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Abstract

Low fertility rates, mortality outstripping the birth rate and population contraction characterize a new demographic transition (the so-called "fifth stage"). This paper seeks to evaluate how this phenomenon has impacted the Japanese economic structure and overall productivity. We test two key mechanisms that have been at play since the mid-2000s: i) a growing complementarity between goods and services consumption, and ii) the substitution of older workers engaged in routine tasks with technological capital. According to Autor and Dorn's (2013) model, this should promote the concentration of low-skilled workers in the service sector, and aggravate productivity gaps between industry and services. Using stochastic frontier models and EU-KLEMS data, we compute industry-by-industry TFP growth frontiers in order to check if theoretical predictions match with Japanese reality.

Keywords: Demographic transition, productivity, technological change, economic structure, Japan.

JEL Classification: J11, J14, O47, O53.

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1 Introduction

"The World Countries are increasingly judged not just by economic output but by the rate they are going grey", once subtitled the Global Aging Institute (Jackson [2013]). Today, this rate is accelerating sharply, and a substantial number of advanced economies are now facing a "*demographic winter*": significant aging, ground-zero fertility, mortality outstripping births, and finally population contraction. This is the so called *fifth stage* of the demographic transition, that post-transition countries seem to be inevitably rushing towards. Japan, with its late but accelerated demographic transition, leads the way in demographic winter. Its aversion to immigration, exceptional life expectancy and structurally low fertility rates have pushed its population into decline since 2008.

This demographic transition has important consequences on the economic structure of Japan. Population aging affects both demand and supply sides. From the demand side we can expect that good and service consumption from elders differs from that of youth, implying that the supply will need to respond to these demand composition changes. From the supply side, we can reasonably guess that elders and youth differ in their skills, implying that firms should adapt their workplace organization to the skill composition of the aging labor force. All in all, we should expect a change in the economic structure of Japan which should also impact productivity. The objective of this paper is precisely to analyze how the the Japanese economic structure has changed along the fifth stage of the demographic transition and how these changes have modified productivity.

Our stylized facts show that from the mid-2000s the birth rate in Japan fell below the mortality rate and never recovered. As a result, the number of hours of work has fallen (in both the industrial and the service sectors) and productivity gains have not managed to compensate this decrease. Older workers, which are less educated than the new generation of workers, seem also to have shifted towards the non-manufacturing sector. This shift is driven by the progressive replacement of unskilled old workers in the industry by computers and robots. These workers have to find a new job in the non-manufacturing sector. Furthermore, as shown in the paper, goods and services are more complementary (or less substitutes) for old people than for young people, therefore population aging should foster a relative increase in the demand of services, which would justify the increase in employment in the service sector.

We incorporate these two last results (i.e. (*i*) the share of old unskilled workers is predictive of ICT (Information and Communication Technologies) adoption in the industry sector; and (*ii*) goods and services are more complementary for old people) into a theoretical setup inspired from Autor and Dorn [2013]'s model but which considers heterogeneous workers not only by skill but also by age. The theoretical setup predicts that population aging has driven a structural change by promoting the concentration of employment in the service sector and a progressive replacement of labor by computer capital in the good sector. We show that, in Japan, this structural change strongly contributes to the decrease in TFP growth during the period 1997-2015, which corresponds to the fifth stage of the technological transition. Moreover, old labor significantly contributes to shift left the frontier of TFP growth in the industry and service sector, while young labor, computer capital and human capital significantly contribute to shift right the frontier in the industry sector (no significant effect arises in the service sector).

Our paper contributes to two streams of literature. Firstly, it contributes to the literature seeking to gain insights on the causes behind secular stagnation in Japan linked to demographic factors. Secondly, it contributes to the literature studying the progressive replacement of some workers by ICT.

The starting point of the first stream of literature is that demographic aging is a contributing factor to secular stagnation and the decline of output per capita through a structural weakness of the demand. In this sense, aging is held responsible for altering the balance between savers and dissavers, worsening the savings glut at the expense of productive investment projects, and contributing to the decline in both short- and long-term real interest rates (Bielecki et al. [2023]; Ferrero et al. [2019]; Gagnon et al. [2021]; Jones [2023]; Kopecky and Taylor [2022]; Liu and Mckibbin [2021]; Papetti [2021]). When this relationship is not immediately apparent, it is recovered in the specific case of zero lower bounds on nominal interest rates (Carvalho et al. [2016]; Eggertsson et al. [2019]). In contrast with the existing literature, our paper focuses on changes in consumption patterns driven by population aging that should have contributed the progressive shift towards the less productive service sector of the economy. This is consistent with the literature emphasizing that an aging workforce is likely to result in a slowdown in labor productivity growth (Basso and Jimeno [2021]; Davis et al. [2022]; Hernæs et al. [2023]; Kim and Song Lee [2023]; Maestas et al. [2023]).

The second stream of economic literature concerns the supply side impact of population aging. It is based on the task content of jobs and focuses on the effect of recent technological change on labor market structure. It suggests that the increase in computing power and the commensurate reduction in its price have promoted a progressive replacement of labor input employed in routine (programmable) tasks by computers and robots. Because these tasks are more prevalent in occupations that are located at the middle of the wage distribution, and since the productivity of educated professionals and managers located at the top of the wage distribution improves due to better ICT, the result is a process of job polarization (Autor et al. [2003], Autor et al. [2006]; Goos and Manning [2007]; Acemoglu and Autor [2011]). The literature on polarization is vast (Ottaviano et al. [2013]; Autor et al. [2014]; Moreno-Galbis and Sopraseuth [2014]; Reshef and Toubal [2024] ; Autor et al. [2008]; Ottaviano and Peri [2012]; Goos et al. [2014]). Our paper also fits in this stream of literature, since we show that the share of unskilled old workers is predictive of ICT adoption, suggesting that these unskilled old workers in the industrial sector were probably implementing routine (programmable) tasks. Up to now, the existing literature on job polarization has simply considered the skill level of medium-low skilled workers that have been replaced by computers and robots. Our paper goes a step further by showing that many of these workers are actually old. We consider both the age and the skill dimension.

Overall, unlike much of the existing literature, our paper addresses both the supply and demand shifts resulting from population aging. These shifts are driving a structural transformation in the economies of countries entering the fifth stage of the demographic transition. The key contribution of this work is the acceptance of the hypothesis that population aging impacts both the demand and supply sides of the economy. By internalizing this hypothesis, we offer predictions on how TFP growth and the composition of TFP in the industrial and service sectors will be affected.

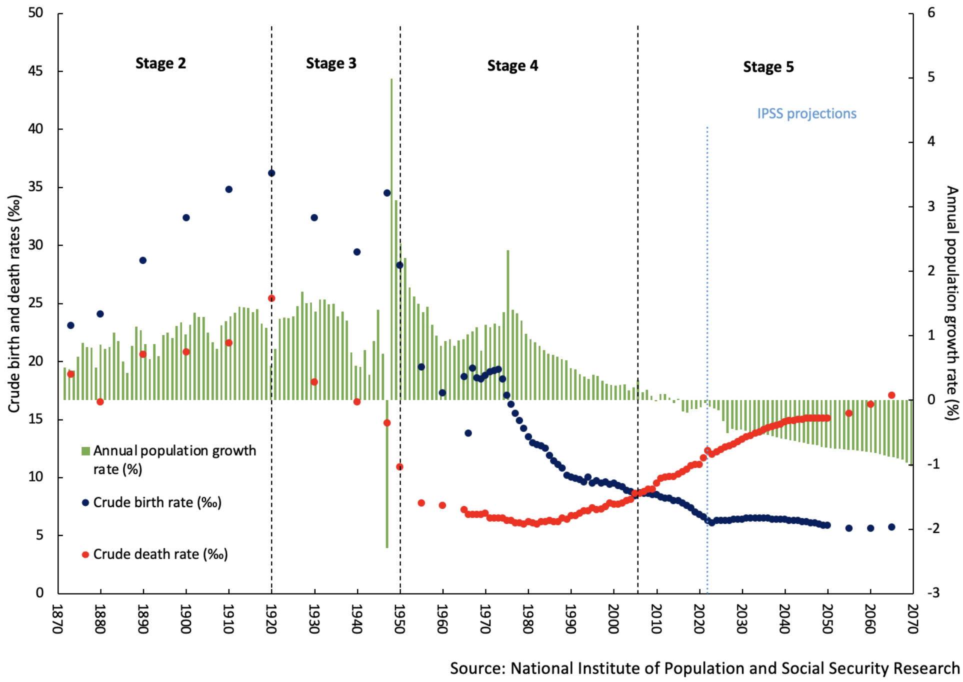
The paper is organized as follows. Section 2 presents stylized facts on demographic transition and its impact on GDP growth in Japan. Section 3 tests whether the share of unskilled old workers is predictive of ICT adoption and whether goods and services are more complementary for elders than youths. The theoretical setup is presented in Section 4, while Section 5 provides estimates the TFP growth frontier and the contribution of elderly population to this growth.

2 Stylized facts

The *demographic transition* emerged as the dominant paradigm in demography from the work of Notestein [1945], himself inspired by the researches of Thompson [1929]. In the last stage of this transition, birth and death rates converge and settle at a low level, leaving demographic growth sluggish. The assumption of smooth growth during this last stage seems though contradicted by the variations observed within countries that have completed their demographic transition. In many cases, fertility levels are insufficient to ensure the replacement of generations, to the point where the number of deaths, positively linked to population aging, sometimes exceeds the number of births. This phenomenon is described as a *demographic winter* (Chesnais [1995], Dumont [2008]), in reference to the negative temperatures in northern regions at this time of year. It is also referred to by other demographers (Kaa [2002], Lesthaeghe [2020]) under the slightly less pessimistic term of *second demographic transition*.

Japan is the country where the consequences of the second demographic transition are most manifest. Its net migration rate (the rate of population change attributable to migratory inflows or outflows) has the lowest sum of deviations from zero among countries in demographic winter since 1950, with a score of 45.9‰, as illustrated in Figure A.3 in Appendix A. Implying that the total population is heavily reliant on shifts in mortality and birth rates.

Figure 1: The Japanese Demographic Transition



In the 1980s, the effects of rapid aging became evident in Japan (see Figure 1), as mortality initiated an upward trend: Stage 5 was reached.[1] From the mid-2000s, the birth rate fell below the mortality rate and never recovered, signaling the establishment

[1]Figures A.1 and A.2 in Appendix A display the patterns of demographic winter for different countries.

of demographic winter. In 2008, Japan even started to experience a decline in its population. According to the National Institute of Population and Social Security Research (IPSS) projections, the gap between mortality and birth rates is expected to widen in the coming decades, exacerbating the decline of the Japanese population.

The economic consequences of demographic winter must be added to those of "standard" demographic aging. Indeed, "standard" demographic aging leads to *(i)* a drop in demand for "non-silver" goods and services; *(ii)* a drop in entrepreneurship and therefore innovation; *(iii)* an increasing burden associated with pensions and services for the elderly; and *(iv)* a drop in the labor force *relative* to the population. Demographic winter, through population decline, involves additional costs since it promotes *(v)* a shrinking of the domestic market; *(vi)* new challenges in service efficiency; *(vii)* a reduced tax base; and *(viii)* a shrinking workforce.

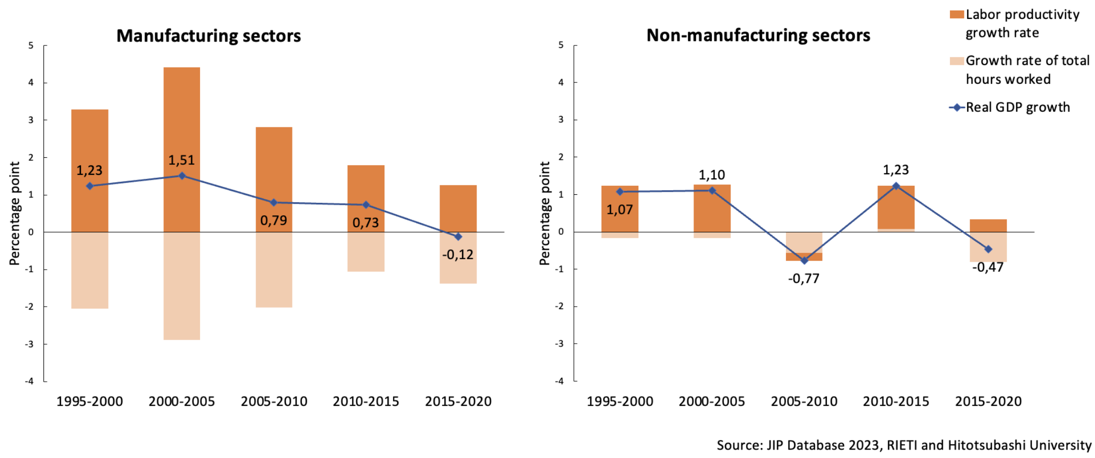
This last point is confirmed in the Japanese case by the decrease in labor supply, and more specifically, the number of hours worked since 1995, both in the manufacturing sector and in the non-manufacturing sector, which predominantly includes service sectors (Figure 2)[2]. This trend has not been reversed by the extension of the working life (one in four individuals beyond the age of 65 is employed in 2022).

The demographic decline of workers indicates that output per worker would need to increase to offset it, but this is increasingly not the case in the manufacturing sector, where real GDP growth has been declining since the 2000s and became negative in the period 2015-2020. This weak performance is paradoxical given Japan's significant investments in human capital, its highly skilled workforce, its research and development activities, as well as its technological leadership (Japan occupies a central position in the electronics and automotive global value chains). The main difference highlighted in Figure 2 between manufacturing and non-manufacturing sectors is that the labor pro-

[2] To see the list of variables as well as the sources used in this section, the interested reader can refer to Appendix B.

ductivity growth rate is significantly higher in the manufacturing sector; however, the decrease in hours worked is also more substantial in this sector.

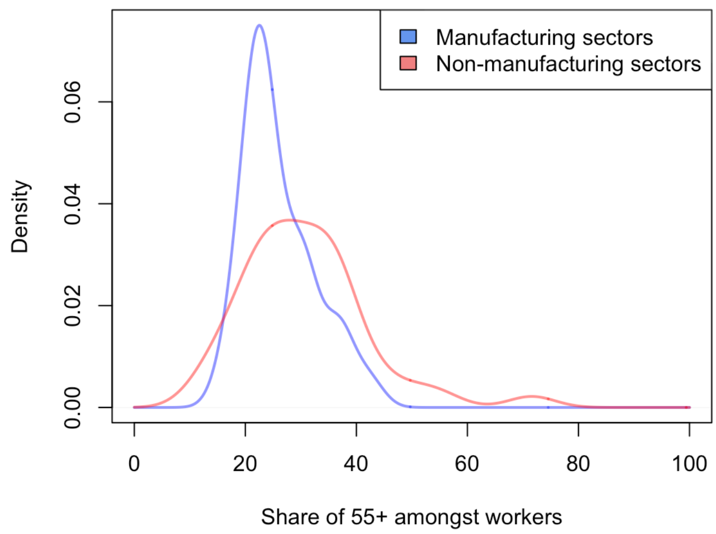
Figure 2: Contribution of hours worked and productivity to GDP growth



Age-composition also differs between the manufacturing and the non-manufacturing sectors. As observed in Figure 3, in non-manufacturing sectors, the peak of the distribution for the proportion of workers aged 55 and above is around 30%, while it is established at around 23% for manufacturing sectors. This suggests that, in non-manufacturing sectors, a higher proportion of workers falls within the 55 and above age group compared to manufacturing sectors. Actually, as revealed by Figure B.1 in Appendix B, the share of old workers in the non-manufacturing sector has continuously increased from 1995, where the share was equal to 20% to 31% by 2020. This is in contrast with the evolution in the manufacturing sector, where the share of workers above 55 years old evolved from 18% in the 90s, to 25% in 2005, to 23% in 2015 to 26% in 2020. Whereas the aging of the workforce has been continuous in the non-manufacturing sector, the progression is more irregular in the manufacturing sector.

This difference in the age composition of the workforce in both sectors is not free of consequences in terms of productivity. As shown in Figure 4, the level of education decreases significantly with age in Japan. Indeed, while 60% of individuals aged 34-

Figure 3: Distribution of older workers by aggregated sector in 2021



39 hold a tertiary degree, only 47% of those aged 55-59 and 38% of those aged 65-69 hold such a diploma. Age composition translates then into skill composition, where education is used as a proxy of skills. And differences in skill composition are likely to contribute to differences in productivity. As illustrated by Figure 5, whether we consider the manufacturing or the non-manufacturing sector, a larger share of old workers is associated with a lower productivity. Economic sectors having a larger share of workers above 55 years old are then likely to display lower productivity. As displayed by Figure B.2 in Appendix B, whereas productivity in the manufacturing sector has clearly followed an upward trend (in spite of the upward and downward spikes in the evolution), the productivity trend is rather decreasing, or at best stable, since the 2000s in the non-manufacturing sector.

All in all, the stylized facts presented in this section suggest that population aging in Japan has not only promoted a decrease in hours of work (that has not been compensated by the improvement in labor productivity) but also an asymmetric reallocation of old workers across sectors, with the non-manufacturing sector employing a larger share of older workers. Because young and old workers differ in their skills, this asymmetric

Figure 4: Educational attainment decreases with age

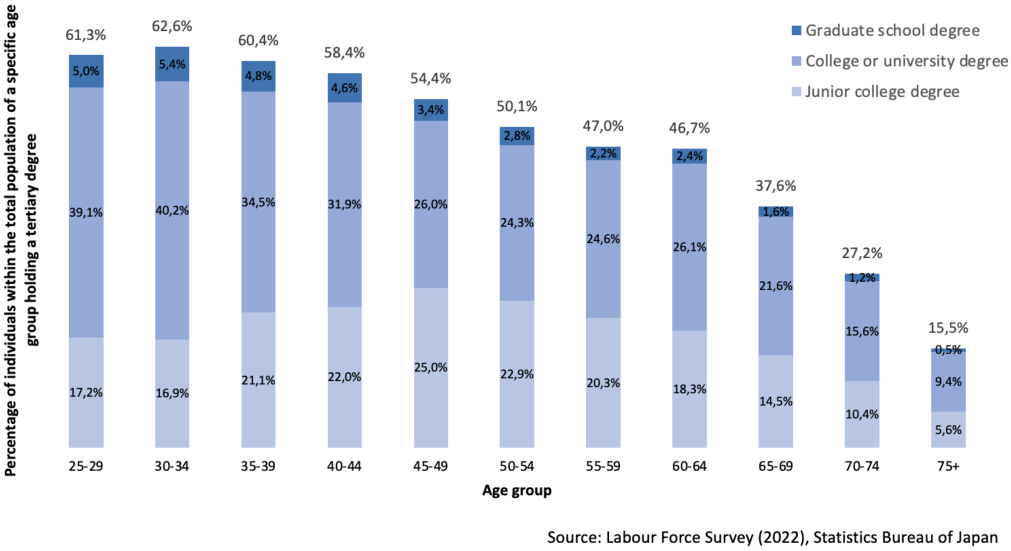
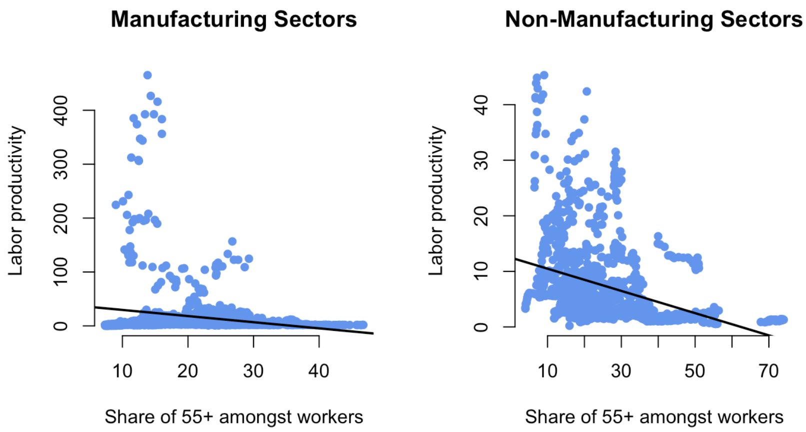


Figure 5: Relationship between labor productivity and the share of old workers in the manufacturing and non-manufacturing sectors.



Note: Each point represents an industry-year pair. The black line is a linear fit of the observations. Productivity is calculated as value added divided by total hours worked. Source: Japan Industrial Productivity Database 2021.

reallocation of old workers has also driven changes in relative productivity across sectors.

3 Some predictive tests

In this section we test the empirical relevance of the two major hypotheses used by the theoretical setup proposed in Section 4 in order to provide predictions on the asymptotic equilibrium. These hypotheses are: *(i)* unskilled older workers are predictive of technological capital adoption within Japanese industry sectors and *(ii)* goods and services are likely to be more complementary (or less substitutable) for the old than for the young in Japan.

The first hypothesis suggests that hours of work performed by unskilled older workers at the beginning of the period is a good predictor of the degree of technological gross fixed capital formation over the subsequent period. To implement this test, we use EU KLEMS data for Japan, 2019 release[3]. It gives us, over the 1995-2015 period, the yearly gross fixed capital formation in Communication Technology and in Information Technology for each sector of Japanese industry. We sum them to obtain ICT gross fixed capital formation. EU KLEMS also provides the cross-classified by labor type proportion of hours worked, by year and sector. Labor types are divided into three age categories (15-29, 30-49, 50 and over), three education categories (high, medium and low education) and by gender. We retain workers aged 50 and over with a low educational attainment, irrespective of their gender. We keep the results only for the initial period, 1995, and call this variable $H\_shares_{j,1995}$.

Following Autor et al. [2003], we fit the following equation:

$$\Delta \log ICT_{j,1995-2015} = \underset{(0.15)}{8.47^{***}} + \underset{(0.03)}{1.30^{***}} \times \underset{(n=441,\, R^2=0.98)}{H\_shares_{j,1995}} \;, \tag{1}$$

where j being the sector-specific subscript and year/sector fixed effects being controlled for. The point estimate of 1.30 (standard error 0.03) for the initial proportion of hours

[3]For more information on the database and the variables used, see Appendix D.

worked by old and low educated workers confirms that this initial proportion is strongly predictive of subsequent ICT adoption. This test therefore provides support for the first hypothesis of our theoretical model: technology adoption is greatest in sectors where old unskilled labor is relatively abundant.

To provide some intuition to the second hypothesis, we now show that in the fifth demographic transition, where the number of elderly people increases rapidly, goods and services are less substitutable in the households' consumption decisions. One reason is that older people consume more services and relatively fewer goods. We run two regressions in which consumption of non-durable goods and services (by the young and the old) is explained by the price of services relative to the price of non-durable goods and by some other explanatory variables capturing the factors influencing the intertemporal trade-off between consumption and savings as well as the specificities of the public pension system in Japan since the nineties. The consumption patterns of young and elderly people are correlated with the ways in which they build up their pensions when they are working. That of the elderly also depends on the amount of pension they receive. Pension income in Japan comes from several sources.

Firstly, we need to consider the level of GDP per-capita and an indicator of stock market performance as explanatory variables for household consumption expenditure. They capture income and financial wealth effects. When working, people build private savings. The individual amount of these savings depends on financial market performance and individual income, which can be proxied by per-capita GDP. For example, during the 1990s and 2000s, the Japanese economy plunged into a long economic depression, during which the economy was trapped in a regime of falling GDP per-capita. These so-called "lost decades" followed the bursting of a bubble in the early 1990s and a series of bankruptcies of financial institutions. For working people, during these years, per-capita income stagnated, and weak wage growth (exacerbated by underemployment and a deflationary loop) led to sluggish consumption. For retired people, consumption also fell during these decades, due to the rise in precautionary savings as life expectancy increased.

Secondly, we include the old-age dependency ratio. In addition to private pensions, households contribute to a pay-as-you-go public pension system (basic and supplementary pensions). In 1994, the public pension system was reformed, raising the retirement age from 60 to 65. As a result, companies are keeping older workers in the workforce. The aim of the reform was to maintain the balance of the pension system by influencing the activity rate of senior citizens. In 2004, the system underwent another reform, this time concerning indexation. The new system, known as macroeconomic indexation, links pension indexation to changes in public pension coverage, growth in life expectancy and comparative wage trends in relation to inflation. To take these factors into account, we consider the old-age dependency ratio as another explanatory variable.

Finally, to take account of the specific influence of population aging on consumption behaviour, we introduce a variable representing the market share of the elderly, defined as the percentage of consumption by the over-60s in the total household consumption market. This variable, which has been rising steadily since 1990, is correlated with the increase in life expectancy after age 60.

We consider quarterly data and estimate the following two equations using the generalized least squares method (Cochrane-Orcutt method):

$$\begin{aligned} C_t^s &= a_0 + a_1(L)P_t + a_2(L)GDP_t + a_3(L)share_t + a_4(L)dep_t + a_5(L)market_t + \epsilon_t^s, \\ C_t^g &= b_0 + b_1(L)P_t + b_2(L)GDP_t + b_3(L)share_t + b_4(L)dep_t + b_5(L)market_t + \epsilon_t^g, \end{aligned} \tag{2}$$

with the following definitions of the variables:

C_t^s, C_t^g: consumption of services and consumption of non-durable goods respectively,

P_t: ratio of the prices of services and the prices of goods,

GDP_t: GDP per-capita,

$share_t$: share price,

dep_t: old-age dependency ratio,

$market_t$: elderly market share,

$\epsilon_t^s, \epsilon_t^g$: error-terms,

$a_k(L)X_t = \sum_{j=0}^{p} a_{kj}X_{t-j}, k = 1, ..., 5;\ b_k(L)X_t = \sum_{j=0}^{q} b_{kj}X_{t-j}, k = 1, ..., 5.$

Let us define $A_k = \sum_{j=0}^{p} a_{kj}$ and $B_k = \sum_{j=0}^{q} b_{kj}$ as the sums of the autoregressive coefficients of a given variable X_k. Then the degree of substitutability between services and goods is defined by the following ratio:

$$\frac{A_1}{B_1} = \frac{\sum_{k=0}^{p} \frac{\partial C_t^s}{\partial P_{t-k}}}{\sum_{k=0}^{q} \frac{\partial C_t^g}{\partial P_{t-k}}} = \frac{\sum_{k=0}^{p} a_{1k}}{\sum_{k=0}^{q} b_{1k}}. \tag{3}$$

We report here the table showing the sums of the estimated coefficients (Table 1)[4].

Table 1: Sum of the coefficients in the regressions of consumption of goods and services

	1994-2005		2006-2023	
	Goods	Services	Goods	Services
Sum of the coefficients				
Real GDP	0.440	-0.182	0.133	2.773
Share price	-0.035	0.055	-0.055	0.045
Old-age dep. ratio	-0.039	0.704	0.008	-0.436
Elderly market	0.022	-0.251	-0.138	1.606
Price ratio	0.095	-1.792	0.133	-0.689

Note: The numbers in this table are computed by summing the estimated lagged coefficients that are statistically significant (at least at 10% level of significance) in the two regressions in Equation 2. Detailed estimations of the ARDL equations are provided in the Appendix in Tables C.1 to C.4. Each number measures the impact of the variables in the rows on the variables in the columns (consumption of goods or services).

[4] A detailed presentation of data sources and regression results are given in Appendix C, where the interested reader can find information on the evolution of consumption in Japan (Figure C.1) and full regression results in Tables C.1, C.2, C.3 and C.4.

Due to data availability, we start in 1994 and, for the sake of comparison, split the sample in two. For the second sub-period, we are in the fifth stage of the demographic transition.

The coefficient of interest is on the last line of the table. As expected, goods and services are substitutes. Indeed, a rise in the price of services relative to goods reduces aggregate demand for services and increases demand for goods. The ratio of coefficients is -18.86 for the first sub-period and -5.16 for the second sub-period. Consequently, during the second sub-period, the degree of substitutability between goods and services decreased (the ratio is 3.5 times lower in absolute terms). This result can be explained by examining the coefficients of the elderly market variable. We see that, over the second sub-period, when the share of elderly consumption expenditure in total consumption increases, it increases consumption of services (we find a positive coefficient of 1.60), whereas it decreases it in the first sub-period. We also note that higher stock market valuations lead to a substitution of goods consumption for services consumption (the signs are negative and positive respectively). A rise in GDP per-capita increases consumption of goods and services during the fifth stage of the demographic transition.

4 Aging labor force and economic structural change: a theoretical setup

As shown in Figure 4, old workers are less qualified than young workers. Population aging should have then increased the share of unskilled old workers in the workforce. If, as predicted by the estimated coefficients of equation (1), the replacement of these workers by computer capital takes place, we should observe changes in the allocation of labor across sectors (old workers loosing their jobs will have to reallocate to another sectors). Moreover, since the relative demand for services also differs between young and old people (see estimation results from equation (2) in Table 1), population aging should have also contributed to a change in the composition of aggregate demand. This should have contributed to changes in the supply (i.e. production) composition and thus in labor distribution across sectors. Both demand and supply changes fostered by population aging should then drive a reallocation of labor across economic sectors.

In this section, we include these phenomena associated with population aging (i.e. replacement of old unskilled workers by computer capital and complementary relation between goods and services for old workers) into the model proposed in Autor and Dorn [2013]. The interested reader can refer to this paper to obtain more details on the model's hypotheses and resolution. In contrast with these authors, we include a third sector producing high qualified services, which allows us to distinguish between personal services employing unskilled workers and the high qualified service sector. Production of goods combines routine labor and computer capital, measured in efficiency units, using the following technology:

$$Y_g = [(\alpha_r L_r)^{\varsigma} + (\alpha_k K)^{\varsigma}]^{1/\varsigma}, \tag{4}$$

with $\varsigma \in (0, 1)$. The elasticity of substitution between routine labor and computer capital is $\sigma_r = 1/(1 - \varsigma)$ and by assumption greater than 1. By implication, K is a relative substitute for routine labor. Suppose that, in an ad-hoc way, we introduce the age dimension in this setup by simply assuming that there are young and old workers and that $\varsigma = f(\phi^U)$, with $\varsigma'(\phi^U) > 0$, where ϕ^U stands for the proportion of old workers in the unskilled workforce. Whereas there are no productivity differences within a skill category across ages, we impose (following the results from our predictive tests) that the larger the share of old workers within unskilled labor, and thus, within routine labor, the higher the substitutability between routine labor and capital.

A second sector, which produces personnel services, uses only manual labor, measured in efficiency units as L_m:

$$Y_s^p = \alpha_p L_m, \tag{5}$$

where $\alpha_p > 0$ is an efficiency parameter. There is a continuum of mass one of low-skill workers, U, who each supply either manual or routine labor, so that $L_m = 1 - L_r = 1-(\phi^U L_r+(1-\phi^U)L_r)$. In contrast with Autor and Dorn [2013], we make the simplifying assumption that low-skill workers have homogeneous skills at performing both manual and routine tasks.

The third sector, which produces highly qualified services, uses only abstract labor, in efficiency units measured as L_a:

$$Y_s^h = \alpha_h L_a, \tag{6}$$

where $\alpha_h > 0$ is an efficiency parameter. For simplicity we are assuming that all qualified workers are employed in this sector. Evidently, one could argue that technological capital complements abstract labor and, therefore, the adoption of technological capital over the past years should have stimulated abstract employment. This is certainly the case, and computer capital intensive sectors have certainly been net employment creators over the past decades. While we acknowledge this stylized fact, we do not model this process since it has essentially concerned younger generations of workers and the paper is focused on old workers. Our focus is on how population aging has modified the economic structure of Japan. As such, we neglect the fact that younger generations are massively employed in highly qualified sectors since these generations are highly educated and the adoption of computer capital in these sectors has promoted employment of highly qualified people.

Computer capital is produced and competitively supplied using the following technology:

$$K = Y_k(t)\frac{e^{\delta t}}{\theta}, \tag{7}$$

where $Y_k(t)$ is the amount of the final consumption good allocated to production of K, $\delta > 0$ is a positive constant, and $\theta = e^{\delta}$ is an efficiency parameter. Capital fully depreciates between periods. Productivity is rising at rate δ, reflecting technological progress. Competition guarantees that the real price of computer capital (per efficiency unit) is equal to marginal (and average) cost. As time advances, this price falls, since $p_K(t) = \frac{Y_k(t)}{K} = \frac{Y_k(t)}{Y_k(t)\frac{e^{\delta t}}{\theta}} = \theta e^{-\delta t}$.

To close the model, Autor and Dorn [2013] model all consumers/workers as having identical CES utility functions defined over consumption of goods and services:

$$u = (c_s^\rho + c_g^\rho)^{1/\rho}, \tag{8}$$

where $\rho < 1$. The elasticity of substitution between goods and services is $\sigma = \frac{1}{1-\rho}$. We introduce the age dimension by assuming that young people have a higher elasticity of substitution between goods and services than old people, i.e. $\rho_y > \rho_o$. This assumption is consistent with findings from the predictive tests in the previous section. Under the hypothesis that the proportion of old workers over the total number of workers equals γ, the aggregate elasticity of substitution between goods and services should equal $\rho = \gamma\rho_o + (1-\gamma)\rho_y$.

Autor and Dorn [2013] solve the asymptotic equilibrium of the model (i.e. when $t \to \infty$ or, equivalently, as $p_k(t) \to 0$). Given that $\lim_{x\to\infty} K(t) = \infty$ the authors prove that the asymptotic level of L_m^* is uniquely solved as follows:

$$L_m^* = \begin{cases} 1, & \text{if} \quad \frac{1}{\sigma} > 1 - \varsigma, \\ \in (0,1), & \text{if} \quad \frac{1}{\sigma} = 1 - \varsigma, \\ 0, & \text{if} \quad \frac{1}{\sigma} < 1 - \varsigma. \end{cases} \tag{9}$$

The asymptotic allocation of low skill labor to services versus goods production depends entirely on whether the elasticity of substitution in production between computer capital and routine labor is higher or lower than the elasticity of substitution in consumption between goods and services (both of which demand low-skill labor). If the production elasticity exceeds the consumption elasticity, technological progress (i.e., a falling computer price p_k) raises relative demand for low-skill labor in service employment; in the limit, all low-skill labor flows from goods into services production. If this inequality is reversed, all low-skill labor eventually concentrates in the goods sector, where it performs routine tasks.

Including in Autor and Dorn [2013]'s model the two hypothesis obtained from the predictive tests in the previous section, that is *(i)* higher substituability of unskilled old workers by computer capital, and *(ii)* higher demand complementarity between goods and services for older workers, we reach the following conclusions on the consequences on population aging:

- Population aging pushes down the elasticity of substitution between goods and services. This increases the likelihood that the elasticity of production between routine labor and capital overcomes the elasticity of consumption between goods and services. According to our model, this will tend to promote a concentration of unskilled labor in the service sector.

- Because there is an increasing share of old people in the working population, technological innovation of machines (or robots) being able to implement the tasks that old workers are not able to implement may be stimulated by population aging. If the elasticity of substitution between technological capital and routine labor increases with population aging, the likelihood that this elasticity overcomes the elasticity of substitution between goods and services increases. According to our model, this pushed unskilled labor towards services.

All in all, when modifying Autor and Dorn [2013]'s model to include the two hypothesis tested in Section 2 for the Japanese economy, it predicts that population aging drives a structural change in this economy, by promoting the concentration of employment in the service sector and a progressive replacement of labor by computer capital on the good sector. Evidently, if this prediction holds, we should observe a change in both the relative sector composition of Total Factor Productivity (TFP) and the factor contribution to the sector TFP. The econometric analysis in the following Section tests these theoretical predictions.

5 Impact of elderly working labor force on the potential growth rate of productivity

In this Section, we investigate the effects of demographic aging on productivity growth rates. Previous empirical work in the literature leads to controversial results for OECD countries. Acemoglu and Restrepo [2017] show that over the period of the 1990s and 2000s, there is no negative association between population aging and a lower level of GDP per capita. On the contrary, they find a positive relationship. Their explanation is that, alongside demographic aging, industrialized economies have experienced waves of labor-replacing innovations, enabling companies to automate certain tasks (e.g. robotisation and artificial intelligence). The inclusion of more labor-saving technological innovations can, according to the authors, be so intense that it not only offsets the negative effects of aging, but even leads to a positive relationship. Similar conclusions are reached by Eggertsson et al. [2019].

On the contrary, other works such as those by Aksoy et al. [2019], and more recently for example Gründler and Potrafke [2023], Kopecky [2023] establish a negative link between aging and total factor productivity (and GDP growth) which can be explained by a drop in the labor force participation rate, and by the fact that aging prevents the creation of innovation when a country is at its technological frontier. Jones [2023] shows that in the United States, demographics account for almost 40% of the gap between GDP per capita and its linear trend in 2019.

In the specific case of Japan, some papers conclude that demographic aging has led to a fall in output per head and overall factor productivity, and is responsible for the country's secular stagnation (e.g. Braun and Ikeda [2022], Westelius and Liu [2016]). The causes identified are a decline in the working-age population, and insufficient investment in human capital (notably through the absence of training plans for non-regular workers in companies).

Compared with the existing literature, we have chosen an empirical framework that takes into account several realities specific to Japan. As the theoretical literature suggests that the aging of a society generally affects the potential growth of an economy, it is important to examine the links between the age composition of workers and productive activity when an economy is approaching its technological frontier. We take up the stochastic frontier methodology here, applying it to the growth rate of total factor productivity. An important question in debate concerning Japan is whether or not the negative effects of demographic aging can be offset by greater investment in some technologies (like computers, digital equipment, or robotics), or equivalently whether the negative effects of aging prevail because of under-investment in new technologies is substitutable for the work of the elderly. In our empirical model, we therefore distinguish several forms of capital and labor as factors influencing Japan's potential growth: ICT capital, linked to information and communication technology equipment, non-ICT capital, and the labor services of young and old workers.

Since population aging is a structural phenomenon that occurs over several decades, it is appropriate to look at how it has affected structural indicators of the economy. As total factor productivity is an important determinant of potential GDP growth, we look at how aging may have affected Japan's ability to set its productivity trajectory at its highest level. A suitable econometric framework to study this question is the stochastic frontiers approach. We give below a summary of the methodology used, in order to facilitate the reading of our econometric results.

One advantage of retaining a stochastic frontier framework is that it also allows us to study the factors that are sources of inefficiency and that can slow productivity growth.

This is the case, for example, if companies are slow to adopt new technologies. In Japan, small and medium-sized businesses adopt new technologies at a slower pace than in most other industrialized countries, and the rate of startup creation is also lower. This slows down their productivity (see Colacelli and Hong [2019]). By working on sectoral data, we want to see whether or not this can explain inefficiencies in productivity across the country as a whole. Other impediments to potential growth in total factor productivity may be low human capital development, difficulties in absorbing innovations by aging workers, and difficulties in generating new ideas. These elements are captured here by the effects of aging workers and intangible capital on the inefficiency term.

5.1 Benchmark equations: a stochastic frontier framework

We consider the following panel data stochastic growth model

$$\begin{aligned} y_{it} &= \alpha_i + X_{it}^{'}\beta + v_{it} - u_{it},\ i = 1, ...N,\ t = 1, ..., T, \\ &= \alpha_i + X_{it}^{'} + \epsilon_{it}. \end{aligned} \tag{10}$$

where y_{it} is the dependent variable, X_{it} is a vector of K independent exogenous variables and α_i is an individual fixed effect. v_{it} and u_{it} are two error terms. v_{it} is a classical disturbance term. When $u_{it} = 0$, y_{it} reaches its highest level (denoted y_{it}^*). If $u_{it} > 0$, or equivalently if $y_{it} < y_{it}^*$, then $(-u_{it})$ is an inefficiency term. To keep with a simple model, we assume that:

- v_{it} follows a symmetric Gaussian distribution and is potentially heteroskedastic: $v_{it} \sim N(0, \sigma_v^2)$,
- u_{it} is non-negative and distributed as a truncated Normal law with homoskedastic variance: $u_{it} \sim N^+(\mu_{it}, \sigma_u^2)$,
- μ_{it} is time-varying and also differs across individuals according to the values of a

vector of variables summarized by a vector Z: $\mu_{it} = Z'_{it}\delta$,

- the error terms are uncorrelated and orthogonal to the vector or explanatory variables: $u_{it} \perp v_{it}$, $X_{it} \perp \epsilon_{it}$,
- α_i is a fixed effect that satisfies the following assumptions : $\alpha_i \perp u_{it}$, $cov(\alpha_i, X_{it}) \neq 0$.

We make these assumptions that allow us to estimate a simple model. The estimator used is that of Greene (see Greene [2005a], Greene [2005b]). More complex models have been proposed in the literature. A summary is given, for example, by Kumbhakar et al. [2022a], Kumbhakar et al. [2022b].

To estimate the model, one first introduces N dummy variables into the model to take account for the fixed effects. Then, the model is estimated using the maximum likelihood method (using the appropriate asymptotic variance-covariance matrix to take account of the heteroskedasticity of the error term v_{it}.). Equation (10) is assumed to be written in log-linear form. In this case, it can be shown that the inefficiency term implies

$$Exp(-u_{it}) = EXP(y^*_{it})/EXP(y_{it}). \tag{11}$$

It can be shown that an estimator of u_{it} is given by the JMLS formula (see Jondrow et al. [1982]) :

$$\begin{aligned}
\hat{u}_{it} &= E[u_{it]}|\hat{\epsilon}_{it}] = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\phi(A_{it})}{1-\Phi(A_{it})} - A_{it}\right], \\
\sigma &= \left[\sigma_v^2 + \sigma_u^2\right]^{1/2}, \\
\lambda &= \sigma_u/\sigma_v, \\
A_{it} &= \lambda/\sigma\hat{\epsilon}_{it.}
\end{aligned} \tag{12}$$

$\phi(A_{it})$ is the density of the standard normal law evaluated at A_{it}, and $\Phi(A_{it})$ is the CDF of the standard normal law evaluated at A_{it}.

5.2 Application to our case

We estimate the following panel stochastic frontier equation (i and t refer respectively to industries and years), where all the variables are expressed as growth rates:

$$\begin{aligned} TFP_{i,t} &= \alpha_i + K_{i,t}^{ICT}\beta_1' + \beta_2 k_{i,t}^{NICT} + \beta_3 L_{i,t}^{Y} + \beta_4 L_{i,t}^{O} + \beta_5 h_{i,t} + V_{i,t} - U_{i,t}, \\ K_{i,t}^{ICT} &= \left(I_{i,t}^{Soft}, I_{i,t}^{Comp}, I_{i,t}^{Comm}\right), \quad V_{i,t} \perp U_{i,t}. \end{aligned} \tag{13}$$

All the variables come from EU-KLEMS database, 2019 release[5]. The definitions of the variables are the following (for more details on the measurement of these variables from data, see Table D.1 in Appendix):

$TFP_{i,t}$: growth rate of total factor productivity,

$I_{i,t}^{Soft}$: growth rate of investment in software equipment,

$I_{i,t}^{Comp}$: growth rate of investment in computer equipment,

$I_{i,t}^{Comm}$: growth rate of investment in communication equipment,

$k_{i,t}^{NICT}$: growth rate of capital (non-ICT),

$L_{i,t}^{Y}$: growth rate of labor services provided by the young,

$L_{i,t}^{o}$: growth rate of labor services provided by the old,

$h_{i,t}$: growth rate of human capital

$V_{i,t}$ and $\epsilon_{i,t}$ are random error terms and $U_{i,t}$ is an inefficiency term.

When $\epsilon_{i,t} = V_{i,t} - U_{i,t} = 0$, Equation (13) is interpreted as the frontier equation of the growth rate of TFP. It measures the highest growth rate of TFP (we call it potential TFP growth). In this equation, the growth rate of ICT capital is broken down into three components (software, communication and computer).

The inefficiency term is $U_{i,t} \sim N^{+}(\mu_{i,t}, \sigma_U)$, with:

[5] The interested reader can find information on data sources in Appendix D.

$$\mu_{i,t} = \alpha_0 + K_{i,t}^{ICT}\alpha_1^{'} + \alpha_2 k_{i,t}^{INT} + \alpha_3 L_{i,t}^{O} + \alpha_4 h_{i,t}. \tag{14}$$

As mentioned earlier, there are several possible causes of inefficiency, which are linked to human capital, and to the spread of new ideas and innovations across different industries. $k_{i,t}^{INT}$ means intangible capital.

Employing old-age workers can have two effects on total factor productivity. Firstly, it can lead to a disorganization of productive activity and generate negative externalities that prevent companies from being on a trajectory where TFP grows at its highest (potential) rate. This would mean that companies are not optimizing the use of factors that are sources of productivity. Figure 6 shows that this was not the case in Japan during the period under investigation. Indeed, this figure shows the estimated *efficiency* scores in the industry and service sectors. The high numbers suggest that companies had their TFP growth close to the potential growth rate. For industry, the scores exceed 80%, and in services, we find numbers larger than 95%. This result is valid whether or not we take account of the old-age workers. In terms of estimation, this finding is corroborated by the fact that the marginal effects of the coefficients of the inefficiency term in Tables 3 and 4, corresponding to Equation (13), are generally insignificant.

Alternatively, the aging of the workforce may affect the medium-term productive capacity of companies, if it leads to a fall in potential TFP. This may be the case, for example, if investment in robots and computers that do more automated work is not enough to offset the negative externalities of aging on TFP.

Was demographic aging an obstacle to achieving the potential growth rate of TFP in Japan? To answer this question, we estimate potential TFP growth over two-sub-periods corresponding respectively to the years before and after the fifth phase of the demographic transition (we interpret the frontier to capture "potential" TFP growth). Due to data availability, the end of the period is 2015 in our sample. We compare the

Figure 6: Efficiency scores: industry vs. services

Note: Efficiency scores are estimated via JLMS estimator, $exp(-E(s \cdot u \mid \varepsilon))$.

results for industry and services[6]. The numbers in Table 2 are obtained by estimating the frontier and then calculating the annual average for each sub-period. We compare the estimated frontier with and without the variable $L_{i,t}^{O}$ as stated in Equation (13). This amounts to looking at the frontier that would have been reached if the workforce had only been made up of a young population, and comparing it with the actual situation.

[6]The classification we adopted to determine whether the sectors fall under industry or services is available in Table D.2, and the relative share of industry and services in total value-added are depicted in Figure D.1 of Appendix D.

Taking all sectors together, Japan experienced losses in potential TFP during both sub-periods, though these losses were less significant from 2006 onwards. These losses occurred against a backdrop of so-called "three lost decades", reflecting economic stagnation in Japan since 1991. The table suggests that demographic aging and the employment of an older workforce has been a factor in accentuating potential productivity losses. We also see that this overall negative trend can be explained by the productivity losses observed in the service sector, in spite of the fact that the industrial sector has been characterised by an increase in productivity gains. The case of the latter sector is interesting, since the entry into the fifth phase of the demographic transition (from 2006 onwards) has weighted heavily on the growth in productivity gains (compare for instance 0.28% and 0.08%).

Table 2: Estimated potential TFP growth

	1994-2005	**2006-2015**
All sectors		
Without aged labor	-0.58	-0.15
With aged labor	-0.29	-0.008
Industry		
Without aged labor	0.25	0.08
With aged labor	0.30	0.28
Services		
Without aged labor	-0.22	-0.08
With aged labor	0.0002	-0.02

Note: Negative numbers indicate potential TFP losses (negative growth rate) and positive numbers reflect an increase in productivity gains (positive growth rate).

The table clearly shows a difference between the industrial and service sectors. The asymmetry between the two (losses in potential TFP growth in services and gains in the other) is explained by the fact that several factors have pushed productivity up in industry and not in services, notably investment in computers, the employment of a young workforce and human capital. Table 3 (industry sector) shows that the coefficients of these variables are significant and offset the negative effect of older workers in the frontier equation. On the other hand, in Table 4 (sector of services), none of the coefficients of the ICT variables, for the frontier, appears to be significant and the two variables that are significant have a negative sign (old-age labor and human capital).

Table 3: Estimation of stochastic frontier panel model for the industry sector: 1995-2015

Frontier		**Coeff.**	**Std. Err.**
	Communication	-0.008	0.016
	Computer	0.060*	0.033
	Software	0.068	0.171
	NICT Capital	-0.019	0.399
	Young-age labor	0.889**	0.401
	Old-age labor	-0.730**	0.334
	Human capital	0.209*	0.116
Inefficiency	**(Marginal Effects)**	**Average**	**Std. Err.**
	Communication	-0.132	0.445
	Computer	0.164	0.550
	Software	-0.136	0.459
	Intang capital	-1.760	5.921
	Old-age labor	0.524	1.762
	Human capital	0.286	0.962
	σ_u	0.662	0.617
	σ_v	0.022***	0.004

Note: *, ** and *** mean significance at 10%, 5% and 1% level of confidence. Estimates are performed with Greene's True Fixed-Effects estimator, and the inefficiency term follows a Truncated Normal distribution. The marginal effects are observation-specific and correspond to the marginal effects of the exogenous determinants on the unconditional mean of inefficiency, $E(u)$.

Table 4: Estimation of stochastic frontier panel model for the sector of services: 1995-2015

Frontier		**Coeff.**	**Std. Err.**
	Communication	-0.009	0.015
	Computer	-0.002	0.016
	Software	0.021	0.019
	NICT Capital	-0.074	0.110
	Young-age labor	-0.179	0.179
	Old-age labor	-0.642**	0.255
	Human capital	-0.083***	0.028
Inefficiency	**(Marginal Effects)**	**Average**	**Std. Err.**
	Communication	0.012*	0.007
	Computer	-0.011	0.007
	Software	0.003	0.002
	Intang capital	-0.031	0.019
	Old-age labor	-0.057	0.035
	Human capital	0.044	0.027
	σ_u	0.372***	0.065
	σ_v	0.020***	0.002

Note: *, ** and *** mean significance at 10%, 5% and 1% level of confidence. Estimates are performed with Greene's True Fixed-Effects estimator, and the inefficiency term follows a Truncated Normal distribution. The marginal effects are observation-specific and correspond to the marginal effects of the exogenous determinants on the unconditional mean of inefficiency, $E(u)$.

6 Conclusion

This paper looks at the impact of demographic aging of the Japanese population on some structural changes in the Japanese economy, and on the growth rate of total factor productivity. Using a simple model with heterogeneous workers, in a modified Autor and Dorn [2013]'s theoretical framework, we highlight two mechanisms. Firstly, firms have an incentive to replace older workers who are less productive than younger ones with capital incorporating more modern technology (e.g. computers or robots). Secondly, older workers' demand for goods and services is more complementary. The model shows that both mechanisms contribute to the reallocation of old workers into the service sector. We then propose an empirical model which reveals that this could explain why potential productivity growth had declined in the industrial sector, and that this had also led to losses in potential productivity growth in the service sector.

Our paper has attempted to make an additional contribution to the current debate on the role of demographic aging in explaining secular stagnation in advanced economies. This is a context in which the rate of potential growth is in long-term decline. Two types of explanation are generally put forward. Either, the literature points to demand-related channels. A common argument is that, in a country where the number of elderly people is increasing but they are now retired, overall savings are growing faster than investment, driving down the rate of return on capital and, consequently, productive investment. Or, the focus is on the supply side, emphasizing the deleterious effects of an aging workforce on productivity.

In our paper, the first message is as follows. On the demand side, it is necessary to look beyond savings by examining how the structure of aggregate consumption is being distorted. If the aging population consumes more and more services, and at the same time, on the labor supply side, older workforce migrates from high-productivity sectors (industry) to lower-productivity sectors (services), we may end up with a situation where there is a high concentration of a less productive population in the sector of activity that is booming and driving growth (i.e. the service sector). This can weaken medium/long-term growth.

A second message is that the idea that simply replacing older workers with robots and computers will prevent any decline in productivity (a favorite argument of Schumpeterian-inspired models) is not necessarily borne out in reality. Our econometric analysis shows that it works in sectors where it has traditionally existed in industry. But in the service sector, where productivity is generally lower, aging has not prevented potential productivity losses in Japan. And with life expectancy increasing rapidly in this sector, it should come as no surprise that, at the aggregate level, the beneficial effects of investment in new technologies are not apparent. An interesting question is whether the case of Japan can be considered as predictive of what could happen in other advanced economies, for which the literature has also highlighted a phenomenon of secular stagnation linked to demographic causes (see Gordon [2015]). For future research, we therefore plan to extend this study to the USA and Europe.

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A Demographic winter and net migration

Figure A.1: The Patterns of Demographic Winter

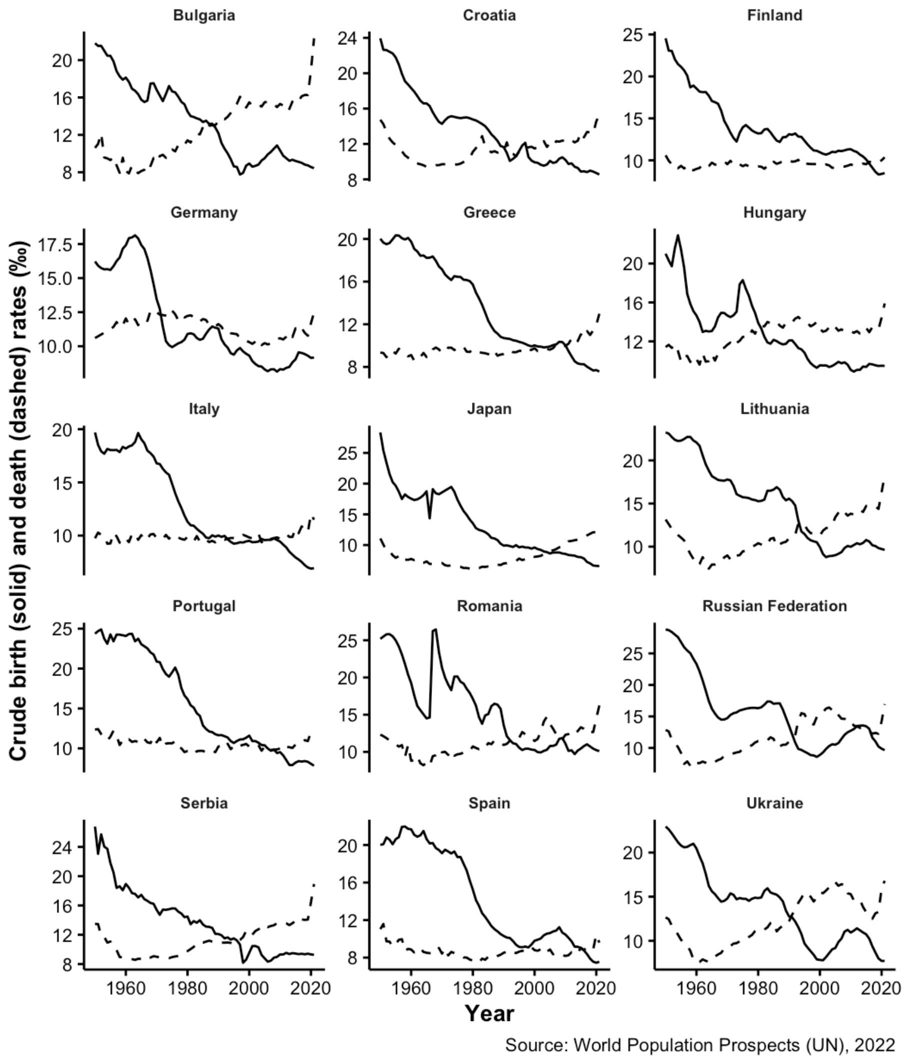


Figure A.2: New Territories in Demographic Winter

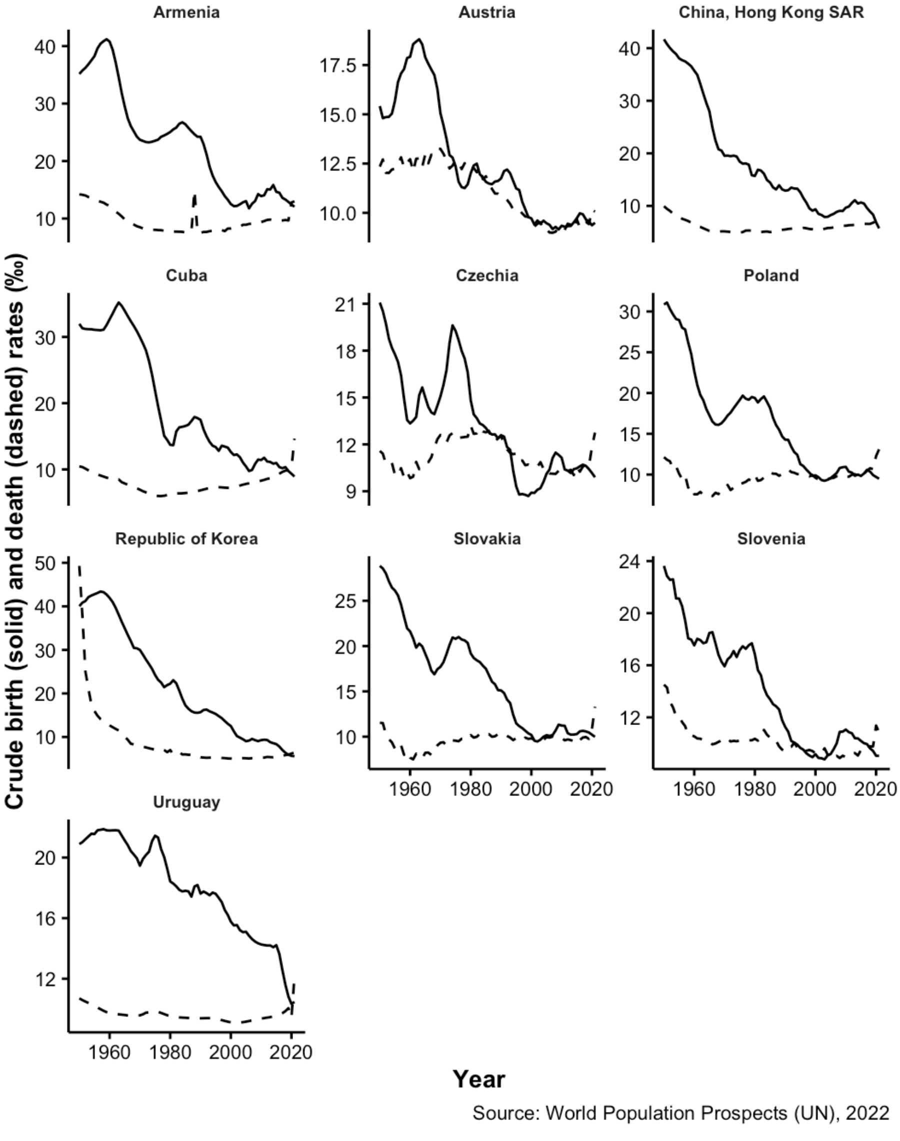
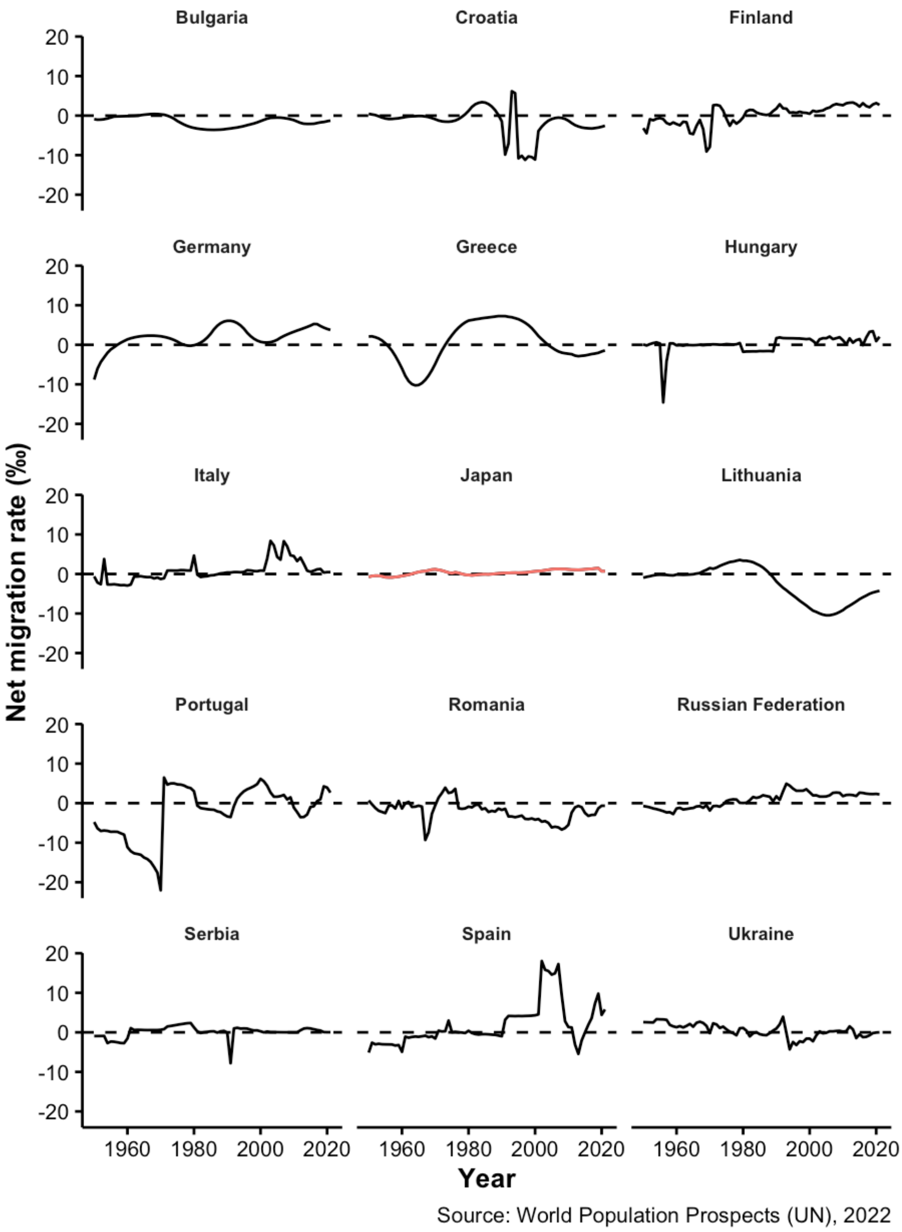


Figure A.3: Level of Net Migration



B Correlation between aging and productivity

In this appendix, we present the database and the variables that were used in our stylized facts in order to measure the correlation between productivity and aging; as well as additional figures to illustrate them.

The database used is the 2021 version of the Japan Industrial Productivity (JIP) Database, published by the Research Institute of Economy, Trade and Industry and Hitotsubashi University. It comprises, for the period 1994-2021, different types of annual data required for estimating total factor productivity (TFP) across 100 industries spanning Japan's economy. In particular, we have selected the following variables:

- *Real value added.* This annual variable is expressed in millions of yen, chain-linked 2015 prices, for each sector.

- *Total hours worked.* This annual variable gives the total number of hours worked by sector (1 000 worker hours).

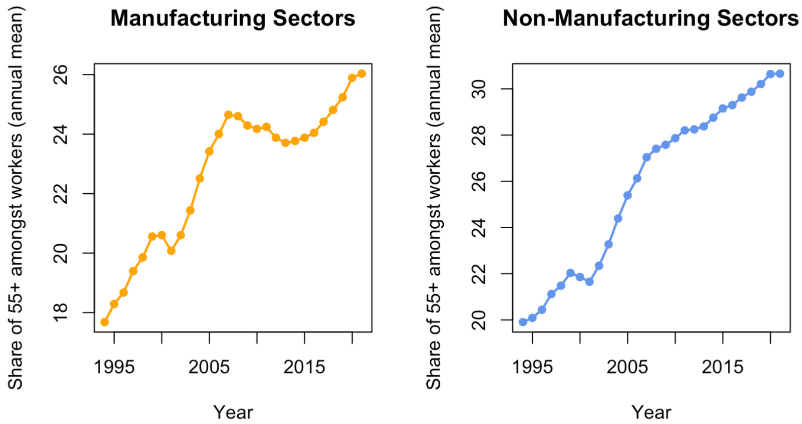
- *Labor productivity.* We calculate this variable by dividing real value added by total hours worked, for each sector, each year.

- *Share of 55+ amongst workers.* This annual variable accounts for the share of workers aged 55 and over. It is calculated in the database as the number of workers aged 55 and over over the total number of workers (%), for each sector.

- *Real GDP growth.* In the database, GDP is annually measured as Laspeyres chain-linked indices.

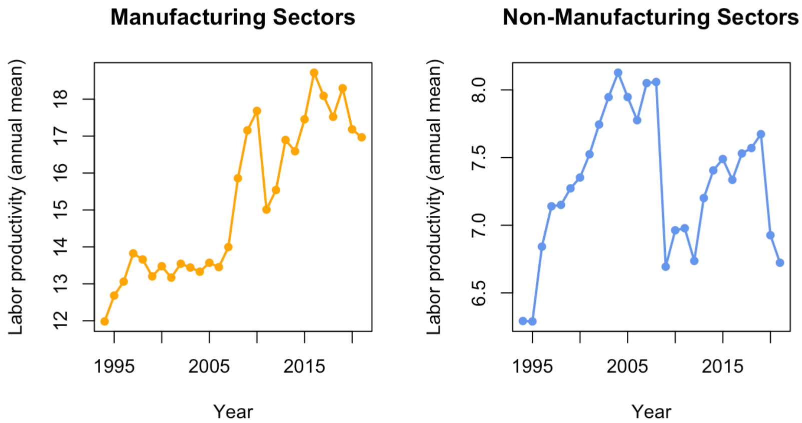
Then, we use the definition of aggregated sectors from the database to separate manufacturing from non-manufacturing sectors. Note that non-manufacturing sectors exclude housing and activities not elsewhere classified.

Figure B.1: Share of old workers (55 years old and above) in the manufacturing and the non-manufacturing sectors



Source: Japan Industrial Productivity Database 2021.

Figure B.2: Average yearly productivity level en the manufacturing and the non-manufacturing sectors



Source: Japan Industrial Productivity Database 2021.

C Regressions of consumption of goods and services

In this appendix, we explain in more detail the regression results of Equation 2.

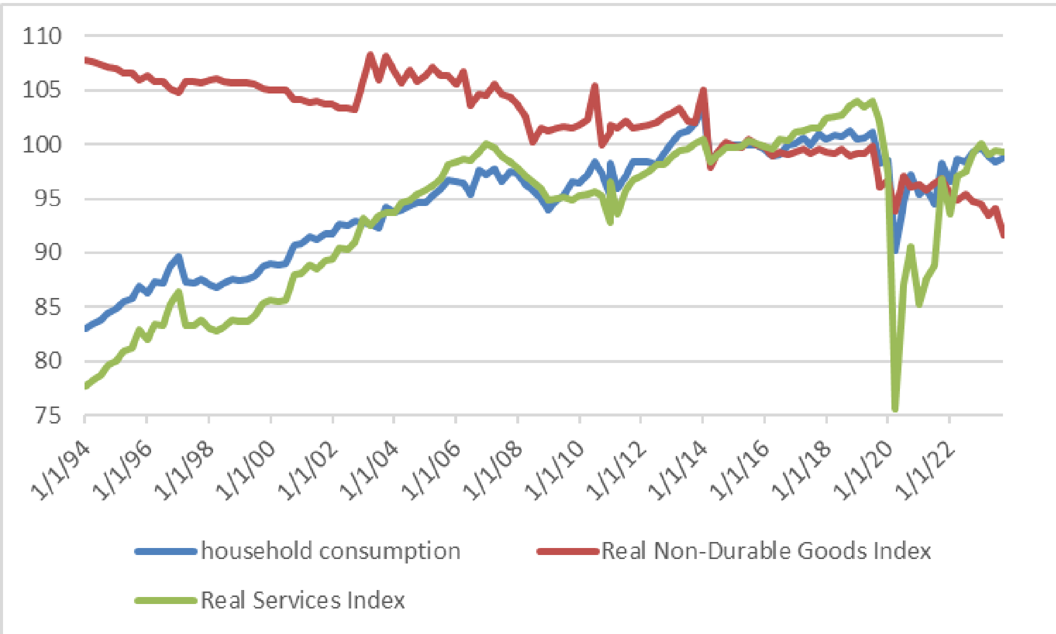
We start with the data sources.

- *Real consumption expenditure on non-durable goods and services.* The available data comes from the Bank of Japan (BOJ) at a quarterly frequency from 2003 to

2023. They are indexes (base 100 = 2015). We backcast these data to 1994 by regressing these variables on total household consumption, and using the estimated coefficients from the regression to calculate forecasts. We construct a quarterly index of total consumption data (base 100 = 2015) from quarterly consumption data obtained from the FRED St. Louis site of the St. Louis Federal Reserve in the USA. The original series is real Consumption of Households for Japan, Billions of Chained 2015 Yen, quarterly, seasonally adjusted.

Figure C.1 shows the series obtained. We can see a steady downward trend in the consumption of non-durable goods, while the consumption of services evolves along an upward trend. We also see a drop corresponding to the during and post-Covid 19 years.

Figure C.1: Evolution of consumption since 1994 in Japan



- *Prices of non-durable goods and services.* They are taken from the BOJ. These are the services producer price index and the corporate goods price index. The original data are monthly. We take observations on a quarterly basis. The indices are base 100 in 2015.

- The *old-age dependency ratio* is obtained from the World Bank annual database. We interpolate the data to get quarterly observations. Then, we convert them to an index (base 100 = 2015).

- *GDP per-capita* comes from FRED Saint-Louis database. Initial annual data (gross domestic product per Capita in current U.S. Dollars) are converted into quarterly data by interpolation and then we construct an index.

- *Elderly market share* data comes from the Japan Finance corporation, 2011, Japan External Trade Organization (JETRO). The series is the percentage of consumption of people over 60 years old in total household consumption market. Initial data are available for the years 1990, 2005, 2010-2015, 2020, and 2024 (forecast). A graph of the series shows that the variable has increased regurlarly since the beginning 1990s. We interpolate the data to fill in the missing observations. Then, annual observations are converted to quarterly observations and transformed into indexes.

- *Market share prices* are taken from OECD at a quarterly frequency and converted to an index (base 100 = 2015).

For the econometric estimation, all variables are log-transformed. We use a GLS estimator (Cochrane-Orcutt procedure) to remove autocorrelation from the residuals. For all explanatory variables, we take a maximum number of lags of 5 quarters. We adopt a top-down selection method for lagged variables, keeping only the significant coefficients in the final regressions with 10%, 5% and 1%. levels of significance. Tables C.1 to C.4 show the results of the various regressions for the sub-periods and by type of consumption (goods and services).

Table C.1: Regression: consumption of goods 1990-2005

Variable	*Lags*	*Coeff.*	*Std. Err.*	sign.	*Variable*	*Lags*	*Coeff.*	*Std. Err.*	sign.
Intercept		2.382	1.924						
Real GDP	0	0.542	0.143	***	Price ratio	0	-	-	-
	1	-0.337	0.157	**		1	-	-	-
	3	-	-	-		3	1.414	0.226	***
	4	0.235	0.136	*		4	-0.723	0.243	***
	5					5	-0.596	0.170	***
Share price	0	-	-	-	**Sum of the coefficients**		*Coeff.*		
	1	-	-	-	Real GDP		0.440		
	2	-0.026	0.012	**	Share price		-0.035		
	3	-	-	-	Old dep. ratio		-0.039		
	4	0.034	0.012	***	Elderly market		0.022		
	5	-0.043	0.013	***	Price ratio		0.095		
Old dep. ratio	0	-	-	-	**Statistics**				
	1	2.116	0.932	**	Adjusted R2		0.810		
	2	-	-	-	Durbin-Watson		0.810		
	3	-	-	-	Rho		2.099		
	4	-0.189	0.094	*					
	5	-1.966	0.939	**					
Elderly market	0	0.108	0.049	***					
	1	0.145	0.054	***					
	4	-0.231	0.047	***					

Note: *,**,*** means significance at 10%, 5%, 1% level of significance.

Table C.2: Regression: consumption of services 1990-2005

Variable	*Lags*	*Coeff.*	*Std. Err.*	sign.	*Variable*	*Lags*	*Coeff.*	*Std. Err.*	sign.
Intercept		9.714	0.916	***					
Real GDP	0	0.402	0.117	***	Price ratio	0	-0.803	0.192	***
	1	-0.584	0.196	***		1	-1.122	0.326	***
	2	-	-	-		2	0.969	0.263	***
	4	-	-			4	-0.836	0.174	***
	5	0.457	0.078	***		5	-	-	-
Share price	0	-	-	-	**Sum of the coefficients**		*Coeff.*		
	1	-	-	-	Real GDP		-0.182		
	2	-	-	-	Share price		0.055		
	3	0.055	0.008	***	Old dep. ratio		0.704		
	4	-	-	-	Elderly market		-0.251		
	5	-	-	-	Price ratio		-1.792		
Old dep. ratio	0	4.464	0.870	***	**Statistics**				
	1	-3.832	0.751	***	Adjusted R2		0.993		
	2	0.473	0.063	***	Durbin-Watson		2.070		
	3	-	-	-	Rho		-0.786		
	4	-4.287	0.901	***					
	5	3.886	0.760	***					
Elderly market	0	0.214	0.066	***					
	1	-0.128	0.047	**					
	2	-	-	-					
	3	-0.158	0.044	***					
	4	-0.179	0.033	***					

Note: **,*** means 5% and 1% level of significance.

Table C.3: Consumption of goods 2006-2023

Variable	*Lags*	*Coeff.*	*Std. Err.*	sign.	*Variable*	*Lags*	*Coeff.*	*Std. Err.*	sign.
Intercept		2.408	0.730	***					
Real GDP	0	0.333	0.065	***	Price ratio	0	-0.262	0.081	***
	3	-	-	-		3	0.395	0.084	***
	4	-	-	-		4	-	-	-
	5	0.183	0.067			5	-	-	-
Share price	0	-0.039	0.010	***	**Sum of the coefficients**		*Coeff.*		
	1	-			Real GDP		0.133		
	2	-			Share price		-0.055		
	3	-			Old dep. ratio		0.008		
	4	0.037	0.014	**	Elderly market		-0.138		
	5	-0.053	0.014	***	Price ratio		0.133		
Old dep. ratio	0	0.400	0.155	**	**Statistics**				
	1	-	-	-	Adjusted R2		0.938		
	2	-	-	-	Durbin-Watson		2.083		
	3	-	-	-	Rho		-0.209		
	4	-0.392	0.176						
Elderly market	0	-0.215	0.076	***					
	2	-0.142	0.068	**					
	4	0.219	0.081	***					

Note: **,*** means 5%, and 1% level of significance.

Table C.4: Regression: consumption of services 2006-2023

Variable	*Lags*	*Coeff.*	*Std. Err.*	sign.	*Variable*	*Lags*	*Coeff.*	*Std. Err.*	sign.
Intercept		-9.416	1.754	***					
Real GDP	0	2.247	0.154	***	Price ratio	0	-0.855	0.208	***
	3	0.526	0.158	***		3	1.011	0.237	***
	4	-	-	-		4	-0.441	0.207	**
	5	-	-	-		5	-0.404	0.211	*
Share price	0	-	-	-	**Sum of the coefficients**		*Coeff.*		
	1	-0.078	0.026	***	Real GDP		2.773		
	2	-	-	-	Share price		0.045		
	3	0.070	0.031	**	Old dep. ratio		-0.436		
	4	0.052	0.027	*	Elderly market		1.606		
	5	-	-	-	Price ratio		-0.689		
Old dep. ratio	0	-0.581	0.228	**	**Statistics**				
	1	0.516	0.189	***	Adjusted R2		0.904		
	2	-	-	-	Durbin-Watson		1.748		
	3	-0.371	0.195	*	Rho		0.491		
Elderly market	3	0.694	0.173	***					
	4	0.913	0.192	***					

Note: *,**,*** means 10%, 5% and 1% level of significance.

D Empirical Model

In this appendix, we present the database and the variables that were used in our empirical model.

We use the EU KLEMS database, 2019 version, released by the Vienna Institute for International Economic Studies. It provides industry-by-industry yearly estimates of the following variables for Japan:

- *TFP*. In EU KLEMS, TFP is being calculated as a residual, i.e. the share of the value added growth that remains when we remove growth in capital services and growth in labor services.

- *Capital Services*. In EU KLEMS, price indices for gross fixed capital formation are derived from the Eurostat series. User costs are then employed to compute the cost shares for each asset, which in turn enables the calculation of capital services growth. Next, the following classification applies:

  - *Non-ICT* comprises: Dwellings (N111), Other buildings and structures (N112), Transport equipment (N1131), Other machinery and equipment (N11O), Cultivated biological resources (N115), Research and development (N1171), Other intellectual property products.

  - *ICT* comprises: Computer hardware (N11321), Telecommunications equipment (N11322), Computer software and databases (N1173).

  - *Intangibles* comprises: Research and development (N1171), Computer software and databases (N1173), Other intellectual property products.

- *Labor Services*. EU KLEMS labor input data, including employment and wage shares by education and age, are sourced from the EU Labour Force Survey (EU LFS). By combining this data with industry-level hours worked, EU KLEMS is able to calculate hours worked by labor type and, ultimately, labor services growth. Note that age-specific labor services are not available in the database; we computed them according to the methodology developed in Esposito [2024].

Table D.1 presents the transformations we applied to these variables in our empirical analysis. Table D.2 shows the classification we used to group industries into either the service or industry sector. Note that this follows the ISIC criteria.

Figure D.1: Industry's Share of Total Value Added (Relative to Services)

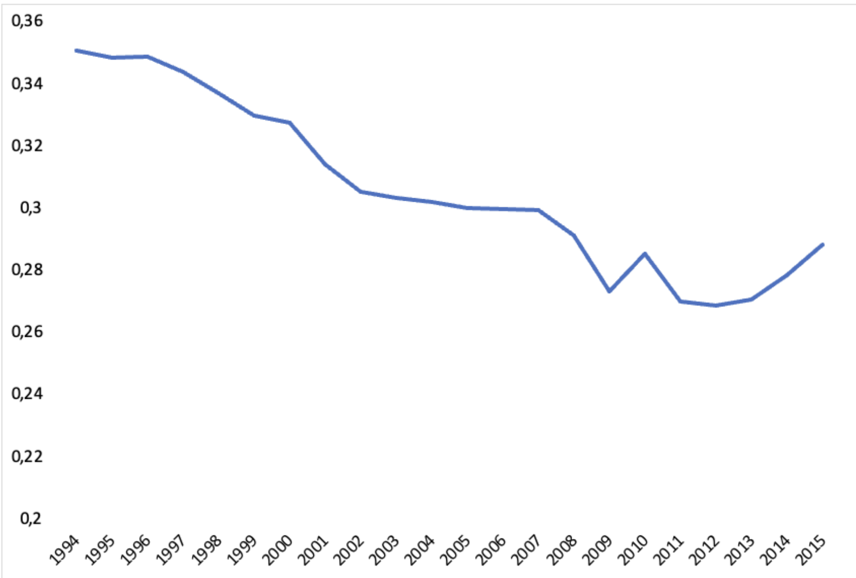


Table D.1: Definition of variables and sources

Variable	*Definition*	*Source*	*Transformation*
$TFP_{i,t}$	TFP (value-added based), volume indices, 2010=100	EUKLEMS Growth Accounts	$\Delta\ln$
$k_{i,t}^{ICT}$	ICT capital services, volume indices, 2010=100	EUKLEMS Growth Accounts	$\Delta\ln$
$k_{i,t}^{NICT}$	Non-ICT capital services, volume indices, 2010=100	EUKLEMS Growth Accounts	$\Delta\ln$
$k_{i,t}^{INT}$	Intangible capital services, volume indices, 2010=100	EUKLEMS Growth Accounts	$\Delta\ln$
$L_{i,t}^{O}$	Growth rate of labour services of the 50+ age group, %	Own calculations based on EUKLEMS Labour Input Data	None
$L_{i,t}^{Y}$	Growth rate of labour services of the 15-49 age group, %	Own calculations based on EUKLEMS Labour Input Data	None
$h_{i,t}$	Growth rate of the share of high-educated hours worked in total hours worked, %	Own calculations based on EUKLEMS Labour Input Data	None
$I_{i,t}^{soft}$	GFCF, chained linked volumes (2010), millions of national currency—Computer software and databases	EUKLEMS Capital Input Data	$\Delta\ln$
$I_{i,t}^{comp}$	GFCF, chained linked volumes (2010), millions of national currency—Computing equipment	EUKLEMS Capital Input Data	$\Delta\ln$
$I_{i,t}^{comm}$	GFCF, chained linked volumes (2010), millions of national currency—Communications equipment	EUKLEMS Capital Input Data	$\Delta\ln$

Table D.2: List of sectors

Sector	Code	Industry	Services
Agriculture, forestry and fishing	A		
Mining and quarrying	B	X	
Manufacturing	C	X	
Electricity, gas, steam and air conditioning supply	D	X	
Water supply; sewerage, waste management and remediation activities	E	X	
Construction	F	X	
Wholesale and retail trade; repair of motor vehicles and motorcycles	G		X
Transportation and storage	H		X
Accommodation and food service activities	I		X
Information and communication	J		X
Financial and insurance activities	K		X
Real estate activities	L		X
Professional, scientific and technical activities	M		X
Market economy (all industries excluding L, O, P, Q, T and U)	MARKT		
Administrative and support service activities	N		X
Public administration and defence; compulsory social security	O		X
Education	P		X
Human health and social work activities	Q		X
Arts, entertainment and recreation	R		X
Other service activities	S		X
Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	T		X
Total - all NACE activities	TOT		
Total industries (A-S)	TOT_IND		
Activities of extraterritorial organisations and bodies	U		X

Source : EUKLEMS, 2021 Release