The Young, the Middle, and the Old: Aging Spillovers in Cities*

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Abstract

This paper estimates the spillover effects of workforce aging on wages through a quasi-experiment featuring retirement age extension in South Korea, which is, particularly notable for its rapid increase in the number of elderly workers. By focusing on local labor markets, we identify the spillover of aging by comparing wages for otherwise similar workers working in cities with different shares of old workers. Our findings indicate that a one percentage point increase in the share of older workers leads to: (i) a one percent decrease in middle-aged workers' wages and (ii) no significant effect on young workers' wages. This result is highly robust to city-level confounding shocks such as exposure to robots, immigration, and the supply of skilled workers. Finally we argue that a model incorporating negative aging spillover provides a plausible explanation for our empirical findings.

JEL classification: E24, J11, J23, R12

Keywords: Aging, Wage, Spillover effect, Local market analysis

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1 Introduction

The aging of the global population is an ongoing demographic trend (Adserà, 2004; Shrestha, 2000) that has significant implications for the labor market and its productivity. For instance, Feyrer (2007) points out that cross-country productivity patterns are strongly correlated with workforce demographics.[1] Therefore, it is crucial to examine the potential negative spillover effects of workforce aging on the labor market outcomes of non-old workers.

The standard competitive labor market model predicts that aging would *lower* old workers' wages but *raise* young workers' wages due to the increase in the relative supply of old workers and hence that the overall effect on the average wage would be indeterminate. Whether the above prediction aligns with the data, however, has not been thoroughly explored in the existing literature, even though it carries significant implications for consumption and savings.[2] This paper aims to fill this void by investigating the possible spillover effects of workforce aging on old and non-old workers' wages across cities in South Korea. Specifically, we explore the extent to which the share of old workers affects the wages of non-old workers in the same city.

We focus on South Korea because it faces two competing demographic forces that make it suitable for our empirical analysis: a visible decline in population growth and a sharp increase in old-aged workers. The Population and Housing Census Report (Statistics Korea, 2022) shows that South Korea's population growth has been in moderate decline, with negative growth rates since 2020. At the same time, the population is rapidly aging as a result of a sharp decline in fertility rates, with Koreans' median age expected to rise the fastest among OECD countries (OECD, 2019).[3] In the labor market, aging is a more challenging problem: Across all regions in South Korea, the share of old workers (aged 55–65) has been increasing from around 15 percent in 2008 to 25 percent in 2020 (Figure 1).

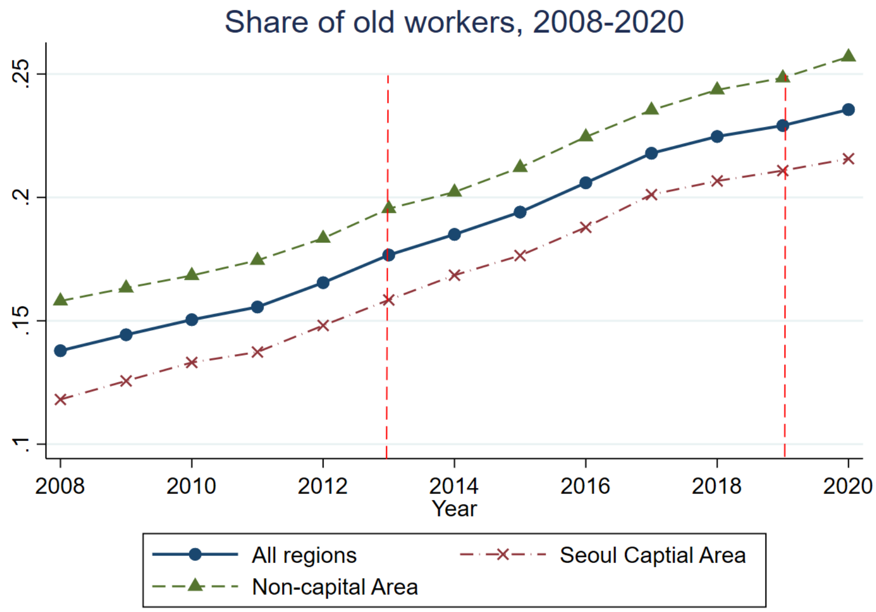
To estimate the spillover from workforce aging, we utilize a cross-city variation based on the premise that a higher *fraction* of older workers in a city may influence the wages of (non-old) workers in the same city. As an exogenous variation, we exploit a policy that delayed mandatory retirement in 2013. In South Korea, until 2013, the traditional retirement age was 55. Due to the reform of the Elderly People Employment Act, the mandatory retirement age was raised to 60 in all public and private sector

[1] This negative association is also found in the U.S. (Maestas, Mullen, and Powell, 2023), Europe (Aiyar and Ebeke, 2016), and Asia (Park, Shin, and Kikkawa, 2021).

[2] For example, Chang, Hong, Karabarbounis, Wang, and Zhang (2022) show that the asset portfolio is heterogenous across workers with different ages and it depends on the labor market status. In addition, the negative effect of aging on the soundness of government budget (Butler and Yi, 2022) can be amplified if the taxable income declines due to aging.

[3] Korea is rapidly approaching an aging society, with the median age rising from 30.7 in 2000 to 43.7 in 2020.

Figure 1: Trend in Share of Old Workers in South Korea 2008-2020



Note: Author's calculations from the Regional Employment Survey.

firms. Actual enforcement of the reform was phased in 2016 for firms with more than 300 employees, and it was later extended to those with fewer than 300 employees in 2017. This delayed mandatory retirement policy has lengthened older workers' employment tenure, leading to a shift in the retirement age for most firms in Korea, which was set at 60 in 2017.

Based on the policy reform, we construct a city-level exposure to the extension of retirement age, the share of workers aged 46 to 48 in 2010 (who were aged 55 to 57 in 2019), and use it as an instrumental variable (IV) to estimate the aging externalities in the labor market. Intuitively, this variable measures the size of birth cohorts who would benefit from the extension of old workers' employment tenure. Our instrument, city-level exposure to policy reform, strongly predicts the change in the share of old workers during 2013–2019 and is not significantly correlated with pre-period (2008–2010) changes in non-old workers' wages.

We first show that workforce aging in Korea has a negative impact on workers' overall wages. Specifically, as the share of old workers rises by 1 percentage point (16 percent), overall wages decrease by 0.76 percent. The negative effect is driven by old (age 55–65) and middle-aged (age 36-–54) workers but there is no significant effect on young workers' wages (age 16–35). This finding is noteworthy because it is inconsistent with the prediction of the standard labor market theory that non-old workers' wages would benefit from workforce aging. The negative effect on old workers' wages is arguably natural due to the increase in their labor supply as more individuals could remain in the workforce beyond the traditional retirement age. Consequently, non-old workers would become relatively scarce in the labor market, and hence their market wage should increase. This finding turns out to be fairly robust; different IVs, altering the age of young workers, controlling for factors potentially affecting wages (immigration, population growth, and changes in skilled workers) do not change the result.

We then argue, à-la Moretti (2004), that the aging spillover effect, which captures various aspects of the negative externality in the labor market in a reduced form manner, can explain our empirical findings. As an example, we may consider capital-experience complementarity (Jaimovich, Pruitt, and Siu, 2013) where capital deepening, which arises from a decline of the capital price (Cummins and Violante, 2002), might direct firms to substitute non-old workers. Firms' endogenous responses to aging through automation (Acemoglu and Restrepo, 2022) could be also captured as a negative spillover effect when young workers do more routine tasks that can be performed by machines. Furthermore, we may think of substitution between old and non-old workers: If old and non-old (especially middle-aged) workers share similar knowledge and experience, the increased share of older workers can put downward pressure on non-old workers' wages because the two types of workers may substitute each other. Moreover, the substitution effect can be further amplified in certain sectors where older workers possess specialized skills or have consumption power. For instance, industries that rely on specific technical expertise or knowledge may prefer retaining or hiring old and experienced workers, potentially crowding out opportunities for younger workers. Additionally, if old workers remain employed, the overall purchasing power in local economies could increase, possibly mitigating the negative effects on workers in non-tradable sectors such as service industries. To this end, we present a simple theory in Section 6 asserting that non-old workers' wages do not increase due to aging when the negative aging spillover effect dominates the supply effect.

The main contribution of our paper is twofold. First, we unveil the causal relationship between aging and (age-specific) wages. Although numerous studies have explored the effect of aging on labor market outcomes, to the best of our knowledge, this paper is the first to study the effects on wages; Acemoglu and Restrepo (2017) examine the effect of aging on economic growth in the context of automation, shedding light on the potential challenges associated with aging workforce.[4] Maestas, Mullen,

[4] Acemoglu and Restrepo (2018) and Acemoglu and Restrepo (2020) also explore the impact of technology, such as automation and robots, on employment and wage inequality. Their research shows the potential displacement of workers by machines, leading to a decline in wages for certain groups.

and Powell (2023) investigate the effect of population aging on economic growth, the labor force, and productivity, providing insights into the broader implications of workforce aging. Bertoni and Brunello (2021) explore the effects of an elevated retirement age on youth employment levels in Italy, revealing that an increase in the retirement age corresponds to a decline in youth employment. Furthermore, Lindh and Malmberg (1999) study the effects of the age structure on economic growth among the OECD countries during the period 1950–1990. Their analysis demonstrates the importance of considering age demographics when studying economic performance. The work that is most closely related to ours is Mohnen (2023), who examines the impact of retirement on the skill composition of young workers. He finds that fewer retirements lead to a decline in high-skill jobs, wages, and job mobility among young workers. Our work instead focuses on how the share of old workers affects non-old workers's wages, even after controlling for individuals' skills and exposure to robots, a factor that can potentially influence the demand for non-old workers disproportionally (Acemoglu and Restrepo, 2020). Furthermore, we employ a policy intervention as a quasi-experiment to uncover spillover effects whereas Mohnen (2023) uses predicted changes in age composition (Bartik-style instrument) for causal interpretation. These methodological distinctions, coupled with differences in the data sources (Korea vs. U.S.), enhance the overall contribution of our study.

Second, our findings provide interesting theoretical and policy implications. Although older workers bring valuable experience and knowledge to the labor market, the increased supply of this demographic group may have implications for the wages of non-old workers. Our results highlight the need to address the potential negative spillover effects on wages, particularly for old and middle-aged workers, as the share of old workers continues to rise. As discussed earlier, the conventional model without considering possible aging spillover might provide incorrect predictions, suggesting that future research needs to incorporate features to generate data-supported predictions on workers' wages. Additionally, by analyzing the substitute relationship between different age groups in the labor market, policymakers can better identify potential challenges and design targeted interventions to mitigate any negative effects on non-old workers' wages. Further, the negative effect on overall wages poses another challenge to the government's budget: In addition to the fact that the number of workers who pay taxes decreases, aging might further hurt the soundness of the government budget because it also lowers tax payers' wages.

The remainder of this paper is organized as follows: In Section 2, we first provide a prediction on the effects of aging on the labor market with the conventional model. Section 3 provides a background of the extension of the retirement age and data for cities across Korea. Section 4 introduces our identification strategy, and then Section 5 presents the empirical results together with several robustness checks. In Section 6, we suggest an alternative model to explain our empirical findings. Finally Section 7 concludes the paper.

2 Effect of Aging on Wages: Predictions from the Standard Model

In this section, we provide a simple model to understand the extent to which the aging of workers affects the wages of employees of different ages (old, middle-aged, and young).[5] The supply of old workers relative to total workers is exogenously given to firms, and hence we focus on a firm's problem in this section. In particular, we consider a firm that produces an output in a perfectly competitive market with the following production function:

$$Y = (\theta_o N_o)^{\alpha_o} (\theta_y N_y)^{\alpha_y}, \tag{1}$$

where subscript o (resp. y) denotes old (resp. non-old) workers, $\theta_i > 0$ is a constant, $N_i > 0$ denotes hours worked, and $\alpha_i \in (0, 1)$ denotes the income share of type $i = o, y$ workers. We assume that $\alpha_y + \alpha_o = 1$.

Throughout this section, we assume that: (1) production technology is given by the Cobb-Douglas function, (2) capital is excluded, and (3) there are only two groups of workers. These assumptions are made to deliver the model's predictions more clearly. Key predictions are preserved when: (1) the CES production function is instead considered, (2) capital is included, and (3) all three types (old, middle-aged, and young) of workers are considered.[6] Particularly, non-old workers include both young and middle-aged workers.

Using the property that the firm will optimize its profit by demanding labor until the wage rate of a worker becomes equal to the marginal productivity of labor, we can obtain the following equation describing the demand function for old workers after taking the first order condition of the firm:

$$\ln w_o = \ln \Theta_o - (1 - \alpha_o) \ln s + \alpha_y \ln (1 - s) - (1 - \alpha_o - \alpha_y) \ln N, \tag{2}$$

where w_o denotes the wage rate of old workers, $\Theta_o \equiv \alpha_o \theta_o^{\alpha_o} \theta_y^{\alpha_y}$, $N \equiv N_o + N_y$, and $s \equiv N_o/N$ denotes

[5] The model is a version of Moretti (2004).

[6] The results are available upon request.

the share of old workers.

Similarly, the demand function for non-old workers is given by:

$$\ln w_y = \ln \Theta_y + \alpha_o \ln s - (1 - \alpha_y) \ln (1 - s) - (1 - \alpha_o - \alpha_y) \ln N, \tag{3}$$

where w_y denotes the wage rate of non-old workers and $\Theta_y \equiv \alpha_y \theta_o^{\alpha_o} \theta_y^{\alpha_y}$.

The implication of the effect of aging on the wage rate of each worker follows:

Proposition 1 (The Effect of Aging on Wages)**.** *Suppose that the production function is given by Equation (1). Then aging of the economy measured by an increase in s* ***lowers*** *old workers' wages while* ***raising*** *non-old workers' wages. Consequently, the effect on the average wage is indeterminate.*

Proof. The effect on age-specific wages is immediate from Equations (2) and (3). Proof of the last part is provided in Appendix A. □

Hence, the conventional model predicts that aging has a negative effect on old workers but a positive effect on non-old workers because the relative supply of old workers increases. As a consequence, the impact on the average wage is uncertain; whether the average wage increases or not depends on whether the positive effect dominates the negative one. In the empirical analysis, we will test if the prediction of the conventional model is supported by data.

3 Institutional Background and Data

In this section, we explain the historical background of the delayed mandatory retirement policy implemented in 2013. We also describe the data used for our empirical analysis and provide some key aspects of the data.

3.1 Background: The Extension of the Retirement Age

In South Korea, in 2013, due to the reform of the Elderly People Employment Act, the mandatory retirement age increased from 55 to 60 years old in all public and private sector firms.[7] The actual enforcement of the reform was in phases:

[7] According to Lee and Cho (2022), the Korean government extended the retirement age for several reasons. Firstly, the declining working-age population necessitated measures to sustain the labor force. Secondly, The reform was directed at safeguarding post-retirement incomes for senior citizens, specifically addressing the significant issue of poverty among them in Korea. Furthermore, the changes were designed to enhance the financial stability of the public pension fund. Thirdly, the extension of the retirement age acknowledged the growing number of healthy seniors desiring to continue working, not only for financial security but also to maintain motivation for a fulfilling life after retirement.

it was implemented in 2016 for firms with more than 300 employees, and later it was extended in 2017 to those with fewer than 300 employees. This means that each firm sets a minimum age requirement of 60 for the termination of the employment relationship. Hence, if employers end the employment agreement before employees turn 60 for a retirement-related reason, it is deemed unlawful.

Since the enforcement of the reform in 2016, the retirement age for most firms in Korea has been set at 60. According to the Establishment Workplace Survey, more than 90% of firms set their retirement age at 60 or higher, while 57% of firms had set their retirement age below 60 before the reform. For instance, in 2013, 23.4% of firms set their retirement at 55, and 22.3% of firms set their retirement age at 58.[8]

As nearly all firms have raised the retirement age, the age structure within firms has significantly altered, not only due to the increased tenure of elderly employees but also due to older workers crowding out the young. For instance, Han (2019) estimates that for every 100 older workers employed owing to the reform, about 20 cases of employment of young workers decreased within a firm. This means that the reform of the retirement age significantly increased the *share* of old workers in the Korean labor market.

Another interesting feature of the reform is that it generates discontinuity inf the retirement age between birth cohorts within firms. Consequently, some cohorts have been able to remain in the labor market longer than earlier cohorts. For instance, consider an employee aged 52 in 2013, working at an establishment with the retirement age at 55. Then, in 2016, one year before the reform was actually enforced for small firms, she would have turned 55 and been required to retire. On the other hand, an employee aged 51 in 2013 would have been 55 in 2017 and would have been employed until 2022. Therefore, depending on the distribution of such advantaged (slightly younger) cohorts, some cities would experience an increase in the share of old workers. We exploit this idiosyncratic variation in the advantaged cohort across cities to estimate the impact of workforce aging on wages. We will discuss the specific form of our instrument in Section 4.2.

3.2 Data: Geography of Workforce Aging in Korean Cities

For our empirical analysis, we mainly use the Regional Employment Survey (RES) of Korea for the years 2008–2019. RES is a biannual survey of households across 162 cities in Korea that provides various individual-level information such as age, gender, educational attainment, employment status, wage, occupation, and industry. Its sample represents those aged 15 or older residing in 231,120 households in 11,556 survey districts nationwide.

[8] See Han (2019) for more details.

From this micro-data, we construct various city-level measures including the share of old workers. Throughout our analysis, we restrict our sample to workers aged between 16 and 65 and exclude those who are in school. We define old workers as workers older than 54 (i.e., age 55–65) because, before the reform, many firms set their retirement age at 55. The geographical unit of analysis is 162 cities of residence across Korea.

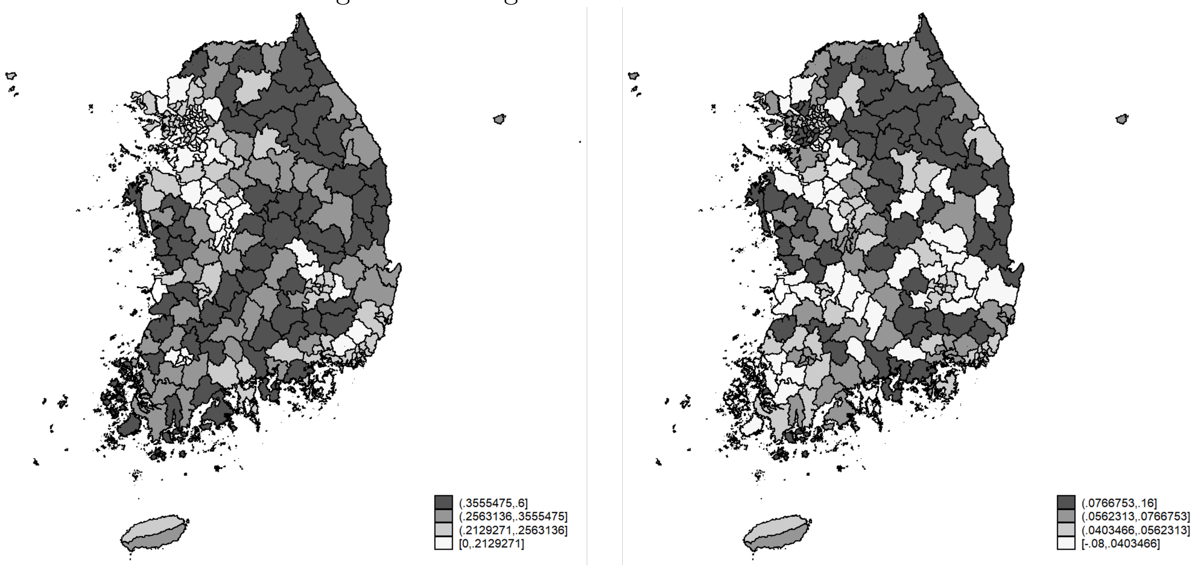
To estimate the impact of workforce aging on non-old workers, we focus on the period between 2013 and 2019. We set the initial year as year 2013 because it is the year of legislation of the policy reform of the retirement age extension in Korea. We do not use the data for the year 2020 and afterwards to remove the potential negative impact of the outbreak of COVID-19. As actual enforcement of the reform was in phases, our analysis measures the short- to medium-term impacts of workforce aging driven by the policy reform.

In Figure 2, we illustrate workforce aging across 162 cities in Korea. The figure on the left shows the share of old workers in 2013, with darker colors indicating larger numbers. In 2013, the average share of old workers across cities is approximately 25%, but there is considerable variation across local areas. For instance, while the share of old workers in some cities exceeds 60% of the workforce, there are cities whose workforce is very young, where the share is less than 15%. We see that many of those young cities are located in the greater Seoul region in general. When we measure the *change* in the share of old workers between 2013 and 2019, in the figure on the right, the average change is 6.4 percentage points (25% increase), with the largest increase of 16 percentage points occurring in the city of Jeongseon, Gangwon province (northeast). Nevertheless, we observe some spatial concentration of workforce aging across cities. Because these spatial concentrations could reflect other local characteristics and shocks that could bias our estimates, we aim to find idiosyncratic variations in workforce aging driven by the policy reform in Section 4.

Next, Table 1 presents the city-level summary statistics for our outcome variables (the regression-adjusted wages) and city-level controls. The city-level regression-adjusted average wage is obtained by conditioning on individual education, gender, and age, following Moretti (2004).[9] Intuitively, this city-specific wage can be viewed as a composition-free wage, as we control for workers' educational attainment. Considerable variation of this city-specific wage can be seen across cities both in 2013 and 2019, and the dispersion becomes larger in 2019. Our first set of control variables includes city-level

[9]Specifically, the regression-adjusted mean wage in city c at time t, $\widehat{\alpha_{ct}}$, is obtained from the following regression: $log(w_{ict}) = \alpha_{ct} + X_{it}\pi_t + u_{ict}$, where X_{it} is a vector of individual characteristics including individual education, gender, and age. This equation is estimated separately for 2013 and 2019.

Figure 2: Changes in the Share of Old Workers



Note: The figure on the left illustrates the spatial distribution for the share of old workers in 2013. The figure on the right illustrates the spatial distribution for the change in the share of old workers from 2013 to 2019. Although the units of observations are cities (n=162), we depict the national map using districts (n=229). We match the regional unit in the map illustration with our unit of observation by assigning the same color to neighboring areas. Source: Regional Employment Survey.

characteristics, all measured in 2013. The average (log) population across cities is 11.11 (about 0.22 million). The mean college graduate share is 24%, and the shares of manufacturing and agricultural employment are 16% and 18%, respectively. The average distance to Seoul, which is intended to control for unobservable characteristics in the greater Seoul region, is about 177 kilometers. These predetermined characteristics likely capture previously ongoing city-level trends that potentially affect the city-specific wages. For instance, the share of college graduates could capture the human capital spillovers from a highly-educated workforce (Moretti, 2004).

We also use two important contemporaneous shocks that control for local demand shifts driven by the initial industrial structure as controls. The standard Bartik index captures exogenous shifts in the local labor demand that are predicted by the initial industry mix (Bartik, 1991). Specifically, the index is constructed as $BIV_c = \sum_s \eta_{sc} \Delta E_s$, where η_{sc} denotes the share of total employment in industry s in city c in 2013, and ΔE_{st} is the national change in the logarithmic value of employment in the same industry between 2013 and 2019. Exposure to robots in Korean cities (Acemoglu and Restrepo, 2020), which is closely related to a demographic change in a country (Acemoglu and Restrepo, 2022), is also similarly constructed: $Robot_c = \sum_s \eta_{sc,2010} \overline{APR_i}$, where $\overline{APR_i}$ represents the adjusted penetration of

Table 1: Summary Statisics

	(1) obs	(2) mean	(3) SD	(4) min	(5) max
Regression-adjusted wage in 2013	162	-0.75	0.08	-0.97	-0.48
Regression-adjusted wage in 2019	162	-0.38	0.75	-0.62	-0.18
(log) population in 2013	162	11.11	1.39	8.50	15.83
Share of college graduates in 2013	162	0.24	0.09	0.11	0.74
Share of manufacturing employees in 2013	162	0.16	0.11	0.02	0.55
Share of agriculture employees in 2013	162	0.18	0.15	0.0009	0.52
Distance to Seoul	162	177.22	107.00	0	477.1
Bartik index	162	0.02	0.05	-0.20	0.34
Exposure to robots	162	0.002	0.006	-0.0001	0.041

Note: This table shows summary statistics of city-level variables from Regional Employment Survey. The city-level regression-adjusted average wage is obtained by conditioning on individual education, gender, and age. The share of those employed in manufacturing and agriculture is based on overall employment.
***p< 0.01, **p< 0.05, *p< 0.1

robots computed in Korea during 2010–2019.[10]

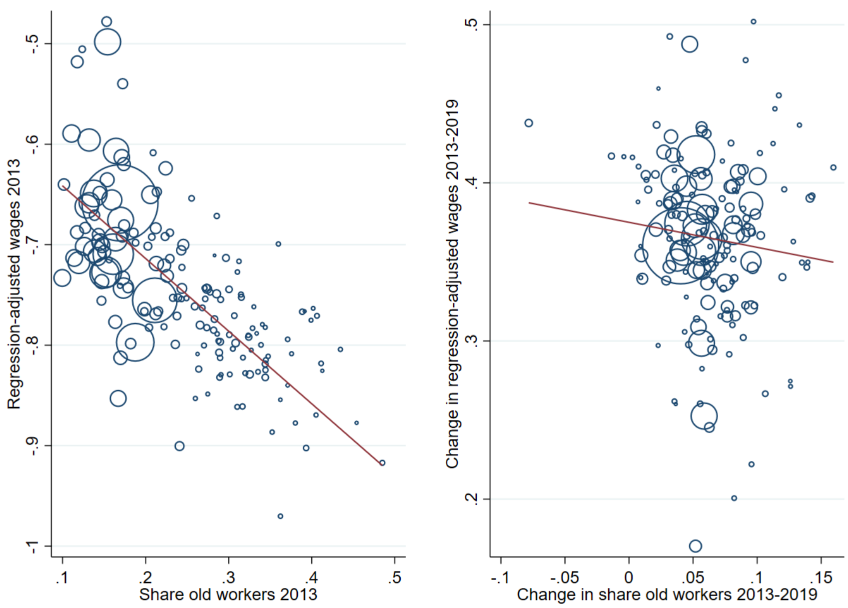
4 Empirical Strategy

4.1 Empirical Specification In this section, we explain our empirical strategy to estimate the spillover effects of workforce aging on non-old workers. Intuitively, we compare otherwise similar individuals who work in cities with different degrees of workforce aging. To do so, following Moretti (2004), we first obtain the regression-adjusted average wage, $\widehat{\alpha_{ct}}$, by conditioning on individual education, gender, and age, and then examine how they vary across cities with different shares of old workers. Figure 3 shows the correlation between the regression-adjusted wage and the share of old workers aged 55 or more out of total employment. The left panel shows the correlation for year 2013, and the right panel plots a similar scatter plot using the changes observed between 2013 and 2019. Both panels of Figure 3 indicate a significant negative correlation between the regression-adjusted wage and the share of old workers. In other words, even after controlling for the individual characteristics, wages are lower in cities with a greater proportion of old workers. However, it is not yet clear whether this association is causal because there are other unobservable characteristics of cities as well as contemporaneous shocks.

To control for those other city-level characteristics and shocks, we estimate the following equation:

[10] The detailed explanation for the construction of this variable is in Acemoglu and Restrepo (2022).

Figure 3: Correlation Between Regression-adjusted Wage and Share of Old Workers



Note: The figure on the left shows the correlation between regression-adjusted wage and the share of old workers in 2013. The figure on the right shows the correlation between the change in regression-adjusted wage and the change in share of old workers during 2013–2019. Regression-adjusted average wage is obtained by conditioning on individual education, gender, and age. The size of the circle represents the local population in 2013. The linear regression fit is weighted by the local population in 2013. The units of observations are cities. Source: Regional Employment Survey.

$$\Delta\widehat{\alpha_{ct}} = \mu + \beta\Delta o_c + \Pi shock_c + \Theta X_c^{2013} + \gamma_{LZ} + \varepsilon_c, \quad (4)$$

where $\Delta\widehat{\alpha_{ct}}$ represents the change in the regression-adjusted wage in city c and Δo_c is the change in the share of old workers (aged 55 to 65) out of the total number of employed individuals (aged 16 to 65). Therefore, the coefficient β measures the percent change in the regression-adjusted wage due to a one percentage point increase in the share of old workers.[11] We include contemporaneous shocks during the period ($shock_c$) as well as predetermined characteristics of cities (X_c) as controls to relieve the concern from the omitted variable bias. The contemporaneous shocks include the robot penetration measure and the standard labor demand shifts in Bartik-style.[12] The city-level characteristics include (log) population, population share of college graduates, share of individuals employed in agriculture and manufacturing, regression-adjusted average wage, all measured as of 2013, and the distance from Seoul. We also include 55 living zone fixed effects to capture aggregate-level trends in average wages.[13] ε_c is the error term.

Although we control for a large set of predetermined economic and geographic variables measured in 2013 as well as some important confounding shocks, there can still be issues that remain owing to unobservable confounding shocks. To address this concern, we exploit the policy reform that significantly benefits certain birth cohorts in Korea.

4.2 Instrument The extension of the retirement age was gradually enforced between 2016 and 2017. Consequently, certain birth cohorts were afforded the opportunity to stay employed for a longer duration than originally expected, in contrast to other cohorts that had to retire earlier. To elaborate, consider an employee who was 52 in 2013. This employee would have had to retire in 2016 because she would turn 55 in 2016. However, another employee who is one year younger (aged 51 years in 2013) would have turned 55 in 2017 and would have been able to remain in the labor force until 2022. Therefore, cities with more workers aged 51 and younger (in 2013) would experience an increase in the share of old workers (aged 55–65).

Therefore, the share of workers aged 49 to 51 in 2013 (who were aged 55 to 57 years in 2019) out of the total working-age (aged 16–65) population in a city will be able to predict the change in the share

[11] A one percentage point increase in the share of old workers is equivalent to a 16 percent increase in that variable.

[12] We also include other contemporaneous shocks as controls to examine the robustness of our findings in Section 5.2.

[13] Living zones are comparable to commuting zones in the United States. They differ from administrative units of regions in that they target residents' actual living area. Living zones consist of 55 zones that encompass all local governments and regions in Korea.

of old workers during 2013–2019. We measure this variable in the year 2010, three years before the reform, which is meant to reduce the correlation with persistent economic factors. Formally, our IV is as follows.

$$IV_c = \frac{age46 - 48_c^{2010}}{L_c^{2010}}, \tag{5}$$

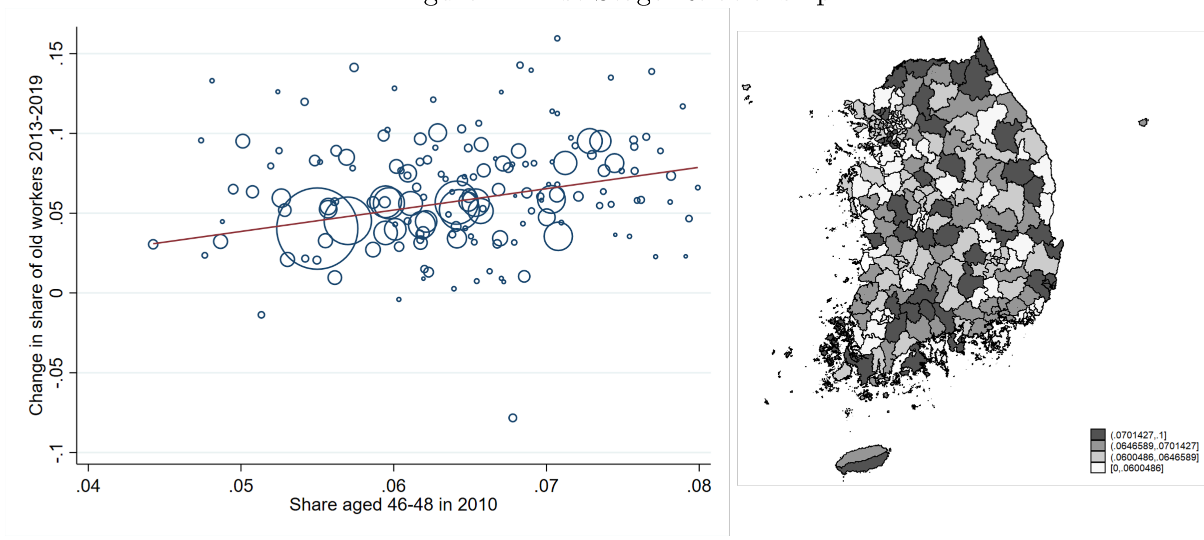
where $age46 - 48_c^{2010}$ is the employment of workers aged between 46 and 48 in city c in 2010, and L_c^{2010} is the working-age population of city c in 2010. Therefore, our IV measures the size of the benefited cohorts relative to the city size. For a robustness check, we also measure this variable in 2008 and examine whether our main results are driven by the choice of a specific year.

Figure 4 shows the spatial distribution of the share of workers aged 46–48 in 2010 and the correlation between our instrument and the change in the share of old workers during 2013–2019. Each circle represents a city, and the straight line indicates the weighted linear fit. The figure already provides a preliminary evidence of a strong positive correlation. It shows no unreasonable outliers, except for one city (Sejong), which is a newly developed city where most of the government institutions were relocated in 2013.[14] Hence, we can partially confirm that the policy reform actually generated an idiosyncratic variation in the change in workforce aging across cities. Moreover, the spatial concentration of our instrument is much weaker than that depicted in Figure 2. We can easily observe that cities with a greater shock (darker color) are sparsely distributed. Therefore, leveraging this variation across cities provides an ideal situation to examine the causal impact of workforce aging on non-old workers' wages.

We present the formal first-stage results in the first three columns of Table 2. The explanatory variable is our instrument, the share of workers aged 46 to 48 in 2010, which captures exogenous variations owing to the policy reform. The dependent variable is the change in the share of old workers during 2013–2019 that corresponds to the y-axis variable in Figure 4. From Columns 1 through 3, we progressively add a variety of controls and shocks, introduced in Section 4.1. All regressions are weighted by working-age population in 2013, and standard errors are clustered by living zone to account for potential correlations across cities within living zones. The coefficients across columns range between 1.1 and 1.3 and are statistically significant at the 1 percent level. For instance, in Column 3, with full controls and fixed effects, a one percentage point increase in the share of workers aged 46 to 48 in 2010 leads to a 1.3 percentage point increase in the share of old workers during 2013–2019. The first stage F-statistics is about 18.

[14] Sejong city shows a 0.8 percentage point decrease in the share of old workers.

Figure 4: First-Stage Relationship



Note: The figure on the left shows the correlation between the instrument (share of workers aged 46 to 48 in 2010) and the change in the share of old workers during 2013–2019. The size of the circle represents the local population in 2013. The linear regression fit is weighted by the local population in 2013. The units of observations are cities. The figure on the right illustrates the regional variation of the instrument for 229 districts in South Korea. We match the regional unit of the map illustration(n=229) with our unit of observation (n=162) by assigning the same color to neighboring areas. Source: Regional Employment Survey.

Table 2: The Extension of Retirement Age and Workforce Aging

Dependent Variable:	(1) ΔShare of old workers (2013–2019)	(2) ΔShare of old workers (2013–2019)	(3) ΔShare of old workers (2013–2019)	(4) Age 16–35 emp. growth (2013–2019)	(5) Age 36–54 emp. growth (2013–2019)	(6) Age 55–65 emp. growth (2013–2019)
Instrument	1.156***	1.269***	1.268***	3.926**	-4.962***	6.368***
	(0.287)	(0.289)	(0.301)	(1.866)	(1.493)	(1.826)
1st-stage F	16.18	16.41	17.74	-	-	-
Controls in 2013	Yes	Yes	Yes	Yes	Yes	Yes
Bartik		Yes	Yes	Yes	Yes	Yes
Robot		Yes	Yes	Yes	Yes	Yes
$Wage$ in 2013			Yes	Yes	Yes	Yes
Living Zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	162	162	162	162	162	162
R-squared	0.546	0.558	0.558	0.635	0.719	0.750

Note: The explanatory variable (instrument) is the share of workers aged 46 to 48 in 2010. The units of observations are cities. Standard errors in parentheses are heteroskedasticity robust and clustered by 55 living zones. All regressions are weighted by the population aged 16 to 65 in 2013.
***p< 0.01, **p< 0.05, *p< 0.1

Although our primary focus is on the wage impact of workforce aging, in Columns 4 through 6 of Table 2, we also explore the effects of extending the retirement age on the employment of different age groups, and consequently, the proportion of old workers. We use the employment growth of young (age 16–54), middle-aged (age 36–54), and old (age 55–65) workers as our dependent variables. In Columns 4 and 5, a one percentage point increase in our instrument (the share of workers aged 46 to 48 in 2010) leads to a 4 percent increase in the employment of young workers but a 5 percent decrease in that of middle-aged workers. As a result, the impact on the employment of non-old workers is not significant. Extending the retirement age increases the share of old workers mainly through the rise in the employment of old workers, as shown in Column 6.

The identifying assumption for using our instrument is that the share of workers aged 46 to 48 in 2010 is not correlated with unobservable determinants of young workers' wages during 2013–2019. In other words, it affects their wages only through workforce aging during the post-reform period. Although this assumption is certainly not testable, we indirectly test the validity of our instrument by examining whether our instrument is significantly correlated with pre-period (2008–2013) changes in regression-adjusted wages and workforce aging. This test has been suggested in exposure designs such as those using the Bartik instrument (Goldsmith-Pinkham, Sorkin, and Swift, 2020). Table 3 presents the results of these falsification tests. We examine the correlations for four outcome variables in Columns 1 through 4: changes in the regression-adjusted wages of all, young (age 16–35), middle-aged (age 36–54), and old (age 55–65) workers. We include full controls and fixed effects in all columns. All regressions are weighted by working-age population in 2013, and standard errors are clustered by living zone. It is reassuring that the estimated coefficients across columns are not statistically significant. In other words, the variation we rely on is not correlated with our outcome variables' pre-trends. In Column 5, we also check whether the instrument captures the pre-period change in the share of old workers. If our instrument predicts workforce aging due to the reform, it should only capture post-reform change in workforce aging, not that for the pre-reform period. Reassuringly again, our instrument does not predict pre-reform changes in workforce aging, as shown in Column 5. Overall, our falsification checks support the validity of our instrument in estimating the spillover effects of workforce aging on young and middle-aged workers.

Table 3: Falsification Tests

Dependent Variable:	(1) $\Delta Wage$ Overall (2008–2013)	(2) $\Delta Wage$ age 16–35 (2008–2013)	(3) $\Delta Wage$ age 36–54 (2008–2013)	(4) $\Delta Wage$ age 55+ (2008–2013)	(5) ΔShare old workers (2008–2013)
Instrument	-0.665	-0.765	-0.345	1.745	0.661
	(0.777)	(0.737)	(1.046)	(1.168)	(0.470)
Controls in 2013	Yes	Yes	Yes	Yes	Yes
Bartik	Yes	Yes	Yes	Yes	Yes
Robot	Yes	Yes	Yes	Yes	Yes
$Wage$ in 2013	Yes	Yes	Yes	Yes	Yes
Living Zone FE	Yes	Yes	Yes	Yes	Yes
Observations	162	162	162	162	162
R-squared	0.575	0.607	0.462	0.713	0.637

Note: The explanatory variable (instrument) is the share of workers aged 46 to 48 in 2010. The dependent variable is the change in the regression-adjusted wage between 2013 and 2019. The units of observations are cities. Standard errors in parentheses are heteroskedasticity robust and clustered by 55 living zones. All regressions are weighted by the population aged 16 to 65 in 2013.
***p< 0.01, **p< 0.05, *p< 0.1

5 Aging Spillover to Workers in Cities

In this section, we estimate the impacts of workforce aging on the wages of young and middle-aged workers in the local labor market. In doing so, we exploit the predetermined variation in the size of birth cohorts that benefited from the extension of the retirement age.

5.1 Benchmark Results To formally examine how workforce aging affects non-old workers' wages, we estimate Equation (4) using Equation (5) as our instrument. Table 4 shows the results. Column 1 examines wages of all workers. Columns 2, 3, and 4 present estimates for young (age 16–35), middle-aged (age 36–54), and old (age 55–65) workers. Panel A first shows our Weighted Least Square (WLS) estimates for comparison. Consistent with Figure 3, the change in regression-adjusted wages is negatively correlated with the change in old workers (Column 1). This estimate is statistically significant at the 1 percent level, and mostly driven by middle-aged workers (Column 3). This suggests that wages are lower in cities with a higher share of old workers, even after controlling for the local skill composition that may be affected by fewer retirees (Mohnen, 2023). However, as there could be unobservable shocks that attract old workers to cities, this correlation does not necessarily indicate a causal impact.

Panel B of Table 4 shows our Two-Stage Least Square (2SLS) estimates, which are our main results.[15] In Column 1, we also find a negative impact of workforce aging on overall workers. As the share of old workers increases by 1 percentage point (16 percent), the overall wages decrease by 0.6 percent. The 2SLS estimate is larger than the WLS estimate in an absolute sense, suggesting that the change in the share of old workers also captures increased labor demand effects. Our instrument corrects for this endogeneity. The overall negative impact is driven by old and middle-aged workers for whom we find significant negative effects. The negative effect on old workers is expected because of the increase in the labor supply of old workers. It simply shows the decrease in wages along the labor demand curve. However, in Column 3, we also find the negative effect on middle-aged workers' wages, while there is no significant impact on young workers' wages. We can interpret this finding as the negative spillover of workforce aging onto middle-aged workers. This is hard to interpret in the standard labor supply model discussed in Section 2, as the increase in the share of old workers implies a decrease (or at least no change) in the labor supply of non-old workers and hence their wages should increase. We present the mechanism of this effect with a formal but simple model in Section 6.

5.2 Robustness Checks Although we use the policy-driven variation in the increase in the share of old workers and control for a rich set of shocks and fixed effects, there may still be other shocks to cities. It is also possible that our results are driven by certain groups of workers or cities. We relieve these concerns by conducting a series of robustness checks. Because our main results are for middle-aged (age 36–54) workers, we perform the robustness checks only for middle-aged workers.[16]

In Columns 1 through 3 of Table 5, we show the robustness of our findings by using a different instrument, redefining the dependent variable, and excluding some observations. We include all controls and shocks that are the same as in Table 4. In Column 1, instead of using the share of workers aged 46 to 48 in 2010, we use the share of workers aged 44 to 46 in cities measured in 2008 as our instrument to further relieve concerns about persistent local economic factors. Although the first-stage power becomes weaker, our estimate on middle-aged workers remains significant. Next, in Column 2, we change our definition of middle-aged workers to those aged 30–50 (instead of 36–54) to see if the results are driven by specific ages. The size of the coefficient is very similar to that in Table 4. In Column 3, we exclude 20 cities with the fastest aging rates. The effect is still consistent.

In the next three columns of Table 5, we further control for other contemporaneous shocks including

[15] We also present the reduced-form estimates in Panel C. These results are similar to those in Panel B.
[16] The results for other groups of workers are similar to Table 4.

Table 4: Effects on Wages

	(1)	(2)	(3)	(4)
Dependent Variable:	$\Delta Wage$ Overall (2013–2019)	$\Delta Wage$ age 16–35 (2013–2019)	$\Delta Wage$ age 36–54 (2013–2019)	$\Delta Wage$ age 55+ (2013–2019)
Panel A: WLS				
ΔShare	-0.321***	-0.131	-0.489***	-0.144
Old Workers	(0.087)	(0.123)	(0.118)	(0.217)
Panel B: 2SLS				
ΔShare	-0.595**	0.219	-1.000***	-1.204**
Old Workers	(0.237)	(0.211)	(0.341)	(0.543)
1st-stage F	17.74	17.74	17.74	17.74
Panel C: Reduced-form				
Instrument	-0.755**	0.277	-1.267**	-1.527**
	(0.339)	(0.348)	(0.525)	(0.660)
Controls in 2013	Yes	Yes	Yes	Yes
Bartik	Yes	Yes	Yes	Yes
Robot	Yes	Yes	Yes	Yes
$Wage$ in 2013	Yes	Yes	Yes	Yes
Living Zone FE	Yes	Yes	Yes	Yes
Observations	162	162	162	162

Note: The dependent variables are the changes in regression-adjusted wages between 2013 and 2019. The explanatory variable in Panels A and B is the change in the share of old workers between 2013 and 2019. The explanatory variable in Panel C is the share of workers aged 46 to 48 in 2010. The units of observations are cities. Standard errors in parentheses are heteroskedasticity robust and clustered by 55 living zones. All regressions are weighted by the population aged 16 to 65 in 2013.
***p< 0.01, **p< 0.05, *p< 0.1

the inflow of immigrants (Column 4), the growth of population (Column 5), and the change in college graduates (Column 6), which are potentially correlated with workforce aging.[17] In all specifications, the estimated effects of workforce aging on middle-aged workers' wages remain stable. Therefore, we conclude that an increase in the share of old workers negatively affects other workers' wages, in particular, prime-aged workers.

Table 5: Robustness Checks for Middle-aged Workers (2SLS)

	(1) Using IV in 2008	(2) Dependent variable: age 30–50	(3) Excluding fastest aging cities	(4) Control: Immigration	(5) Control: Population growth	(6) Control: ΔCollege educated
ΔShare Old Workers	-0.898** (0.442)	-1.046*** (0.308)	-0.987*** (0.342)	-1.041*** (0.310)	-0.986*** (0.363)	-1.353*** (0.332)
1st-stage F	9.79	17.74	24.02	17.54	15.12	9.84
Controls in 2013	Yes	Yes	Yes	Yes	Yes	Yes
Bartik	Yes	Yes	Yes	Yes	Yes	Yes
Robot	Yes	Yes	Yes	Yes	Yes	Yes
$Wage$ in 2013	Yes	Yes	Yes	Yes	Yes	Yes
Living Zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	162	162	142	162	162	162
R-squared	0.786	0.774	0.804	0.781	0.780	0.739

Note: The dependent variables are the changes in regression-adjusted wages between 2013 and 2019. The explanatory variable is the change in the share of old workers between 2013 and 2019. The units of observations are cities. Standard errors in parentheses are heteroskedasticity robust and clustered by 55 living zones. All regressions are weighted by the population aged 16 to 65 in 2013.
***p< 0.01, **p< 0.05, *p< 0.1

5.3 Results by Sector One potential heterogeneity of our results could be that the negative spillover effects of aging on non-old workers vary by tradability of sectors. As old workers remain employed (rather than be retired) in local economies, the overall purchasing power in local economies could increase, potentially mitigating the negative effects on workers in non-tradable sectors (such as service industries). On the other hand, workers in tradable industries (such as manufacturing) would not benefit from the increase in purchasing power.

To measure this sectoral heterogeneity, we estimate the effect of workforce aging on workers in cities

[17] Since directly controlling for the change in college graduates may introduce endogeneity problems, we impute the change in college graduates to control for the change in local human capital. The detailed procedure for this imputation is explained in the Appendix.

by examining two broad sectors: manufacturing and service industries. We measure the regression-adjusted wages for non-old workers (aged 16–54) only to mainly estimate the negative spillover effects. Table 6 shows significant heterogeneity among workers in different sectors. Comparing the 2SLS estimates in the manufacturing (Column 2) and service (Column 4) sectors, the negative effect on non-old workers is twice as much in manufacturing than in service. Specifically, a one percentage point increase in the share of old workers leads to a 1 percent decrease in wages in the manufacturing sector, while it shows only a 0.5 percent decrease in the service sector.

This finding that the negative effect of workforce aging is smaller in the service sector is consistent with the literature on the local employment multiplier such as Moretti (2010) and Moretti and Thulin (2013). As old workers remain employed in the local labor market, the demand for local services increases, and it also raises labor demand in the service sector. This offsets the negative effects of aging, mainly in non-tradable sectors.

Table 6: Effects on Wages by Sector

	(1)	(2)	(3)	(4)
	Manufacturing		**Service**	
	(WLS)	(2SLS)	(WLS)	(2SLS)
ΔShare	-0.061	-1.069**	-0.425***	-0.511*
Old Workers	(0.173)	(0.433)	(0.114)	(0.269)
1st-stage F	17.74	17.74	17.74	17.74
Controls in 2013	Yes	Yes	Yes	Yes
Bartik	Yes	Yes	Yes	Yes
Robot	Yes	Yes	Yes	Yes
$Wage$ in 2013	Yes	Yes	Yes	Yes
Living Zone FE	Yes	Yes	Yes	Yes
Observations	162	162	162	162
R-squared	0.734	0.680	0.712	0.711

Note: The dependent variables are the changes in regression-adjusted wages of denoted sectors between 2013 and 2019. The explanatory variable is the change in the share of old workers between 2013 and 2019. The units of observations are cities. Standard errors in parentheses are heteroskedasticity robust and clustered by 55 living zones. All regressions are weighted by the population aged 16 to 65 in 2013.
***p< 0.01, **p< 0.05, *p< 0.1

6 Inspecting the Mechanism: the Role of Aging Externality

The second part of Proposition 1 in Section 2 is that aging will raise the non-old workers' wages. This is because non-old workers become relatively scarce, and hence the (relative) demand for such workers increases in the model. Consequently, the non-old workers' wage rate should increase without any ambiguity. However, this is inconsistent with the empirical result reported in Table 4 that aging does not have any significant impact on young workers' wages while it can have a significant negative impact on middle-aged workers. This inconsistency suggests that we need an alternative mechanism to explain our empirical findings.

We suggest that aging spillover (or externality) might be a candidate to explain our empirical findings: In particular, we introduce the aging spillover à-la Moretti (2004) into the model discussed in Section 2 and show that our findings can be explained when there is a sizable negative aging externality of older workers on middle-aged workers.

We keep the same assumption on the production function (Equation (1)) but introduce aging externality in the spirit of Moretti (2004). In particular, we now assume that θ_i for $i = y, o$ is not a constant but is governed by the following rule:

$$\ln \theta_i = \phi_i + \gamma_i s, \tag{6}$$

where $i = y, o$ and $\phi_i > 0$ is a constant. In this specification, γ_i measures the extent to which the share of old workers affects the productivity of each type of worker. If $\gamma_i = 0$ for all i, then there is no externality of aging on workers, returning to the model discussed in the previous section. If $\gamma_i > 0$, there is a positive externality: This captures the idea that aging can increase the productivity of type i worker through human capital spillover (e.g., learning from aged (and more experienced) workers), which increases demand for type i worker more than the model discussed in the previous section. Lastly, departing from Moretti (2004), we also allow negative externality; $\gamma_i < 0$ implies that there is a negative spillover effect of aging on type i workers. This captures the possibility that older workers might substitute non-old workers. For instance, capital-experience complementarity (Jaimovich, Pruitt, and Siu, 2013) implies that capital deepening might lead firms to substitute young workers more than a model without negative externality suggests because workers with more experience (i.e., older workers) are relative complements to capital. Similar to Moretti (2004), we assume that $\gamma_o \geq 0$ so that aging cannot have negative spillover on old workers.

Notice that the formula for labor demand is preserved (Equations (2) and (3)) if the firm is assumed to not be endogenizing the externality. However, the effect of aging (s) on the wage is now different at equilibrium due to the spillover effect. The following proposition summarizes the prediction of the model with aging externality.

Proposition 2 (The Effect of Aging on Wages with Aging Spillover)**.** *Suppose that the production function is given by Equation* (1) *and there is an aging externality governed by Equation* (6)*. Then aging of the economy measured by increases in s impacts workers' wages as follows.*

$$\frac{d\ln w_o}{ds} = \alpha_o\gamma_o + \alpha_y\gamma_y - \frac{1-\alpha_o}{s} - \frac{\alpha_y}{1-s}, \tag{7}$$

$$\frac{d\ln w_y}{ds} = \alpha_o\gamma_o + \alpha_y\gamma_y + \frac{\alpha_o}{s} + \frac{1-\alpha_y}{1-s}. \tag{8}$$

Proof. Differentiation of Equations (2) and (3) by taking Equation (6) into account yields the above conditions. □

We first note that $\gamma_o = \gamma_y = 0$ yields a clear prediction, as presented in Proposition 1. For simplicity, let $\Omega_y \equiv \frac{\alpha_o}{s} + \frac{1-\alpha_y}{1-s} > 0$, which measures the effect of aging on non-old workers' wages without aging externality. Different from Proposition 1, we can now obtain the condition to generate a prediction that is consistent with our empirical finding that aging can result in lower wages for non-old workers:

Corollary 1 (Role of Negative Spillover on Non-Old Workers)**.** *Suppose that Proposition 2 holds. Then aging can lower non-old workers' wages when* $\gamma_y < \frac{-\Omega_y - \alpha_o\gamma_o}{\alpha_y} < 0$*. Hence, substantially high negative aging spillover on non-old workers is required.*

Therefore, our model suggests that there is room for introducing negative aging externality to explain the finding that aging can lower non-old workers' wages. Additionally, the non-significant impact of aging on relatively young workers (Column 2 of Table 4) might reflect the fact that there is no significant spillover effect of old workers on young workers (age 16-35).[18]

The above corollary further puts a restriction on the degree of aging externality on old workers (γ_o) to be consistent with the empirical fact:

[18] Or it can be a consequence of the fact that young workers receive much lower wages than middle-aged workers, and hence substitution of young workers with old workers is not necessary for firms to reduce their production costs. In particular, the log wage of young workers is 0.184 and that of old workers is 0.143 whereas that of middle-aged workers is 0.366 in 2019.

Corollary 2 (Restriction on Positive Externality on Old Workers)**.** *Suppose that Proposition 2 holds. Then aging can lower old workers' wages when* $\gamma_o < \frac{\Omega_o - \alpha_y \gamma_y}{\alpha_o}$, *where* $\Omega_o \equiv \frac{1-\alpha_o}{s} + \frac{\alpha_y}{1-s}$ *and* $\Omega_o - \alpha_y \gamma_y > 0$. *Hence, substantially low aging externality on old workers is required to explain our empirical finding that aging lowers old workers' wages.*

7 Conclusion

Workforce aging is a significant demographic trend that has important implications for labor market dynamics. By exploring whether a higher share of old workers generates negative spillover effects on other workers' wages in South Korea, this paper provides further comprehension of how the demographic shift can impact labor market outcomes.

Specifically, by examining data from South Korea, a country that has seen the most rapid increase in its elderly population, we have uncovered compelling evidence indicating that an increased proportion of older workers has adverse effects on both older and middle-aged workers. Interestingly, this phenomenon does not appear to significantly impact younger workers. We also discuss the direction of future theories by showing the importance of considering the spillover effects of aging.

Our findings offer valuable guidance for policymakers in tailoring targeted interventions to mitigate potential adverse repercussions and foster a labor market characterized by fair wage outcomes across age demographics. Furthermore, in the realm of economic forecasting, it may be prudent to adopt a more conservative approach when estimating future national income and budgetary trajectories, especially in terms of revenue generated from taxes. This is because our findings suggest that aging could expedite the strain on the national pension system to a greater extent than initially anticipated.

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A Appendix A. Proof of Proposition 1

To prove the last part of Proposition 1, we define the average wage as $\bar{w} = (w_o N_o + w_y N_y)/N = w_o s + w_y(1-s)$. To examine the effect of population aging (increases in s) on the average wage, we differentiate $\bar{w}$ with respect to s:

$$\frac{d\bar{w}}{ds} = \frac{dw_o}{ds}s + w_0 + \frac{dw_y}{ds}(1-s) - w_y. \tag{9}$$

Since log preserves the sign of the derivatives, $\frac{dw_o}{ds} < 0$ and $\frac{dw_y}{ds} > 0$. Hence, we cannot sign $\frac{d\bar{w}}{ds}$.

B Appendix B. Data Appendix: The Change in the Proportion of College Graduates

To construct the predicted change in the proportion of college-educated workers, we impute the change in the proportion of college graduates from city c between 2013 and 2019 in the following way:

$$\widehat{\Delta H_c} = \sum_a s^a_{c,2013} \cdot \Delta H^a, \tag{10}$$

where the first term $s^a_{c,2013}$ is the share of workers with age a in city c for year 2013, and ΔH^a is the national change in the proportion of college graduates of age a between 2013 and 2019.