behavior is closed by calculating the cohort-specific consumption growth rate:

$$\frac{C^o_{t+1}}{C^y_t} = \frac{(1-p)\int_0^1 c^o_{i,t+1} di}{\int_0^1 c^y_{i,t} di} = \frac{\beta (1-p)^2}{1-\beta} R_{t+1} \tag{12}$$

This cohort-specific consumption growth rate measures the growth of consumption of the younger cohort in period t to the next period $t+1$ and it differs from the aggregate consumption growth rate measures the growth of consumption of all individuals living in period t to all individuals living in the next period $t+1$. The former focuses on a single cohort, while the latter considers different cohorts. When the economy is on its long-run balanced growth path, the cohort-specific and the aggregate consumption growth rates become equal (Baldanzi et al., 2019).

Production

The economy is formed by four production sectors: a final product sector, two intermediate task sectors, and a research sector. The final product is produced competitively by combining units of non-automated tasks x^n_{jt} and units of automated tasks x^a_{ut}, following this equation:

$$Y_t = \int_0^{N_t} \left(x^n_{jt} \right)^{\alpha} dj \int_0^{A_t} \left(x^a_{ut} \right)^{1-\alpha} du \tag{13}$$

where $0 < \alpha < 1$. Y_t denotes the final product level in period t, N_t and A_t are the number of non-automated and automated tasks in period t, respectively, and α measures the productivity level of non-automated tasks. Our model embodies a task framework close to that detailed in the papers of Acemoglu and Restrepo (2019) and Hémous and Olsen (2022), who distinguish between tasks which have not been technologically automated in the sense that they are produced by using labor only, and tasks which have been automated and it is profitable to produce them with capital alone. In other words, it is assumed that capital has a comparative advantage in automated tasks, while labor has a comparative advantage in non-automated tasks, being automated and non-automated tasks complementary at the aggregate level. An example is the financial market. Banks make use of automated tasks to process documents (e.g., invoices) and to get customer data (e.g., process mining to risk mitigation), but also use non-automated tasks such as the personal attention of financial advisors (Zhang et al, 2021). This complementarity between automated and labor-intensive tasks at aggregate level is also assumed by Aghion et al. (2019).

Because the final product is produced competitively, the prices of each unit of task equal their marginal products:

$$q^n_{jt} = \frac{\partial Y_t}{\partial x^n_{jt}} = \alpha \int_0^{A_t} \left(x^a_{ut} \right)^{1-\alpha} du \left(x^n_{jt} \right)^{\alpha-1} \tag{14}$$

$$q^a_{ut} = \frac{\partial Y_t}{\partial x^a_{ut}} = (1-\alpha) \int_0^{N_t} \left(x^n_{jt} \right)^{\alpha} dj \left(x^a_{ut} \right)^{-\alpha} \tag{15}$$

where q^n_{jt} and q^a_{ut} are the prices of the non-automated task j and the automated task a, respectively. For simplicity, we assume that each non-automated task j is made by self-employed workers in such a way that a unit of non-automated task requires a unit of labor weighted by the skill endowment of each worker. The total labor of the economy L_t is the sum of labor units supplied by workers weighted by their level of skill, being a share assigned to non-automated tasks, $L^n_t = \int_0^{N_t} \left(x^n_{jt} \right) dj$ and the rest allocated to the research sector, as will be explained below. Thus, $q^n_{jt} = w^n_t$, with w^n_t denoting the wage rate in the non-automated tasks sector.

Each automated task u is produced by a single monopolistic competitive firm which uses capital as input and is infinitely protected by a patent,p^a_t. This firm maximizes its profit $\pi^a_{jt} = q^a_{ut} x^a_{ut} - r_t x^a_{ut}$, subject to its demand given by Eq. (15). As usual, the optimal solution is obtained from equalizing the marginal income to marginal cost:

$$(1-\alpha)^2 \int_0^{N_t} \left(x^n_{jt} \right)^{\alpha} dj \left(x^a_{ut} \right)^{-\alpha} = r_t \tag{16}$$

where r_t is the interest rate. Because of $x^n_{jt} = x^n_t$ and $x^a_{ut} = x^a_t$, the profit of whatever monopolistic competitive firm takes the following value:

$$\pi^a_t = \frac{\alpha}{1-\alpha} r_t x^a_t \tag{17}$$

Each monopolistic firm benefits from a mark-up which allows them to pay the price of the patent that gives it the exclusive right to provide a particular automated task. Consequently, the value of the patent must be equal to the sum of the discounted present value of the profit flow. Derived from this, the following no-arbitrage condition is obtained (Futagami and Konishi, 2019):

$$r_{t+1} p^a_t = \pi^a_t + p^a_{t+1} - p^a_t \tag{18}$$

Following Romer (1990), the research sector uses as inputs both previous knowledge about automation and labor units weighted by skill level:

$$A_t - A_{t-1} = B A_{t-1} L^A_t \tag{19}$$

where $A_t - A_{t-1}$ measures the onset of new automated tasks, B is a scale parameter and L^A_t represents the amount of labor weighted by the skill level devoted to automation progress. Each new advance in automation corresponds to a new automatized task, so A is a count of the number of automatized tasks. We assume that advances in automation expand the set of automated tasks and, at the same time, the discovery of automated tasks is more feasible. For instance, computing software which performs data mining and data organization, paves the way for further innovations in automation or digitalization. Even so, human participation and human capabilities such as creativity, flexibility and intuition are indispensable in the innovation process. Developing new innovations is inherently complex and difficult to fully replace with AI. Therefore, the nexus of the automation and humans in charge of implementing it helps innovation processes by reducing both their riskiness and their cost (Haefner et al. 2021). This differs from Acemoglu and Restrepo (2019) and Hémous and Olsen (2022), who consider that automation innovation modifies the manufacturing process of existing tasks by changing from a manual production method to an automated one while, at the same time, new non-automated tasks are created. As a result, labor remains necessary. Our model reflects that automation becomes increasingly important in the economy since automation innovations increase the number of automated tasks while the non-automated tasks number remain constant. Labor is required because the creation of new robots or software or other automation advances will always require human intervention. In addition, whereas the analyses of Acemoglu and Restrepo (2019) and Hémous and Olsen (2022) highlight the displacement of workers from jobs more susceptible to automation toward new jobs in which labor has a comparative advantage, our framework emphasizes the displacement of older workers toward retirement as a result of skill mismatches intrinsic to automation.

The growth rate of automated tasks $g_{A,t}$ is:

$$g_{A,t} = \frac{A_t - A_{t-1}}{A_{t-1}} = BL_t^A \tag{20}$$

Automation innovation is made by competitive firms which leads to the fulfillment of the condition $p_t^a BA_t = w_t^A$, being w_t^A the wage rate in the research sector.[4] Observe that the stock of technological knowledge of the economy as a whole is non-rival, but each monopolistic competitive firm is protected by a patent which covers the costs of its automation investment.

Equilibrium and balanced growth path

Incorporating $K_t = A_t x_t^a$ and $L_t^n = N_t x_t^n$ into Eqs. (14) and (16), we obtain the wage rate in non-automated sector and the interest rate:

$$\omega_t^n = \alpha N_t^{1-\alpha} \widehat{k}_t^{1-\alpha} \tag{21}$$

$$r_t = (1-\alpha)^2 N_t^{1-\alpha} \widehat{k}_t^{-\alpha} \tag{22}$$

where $\widehat{k}_t = \frac{K_t}{A_t L_t^N}$ is the effective capital and $\omega_t^n = \frac{w_t^n}{A_t}$ is the effective wage rate. Assuming as usual a perfect annuity market (Blanchard, 1985), the capital income unexpectedly left by workers who die at the end of their first period of life is shared by the workers who survive to old age, which determines a return on savings equal to $R_t = \frac{r_t}{1-p}$.

Regarding the inputs, the amount of total labor weighted by the skill level is the sum of the average skill level of young individuals, $\bar{\theta} = \int_0^1 idi = \frac{1}{2}$, multiplied by their size (normalized to 1), and the average skill level of the surviving older labor force, $\bar{\delta}\bar{\theta}_t = \frac{1}{1-i_t^*} \int_{i_t^*}^1 \frac{(1-p)^\gamma \theta_i^{1+\sigma}}{\left(\frac{A_t}{A_{t-1}}\right)^\psi} di = \frac{(1-p)^\gamma}{z_t (1+g_{A,t})^\psi} \frac{1-(1-z_t)^{2+\sigma}}{2+\sigma}$, multiplied by their size, z_t, that it is to say:

$$L_t = \frac{1}{2} + \frac{(1-p)^{\gamma+1}}{(1+g_{A,t})^\psi} \frac{1-(1-z_t)^{2+\sigma}}{2+\sigma} \tag{23}$$

Observe that a higher skill misalignment because of advances in automation has twofold negative effects on the elderly labor supply. On the one hand, the skill level of those senior workers who decide to remain in the labor market lowers and on the other hand, the number of senior workers who decide to retire increases. Therefore, in those aging countries in which automation progress makes the decline of skills sharper as the population ages, the participation of older workers will be lessened and less productive.

Focusing now on the capital input, its aggregate stock K_t can be calculated as the sum of the individual savings from all the members belonging to the cohort born in *t-1*, those who retire and those who keep working:

$$K_t = \int_0^{i_t^*} \left(\frac{1-p}{1-\beta p}\right) \beta w_{t-1} \theta_i di + \int_{i_t^*}^1 \left(\frac{1-p}{1-\beta p}\right) \left[\beta w_{t-1} \theta_i - (1-\beta) \frac{w_t \delta_{i,t} \theta_i}{(1-p) R_t}\right] di. \tag{24}$$

Incorporating (5), (9), (21), (22) and $w_t^n = w_t^A = w_t$ to Eq. (24), it can be written as:

$$K_t = \alpha \left(\frac{1-p}{1-\beta p}\right) \left\{ \frac{\beta}{2} N_{t-1}^{1-\alpha} \widehat{k}_{t-1}^{1-\alpha} - \frac{(1+g_{A,t})^{1-\psi} (1-\beta)(1-p)^\gamma \widehat{k}_t}{(1-\alpha)^2} \Omega(z_t) \right\} A_{t-1} \tag{25}$$

with $\Omega(z_t) = \frac{1-(1-z_t)^{\sigma+2}}{\sigma+2}$. This equation shows that, although higher life expectancy levels imply greater savings to financially secure the period of old age, individuals who choose to extend their working life save less. Therefore, the aggregate stock of capital depends negatively on the elderly labor participation since those individuals who remain working when older decide to save less because of the extra wage income obtained from the longer working life. Interestingly, the effect of the automation growth rate has an ambiguous effect on the aggregate savings, playing a key role the elasticity of skill misalignment to automation advances ψ. The intuition is as follows. Like in Irmen (2021), in our model automation advances appear as labor-augmenting technical change, which positively affects labor productivity and, hence, boosts wages over time. However, automation advances also damage individual labor productivity via aging-and-tech job vulnerability. If $\psi < 1$ older workers who choose to extend their working lives benefit from a higher wage than in their youth which compensates to a greater extent for the decline in their individual productivity due to their aging and skill mismatch. This pushes them to save less to finance the consumption in the second period and, hence, faster automation advances go hand in hand with a lower aggregate saving. However, if the skill mismatch resulting from automation advances is noteworthy, $\psi > 1$ these workers anticipate a loss of purchasing power, which leads them to save relatively more. Finally, when $\psi = 1$, both opposite effects offset each other.

Substituting (21) and (22) into (11), the following association among the elderly labor force, the automation progress and the effective capital level is obtained:

$$\widehat{k}_t = \frac{\Lambda(1-\alpha)^2 (1+g_{A,t})^{\psi-1}}{(1-p)^{\gamma+1} (1-z_t)^\sigma} N_{t-1}^{1-\alpha} \widehat{k}_{t-1}^{1-\alpha} \tag{26}$$

for any given $\widehat{k}_{t-1}$. Expression (26) shows that the higher the effective capital level, both the higher the wage rate and the lower the interest rate, and hence, the greater the incentives to remain in the labor market. Therefore, this expression shows a positive relationship between the effective capital level and elderly labor supply, all other variables being equal. Consistently with Eq. (25), the relationship between the effective capital level and the automation growth rate can be positive, null or negative depending on the automation elasticity of the decline in skills when old, being the explanation in economic terms equal. Skill misalignment as a consequence of automation advances accelerates the decline of individual productivity as individuals become older and, at the same time, these advances act as labor-augmenting technology at an aggregate level.

Additionally, the fraction of effective labor assigned to the non-automated task sector, $l_t^n = \frac{L_t^n}{L_t}$, and automation advances, $l_t^A = \frac{L_t^A}{L_t}$, will be constant in equilibrium because both the labor remuneration and the labor productivity growth rate[5] is the same regardless of the sector. Therefore, $l_t^n = l^n$ and $l_t^A = l^A$, with $l^n + l^A = 1$.

From Eqs. (23) and (25), and rewriting $L_t^n = l^n L_t$, we obtain that:

$$\widehat{k}_t = \frac{\beta(1+g_{A,t})^{\psi-1}}{\frac{(1-\beta p)(1-l^A)}{\alpha(1-p)} + \left[\frac{(1-\beta p)(1-l^A)}{\alpha} + \frac{(1-\beta)}{(1-\alpha)^2}\right] 2(1-p)^\gamma \Omega(z_t)} N_{t-1}^{1-\alpha} \widehat{k}_{t-1}^{1-\alpha} \tag{27}$$

As Eq. (24), Eq. (28) also highlights the two opposite effects of

[4] When $p_t^a BA_t < w_t^A$, research in automation is not conducted because the profit of the firms in this sector is negative.

[5] The labor share of each sector would evolve over time by assuming a different labor productivity growth rate among sectors (Hashimoto and Tabata, 2010).

automation progress on labor productivity since automation (or digitalization) progress is the engine of economic growth and, simultaneously, automation provokes a gap between the skills offered by senior workers and those demanded by new production methods.

Equations (26) and (27) determine the dynamic behavior of the economy. Equalizing both equations:

$$\frac{\Lambda(1-\alpha)^2}{(1-p)^{\gamma+1}(1-z_t)^{\sigma}}=\frac{\beta}{\frac{(1-\beta p)\left(1-l^A\right)}{\alpha(1-p)}+\left[\frac{(1-\beta p)\left(1-l^A\right)}{\alpha}+\frac{(1-\beta)}{(1-\alpha)^2}\right]2(1-p)^{\gamma}\Omega(z_t)},$$

can be observed that there is no transitional dynamics in the elderly labor participation z, which always takes its long-run value, z^* and, neither effective labor force L^* nor the growth rate of automation progress, $g_A{}^*$ show transitional dynamics. Only changes in the structural parameters of the economy could explain a change in the elderly labor participation and the growth rate of automation innovations. However, according to Eq. (26) (or (27)), the capital-effective labor ratio evolves along the time approaching the long-run value $\widehat{k}^*$, as depicted in Fig. 1.

In the steady state, the aggregate consumption, the cohort consumption, the aggregate capital, the aggregate production, the wage rate and the number of automated tasks grow at the same rate, g^*, while the rate of interest, the activity rate of older people, and the number of non-automated tasks are constant.

From Eqs. (12), (22) and (26) evaluated at the steady state, we obtain the following relationship between elderly labor participation and the economic growth rate in the steady state:

$$z^*=1-\left[\frac{(1-\beta)\Lambda}{\beta(1-p)^{\gamma+2}}\right]^{\frac{1}{\sigma}}(1+g^*)^{\frac{\psi}{\sigma}} \tag{28}$$

It holds that:

$$\frac{dz^*}{dg^*}=-\left[\frac{(1-\beta)\Lambda}{\beta(1-p)^{\gamma+2}}\right]^{\frac{1}{\sigma}}\frac{\psi}{\sigma}(1+g^*)^{\frac{\psi}{\sigma}-1}<0$$

Equation (28) establishes that the economic growth rate negatively affects elderly labor participation through two channels. The first one is via the mentioned skill misalignment linked to automation and digitalization advances. The faster new techniques that spread automation and digitalization in the economy, the easier it is for a mismatch to arise

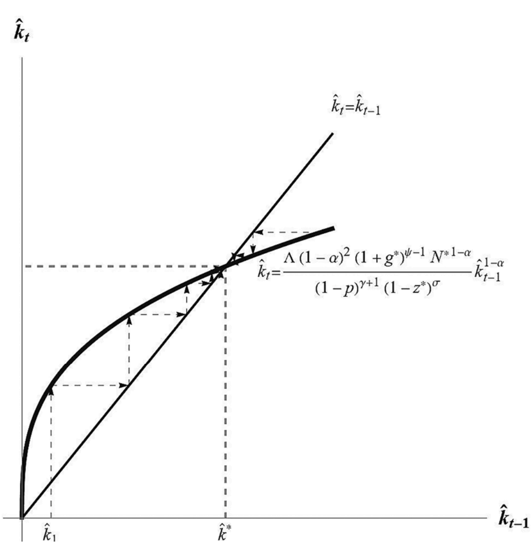

Fig. 1. Dynamics of capital per effective labor.

between these new methods and the current skills of senior workers and, hence, the higher the incentives to retire. The second one is via the interest rate. Equation (12) evaluated at the steady state shows that a higher rate of economic growth will be accompanied by a higher interest rate, that it is to say, a greater return on individual savings, which in turn will reduce the incentive to continue working during old age. In other words, Eq. (28) captures *the elderly labor supply* curve in relation to the progress in automation and digitization in the steady state. Note that this curve can be concave, lineal or convex, depending on the ratio of the elasticity ψ (the impact that advancements in automation at aggregate level have on the individual skill decline as they become older) and the elasticity σ (how long an individual retains the skills of his or her prime working life).

By using Eqs. (12), (14), (16), (17), (18), (20), and (23) evaluated at the steady state (see Appendix 1), another association between elderly labor participation and the economic growth rate in the steady state can be obtained:

$$z^*=1-\left\{1-\frac{(2+\sigma)(1+g^*)^{\psi}}{B(1-p)^{\gamma+1}}\left[g^*-\frac{B}{2}+\frac{(1-\beta)}{\beta(1-p)(1-\alpha)}(1+g^*)\right]\right\}^{\frac{1}{2+\sigma}} \tag{29}$$

with $g^*-\frac{B}{2}+\frac{(1-\beta)}{\beta(1-p)(1-\alpha)}(1+g^*)\rangle 0$.

It holds that:

$$\frac{dz^*}{dg^*}=\frac{1}{B(1-p)^{\gamma+1}}\left\{1-\frac{(2+\sigma)}{B(1-p)^{\gamma+1}}\left[\left(g^*-\frac{B}{2}\right)(1+g^*)^{\psi}+\frac{(1-\beta)}{\beta(1-p)(1-\alpha)}(1+g^*)^{\psi+1}\right]\right\}^{\frac{1}{2+\sigma}-1}\left[(1+g^*)^{\psi}+\left(g^*-\frac{B}{2}\right)\psi(1+g^*)^{\psi-1}+\frac{(1-\beta)(\psi+1)}{\beta(1-p)(1-\alpha)}(1+g^*)^{\psi}\right]\rangle 0$$

Equation (29) captures *the elderly labor demand* curve in relation to progress in automation and digitization in the steady state. This curve captures that the engine of economic growth is automation innovation which, in turn, requires effective labor as an input. Although current automation makes future automation innovations, humans embed creativity, adaptability and judgment, qualities that machines now or in the near future do not possess, but are extremely necessary for innovation. The faster automation advances, the greater the demand for effective labor resources by the research sector, regardless of whether this input comes from young workers or highly skilled older workers.

Choosing $\psi\geq 1$ and$\sigma\in(0,1)$,[6] the graphical representation of Eqs. (28) and (29) is shown in Fig. 2. The equilibrium in steady state is labeled as the point E. It may seem surprising that the supply curve is decreasing while the demand curve is increasing. The reason is that these are not the usual curves that relate the price of the input with its supply or demand, but in this case, they relate the demand and supply of effective labor input from senior workers with the degree of innovation in the economy. On one hand, in this model it has been assumed that future advances in automation will require qualities that are only present in humans. This assumption, together with the assumption that current advances in automation favor the emergence of new breakthroughs, explains that the higher the pace of innovation, the greater the demand for effective labor, and therefore the greater the demand for skilled senior workers with the necessary qualities to innovate. On the other hand, it has been highlighted that the advances in automation make it inevitable that there will be a mismatch between current and future skills. This fact pushes older workers toward retirement, and as a result, very rapid advances are negatively related to the participation rate of older workers in the labor market.

[6] Another parameter option might change the shape of elderly labor supply and demand curves (convex, lineal or concave) without modifying the results.

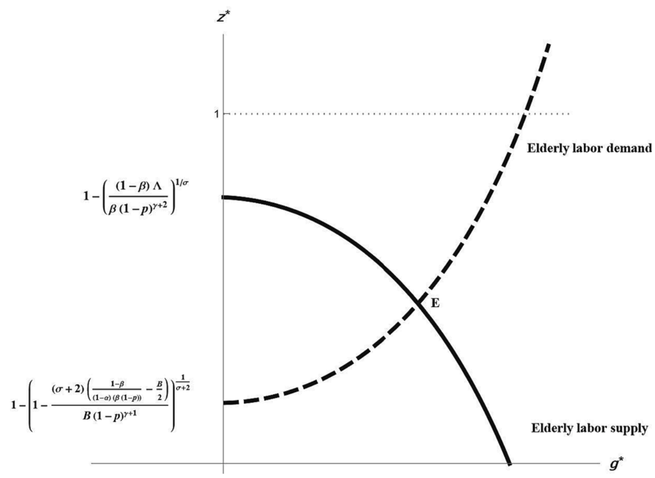

Fig. 2. The activity rate of old people z^* and the economic growth rate g^* in the steady state.

Fig. 2 establishes that the existence of an interior solution requires the fulfillment of the following condition:

$$\Lambda < \frac{\beta(1-p)^{\gamma+2}}{(1-\beta)}\left\{1-\frac{(2+\sigma)}{B(1-p)^{\gamma+1}}\left[\frac{(1-\beta)}{\beta(1-p)(1-\alpha)}-\frac{B}{2}\right]\right\}^{\frac{\sigma}{2+\sigma}}$$

which it holds when the utility of leisure from retirement Λ is not sufficiently high to make an interior solution impossible. Otherwise, all individuals would decide to retire in their second period of life.

Results and discussion

Based on Eqs. (28) and (29), it can be deduced that the relevant parameters regarding economic growth g^* and the labor force participation rate of older people z^* are Λ, which captures the utility of leisure time in the second stage of life; σ, which measures the elasticity of the decline in skills that each individual experiences as they age with respect to the skill level that the individual exhibits during their working life in adulthood; *1-p*, which reflects the individual's life expectancy and also reflects their health level when facing active retirement; and Ψ, which reflects how advances in automation in the economy increase the gap between the individual's skills and the skills that companies need. Among these four parameters, public intervention plays a role in changes in longevity *1-p* and in the degree of mismatch between the skills possessed by older workers and the skills required by new advances in automation Ψ. In this section, the effects of changes in these parameters are analyzed. Furthermore, some interventions that promote automation advancement and an extension of working life are explored, with the purpose of identifying which measures may help with the financing of social security systems.

Regarding longevity improvements, an increase in parameter *1-p* corresponds to a greater compression of morbidity, meaning that the decline in productivity of any worker due to aging becomes less pronounced. Besides, as longevity improves, the premium from the annuity market decreases. On one hand, an increase in life expectancy increases the utility of leisure $\left(\frac{\partial\Lambda}{\partial(1-p)}>0\right)$, which pushes some toward retirement. If $\varepsilon_{1-p,\Lambda}$ which represents the elasticity of Λ with respect to *1-p* is enough fall, these forces provide an incentive to individuals to extend their working life, leading to an increase in the labor supply of older workers. In graphical terms, the elderly labor supply as a function of automation advances moves to the right. Concerning the elderly labor demand, Eq. (12) evaluated at the steady-state equilibrium indicates that, for the same economic growth rate, an increase in the probability of surviving the second period leads to a decrease in the interest rate. As a consequence, automated companies face lower costs, which, in turn, encourages the purchase of patents. As a result of the increase in research activity, the demand for older workers, equipped with creativity, intuition, experience, and good judgment rises. This shifts the labor demand curve for senior workers to the right. Fig. 3 illustrates both curves' movements. It is clear that an improvement in longevity or, in other words, a greater compression of morbidity increases the pace of automation advances. The effect on the labor participation of older workers in the labor market is graphically ambiguous but it can be shown that the elderly participation in the labor market rises for $\varepsilon_{1-p,\Lambda} \leq 1$ (see Appendix 2).

Focusing now on the parameter Ψ, an increase in the mismatch between the skills possessed by older workers and the skills required by new advances in automation pushes workers more strongly towards retirement because the decline in skills linked to age-and-tech vulnerability becomes sharper. As a result, the labor supply of older workers decreases. The effect is twofold: a lower share of skilled older workers will decide to remain in the workplace and those who remain working will be less productive due to a higher skill mismatch. This moves elderly labor supply as a function of automation innovations to the left. With respect to the demand of elderly labor, in this framework the parameter ψ does not cause any reallocation of workers between the manual task sector and the research sector (see equation (1.iv) in Appendix 1), but the fact that workers become less productive reduces economic activity in both sectors, leading to a lower demand for effective labor input and, hence, pushing elderly labor demand to the left. As a result of the decline in labor supply and demand, the economic growth of the economy decreases, as well as the labor force participation rate of older workers in the job market (Fig. 4). The latter can be analytically verified (see Appendix 3).

The obtained results support that the greater the compression of morbidity (higher *1-p*) and/or the smaller the gap between the skills that senior workers possess and those demanded by advances in automation (lower ψ), the higher the economic growth and the participation rate of older individuals. Logically, both effects have a positive impact on the sustainability of social security finances. Our framework is not rich enough to give a recommendation on how to increase *1-p*, except for the need for preventive health throughout the working life, not just at the end of it. More can be said with respect to how to reduce ψ. Lifelong learning, particularly when close to retirement age, emerges as an effective tool both to mitigate the tension from emerging skill requirements and keeping senior workers in the labor market longer. Automation advances offer workers the opportunity to prolong their careers via collaborative robots and intelligent tools and, at the same time, require continuously evolving skills to optimize the technology

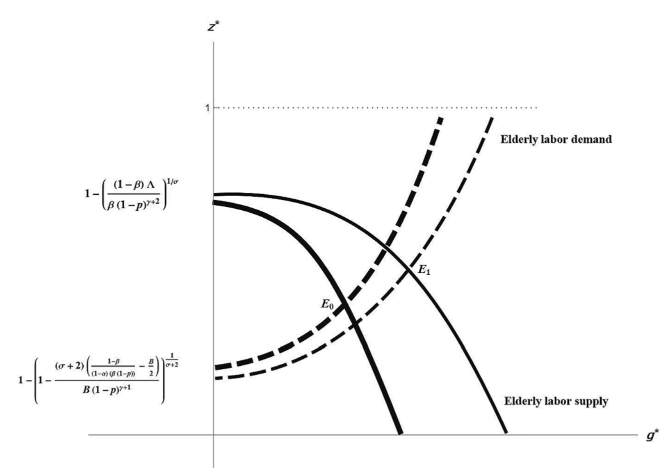

Fig. 3. Effects of an increase in life expectancy (higher *1-p*) on the activity rate of old people z^* and the economic growth rate g^*.

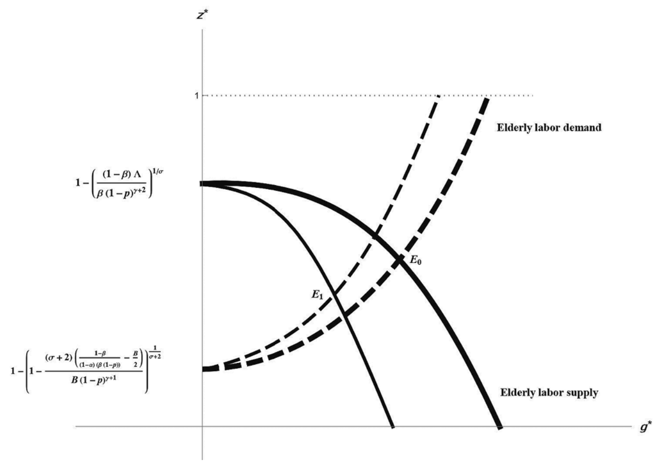

Fig. 4. Effects of worsening matches between skills and automation advances (higher ψ) on the activity rate of old people z^* and the economic growth rate g^*.

(Calzavara et al. 2020). Closing the gap between the current skills of senior workers and the skills required by automation and digitalization necessitates training courses targeted at this group. The questions that immediately emerge are many: Should all senior workers participate in these training courses? Who finances these training courses? Should it be the workers themselves, the companies, or the government through taxes? If it's the government who provides training courses, in which group (workers or firms) should these taxes fall, and what type of taxes should they be?

Our analysis points out that not all the elderly workers close to their "normal" retirement age[7] should participate in training courses to update their skills. When older workers freely decide on their training, only those whose skill level is lower but closer to the θ_{i^*} level and those whose skill level is higher than this level will opt to take these training courses. Additionally, it must be fulfilled that the decrease in vulnerability related to aging and technology as a result of this training must compensate for the cost of that training. If workers have very low skill levels, they will choose not to undergo training, because they desire to retire with or without training. Only those close to the θ_{i^*} level and those higher to this level will opt to undergo training if the benefits of this training are higher than its costs. Consequently, the target population for training should be older workers who are already considering extending their working lives but lack updated skills, as well as those with lower qualifications but close to the θ_{i^*} level, who would change their minds and extend their working lives after receiving the training.

Who should pay for this training? The cost of this training might be borne by individuals who benefit from this extra training. The employing companies also might finance the training, but in our model, the cost will be passed on to the workers due to the assumption of a perfect competition context. If the employer decides to finance the training cost in a proportional way to the workers' wage, those individuals who still find it convenient to retire before or after training will be the losers. The government also might provide the training. In fact, some governments are implementing Individual Learning Accounts which are targeted directly towards individuals to give them autonomy in their upskilling decisions. This policy tool seems to be achieving positive results (Vodopivec et al., 2019) because it takes into account workers' heterogeneity. However, as has been evident before, a linear tax on all workers is not optimal. Another option for financing this training could be the so-called "robot tax". In a world where machines and robots are increasingly prevalent, the tax on robots is generating a wide debate both at the academic level and on the street. In our model, since automated task firms are not competitive, taxing their revenue could lead to an efficiency loss, as it would distance them further from the competitive solution. A lump-sum tax or a benefit tax would not cause such distortion, which is according to recent analysis in a much more realistic environment with income tax restrictions. For example, Guerreiro et al. (2022) establish that a non-zero robot tax is generally optimal. Gasteiger and Prettner (2022) add the nuance that a robot tax raises per capita income as the robot tax is comparatively low and for a closed economy. The explanation is that a relatively high tax might discourage increased adoption of automation and, in the context of an open economy, the effective implementation of a robot tax necessitates a collective effort by all countries to prevent the relocation of production to regions where no such tax is imposed. They also claim that a robot tax cannot induce a takeoff toward positive long-term growth. Prettner and Strulik (2020) go further by asserting that a robot tax does damage economic growth by reducing the incentives to invest in automation. On the whole, the tax on robots is a complex and open question with no clear answer (Costinot and Werning, 2023).

Additionally, besides this economic perspective, one must not forget that the perceptions and opinions of the workers and employees themselves also play a relevant role. Managers are reluctant to train workers near retirement, who they perceive as less flexible and less resilient to changes (Caliendo et al. 2023). Older employees seem to be less motivated to adapt to new technologies, which are frequently perceived as difficult to use (Hauk et al, 2018). The stereotype of older workers being less willing to engage in self-development might instill a reduced interest in training on the part of firms and workers (Zwick, 2015). In this context, a better understanding of how human resource management practices can support the age-diverse workforce is becoming crucial. Fasbender et al (2022) find that employees' supervisors have an important role by fostering a positive attitude among their employees toward news technologies through age-specific mentoring programs and by giving job autonomy to older employees. Self-reflective interventions among supervisors towards raising awareness of the challenge of reducing aging-and-tech job vulnerability have been effective, and might slow the loss of the intellectual capital and the relational capital experienced employees bring, with their extensive professional networks.

It is worth noting that our analysis is based on a simple and particular specification on the age-productivity profile. Alternative modeling of the decline of productivity as people age might have been considered. Previous empirical evidence is not conclusive and the age-productivity profile is still an open question. Some studies have estimated age-productivity profiles that increase up to the age of 50–55 years, and then remain flat (Cardoso et al., 2011). Dostie (2011) and Mahlberg et al. (2013) find a concave relationship between age and productivity level. Börsh-Supan and Weiss (2016) do not detect a decline of productivity among older workers. Closer to automation and digitalization issues, Ilmakunnas and Miyakoshi (2013) find that the effect of the interaction between Information and Communication Technologies (ICT) and aging on productivity varies quite a lot from one country to another. This view is supported by Lee et al. (2020) who detect a complementary effect between ICT capital and older workers for both highly- and less-educated workers in Japan, but only for less-educated workers in Korea. It is likely that the age-productivity profile depends on the time and place in which individuals' working lives run and the characteristics of the job they perform. Deeper research is required.

Another important caveat of this framework is that it has been assumed to be a fully R&D-based endogenous growth model. As a result, the effective labor input must be constant because a growing effective

[7] We define the normal retirement age as the age at which people usually leave the labor market. The concept of what constitutes "normal" retirement age depends on several contextual factors, including sociodemographic characteristics, cultural and organizational norms, and country-specific government pension and employer-provided pension rules (Fisher et al. 2016). Additionally, the OECD defines the normal retirement age in a given country as the age of eligibility of all schemes combined without penalty,based on a full career after labor market entry at age 22 (OECD,2021).

labor input would imply an increasing economic growth rate, a characteristic known as the scale effect problem (Jones, 1995). However, recent empirical evidence (Kruse-Andersen, 2023) provides support semi-endogenous R&D-based models, e.g., Li (2001), as well as a particular model of less-than-exponential growth designed by Groth et al. (2010). Exploring these frameworks embedded in inevitable skill mismatches among present and future skills of senior workers together with endogenous retirement decisions is in our research agenda.

Conclusions

The present paper addresses the role of older workers' labor participation in the association between aging and automation. The inclusion of an endogenous retirement age for individuals allows for behavioral adjustments as a consequence of both population aging and automation advances. Aging pushes highly-skilled senior workers to remain active which fuels automation innovation because those who delay their retirement are those endowed with indispensable skills to innovate. Therefore, improvements in longevity induce a positive level effect on the highly-skilled older labor supply which, in turn, positively affects automation advances. Furthermore, as the economy grows, wages grow at the same rate which also acts as a force in favor of delaying the retirement of high-skilled individuals. Meanwhile, automation advances also provoke a misalignment with existing skills which jeopardizes the permanence of older workers in the labor market, mostly those less skilled. In other words, automation advances emerge as a force which pushes those largely senior workers who are less-skilled toward retirement, and/or those whose skills become outdated.

Imposing restrictions on early retirement plans and/or increasing the age of compulsory retirement are at the heart of the policy agenda in many OECD countries. These countries are pushing more workers toward a later exit from the labor market (OECD, 2021). Our analysis highlights that these measures are not sufficient to ensure that workers continue working at an older age. Automation might penalize longer working lives if older workers have limited training possibilities for continuously upgrading their skills hand-in-hand with advances in automation. The access to lifelong learning emerges as a key factor. In the context of aging and in which developed countries are moving toward knowledge-intensive activities, the amount of effective labor is becoming more dependent on the upskilling of the current workforce than on the up-to-date skills of new labor market entrants. New automation technologies are reshaping the employment landscape and managers should be given guidance and greater encouragement to ensure an accessible pathway to continuous upskilling of workers who are considering the possibility of extending their working lives. The role of governments is to build well-adapted adult learning systems to tackle skills obsolescence and maintain the employability of older workers. The question of who bears the cost of this training in economies that are becoming increasingly automated is a subject of debate.

Moreover, the growing diversity among older workers adds complexity to the challenge of developing and implementing appropriate pension policies. While it's evident that pension rights should be actuarially neutral, addressing inequality presents a multifaceted dilemma. Introducing more specific retirement eligibility criteria based on individuals' skills and the physical demands of their occupations could potentially create distorted incentives. Furthermore, alternative welfare programs like disability and unemployment schemes may inadvertently encourage early retirement. The optimal solution lies in directing policy efforts toward actively reducing the heterogeneity of older workers. This involves providing highly-skilled older workers with opportunities to update their skills and stay current with rapidly evolving technologies. Simultaneously, personalized action plans should be offered to low-skilled older workers who are at a higher risk of job displacement due to automation, helping them navigate such challenges.

Authors' Contributions

All authors contributed to the study conception and design of the theoretical framework. The solution of the model and its analysis were performed by Rosa Aisa, Josefina Cabeza and Jorge Martin. All authors read and approved the final manuscript.

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.

Acknowledgement

None

Appendix 1:. Derivation of Eq. (29)

By evaluating Eqs. (14) and (16) at the steady state,[8] we obtain:

$$\frac{\omega}{r} = \frac{\alpha x^a}{(1-\alpha)^2 N x^n} \tag{1.i}$$

Additionally, considering Eqs. (17) and (18) in the steady state $\pi^a = \frac{\alpha}{1-\alpha} r x^a, \pi^a = r p^a$, together with $Bp^a = \omega^A$:

$$x^a = \frac{(1-\alpha)\omega}{\alpha B} \tag{1.ii}$$

Combining (1.i), (1.ii), and Eq. (12), we arrive at the steady state expression:

$$N x^n = \frac{(1-\beta)(1+g)}{\beta(1-p)(1-\alpha)B} \tag{1.iii}$$

and taking $Nx^n = l^n L$ into account, the latter expression can be expressed as:

$$l^n L = \frac{(1-\beta)(1+g)}{\beta(1-p)(1-\alpha)B} \tag{1.iv}$$

Finally, with the consideration of $l^A = 1 - l^n$ and utilizing Eqs. (20), (23) and (1.iv), some algebraic manipulations yield Eq. (29).

[8] For clarity, we drop the asterisk.

$$g = Bl^{A}L = B\left[1-\frac{\frac{(1+g)(1-\beta)}{\beta(1-p)(1-\alpha)B}}{L}\right]L = BL-\frac{(1+g)(1-\beta)}{\beta(1-p)(1-\alpha)} =$$

$$= \frac{B}{2}+\frac{B(1-p)^{\gamma+1}}{(1+g)^{\psi}}\frac{1-(1-z)^{2+\sigma}}{2+\sigma}-\frac{(1+g)(1-\beta)}{\beta(1-p)(1-\alpha)}\rightarrow$$

$$z = 1-\left\{1-\frac{(2+\sigma)(1+g)^{\psi}}{B(1-p)^{\gamma+1}}\left[g-\frac{B}{2}+\frac{(1-\beta)(1+g)}{\beta(1-p)(1-\alpha)}\right]\right\}^{\frac{1}{2+\sigma}}. \tag{29}$$

Appendix 2

Effects of *1-p* (probability of surviving to the second period) on *z* (elderly participation in the workforce) and g (economic growth rate) in the steady state

Equation (28) is rearranged, and natural logarithms are applied to both sides of the equation:

$$ln(1-z) = ln\left(\frac{(1-\beta)}{\beta}\right)+\frac{1}{\sigma}ln(\Lambda)-\frac{\gamma+2}{\sigma}ln(1-p)+\frac{\psi}{\sigma}ln(1+g) \tag{28a}$$

The differentiation of (28a) concerning *z*, *g* and *1-p* leads to:

$$\frac{-dz}{(1-z)} = \frac{1}{(1-p)\sigma}\left[\varepsilon_{1-p,\Lambda}-(\gamma+2)\right]d(1-p)+\frac{\psi}{\sigma(1+g)}dg \tag{2.i}$$

where $\varepsilon_{1-p,\Lambda}$ represents the elasticity of Λ with respect to *1-p*. It is worth noting that the term Λ captures the utility from leisure time during retirement. This elasticity is positive due to the fact that higher life expectancy leads to lower morbidity at the end of life, resulting in greater enjoyment of free time during this period. Moving on to Eq. (29), after reordering terms and applying natural logarithms to both sides, we derive:

$$ln(1-z) = \frac{1}{2+\sigma}ln\left(1-\frac{(2+\sigma)(1+g)^{\psi}}{B(1-p)^{\gamma+1}}\left[g-\frac{B}{2}+\frac{(1-\beta)(1+g)}{\beta(1-p)(1-\alpha)}\right]\right) \tag{29a}$$

The differentiation of (29a) concerning *z*, *g*, and *1-p* implies that:

$$\frac{dz}{(1-z)} = \frac{(1+g)^{\psi}\left\{\Phi\left[\frac{\psi}{1+g^{*}}dg-\frac{(\gamma+1)}{1-p}d(1-p)\right]+\left[1+\frac{(1-\beta)}{\beta(1-p)(1-\alpha)}\right]dg\right\}}{B(1-p)^{\gamma+1}\left[1-\frac{(2+\sigma)(1+g)^{\psi}}{B(1-p)^{\gamma+1}}\Phi\right]}$$

with $\Phi = g-\frac{B}{2}+\frac{(1-\beta)(1+g)}{\beta(1-p)(1-\alpha)}$, and $0<\Phi<1$.

By employing (2.i) and (2.ii) in some algebraic manipulations, we obtain:

$$\frac{dg}{d(1-p)} = \frac{\left\{\frac{1}{(1-p)\sigma}\left[(\gamma+2)-\varepsilon_{1-p,\Lambda}\right]+\frac{(\gamma+1)(1+g)^{\psi}}{B(1-p)^{\gamma+2}\left[1-\frac{(2+\sigma)(1+g)^{\psi}}{B(1-p)^{\gamma+1}}\Phi\right]}\right\}}{\left\{\frac{(1+g)^{\psi}\left[\Phi\frac{\psi}{1+g}+1+\frac{(1-\beta)}{\beta(1-p)(1-\alpha)}\right]}{B(1-p)^{\gamma+1}\left[1-\frac{(2+\sigma)(1+g)^{\psi}}{B(1-p)^{\gamma+1}}\Phi\right]}+\frac{\psi}{\sigma(1+g)}\right\}}$$

Thus, if $\varepsilon_{1-p,\Lambda}<(\gamma+2)$, $\frac{dg}{d(1-p)}>0$.

Additionally, by utilizing (2.i) and (2.iii) and performing some manipulations, we have:

$$\frac{dz}{d(1-p)} = \frac{(1-z)}{(1-p)\sigma}\left[(\gamma+2)-\varepsilon_{1-p,\Lambda}\right]\left(1-\frac{\left\{1+\frac{\sigma(\gamma+1)(1+g)^{\psi}}{B(1-p)^{\gamma+1}\left[1-\frac{(2+\sigma)(1+g)^{\psi}}{B(1-p)^{\gamma+1}}\Phi\right]\left[(\gamma+2)-\varepsilon_{1-p,\Lambda}\right]}\right\}}{\left\{1+\frac{(1+g)^{\psi}\left[\Phi\frac{\psi}{1+g}+1+\frac{(1-\beta)}{\beta(1-p)(1-\alpha)}\right]}{B(1-p)^{\gamma+1}\left[1-\frac{(2+\sigma)(1+g)^{\psi}}{B(1-p)^{\gamma+1}}\Phi\right]\frac{\psi}{\sigma(1+g)}}\right\}}\right)$$

The latter equation establishes that it is sufficient for $\varepsilon_{1-p,\Lambda}\le 1$, to observe that $\frac{dz}{d(1-p)}>0$.

Appendix 3

Effects of ψ(automation elasticity of the skill mismatch) on *z* (elderly participation in the workforce) and *g* (economic growth rate) in the steady state

The expression (28) is rearranged, and natural logarithms are applied:

$$ln(1-z) = ln\left(\left[\frac{(1-\beta)\Lambda}{\beta(1-p)^{\gamma+2}}\right]^{\frac{1}{\sigma}}\right) + \frac{\psi}{\sigma}ln(1+g) \tag{28b}$$

We differentiate Eq. (28b) with respect to the variables z, g, and ψ:

$$\frac{-dz}{(1-z)} = \frac{1}{\sigma}ln(1+g)d\psi + \frac{\psi}{\sigma(1+g)}dg \tag{3.i}$$

Likewise, we rearrange and apply natural logarithms to Eq. (29):

$$ln(1-z) = \frac{1}{2+\sigma}ln\left(1 - \frac{(2+\sigma)(1+g)^{\psi}}{B(1-p)^{\gamma+1}}\left[g - \frac{B}{2} + \frac{(1-\beta)(1+g)}{\beta(1-p)(1-\alpha)}\right]\right) \tag{29b}$$

Then, we differentiate Eq. (29b) with respect to the variables z, g, and ψ:

$$\frac{dz}{(1-z)} = \frac{(1+g)^{\psi}}{B(1-p)^{\gamma+1}} \frac{\Phi\left[ln(1+g)d\psi + \frac{\psi}{(1+g)}dg\right] + \left[1 + \frac{(1-\beta)}{\beta(1-p)(1-\alpha)}\right]dg}{\left\{1 - \frac{(2+\sigma)(1+g)^{\psi}}{B(1-p)^{\gamma+1}}\Phi\right\}} \tag{3.ii}$$

with $\Phi = g - \frac{B}{2} + \frac{(1-\beta)(1+g)}{\beta(1-p)(1-\alpha)}$, and $0 < \Phi < 1$.

By combining (3.i) and (3.ii) and after some algebraic manipulation, we derive:

$$\frac{dg}{d\psi} = -\frac{\left(\frac{1}{\sigma} + \frac{(1+g)^{\psi}\Phi}{B(1-p)^{\gamma+1}\left[1 - \frac{(2+\sigma)(1+g)^{\psi}\Phi}{B(1-p)^{\gamma+1}}\right]}\right)ln(1+g)}{\left(\frac{\psi}{\sigma(1+g)} + \frac{(1+g)^{\psi}\left[\frac{\psi\Phi}{(1+g)} + 1 + \frac{(1-\beta)}{\beta(1-p)(1-\alpha)}\right]}{B(1-p)^{\gamma+1}\left[1 - \frac{(2+\sigma)(1+g)^{\psi}\Phi}{B(1-p)^{\gamma+1}}\right]}\right)} \tag{3.iii}$$

Hence, $\frac{dg}{d\psi} < 0$.

Moreover, from (3.i) and (3.ii), it is revealed that:

$$\frac{dz}{d\psi} = -\frac{(1-z)ln(1+g)}{\sigma}\left(1 - \frac{\left\{\frac{1}{\sigma} + \frac{(1+g)^{\psi}\Phi}{B(1-p)^{\gamma+1}\left[1 - \frac{(2+\sigma)(1+g)^{\psi}\Phi}{B(1-p)^{\gamma+1}}\right]}\right\}}{\left\{\frac{1}{\sigma} + \frac{(1+g)^{\psi}\frac{(1+g)}{\psi}\left[\frac{\psi\Phi}{(1+g)} + 1 + \frac{(1-\beta)}{\beta(1-p)(1-\alpha)}\right]}{B(1-p)^{\gamma+1}\left[1 - \frac{(2+\sigma)(1+g)^{\psi}\Phi}{B(1-p)^{\gamma+1}}\right]}\right\}}\right).$$

where we can be observed that $\frac{dz}{d\psi} < 0$.

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