Aging Out of Monopsony: Evidence from Korea's Retirement Age Reform

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Abstract

This paper investigates the causal impact of workforce aging on monopsony power in the labor market, exploiting a major legislative reform in South Korea that mandated a minimum retirement age of 60. Using detailed biennial establishment-level panel data, I estimate establishment-level markdowns and implement two-stage least squares (2SLS) regressions with an instrument based on pre-policy retirement ages and industry-region-specific trends in workforce aging. The results show that an increase in the share of workers aged 55 and over significantly reduces markdowns, indicating a weakening of monopsony power. Mechanism analyses suggest that this effect is primarily driven by rising labor costs under Korea's seniority-based wage system, rather than changes in the output elasticity of labor or markups. Moreover, the effects are stronger among establishments that did not adopt offsetting mechanisms such as the wage peak system or the suppression of wage or employment growth for younger workers.

Keywords: Workforce Aging, Retirement Age, Markdown, Monopsony, IV Estimation

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1 Introduction

Aging populations are reshaping labor markets around the world, prompting responsive policies and changes in firm behavior. While considerable attention has been devoted to the challenges and implications of workforce aging, much less is known about how it affects power dynamics between firms and workers. In particular, as wages may be directly and indirectly influenced by shifts in the age composition within firms, a natural question arises: how does an aging workforce affect firms' power in the labor market? This study seeks to address this question by exploring the impact of workforce aging on labor market monopsony.

The notion that firms possess market power in wage-setting, particularly with the increasing concentration of employers in labor markets (Azar et al. (2020); Azar et al. (2022a); Berry et al. (2019); Naidu et al. (2018)), is recently receiving attention in economics. The traditional view of labor market monopsony as a theoretical curiosity or a concept limited to a few company towns in the past is rapidly changing, spurred by various methods to measure the degree of labor market concentration (Ashenfelter et al. (2022)).

Markdown, a concept developed in industrial organization (IO) and labor literature, serves to directly quantify the level of employer market power. It typically represents the discrepancy between the marginal revenue product of labor (MRPL) and workers' wages. In the framework outlined by Yeh et al. (2022), markdown is defined as the ratio between a firm's (or establishment's) MRPL to the wage it pays its workers. In a perfectly competitive labor market, MRPL equals workers' wages, resulting in markdowns of unity. However, when markdowns exceed unity, employers compensate workers less than dollar-for-dollar for each unit of revenue generated at the margin.

Seminal literature in empirical IO and labor economics have developed various methods to estimate markdowns.[1] Notably, Mertens (2022) and Yeh et al. (2022) show that a

[1] Methods to estimate markdowns include additive random utility models (Chan et al. (2024); Lamadon et al. (2022)), monopsonistic competition models (Staiger et al. (2010); and Berger et al. (2022)), differentiated jobs frameworks (Azar et al. (2022b); Card et al. (2018)), and production function estimation methods (Mertens (2022); Yeh et al. (2022)).

firm's markdown can be decomposed into three components: the output elasticity of labor (positively related), the labor share of revenue (negatively related), and the product markup (negatively related). However, specific sources of monopsony have yet to be thoroughly examined. Apart from Casacuberta and Gandelman (2023), which identifies the causal relationship between unionization and markdowns, no study empirically investigates the causes of markdown variation. This study aims to fill this void in the literature by investigating the extent to which workforce aging can affect markdowns, in the context of South Korean manufacturing establishments.[2]

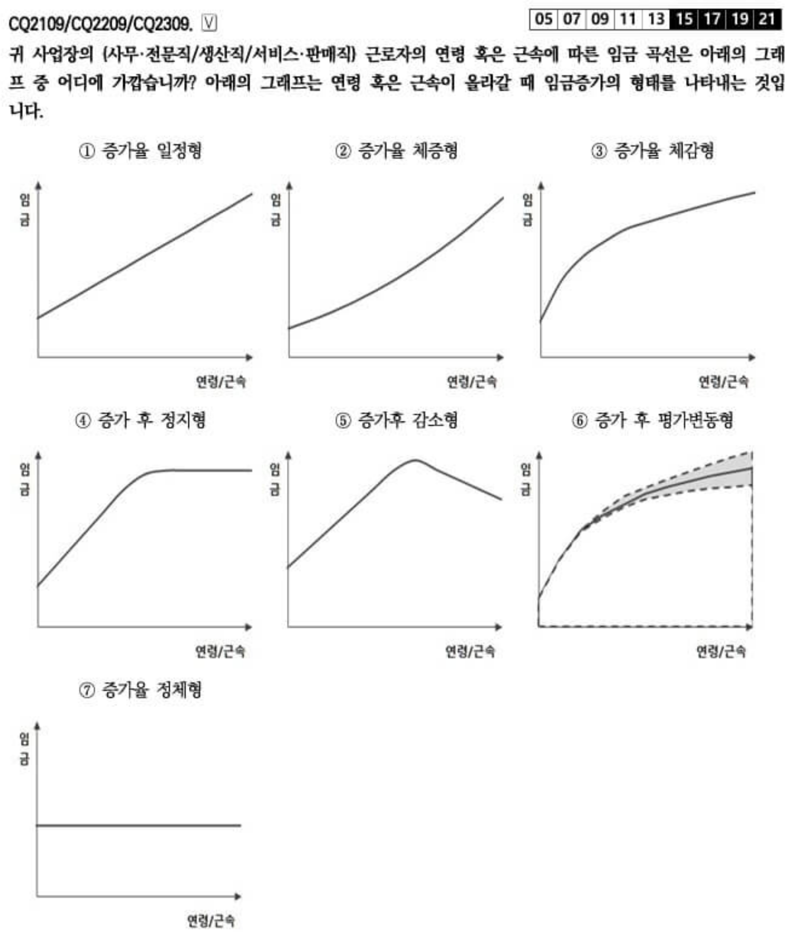
I focus on on the case of Korea for the following reasons. First, it offers a policy background well-suited for causal inference. In response to Korea's rapidly aging population and shrinking working-age labor force, the National Assembly passed a major legislative reform in 2013. The revised law mandated that all establishments set a minimum retirement age of 60. Because many establishments had previously adopted retirement ages in the mid-to-late 50s, the policy induced a substantial shift in establishments' internal age structures, particularly among those with initially lower retirement ages. Therefore, Korea's retirement age extension provides a compelling setting to examine the labor market consequences of an aging workforce while mitigating concerns about endogeneity.

Second, a defining feature of Korea's labor market is its strong reliance on a seniority-based wage system. According to a 2019 report by the Korea Development Institute (KDI)[3], Korea showed the highest wage growth among OECD countries when years of service increased from 10 to 20, with wages rising by 15.1%. Additionally, as shown in Figure 1 and Table 1, the majority of establishments covered by the Workplace Panel Survey (WPS), which I primarily use in this study, exhibit wage profiles that increase with age.

Given this context, I hypothesize that (i) markdowns would decrease more in establishments experiencing larger increases in the share of older workers, due to rising labor shares of revenue under a seniority-based wage system, and (ii) establishments that successfully mitigated rising labor costs would be more likely to preserve their monopsony power. Mech-

[2] I use "South Korea" and "Korea" interchangeably throughout this paper.
[3] https://www.kdi.re.kr/research/focusView?pub_no=18297

Figure 1: Survey Question on Wage Profile Type Category



anisms to offset labor cost pressures from the retirement age reform include the adoption of the wage peak system and the suppression of wage or employment growth for relatively younger workers.

To empirically test these hypotheses, I exploit biennial establishment-level panel data from the Workplace Panel Survey (WPS) to estimate establishment-level markdowns and examine how changes in the share of older workers affect these markdowns. To address potential endogeneity in workforce composition, I implement two-stage least squares (2SLS) regressions. The instrumental variable is constructed using the interaction between the establishment's pre-policy retirement age and industry-region-specific trends in workforce aging.

The results consistently show that increases in the share of workers aged 55 and over

Table 1: Proportion of Establishments by Wage Profile Type

	number of obs.	1,2,3,or 6	4,5,or 7
Production			
proportion in 2014	1,328	0.822	0.178
proportion in 2016	1,114	0.704	0.296
proportion in 2018	1,064	0.728	0.272
proportion in 2020	992	0.735	0.265
Clerical/Professional			
proportion in 2014	1,362	0.818	0.182
proportion in 2016	1,117	0.715	0.285
proportion in 2018	1,092	0.740	0.260
proportion in 2020	1,000	0.753	0.247

significantly reduce markdowns, indicating a weakening of monopsony power. Mechanism analysis reveals that the reduction is driven primarily by an increase in labor's share of revenue under Korea's seniority-based wage system, rather than changes in markups or the output elasticity of labor. Moreover, the effects are stronger among establishments that did not adopt cost-offsetting mechanisms, such as the wage peak system or suppression of wage and employment growth for younger workers. These findings highlight how workforce aging can reduce employer market power in imperfect labor markets, but also emphasize that firm responses can significantly shape the incidence and magnitude of this effect.

The remainder of this paper is organized as follows: Section 2 elaborates on the policy background and data. Section 3 details the markdown estimation procedures and introduces the identification strategy with an IV. Section 4 reports the findings and discusses several potential mechanisms. Finally, Section 4 concludes.

2 Institutional Background and Data

2.A Policy Background

In response to rapid demographic aging and the resulting decline in the working-age population, which necessitated measures to sustain the labor force, the South Korean National Assembly enacted a legislative reform of the Elderly Employment Act in 2013. Prior to the reform, many establishments had adopted retirement ages below 60, often in the mid-to-late 50s. However, the revised legislation mandated that all public and private sector establishments set a minimum retirement age of 60.

Establishments varied in the timing of retirement age extension. The legislative reform stipulated that implementation would be phased: beginning in 2016 for establishments with more than 300 employees and in 2017 for those with fewer than 300. The period between 2013 and the enforcement year (2016 or 2017) served as a preparation phase. Thus, since 2017, it has been unlawful for any firm to terminate employment for retirement-related reasons before age 60 (Lee et al. 2025). Given this timeline, some establishments extended the retirement age during the preparation phase, while others adopted the change exactly in the enforcement year. After the mandatory retirement age of 60 came into full effect in 2016 and 2017, the proportion of establishments with a retirement age below 60 dropped to nearly zero (Han 2019).

Within this policy context where the reform effectively extended the statutory employment duration for older workers, it is reasonable to expect that establishments with a pre-policy retirement age below 60 would see an increase in the employment of older workers after the reform, whereas those with a pre-policy retirement age of 60 or above would experience little to no change. Additionally, in establishments with a pre-policy retirement age below 60, the exogenous shift in workforce age composition was also partly driven by older workers crowding out younger ones. Faced with higher labor costs for older workers following the reform, some establishments responded by reducing their employment of younger workers. For example, Han (2019) estimates that for every 100 older workers retained due to the policy, the number of younger workers within a firm declined by approximately 20. These aspects suggest that the reform significantly increased the share of older workers in the Korean labor market, with the extent of the increase depending on each establishment's pre-policy retirement age. Treating the 2013 legislative reform as an exogenous policy shock, I exploit cross-establishment variation in pre-policy retirement ages to construct an instrumental variable, which is described in detail in Section 3.B.2.

Another notable feature of the reform is that the enforcement of the retirement age extension generated mixed responses from employers with respect to wages. While the reform legally restricted early retirements, some establishments introduced offsetting mechanisms such as the wage peak system, wherein wages are reduced after a certain age in exchange for employment guarantees until retirement. Other firms curbed or even reduced wage growth for relatively younger workers, producing significant negative spillover effects of workforce aging (Lee et al., 2025). In Section 4.C, I examine these heterogeneous institutional responses to dissect the mechanisms through which aging-induced labor supply shifts interact with employer market power.

2.B Data

I primarily use the Workplace Panel Survey (WPS) to estimate markdowns and address the core research questions. Managed by the Korean Labor Institute, the WPS is designed to systematically capture trends in labor demand, employment structure, and labor-management relations in Korea. It is an unbalanced panel dataset at the establishment level, available biennially from 2005 to 2021.[4]

Crucially, the WPS provides establishment-level information essential for this study, including the total number of workers, the number of workers aged 55 and over, the official retirement age, and input and output variables listed under the financial status category, which are necessary for production function estimation.[5] Since the majority of establishments in the

[4] Most information in a given survey year refers to the previous year. For example, variables reported in the 2013 wave reflect conditions in 2012.

[5] From the 2015 wave onward, the dataset includes the number of workers aged 55 and over, as well as

dataset belong to the manufacturing sector and many financial variables are missing for firms outside this sector, I restrict the sample to manufacturing establishments in this research.

Table 2 presents summary statistics on retirement age for every two years, calculated using WPS data. As shown in the table, the average retirement age exhibits a noticeable increase between 2012 and 2014, stabilizing around age 60 with a gradual upward trend thereafter. Similarly, Table 3 reports summary statistics for the share of workers aged 55 and over for post-reform years. The data clearly show a consistent increase in the average share of older workers following the implementation of the reform.

Table 2: Descriptive Statistics of the Retirement Age

	number of obs.	mean	std. dev.	min.	max
rtage in 2008	740	56.73	2.13	45	65
rtage in 2010	815	56.91	2.17	44	69
rtage in 2012	837	57.38	2.33	40	68
rtage in 2014	1,133	59.33	2.22	52	65
rtage in 2016	975	59.82	1.86	55	67
rtage in 2018	979	59.97	1.61	55	65
rtage in 2020	926	60.12	1.45	55	70

Notes: The units of observation are establishments. The sample is restricted to establishments in the manufacturing industry.

3 Empirical Strategy

3.A Markdown Estimation

I follow the markdown estimation framework developed by Yeh et al. (2022), which is based on the ”proxy variable” production functions estimation methods (Olley and Pakes (1996); Levinsohn and Petrin (2003); De Loecker and Warzynski (2012); Ackerberg et al.

those under 35. Prior to 2015, it provides the number of workers aged 50 and over, and those under 30.

Table 3: Descriptive Statistics of the Share of Workers Aged 55 and Older

	number of obs.	mean	std. dev.	min.	max
55^{+} share in 2014	1,453	0.128	0.139	0	1
55^{+} share in 2016	1,231	0.144	0.153	0	1
55^{+} share in 2018	1,196	0.156	0.157	0	1
55^{+} share in 2020	1,108	0.184	0.173	0	1

Notes: The units of observation are establishments. The sample is restricted to establishments in the manufacturing industry.

(2015)). Although complex, this framework does not rely on many restrictive assumptions, and most importantly, it does not require any assumptions about the sources of monopsony power (Yeh et al. (2022)). From the perspective of attempting to identify the significant driver of labor market power, this framework appears to be well-suited.

Yeh et al. (2022) adopts the typical duality between profit maximization and cost minimization to obtain markdowns, demonstrating that a firm's markdown correlates directly with its perceived elasticity of labor supply.

$$v = \frac{R'(l^*)}{w(l^*)} = \epsilon_s^{-1} + 1 \tag{1}$$

In the above identity (1), $R(l)$ represents revenues where all inputs are evaluated at their optimum except for labor l, $w(l)$ represents wages, and ϵ_s^{-1} indicates the perceived inverse elasticity of labor supply for the firm. The markdown, v, is calculated as the ratio of the marginal revenue product of labor (MRPL) to the wage, or the inverse of the labor supply elasticity plus one.

However, estimating a firm's perceived elasticity of labor supply poses a challenge. Drawing on insights from Hall (1988), De Loecker (2011), and De Loecker and Warzynski (2012), Yeh et al. (2022) employs the "production approach" to derive markdowns. This approach rests on the idea that the output elasticity of an input captures the benefit from an additional unit of that input, while the input's share of revenue reflects its cost. If the wedge (ratio) between them exceeds unity, the marginal benefit surpasses its costs, implying that the firm may be exercising market power, either through output markups or input markdowns (Yeh et al. (2022)). Thus, intuitively, by adjusting the wedge for labor using the wedge for an input that is not subject to any monopsony power—and therefore capturing only market power in output markets—, it becomes possible to isolate the portion of the wedge attributable specifically to labor market power. Expanding on this concept and incorporating certain assumptions, Yeh et al. (2022) subsequently present the following form of the markdown.

$$v_{it} = \frac{\theta^l_{it}}{\alpha^l_{it}} \cdot (u^f_{it})^{-1} = \frac{\theta^l_{it}}{\alpha^l_{it}} \cdot \frac{\alpha^f_{it}}{\theta^f_{it}} \tag{2}$$

With f representing a "flexible input"—a static input free of adjustment costs and not subject to monopsony forces—θ^l_{it} and θ^f_{it} denote firm i's output elasticity of labor l and that of flexible input f, respectively. α^l_{it} and α^f_{it} denote firm i's labor share of revenue and flexible input's share of revenue, respectively. Firm i's product markup, denoted as u^f_{it}, is expressed as a ratio of θ^f_{it} to α^f_{it}. The index t denotes time.

Thus, information on output elasticities and revenue shares is sufficient for constructing markdowns. While revenue shares are directly observable in the data, output elasticities should be estimated. To accomplish this, I estimate production functions using "proxy variable" methods, as outlined by Olley and Pakes (1996), Levinsohn and Petrin (2003), De Loecker and Warzynski (2012), and Ackerberg et al. (2015). Particularly, I rely on standard assumptions from Ackerberg et al. (2015), and follow the steps suggested by Yeh et al. (2022) to estimate parameters for each industry-specific production function.

Specifically, I consider the setting where the log output (y_{it}) is expressed as the sum of the log-transformed translog production function ($f(\mathbf{x}_{it}; \beta)$), productivity ($w_{it}$), and measurement error (ϵ_{it}).[6] The vector $\mathbf{x}_{it}$ contains the first-order, cross, and second-order terms of the log inputs vector $\tilde{\mathbf{x}_{it}} = (l_{it}, k_{it}, m_{it})'$, which comprises labor, capital, and intermediate

[6]The translog specification is selected for the functional form of the production function because it can provide a second-order approximation to any differentiable production function.

input.[7]

$$y_{it} = f(\mathbf{x}_{it}; \beta) + w_{it} + \epsilon_{it} \tag{3}$$

Here, the vector $\mathbf{x}_{it}$ may be endogenous due to the unobserved productivity parameter (Yeh et al. (2022)). Therefore, based on the method proposed by De Loecker and Warzynski (2012), I construct the instrument vector $\mathbf{z}_{it}$ by including the lagged values of all inputs in $\mathbf{x}_{it}$ except capital, in order to obtain consistent production parameters.[8]

Intermediate inputs are designated as the flexible input, which is consistent with the approach of Mertens (2022). Basu (1995), De Loecker and Warzynski (2012), and Yeh et al. (2022) treat materials as the flexible input, supported by Atalay (2014)'s finding that material input prices generally do not vary with quantity. Other studies suggest energy as an alternative flexible input (Kim (2017); Hong (2021); Hong (2022); Hong (2023)). Since intermediate inputs in the WPS data are expected to primarily reflect spending on materials and energy, my choice aligns well with established conventions in the empirical industrial organization literature.

Given this setting and the relevant input and output variables in the WPS dataset, I follow the three steps devised by Yeh et al. (2022) to estimate production function parameters β for each industry-specific production function.[9]

1. Run a third-order polynomial regression of y_{it} on the inputs $\tilde{\mathbf{x}_{it}}$ and interactions, as well as a set of year fixed effects. Obtain nonparametric estimates of log output ϕ_{it} free of measurement error.

2. Construct an estimate of productivity as $\hat{w}_{it}(\tilde{\beta}) = \hat{\phi}_{it} - f(\mathbf{x}_{it}; \tilde{\beta})$ and run a third-order

[7]Although Yeh et al. (2022) distinguishes between materials and energy inputs in the input vector, the WPS data does not provide the necessary information to make this distinction. Intermediate inputs are estimated by subtracting direct production labor costs and direct depreciation expenses from the cost of goods sold. The residual component is expected to primarily reflect spending on materials and energy.

[8]Instead of the lagged value of capital, the current (non-lagged) value of capital is included in $\mathbf{z}_{it}$.

[9]Observations with improperly defined input or output variables (negative, zero, or missing), as well as observations with extreme input values (less than the second percentile or more than the 98th percentile) or extreme share of the flexible input expenditure relative to total cost (less than 0.02 times the mean or more than 50 times the mean), are dropped from the sample.

polynomial regression of $\hat{w}_{it}(\tilde{\beta})$ on $\hat{w}_{it-1}(\tilde{\beta})$ to obtain estimates of productivity shocks $\eta_{it}(\tilde{\beta})$.

3. Obtain estimates $\hat{\beta}$ of the production function parameters β through the GMM system induced by the moment conditions $E(\eta_{it}(\beta) * \mathbf{z}_{it}) = \mathbf{0}$.

As illustrated in the equations (4) and (5) below, output elasticities of labor l and flexible input m can be expressed as a linear function of the inputs $\tilde{\mathbf{x}_{it}}$, combined with β coefficient estimates, under the translog specification (Yeh et al. (2022)). Using the estimated β, it becomes possible to compute output elasticity of labor and materials for establishment i in industry j in year t. I recover the biennial establishment-level markdowns by plugging the calculated output elasticity values into the expression (2).

$$\theta^{l}_{ijt}(\tilde{\mathbf{x}_{it}}, \hat{\beta}) = \hat{\beta}^{jt}_{l} + \hat{\beta}^{jt}_{kl}k_{it} + \hat{\beta}^{jt}_{lm}m_{it} + \hat{\beta}^{jt}_{lo}o_{it} + \hat{\beta}^{jt}_{ll}l_{it} \tag{4}$$

$$\theta^{m}_{ijt}(\tilde{\mathbf{x}_{it}}, \hat{\beta}) = \hat{\beta}^{jt}_{m} + \hat{\beta}^{jt}_{km}k_{it} + \hat{\beta}^{jt}_{lm}l_{it} + \hat{\beta}^{jt}_{mo}o_{it} + \hat{\beta}^{jt}_{mm}m_{it} \tag{5}$$

Table 4: Descriptive Statistics of Markdowns

	# obs.	median	mean	std. dev.
Weight = WPS Weight $\times$ *Employment*				
MD	4,134	1.39	1.66	1.24
MD after 2014	2,466	1.42	1.69	1.16
MD in 2014	351	1.41	1.72	1.36
MD in 2016	700	1.39	1.62	1.03
MD in 2018	695	1.42	1.67	1.06
MD in 2020	720	1.46	1.75	1.25

Notes: The units of observation are establishments. The sample is restricted to establishments in the manufacturing industry. All values are calculated using weights equal to the product of the WPS sampling weights and establishment-level employment.

Table 4 provides the summary statistics of the overall establishment-level markdowns.

All values are calculated using weights equal to the product of the WPS sampling weights and establishment-level employment.[10] The average markdown exceeds unity, indicating that the typical manufacturing establishment operates in a monopsonistic environment, where employers compensate workers less than one-to-one for each unit of revenue generated at the margin. A markdown of 1.66 suggests that a worker earns approximately KRW 600 for every additional KRW 1000 generated. Moreover, there is substantial variation in markdowns across establishments, as evidenced by the large standard deviation values.

To further examine heterogeneity in markdowns, I conduct the variance decomposition process demonstrated in Yeh et al. (2022) and Casacuberta and Gandelman (2023). The natural log transformation of the multiplicative expression for v_{it} in the expression (2) results in equation (6), and applying the variance decomposition yields equation (7).

$$\log(v_{it}) = \log(\theta^l_{it}) - \log(\alpha^l_{it}) - \log(u_{it}) \tag{6}$$

$$\begin{aligned} V(\log(v_{it})) = {} & V(\log(\theta^l_{it})) + V(\log(\alpha^l_{it})) + V(log(u_{it})) \\ & + 2[-COV(\log(\theta^l_{it}), \log(\alpha^l_{it})) - COV(\log(\theta^l_{it}), \log(u_{it})) + COV(\log(\alpha^l_{it}), \log(u_{it})) \end{aligned} \tag{7}$$

Table 5 documents the calculated value and the relative contribution of each component in the equation (7). Consistent with findings from Yeh et al. (2022) and Casacuberta and Gandelman (2023), the variation in markdowns is primarily attributed to variations in output elasticities of labor and labor shares, along with their covariance. In contrast, variations in markups contribute little to markdown variability.

3.B The Impact of Workforce Aging on Markdowns

To examine the causal relationship between the growth in an establishment's share of older workers and its monopsony power in the labor market, I initiate with a simple re-

[10] The sampling weights ensure representativeness of the manufacturing sector, while the inclusion of employment follows the approach of Yeh et al. (2022) and Casacuberta and Gandelman (2023).

Table 5: Variance Decompostion of Markdowns

		Variance	Relative Contribution
Markdown	v_{it}	0.369	1.0000
Elasticity	θ^l_{it}	0.577	1.563
Labor Share	α^l_{it}	0.367	0.995
Markup	u_{it}	0.018	0.049
		Covariance	Relative Contribution
	θ^l_{it},α^l_{it}	0.308	-1.669
	θ^l_{it},u_{it}	-0.009	0.049
	α^l_{it},u_{it}	0.011	-0.060

Notes: The relative contributions are computed by dividing each component's variance by the total variance of markdowns. Additionally, the contributions of covariance terms are adjusted by multiplying them by -2.

gression analysis. The estimation leverages variation in biennial changes in the share of workers aged 55 and over and in markdowns across approximately 400 establishments from 2014 to 2020. I control for a set of establishment-level characteristics that could potentially bias estimation results and incorporate establishment and time fixed effects (or alternatively, industry-by-time and region-by-time fixed effects) to account for unobserved confounding factors. The regressions use weights equal to the product of WPS sampling weights and establishment-level employment, and standard errors are clustered at the establishment level.

However, two major endogeneity concerns remain in this baseline regression framework. First, establishments' decisions to adjust the employment of older workers are unlikely to be random, implying that changes in the 55+ share may be influenced by unobserved and uncontrolled, time-varying, establishment-level confounding factors. Second, reverse causality problem could exist; the age structure of an establishment's workforce and the level of older worker employment may be affected by changes in labor market concentration. To address these endogeneity issues, I employ an instrumental variable approach, which is explained in detail in Section 3.B.2.

3.B.1 Econometric Specification

The regression used in the analysis is presented in equation (8) below,

$$\Delta \ln(MD_{et}) = \beta_0 + \beta_1 \, \Delta \ln(55^{+}share_{et}) + \mathbf{X}_{et}{}'\beta_{\mathbf{2}} + \gamma_e + \delta_t \text{ (or } \nu_{i(e)t} + \mu_{r(e)t}) + \epsilon_{et} \quad (8)$$

where the variable MD_{et} denotes the markdown of establishment e in year $t \in \{2014, 2016, 2018\}$. The dependent variable, $\Delta \ln(MD_{et})$, represents the log change in markdown in establishment e from year t to $t+1$. Similarly, the main independent variable $\ln(55^{+}share_{et})$ signifies the log change in the share of workers aged 55 and over from year t to $t+1$.

The vector of establishment-level controls, denoted as $\mathbf{X}_{et}{}'$, consists of the following variables measured in year t: (log) total sales, (log) cost of goods sold, capital-labor ratio, liability-asset ratio, number of labor unions, share of unionized workers, share of male workers, degree of automation/standardization/task repetitiveness, R&D investment dummy, process innovation dummy, organizational innovation dummy, ratio of regular (permanent) workers, retirement benefit scheme category, and retirement pension scheme dummy. These variables capture key establishment characteristics that are likely correlated with monopsony power. For example, Casacuberta and Gandelman (2023) find a significant negative effect of labor unions on markdowns. Sharma (2023) link monopsony power to gender, while Lehr (2024) and Parra and Marshall (2024) relate it to innovation. Azar et al. (2023) and Bachmann et al. (2022) examine the relationship between monopsony power and the adoption of automation or variation in job tasks.

In addition, the term γ_e denotes establishment fixed effects, which control for the effects of time-invariant establishment-specific factors, and δ_t represents time fixed effects that absorb common shocks in each year. As a robustness check, I also estimate the specification with (two-digit) industry-by-year fixed effects ν_{jt} and (city and province) region-by-year μ_{jt}, in place of year fixed effects. This helps address concerns that unobserved, time-varying industry-level and region-level shocks may bias the estimates.

Given this setup, the coefficient β_1 quantifies the percent change in markdown associated with a one percent increase in the share of workers aged 55 and over, while holding other explanatory variables constant.

3.B.2 Instrumental Variable Approach

To address the remaining concern of endogeneity and enable more robust causal inference, I devise an instrumental variable (IV) for the endogenous 55+ share. Specifically, based on the policy details discussed in Section 2, the IV is defined as:

$$\text{IV}_{et} = \left(\frac{\max(0,\ 60 - rtage_{e,2012}) + 1}{5}\right) \cdot \left(\frac{1}{N_{i(e)r(e)t}} \sum_{e' \in \mathcal{G}_{i(e)r(e)t}} \Delta \ln(55^{+} share_{e't})\right) \quad (9)$$

where $rtage_{e,2012}$ denotes the pre-policy retirement age of establishment e in 2012, $\mathcal{G}_{i(e)r(e)t}$ represents the set of establishments in (two-digit) industry $i(e)$ and (city/province-level) region $r(e)$ to which e belongs, at time t, and $N_{i(e)r(e)t}$ is the number of establishments in group $(i(e), r(e), t)$.

Accordingly, the IV assigns higher predicted aging to establishments that had lower pre-policy retirement ages through the left term.[11] This construction is based on the rationale that pre-policy retirement ages determine differential exposure to the reform: the lower the pre-policy retirement age, the greater the policy intensity and the higher the probability of a post-policy increase in the share of older workers.

The IV also assigns higher predicted aging to establishments belonging to industry-region groups that, on average, experienced greater (log) increases in the share of older workers through the right-hand term. This is based on the idea that establishments within the same industry-region are likely to face similar labor supply conditions, and thus changes in the share of older workers are also likely to be similar within those groups.[12]

[11]I apply the max function because policy intensity is zero for establishments that already had a retirement age of 60 or higher prior to the legislative reform. Additionally, I add 1 to avoid the entire IV becoming zero and normalize the term by dividing by 5 so that it takes the form of a share.

[12]This approach is conceptually similar to methodologies in prior studies that construct IVs based on re-

Crucially, this IV is likely to introduce exogenous variation in the independent variable, as it is unlikely that the introduction of the mandatory retirement age of 60 was anticipated when establishments set their retirement ages prior to 2013. Therefore, given this temporal separation, the correlation between the IV and unobservable determinants of post-policy markdown changes is improbable, conditional on controls.

4 Results

4.A IV First-Stage and Falsification Tests

Table 6 presents the formal first-stage regression results. The explanatory variable is the IV, and the dependent variable is the log change in the 55+ share. Column (1) reports the regression result using only the IV. Columns (2) and (3) sequentially add establishment fixed effects, time fixed effects, and the control variables outlined in Section 3.B.1. Column (4) replaces the time fixed effects with industry-by-time and region-by-time fixed effects. Across all columns, the IV estimates are positive and statistically significant, with the smallest first-stage F-statistic around 50, confirming the instrument's relevance.

The identifying assumption for using the IV is that, conditional on the control variables, the IV affects changes in markdowns solely through changes in the share of workers aged 55 and over. While it is not possible to directly verify this exclusion restriction assumption, I assess the validity of the instrument indirectly by examining whether the IV—or its individual components—is significantly correlated with pre-policy markdown changes over the periods 2006–2008, 2008–2010, and 2010–2012.

First, as shown in regression equations (10) and (11), I regress pre-policy changes in markdowns on either the full IV or its shift component. Specifically, I examine whether eight-year lagged changes in markdowns during the pre-policy periods (2006, 2008, and 2010) are significantly associated with the IV or the shift component. The results reported in Table 7 reassuringly show no meaningful relationship between either the IV or the shift term and

gional labor supply conditions (e.g., Dustmann et al. 2005; Cortes 2008; Parrotta et al. 2014).

Table 6: First-Stage Regression

Dependent Variable: $\triangle \ln(55^{+} share_{et})$	(1)	(2)	(3)	(4)
IV_{et}	1.245***	1.230***	1.211***	1.104***
	(0.111)	(0.156)	(0.140)	(0.155)
Estab FE		✓	✓	✓
Time FE		✓	✓	
Controls			✓	✓
Industry-Time FE				✓
Region-Time FE				✓
F-Stat	124.76	69.22	74.89	50.66
Obs.	1,144	998	998	991

*p < 0.10, **p < 0.05, ***p < 0.01

pre-policy changes in markdowns, supporting the plausibility of the exclusion restriction.

$$\Delta \ln(MD_{e(t-8)}) = \beta_0 + \beta_1 \, IV_{et} + \mathbf{X}_{e(t-8)}{'}\beta_{\mathbf{2}} + \gamma_e + \delta_t + \epsilon_{et} \tag{10}$$

$$\Delta \ln(MD_{e(t-8)}) = \beta_0 + \beta_1 \frac{1}{N_{i(e)r(e)t}} \sum_{e' \in \mathcal{G}_{i(e)r(e)t}} \Delta \ln(55^{+} share_{e't}) + \mathbf{X}_{e(t-8)}{'}\beta_{\mathbf{2}} + \gamma_e + \delta_t + \epsilon_{et} \tag{11}$$

Second, as highlighted in regression equation (12), I regress pre-policy changes in markdowns on the 2012 retirement age interacted with time dummies. Specifically, $t \in 2006, 2008, 2010$, with k_1 and k_2 denoting the included years and k_3 serving as the omitted baseline year. Since the core identifying variation for IV exogeneity stems from the pre-policy retirement age in 2012, I test whether this variation is significantly correlated with markdown changes in the years preceding the policy by interacting $rtage_{e,2012}$ with time indicators for 2006, 2008, and

Table 7: IV Falsification Test 1

Dependent Variable: $\triangle \ln(MD_{e(t-8)})$	(1)	(2)	(3)	(4)
IV_{et}	0.002	0.092		
	(0.093)	(0.156)		
$Shift$			-0.001	0.084
			(0.088)	(0.142)
Controls	✓	✓	✓	✓
Estab FE	✓	✓	✓	✓
Time FE	✓		✓	
Industry-Time FE		✓		✓
Region-Time FE		✓		✓
Obs.	329	317	329	317

*p < 0.10, **p < 0.05, ***p < 0.01

2010. Reassuringly, the coefficient estimates reported in all columns of Table 8 are statistically insignificant, regardless of which combination of time dummies is used.[13] Overall, the variation underpinning the IV does not appear to correlate with pre-trends in markdowns.

$$\Delta \ln(MD_{et}) = \beta_0 + \sum_{k\in\{k_1,k_2\}} \beta_k \cdot (\mathbb{I}\{t=k\} \times rtage_{e,2012}) + \mathbf{X}'_{et}\beta_{\mathbf{2}} + \gamma_e + \delta_t + \epsilon_{et} \quad (12)$$

4.B 2SLS Results

The main 2SLS results, capturing the causal effects of workforce aging on markdowns, are presented in Table 9. Across all columns, which incorporate different combinations of fixed effects and control variables, the results consistently show a statistically significant de-

[13]Columns 1 through 3 each present the results when only one time dummy is used in the interaction. Column 4 displays the results when $k_1 = 2006$ and $k_2 = 2008$.

Table 8: IV Falsification Test 2

Dependent Variable: $\triangle \ln(MD_{e(t)})$	(1)	(2)	(3)	(4)
$rtage_{e2012} \times \mathbb{I}\{t = 2006\}$	0.023			0.003
	(0.023)			(0.027)
$rtage_{e2012} \times \mathbb{I}\{t = 2008\}$		-0.039		-0.038
		(0.027)		(0.031)
$rtage_{e2012} \times \mathbb{I}\{t = 2010\}$			0.021	
			(0.026)	
Controls	✓	✓	✓	✓
Estab FE	✓	✓	✓	✓
Industry-Time FE	✓	✓	✓	✓
Region-Time FE	✓	✓	✓	✓
Obs.	649	649	649	649

*p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01

cline in markdowns. In particular, the estimate in Column (4), which includes both industry-by-time and region-by-time fixed effects, suggests that a 1% increase in the share of workers aged 55 and over leads to approximately a 0.1% reduction in markdowns.

To better interpret the economic significance of this estimate, I conduct a simple back-of-the-envelope calculation. Connecting the fact that the average biennial increase in the share of workers aged 55 and over was about 13% during the sample period with the earlier 2SLS regression results implies an average markdown reduction of roughly 1.3%. Applying this 1.3% reduction to the average markdown of 1.657 yields a new markdown of approximately 1.635.[14] These figures indicates that if a worker previously received KRW 6,035 for every KRW 10,000 they generated in value, they would now receive around KRW 6,116.

While this may appear to be a modest improvement, I further examine its implications using actual average annual wage information for a first-year general manager (department

[14] $1.657 - 1.657 \times 13\% \times 0.1 \approx 1.635$

head) from the WPS dataset.[15] Assuming the marginal revenue product of labor (MRPL) remains constant, the estimated reduction in the markdown implies a wage gain of approximately KRW 700,000 per year.[16] This calculation result underscores that the effect of workforce aging on monopsony power is economically meaningful and far from negligible.

Table 9: 2SLS Regressions

Dependent Variable: $\triangle \ln(MD_{e(t)})$	(1)	(2)	(3)	(4)
$\triangle \ln(55^{+}share_{et})$	-0.077**	-0.112**	-0.136**	-0.101*
	(0.036)	(0.056)	(0.068)	(0.059)
Estab FE		✓	✓	✓
Time FE		✓	✓	
Controls			✓	✓
Industry-Time FE				✓
Region-Time FE				✓
F-Stat	124.76	69.22	74.89	50.66
Obs.	1,144	998	998	991

*p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01

4.C Mechanisms

To break down the underlying mechanisms, I separately examine the effects on the three components that constitute the markdown, as defined in equation (2). Columns 2 through 4 of Table 10 present the respective results for the output elasticity of labor (θ^{l}_{et}), labor's revenue share (α^{l}_{et}), and the product markup (μ_{et}). The results suggest that an increase in the share of older workers does not significantly affect output elasticity or markup, but instead raises labor costs, and thereby leading to a reduction in the markdown.

[15] According to the data, a representative first-year general manager earns KRW 54,000,000 annually.

[16] KRW $54,000,000 \times 1.3\% \approx$ KRW $700,000$

Table 10: 2SLS Regressions - Decomposed Effects

	(1) $\Delta\ln(MD_{et})$	(2) $\Delta\ln(\theta^l_{et})$	(3) $\Delta\ln(\alpha^l_{et})$	(4) $\Delta\ln(\mu_{et})$
$\triangle\ln(55^+share_{et})$	-0.101*	0.060	0.151***	0.011
	(0.059)	(0.067)	(0.045)	(0.011)
Controls	✓	✓	✓	✓
Estab FE	✓	✓	✓	✓
Industry-Time FE	✓	✓	✓	✓
Region-Time FE	✓	✓	✓	✓
F-Stat	50.66	50.66	50.66	50.66
Obs.	991	991	991	991

*p < 0.10, **p < 0.05, ***p < 0.01

Therefore, the causal chain underlying the results can be interpreted as follows: the retirement age reform increased the share of older workers, which—within the context of Korea's seniority-based wage system—led to an increase in labor costs. This, in turn, resulted in a structural decline in the markdown. Given this narrative, it becomes crucial to explore how the effects varied depending on how establishments responded to the policy and the resulting labor cost pressures, and to identify which establishments were able to preserve their monopsony power.

One possible response was the adoption of the wage peak system, which is a policy tool directly associated with the retirement age extension initiative. The wage peak system is a scheme in which employees—typically from their mid- to late-50s onward—receive guaranteed or extended employment in exchange for a reduction in wages. Establishments that adopted this system are likely to have experienced a smaller increase in labor costs and, therefore, a weaker reduction in markdowns.

By similar logic, establishments that indirectly responded to the reform by limiting or reducing wage growth for relatively younger workers or by limiting or reducing their employment, both of which are well-documented phenomena in Korean labor market, would have also experienced smaller increases in labor costs and, thus, likely retained more of their monopsony power.

Table 11 first examines the case of the wage peak system. Columns (1) and (2) present the 2SLS results for the change in markdowns and the change in the labor share of revenue for the subsample of establishments that adopted the wage peak system, while Columns (3) and (4) show the results for those that did not. As expected, establishments that did not adopt the wage peak system exhibit a clear pattern of markdown reduction driven by rising labor costs. In contrast, establishments with the wage peak system avoided a statistically significant increase in labor costs and kept their monopsony power.

Table 11: 2SLS Regressions - Wage Peak System Subsample

	Wage Peak System		*No Wage Peak System*	
	(1)	(2)	(3)	(4)
	$\Delta\ln(MD_{et})$	$\Delta\ln(\alpha^l_{et})$	$\Delta\ln(MD_{et})$	$\Delta\ln(\alpha^l_{et})$
$\triangle\ln(55^{+}share_{et})$	-0.012	0.175	-0.116**	0.139**
	(0.111)	(0.129)	(0.055)	(0.055)
Controls	✓	✓	✓	✓
Estab FE	✓	✓	✓	✓
Industry-Time FE	✓	✓	✓	✓
Region-Time FE	✓	✓	✓	✓
F-Stat	9.07	9.07	32.63	32.63
Obs.	410	410	558	558

*p < 0.10, **p < 0.05, ***p < 0.01

In Table 12, I classify establishments into two groups based on the log change in the annual wage of first-year assistant managers between 2014 and 2020.[17] Establishments with

[17] According to the WPS data, the average time it takes for a new employee to be promoted to assistant manager is around 8 years, suggesting that first-year assistant managers generally belong to a relatively young

wage growth above the median are shown on the right (Columns (3) and (4)), while those with below-median or declining wages are shown on the left (Columns (1) and (2)). As anticipated, the establishments on the right show statistically significant markdown reductions, whereas those that limited wage growth of relatively younger workers did not experience increases in labor costs and, accordingly, show no markdown reduction.

Table 12: 2SLS Regressions - Younger Workers' Wage Growth Subsample

	Below-Med Wage Growth		*Above-Med Wage Growth*	
	(1)	(2)	(3)	(4)
	$\Delta\ln(MD_{et})$	$\Delta\ln(\alpha^l_{et})$	$\Delta\ln(MD_{et})$	$\Delta\ln(\alpha^l_{et})$
$\triangle\ln(55^{+}share_{et})$	0.044	0.059	-0.302***	0.312***
	(0.074)	(0.056)	(0.108)	(0.098)
Controls	✓	✓	✓	✓
Estab FE	✓	✓	✓	✓
Industry-Time FE	✓	✓	✓	✓
Region-Time FE	✓	✓	✓	✓
F-Stat	25.19	25.19	19.27	19.27
Obs.	556	556	420	420

*p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01

Finally, Table 13 classifies establishments according to the percentage change in the number of workers aged 35 and under between 2014 and 2020. Establishments with above-median increases are on the right (Columns (3) and (4)), while those with below-median or declining employment are on the left (Columns (1) and (2)). Again, the results reveal that only establishments on the right experienced significant markdown reductions, while those that responded by restricting employment growth of relatively younger workers managed to avoid increases in labor costs and thus saw no markdown reduction.

age group.

Table 13: 2SLS Regressions - Younger Workers' Emplyment Growth Subsample

	Below-Med Employment Growth		*Above-Med Employment Growth*	
	(1)	(2)	(3)	(4)
	$\Delta \ln(MD_{et})$	$\Delta \ln(\alpha_{et}^{l})$	$\Delta \ln(MD_{et})$	$\Delta \ln(\alpha_{et}^{l})$
$\triangle \ln(55^{+} share_{et})$	-0.114	0.094	-0.109*	0.197**
	(0.073)	(0.064)	(0.066)	(0.078)
Controls	✓	✓	✓	✓
Estab FE	✓	✓	✓	✓
Industry-Time FE	✓	✓	✓	✓
Region-Time FE	✓	✓	✓	✓
F-Stat	51.65	51.65	19.67	19.67
Obs.	444	444	528	528

*p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01

5 Conclusion

This paper examines how the extension of the statutory retirement age in South Korea, introduced through a 2013 legislative reform, affected labor market monopsony power. Specifically, exploiting establishment-level panel data and using an instrumental variable based on pre-policy retirement ages, I estimate the causal impact of workforce aging on wage-setting power. The analysis reveals that increases in the share of workers aged 55 and over significantly reduce markdowns, primarily through rising labor costs under Korea's seniority-based wage system. These effects are stronger among establishments that did not adopt offsetting mechanisms, such as the wage peak system or the suppression of wage or employment growth for younger workers.

Whether the reduction in monopsony power caused by workforce aging is a positive or negative outcome depends on its broader interpretation. On the surface, one could argue that aging improves wage-setting efficiency by narrowing the gap between wages and MRPL. However, a closer look reveals potential welfare losses: while older workers may be paid closer to their MRPL, younger workers could face layoffs or wage suppression, possibly leading to overall losses that outweigh the gains. Additionally, policies that appear beneficial such as the wage peak system may unintentionally help firms maintain their monopsony power. These insights highlight the importance of evaluating not only the direct but also the unintended consequences of labor policies. Future research could explore these dynamics further through rigorous welfare analyses.

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