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ABSTRACT

Technological progress may be less beneficial for older workers than younger workers. In this paper, we empirically examine the impact of technological change on the wage share of older workers. More specifically, we look at five different types of technological advancement using data from 30 European and Asian countries that are at the forefront of global population aging. Our findings indicate that recent technological developments centered on information and communication technology, software, and robots do not adversely affect older workers. One possible explanation is that older workers may be more open to learning and adopting new technologies than widely presumed.

Keywords: aging, older workers, wage share, capital, information communication technologies, robots

JEL codes: E24, E25, J01, J11, O11

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1. Introduction

The impact of technological change is not neutral across subgroups. For example, it is widely recognized that recent technological improvements have disproportionately benefited skilled workers, widening the wage gap between skilled and unskilled workers.[1] While the differential effects of technological progress on the skilled versus the unskilled has been extensively examined, their differential effects on workers of different age groups, the central focus of our paper, has not been investigated as much.

On one hand, a branch of the literature points out that older workers gain less from technological progress.[2] For example, Friedberg (2003) argued that older workers have less incentive to catch up with new technology.[3] Weinberg (2004) said that older workers are less able to adapt to new technologies. Schleife (2006) confirmed that the probability of using a computer declines as workers get older. Since a sizable wage gap separates workers who use a computer at work and those who don't (Krueger 1993), older workers will be paid less. Bartel and Sicherman (1993) found that technological progress induces older workers to retire early. Firm-level evidence confirms that older workers are adversely affected by new technologies. Meyer (2009) observed that firms with a higher share of older employees are less likely to adopt information and communication technology (ICT). Beckmann (2007) found that the adoption of technological and organizational innovations

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[1] Among others, Bound and Johnson (1992) and Katz and Murphy (1992) offer details.

[2] This literature is also consistent with studies that examine the macroeconomic effects of aging on economic growth. While there has been some debate, the vast majority of studies found that population aging has a negative effect on economic growth. According to a survey by Jones (2020), theoretical models of endogenous growth predict that a smaller population means fewer researchers who, in turn, generate fewer innovative ideas and ultimately lead to lower living standards.

[3] Using individual-level data from the Current Population Survey and the Health and Retirement Study, Friedberg (2003) found that older workers use computers less than prime-age workers. Impending retirement reduces the incentives to learn computer skills.

decreases firms' demand for older workers. Liang et al. (2018) argued that the domination of key senior positions by older workers can impede entrepreneurship by blocking younger workers from acquiring human capital, especially managerial skills, through on-the-job training.

On the other hand, an emerging strand of literature emphasizes that older workers are not necessarily harmed by technological advances.[4] For instance, Friedberg (2003) found that older workers who use computers choose to delay their retirement. Considering rapid improvement in life expectancy and general health of the elderly aged 60 to 79, Matsukura et al. (2018) estimated that their untapped work capacity amounts to more than 11 million workers in 2010. Furthermore, due to low substitutability between older and younger workers, tapping this capacity does not pose any serious threat to the employment opportunities of younger workers. ADB (2018) explores the possibility that the adoption of automation and artificial intelligence, which reduces the relative importance of physical and manual work, enables more older workers to participate in the labor market and enhances their productivity. Hence, technological progress has the potential to improve the welfare of older workers if they adapt well to it. A recent article in Dice (Kolakowski 2018) suggested that older workers may be less vulnerable to the job-destroying effects of automation due to their experience and accumulated knowledge.

[4] Acemoglu and Restrepo (2018) theoretically challenged the conventional wisdom and developed a directed technological change model in which an aging population, by encouraging more active adoption of automation technology, promotes growth. In their model, agents choose directed innovation and technology adoption in response to changing environments. Since aging creates labor shortage, automation that allows machines to perform tasks previously performed by labor become more attractive. While they emphasize the endogenous nature of technological progress, we treat technological progresses as exogenous.

Park et al. (2021, 2022) observed that increases in robot density reduce the productivity advantage of young age groups vis-à-vis older age groups. Aiyar, Ebeke, and Shao (2016) found that broadening access to health services, improving workforce training, increasing labor market flexibility, and promoting innovation via more research and development (R&D) can ameliorate the negative effects of an aging workforce. Lee et al. (2020) also found that attainment of ICT skills and participation in job-related training can help workers aged 50–64 retain high wages.

In this paper, we investigate the relationship between technological improvements and wage structure across different age groups using the sample of 28 European Union (EU) countries and 2 advanced Asian countries, Japan and the Republic of Korea. We examine which age group (young, middle-aged, or older) benefits the most from technological improvements, which encompass (i) capital deepening, (ii) ICT capital deepening, (iii) human capital accumulation, (iv) use of software, and (v) adoption of robot technology. By examining the impact of five different types of technological improvement on wage shares, we can assess which type is most beneficial for older workers.

We find that higher education attainment is beneficial for both middle-aged and older workers but more so for the former. This is especially true for female workers. When we divide capital into ICT and non-ICT capital, we find that increase in the growth rate of non-ICT capital lowers the wage share of older workers but not those of middle-aged workers. This occurs only for male workers. In contrast, an increase in the growth rate of ICT capital does not affect the demographic structure of wage shares regardless of gender. A higher growth rate of intangible software and databases benefit older workers but lowers the wage share of middle-aged workers. This effect is pronounced for male workers. Finally, an increase in the growth rate of installed robots is beneficial for older workers but lowers the wage share of middle-aged workers in service industries. This is especially true for male workers. Overall, our evidence indicates that recent technological developments, centered on ICT capital, software, and robots, do not adversely affect older workers. The study most closely linked to our approach is Blanas et al. (2020). They investigated how various types of machines affect the demand for workers of different groups of age, education, and gender in 10 advanced countries. They found that the adoption of software and robots to replace workers who perform routine tasks reduced the demand for low- and medium-skilled young and female workers in manufacturing industries, but raised the demand for older and male high-skilled workers in service industries. There are three main differences with our paper. First, while they look at the demand for workers, we investigate wage share, which also captures changes in the wage rate. Second, while they consider different skill groups of workers, we look at the effects on different age groups and also consider the effects of increasing skill level (education). Finally, we expand the number of sample countries to 30 advanced countries, including 2 advanced Asian countries.

The rest of the paper is organized as follows: section 2 reports the evolution of wage shares of middle-aged and older workers in different industries, section 3 lays out our empirical framework, section 4 discusses our empirical findings, and section 5 concludes.

2. The Evolution of Wage Shares of Middle-aged and Older Workers by Industry

In this section, we report the evolution of wage shares of middle-aged and older workers in different industries. We collect most data from EU KLEMS Release 2019. In the EU KLEMS data set, labor data, including wage shares are broken down into 18 different categories. First, workers are classified by three different age groups—young (aged 15–29), middle-aged (aged 30–49), and older (aged 50 and above) workers. Second, workers are also divided by educational attainment—low- (no formal qualifications), medium- (intermediate), and high-educated (university graduates) workers. Finally, wage shares are also classified by gender. Hence, in total there are 18 (=3×3×2) categories for wage shares.

Therefore, for each age group, there are six sub-categories. These are low-education males, medium-education males, high-education males, low-education females, medium-education females, and high-education females. By summing up across these six sub-categories, we can derive the wage share of an age group. To illustrate the evolution of wage shares of different age groups, Figure 1 illustrates wage shares of middle-aged and older workers averaged across the 30 sample countries. We selected eight major industries—(i) agriculture, forestry, and fishing; (ii) total manufacturing; (iii) construction; (iv) wholesale and retail trade and repair of motor vehicles and motorcycles; (v) information and communications; (vi) financial and insurance activities; (vii) professional, scientific, technical, administrative, and support service activities; and (viii) other service activities.

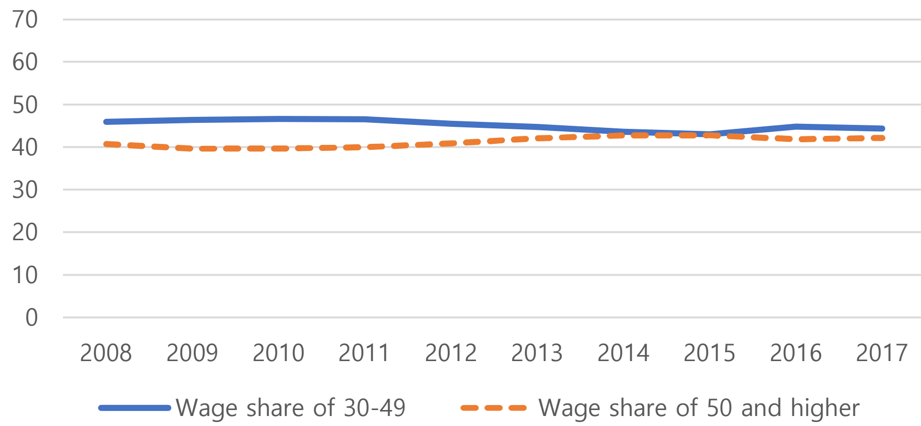
Figure 1(a) shows that the wage share of older workers is comparable to that of middle-aged workers. Both wage shares are over 40, at 41 (older workers) and 46 (middle-aged workers) in 2008. During the sample period, the wage share of older workers increased from 40 to 43 in 2014 and dropped back to 42 in 2017. In contrast, the wage share of middle-aged workers decreased from 46 to 43 in 2014 and rose slightly to 44 in 2017. In other industries, the overall picture is similar except that the wage share of older workers is lower. For example, in Figure 1(b) on the total manufacturing industry, the wage share of older workers is less than 30 and that of middle-aged workers is higher than 50 during the entire sample period. However, even in the total manufacturing industry, the share of older workers increased from 26 to 28 and that of middle-aged workers did not change much.

The gap between the two shares is largest in the information and communications industry, as reported in Figure 1(e). In this industry, the wage share of middle-aged workers is over 60 and that of older workers is lower than 20 during the entire sample period. Even in this industry, however, while the wage share of middle-aged workers remained stable, that of older workers increased from 17 in 2008 to 19 in 2017. Overall, Figure 1 shows that the share of older workers increased, and that of middle-aged workers remained stable during the sample period.

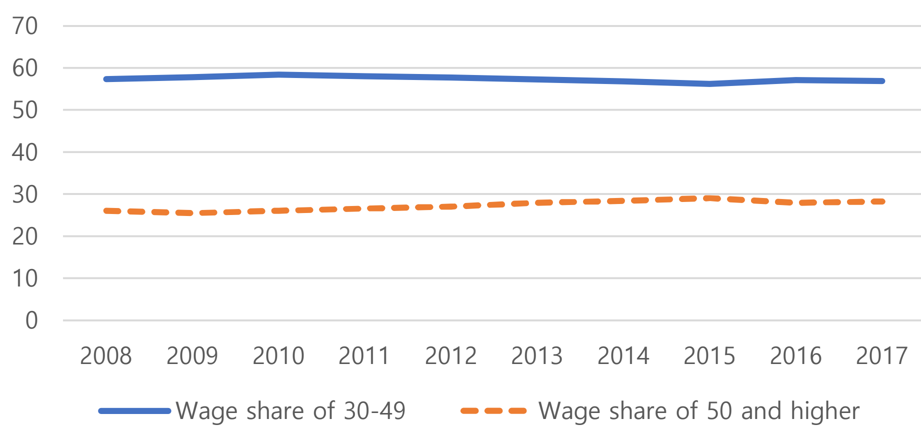
Note that the eight graphs in Figure 1 are averages across the 30 sample countries. While not reported, the shares for individual countries vary substantially. In the empirical analysis, we will utilize cross-country variation that is associated with individual country-specific characteristics of technological progresses.

Figure 1: Average Wages Shares of Middle and Older-age Workers Across Countries for Major Industries

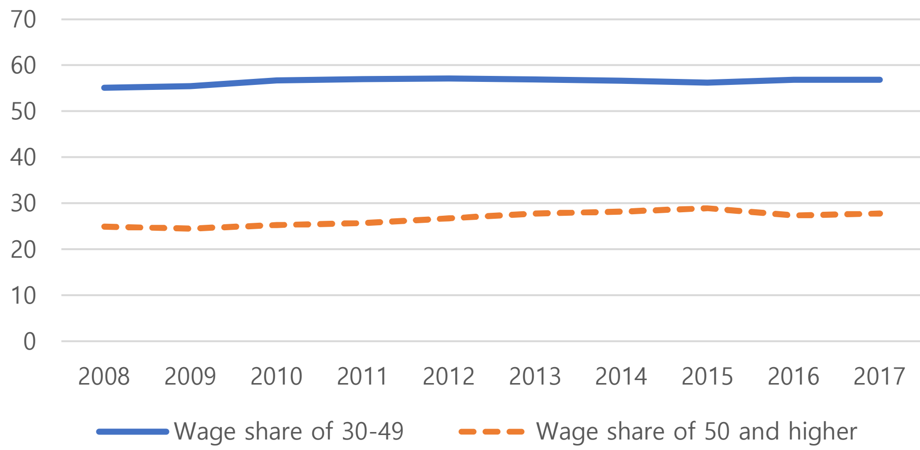
(a) Agriculture, Forestry, and Fishing



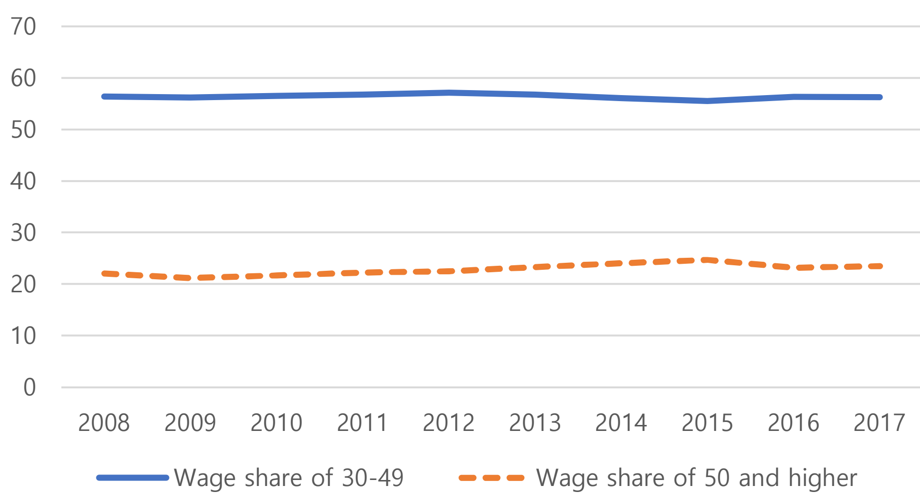
(b) Total Manufacturing

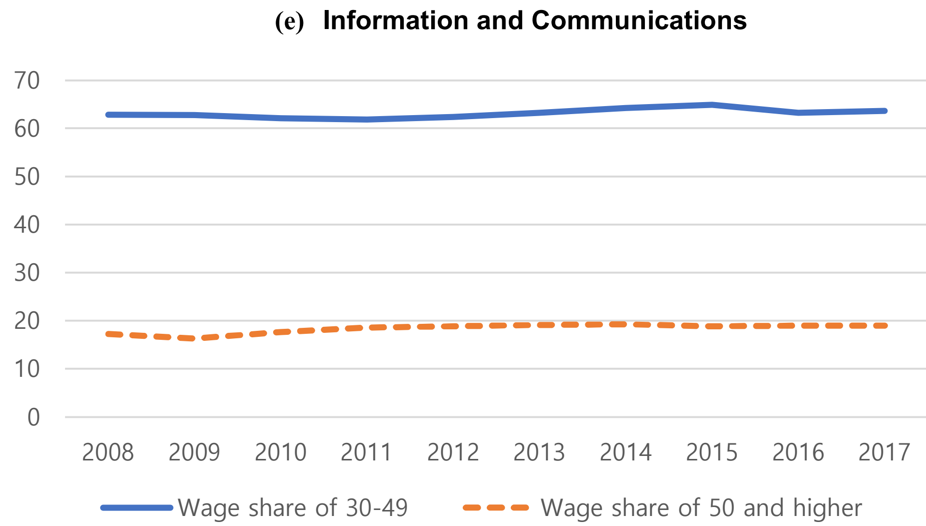


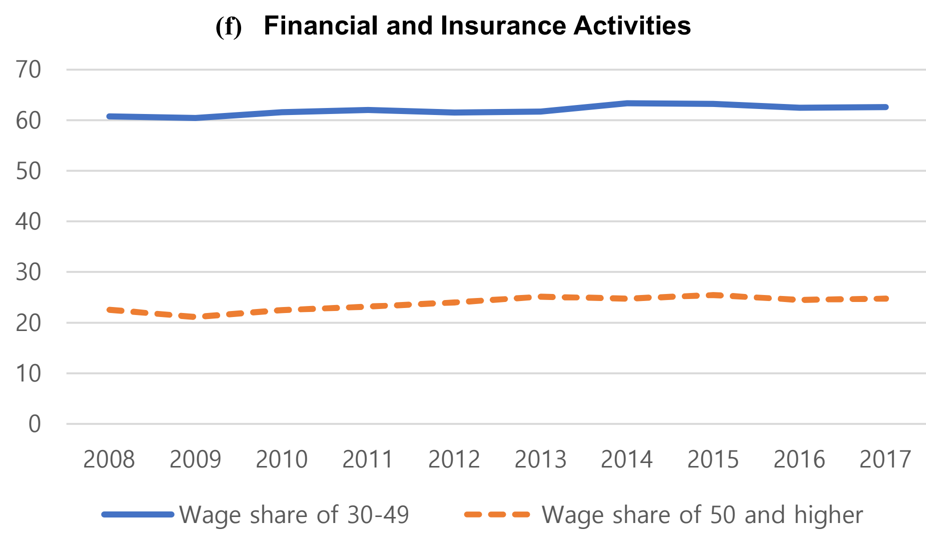
(c) **Construction**



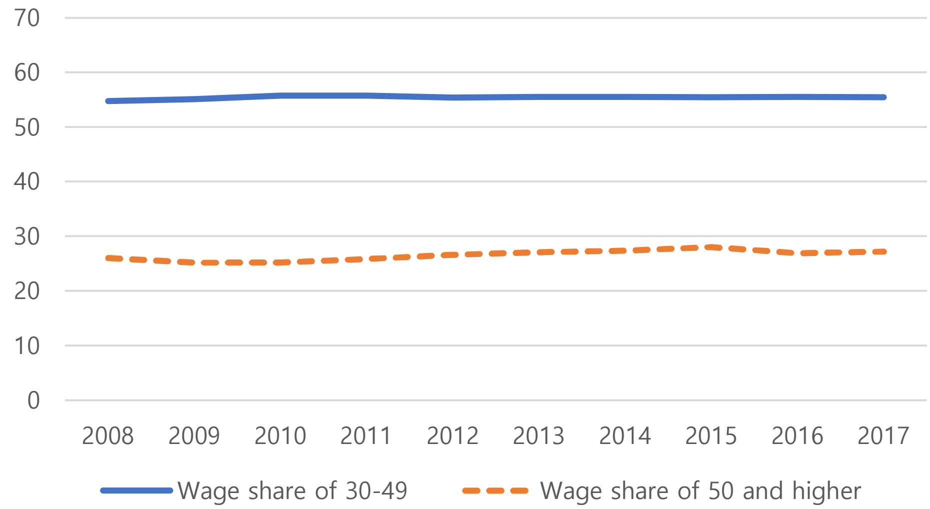
(d) **Wholesale and Retail Trade and Repair of Motor Vehicles and Motorcycles**



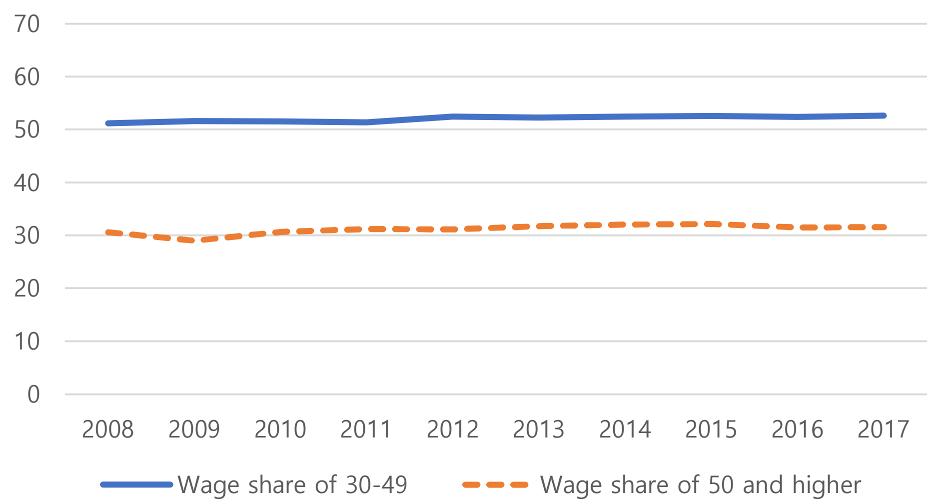

(e) Information and Communications
70
60
50
40
30
20
10
0
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
Wage share of 30-49
Wage share of 50 and higher


(f) Financial and Insurance Activities
70
60
50
40
30
20
10
0
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
Wage share of 30-49
Wage share of 50 and higher

(g) Professional, Scientific, Technical, Administrative, and Support Service Activities



(h) Other Service Activities



Notes: Data are collected from EU KLEMS Release 2019. The sample covers 28 European Union countries and 2 Asian countries, Japan and the Republic of Korea. For each industry, we calculate average shares of middle-aged workers (30–49) and older age workers (50 and higher) across countries.

Source: Authors' calculations.

3. Empirical Framework

In this section, we lay out our empirical framework. To investigate the impact of technological progresses on different age groups, we assume that a representative firm in industry i in country c minimizes a translog cost function:[5]

$$lnCost_{it}^{c} = b_0 + \sum_{a=1}^{A} \alpha_a \ln(W_{ait}^{c}) + \sum_{a=1}^{A}\sum_{a'=1}^{A} \beta_{aa'} \ln(W_{ait}^{c}) \ln\left(W_{a'it}^{c}\right) + \beta_K \ln(K_{it}^{c})$$

$$+ \textstyle\sum_{a=1}^{A} \beta_{aK} \ln(K_{it}^{c}) \ln(W_{ait}^{c}) + \beta_{VA} \ln(VA_{it}^{c}) + \sum_{a=1}^{A} \beta_{aVA} \ln(VA_{it}^{c}) \ln(W_{ait}^{c}) \qquad (1)$$

where $Cost_{it}^{c}$ is the cost function, K_{it}^{c} is the aggregate capital, and VA_{it}^{c} is the value added, of a representative firm in industry i in country c at time t, and W_{ait}^{c} is the wage rate of labor belonging to age group a in industry i in country c at time t. Note that, from the envelope theorem, we can derive the demand for labor of age group a in industry i in country c at time t, l_{ait}^{c}, which is equal to $\frac{\partial Cost_{it}^{c}}{\partial W_{ait}^{c}}$. However, the demand for labor is highly nonlinear and hence the parameters are not easily estimable. In contrast, we can derive wage shares that can be denoted as linear in parameters. In logarithmic form, $\frac{\partial \ln\,(Cost_{it}^{c})}{\partial \ln\,(W_{ait}^{c})} = \frac{\partial Cost_{it}^{c}}{\partial W_{ait}^{c}} \frac{W_{ait}^{c}}{Cost_{it}^{c}} = l_{ait}^{c} \frac{W_{ait}^{c}}{Cost_{it}^{c}} = WS_{ait}^{c}$, where WS_{ait}^{c} is the static equilibrium

5 Denny and Pinto (1978) provide an example for the derivation of the equations in this study.

wage share of age group a in industry i in country c at time t. Then it is straightforward to derive the wage share as follows:

$$WS_{ait}^{c} = \alpha_a + \sum_{a'=1}^{A} \beta_{aa'} \ln(W_{a'it}^{c}) + \beta_{aK} \ln(K_{it}^{c}) + \beta_{aVA} \ln(VA_{it}^{c}) \quad (2)$$

In this study, the total number of age groups, A, is 3. Since the sum of wage shares of all age groups is equal to 1, there will be restrictions on the parameters. Further, since by symmetry, $\beta_{aa'} = \beta_{a'a}$ for all a and a' and by homogeneity, $\frac{dln(WS_{ait}^{c})}{dln\bar{W}} = 1$, where $\bar{W}$ is the common wage rate for all a, i, and c, the following equations hold:

$$\sum_{a=1}^{A} \alpha_a = 1$$

$$\sum_{a=1}^{A} \beta_{aVA} = 1$$

$$\sum_{a=1}^{A} \sum_{a'=1}^{A} \beta_{aa'} = 1$$

By using the restrictions, three equations for $a = 1,2,3$ reduce to two equations for $a = 2,3$ as follows:[6]

$$WS_{ait}^{c} = \alpha_a + \sum_{a'=2}^{A} \beta_{aa'} \ln(W_{a'it}^{c}/W_{1it}^{c}) + \beta_{aK} \ln(K_{it}^{c}) + \beta_{aVA} \ln(VA_{it}^{c}) \quad (3)$$

In the following empirical analyses, we will consider the young-age group as the reference group, i.e., group 1 ($a = 1$).

[6] For example, Aubert et al. (2006).

Since the units of K_{it}^{c} and VA_{it}^{c} may differ across industries and countries, it is still not easy to estimate equation (3). For the empirical analyses, we further take a 2-year difference of equation (2) as follows:

$$WS_{ait+2}^{c} - WS_{ait}^{c} = \sum_{a'=2}^{A} \beta_{aa'} \left(\ln\left(\frac{W_{a'it+2}^{c}}{W_{1it+2}^{c}}\right) - \ln\left(\frac{W_{a'it}^{c}}{W_{1it}^{c}}\right) \right) + \beta_{aK}(\ln(K_{it+2}^{c}) - \ln(K_{it}^{c}))$$

$$+\beta_{aVA}(\ln(VA_{it+2}^{c}) - \ln(VA_{it}^{c})) + \mu_c + \delta_i + \varepsilon_{ait} \qquad (4)$$

Note that we take a 2-year difference instead of a 1-year difference to capture the medium- to long-term trend. In the next section, we will estimate various forms of equation (4). Note that we also add three additional terms - μ_c and δ_i, which reflect country and industry effects that capture different trends that may remain even after differencing, and ε_{ait}, which captures stochastic measurement errors. In estimating equation (4), we need to address three issues. First, we need to suppress the constant term since the equation is differenced. Second, the error terms ε_{2it} for age group 2 ($a = 2$) and ε_{3it} for age groups 3 ($a = 3$) are likely to be contemporaneously correlated. To address this problem, we adopt seemingly unrelated regressions and estimate equation (4) for age groups 2 and 3 simultaneously. Third, ε_{ait} is likely to be serially correlated[7]. To address this problem, we report clustering standard errors that allow for serial correlations within clusters of observations of the same industry and country.

[7] This is especially true if we add an error term to equation (3) since equation (4) is derived by differencing and hence, affected by both current and lagged error terms of equation (3).

4. Empirical Findings

In this section, we discuss our empirical findings. We report the summary statistics of the data in Table 1. On average, hour shares of young workers are 18.7, 52.0 for middle-aged workers, and 29.3 for older workers and their wage shares are 15.3 (young workers), 54.5 (middle-aged workers), and 30.2 (older workers). The wage share relative to the hour share is highest for middle-aged workers, reflecting a high wage rate, and lowest for young-aged workers, reflecting their low wage rate. The standard deviation of both hour and wage shares of young, middle-aged, and older workers is quite large, indicating that their values vary quite a lot across industries, countries, and years.

Table 1: Summary Statistics

Variables	Count	Mean	SD	Minimum	Maximum
Hour share of young-age workers	2,181	18.71	7.87	3.19	60.83
Hour share of middle-aged workers	2,181	51.98	8.06	20.17	79.41
Hour share of older-age workers	2,181	29.31	9.24	3.61	73.99
Hour share of young-age male workers	2,181	10.47	5.47	1.03	42.32
Hour share of middle-aged male workers	2,181	30.37	12.75	4.91	67.37
Hour share of older-age male workers	2,181	17.62	8.85	1.96	52.01
Hour share of young-age female workers	2,181	8.24	5.81	0.30	37.10
Hour share of middle-aged female workers	2,181	21.61	11.31	0.45	58.42
Hour share of older-age female workers	2,181	11.69	7.69	0.18	45.61
Wage share of young-age workers	2,181	15.30	7.30	1.69	50.89
Wage share of middle-aged workers	2,181	54.47	7.87	19.59	78.23
Wage share of older-age workers	2,181	30.23	9.48	2.73	70.30
Wage share of young-age male workers	2,181	8.96	5.21	0.61	43.68
Wage share of middle-aged male workers	2,181	33.77	13.09	4.86	69.02
Wage share of older-age male workers	2,181	19.37	9.22	2.52	52.50
Wage share of young-age female workers	2,181	6.34	4.90	0.17	31.93
Wage share of middle-aged female workers	2181	20.70	11.18	0.48	61.53

Variables	Count	Mean	SD	Minimum	Maximum
Wage share of older-age female workers	2,181	10.87	7.76	0.14	47.32
Hour share of high-educated workers	2,181	32.74	20.03	1.43	88.40
Hour share of medium-educated workers	2,181	49.10	17.58	3.17	93.27
Hour share of low-educated workers	2,181	18.16	17.06	0.16	95.01
Hour share of high-educated male workers	2,181	16.80	10.39	0.73	61.21
Hour share of medium-educated male workers	2,181	29.77	17.12	1.20	83.68
Hour share of low-educated male workers	2,181	11.89	13.54	0.01	79.62
Hour share of high-educated female workers	2,181	15.94	13.71	0.27	64.99
Hour share of medium-educated female workers	2,181	19.33	12.49	0.84	62.86
Hour share of low-educated female workers	2,181	6.28	7.57	0.01	69.84
△Hour share of young-age workers	2,181	-0.45	2.90	-21.05	24.53
△Hour share of middle-aged workers	2,181	-0.18	3.76	-27.10	30.60
△Hour share of older-age workers	2,181	0.63	3.37	-30.69	21.98
△Hour share of young-age male workers	2,181	-0.19	2.11	-11.72	23.25
△Hour share of middle-aged male workers	2,181	-0.11	3.40	-34.82	21.26
△Hour share of older-age male workers	2,181	0.37	2.83	-30.34	18.78
△Hour share of young-age female workers	2,181	-0.26	1.80	-13.09	11.44
△Hour share of middle-aged female workers	2,181	-0.07	2.50	-14.31	19.83
△Hour share of older-age female workers	2,181	0.26	2.07	-16.66	17.33
△Wage share of young-age workers	2,181	-0.44	2.74	-20.99	21.68
△Wage share of middle-aged workers	2,181	-0.22	4.04	-24.85	35.35
△Wage share of older-age workers	2,181	0.66	3.75	-35.23	19.51
△Wage share of young-age male workers	2,181	-0.20	2.08	-16.71	20.94
△Wage share of middle-aged male workers	2,181	-0.21	3.77	-32.03	24.62
△Wage share of older-age male workers	2,181	0.37	3.34	-33.80	21.55
△Wage share of young-age female workers	2,181	-0.25	1.64	-14.01	12.01
△Wage share of middle-aged female workers	2,181	-0.01	2.61	-14.27	20.55
△Wage share of older-age female workers	2,181	0.29	2.14	-17.11	12.93
△Hour share of high-educated workers	2,181	1.01	3.51	-18.33	24.92
△Hour share of medium-educated workers	2,181	-0.40	4.00	-26.32	42.20
△Hour share of low-educated workers	2,181	-0.61	3.16	-44.76	26.42
△Hour share of high-educated male workers	2,181	0.47	2.74	-18.47	16.06
△Hour share of medium-educated male workers	2,181	-0.08	3.39	-26.59	34.48
△Hour share of low-educated male workers	2,181	-0.32	2.66	-46.05	26.66

Variables	Count	Mean	SD	Minimum	Maximum
△Hour share of high-educated female workers	2,181	0.54	2.43	-12.79	14.88
△Hour share of medium-educated female workers	2,181	-0.31	2.62	-17.81	15.43
△Hour share of low-educated female workers	2,181	-0.29	1.41	-9.94	11.31
Growth rate of value added	2,007	2.05	11.00	-80.54	75.31
Growth rate of capital services	1,438	2.67	6.03	-32.7	37.0
Growth rate of non-ICT capital services	1,437	2.41	5.91	-33.5	37.0
Growth rate of ICT capital services	1,421	5.08	19.4	-89.4	99.0
Growth rate of intangible software and databases capital services	661	-1.58	134.4	-553.7	561.8
Growth rate of robot stock	299	11.6	29.0	-75.4	140.0

△ = change, SD = standard deviation.

Notes: Data are collected from EU KLEMS Release 2019. The sample covers 28 European Union countries and 2 Asian countries, Japan and the Republic of Korea. The sample period is from 2008 to 2017. Young, middle and older age workers refer to those aged 15–29, 30–49 and 50+, respectively. Definitions of high, medium and low-educated workers slightly differ across countries, but generally they refer to college graduates, intermediate and no formal qualifications, respectively. Operational stock of industrial robots at the end of the year Robot stock data are collected from the International Federation of Robots (IFR). Then the robot stock data are constructed by applying the perpetual inventory method with 10% depreciation rate and by equalizing the initial stock value in 1993 to the same-year operational stock provided by the IFR. The growth rate is calculated by log-difference.

Source: Authors' calculations.

On average, there is a decrease over time in both hour (by 0.45) and wage (by 0.44) shares of young workers. Likewise, there is also a decrease over time, on average, in both hour (by 0.18) and wage (by 0.22) shares of middle-aged workers. In contrast, there is an increase in both hour (by 0.63) and wage (by 0.66) shares of older workers. While there are some degrees of difference, how the hour and wage shares move closely suggest that the change in wage shares is likely to reflect the change in hours rather than the wage rate. This is consistent with Aubert et al. (2006), who found that new technologies affect older workers primarily through reduced employment opportunities.

However, to repeat, the standard deviation of changes in both hour and wage shares of young, middle-aged, and older workers is large.

On average, the growth in industry-level value-added service is 2.1% and 2.7% for capital service. When we divide capital into ICT and non-ICT capital, ICT capital grows more than twice as fast as the non-ICT capital. Interestingly, the biennial growth rate of intangible software and database capital services is negative at –1.6%, but its standard deviation is quite large, indicating that it varies a lot across industries, countries, and years. The biennial growth rate of the robot stock is also high at 11.6% and its standard deviation is quite large.

Figure 1 and Table 1 show that during the sample period from 2008 and 2017, if wage rates that can be inferred from changes in wage and hour shares accurately reflect the productivity of workers, there is not much evidence that the productivity of older workers fell over time. This is striking given that on average, the hour share of older workers increased dramatically since most sample economies are aging. In the next tables, we will investigate more formally how technological progress affects different age groups, paying special attention to older workers.

In Table 2, we report the estimation results of equation (4). As noted, we apply the method of seemingly unrelated regressions to two equations where the dependent variables are the change in wage shares of workers aged 30–49 and 50 and above. The estimated results are reported in pairs of columns (1) and (2); (3) and (4); (5) and (6); (7) and (8); (9) and (10); and (11) and (12). We do not include a constant term in the regression but include year dummies in every column. We report both cases where both country and industry dummies are included and where they are not included. In columns (1) to (4), we use all industry classifications listed in the Appendix. In columns (5) to (8), we exclude agriculture and mining industries. In columns (9) to (12), we further exclude public industries—i.e., public administration and defense; health and social work; real estate activities; education; and activities of extraterritorial organizations and bodies. Numbers in brackets are clustering standard errors and ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

In all equations, the estimated coefficients of changes in wage ratios are highly statistically significant. However, the estimated coefficients of the growth rates of capital and value-added service are not statistically significant in any column. Hence, capital accumulation or growth of output per se is not associated with changes in wages shares of different age groups. R-squared values suggest that the fitting of the model is best when we use the third sample where we exclude agriculture, mining, and public industries. Therefore, all the tables henceforth will be based on the third sample.[8]

[8] While not reported, the regression results based on other samples are qualitatively similar.

Table 2: Changes in Wages Shares of Middle-aged and Older-age Workers, by Industry

Variables	(1) Middle	(2) Older	(3) Middle	(4) Older	(5) Middle	(6) Older	(7) Middle	(8) Older	(9) Middle	(10) Older	(11) Middle	(12) Older
△log (wage ratio of middle to older-age workers)	14.2***	-13.9***	14.5***	-13.3***	14.2***	-13.9***	14.5***	-13.3***	14.2***	-13.9***	14.5***	-13.3***
	[1.3]	[1.4]	[1.3]	[1.4]	[1.3]	[1.4]	[1.3]	[1.4]	[1.3]	[1.4]	[1.3]	[1.4]
△log (wage ratio of middle to young-age workers)	9.9***		9.9***		9.9***		9.9***		9.9***		9.9***	
	[1.3]		[1.3]		[1.3]		[1.3]		[1.3]		[1.3]	
△log (wage ratio of older to young-age workers)		4.4***		4.9***		4.4***		4.9***		4.4***		4.9***
		[1.1]		[1.1]		[1.1]		[1.1]		[1.1]		[1.1]
△log (capital services)	-0.5	-1.9	-1.0	-1.5	-0.5	-1.9	-1.0	-1.5	-0.5	-1.9	-1.0	-1.5
	[1.7]	[1.4]	[1.8]	[1.6]	[1.7]	[1.4]	[1.8]	[1.6]	[1.7]	[1.4]	[1.8]	[1.6]
Growth rate of value added	-0.0	0.0	-0.0	0.0	-0.0	0.0	-0.0	0.0	-0.0	0.0	-0.0	0.0
	[0.0]	[0.0]	[0.0]	[0.0]	[0.0]	[0.0]	[0.0]	[0.0]	[0.0]	[0.0]	[0.0]	[0.0]
Sample	1	1	1	1	2	2	2	2	4	4	4	4
Year dummies	√	√	√	√	√	√	√	√	√	√	√	√
Country dummies			√	√			√	√			√	√
Industry dummies			√	√			√	√			√	√
Observations	1,372	1,372	1,372	1,372	1,372	1,372	1,372	1,372	1,372	1,372	1,372	1,372
R-squared	0.156	0.243	0.175	0.255	0.161	0.264	0.183	0.281	0.178	0.292	0.193	0.303

△ = change.

Notes: The dependent variable is the change in wage shares of workers aged 30–49 and 50 and above. We apply the seemingly unrelated regressions to simultaneously estimate columns (1) and (2); (3) and (4); (5) and (6); (7) and (8); (9) and (10); and (11) and (12). We do not include a constant term in the regression. We include year dummies in every column. We also include both country and industry dummies in columns in (3), (4), (7), (8), (11), and (12), and not in columns (1), (2), (5), (6), (9), and (10). In columns (1) to (4), we use all industry classifications listed in the Appendix. In columns (5) to (8), we exclude agriculture and mining industries. In columns (9) to (12), we further exclude public administration and defense, health and social work, real estate activities, education, and activities of extraterritorial organizations and bodies. Numbers in brackets are clustering standard errors and ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Source: Authors' calculations.

In Table 3, to examine the impact of technological progresses on wage shares of different age groups, we introduce human capital accumulation as an additional explanatory variable and divide capital services into ICT and non-ICT capital services.[9] Again, we estimate a pair of equations simultaneously. In columns (1) to (4), we introduce human capital as an additional variable, which is proxied by the increase in hour share of high-educated workers. Whether country and industry dummies are included [columns (3) to (4)] or not [columns (1) to (2)], the estimated coefficients of change in the hour share of high-educated workers are small and not statistically significant. In contrast, when we divide capital services into ICT and non-ICT capital services, whether country and industry dummies are included [columns (7) to (8)] or not [columns (5) to (6)], the coefficient of change in non-ICT capital services is negative and statistically significant for older workers. The estimated coefficients indicate that increase in the growth rate of non-ICT capital services by 1% point lowers the wage share of older workers by 0.036 to 0.038.

Interestingly, our evidence suggests that it is non-ICT capital rather than ICT capital that lowers the wage share of older workers. In the literature, there are studies that emphasize that ICT is not neutral across different age groups but favors younger workers. The main reason is that older workers are less able to adapt to new technologies (Weinberg 2004). Using French firm-level data, Aubert, Caroli and Roger (2006) found that the wage bill share of older workers is lower in innovative firms. However, unlike past

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[9] To justify the empirical specification, we can add education as an additional factor or divide capital into ICT and non-ICT capital in equation (1).

ICT developments, some aspects of recent ICT developments favor physically weaker workers such as older workers. For example, Weinberg (2000) showed that introducing computers, by changing skill requirements and de-emphasizing physical strength, increases the demand for female workers. Our results are consistent with this interpretation of ICT capital.

Table 3: Education, ICT Capital, and Changes in Wage Share of Middle-aged and Older Workers, by Industry

Variables	(1) Middle	(2) Older	(3) Middle	(4) Older	(5) Middle	(6) Older	(7) Middle	(8) Older
△log (capital services)	-0.3	-2.4	-0.6	-2.6				
	[2.3]	[1.8]	[2.6]	[2.0]				
△Hour share of high-educated workers	-0.0	0.0	-0.0	0.0				
	[0.0]	[0.0]	[0.0]	[0.0]				
△log (non-ICT capital services)					1.4	-3.6*	1.3	-3.8*
					[2.2]	[2.0]	[2.5]	[2.3]
△log (ICT capital services)					-0.3	-0.1	-0.1	-0.1
					[0.7]	[0.6]	[0.8]	[0.6]
Growth rate of value added	0.5	-1.0	0.3	-0.8	0.3	-0.9	0.2	-0.7
	[1.2]	[0.9]	[1.3]	[1.0]	[1.2]	[0.9]	[1.3]	[1.0]
Year dummies	√	√	√	√	√	√	√	√
Country dummies			√	√			√	√
Industry dummies			√	√			√	√
Observations	914	914	914	914	903	903	903	903
R-squared	0.187	0.299	0.230	0.334	0.186	0.299	0.229	0.334

△ = change, ICT = information and communication technology.

Notes: The dependent variable is the change in wage shares of workers aged 30–49 and 50 and above, respectively. We include as regressors changes in wage ratios of middle-aged to older workers and middle-aged to young workers in odd-numbered columns, and changes in wage ratios of older to young workers and older to middle-aged workers in even-numbered columns, but their estimated coefficients are not reported. We apply the seemingly unrelated regressions to simultaneously estimate columns (1) and (2); (3) and (4); (5) and (6); and (7) and (8). We do not include a constant term in the regression. We include year dummies in every column. We also include both country and industry dummies in columns in (3), (4), (7), and (8), and not in columns (1), (2), (5), and (6). Numbers in brackets are clustering standard errors and ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Source: Authors' calculations.

In Table 4, we further examine the impact of technological progresses on the wage shares of different age groups by introducing intangible software and database capital services [columns (1) to (4)] and robot stock [columns (5) to (12)] as additional explanatory variables. Whether country and industry dummies are included [columns (3) and (4)] or not [columns (1) and (2)], an increase in intangible software and database capital services lowers the share of middle-aged workers and raises the share of older workers. In contrast, whether country and industry dummies are included [columns (7) and (8)] or not [columns (5) and (6)], an increase in the growth rate of robot stock does not affect the share of middle-aged or older workers with statistical significance. However, if we include only service industries in columns (9) to (12), an increase in the growth rate of robot stock lowers the share of middle-aged workers and raises the share of older workers with statistical significance. Except for column (10), the change in robot stock is statistically significant at the 1% or 5% level. The estimated coefficients imply that an increase in the growth rate of the robot stock by 1% point lowers the wage share of middle-aged workers by 0.008 to 0.015 and raises the wage share of older workers by 0.005 to 0.015. Our results are consistent with recent studies such as Park et al. (2022), which provide empirical evidence that more robot installations make the workplace less physically demanding and thus friendlier to older workers.

Table 4: Software, Robots, and Changes in Wage Share of Middle-aged and Older Workers, by Industry

Variables	(1) Middle	(2) Older	(3) Middle	(4) Older	(5) Middle	(6) Older	(7) Middle	(8) Older	(9) Middle	(10) Older	(11) Middle	(12) Older
△log (capital services)	3.1	-1.2	2.2	-1.6	2.3	-4.2	2.5	-7.8***	0.2	2.1	-0.2	-4.6
	[3.0]	[3.6]	[3.3]	[2.0]	[3.2]	[3.1]	[3.4]	[2.8]	[3.3]	[28.9]	[4.4]	[5.5]
△log (intangible software and databases capital services)	-0.2*	0.2**	-0.2**	0.2*								
	[0.1]	[0.1]	[0.1]	[0.1]								
△log (robot stock)					-0.0	-0.0	-0.0	0.0	-0.8**	0.7	-1.5***	1.5**
					[0.3]	[0.3]	[0.2]	[0.3]	[0.4]	[0.7]	[0.4]	[0.6]
Growth rate of value added	0.3	-1.1	0.6	-1.3	-7.4***	0.7	-4.5***	-0.2	-8.0***	0.3	-7.0***	0.8
	[1.3]	[1.2]	[1.3]	[1.3]	[1.2]	[1.5]	[1.4]	[1.5]	[1.5]	[2.4]	[1.6]	[2.1]
Year dummies	√	√	√	√	√	√	√	√	√	√	√	√
Country dummies			√	√			√	√			√	√
Industry dummies			√	√			√	√			√	√
Observations	412	412	413	413	88	88	88	88	54	54	54	54
R-squared	0.228	0.425	0.331	0.464	0.391	0.417	0.606	0.657	0.380	0.405	0.599	0.683

△ = change.

Notes: The dependent variable is the change in wage shares of workers aged 30–49 and 50 and above. We include as regressors changes in wage ratios of middle-aged to older workers and middle-aged to young workers in odd-numbered columns, and changes in wage ratios of older to young workers and older to middle-aged workers in even-numbered columns, but their estimated coefficients are not reported. We apply the seemingly unrelated regressions to simultaneously estimate columns (1) and (2); (3) and (4); (5) and (6); (7) and (8); (9) and (10); and (11) and (12). We include only service industries in columns (9) to (12). We do not include a constant term in the regression. We include year dummies in every column. We also include both country and industry dummies in columns in (3), (4), (7), (8), (11), and (12), and not in columns (1), (2), (5), (6), (9), and (10). Numbers in brackets are clustering standard errors and ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Source: Authors' calculations.

In Tables 5 and 6 we report the same regression results as in Tables 3 and 4 except that we use shares of middle-aged and older male workers as the dependent variables. These equations can be derived if we divide workers into six age groups ($A = 6$)—young, middle-aged, and older male workers and young, middle-aged, and older female workers. In principle, we need to estimate the six equations simultaneously. But to be consistent with the other tables, we estimate the two most closely related equations—i.e., middle-aged male workers and older male workers—simultaneously. However, following the theoretical specifications, we include all five wage ratios as regressors. For example, when we use the share of middle-aged male workers as a dependent variable, we use the change in the ratio between the wage of middle-aged workers and for the wages of the five other age groups, i.e., young male workers, older male workers, young female workers, middle-aged female workers, and older female workers. The estimated coefficients of these wage ratios are mostly statistically significant but to save space, those estimates are not reported.

Table 5: Education, ICT Capital, and Changes in Wage Share of Middle-aged and Older Male Workers, by Industry

Variables	(1) **Middle**	(2) **Older**	(3) **Middle**	(4) **Older**	(5) **Middle**	(6) **Older**	(7) **Middle**	(8) **Older**
△log (capital services)	1.4	-3.1**	1.4	-3.9**				
	[2.6]	[1.5]	[2.8]	[1.8]				
△Hour share of high-educated male workers	0.2**	0.1**	0.2**	0.1**				
	[0.1]	[0.1]	[0.1]	[0.1]				
△log (non-ICT capital services)					3.1	-3.5**	3.2	-4.3**
					[2.5]	[1.6]	[2.6]	[1.9]
△log (ICT capital services)					-0.3	-0.3	-0.1	-0.3
					[0.7]	[0.6]	[0.8]	[0.7]

Variables	(1) Middle	(2) Older	(3) Middle	(4) Older	(5) Middle	(6) Older	(7) Middle	(8) Older
Growth rate of value added	0.3	-1.3	-0.4	-1.4	-0.1	-1.4*	-0.9	-1.4
	[1.2]	[0.8]	[1.2]	[0.9]	[1.2]	[0.8]	[1.2]	[0.9]
Year dummies	√	√	√	√	√	√	√	√
Country dummies			√	√			√	√
Industry dummies			√	√			√	√
Observations	914	914	914	914	903	903	903	903
R-squared	0.128	0.202	0.163	0.233	0.114	0.195	0.149	0.227

△ = change, ICT = information and communication technology.

Notes: The dependent variable is the change in wage shares of male workers aged 30–49 and 50 and above. We include as regressors changes in wage ratios of middle-aged male workers to young male workers, older male workers, young female workers, middle-aged female workers, and older female workers in odd-numbered columns, and changes in wage ratios of older male workers to young male workers, middle-aged male workers, young female workers, middle-aged female workers, and older female workers in even-numbered columns, but their estimated coefficients are not reported. We apply the seemingly unrelated regressions to simultaneously estimate columns (1) and (2); (3) and (4); (5) and (6); and (7) and (8). We do not include a constant term in the regression. We include year dummies in every column. We also include both country and industry dummies in columns in (3), (4), (7), and (8), and not in columns (1), (2), (5), and (6). Numbers in brackets are clustering standard errors and ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Source: Authors' calculations.

In Table 5, whether country and industry dummies are included [columns (3) to (4)] or not [columns (1) to (2)], the estimated coefficients of change in hour share of high-educated male workers are all positive and statistically significant. However, the estimated coefficients for middle-aged male workers are twice as large as those for older male workers, implying that additional education benefits middle-aged male workers more than older male workers. In line with the results in Table 3, the estimated coefficients of change in non-ICT capital services are negative and statistically significant at the 5% level for the wage share of older male workers. In contrast, the estimated coefficients of change in ICT capital services are not statistically significant for either middle-aged workers or for older male workers.

Table 6 reports the impact of intangible software and database capital services [columns (1) to (4)] and installed robots on middle-aged and older male workers [columns (5) to (12)]. Whether country and industry dummies are included [columns (3) and (4)] or not [columns (1) and (2)], more intangible software and database capital services raises the share of older male workers. In contrast to Table 4, the coefficient of change in intangible software and database capital services is not statistically significant for middle-aged male workers. The estimated coefficients suggest that change in the growth rate of intangible software and databases capital services by 1% point raises the wage share of older male workers by 0.002. In line with the results in Table 4, an increase in the growth rate of the robot stock does not affect the share of middle-aged or older workers with statistical significance in columns (5) to (8). However, if we include only service industries in columns (9) to (12), an increase in the growth rate of the robot stock lowers the share of middle-aged workers and raises the share of older workers with statistical significance when we include country and industry dummies in columns (11) and (12). The estimated coefficients indicate that an increase in the growth rate of robot stock by 1% point lowers the wage share of middle-aged workers by 0.02 and raises the wage share of older workers by 0.017. If we exclude the country and industry dummies, the sign of the coefficients is the same as in columns (9) to (10), but not statistically significant.

Table 6: Software, Robots, and Changes in Wage Share of Middle-aged and Older Male Workers, by Industry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	**Middle**	**Older**	**Middle**	**Older**	**Middle**	**Older**	**Middle**	**Older**	**Middle**	**Older**	**Middle**	**Older**
△log (capital services)	3.9	-5.5***	3.9	-7.2***	0.7	-4.9	-1.0	-9.1***	-1.1	-5.6	-5.7	-4.9
	[3.2]	[1.6]	[3.4]	[1.8]	[2.9]	[3.2]	[3.2]	[3.0]	[3.9]	[4.4]	[5.1]	[6.0]
△log (intangible software and	-0.1	0.2**	-0.1	0.2*								
databases capital services)	[0.1]	[0.1]	[0.1]	[0.1]								
△log (robot stock)					-0.1	0.1	-0.2	-0.0	-0.7	0.8	-2.0***	1.7**
					[0.3]	[0.2]	[0.2]	[0.2]	[0.5]	[0.6]	[0.6]	[0.7]
Growth rate of value added	0.3	-2.4**	-0.7	-2.5**	-7.1***	0.5	-4.3***	-0.2	-7.8***	1.0	-7.0***	2.0
	[1.5]	[1.0]	[1.5]	[1.0]	[1.4]	[1.4]	[1.6]	[1.4]	[2.0]	[2.0]	[2.0]	[1.6]
Year dummies	√	√	√	√	√	√	√	√	√	√	√	√
Country dummies			√	√			√	√			√	√
Industry dummies			√	√			√	√			√	√
Observations	413	413	413	413	88	88	88	88	54	54	54	54
R-squared	0.139	0.291	0.231	0.341	0.347	0.419	0.527	0.622	0.340	0.431	0.545	0.652

△ = change.

Notes: The dependent variable is the change in wage shares of male workers aged 30–49 and 50 and above. We include as regressors changes in wage ratios of middle-aged male workers to young male workers, older male workers, young female workers, middle-aged female workers, and older female workers in odd-numbered columns, and changes in wage ratios of older male workers to young male workers, middle-aged male workers, young female workers, middle-aged female workers, and older female workers in even-numbered columns, but their estimated coefficients are not reported. We apply the seemingly unrelated regressions to simultaneously estimate columns (1) and (2); (3) and (4); (5) and (6); (7) and (8); (9) and (10); and (11) and (12). We include only service industries in columns (9) to(12). We do not include a constant term in the regression. We include year dummies in every column. We also include both country and industry dummies in columns (3), (4), (7), (8), (11), and (12), and not in columns (1), (2), (5), (6), (9), and (10). Numbers in brackets are clustering standard errors and ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Source: Authors' calculations.

Now we turn to the impact of technological progresses on female workers. Tables 7 and 8 are the same as Tables 5 and 6 except that we use shares of middle-aged and older female workers rather than male workers as dependent variables. As in Tables 5 and 6, we estimate the two most closely related equations, middle-aged female workers and older female workers, simultaneously by using the method of seemingly unrelated regressions. We also include as regressors all five wage ratios. The estimated coefficients of these wage ratios are mostly statistically significant but not reported.

In Table 7, whether country and industry dummies are included [columns (3) and (4)] or not [columns (1) and (2)], the estimated coefficients of change in the hour share of high-educated female workers are positive and statistically significant for middle-aged workers but not for older female workers. Hence, the impact of additional education is even stronger for middle-aged female workers than middle-aged male workers. Unlike the results in Table 5, the change in ICT or non-ICT capital services is not statistically significant for both medium-aged and older female workers. Hence, capital accumulation, whether ICT or non-ICT, does not affect the demographic wage structure of female workers.

Table 7: Education, ICT Capital, and Changes in Wage Share of Middle-aged and Older Female Workers, by Industry

Variables	(1) Middle	(2) Older	(3) Middle	(4) Older	(5) Middle	(6) Older	(7) Middle	(8) Older
△log (capital services)	-1.8	-0.4	-2.0	0.3				
	[1.4]	[1.2]	[1.6]	[1.4]				
△Hour share of high-educated female workers	0.4***	0.1	0.4***	0.1				
	[0.1]	[0.0]	[0.1]	[0.0]				
△log (non-ICT capital services)					-0.7	-1.3	-0.9	-0.8
					[1.7]	[1.3]	[1.8]	[1.4]
△log (ICT capital services)					-0.1	0.4	-0.1	0.4
					[0.5]	[0.3]	[0.5]	[0.4]
Growth rate of value added	0.8	0.3	1.3*	0.4	0.5	0.3	1.1	0.5
	[0.7]	[0.5]	[0.8]	[0.6]	[0.8]	[0.5]	[0.9]	[0.6]
Year dummies	√	√	√	√	√	√	√	√
Country dummies			√	√			√	√
Industry dummies			√	√			√	√
Observations	914	914	914	914	903	903	903	903
R-squared	0.222	0.296	0.246	0.325	0.113	0.297	0.143	0.325

△ = change, ICT = information and communication technology.

Notes: The dependent variable is the change in wage shares of female workers aged 30–49 and 50 and above. We include as regressors changes in wage ratios of middle-aged female workers to young female workers, older female workers, young male workers, middle-aged male workers, and older male workers in odd-numbered columns, and changes in wage ratios of older female workers to young female workers, middle-aged female workers, young male workers, middle-aged male workers, and older male workers in even-numbered columns, but their estimated coefficients are not reported. We apply the seemingly unrelated regressions to simultaneously estimate columns (1) and (2); (3) and (4); (5) and (6); and (7) and (8). We do not include a constant term in the regression. We include year dummies in every column. We also include both country and industry dummies in columns in (3), (4), (7), and (8), and not in columns (1), (2), (5), and (6). Numbers in brackets are clustering standard errors and ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Source: Authors' calculations.

Finally, Table 8 reports the impact of intangible software and database capital services [columns (1) to (4)] and installed robots on middle-aged and older female workers [columns (5) to (12)]. If country and industry dummies are not included [columns (1) and (2)], an increase in the growth rate of intangible software and database capital services lowers the wage share of middle-aged female workers with statistical significance. However, its impact on the wage share of older female workers is not statistically significant. In contrast, if country and industry dummies are included [columns (3) and (4)], its impact is not statistically significant for the wage share of both middle-aged and older female workers. We also report the impact of installed robots on the wage shares of female workers when the manufacturing industry is included [columns (5) to (8)] and not [columns (9) to (12)]. Unlike the results for male workers, an increase in the growth rate of the robot stock does not affect the share of middle-aged and older female workers with statistical significance even when the manufacturing industry is excluded. Hence, the impact of robots on the demographic wage share structure of female workers is weak.

Table 8: Software, Robots, and Changes in Wage Share of Middle-aged and Older Female Workers, by Industry

Variables	(1) Middle	(2) Older	(3) Middle	(4) Older	(5) Middle	(6) Older	(7) Middle	(8) Older	(9) Middle	(10) Older	(11) Middle	(12) Older
△log (capital services)	0.6	1.8	-0.5	4.7***	2.0	0.5	4.0***	1.1	2.1	0.8	5.0**	1.3
	[1.7]	[1.5]	[2.1]	[1.6]	[1.7]	[0.9]	[1.3]	[1.3]	[1.6]	[0.9]	[2.2]	[1.4]
△log (intangible software and databases capital services)	-0.2*	0.1	-0.1	0.1								
	[0.1]	[0.1]	[0.1]	[0.1]								
△log (robot stock)					0.1	-0.1	0.3	0.0	-0.2	-0.1	0.2	0.1
					[0.2]	[0.1]	[0.2]	[0.1]	[0.3]	[0.1]	[0.3]	[0.2]
Growth rate of value added	0.4	1.3*	1.3	1.4	-0.2	0.4	-0.3	0.1	-0.6	-0.2	-0.6	-0.3
	[1.0]	[0.8]	[1.1]	[0.9]	[0.7]	[0.4]	[0.7]	[0.4]	[0.8]	[0.5]	[1.0]	[0.5]
Year dummies	√	√	√	√	√	√	√	√	√	√	√	√
Country dummies			√	√			√	√			√	√
Industry dummies			√	√			√	√			√	√
Observations	413	413	413	413	86	86	86	86	53	53	53	53
R-squared	0.233	0.328	0.219	0.355	0.205	0.227	0.296	0.206	0.186	0.083	-0.07	-0.19

△ = change.

Notes: The dependent variable is the change in wage shares of female workers aged 30–49 and 50 and above. We include as regressors changes in wage ratios of middle-aged female workers to young female workers, older female workers, young male workers, middle-aged male workers, and older male workers in odd-numbered columns, and changes in wage ratios of older female workers to young female workers, middle-aged female workers, young male workers, middle-aged male workers, and older male workers in even-numbered columns, but their estimated coefficients are not reported. We apply the seemingly unrelated regressions to simultaneously estimate columns (1) and (2); (3) and (4); (5) and (6); (7) and (8); (9) and (10); and (11) and (12). We include only service industries in columns (9) to (12). We do not include a constant term in the regression. We include year dummies in every column. We also include both country and industry dummies in columns in (3), (4), (7), (8), (11), and (12), and not in columns (1), (2), (5), (6), (9), and (10). Numbers in brackets are clustering standard errors and ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Source: Authors' calculations.

5. Conclusion

While technological progress benefits the aggregate economy, it often has differential effects on the wage shares of different groups of workers. For instance, large empirical literature found that skilled workers benefit more from technological change than unskilled workers because they are better able to learn, adapt to, and benefit from new technologies. In this paper, we empirically investigated whether technological progress has a differential impact on the wage shares of different age groups of workers. Of particular interest to us is whether older workers benefit less from technological change. Older workers are widely viewed as being less savvy with new technologies such as ICT. They also face less incentive to learn new technologies since they have a shorter remaining working life. Therefore, technological progress may have a negative effect on the wage share of older workers. We analyzed data from 30 advanced European and Asian economies and examined the effect of five different types of technological advancement on wage shares of different age groups to better understand the link between technology and demographic structure of wages. Our empirical analysis yielded a number of interesting and significant findings. We found that more education is generally beneficial for both middle-aged and older workers but more so for middle-aged workers, especially for females. When we divided capital into ICT and non-ICT capital, we found that an increase in the growth rate of non-ICT capital lowers the wage share of older workers but not that of middle-aged workers. This is true only for male workers. In contrast, an increase in the growth rate of ICT capital does not affect the demographic structure of wage shares of both male and female workers. These results are somewhat surprising since one might expect older workers to be more comfortable with non-ICT capital than ICT capital. An increase in the growth rate of intangible software and databases is beneficial for older workers but lowers the wage share of middle-aged workers. This is especially true for male workers. Finally, an increase in the growth rate of installed robots is beneficial for older workers but lowers the wage share of middle-aged workers in service industries. Again, this is especially true for male workers.

Overall, our evidence indicated that recent technological developments centered on ICT capital accumulation, software, and robots do not adversely affect older workers. Therefore, our evidence failed to substantiate widespread concerns that technological advances will leave behind older workers, who may be unwilling and unable to adapt to and take advantage of new technologies. Such concerns are especially pronounced in advanced countries that are at the forefront of global population aging. One possible explanation for the lack of a negative impact of technological progress on older workers is that older workers may be more open to and capable of learning new technologies than widely presumed. While our analysis yielded some interesting insights on the nexus between technology and the demographic structure of wages, it is far from definitive and there is plenty of scope for further research. For instance, when data become available, it would be worthwhile to analyze the impact on the wage share of older workers of artificial intelligence and other technologies that have far-reaching effects on the labor market.

Appendix: Industry Classifications

Industry	ISIC rev.4
Agriculture, forestry, and fishing	01–03
Mining and quarrying	05–09
Total manufacturing	10–33
Electricity, gas, steam, and air conditioning supply	35
Water supply; sewerage, waste management, and remediation activities	36–39
Construction	41–43
Wholesale and retail trade, repair of motor vehicles and motorcycles	45–47
Transportation and storage	49–53
Accommodation and food service activities	55–56
Information and communication	58–63
Financial and insurance activities	64–66
Real estate activities	68
Professional, scientific, technical, administrative, and support service activities	69–75, 77–82
Public administration and defense; compulsory social security	84
Education	85
Health and social work	86
Arts, entertainment and recreation	90–93
Other service activities	94–96
Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	97–98

Note: Industry classifications follow EU KLEMS Release 2019.

Source: Authors' compilation.

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Technology and Wage Share of Older Workers

Technological progress may be less beneficial for older workers than younger workers. The authors empirically examine the impact of technological change on the wage share of older workers, using data from 30 countries that are at the forefront of global population aging. They find that recent technological developments centered on information and communication technology, software, and robots do not adversely affect older workers. This suggests that older workers may be more open to learning and adopting new technologies than widely presumed.

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