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Workforce Aging and Potential Output Growth

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Abstract

In the literature on secular stagnation, demographic aging is widely blamed for lowering the IS curve of aggregate demand and therefore the natural interest rate. However, very little is said about the impact of workforce aging on long-term aggregate supply, or so-called potential GDP. To fill this gap, this study delves into the effects of workforce aging on two key components of the remarkably sluggish potential GDP growth of developed countries: hours worked and labour productivity. First, using a novel macro-accounting decomposition of EU-KLEMS data, we find that old-labour input has the highest contribution to growth, through both increased hours worked and shifts in labour composition in the EU, US and Japan. Second, we use panel stochastic frontier models highlighting that, however, old workers have an adverse effect on labour productivity growth frontier—though increasing technical efficiency, i.e., reducing the distance to this frontier.

Keywords: Demographic Aging; Potential Growth; Labour Input; Stochastic Frontier Analysis; Labour Productivity and EU-KLEMS.
JEL Classification: J11, J21, J24.

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1 Introduction

Recent years have witnessed discussions on the impact of rising old-age dependency ratios (OADR) on high-income countries' GDP growth. Indeed, a higher OADR is blamed for reducing hours per capita, inducing a bias towards the service sector, fueling the saving glut at the expense of productive investments, and precipitating the decline in short- and long-term interest rates, among others (Eggertsson et al., 2019; R. J. Gordon, 2015; Jones, 2022; Kopecky, 2022).

However, the impacts of declining fertility rates and increasing life expectancy are not confined to the general population. They reshape the demographic composition of the workforce. As illustrated in Figure A.1 in Appendix, there is a noticeable shift in the workforce towards a higher proportion of older workers. By 2019, over one-fifth of European workers fall into the 'older' category (aged 55 and above), marking almost a twofold increase since 2004. Additionally, Figure A.2 in Appendix demonstrates that workforce aging is pronounced in Eastern and Northern European countries, as well as in Germany, Italy, Portugal and Switzerland, for example.

Simultaneously, as depicted in Figure A.3 in Appendix, there has been a persistent stagnation (if not a decline) of potential growth in high-income countries since the 1980s. Sluggishness of potential growth, defined in our study as the rate of expansion an economy can sustain at full capacity and employment, is referred to as secular stagnation.

Though increasing OADR have been extensively identified as a factor fueling secular stagnation through demand effects, few studies have focused on the role of workforce aging in long-term GDP growth prospects. Yet, previous findings showed that workforce aging can exert a strong negative macroeconomic impact through factors such as labour productivity, the pace of innovations, automation adoption as well as human capital quantity and quality, given individual skills typically evolve over the life-cycle (Brunello and Wruuck, 2021; Earl et al., 2017).

In this paper, our objective is to assess how the workforce aging influences potential GDP growth rate. Our approach involves two main steps.

Firstly, we quantify the impact of the workforce aging on annual GDP growth rate using age-specific labour supply (L) in an accounting framework. To this end, we extend the existing EU-KLEMS accounting decomposition methodology by introducing age-related heterogeneity of labour supply. This allows us to isolate age-specific workforce contributions to GDP growth, termed as age-specific "labour services". Accordingly, we apply this methodology to reprocess EU-KLEMS data for the US, Japan and the EU. Contrasting the results from existing econometric analyses, our accounting decomposition reveals that older workers are those who contribute the most to potential GDP growth. Indeed, not only do their annual working hours increase more than other age groups, but these hours also become increasingly higher paid.

In a second step, we focus our attention to labour productivity growth ($\frac{Y}{L}$). Specifically, we evaluate the impact of the previously calculated old-labour services on the labour productivity growth frontier. To achieve this, we use stochastic frontier models on a panel comprising 25 high-income countries. We find that the impact of the older workforce growth on the potential growth of labour productivity is negative, mirroring the effects observed for other age groups. However, we observe that old workforce growth enhance technical efficiency, i.e., brings labour productivity closer to its maximum potential.

The remainder of the paper is structured as follows. Section 2 presents a literature review and highlights our contributions. Section 3 describes the methodology as well as the practical implementation of age-specific labour-services accounting. Section 4 presents panel stochastic frontier models for labour productivity growth. Section 5 concludes.

2 Literature Review

Aging and Secular Stagnation

Secular stagnation and demography often have been associated. The seminal work of Hansen (1939) already highlighted that the drastic decline in population growth was one of the factors behind the below full-employment steady state and US negative growth prospects since the first quarter of the 20^{th} century. Nowadays, the demographic slowdown is embodied in the aging process, referring to the increase in the weight of the elderly in the population. Its two drivers are the increase in life expectancy and the decrease in fertility rates, particularly when below the generation replacement level. By affecting the age structure of societies and sometimes leading to population shrinking, aging is largely blamed for being a headwind to growth prospects in high-income countries[1] (Mason et al., 2022).

Correspondingly, and following Summers (2014), the lion's share of existing research is centered around the viewpoint that demographic aging is a contributing factor to secular stagnation and the decline of output per capita through a structural weakness of aggregate *demand*. For example, aging is blamed for affecting the saver-dissaver composition and exacerbating the saving glut at the expenses of productive investment projects, sustaining a decline in short- and long-term real interest rates (Bielecki et al., 2018; Ferrero et al., 2017; Gagnon et al., 2021; Jones, 2022; Kopecky, 2022; Liu and McKibbin, 2022; Papetti, 2019). When this relationship is not found at first sight, it is recovered in the particular case of zero lower bounds on nominal interest rates (Carvalho et al., 2016; Eggertsson et al., 2019)[2]. In other words, aging would shift the IS curve of Figure 1 to the left, and therefore lower the natural interest rate i^*, the interest rate needed to achieve full employment.

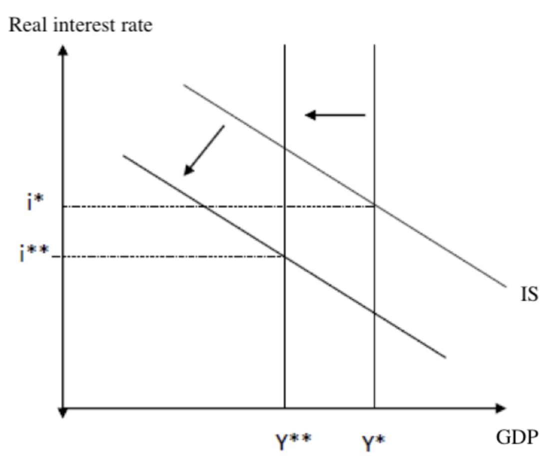


Figure 1: A graphical illustration of secular stagnation

[1]In the case of low-income countries, on the contrary, aging would favor economic growth by raising the probability to experience a positive first demographic dividend that would boost the rate of income growth per consumer.

[2]Aging can have a positive impact on output growth by generating capital deepening through lower interest rates. But this mechanism breaks down when interest rates are too low, leading to excess savings.

Aging and GDP Growth: supply-side perspectives

It may seem surprising that significantly less studies have shed light on the role of demographic aging in the stagnation of Y^*, i.e. the long-term aggregate *supply*, or so-called potential GDP, despite reflecting the productive potential of advanced economies and being also decisive for i^*. For Gordon (2015), aging would be a *headwind* to future potential growth by reducing hours per capita, and therefore constrain output per capita to grow slower than productivity. Accordingly, a small strand of the literature deals with quantifying the impacts of aging on growth in national income through supply aggregates.

Most of these findings focus on *actual* GDP growth and emphasize that an aging workforce is likely to result in a slowdown in labour productivity growth (Aiyar et al., 2016; Basso and Jimeno, 2021; Davis et al., 2020; Feyrer, 2002) or in the pace of innovations, as a higher proportion of retirees is often associated with a decreased likelihood of generating patents (Aksoy et al., 2019). Yet, it is worth noting that there is no consensus, since conversely, few studies suggest a positive effect of aging on output growth by encouraging companies to adopt automation technologies (Acemoglu and Restrepo, 2017; Jacobs and Heylen, 2021).

The existing literature on long-term GDP growth have rather focused on how aging does play on the availability of human capital. In the last stages of the demographic transition, higher growth rate in old-age dependency ratio is associated with a higher optimal level of education and technical change (Ziesemer and von Gässler, 2021); as well as a slowdown in growth rate of human capital quantity, though not necessarily in human capital quality (Cervellati et al., 2017), experience gains becoming non negligible as individuals age.

Propositions

Previous findings offer very few empirical evidence on the impact of aging on *potential* GDP growth. Studies explicitly focusing on this issue are very scarce (R. Gordon, 2013; Storm, 2019). Plus, the literature focuses on labour productivity growth without expanding over the labour input. However, the influence of aging on the quantity and quality of hours worked, i.e. on labour services, cannot be neglected. If we denote L as the number of hours worked, then we have $Y = \frac{Y}{L}L$. This implies that $g = g_{\frac{Y}{L}} + g_L$, where g represents the growth rates of the respective terms, and where subsequently, (potential) GDP growth rate depends on (potential) growth of hours worked and in (potential) labour productivity. A somewhat similar approach that interested readers can refer to is Maestas et al. (2023), who disentangle employment growth from labour productivity growth when assessing the effects of aging on actual GDP growth in the US.

Therefore, the added value of our approach is twofold: firstly, the relationship between workforce aging and labour services has, to the best of our knowledge, never been quantified in the literature; and secondly, neither age-specific labour services nor age-specific labour productivity have been (co)evaluated for their impact on potential GDP.

In what follows, we assess the impact of aging on labour input contributions to trend GDP growth; as well as on the frontiers of labour productivity growth in a panel of high-income countries.

3 Aging, labour services and growth

In this section, we propose a new accounting decomposition allowing to calculate the contribution of each age group to labour input growth, namely labour services. For this purpose, we adapt the existing methodology by introducing heterogeneity of labour type by age. This also enables to identify the contributions of each age group to the quantity and composition of hours worked, two channels of labour services. We then reprocess EU-KLEMS data to identify the role of old labour input on the trend[3] component of GDP growth rate for the US, Japan and the EU.

3.1 Methodology

Labour services aim to measure quantitative and qualitative changes in labour input over time. Their construction is generally based on the methodology of Gollop et al. (1980). For each labour type[4], it is assumed that the flow

[3]Trend output refers to medium-term average growth capacity of an economy, which stricto sensu differs from potential output. However, over the medium- and long-run, both measures converge. Thus, because we use long periods, we can use them both indifferently in the present study.

[4]Traditionally, in EU-KLEMS, labour types are cross-classified by educational attainment, gender and age. More details are given in the next subsection.

of labour services is proportional to hours worked, and that labour is paid at marginal productivity. The flow of labour services is calculated by aggregating the volume of hours worked by each labour type, the latter being weighted by labour-type period-average share of labour compensation:

$$\Delta \ln L_{jt} = \sum_{l} \bar{v}^{L}_{ljt} \Delta \ln H_{ljt} \tag{1}$$

where $\Delta \ln L_{jt}$ denotes the growth of labour services in industry j and period t, and $\Delta \ln H_{ljt}$ denotes the growth in hours worked by labour type in industry j, period t. Plus, $\bar{v}^{L}_{ljt} = \frac{(v^{L}_{ljt} - v^{L}_{ljt-1})}{2}$ denotes the Divisia index of nominal cost shares of labour type l. The nominal cost shares of labour type l in industry j are computed as follows:

$$v^{L}_{ljt} = \frac{p^{L}_{ljt} H_{ljt}}{\sum_{l} p^{L}_{ljt} H_{ljt}} \tag{2}$$

where p^{L}_{ljt} is the hourly wage of labour input l in industry j. Note that $\sum_{l} v^{L}_{ljt} = 1$.

In EU-KLEMS data, labour services are only available at aggregate level, i.e. without distinction according to demographic characteristics. Therefore, we propose a further decomposition of labour services flows allowing to differentiate them by age. Then, Equation 1 becomes:

$$\Delta \ln L_{jt} = \Delta \ln L_{Y,jt} + \Delta \ln L_{M,jt} + \Delta \ln L_{O,jt} \tag{3}$$

where $\Delta \ln L_{Y,jt}$, $\Delta \ln L_{M,jt}$ and $\Delta \ln L_{O,jt}$ respectively denote growth in labour services in industry j, period t, coming from young, middle-aged and older labour types. Young, middle-aged and older labour services are themselves obtained as follows:

$$\begin{aligned} \Delta \ln L_{Y,jt} &= \sum_{l \in Y} \bar{v}^{L}_{ljt} \Delta \ln H_{ljt}, \\ \Delta \ln L_{M,jt} &= \sum_{l \in M} \bar{v}^{L}_{ljt} \Delta \ln H_{ljt}, \\ \Delta \ln L_{O,jt} &= \sum_{l \in O} \bar{v}^{L}_{ljt} \Delta \ln H_{ljt} \end{aligned} \tag{4}$$

where $\bar{v}^L_{ljt}\Delta \ln H_{ljt}$ is being summed over each labour type l whose age respectively falls within the range that defines him as young (Y), middle-aged (M) and older (O), regardless of other socio-demographic characteristics.

In EU-KLEMS methodology, growth of labour services is usually split into two components: the growth in hours worked and the change in labour composition in terms of the specific characteristics of each labour type. Following O'Mahony et al. (2009), we can decompose labour services growth as follows:

$$\Delta \ln L_{jt} = \sum_l \bar{v}^L_{ljt}\Delta \ln \frac{H_{ljt}}{H_{jt}} + \Delta \ln H_{jt} = \Delta \ln LC_{jt} + \Delta \ln H_{jt} \tag{5}$$

where $\bar{v}^L_{ljt}$ still being the period-average labour compensation share in total labour costs and $\Delta \ln \frac{H_{ljt}}{H_{jt}}$ being growth in the share of hours worked by labour type l in total hours worked of industry j. $\Delta \ln H_{jt}$ accounts for changes in total hours worked while $\Delta \ln LC_{jt}$ accounts for changes in labour composition, e.g. changes in proportions of each labour type within the labour force and influencing the flow of labour services beyond the number of hours worked. Indeed, productivity differs between labour types, and solely accounting for hours worked does not encompass this heterogeneity. Typically, an increase in the share of old and experienced workers in labour force, with relatively high wages and marginal outputs, will yield an additional gain on labour services growth. This is why the change in labour composition rises with $\bar{v}^L_{ljt}$, which, under our assumptions, mirrors labour-type productivity.

Similarly to Equation 3, labour composition growth can be decomposed into contributions from young, middle-aged and older workers[5]:

$$\Delta \ln LC_{jt} = \Delta \ln LC_{Y,jt} + \Delta \ln LC_{M,jt} + \Delta \ln LC_{O,jt} \tag{6}$$

Then, it is possible to obtain the growth in hours worked by age group by rearranging equation 5:

[5]To obtain labour composition growth by age, we sum labour composition components over each labour type l belonging to a specific age group. More precisely, labour composition growth can be derived for young, middle-aged and older workers as follows: $\Delta \ln LC_{Y,jt} = \sum_{l\in Y} \bar{v}^L_{ljt}\Delta \ln \frac{H_{ljt}}{H_{jt}}$, $\Delta \ln LC_{M,jt} = \sum_{l\in M} \bar{v}^L_{ljt}\Delta \ln \frac{H_{ljt}}{H_{jt}}$ and $\Delta \ln LC_{O,jt} = \sum_{l\in O} \bar{v}^L_{ljt}\Delta \ln \frac{H_{ljt}}{H_{jt}}$.

$$\Delta \ln H_{lj} = \Delta \ln L_{lj} - \Delta \ln LC_{lj} \tag{7}$$

Labour services have a direct impact on the growth rate of gross output as a contributing factor, as shown in the following equation:

$$\Delta \ln Y_{jt} = \bar{w}^K_{jt} \Delta \ln K_{jt} + \bar{w}^L_{jt} \Delta \ln L_{jt} + \Delta \ln A_{jt} \tag{8}$$

where $\Delta \ln Y$ is gross output growth rate, $\Delta \ln K$ is capital accumulation, $\Delta \ln L$ is change in labour services and $\Delta \ln A$ is the change in total factor productivity (TFP). $\bar{w}^K_{jt}$ and $\bar{w}^L_{jt}$ are Divisia shares of capital and labour costs in gross output, satisfying by definition $\bar{w}^K_{jt} + \bar{w}^L_{jt} = 1$.
The contribution of labour input to gross output growth is then defined as follows:

$$GOConL_{ljt} = \bar{w}^L_{ljt} \Delta \ln L_{ljt} = \bar{w}^L_{ljt} \Delta \ln LC_{ljt} + \bar{w}^L_{ljt} \Delta \ln H_{ljt} \tag{9}$$

where the only change from Equation 8 consists in weighting all the terms by the Divisia share of labour costs in gross output, $\bar{w}^L_{ljt}$. Using the above steps then allows to obtain the age-specific contributions of labour composition growth, hours worked growth and labour services growth to gross output growth rate.

3.2 Data and Compilation

We use data from the EU-KLEMS, 2023 release (Bontadini et al., 2023). These data allow us to obtain age-specific values of labour services and their effects on growth for the US (1995-2019), European Union (2008-2019) and Japan (1995-2019). The EU-KLEMS, 2021 release (Stehrer and Sabouniha, 2023) is also used to obtain data for Japan prior to 2008. As the European Union is not included in the original database, we retrieve it by averaging all national values from countries belonging to the EU in 2020 (including the UK)[6]. Moreover, we restrict the analysis until 2019, leaving Covid period aside[7].

The EU-KLEMS data used for this analysis can be split into two parts. The first contains national account data. For each country and industry, it

[6] Due to missing values, the 2020 European Union is represented here by 24 countries instead of 28. The missing countries are Malta, the Czech Republic, Greece and Cyprus.

[7] Indeed, the effects of the pandemic are still very uncertain for what concerns future growth prospects, and its inclusion may bias the results.

provides yearly information on total hours worked (H_EMP), total labour compensation in volume (LAB) and gross output in volume (GO). The second cross-classifies, by year, country and industry, the shares of employment by labour type in total industry employment (H_shares) and the shares of labour compensation by labour type in total industry labour compensation (W_shares). In this section, we focus on the total economy, but this exercise can easily be replicated to provide an industry-by-industry analysis.

In the standard classification, described in Table 1, EU-KLEMS cross-classifies a total of 18 (2x3x3) labour types according to age, gender, and educational attainment. We aggregate these labour types by age, summing the outcomes from individuals with distinct gender and education as long as they belong to the same age group. For instance, our 15-29 category includes both men and women with low, medium, or high levels of education. Thus, we obtain three labour types: young (15-29), middle-aged (30-49), and older (50+) workers. It is worth noting that the cross-classification of labour type is different for the US, as shown in Table 2. Accordingly, we reduce the number of age groups, to obtain three: the 15-34, the 35-54 and the 55+, which we also refer to as young, middle-aged and older workers. Then, we repeat the same procedure as with standard classification.

Then, we follow Section 3.1 methodology. It allows to obtain, per country, the contribution of each age group to annual labour input growth (so-called labour services growth), as well as the contribution of each age group to labour composition growth and to hours worked growth. Finally, in order to capture the effect of age-group contributions on gross output growth rate, we multiply them by the Divisia share of labour costs in gross output ($\frac{LAB}{GO}$).

3.3 Results

Labour Input by Age

Henceforth, we can estimate the volume of labour services by age in total economy. Figure 2 highlights a steady increase in the proportion of hours worked by older workers in the US, Japan and the EU. In the US, old labour represented 10% of total hours worked in 1995. By 2019, it accounts for 20%. In the US, this increase was initially to the detriment of young hours worked and subsequently also of middle-aged hours worked. In Japan, young and middle-aged hours worked fell together until the early 2000s, but since then

Table 1: **EU-KLEMS standard labour-type classification**

Gender	Age	Education
Male	15-29	High Educated
Female	30-49	Medium Educated
	50+	Low Educated

Note: Following this order, each of these attributes is assigned an entire number ranging from 1 to 3 (from 1 to 2 for gender). For instance, men aged between 30 and 49 years old with a high level of education will correspond to labour type 1.2.1.

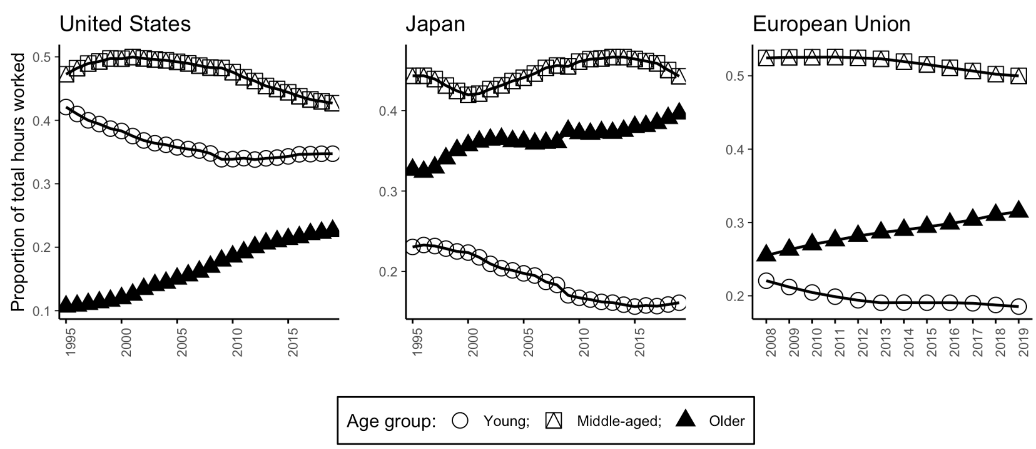
Table 2: **EU-KLEMS US labour-type classification**

Gender	Age	Education
Male	15-18	Less than a high school diploma education group
Female	19-24	A high school diploma (or GED) education group
	25-34	Some college education group
	35-44	A college degree education group
	45-54	More than a college degree education group
	55-64	
	65+	

young hours worked in particular have declined.

Figure 3 shows a similar pattern in terms of wage distribution. Indeed, the share of older workers' wages in total wages has also risen in these three regions over time. In the US and Japan, this share increased at the expense of middle-aged workers until the 2000s, and then mainly at the expense of young workers. There are two combined effects here: first, wages increase along the life cycle because of accumulated experience and second, old workers represent an increasing share of the labour force.

Figure 2: Total economy labour input (hours) into shares for young, middle-aged and older workers

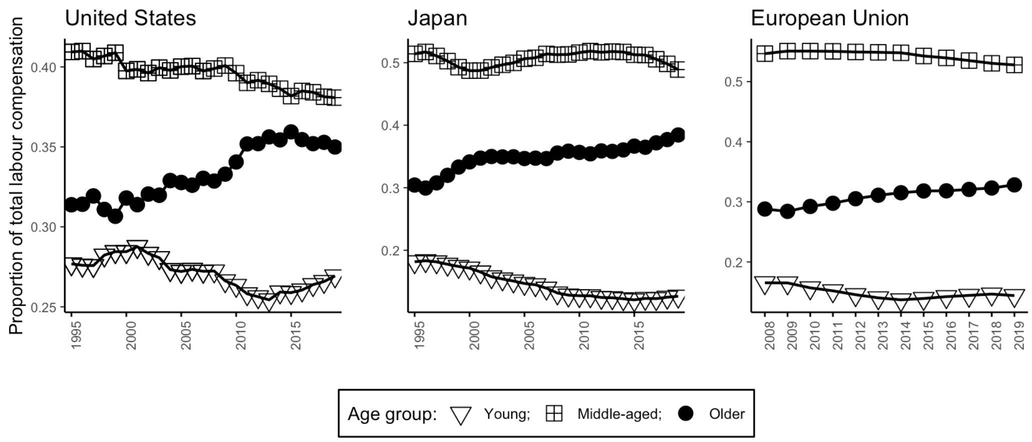


Source: EU-KLEMS and own calculations

Table 3 displays the period-average hours worked, labour composition and labour services growth by age group. When aggregating all age categories, we find that labour composition contribution to labour services is, in absolute terms, marginal when compared to hours worked contribution, yet consistently positive.
However, this does not hold when breaking labour composition growth into age groups. Indeed, labour composition is responsible for most of the variation of labour services when specifically considering older workers; accounting for 0.60 of the 0.67 EU labour input growth rate, and 1.03 of the 1.30 US labour input growth rate[8]. On average, hours worked by old workers also

[8] By the way, in absolute terms, the same holds for young labour type in all regions.

Figure 3: Total economy labour compensation into shares for young, middle-aged and older workers



Source: EU-KLEMS and own calculations

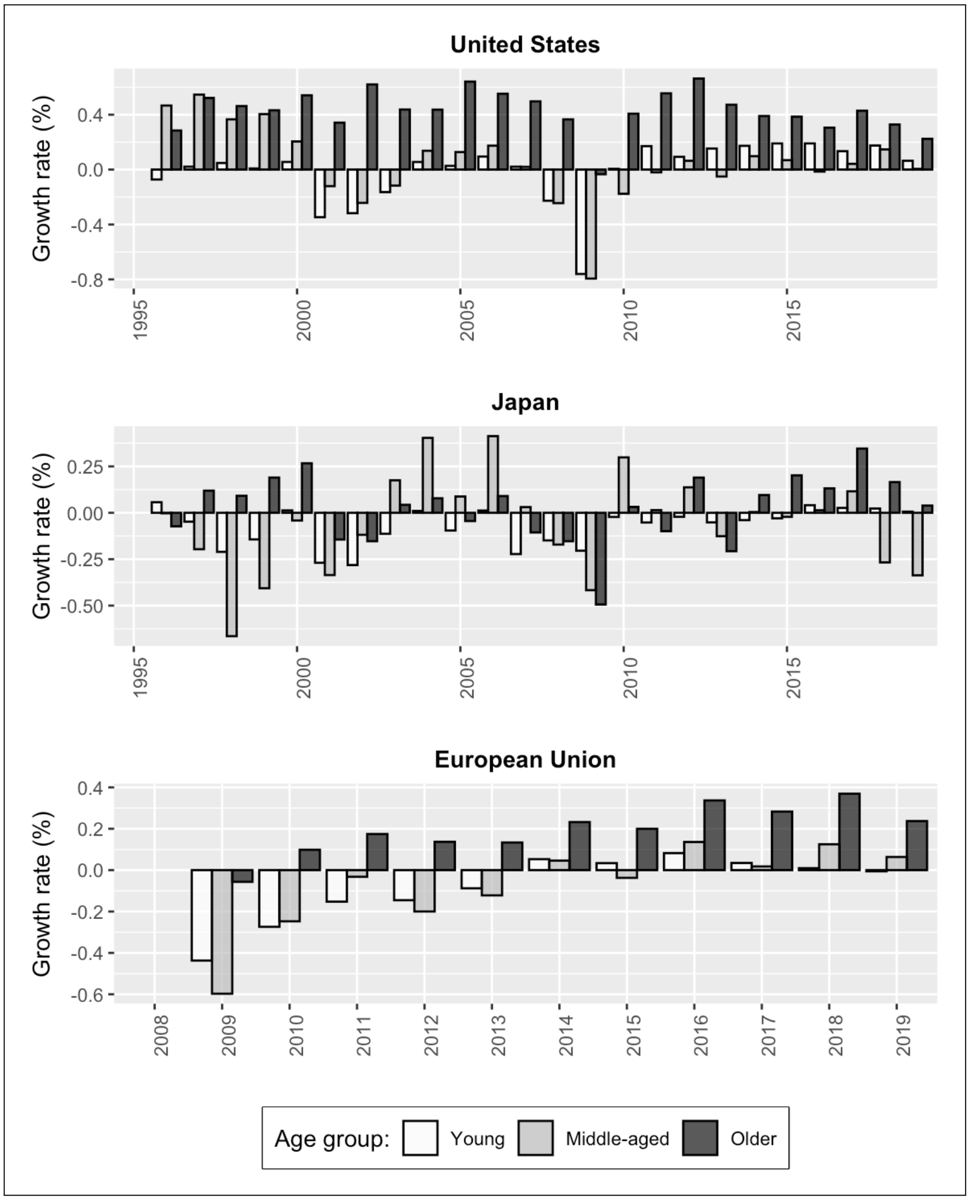
tend to positively contribute to labour services. This is not the case in Japan, where there has been a general decrease in the growth of hours worked, however the fall for old workers is smaller than that of middle age workers. All in all, we find that on average, older workers positively contribute to labour services growth in US, Japan and EU, which is not systematically true for the other age categories.

Old Labour Input and Growth

To see if the same conclusions hold for the impact of old-labour services on growth, we calculate, for each country, the contribution of each age group's labour service to the annual gross output growth rate. Results are displayed in Figure 4. A detailed accounting comprising the separated hours worked/labour composition contributions is available for the US, Japan and EU, respectively in Figure A.4, A.5 and A.6 in Appendix.

The contribution of old-labour services to growth was almost always positive over the period studied for the US and the EU. Years following the Great Financial Crisis were the exception with a contraction of old-labour services, but it is interesting to note that at this time the latter remained less deleterious to growth than that of the young and middle-aged. Old-labour

Figure 4: Labour services: Contribution of young, middle-aged and older workers to gross output growth



Source: EU-KLEMS and own calculations

Table 3: Labour input growth rates into age group contributions

		Country		
	Age	**US: 1996-2019**	**Japan: 1996-2019**	**EU: 2009-2019**
Hours worked (1)	Young	0.21	-0.07	0.03
	Middle-aged	0.31	-0.22	0.09
	Older	**0.26**	**-0.17**	**0.07**
	Total	0.78	-0.47	0.19
Labour composition (2)	Young	-0.22	-0.18	-0.27
	Middle-aged	-0.16	0.03	-0.23
	Older	**1.03**	**0.26**	**0.60**
	Total	0.65	0.10	0.10
Labour services (1+2)	Young	-0.02	-0.25	-0.25
	Middle-aged	0.15	-0.20	-0.14
	Older	**1.30**	**0.09**	**0.67**
	Total	1.42	-0.36	0.29

Note: Growth rates are period-average volume growth rates (in %). Figures might not add due to the rounding. Own calculations based on EU-KLEMS database.

services account for an average of 0.4 points of output growth per year in the US, and 0.2 points (although rising steadily) in the EU. The situation in Japan is more mixed. Prior to the 2000s, old-labour were the only labour type to contribute positively to output growth. Thereafter, its contribution to output growth fluctuated around 0; then, like the one of other age groups, fell sharply and became a headwind to gross output growth in the wake of the Great Financial Crisis. Since 2014, old-labour again make a positive contribution to output growth, accounting for around 0.2 growth points. In all three areas, it is mainly the contribution of hours worked that fluctuates, while growth in labour composition have much less variance, as shown in Figures A.4, A.5 and A.6 in Appendix.

Overall, the persistence of the contribution of old-labour services to growth in the US and the EU along the period suggests that old labour input have a positive contribution to trend GDP growth. This contribution fluctuates more in the case of Japan, revealing that old labour input (and particularly hours worked) is more sensitive to the business cycle in this country. For this reason, it is difficult to draw conclusions about the role of the elderly workforce in Japan's trend growth. Nevertheless, from Figure A.5 in Appendix, we can consider that the old-age labour composition contribution has affected the economy's trend growth, with a contribution that was first positive, then negative, and finally positive.

4 Aging and labour productivity frontiers

In this section, we focus on the growth of labour productivity potential, $g^*_{\frac{Y}{L}}$, which, after labour input growth g^*_L, is the second determinant of long-term output growth. Consequently, we use an econometric method based on frontier analysis. Specifically, we use stochastic frontier analysis to capture the effect of previously computed age-specific labour services on potential labour productivity and inefficiencies. Using panel data, we estimate country-specific labour productivity frontiers in order to assess how it is affected by age-specific labour services.

4.1 A Panel Stochastic Frontier Model

Within the literature on secular stagnation, studies attempting to link aggregate productivity to demographic aging predominantly use the OLS estimator (Acemoglu and Restrepo, 2017; Aiyar et al., 2016; Feyrer, 2002) in a framework that assumes that the production function is of the Cobb-Douglas type. However, in the context of our study, the OLS estimator is not the most appropriate choice. This is because the OLS estimator relies on actual productivity and does not enable to compute the productivity potential. Instead, we use stochastic frontier (SF) analysis. Stochastic frontier models aim to determine the frontier of the dependent variable, i.e. the level of output if all inputs were utilized efficiently; and to compute inefficiencies as the gap between actual output and the frontier. Its main difference with the OLS estimator is that it assumes stochastic variability of the inefficiency term, included in the error term.

The related literature has shown that estimating stochastic frontier models using panel data avoids strong distributional assumptions and improves stochastic frontier modelling (Battese and Coelli, 1992; Kumbhakar, 1990; Schmidt and Sickles, 1984). The data we use in this application is therefore a panel, observed for N = 25 countries of the EU-KLEMS project (for the list of countries, see Table A.1 in Appendix), for the period 2009-2019 (T = 11), representing 268 observations in total.

Preliminary tests

We first determine if using a SF model is econometrically relevant, i.e. if a frontier does exist. Following Schmidt et al. (1984) and Holý et al. (2022), we build a standard linear regression model, estimate it by the OLS and test normality (and in particular the sample skewness) of the residuals using the test of D'Agostino et al. (1990). According to the results, displayed in Table A.2 in Appendix, we can reject the hypothesis that the residuals are normally distributed at the 1% level. Additionally, the p-value of 0.0106 indicates that we can accept the skewed alternative at the 5% significance level. In particular, the output variable exhibits a negative skewness (-0.38). Consequently, using a SF model is suitable with our data.

Secondly, as our explanatory variables are non-static, we consider the time-varying model to be adapted. And as our data set presumably contains great amount of latent time-invariant heterogeneity, we opt for the time-varying model with country-specific intercepts of Greene (2005a), namely the "true" fixed effects (TFE) model[9]. For a survey of all the SF estimators and their practical implementation in Stata, the interested reader can refer to Belotti's work (Belotti and Ilardi, 2012; Belotti et al., 2012).

Thirdly, we determine the distribution of the inefficiency variable. As suggested by Stevenson (1980), we start with the normal truncated-normal distribution and test for the adequacy of this specification by computing the t-statistic for μ. The mode μ being not significantly different from zero (the associated p-value is 0.550), we assume in what follows that the errors are half-normally distributed, with zero mode.

Model specification

Finally, we have the following stochastic frontier model, where all variables are expressed in annual growth rates, for country i, year t:

[9] In particular, this model allows to reduce the bias by disentangling time-varying inefficiency from unobserved country-specific time invariant heterogeneity.

$$LP_{it} = \alpha_i + \alpha_1 TFP_{it} + \alpha_2 CAP_{it}^{ICT} + \alpha_3 CAP_{it}^{NICT} + \alpha_4 CAP_{it}^{INT} + \alpha_5 L_{it}^{Y} + \alpha_6 L_{it}^{M} + \alpha_7 L_{it}^{O} + \alpha_8 HC_{it} + \varepsilon_{it} \tag{10}$$

$$\varepsilon_{it} = v_{it} - u_{it} \tag{11}$$

$$u_{it} \sim N^{+}(0, \sigma_u^2) \qquad v_{it} \sim N(0, \sigma_v^2) \tag{12}$$

In Equation 10, the output variable is LP, hourly labour productivity. It depends on total factor productivity (TFP); ICT and non-ICT capital services (respectively CAP^{ICT} and CAP^{NICT}); CAP^{INT}, intangible capital services; young, middle-aged and old-labour services (respectively L^{Y}, L^{M} and L^{O}); and HC, the country's human capital, proxied by the proportion of highly educated labour. For more details, a description of the variables and sources used is available in Table A.4 in Appendix. Note that age-specific labour services have been calculated using previous' section methodology. In addition, we computed HC according to the methodology depicted in Appendix. The variable α_i is a unit-specific common intercept. The residual term includes a (non-negative) time-varying technical inefficiency variable: the distance to the frontier u_{it}, that is, failure to maximize the output with the given inputs. It follows a half-normal distribution with homoscedastic variance. Finally, v_{it} is the random error term representing the usual statistical noise.

4.2 Identification strategy and results

Column (1) in Table 4 shows estimates of Equation 10 by Maximum Likelihood Dummy Variable. However, before interpreting it, several identification issues must be resolved.

First, since the number of countries is relatively large compared to the length of our panel, incidental parameter problem is likely to be encountered, as reported by Greene (2005b) and Wang and Ho (2010). An associated consequence would be inconsistent estimates of the variance parameters and of postestimation inefficiencies. We therefore use the Marginal Maximum Likelihood Within estimator of Chen et al. (2014) providing consistent estimates of the frontier parameters and error variance, that are subsequently reported in column (2). The results are very similar to (1), which not completely surprising since T $\geq$ 10.

Second, it should be noted that estimations (1) and (2) might suffer from a potential endogeneity bias. Indeed, labour productivity frontier might affect the use of digital technology, since most productive firms are also more likely to adopt these technologies (Cette et al., 2022). We would therefore have to deal with a simultaneity problem concerning CAP^{ICT} and CAP^{INT}. Plus, there might exist an unobservable confounding factor linked to CAP^{ICT}, CAP^{INT}, and also influencing labour productivity frontier. In particular, demographic shifts towards aging can fuel the diffusion of technologies through rising old-age dependency rates (Jacobs and Heylen, 2021). In order to tackle this endogeneity issue, we use the instrumental variable approach. Specifically, we instrument CAP^{ICT} and CAP^{INT} by their respective lags. We include only one lag so there is no risk of over-fitting[10]. We also add $OADR_{it}$, the old-age dependency ratio, to capture the unobservable confounding factor. Then, we use the estimator of Karakaplan (2017) allowing to fit endogenous stochastic frontier models. Results are reported in column (3). Note that, according to the Karakaplan and Kutlu's endogeneity test (see Table A.3 in Appendix), a correction for endogeneity is not needed here. In what follows, we therefore refer to column (1) for our interpretations.

Results in Table 4 show that as expected, growth in TFP, intangible capital, NICT capital and in human capital have a positive impact on productivity growth boundaries. Note that this impact is nevertheless of greater magnitude for TFP, an increase of 1% in TFP growth leading to an increase of 0.97% on the frontier of labour productivity growth. Conversely, the impact of all labour input types on the frontier is negative, though being less negative as workers belong to older age groups. Indeed, an increase of 1% in old-age (resp. middle-aged and young-age) labour services growth would result to a decrease of 0.32% (resp. 0.44% and 0.57%) of the boundary. Figure 5 points out that this relationship remains true every year, with the global frontier without old-age labour being systematically higher than the global frontier with old-age labour. This suggests the existence of substitutability between investment in capital (ICT, NICT, intangible) and employment of the labour force. By contrast, the efficiency scores in Figure 6 reveal that on average, over the period, the inclusion of old-age labour reduces inefficiency with respect to potential productivity limits. This could be explained by the experience gains accumulated over the life cycle.

[10]Indeed, since we have T = 11, we would have 2*(11 - 1) = 20 instruments, and this number is strictly lower than N = 25 countries.

Table 4: True fixed effects SFA models for labour productivity

	(1) MLDV	(2) MMLV	(3) IV
TFP	0.967***	0.968***	0.971***
	(78.70)	(75.39)	(16.98)
ICT capital	-0.00243	-0.00239	-0.0685
	(-0.35)	(-0.33)	(-1.17)
NICT capital	0.455***	0.456***	0.820*
	(25.82)	(24.73)	(2.34)
Intangible capital	0.0307***	0.0304***	-0.119
	(4.67)	(4.40)	(-0.84)
Old labour	-0.319***	-0.317***	-0.0970
	(-8.85)	(-8.36)	(-0.48)
Middle-aged labour	-0.444***	-0.443***	-0.561***
	(-16.89)	(-16.08)	(-4.81)
Young labour	-0.568***	-0.569***	-0.708***
	(-12.64)	(-12.03)	(-6.15)
Human capital	0.0490***	0.0493***	0.0392*
	(7.93)	(7.53)	(2.55)
OADR			16.00
			(1.34)
σ_u	0.487***		
	(9.54)		
σ_v	0.265***		
	(9.81)		
λ	1.837***	1.759***	
	(25.74)	(5.06)	
N	268	268	243

Note: t statistics in parentheses * p<0.05, ** p<0.01, *** p<0.001. Columns (1), (2) and (3) are respectively estimated by Maximum Likelihood Dummy Variable, Marginal Maximum Likelihood Within estimator and Maximum Likelihood based methodology.

Figure 5: Global productivity growth frontier

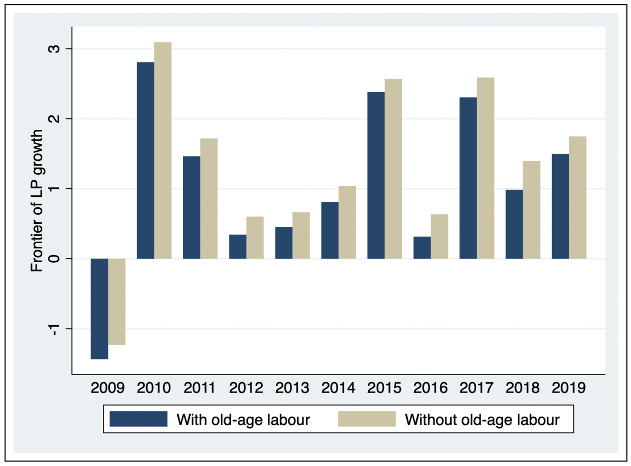


Figure 6: Distance to the frontier

To finish with, and in order to determine if there is any heterogeneity among the countries of our sample, we also provide a comparative analysis. Figure 7 reveals that that the distribution of labour productivity frontiers is symmetric across countries. In other words, the comparative performance of countries is such that no country or group of countries consistently out-performs or under-performs relative to the frontier. Additionally, Figure 8 plots estimates of the frontiers of labour productivity growth over time for France, Germany, Spain, UK and Italy. We observe that, beginning with significant heterogeneity following the Great Financial Crisis, the borders of these countries converged to a small range (between 0% and 1%) by 2019. Some countries, such as France and Italy, have consistently maintained positive frontier values since 2009, whereas Germany, and later the UK and Spain, have occasionally experienced labour productivity drops establishing frontiers below zero.

Figure 7: Distribution of frontiers across countries

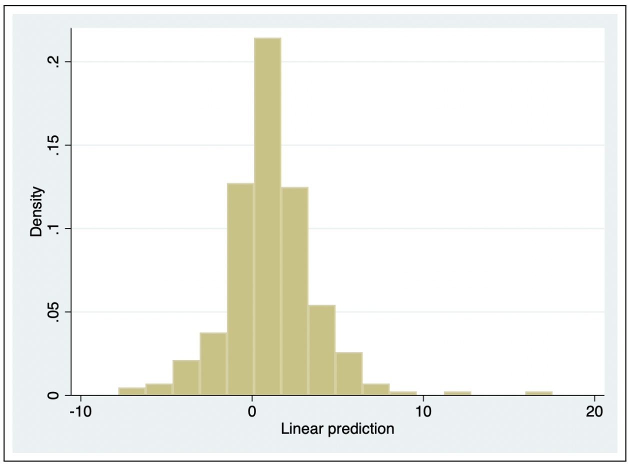


Figure 8: Frontiers of labour productivity growth

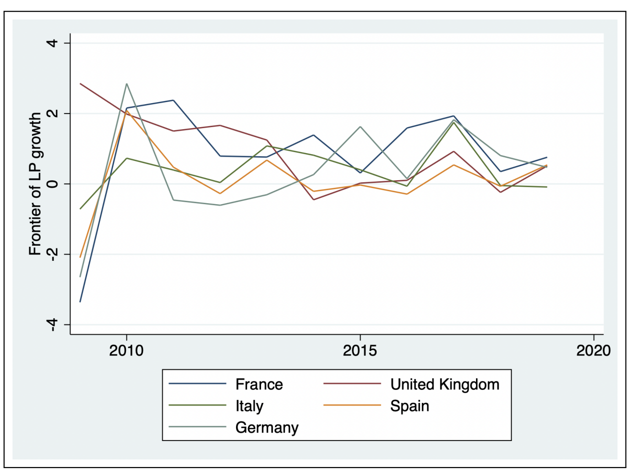


Figure 9 plots the distribution of efficiency scores across countries. The distribution of technical efficiency is right-skewed, indicating that a larger number of countries exhibit high efficiency levels (above 0.7) while fewer countries' labour productivity growth is well below the frontier level. This highlights that while many nations of our sample perform well, there are still disparities. In this respect, Figure 10 compares technical inefficiency in the presence and absence of old labour input for each country in the sample. For most of the countries, the inclusion of older workers increases the closeness of the economy to its potential. However, this is not true for a small group of countries, composed of Luxembourg, Netherlands, Lithuania, Ireland, Croatia and Greece. In Luxembourg in particular, inefficiencies are almost doubled in the presence of workers aged 50 and over.

Figure 9: Distribution of efficiency across countries

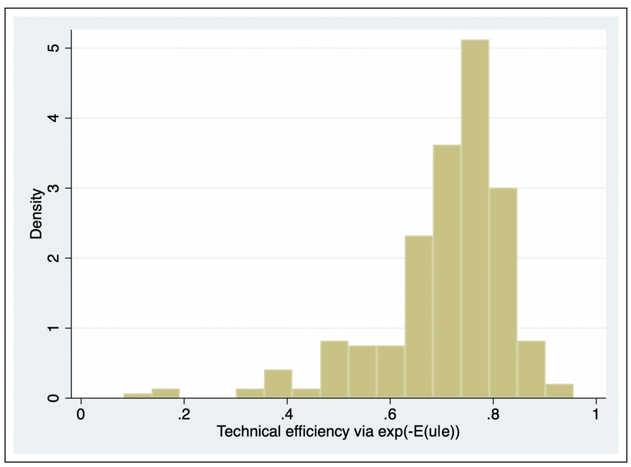


Figure 10: Average technical inefficiency by country

5 Conclusion

In this paper, we empirically assessed the influence of workforce aging on the labour input and the labour productivity components of potential output growth.

The first results, coming from a novel decomposition of KLEMS databases, contradict the usual intuitions according to which aging of the workforce represents a a headwind to growth. In the US, European countries, and to a lesser extent in Japan, older workers lastingly have higher labour input growth, and higher contribution to trend GDP growth through labour than their younger counterparts. Not only are their working hours increasing more than the other age groups (hours worked effect), but these worked hours are increasingly more highly payed and therefore supposed more productive (labour composition effect). Policy implications from this accounting exercise should however be drawn with caution, as these results are based on the strong assumption that labour is compensated according to its marginal productivity.

The second set of results stems from examining the impact of workforce aging on labour productivity potential. By applying stochastic frontier models to a panel of 25 high-income countries, we demonstrated that, similar to other age groups, older labour input negatively affected the boundaries of labour productivity growth during the 2009-2019 period. These findings align with previous research relying on OLS approach, but also suggest that an aging workforce may contribute to reduce inefficiencies in the production process, with heterogeneous effects across countries.

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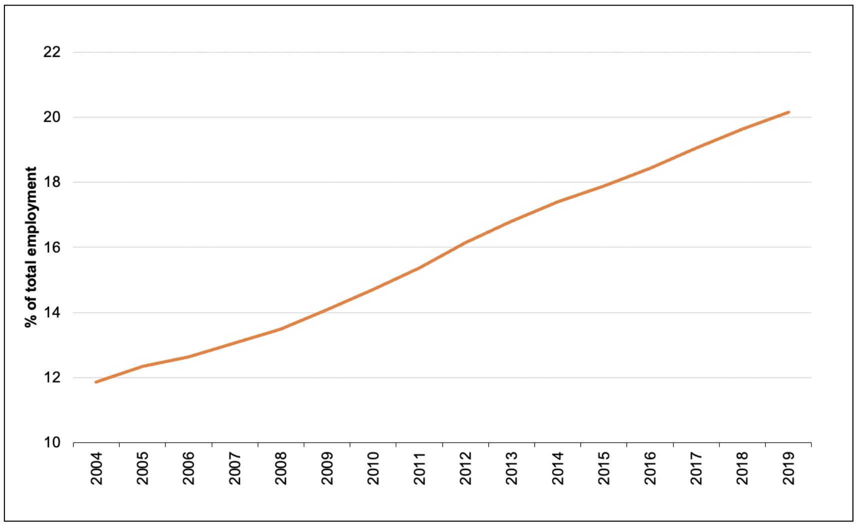
Appendix

Figure A.1: Share of old (55+) workforce in total employment in EU-27



Source: Eurostat

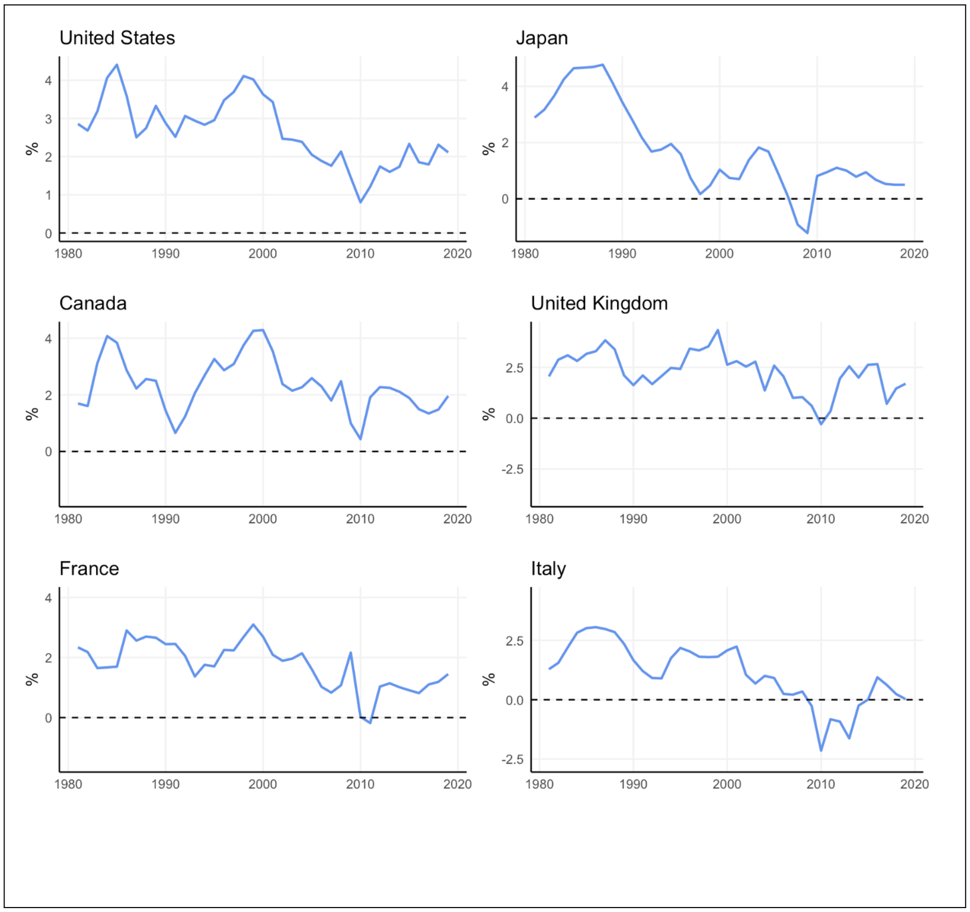
Figure A.2: Share (%) of 55-74 y.o. workers in total employment, in 2019

EU-27	**19,90**
Belgium	17,22
Bulgaria	21,84
Czechia	19,01
Denmark	21,44
Germany	23,74
Estonia	24,22
Ireland	17,51
Greece	17,39
Spain	17,75
France	17,75
Croatia	17,18
Italy	21,72
Cyprus	17,84
Latvia	24,21
Lithuania	23,90
Luxembourg	11,48
Hungary	17,19
Malta	14,62
Netherlands	20,96
Austria	16,56
Poland	16,96
Portugal	21,33
Romania	16,55
Slovenia	15,64
Slovakia	17,38
Finland	22,05
Sweden	21,57
Iceland	21,94
Norway	20,66
Switzerland	20,55
United Kingdom	19,95

Legend: < 15 | 15-20 | > 20

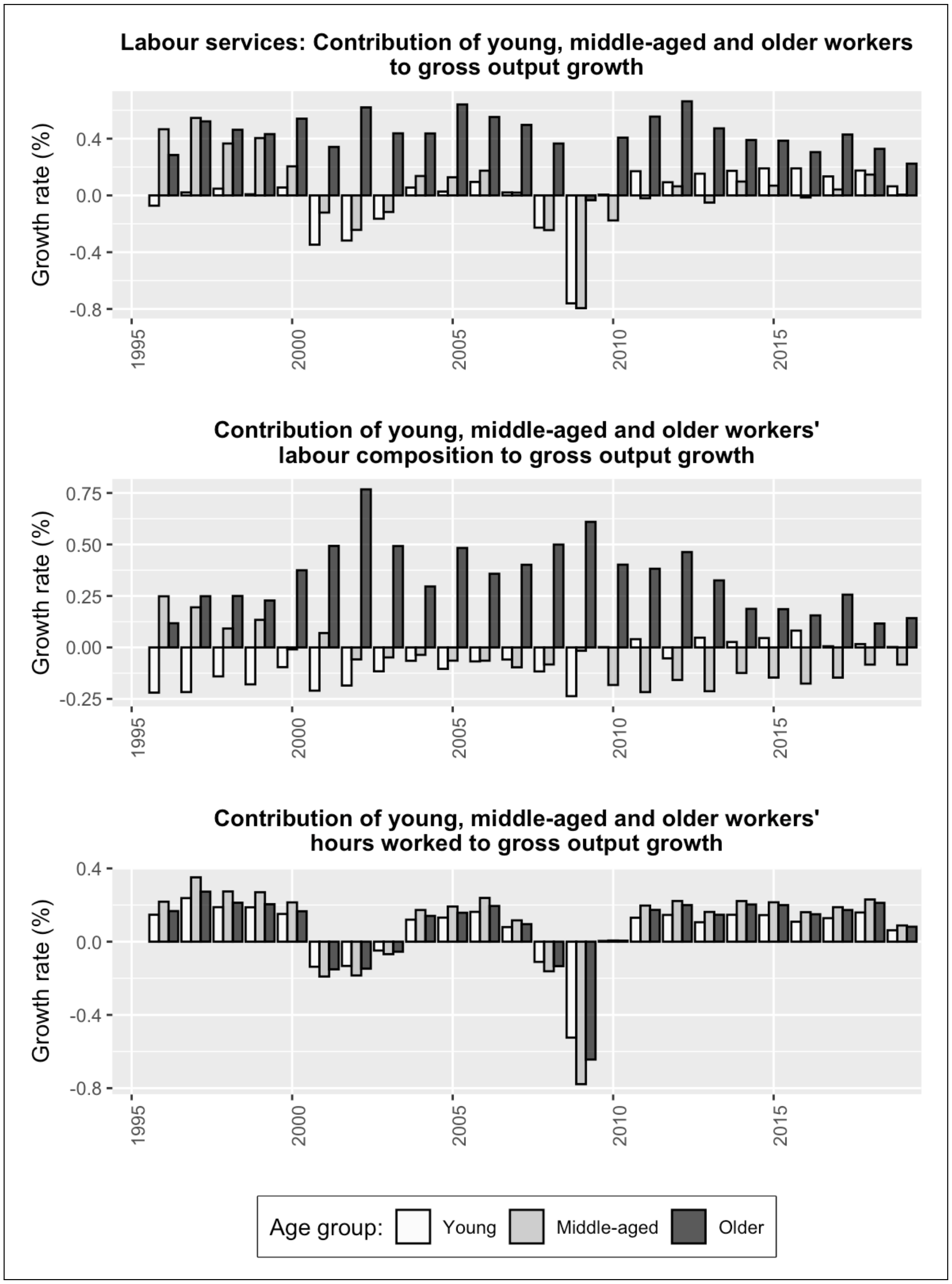
Source: Eurostat

Figure A.3: Potential growth projections



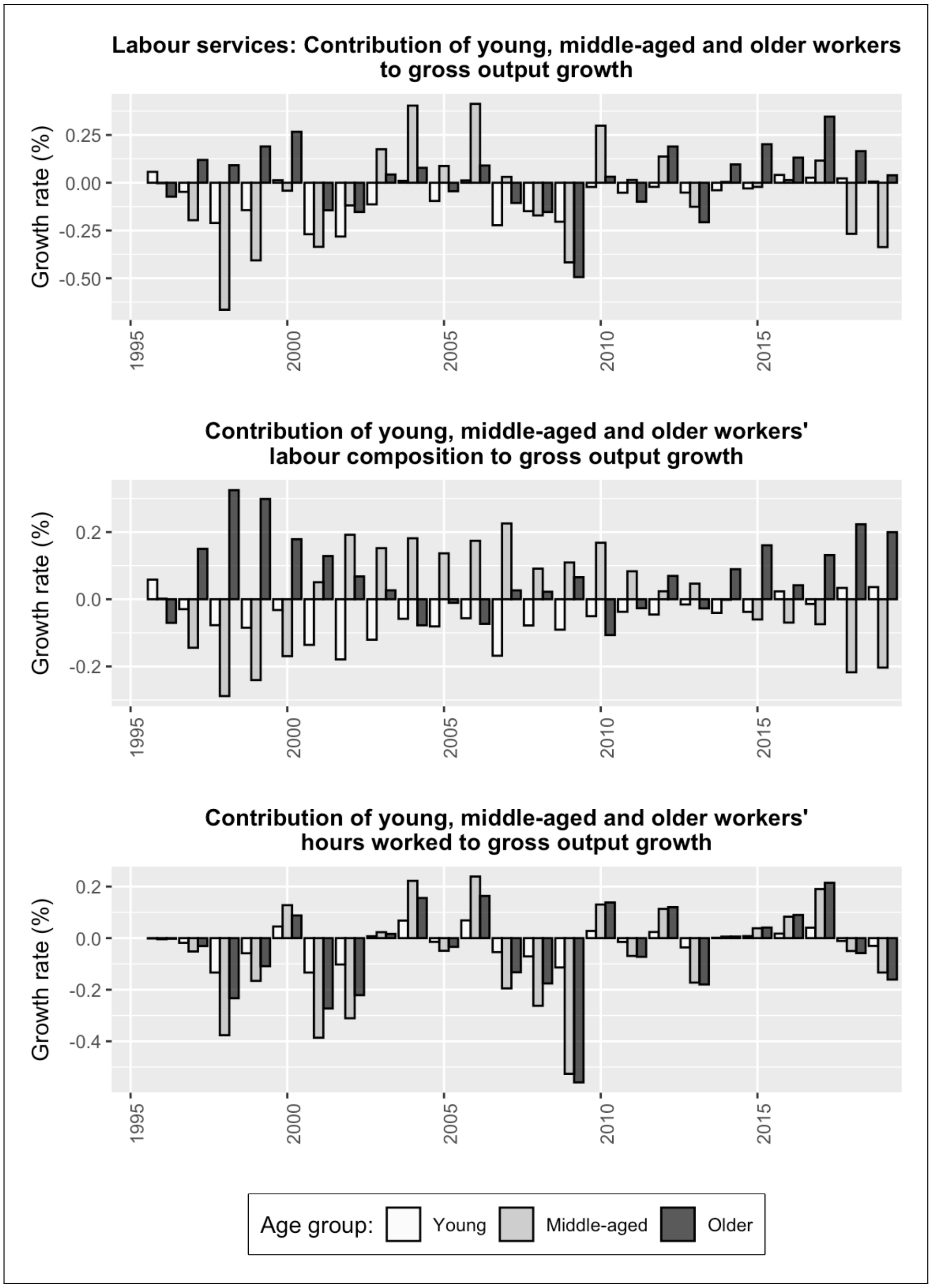
Source: Kilic Celik, S., M. A. Kose, F. Ohnsorge, and F. U. Ruch. 2023. "Potential Growth: A Global Database." (Multivariate Filter)

Figure A.4: US labour services decomposition



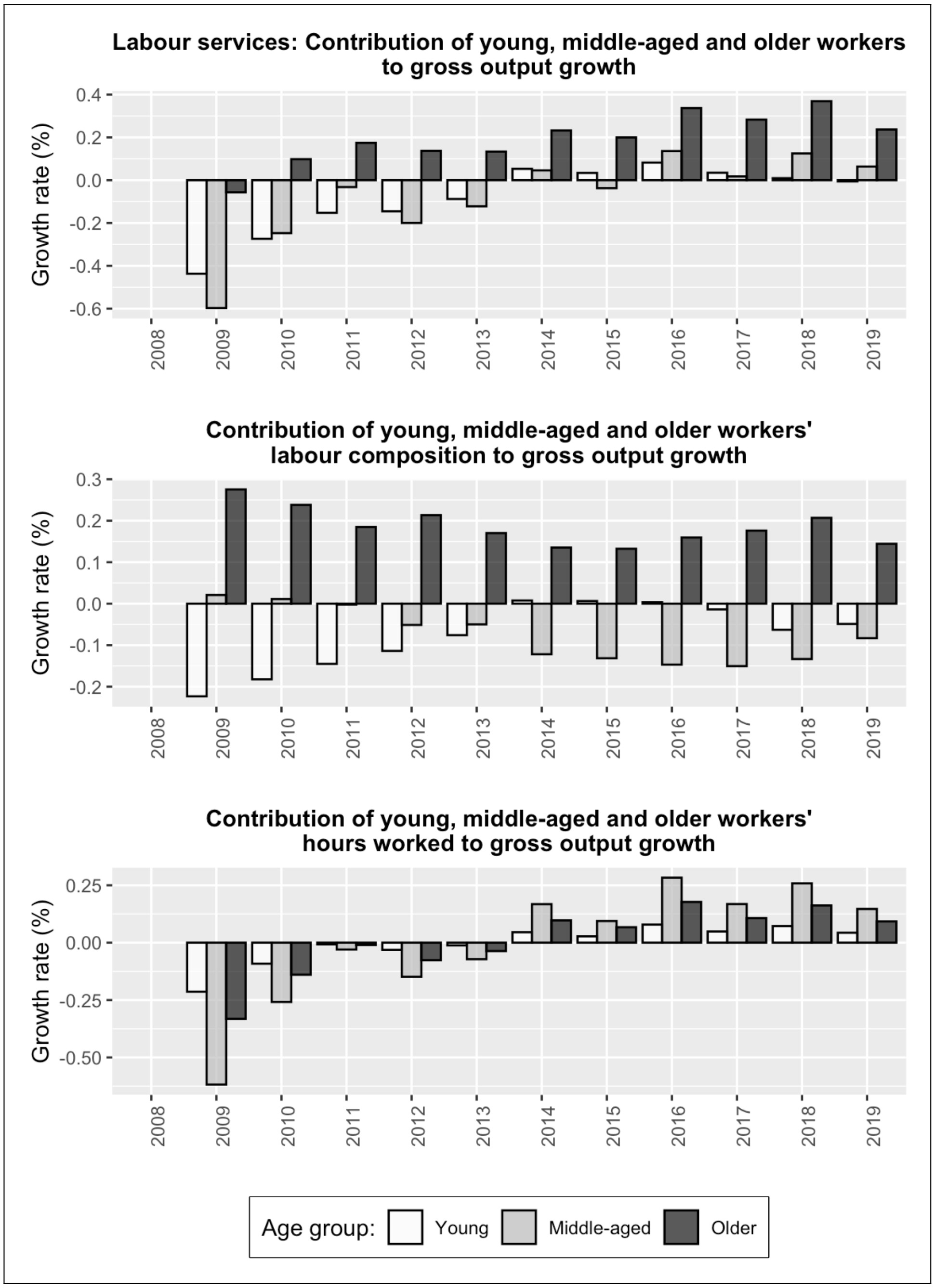
Source: EU-KLEMS and own calculations

Figure A.5: Japan labour services decomposition



Source: EU-KLEMS and own calculations

Figure A.6: EU labour services decomposition



Source: EU-KLEMS and own calculations

Table A.1: List of the countries

Countries of the sample	Austria; Belgium; Bulgaria; Cyprus; Czechia; Germany; Denmark; Estonia; Greece; Spain; Netherlands; Romania; Slovenia; Finland; France; Croatia; Hungary; Ireland; Italy; Lithuania; Luxembourg; Latvia; Portugal; Sweden; United Kingdom

Table A.2: Skewness and kurtosis tests for normality

				Joint test	
Variable	Obs	Pr(skewness)	Pr(kurtosis)	Adj chi2(2)	Prob > chi2
resid	268	0.0106	0.0000	41.20	0.0000

Table A.3: Endogeneity test

Hypotheses:	
H_0: Correction for endogeneity is not necessary	H_a: Endogeneity correction needed
(1) $\eta 1\_CAPICT = 0$	(2) $\eta 2\_CAPIntang = 0$
$\chi^2(2) = 1.51$, Prob $> \chi^2 = 0.4700$	
Result: Cannot reject H_0 at 10% level.	

Table A.4: Definition of variables and sources

Variable	*Definition*	*Source*	*Transformation*
$LP_{i,}$	Labour productivity growth rate (hours worked)	EUKLEMS	None
TFP_{it}	TFP (value added based), volume indices, 2015=100	EUKLEMS	$\Delta \ln$
CAP_{it}^{ICT}	ICT capital services, volume indices, 2015=100	EUKLEMS	$\Delta \ln$
CAP_{it}^{NICT}	Non-ICT capital services, volume indices, 2015=100	EUKLEMS	$\Delta \ln$
CAP_{it}^{INT}	Intangible capital services, volume indices, 2015=100	EUKLEMS	$\Delta \ln$
L_{it}^{Y}	Growth rate of labour services of the 15-29 age group	Own calculations based on EUKLEMS	None
L_{it}^{M}	Growth rate of labour services of the 30-49 age group	Own calculations based on EUKLEMS	None
L_{it}^{O}	Growth rate of labour services of the 50+ age group	Own calculations based on EUKLEMS	None
HC_{it}	Growth rate of the share of high-educated hours worked in total hours worked	Own calculations based on EUKLEMS	None
$OADR_{it}$	Old-age dependency ratio ($\frac{65+}{15-64}$ years old)	UN World Population Prospects	$\Delta \ln$

Computation of the Human Capital variable:

Again, we use the data from the labour accounts of EU-KLEMS. First, we sum the shares of hours worked in total hours worked by each of the 18 labour types (H_shares) over gender and age. Thus, we obtain H_shares for only three labour types: high educated, medium educated, and low educated. Then, we only keep hours worked by high educated labour type ($edu = 3$), and calculate their annual growth rate for every country of the sample. This gives us HC_{it}.