Workforce Aging, Technology, and Inter-Generation Inequality

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Abstract

Population aging affects the labor market by changing the labor supply, the age composition of the labor force, and the capital stock. This leads to a non-linear (potentially non-monotonic) effect on the adoption of new technologies. I empirically document this relation using sector-level data for 10 Western European countries in the period 1995-2015. To highlight the mechanisms behind these findings and provide a quantitative assessment of the macroeconomic consequences of aging, I build a dynamic task-based model with R&D driven growth and endogenous skill acquisition. Aging of the population increases the capital to labor ratio which increases the adoption of new (labor-saving) technology. The relation reverses as skilled workers (employed in new technology and in the R&D sector) become scarce due to the increasing scarcity of young workers with a comparative advantage in skills acquisition. The combination of these effects describes a reversed U-shaped relation between aging and adoption of new technology. I calibrate the model using European countries and show that aging of the population is predicted to increase production growth due to higher capital accumulation. This effect is only partially offset by the negative effect going through the R&D sector. Aging, moreover, exacerbates the inter-generation wage inequality explaining a large fraction of the wage inequality increase in the period 2000-2020.

1 Introduction

Around the world, and especially in industrialized countries, populations are aging. The median age of the populations and the fraction of elderly people are climbing, while fertility rates are falling. An aging population has profound implications in the labor market as it

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changes the relative supply of inputs in the economy affecting the labor supply, the composition of the labor force, and the capital stock in the economy through the consumption and saving behavior of the households. Since the supply of inputs determine the adoption of different technologies with different productivity, aging affects economic growth. Moreover, since workers across different age categories are heterogeneous in their ability to operate with different technologies, aging also affects between-generation inequalities.

In the last decades the working-age population has been consistently declining in all the major economies in Europe. This trend is shared by most of the developed countries in the world. The population aging process also affects the composition of the labor force. Indeed, from 1995 to 2015 the fraction of prime-aged workers (from 25 to 50 years old) in the EU15 countries has declined, while the fraction of old workers (50+ years old) has increased. The reduction in the working-age population reduces the labor supply and affects the capital stock, while the change in the labor force composition affects the human capital composition in the economy. These effects influence the incentives firms have in introducing new technologies.

Recent literature has already analyzed the effect of aging on the adoption of automated technology. In particular, Acemoglu and Restrepo (2018a) shows that an increase in the ratio of older to middle-aged workers is associated with greater adoption of automated technologies, while Abeliansky and Prettner (2017) shows that a reduction in the population growth is associated with an increase in robot adoption which can increase GDP growth as shown in Acemoglu and Restrepo (2017b). However, different from these papers which consider an automated technology that allows human labor to be perfectly substituted with machines, I consider a new technology that still requires human labor to be operated highlighting the complementarity between technology and the different types of labor as highlighted by Chari and Hopenhayn (1991).

In the empirical analysis, I consider Information and Communication Technologies (ICT) as a proxy for the new technology. I document a sector-level reversed U-shaped relation linking the share of old workers and the adoption of ICT. As the population ages and the aggregate labor supply reduces, producers have an incentive to adopt new (labor-saving) technologies. However, since old (50+ years old) and young workers (between 25 and 49 years old) differ in their human capital, with young workers having a comparative advantage in the use of the new technology, the scarcity of young workers reverses the relation. Therefore, the relation linking aging and new technology adoption is non-linear and potentially non-monotonic: adoption of new technology initially increases as producers respond to the relative scarcity of the aggregate labor supply, and then it decreases for higher levels of aging as the economy is constrained by the scarcity of young labor input that have a comparative advantage in the acquisition of skilled used in new technology. I also find that aging of the population is associated with higher young to old wage ratio suggesting that young and old labor are not perfect substitutes.

To formally describe these mechanisms, I consider an R&D growth task-based model with two different technologies, new and vintage, and two types of workers, skilled and unskilled. I assume that new technology is relatively labor-saving and it requires skilled workers to be used. Skills are acquired through education when young. However, since new technology evolves over time through R&D, skills become obsolete after one period (around 25 years). Elderly workers, therefore, need to train in order to stay updated with the new technology. Since elderly people face different incentives (lower working time left to spread the training costs) and higher skill acquisition costs, not all the young skilled train when old. In this sense, young workers have a comparative advantage in skills acquisition and, therefore, in new technology.

The demographic change is defined as an increase in the share of old agents in the economy who individually supply less labor with respect to young agents as they are partially in the working-age period and partially in the retirement period. This definition of demographic change captures the two effects in the labor market that we observe in the data: a reduction in the aggregate labor supply and an increase in the share of old workers. I use a task-based approach allowing for endogenous shares of inputs that depend on the relative supply of labor inputs in the economy. This particular feature makes task-based models suitable to investigate the effects of changes in the composition of inputs in the economy driven by the demographic process. An aging population, indeed, reduces the aggregate labor supply and increases the capital stock through the saving decision of the agents leading to a higher capital to labor ratio. Moreover, aging changes the age composition of the labor force increasing the relative labor supply of old who differ with respect to young workers in their ability to acquire complementary skills to new technology. The interplay of these different effects on the labor market describes the non-linear (potentially non-monotonic) dynamic of technological adoption as the population ages.

This model is based on four main assumptions. I assume that: 1) new technology is labor-saving with respect to vintage technology; 2) new technology tasks and the R&D sector employ skilled workers, 3) a fraction of old agents works, a fraction is retired, and 4) skill acquired in period t become obsolete in period $t+1$. Assuming that new technology is labor-saving is a natural assumption when thinking of technological progress as automation of tasks as in Acemoglu and Autor (2011) or Acemoglu and Restrepo (2018b). Moreover, a consistent part of the literature finds that higher technological adoption generally has negative effects on employment.[1] However, as argued in Krusell et al. (2000), Brynjolfsson and McAfee (2014) and Autor (2015) new technologies have different degrees of complementarity with the human labor depending on the tasks performed and the type of worker. I, therefore, assume that new technology tasks and R&D only employ skilled workers. Since young workers have a higher ability to learn and have higher incentives to acquire skills (young are fully in the working age period while old workers only partially), this assumption implies that young workers are more complementary to new technology with respect to old workers. Indeed, a large literature has shown that aging is related to slower information processing, lower learning aptitude toward new technologies (Weinberg, 2004), and lower problem-solving abilities in technology-rich environments (PIAAC data) implying that younger workers have a comparative advantage in the use of new technology (Dorn et al., 2009).[2] I then assume that a share of older workers supply labor, while the rest is retired. This assumption can be motivated by recognizing that, while young people are fully in the working-age, the elderly are partially in the working-age and partially in the retirement period.[3] Finally, I assume that skill acquired in period t become obsolete in period $t+1$. This is assumption is motivated by the fact that new technology in this framework evolves over time due to the R&D process and, since each period is quite long (25 years), it is plausible to assume that the human capital acquired in the previous period depletes.

The rest of the paper is structured as follows: in the next paragraph, I present the contribution of this paper with respect to recent literature while, in Section 2, I document the non-linear (potentially non-monotonic) relation linking aging and adoption of ICT and the relation linking aging and inter-generation wage inequality. In Sections 3, I present the model, while in Section 4, I analyze the effect of an aging population on the different technology margins, production growth, and inequality. In Section 5, I analyze the dynamic predictions of the calibrated model. Finally, in Section 6, I conclude.

[1] Frey and Osborne (2017) finds that about 47% of total US employment is at high risk of being substituted by ICT within the next 20 years. Similar results are those of Bowles (2014), who repeated the study for the European Union countries. Analyzing tasks within occupations, rather than occupations themselves, Bonin et al. (2015) argues that the potential job losses due to technological change are about 12% for Germany. Following the same approach, Arntz et al. (2016) finds that between 6 and 12% of occupations are at high risk of automation among the OECD countries.

[2] See also Börsch-Supan et al. (2005) and Boockmann and Zwick (2004)

[3] This assumption is not necessary to obtain the reversed U-shaped relation between aging and new technology adoption as the accumulation of capital in the context of an aging population has similar effects of a reduced labor supply.

Literature Review This paper is related to some recent literature. The first branch of the literature I refer to is literature analyzing the implications of the introduction of new technologies on the labor market. Early works such as Autor et al. (2003), Goos and Manning (2007), and Autor and Dorn (2013) show evidence suggesting that automation of routine jobs has been associated with greater wage inequality and the decline of middle-skill occupations. More recently, Graetz and Michaels (2017) and Acemoglu and Restrepo (2017a) have estimated the effects of the adoption of robotics technology on employment and wages. Although complementary, my approach is quite different from this literature as I focus on the determinants of the adoption of new technologies depending on the composition of the inputs supplied instead of the implications on the labor market of the adoption of new technologies.

Second, recent literature has analyzed the costs of an aging population at the macroeconomic level (Baldwin and Teulings, 2014); however, besides Abeliansky and Prettner (2017), Acemoglu and Restrepo (2017a) and Acemoglu and Restrepo (2018a), not much research has been done yet on the impact of aging on technology adoption. Differently from Abeliansky and Prettner (2017) who focus on the effect of the slowdown of population growth on the different types of capital, and from Acemoglu and Restrepo (2018a) who consider the change in the age composition of labor, I consider both of these effects. Although I use a similar approach, our results differ from those in Acemoglu and Restrepo (2018a) due to the different definition of technology; while they consider an automated technology replacing labor, I consider a labor-saving technology in which young workers have a comparative advantage. Moreover, I also introduce an overlapping generation model (Diamond, 1965) allowing for endogenous capital.

Finally, the conceptual approach builds on directed technological change literature that was introduced and developed in a series of papers by Acemoglu (1998, 2002, 2007, 2010), while the theoretical framework is based on task-based models (Zeira, 1998; Acemoglu and Zilibotti, 2001; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018b) which allows for endogenous shares of inputs. This particular feature makes task-based models suitable to investigate the effects of changes in the composition of inputs in the economy driven by the demographic process.

2 Empirical Evidence

In this section, I analyze the relation linking aging with the adoption of technologies and the evolution of the young-to-old wage ratio as the population ages.

2.1 Technology Adoption

As a proxy for technology adoption, I use investment in ICT measured as the share of capital allocated to hardware, software, and databases.[4] I use sector-level data from EU KLEMS in the period between 1995 and 2015 for 10 Western European countries.[5] As a proxy for the age variable, I consider the ratio between workers above 50 and those between 25 and 49 using population and employment data from Eurostat. As we can see from Figure 1, the relation linking age (in the x-axis) and investment in ICT (y-axis) is not linear. In particular, for most of the countries, the relation appears to have a reversed-U shape. In order to test this hypothesis, I run the following quadratic model:

$$ICT_{s,t,c} = \beta_0 + \beta_1 \; Age_{s,t,c} + \beta_2 \; Age^2_{s,t,c} + \Gamma X, \tag{1}$$

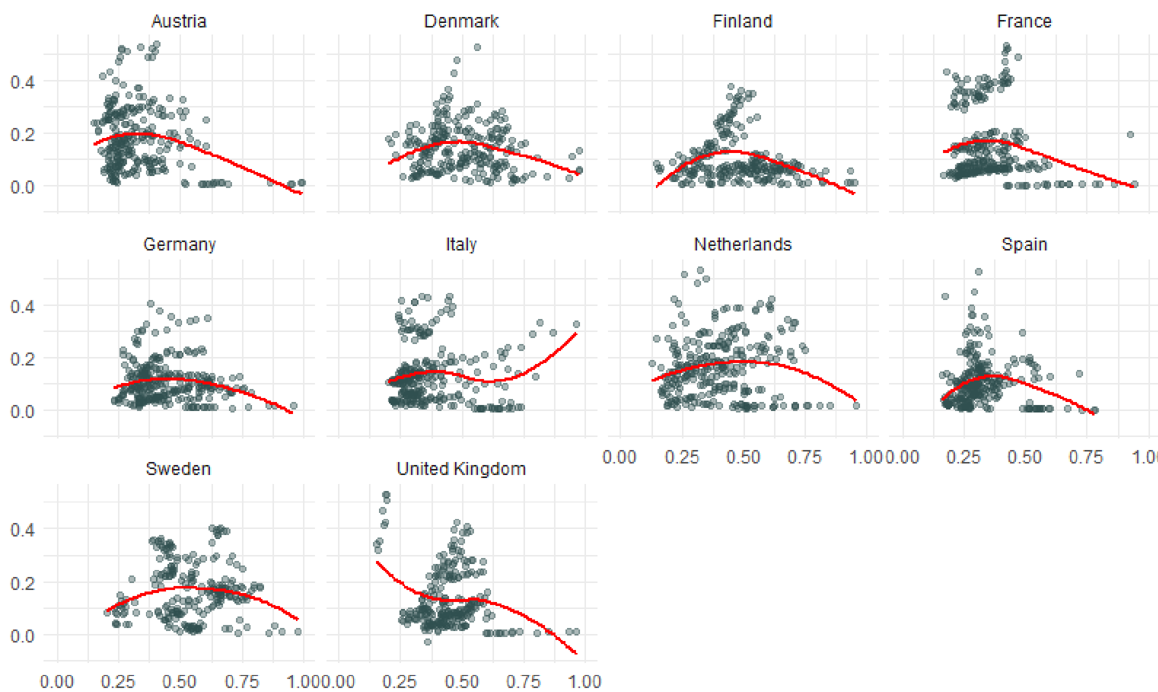

Figure (1) Raw relation between Age (ratio between workers above 50 and those between 25 and 50, on the x-axis) and Technological adoption (share of ICT investment, on the y-axis). EU KLEMS sector-level data (1995-2015). The curves are produced using local averaging.

where X are time, sector, and country dummies. Sector dummies control for the different use of ICT in the different sectors, time dummies control for the time trend in the use of

[4]See the appendix for the description of the variables.

[5]Austria, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, Sweden, and the United Kingdom. We use countries for which we have complete data excluding Luxembourg.

ICT, while country dummies control for country fixed effects. Columns (1), (2), and (3) present the coefficient estimates of the linear model (i.e., the model without the quadratic term). Results of the linear model are not consistent across the different specifications. In particular, the richest specification with sector, time, and country fixed effects shows no relation linking demography to ICT adoption. Once we introduce the quadratic term, instead, the estimated β_1 is positive and the estimated β_2 is negative and consistent for all the specifications considered suggesting a reversed-U shape relation between age and technology adoption. A possible caveat of using sector-level data is that as workers age, they may switch between sectors. As a robustness check addressing such a concern, I repeat the analysis using country-level observations. Table 5 in the appendix shows that, in the richest specification with time and country fixed effects, the country-level results are consistent with the sector-level results.

Table (1) Relation between age and ICT investment. EU KLEMS sector-level data (1995-2015) for 10 Western European countries.

	Dependent variable:					
	ICT					
	(1)	(2)	(3)	(4)	(5)	(6)
Age	−0.093***	0.104***	0.044	0.245***	0.356***	0.357***
	(0.024)	(0.029)	(0.038)	(0.084)	(0.077)	(0.093)
Age^2				−0.302***	−0.221***	−0.246***
				(0.072)	(0.063)	(0.067)
Time fixed effects		✓	✓		✓	✓
Sector fixed effects		✓	✓		✓	✓
Country fixed effects			✓			✓
Observations	2,800	2,800	2,800	2,800	2,800	2,800
R^2	0.005	0.367	0.379	0.011	0.370	0.382
Adjusted R^2	0.005	0.359	0.369	0.011	0.362	0.372

Note: *p<0.1; **p<0.05; ***p<0.01

To analyze the contribution of the different investments which make up the ICT investment, I repeat the analysis separately considering Information Technology (IT), Communication Technology (CT), and Software and Database (Software and DB). Table 2 shows that the reversed-U shape relation linking age and ICT is driven almost exclusively by Software and DB technology. IT only marginally contributes to the shape of the relation, while CT negatively relates to age.

Table (2) Relation between age and ICT investment and its different components: Information Technology (IT), Communication Technology (CT), Software and Database (Software & DB). ICT = IT + CT + Software & DB. EU KLEMS sector-level data (1995-2015) for 10 Western European countries.

	Dependent variable:			
	ICT	IT	CT	Software & DB
	(1)	(2)	(3)	(4)
Age	0.357***	0.021*	−0.026*	0.362***
	(0.093)	(0.012)	(0.014)	(0.090)
Age^2	−0.246***	−0.017*	0.012	−0.241***
	(0.067)	(0.009)	(0.010)	(0.064)
Time fixed effects	✓	✓	✓	✓
Sector fixed effects	✓	✓	✓	✓
Country fixed effects	✓	✓	✓	✓
Observations	2,800	2,800	2,800	2,800
R^2	0.382	0.551	0.346	0.314
Adjusted R^2	0.372	0.543	0.336	0.303
Note:				*p<0.1; **p<0.05; ***p<0.01

The impact of the workforce age structure on the different components of ICT depends on the different degrees to which these technologies are labor-saving and on the different levels of complementarity with different types of labor. In particular, the more the technology is labor-saving, the more it is adopted as the labor force reduces or the capital is accumulated due to aging. Table 3 shows that, while IT is independent on the fraction of the working-age population, the amount of CT increases with the working-age population suggesting a certain degree of complementarity with the labor force. On the contrary, Software and DB technology increases with a reduction in the fraction of the working-age population suggesting a certain degree of substitutability with the labor force. As Software and DB technology can substitute labor, as the population ages and the labor supply declines relative to capital, the adoption of Software and DB technology, therefore, increases.

Software and DB technology, however, requires peculiar skills to be operated (programming and ICT knowledge in general). Since these skills are mostly held by young workers as they have a more recent education, the relation reverses as young workers become scarce due to aging. The interaction between the substitutability property of Software and DB (and ICT in general) with respect to labor and the complementarity with skills held by young workers explains the reversed-U shaped relation between age and Software and DB technology described in Table 2.

CT instead increases as the fraction of the working-age population increases (Table 2) meaning that it is complementary to the labor force. Therefore, as the population ages and the labor supply reduces, also investments in CT reduce (Table 2). However, CT and IT differ with respect to Software and DB technologies in terms of the skills that are required to be operated. In particular, while CT and IT require no particular skills to be used, Software and DB technology requires programming skills that are mostly held by young workers. This explains why aging has almost no effect on CT and IT investment, but it greatly affects Software and DB technology (Table 2).

2.2 Wages

As the population ages, young workers become scarcer in the economy. Under the assumption that young and old workers are different in terms of their complementarity with respect to technologies, we expect an increase in young workers' wages relative to old workers' wages as the population ages. Table 4, indeed, shows that there exists a positive relationship between the young-to-old wage ratio and aging. This relation is robust to the inclusion of sector, time and country fixed effects. To control for the heterogeneity of the relevance of the age variable to determine wages across sectors, I also include the $Age \times Sector$ fixed effects interaction term. Introducing this interaction term allows us to control for unobserved variables determining wages in the different sectors, such as experience. The relevance of the inclusion of the interaction term can be seen from the fact that the point estimate substantially increases and the estimation becomes slightly more precise (i.e., the standard

Table (3) Relation between fraction of the working-age population (15-64) and ICT investment and its different components: Information Technology (IT), Communication Technology (CT), Software and Database (Software & DB). ICT = IT + CT + Software & DB. EU KLEMS country-level data (1995-2015) for 10 Western European countries.

	Dependent variable:			
	ICT	IT	CT	Software & DB
	(1)	(2)	(3)	(4)
Working-age share	−1.085***	−0.068	0.206***	−1.223***
	(0.155)	(0.061)	(0.077)	(0.127)
Country fixed effects	✓	✓	✓	✓
Observations	206	206	206	206
R^2	0.494	0.256	0.062	0.489
Adjusted R^2	0.437	0.171	−0.046	0.431
Note:				*p<0.1; **p<0.05; ***p<0.01

Table (4) Relation between age and young to old wage ratio. EU KLEMS sector-level data (2008-2015) for 26 European countries and the US.

	Dependent variable:				
	Young to Old Wage Ratio				
	(1)	(2)	(3)	(4)	(5)
Age	0.141***	0.217***	0.156***	0.227***	0.517***
	(0.008)	(0.011)	(0.011)	(0.010)	(0.022)
Time fixed effects		✓	✓	✓	✓
Sector fixed effects		✓	✓	✓	✓
Country fixed effects			✓	✓	✓
Age × Sector fixed effects				✓	✓
Age × Country fixed effects					✓
Observations	4,554	4,554	4,554	4,554	4,554
R^2	0.062	0.197	0.412	0.428	0.369
Adjusted R^2	0.062	0.191	0.405	0.421	0.361

Note: *p<0.1; **p<0.05; ***p<0.01

error reduces). Results are also robust to the inclusion of the *Age* $\times$ *Country* fixed effects interaction term which controls for the heterogeneity of the relevance of age to determine wages across countries. Also in this case the point estimate increases.

To summarize our empirical evidence, I find a reversed-U shape relation linking age and ICT investments. This relation is almost completely driven by the Software and DB component of ICT. Software and DB technology is labor-saving in the sense that it is negatively related to the fraction of the working-age population in the economy. Moreover, Software and DB technology requires skills to be used. Since the relation between age and ICT is driven by Software and DB technology, in the following theoretical model, I define the new technology as being labor-saving and complementary with skilled workers. Aging also affects the relative wage of the different types of workers (young and old) as it changes the relative supply of the different labor inputs in the economy. In particular, I document a positive relationship between the aging and the young-to-old wage ratio suggesting that young and old workers are not perfect substitutes. In the rest of the paper, I formalize and rationalize these findings using a theoretical model.

3 Model

3.1 Supply side

3.1.1 Production technology

I consider an economy producing in period t a unique final good Y_t by combining a unit measure of tasks, $y_t(i)$ with $i \in [0, 1]$, with unitary elasticity of substitution:

$$Y_t = exp\left\{\int_0^1 \ln y_t(i)\ di\right\}. \tag{2}$$

Each task can be produced either using *new* (n) technology ($y_{n,t}(i)$), *vintage* (v) technology ($y_{v,t}(i)$) or a linear combination of the two:

$$y_t(i) = \underbrace{A_t \cdot \mu_n(i) \cdot \ell_{n,t}(i)^{\alpha} k_{n,t}(i)^{1-\alpha}}_{y_{n,t}(i)} + \underbrace{\mu_v(i) \cdot \ell_{v,t}(i)^{\beta} k_{v,t}(i)^{1-\beta}}_{y_{v,t}(i)}, \tag{3}$$

where $\ell_{n,t}(i)$ ($\ell_{v,t}(i)$) and $k_{n,t}(i)$ ($k_{v,t}(i)$) are labor and capital used in new (vintage) technology, $\mu_n(i)$ ($\mu_v(i)$) is the task-specific productivity of task i using new (vintage) technology, and α (β) is the output elasticity of labor using new (vintage) technology. A_t is a measure of the productivity of new technology compared to vintage technology and it is determined through R&D.

Throughout, I impose the following assumptions:

Assumption 1: *The ratio $\mu_n(i)/\mu_v(i)$ is decreasing in i.*

Assumption 2: $\alpha < \beta$.

Assumption 1 describes a productivity schedule in which new technology is relatively more efficient in the production of low-indexed tasks, and vintage technology is more efficient in the production of high-indexed tasks. This productivity schedule implies that there exists a threshold task $I_t \in [0,1]$ such that only new technology is used to produce tasks $i < I_t$, and only vintage technology is used to produce tasks $i \geqslant I_t$. This implies that we can rewrite the task production function (3) of task i as:

$$y_t(i) = \begin{cases} y_{n,t}(i) & \text{if } i \in [0, I_t) \\ y_{v,t}(i) & \text{if } i \in [I_t, 1]. \end{cases}$$

The threshold I_t represents the fraction of tasks that are produced using new technology, and it can be interpreted as a measure of new technology adoption.

Assumption 2 states that the output elasticity of labor (or labor share) of the new technology task production function is smaller than the vintage technology one. This assumption capture the idea that the new technology is labor-saving with respect to the vintage technology.

3.1.2 Task producers

I recover the demand of each task by maximizing the net output with respect to task i:

$$\max_{\{y_t(i)\}} \quad Y_t - \int_0^1 p_t(i) y_t(i) di. \tag{4}$$

where $p_t(i)$ is price of task i. From problem (4) I get the demand for task i:

$$y_t(i) = \frac{Y_t}{p_t(i)}. \tag{5}$$

Producers of tasks are price takers. For tasks $i \in [0, I_t)$, they maximize profits taking the price of tasks, $p_t(i)$, the price of new capital, $R_{n,t}$, and the wages of workers employed in tasks produced using new technology, $w_{n,t}$, as given:

$$\max_{\{\ell_{n,t}, k_{n,t}\}} \quad p_t(i) \cdot y_t(i) - w_{n,t} \cdot \ell_{n,t}(i) - R_{n,t} \cdot k_{n,t}(i). \tag{6}$$

Using the demand of task i in equation (5), and the FOC from problem (6), I get the following demands for labor and capital for tasks produced using new technology:

$$\ell_{n,t}(i) = \frac{\alpha Y_t}{w_{n,t}} \tag{7}$$

$$k_{n,t}(i) = \frac{(1-\alpha)Y_t}{R_{n,t}}. \tag{8}$$

Similarly, I recover the demands for labor and capital for tasks produced using vintage technology (i.e., $i \in [I_t, 1]$):

$$\ell_{v,t}(i) = \frac{\beta Y_t}{w_{v,t}}, \tag{9}$$

$$k_{v,t}(i) = \frac{(1-\beta)Y_t}{R_{v,t}}. \tag{10}$$

3.1.3 R&D sector

The R&D sector produces the blueprints for new technology machines. We consider the following R&D production function:

$$A_t = A_{t-1} + \bar{\delta}_t \cdot \ell_{A,t} \tag{11}$$

where $\ell_{A,t}$ is the labor employed in the R&D sector in period t, and $\bar{\delta}_t \equiv \frac{\delta \cdot A_{t-1}^{\eta}}{\ell_{A,t}^{1-\lambda}}$ captures the intertemporal spillovers (measured by η) and the congestion externality (measured by $(1-\lambda)$ with $\lambda \in [0,1]$). Profits are given by the revenues generated by selling patents at price $p_{A,t}$ net of labor costs, $w_{A,t}\ell_{A,t}$ (i.e., $p_{A,t}\bar{\delta}_t\ell_{A,t} - w_{A,t}\ell_{A,t}$). Optimality requires that $w_{A,t} = p_{A,t}\bar{\delta}_t$.

3.1.4 New technology capital producer

New technology capital, $k_{n,t}(i)$, is produced using capital. We consider a linear production function such that to produce one unit of new technology capital, a unit of capital is required. Producers of new technology use patents from the R&D sector as input. We assume that those firms have a certain degree of market power and free entry. This implies that profits π_t must be equal to the patent cost $p_{A,t}$. New technology producers face the following profit maximization problem:

$$\max_{x_t} R_{n,t}(x_t) \cdot x_t - R_t x_t, \tag{12}$$

where R_t is the price of one unit of capital in period t and $x_t \equiv \int_0^{I_t} k_{n,t}(i)\, di$ is the aggregate demand of new technology capital. Optimality requires:

$$R_{n,t} = \frac{R_t}{1-\alpha I_t}, \tag{13}$$

and:

$$\pi_t = \left(\frac{\alpha I_t}{1-\alpha I_t}\right) x_t R_t. \tag{14}$$

3.1.5 Market Clearing Conditions

The population in the economy is normalized to one. Therefore, $N^y + N^o = 1$, where N^y and N^o represent the fraction of young and old respectively. I impose the following assumptions:

Assumption 3: *Tasks produced using new technology and the R&D sector employ skilled workers.*

Assumption 4: *Young agents inelastically supply one unit of labor, while old agents supply $\phi \in [0,1]$ units of labor.*

Assumption 3 captures the idea that in order to operate with new technologies or produce the new technology blueprints, skills are required. Assumption 4, instead, captures the idea that a share of old people retires and does not participate to the labor force. We can, therefore, interpret ϕ as a retirement age parameter. We define γ_t^A as the share of skilled workers that is employed in the R&D sector, and γ_t^y and γ_t^o as the share of skilled workers among young and old respectively which are endogenous depending on the skill acquisition choices of the agents. Assumption 3 and Assumption 4 imply the following market clearing conditions:

$$\ell_{A,t} = \gamma_t^A \left(\gamma_t^y \cdot N^y + \gamma_t^o \cdot \phi N^o\right) \equiv L_{A,t}, \tag{15}$$

$$\int_0^{I_t} \ell_{n,t}(i)\ di = \left(1-\gamma_t^A\right)\left(\gamma_t^y \cdot N^y + \gamma_t^o \cdot \phi N^o\right) \equiv L_{n,t}, \tag{16}$$

$$\int_{I_t}^1 \ell_{v,t}(i)\ di = \left(1-\gamma_t^y\right) \cdot N^y + \left(1-\gamma_t^o\right) \cdot \phi N^o \equiv L_{v,t}, \tag{17}$$

where the left-hand side (right-hand side) of the equations (15), (16), and (17) are the aggregate labor demands (aggregate labor supplys) in the R&D sector, and for tasks produced with new and vintage technology respectively.

The Cobb-Douglas structure of the production aggregator implies that the expenditures $p_t(i)y_t(i)$ are constant in i. This also implies that the labor demand is constant across tasks.[6]

[6] To show this, we can use the FOC with respect to labor in problem (6) together with the Cobb-Douglas condition $p_t(i)y_t(i) = p_t(i')y_t(i') \ \ \forall\ i, i' \in [0,1]$.

We can, therefore, rewrite:

$$\ell_{n,t} = \frac{L_{n,t}}{I_t} \tag{18}$$

$$\ell_{v,t} = \frac{L_{v,t}}{1 - I_t}. \tag{19}$$

Similarly, we can write the market clearing conditions for the capital market as:

$$k_{n,t} = \frac{\gamma_t^k \cdot K_t}{I_t}, \tag{20}$$

$$k_{v,t} = \frac{(1 - \gamma_t^k) \cdot K_t}{1 - I_t}, \tag{21}$$

where K_t is the capital stock in the economy in period t and $\gamma_t^k \in [0, 1]$ is the fraction of capital allocated to tasks produced using new technology in period t which is endogenously determined.

3.1.6 Partial equilibrium

Given the capital stock and the allocation young and old workers to new and vintage technology tasks (γ_t^y and γ_t^o) and the share of skilled workers in the R&D sector (γ_t^A), the fraction of young and old agents in the economy, we can characterize the equilibrium value of output, new technology adoption, factor prices, and input allocation shares. From the factor demands described in equations (7), (8), (9), and (10), the market clearing conditions in equations (18), (19), (20), and (21), we recover the factor prices and the input allocation shares:

$$R_{n,t} = (1 - \alpha) I_t \cdot \frac{Y_y}{\gamma_t^k K_t}, \tag{22}$$

$$R_{v,t} = (1 - \beta)(1 - I_t) \cdot \frac{Y_t}{(1 - \gamma_t^k) K_t}, \tag{23}$$

$$w_{n,t} = \alpha I_t \cdot \frac{Y_t}{L_{n,t}}, \tag{24}$$

$$w_{v,t} = \beta(1 - I_t) \cdot \frac{Y_t}{L_{v,t}}, \tag{25}$$

$$\gamma_t^k = \frac{(1 - \alpha) I_t (1 - \alpha I_t)}{1 - \varepsilon_t}, \tag{26}$$

where we have recovered the price of capital as:

$$R_t = \frac{dY_t}{dK_t} = (1 - \varepsilon_t) \cdot \frac{Y_t}{K_t} = \gamma_t^k R_{n,t} + (1 - \gamma_t^k) R_{v,t}, \tag{27}$$

where $\varepsilon_t \equiv \alpha I_t + \beta(1 - I_t)$.

We can show that the aggregate production function can be rewritten as follows:

$$Y_t = B_t \cdot \left(\frac{L_{n,t}}{\alpha I_t}\right)^{\alpha I_t} \left(\frac{L_{v,t}}{\beta(1-I_t)}\right)^{\beta(1-I_t)} \left(\frac{K_t}{1-\varepsilon_t}\right)^{1-\varepsilon_t}, \tag{28}$$

where:

$$B_t \equiv e^{\int_0^{I_t} \ln A_t \mu_n(i) \alpha^\alpha [(1-\alpha)(1-\alpha I_t)]^{1-\alpha} \, di + \int_{I_t}^1 \ln \mu_v(i) \beta^\beta \left[(1-\beta)+\frac{\alpha(1-\alpha)I_t^2}{1-I_t}\right]^{1-\beta} \, di} \tag{29}$$

Equation (28) shows that the factor shares in this model are endogenous depending on the threshold tasks I_t. In particular, by allowing task producers to choose between technologies with different output elasticity of labor (α and β for new and vintage technology respectively), they optimally choose the technology depending on the supply of inputs. At the aggregate level, therefore, the supply of inputs endogenously determines the factor shares. We, then, pin down the share of skilled workers in the R&D sector (γ_t^A), by imposing the no arbitrage condition on the wages of workers in the R&D sector and the workers using new technology:

$$w_{A,t} = w_{n,t}. \tag{30}$$

As the last step, to fully characterize the partial equilibrium, we need to pin down the threshold task I_t. This can be done by noting that in task $i = I_t$ a task producer should break even either using new or vintage technology. In other words, it must hold that the price of the task $i = I_t$ is the same when using new or vintage technology:

$$p_{n,t}(I_t) = p_{v,t}(I_t), \tag{31}$$

where $p_{n,t}(i)$ ($p_{v,t}(i)$) is the price of task i when the task is produced using new (vintage) technology.[7]

3.2 Household side

As we have seen in the previous section, the supply of inputs determines the aggregate production function in the economy. In this section, we determine the supply of inputs such as the different types of labor and capital by analyzing the household utility maximization problem.

[7] $p_{n,t}(i) = [A_t \mu_n(i)]^{-1} \cdot \left(\frac{w_{n,t}}{\alpha}\right)^\alpha \cdot \left(\frac{R_{n,t}}{1-\alpha}\right)^{1-\alpha}$ and $p_{v,t}(i) = \mu_v(i)^{-1} \left(\frac{w_v}{\beta}\right)^\beta \cdot \left(\frac{R_{v,t}}{1-\beta}\right)^{1-\beta}$, i.e., the price of producing a task using either technology negatively depends on the technology task-specific productivity, and it is increasing in the average price of factors weighted by the respective shares. The derivation is straightforward using the FOC from the maximization problem (6).

3.2.1 Consumption and skill acquisition

Agents live for two periods. In the first period, agents are young and inelastically supply one unit of labor, while in the second period, they are old and inelastically supply $\phi \in [0,1]$ units of labor.[8] Agents gain utility from consumption and suffer disutility from acquiring the skills necessary to use new technologies. No skill acquisition is required to produce using vintage technologies. Agents can acquire skills when they are young and train when old to keep those skills. We can interpret the acquisition of skills when young as education, and the acquisition of skills when old as a refresher training in order to stay updated with the new technology. Indeed, since the new technology evolves over time through the R&D process, in order to keep using such a technology, workers need to acquire skills also when old. This assumption is motivated by the length of each period, 25 years. It is, indeed, plausible to assume that if the agents do not engage in some training to use new technology, such a technology develops so to render skills acquired in the previous period obsolete. Therefore, if a worker does not train when old, the worker switches to vintage technologies.

We further assume that agents are heterogeneous in terms of their ability a such that with higher a, agents suffer a lower disutility from acquiring skills. Therefore, an agent of type $\{j, j'\}$ with ability a, where j and j' correspond to the agent type in terms of the technologies that uses when young and old respectively, i.e., $j, j' \in \{n, v\}$, faces the following lifetime utility maximization problem:

$$\max_{\{C_t^y(j,j'), C_{t+1}^o(j,j')\}} U(j,j') = \log C_t^y(j,j') - \mathbb{1}_{j=n} e^y(a) + \rho[\log(C_{t+1}^o(j,j') - \mathbb{1}_{j,j'=n} e^o(a)] \qquad \text{s.t.} \tag{32}$$

$$C_t^y(j,j') = w_{j,t}^y - S_t(j,j'),$$

$$C_{t+1}^o(j,j') = \phi \; w_{j',t+1}^o + (1 + r_{t+1}) \cdot S_t(j,j'),$$

where the functions $e^y(a)$ and $e^o(a)$ are respectively the cost of education and the cost of training and depend on the ability of the agent. The indicator functions indicate that the young agent suffers disutility only if she undertakes education, and that the old agent suffers disutility only if she engages in training. We further assume that in order to be able to use new technology when old, the worker needs to have both undertaken education when young and training when old, i.e., $\mathbb{1}_{j,j'=n}$. Furthermore, ρ is the discount rate, and r_{t+1} is

[8] I define as young, prime-aged workers from 25 to 50 years old, and as old, people from 50 to 75 meaning that While young agents are fully in the working-age period, the old agents are partially in the working-age and partially in the retirement period. We, therefore, interpret ϕ as the retirement age which we assume to be exogenously determined.

the net price of capital in period $t+1$ with capital depreciation (δ_k) already deducted, i.e., $r_{t+1} = R_{t+1} - \delta_k$. Since the model divides human life into two periods, each period is quite long (in historical time) and it is thus reasonable to assume that capital fully depreciates within the period ($\delta_k = 1$) implying $R_{t+1} = 1 + r_{r+1}$. From the FOC of problem (32), we obtain the following consumption ($C_t^y(j,j'), C_{t+1}^o(j,j')$) and saving ($S_t(j,j')$) choices:

$$C_t^y(j,j') = \frac{1}{1+\rho}\left(w_{j,t}^y + \frac{\phi w_{j',t+1}^o}{R}\right), \tag{33}$$

$$C_{t+1}^o(j,j') = \frac{\rho R}{1+\rho}\left(w_{j,t}^y + \frac{\phi w_{j',t+1}^o}{R}\right), \tag{34}$$

$$S_t(j,j') = \frac{1}{1+\rho}\left(\rho w_{j,t}^y + \frac{\phi w_{j',t+1}^o}{R}\right). \tag{35}$$

Since both the cost of education and the cost training are declining in abilities, there exists two thresholds a^y and a^o such that if $a > a^y$ the young agent undertakes education, and if $a > a^o$ the old agent engage in training. In order to pin down these thresholds, consider the problem of the old. If the old worker has not undertaken education when young, i.e., $j = v$, then she is prevented from engaging training when old, i.e., $j' = v$. If the agent has undertaken education when young, i.e., $j = n$, when old must decide whether to engage in training or not. An old agent is indifferent whether to engage in training if the utility of working with new technology and paying the cost of training is equal to the utility of working with vintage technology without paying the cost of training, i.e.:

$$\log C^o(n,n) - e^o(a) = \log C^o(n,v). \tag{36}$$

Solving the equation (36) for a, we pin down a_t^o. In order to pin down a_t^y, we consider the problem of the young. If $a > a_t^o$ then $j' = n$ which also implies that $j = n$. If $a \leqslant a_t^o$ then $j' = v$. Therefore, given that $j' = v$, a young agent is indifferent between getting education or not if the utility of getting education is the same as the utility of not undertaking it, i.e.:

$$U(n,v) = U(v,v). \tag{37}$$

Solving equation (37) for a, we pin down a_t^y such that if $a \leqslant a_t^y$ the young agent does not undertake education, while if $a > a_t^y$ she takes it.

This implies that we partition the ability space such that if $a \leqslant a_t^y$ the agent does not acquire skills when young and does not engage in training when old; if $a_t^y < a \leqslant a_t^o$ the agent acquires skills when young but does not engage in training when old; and if $a > a_t^o$ the agent acquires skills when young and engages in training when old, i.e.:

$$j, j' = \begin{cases} v, v & \text{if} \quad a \leqslant a_t^y \\ n, v & \text{if} \quad a_t^y < a \leqslant a_t^o \\ n, n & \text{if} \quad a_t^o < a. \end{cases} \tag{38}$$

In order to recover the thresholds a_t^y and a_t^o, we solve $U(v,v) = U(n,v)$ and $U(n,v) = U(n,n)$ for a.

Assuming that a is distributed according to a cumulative distribution function F, the share of young workers and old workers employed in the production of tasks using new technology are respectively $\gamma_t^y = 1 - F(a_t^y)$ and $\gamma_t^o = 1 - F(a_t^o)$, where, since $a_t^y < a_t^o$, $\gamma_t^y > \gamma_t^o$ which reflect the assumption that younger workers have a comparative advantage in the use of new technology.

Finally, we assume that generations reproduce at rate n_f which implies that $N_{t+1}^y = (1 + n_f)N_t^y$, and, since agents survive to the second period with probability one, $N_{t+1}^o = N_t^y$.[9]

3.2.2 General equilibrium

The stock of capital in the economy is determined by the the consumption and saving decisions of the agents in the economy, the demographic process, and the feasibility constraint, $K_{t+1} = N_t^y \cdot \bar{S}_t$ where $\bar{S}_t$ is the average savings in the economy in period t defined as:

$$\bar{S}_t = \gamma_t^y \gamma_t^o \cdot S_t(n,n) + \gamma_t^y (1 - \gamma_t^o) \cdot S_t(n,v) + (1 - \gamma_t^y) \cdot S_t(v,v). \tag{39}$$

We define $\tilde{k}_t$ as the capital allocated per worker $\left(\text{i.e., } \tilde{k}_t \equiv \frac{K_t}{L_{n,t} + L_{v,t}}\right)$ in period t, and define the steady state capital such that $\tilde{k}_{t+1} = \tilde{k}_t = \tilde{k}$.[10]

The steady state capital and the share of young and old workers employed in the new and vintage tasks (i.e., γ_t^y and γ_t^o) together with the partial equilibrium results allows us to characterize the general equilibrium.

4 Aging Analysis

In this section, I analyze how an aging population defined as an increase in the share of old workers with respect to the share of young workers affects the labor market in terms of

[9] We analyze the effects of a change in longevity compared to a change in fertility rates in a further section.

[10] Defining k_t as the capital allocated per worker in new or vintage technology, i.e., $\tilde{k}_t \equiv \frac{(1-\gamma_t^k)K_t}{L_{n,t}}$ or $\tilde{k}_t \equiv \frac{\gamma_t^k K_t}{L_{v,t}}$, we obtain the same results.

supply of educated and trained workers, adoption of new technology, allocation of capital, and wages. An aging of the population affects the supply of inputs in the economy by reducing the aggregate labor supply, increasing the supply of old labor, reducing the supply of young labor, and affecting the capital stock in the economy through the consumption and saving decisions of the households. In turns, these changes affect the incentives agents have to undertake education or engaging in training with effects on the supply of educated or trained workers which themselves affect the technology adoption of firms.

Task-based models are particularly well suited to analyze changes in the supply of factors that have different degrees of complementarity with different technologies. Indeed, in this framework firms do not only adapt their demand of inputs depending on the relative supply of factors but also choose the technology to use. Since technologies differ in terms of the output elasticity of inputs, as the supply of factor changes and firms optimally choose the technology to adopt, the aggregate factor shares change as well with effects that standard models do not capture.

4.1 Toy model analysis ($e^y = 0, e^o = +\infty$, and No R&D)

We consider now a special case that allows us to highlight the main mechanisms at play affecting the adoption of technology as population ages. We assume 1) no R&D sector (i.e., $A_t = A$) and 2) that the cost of education of young workers is zero ($e^y = 0$) and that there is no possibility for old workers to engage in training ($e^o = +\infty$). This implies that young workers can use either technology, while old workers can only use vintage technology (i.e., $\gamma^o = 0$).[11] We can distinguish between two different cases: the case in which the labor market is *not partitioned* and the young labor constraint is slack (i.e., $\gamma^y \in (0, 1)$) meaning that young workers are employed in the production of tasks produced either with new or vintage technology, and the case in which the labor market is *partitioned* and the young labor constraint is binding (i.e., $\gamma^y = 1$) meaning that all young workers are employed in the production of tasks using new technology and all old workers produce using vintage technology. When the labor market is not partitioned, optimality requires that the wages of the workers in new and vintage technology are the same. Since young workers can either use new and vintage technology without undertaking any costly education and there is no scarcity of young labor, young and old workers are "as perfect substitutes". If the labor market is partitioned meaning that there is scarcity of young labor, wages differ since young and old

[11]We assume $e^o = +\infty$ to simplify the analysis. What is required to have that old workers only use vintage technology is that the cost of training is sufficiently high, i.e., $e^o > \tilde{c}^o$ where $\tilde{c}_o$ is such that an old worker never finds it optimal to engage in training.

workers are not perfect substitutes. In this latter case, wages will depend on the respective labor supplies. It can be shown that there exists a threshold value $\hat{N}^o \in (0,1)$ such that for $N^o < \hat{N}^o$, the young labor constrain is slack (i.e., the labor market is not partitioned), and for $N^o \geqslant \hat{N}^o$, the young labor constraint is binding (i.e., the labor market is partitioned).[12]

In this simplified model, we can rewrite equation (28) as follows:

$$Y = \begin{cases} B \cdot \left(\frac{N^y + \phi N^o}{\varepsilon}\right)^{\varepsilon} \cdot \left(\frac{K}{1-\varepsilon}\right)^{1-\varepsilon} & \text{if } N^o < \hat{N}^o \\ B \cdot \left(\frac{N^y}{\alpha I}\right)^{\alpha I} \cdot \left(\frac{\phi N^o}{\beta(1-I)}\right)^{\beta(1-I)} \cdot \left(\frac{K}{1-\varepsilon}\right)^{1-\varepsilon} & \text{if } N^o \geqslant \hat{N}^o, \end{cases} \tag{40}$$

Equation (40) reflects the consideration discussed above regarding the different degree of substitutability between young and old labor inputs in the situation of slack or binding young labor constraint. In the case of a slack input constraint ($N^o < \hat{N}^o$), young and old labor are perfect substitutes and they enter the aggregate production function as a single input. In the case of a binding input constrain ($N^o \geqslant \hat{N}^o$), young and old labor enter the aggregate production function as different inputs which are imperfect substitutes.

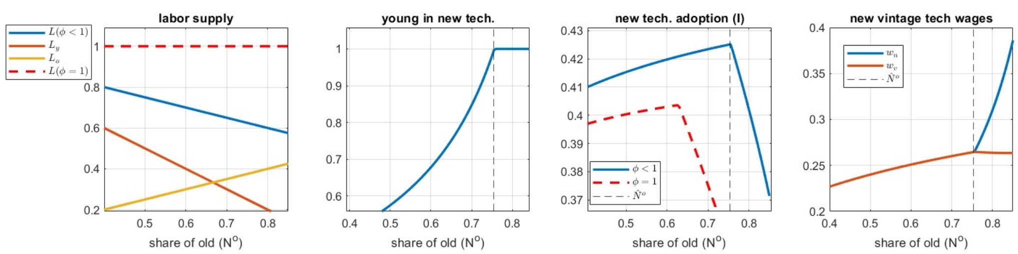

Figure (2) Aging analysis (toy model)

Figure (2) shows the effect of an aging population on the aggregate labor supply, the age composition of the labor supply, the allocation of young labor to new technology, the adoption of new technology, and wages. We observe that as population ages, since old workers only supply a fraction of their time working (i.e., $\phi \in [0,1]$), the aggregate labor supply reduces. The reduction in the aggregate labor supply, increases the incentives of firms to use new (labor-saving) technology leading to an increase in the share of tasks produced with new technology, I, and an increase the share of young workers employed in new technology, γ^y. As population increases further and the young labor scarcity hits the economy ($\gamma^y = 1$), the relation between new technology adoption and aging reverses. Indeed, although the aggregate labor supply keep declining, firms are constrained in the use of new technology by the scarcity of young labor. A further aging of the population, therefore, by reducing the

[12]The threshold age is defined as $\hat{N}^o = \frac{\beta(1-I)}{\phi \cdot \alpha I + \beta(1-I)}$. We find $\hat{N}^o$ by solving $\gamma^y(\hat{N}^o) = 1$ where $\gamma^y(N^o)$ is such that $w_n = w_v$.

share of young workers makes the young labor constraint tighter leading to a lower adoption of new technology. The effect of an aging population on wages depends on whether the young labor constraint is binding or not. Initially, as there is no scarcity of young workers, the wages of young and old workers is the same as they are as perfect substitutes and are increasing as the capital per worker increases. As the young labor constraints binds, wages start to diverge, reflecting the higher productivity of young workers in new technology as they become increasingly scarce.

From this analysis, we can disentangle three different channels through which aging affects the economy: the *labor supply channel* which induces an increase in the adoption of new technology until the young labor constraint binds, the *age composition of labor channel* which determines the tightness of the young labor constraint and explains why the relation between aging and new technology adoption reverses, and the *capital channel* which captures the effect of an increase in the capital share in the economy as population ages. Since an aging of the population increases the share of old agents that supply capital to the economy, aging increases the capital stock leading to a higher incentive to adopt new technology which is labor-saving (or capital-intensive). Therefore, the capital channel works in the same direction of the labor supply channel as a reduction in the labor supply or an increase in the capital stock both increase the capital per worker which increases the incentives to adopt new technology. To disentangle these two channels, set $\phi = 1$. When $\phi = 1$, indeed, the increase in the adoption of new technology is only due to the capital channel as the aggregate labor supply stays constant (red dotted line).

This simplified framework allowed us to highlight and disentangle the main mechanisms at play determining the adoption of technology and the wage differential across age categories. However, given the assumption of no education costs for the young and no possibility of training for the old, this framework does not allow us to analyze the wage inequality between and within age categories across the different technologies used in production. Including education and training costs in the next section, we proceed with such analysis.

4.2 Complete model analysis

We now turn to the complete model in which education costs for the young and training costs for the old are included to analyze the effect of an aging population on technological adoption, between and within generation wage inequality, and other key macroeconomic variables.

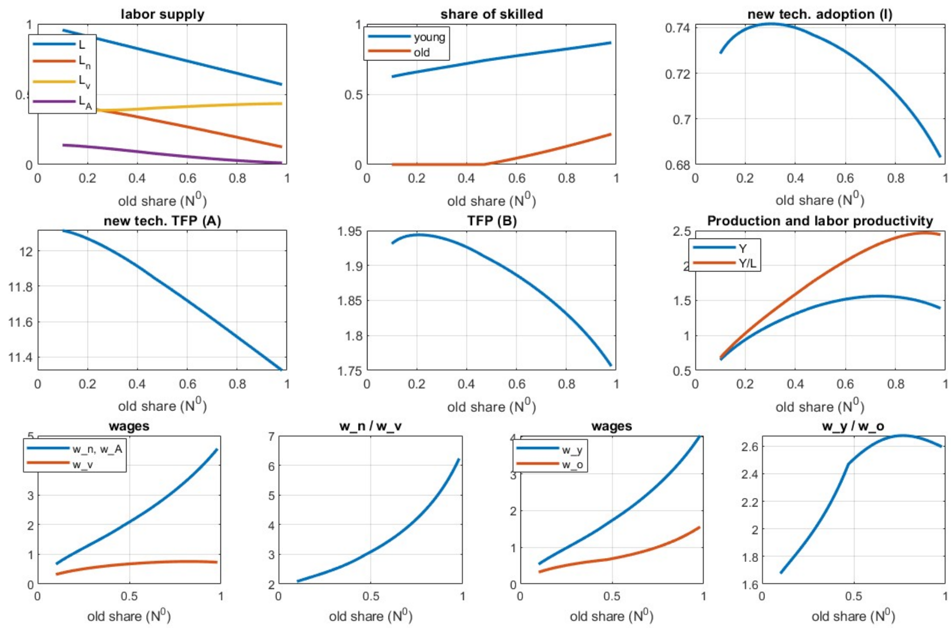

Figure (3) Aging analysis (complete model)

Figure (3) shows that including education costs for the young and the possibility to engage in training for the old introduces heterogeneity within age categories as a fraction of both young and old workers is employed in tasks produced using new technology. However, since the threshold ability of the old is higher than the threshold ability of the young ($a^o > a^y$), the share of old workers employed in tasks produced with new technology is lower than the share of young workers (i.e., $\gamma^o < \gamma^y$). This means that not all old workers with education (acquired when young) find it optimal to engage in training when old and, therefore, switch to tasks produced using vintage technology. In particular, for low levels of aging, no old worker trains as in the economy there are still many young workers who have a comparative advantage in skill acquisition. As population ages, the increase in the capital per worker (due to both the reduction in the labor supply and the increase in the capital stock) increases the incentives to adopt new technologies which leads to an increase in the share of tasks produced with new technology and an increase in both the share of young and old workers employed in tasks produced with new technology (for values after $\gamma^o > 0$). However, since the acquisition of skills for both young and old is increasingly costly as the share of workers in new technology increases, as population ages further, adoption of new technology reduces.

The effect on new technology intensity (or TFP of new technology, A) reduces as population ages as the absolute number of workers with skills reduces reducing also the workers in the R&D sector. The effect of the two technology margin (extensive margin, I, and intensive margin, A) is reflected in the aggregate TFP, B, which slightly increases for small levels of aging and the reduces. As population ages, production increases sustained by the increase in labor productivity which is driven by the increase in the capital per worker. However, the increase is concave as the scarcity of educated young and trained old workers limits production since education and training are increasingly costly as population ages.

Wages of both new (or R&D, i.e., skilled) and vintage technology tend to increase as population ages as the capital per worker increases, however wages in new technology increase faster as the average cost of acquiring education and engaging in training is increasing in the share of people employed in new technology (which increases as population ages). This implies that the ratio between new and vintage technology wages is convex in the share of old people in the economy. The average wages of the young and of the old diverge following the divergence of the wages of the skilled and unskilled workers. This reflects the comparative advantage of young workers in skill acquisition. The young to old wage ratio is, indeed, increasing at the beginning. However, the ratio stabilizes as a share of old workers starts to train.

5 Dynamic Analysis - PRELIMINARY

5.1 Calibration

Calibration is still preliminary and incomplete.

parameter	description	value	source (and potential targets)
α	new tech. labor share	0.6	labor share EA19, 2000 = 0.63
β	vintage tech. labor share	0.72	labor share, historical max EA12, 1975
ϕ	retirement age parameter	0.56	average retirement age Europe 2000
η	R&D spillover	0.7	Prettner and Strulik (2020)
λ	R&D congestion externality	0.49	Prettner and Strulik (2020)
δ	R&D efficiency	0.55	Prettner and Strulik (2020)
ρ	social planner discount	0.277	0.95^{25}
χ	cognitive ability loss	0.89	PIAAC (problem solving in tech. rich environment)
A_0	initial new tech. TFP	11	R&D employment share EU19, 2000 = 0.01
θ^y	skill acquisition cost (young)	1	young in training EU25, 2004 (25-34) = 0.502
θ^o	skill acquisition cost (old)	1.2	old in training EU25, 2003 (55-65) = 0.295

5.2 Results

In this analysis, I consider the dynamics of the model starting from year 2000 (as the calibration is in year 2000). I consider two different situations, a non-aging baseline situation in blue, and a situation in which aging occurs in red. The comparison between these two situations allows us to highlight the effect of an aging population over time on the relevant macroeconomic variables.

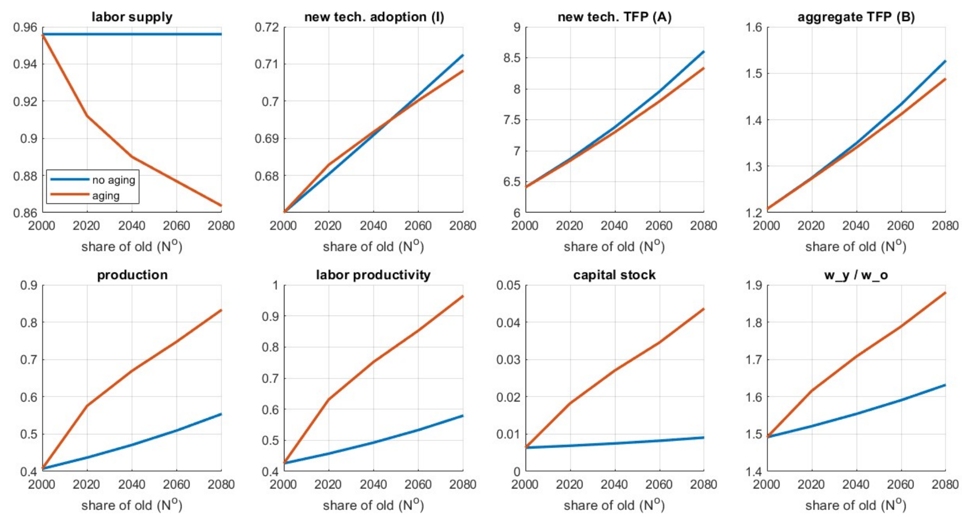

Figure (4) Dynamic analysis

With no aging, the labor supply stays constant over time and new technology TFP (A_t) increases over time driven by the R&D sector. Since new technology becomes more productive over time, adoption (I_t) on this technology increases over time. The effect on the aggregate TFP (B_t) is the combination of the increase of technology adoption and technology intensity, i.e., aggregate TFP is increasing as well. Production and labor productivity increase as well driven by the higher aggregate TFP. Capital stock slightly increase following the increase in production. Over time, the young to old wage ratio is increasing as a result of the increase in the intensity of new technology in which young workers have a comparative advantage.

When we consider the situation with aging, we observe a reduction in the labor supply. Initially,this triggers a positive effect on new technology adoption relative to the non-aging case. However, as aging goes further, the effect on new technology adoption is negative relative to the non-aging case due to the scarcity of young workers who have a comparative advantage in skill acquisition. The effect on new technology intensity is negative relative to the non-aging case as the adoption of skilled workers in R&D reduces as population ages. This negative effect is then observed also in the aggregate TFP. The effect of aging on production and productivity is positive driven by the higher capital accumulation triggered by aging. Finally, the effect of aging on the young to old wage ratio is positive and it explains a large share of the increase in the ratio over the period 2000-2020, and it is predicted to contribute to such increase in the future as well.

6 Conclusion

In this paper, I provide new empirical evidence on the relation between aging and adoption of ICT. IN particular, I find that the relation is non-linear and potentially non-monotonic driven by Software and database technology which is labor-saving (negatively correlated with the share of population in the working age) and it requires skills to be operated. I also find that aging increases the young to old wage ratio suggesting that young and old workers are not perfect substitutes and have different degrees of complementarity with the different technologies. To highlight the mechanisms driving such results and to quantify the macroeconomic implications in terms of growth and inequality, I implement an R&D growth task based model with endogenous education. I find that aging has a positive effect on economic growth due to capital accumulation. This effect is only partially offset by the negative effect going through the R&D sector. Finally, I find that aging explains a large share of the between generation inequality in the period 2000-2020.

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.1 Data and Variables

As a proxy for investments in new technologies (the dependent variable), I consider the fraction of ICT capital stock using data from EU KLEMS. As a proxy for the aging variable, I use population and employment data from Eurostat. While EU KLEMS investment data are already harmonized in accordance with the industry classification NACE Rev.2, data from Eurostat use NACE Rev.1.1 classification for data until 2007, and NACE Rev.2 classification for data from 2008. To harmonize the different NACE classifications for the Eurostat data, I used the correspondence table proposed by Perani et al. (2015) which is reported below. I consider the period from 1995 to 2015 for the countries for which sector-level data are available in the period considered, i.e., Austria, Germany, Denmark, Spain, Finland, France, Italy, Luxembourg, Netherlands, Sweden, and United Kingdom. The value-added data used to define productivity at the sector-level are taken from the EU KLEMS dataset as well.

The ICT investment variable is constructed in the following way:

$$ICT_{s,t,c} = \frac{IT_{s,t,c} + CT_{s,t,c} + Soft\_DB_{s,t,c}}{total\_GFCF_{s,t,c} - RD_{s,t,c}}$$

where $IT_{s,t,c}$, $CT_{s,t,c}$, $Soft\_DB_{s,t,c}$, $total\_GFCF_{s,t,c}$, and $RD_{s,t,c}$ are computer hardware, telecommunication equipment, computer software and databases investments, total investments, and R&D investments respectively in at time t, in sector s, in country c. The age variable is defined as the ratio between the number of workers aged 50 or older and those aged between 25 and 49 (prime-aged workers) for each sector, time and country. The productivity variable is defined as the value-added per hour worked.

.2 Tables

Table (5) Relation between age and ICT investment. EU KLEMS country-level data (1995-2015) for 10 Western European countries.

	Dependent variable:					
	ICT					
	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.201***	0.102***	0.090***	0.120	−0.023	0.268***
	(0.022)	(0.028)	(0.027)	(0.186)	(0.193)	(0.080)
Age^2				0.099	0.151	−0.217**
				(0.225)	(0.233)	(0.092)
Time fixed effects		✓	✓		✓	✓
Country fixed effects			✓			✓
Observations	206	206	206	206	206	206
R^2	0.298	0.402	0.921	0.299	0.404	0.924
Adjusted R^2	0.295	0.334	0.908	0.292	0.332	0.910
Note:				*p<0.1; **p<0.05; ***p<0.01		

Table (6) Correspondence table (Perani et al. (2015)) used to harmonize NACE Rev.1 with NACE Rev.2 classification.

NACE Rev.1.1		NACE Rev.2	
Section	**Description**	**Section**	**Description**
A, B	Agriculture, Hunting and Forestry (A), Fishing (B)	A	Agriculture, Forestry and Fishing
C	Mining and quarrying	B	Mining and quarrying
D	Manufacturing	C	Manufacturing
E	Electricity, gas and water supply	D, E	Electricity, gas, steam and air conditioning supply (D), Water supply, sewerage, waste management and remediation activities (E)
F	Construction	F	Construction
G	Wholesale and retail trade: repair of motor vehicles, motorcycles and personal and household goods	G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Hotels and restaurants	I	Accommodation and food service activities
I	Transport, storage and communications	H, J	Transportation and storage (H), Information and communication (J)
J	Financial intermediation	K	Financial and insurance activities
K	Real estate, renting and business activities	L, M, N	Real estate activities (L), Professional, scientific and technical activities (M), Administrative and support service activities (N)
L	Public Administration and defence; compulsory social security	O	Public administration and defence; compulsory social security
M	Education	P	Education
N	Health and social work	Q	Human health and social work activities
O	Other community, social and personal services activities	R, S	Arts, entertainment and recreation (R), Other service activities (S)
P	Activities of private households as employers and undifferentiated production activities of private households	T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
Q	Extraterritorial organizations and bodies	U	Activities of extraterritorial organizations and bodies

Table (7) Relation between Age and IT investment. EU KLEMS sector-level data (1995-2015) for 10 Western European countries.

	Dependent variable:					
	IT					
	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.003	0.023***	0.0004	0.072***	0.059***	0.012
	(0.003)	(0.004)	(0.005)	(0.012)	(0.010)	(0.011)
Age^2				−0.063***	−0.033***	−0.010
				(0.010)	(0.009)	(0.008)
Sector fixed effects		✓	✓		✓	✓
Time fixed effects		✓	✓		✓	✓
Country fixed effects			✓			✓
Observations	3,272	3,272	3,272	3,272	3,272	3,272
R^2	0.0002	0.392	0.546	0.012	0.395	0.546
Adjusted R^2	−0.0001	0.386	0.540	0.011	0.388	0.540

Note: *p<0.1; **p<0.05; ***p<0.01

Table (8) Relation between Age and CT investment. EU KLEMS sector-level data (1995-2015) for 10 Western European countries.

	Dependent variable:					
	CT					
	(1)	(2)	(3)	(4)	(5)	(6)
Age	−0.022***	−0.015***	−0.012**	−0.024**	−0.046***	−0.022*
	(0.003)	(0.004)	(0.005)	(0.010)	(0.011)	(0.012)
Age^2				0.002	0.028***	0.008
				(0.009)	(0.009)	(0.009)
Sector fixed effects		✓	✓		✓	✓
Time fixed effects		✓	✓		✓	✓
Country fixed effects			✓			✓
Observations	3,272	3,272	3,272	3,272	3,272	3,272
R^2	0.015	0.180	0.361	0.015	0.182	0.361
Adjusted R^2	0.015	0.171	0.352	0.015	0.173	0.352

Note: *p<0.1; **p<0.05; ***p<0.01

Table (9) Relation between Age and investment in software and database. EU KLEMS sector-level data (1995-2015) for 10 Western European countries.

	Dependent variable:					
	Software & DB					
	(1)	(2)	(3)	(4)	(5)	(6)
Age	−0.037*	0.148***	0.046	0.258***	0.454***	0.325***
	(0.020)	(0.024)	(0.033)	(0.066)	(0.062)	(0.079)
Age^2				−0.272***	−0.280***	−0.222***
				(0.058)	(0.053)	(0.057)
Sector fixed effects		✓	✓		✓	✓
Time fixed effects		✓	✓		✓	✓
Country fixed effects			✓			✓
Observations	3,272	3,272	3,272	3,272	3,272	3,272
R^2	0.001	0.299	0.321	0.008	0.305	0.324
Adjusted R^2	0.001	0.291	0.311	0.007	0.297	0.314

Note: *p<0.1; **p<0.05; ***p<0.01