Old Workers, New Capital*

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Abstract

How does workforce aging affect corporate investment? We investigate this question using comprehensive matched employer-employee data. Exploiting variation in the age of newly hired workers, we find that firms hiring older workers significantly boost capital investment. Specifically, a typical increase in the average age of new hires raises investment rates by 0.3 percentage points—a 2.6% increase relative to the sample mean. To establish causality, we implement a shift-share instrumental variable approach that leverages industry-level demographic trends interacted with firms' initial workforce composition. Our results are consistent with a model where firms optimally choose between hiring younger and older workers who differ in productivity and wages.

Keywords: corporate investment, workforce aging, labor heterogeneity.
JEL Classifications: G30, G31, J1.

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1 Introduction

The graying of the global workforce represents one of the most profound economic transformations of our time. Across developed economies, workforce demographics are shifting rapidly: the median worker age is expected to climb from 27 years in 2000 to 37 years by 2050 (Lutz et al., 2008), reflecting broader demographic shifts as populations age and fertility rates decline. Figure 1 illustrates this transformation vividly: Canada's population has aged steadily over five decades, while the composition of the workforce has shifted dramatically towards older workers. Similarly, the percentage of Americans over 65 has risen to over 17% today and is projected to reach 23% by 2050 (U.S. Census Bureau, 2023). Yet despite extensive research on demographic transitions and their economic implications, we know surprisingly little about how these shifts reshape corporate decision-making. Does an aging workforce constrain investment or do older workers actually complement capital formation?

This question has profound policy implications that have been recognized for over two decades. In his 2004 Jackson Hole address (Greenspan, 2004), Federal Reserve Chairman Alan Greenspan identified a fundamental tension: "With slowed labor force growth, the amount of new equipment that can be used productively could be more limited, and the return to capital investment could decline as a consequence. Yet it is possible that the return to certain types of capital—particularly those embodying new labor-saving technologies—could increase". Greenspan's specific concern was whether aging would constrain capital deepening—the increase in capital per worker that historically drove much of U.S. productivity growth. Yet this fundamental question remains empirically unresolved. While existing research documents negative macroeconomic effects of population aging (Maestas et al., 2023; Bloom et al., 2024), firm-level evidence suggests a more complex relationship: companies regularly pay substantial premiums to attract experienced workers and many actively recruit older employees despite their higher labor costs (Bersin and Chamorro-Premuzic, 2019). This apparent contradiction between macro-level constraints and firm-level behavior suggests important distinctions between the challenges of managing an aging existing workforce and the economic benefits of hiring experienced workers.

In this paper, we examine how workforce aging affects corporate investment policy. We develop a model where firms optimally choose between hiring younger and older workers who differ in productivity and wages. When older workers are more productive—as evidenced by the wage premiums they command (e.g., Burtless, 2013)—the model predicts that hiring them increases the marginal return to capital investment due to complementarity between labor and capital. This complementarity drives capital deepening: firms respond to hiring more productive older workers by investing more in physical capital. The model generates several testable predictions: firms hiring older workers should invest more in capital, this effect should be stronger in capital-intensive industries, and the investment response should be larger for firms with initially younger workforces.

To test the model's predictions, we use comprehensive employer-employee matched data from Canada covering the period between 2001 and 2020, which links administrative records for all Canadian workers and the universe of both private and public firms (e.g., Abowd et al., 2004; Bonhomme et al., 2019). The main benefit of these data is that it allows us to precisely link each firm with its employees and therefore obtain a complete overview of workforce characteristics such as age, earnings, employment history, and industry experience. These data allow us to track corporate investment decisions across all private and public firms in the economy and to construct precise measures of workforce demographics, overcoming the limitations of studies focused only on firm-level characteristics. Our identification strategy exploits variation in the age of newly hired workers through a shift-share instrumental variable approach (Bartik, 1991). The instrument leverages industry-level demographic trends interacted with firms' initial workforce composition. This design addresses concerns about endogenous hiring decisions by exploiting plausibly exogenous variation in labor market demographics driven by broad macroeconomic forces rather than firm-specific factors.

Our empirical analysis reveals that the endogenous nature of hiring and investment decisions generates substantial bias in conventional estimates. Simple OLS regressions show only a modest positive association between hiring older workers and investment. This likely reflects downward bias: demographic shifts may force firms to hire older workers while simultaneously constraining investment due to shrinking labor markets or reduced growth opportunities in aging economies, creating a spurious negative correlation that obscures the true productivity benefits of experienced workers. Our empirical strategy addresses these endogeneity concerns by exploiting industry-level demographic trends that differentially affect firms based on their initial workforce composition. We document a critical pattern: when industries experience workforce aging, firms with older initial workforces respond by hiring younger workers and exhibit lower investment, while firms with younger initial workforces hire relatively older workers and exhibit higher investment. Our instrumental variable estimates isolate the causal effect by exploiting this substitution: firms that hire older workers invest substantially more—a 2.2 percentage point increase for each additional year in average hire age. Considering the average year-to-year shift in average age of hired workers (0.14 years), the causal effect implies a 2.6% increase in investment relative to the sample mean. This economically large effect represents a local average treatment effect (LATE) for firms whose hiring responds to demographic shifts, and is masked in simple correlations because demographic pressures create offsetting negative correlations that obscure the positive productivity complementarity. To confirm this operates through genuine productivity improvements, we show that hiring older workers significantly increases total factor productivity, full-time equivalent productivity, and sales, demonstrating that experienced workers enhance production efficiency and thereby justify higher capital investment.

The instrumental variable estimates confirm this causal relationship and reveal economically meaningful effects. This effect represents substantial capital deepening: firms that hire more experienced workers optimally respond by increasing their capital stock per worker, consistent with the productivity complementarity between experienced labor and physical capital emphasized in our model. Crucially, the large magnitude relative to the OLS estimate confirms that intentional hiring of older workers—as opposed to passive demographic adjustments—drives investment increases.

The result proves robust to including extensive controls for workforce characteristics (age and tenure of existing employees, turnover patterns of departing workers), firm characteristics (profitability, size, tangibility, age), and both firm and province-by-year fixed effects that absorb unobserved firm heterogeneity and regional economic conditions. The first-stage results show a strong relationship between the instrument and the age of new hires, with F-statistics well above conventional thresholds, addressing weak instrument concerns. Our identification strategy proves robust across multiple specifications: the results hold when using alternative industry classifications, different measures of demographic change, and various age thresholds for defining older workers. Importantly, the effects persist when examining only unpredictable components of industry demographic shifts, strengthening the causal interpretation. We also show that future demographic changes do not predict past investment outcomes and our instrument does not affect predetermined firm characteristics (Borusyak et al., 2022), supporting the validity of our exclusion restriction.

Our heterogeneity analysis confirms the model's predictions about when capital deepening effects should be strongest. Consistent with Prediction 2, the investment response to hiring older workers is concentrated entirely among capital-intensive firms: labor-intensive firms show statistically insignificant effects, while capital-intensive firms exhibit large, significant increases. This pattern confirms that physical capital complementarity drives our results—where capital matters less for production, older workers' productivity advantages fail to generate additional investment. The effects are also substantially stronger for firms with initially younger workforces (Prediction 3), with nearly three times larger coefficients than firms with predominantly older workforces, reflecting diminishing marginal returns to experience. These cross-sectional patterns provide compelling evidence that capital-labor complementarity, rather than alternative mechanisms, drives our results.

Our analysis contributes to several strands of literature. First, we add to the growing labor and finance literature examining how workforce heterogeneity affects corporate policies.[1] Existing research examines how labor market frictions affect financing (Matsa, 2010; Michaels et al., 2019; Monacelli et al., 2023), how employment protection influences investment (Agrawal and Matsa, 2013), how workforce restructuring affects firm outcomes (Lagaras, 2017; Araujo et al., 2023), and how labor mobility shapes capital allocation (Shen, 2021; Jeffers, 2023; Sanati, 2025). We demonstrate that workforce age composition—a dimension of labor heterogeneity largely unexplored in corporate finance—causally affects capital investment. Most closely related, Ouimet and Zarutskie (2014) and Derrien et al. (2023) show that younger workers' distinct skills and risk preferences lead them to work for more innovative firms, while Kecht et al. (2025) documents that older CEOs pursue more conservative strategies. We complement this research by showing that strategically hiring expe-

[1] See Matsa (2018) for an excellent survey.

rienced workers enhances investment through capital-labor complementarity, distinguishing workforce composition effects from leadership age effects.[2]

Second, we provide micro-level evidence on how firms can benefit from strategic responses to labor market pressures. While much research documents how labor market constraints—whether from demographic shifts (Maestas et al., 2023) or hiring frictions (Le Barbanchon et al., 2024)—limit firm performance, we show that workforce composition choices can create value through productivity complementarity. This reveals an important asymmetry: labor market factors can either constrain or enhance firm outcomes depending on whether they represent external frictions or internal strategic choices. Our findings demonstrate that micro-level responses can partially offset macro-level constraints, reconciling the tension between aggregate demographic pressures and firm-level investment opportunities.

Third, our empirical strategy contributes to the growing use of shift-share instrumental variables in corporate finance. Following recent applications to mortgage markets (Fonseca and Liu, 2024), zombie lending (Acharya et al., 2024), hiring difficulties (Le Barbanchon et al., 2024), and employment concentration (Avenancio-León et al., 2025), we demonstrate how shift-share designs can address endogeneity when firms' hiring and investment decisions are jointly determined. Our implementation exploits industry-level demographic trends interacted with firm-specific workforce exposure, providing a template for identifying causal

[2] A broader labor economics literature studies worker experience (Ben-Porath, 1967; Jovanovic, 2014; Lagakos et al., 2018; Engbom, 2019; Guvenen et al., 2021) and demographic change (Aksoy et al., 2019; Karahan et al., 2019).

effects of workforce characteristics on corporate policies.

The rest of the paper proceeds as follows. Section 2 develops a theoretical model of workforce age and capital investment. Section 3 describes our data and empirical strategy. Section 4 presents our main results, robustness tests, and heterogeneity analysis. Section 5 concludes with policy implications.

2 Model

To analyze how hiring older workers affects capital deepening, we develop a model of labor age heterogeneity building on Krusell et al. (2000) and Borjas (2003). The key innovation is allowing firms to optimally choose between older and younger workers who differ in both wages and productivity. This creates a direct link between workforce composition and capital investment decisions: when older workers are more productive, hiring them increases the marginal return to capital, driving capital deepening through complementarity between labor and physical capital.

Consider a static economy with a unit mass of risk-neutral firms. We first characterize the single-firm problem and then embed it in a labor market equilibrium to endogenize wages and derive aggregate implications.

2.1 Firm Optimization Problem

The firm produces output y using decreasing-return-to-scale Cobb-Douglas technology with labor $l \geq 0$ and capital $k \geq 0$:

$$y = Al^{\alpha}k^{\beta},$$

where $\alpha > 0$ and $\beta > 0$ are capital and labor shares, respectively, with $\alpha + \beta < 1$, and $A \geq 0$ is total factor productivity.

The key innovation is that labor is composed of young workers $l_y \geq 0$ and old workers $l_o \geq 0$ whose labor is combined through a constant elasticity of substitution (CES) aggregator:

$$l = \left[\eta l_y^{\rho} + (1-\eta) l_o^{\rho}\right]^{1/\rho}, \tag{1}$$

where $\eta \in (0,1)$ governs young workers' productivity share and $\rho \leq 1$ determines the elasticity of substitution between worker types.[3] Young and old workers earn wages $w_y > 0$ and $w_o > 0$ respectively, so that the total cost of employing l_y younger and l_o older workers is $w_y l_y + w_o l_o$.

The firm invests in k units of capital and forgoes rk in returns where $r > 0$. After production, a fraction $\delta \in [0,1]$ of capital depreciates. As a result, the cost of capital is

[3] The elasticity of substitution between the two types of labor is $\frac{1}{1-\rho}$. When $\rho = 1$, worker types are perfect substitutes; when $\rho \to -\infty$, they are perfect complements.

given by $(r+\delta)k$.

The value of the firm is given by its profits

$$V = \max_{k,l_o,l_y \geq 0} Al^{\alpha}k^{\beta} - (r+\delta)k - w_y l_y - w_o l_o.$$

This objective function comprises of production revenues (first term), capital costs (second term), and wage payments to young and old workers (final terms). The firm simultaneously chooses capital investment and hiring to maximize its value.

2.2 Labor Market Equilibrium

We embed the single-firm model into a labor market equilibrium to endogenize wages. There is a unit mass of homogeneous firms $j \in [0,1]$ that each hires young and old workers and have optimal labor demands $l_{y/o}(w_y, w_o)$ that depend on market wages. The aggregate labor supply is fixed at $L_y > 0$ for young workers and $L_o > 0$ for old workers.

We focus on an equilibrium in which wages (w_y, w_o) are determined so that labor markets clear. That is, labor demand must equal labor supply for each worker type:

$$\int_0^1 l_y(w_y, w_o)dj = L_y \quad \text{and} \quad \int_0^1 l_o(w_y, w_o)dj = L_o.$$

2.3 Theoretical Predictions

We now analyze the model to derive testable predictions about how workforce age affects investment. We characterize optimal firm behavior and show how hiring older workers influences investment.

Optimal Firm-Level Policies

The firm's capital choice balances investment costs (user cost of capital $r + \delta$) against production benefits:

$$MPK = \underbrace{\beta A l^{\alpha} k^{\beta-1}}_{\text{Marginal benefit}} = \underbrace{r + \delta}_{\text{Marginal cost}} = MCK.$$

Investment benefits depend on workforce composition through l. Therefore, hiring decisions directly influence investment incentives.

The firm's hiring decisions balance wages against the marginal productivity of labor:

$$MPL_y = \underbrace{A\alpha\eta k^{\beta} l^{\alpha-\rho} l_y^{\rho-1}}_{\text{Marginal benefit}} = \underbrace{w_y}_{\text{Marginal cost}} = MCL_y, \quad (2)$$

$$MPL_o = \underbrace{A\alpha(1-\eta) k^{\beta} l^{\alpha-\rho} l_o^{\rho-1}}_{\text{Marginal benefit}} = \underbrace{w_o}_{\text{Marginal cost}} = MCL_o. \quad (3)$$

Both marginal products of labor are affected by capital k, confirming that hiring and investment decisions are jointly determined.[4]

Worker Heterogeneity

Without differences between older and younger workers in terms of productivity ($\rho = 1$ and $\eta = \frac{1}{2}$), the labor aggregator simplifies to $l = \frac{l_o + l_y}{2}$ and equilibrium wages are equal $w_o = w_y$. Since we observe substantial wage differentials in our data—older workers earn roughly 95% more than younger workers—productivity must differ across age groups ($\rho \neq 1$ and/or $\eta \neq \frac{1}{2}$). This motivates our focus on age-based productivity differences.

Hiring Older Workers and Investment

To study how hiring older workers affects investment, we analyze how substituting a younger for older worker affects investment:

$$\Delta := \frac{\partial k}{\partial l} \left(\frac{\partial l}{\partial l_o} - \frac{\partial l}{\partial l_y} \right), \tag{4}$$

where $\frac{\partial k}{\partial l} > 0$ because capital and labor are complements in the production function and $\frac{\partial l}{\partial l_o} - \frac{\partial l}{\partial l_y}$ captures how substituting towards older workers affects the labor aggregator.

[4] Using the first-order conditions, we can also determine the equilibrium wage premium for older workers, which equals:

$$\frac{w_o - w_y}{w_y} = \frac{1-\eta}{\eta} \left(\frac{l_y}{l_o} \right)^{1-\rho} - 1 = \frac{1-\eta}{\eta} \left(\frac{L_y}{L_o} \right)^{1-\rho} - 1,$$

where the premium depends on relative labor supply ($\frac{L_y}{L_o}$) and productivity parameters (η and ρ).[5] In particular, more productive older workers (lower η) command a higher wage premium $\frac{w_o - w_y}{w_y}$.

At the firm optimum, we have:

$$\frac{\partial l}{\partial l_o} - \frac{\partial l}{\partial l_y} = \frac{1}{\alpha A k^{\beta} l^{\alpha-1}}(MPL_o - MPL_y) = \frac{1}{\alpha A k^{\beta} l^{\alpha-1}}(w_o - w_y).$$

This equation shows that substituting younger for older workers increases the total labor aggregator when older workers are more productive. Since wages equal marginal productivity in equilibrium (Equations 2 and 3), higher wages for older workers imply higher productivity. Therefore, shifting employment toward older workers increases the firm's labor aggregator l when $w_o > w_y$. Given the capital-labor complementarity, this leads to higher capital investment—that is, capital deepening occurs as firms increase the capital stock per unit of effective labor. Thus, $\Delta > 0$ when $w_o > w_y$, confirming that hiring older workers increases investment because these workers are more productive.[6] Therefore, the model predicts that:

Prediction 1 (Hiring Older Workers and Investment)**.** *Hiring older workers increases capital investment.*

We test this core prediction empirically in Section 4.

[6] In practice, older workers earn a significant wage premium. In our data, $\frac{w_o - w_y}{w_y} \approx 95\%$.

Equilibrium Implications

The firm-level results also hold in a labor market equilibrium. The impact of workforce aging on aggregate investment while keeping total employment fixed is:

$$\frac{\partial k}{\partial l}\left(\frac{\partial l}{\partial L_o}-\frac{\partial l}{\partial L_y}\right)=\frac{\partial k}{\partial l}\left(\frac{\partial l}{\partial l_o}-\frac{\partial l}{\partial l_y}\right)=\frac{\partial k}{\partial l}\frac{1}{\alpha A k^{\beta} l^{\alpha-1}}\left(w_o-w_y\right), \tag{5}$$

where the equality follows from $l_{y/o}=L_{y/o}$ since there is a unit mass of homogeneous firms. This creates a *workforce aging channel*: when the economy ages (higher $\frac{L_o}{L_o+L_y}$), aggregate investment increases because older workers are more productive and complement physical capital. This represents capital deepening at the economy level: the substitution toward more productive workers raises the optimal capital-to-labor ratio, increasing investment even as the workforce ages.

However, demographic transitions also involve declining labor supply. This creates a second, well-established channel where reduced labor availability constrains capital investment:

$$-\frac{\partial k}{\partial l}\frac{\partial l}{\partial L_{y/o}}=-\frac{\partial k}{\partial l}\frac{\partial l}{\partial l_{y/o}}<0. \tag{6}$$

This *labor supply channel* shows that demographic constraints (declining L_y or L_o) reduce aggregate investment by shrinking the effective labor force.

Our model thus reveals two distinct channels through which demographic change affects firms, with opposing implications for investment. The *workforce aging channel* shows that hiring older workers boosts investment (Equation (5)) because these workers are more productive and complement physical capital. Conversely, the *labor supply channel* demonstrates that demographic transitions reduce aggregate labor supply (Bloom et al., 2010), which constrains investment (Equation (6)) by shrinking the effective workforce.

The workforce aging channel provides a new perspective on demographic transitions by identifying a mechanism through which firms can offset—and potentially reverse—the productivity declines typically associated with population aging (Maestas et al., 2023). This finding complements Acemoglu and Restrepo (2017), who demonstrate how strategic technology adoption can mitigate negative demographic effects. We extend this insight by showing how optimal hiring policies exploit the complementarity between experienced workers and physical capital, enabling firms to transform demographic pressures into sources of competitive advantage.

Impact of Labor Intensity and Worker Composition

The model also generates additional testable predictions about heterogeneity across firms and industries, which we test in Section 4.3. Concretely, the model predicts that the investment response to workforce aging varies systematically across firms. Panel A of Figure 2 shows how the effect varies with labor intensity (different values of α and β while keeping $\alpha + \beta$ fixed). For more labor-intensive industries (higher α, lower β), substituting toward older workers has less impact on investment because capital plays a smaller role and is therefore less sensitive to labor productivity changes.

Prediction 2 (Labor Intensity and Investment)**.** *The investment response to workforce aging should be weaker in more labor-intensive industries and firms.*

Panel B of Figure 2 shows how the effect varies with existing workforce composition. As the fraction of older workers increases, the marginal productivity gap between worker types narrows, weakening the investment response to further aging. There are decreasing returns to having more older workers.

Prediction 3 (Workforce Age and Investment)**.** *The investment response to hiring older workers should be smaller for firms that already have predominantly older workforces.*

We test predictions 2 and 3 empirically in Section 4.3.

3 Data and Empirical Strategy

Our model generates three testable predictions about the relationship between workforce aging and corporate investment: hiring older workers should increase investment (Prediction 1), this effect should be stronger in capital-intensive firms (Prediction 2), and the investment response should be larger for firms with initially younger workforces (Prediction 3). We test these predictions using comprehensive Canadian employer-employee data that uniquely allows us to observe both firm investment decisions and the complete age structure of their workforces.

3.1 Sample Construction

Testing our model's predictions requires overcoming two main empirical challenges. First, we need to observe the age of every worker to precisely measure the key treatment variable (average age of hired workers). Second, we must address the endogeneity of workforce composition and firm policies, which our model shows are jointly determined in equilibrium. We address both challenges using comprehensive employer-employee data for the universe of Canadian firms combined with a shift-share instrumental variable approach (Bartik, 1991).

We use the Canadian Employer-Employee Dynamics Database (CEEDD), compiled by Statistics Canada, which links administrative tax records to firm financial statements. These data have recently been used to study revenue and productivity spillovers across firms (Baum-Snow et al., 2024), earnings inequality and dynamics across workers and firms (Bowlus et al., 2022), and the effect of wealth on entrepreneurship (d'Astous et al., 2025). The comprehensive coverage allows us to precisely measure workforce characteristics, link them to employers, and track employment relationships over time. Such employer-employee matched data have become increasingly important when studying labor markets with firm and worker heterogeneity (e.g. Abowd et al., 2004; Bonhomme et al., 2019). Our contribution is to use these data to test how workforce age affects corporate investment.

The data integrate three primary sources: T1 Personal Master Files (T1PMF) provide demographic characteristics and income; T4 Records of Employment (T4ROE) link employees to employers with complete work histories, including hiring dates, separation dates, and reasons for separation; and the National Accounts Longitudinal Microdata File (NALMF) provides firm balance sheets, including investment and asset data, along with industry classifications and geographic locations. This combination allows us to precisely measure workforce characteristics for every employee, link them to their employers' investment decisions, and track employment relationships over time, all of which are essential for our empirical strategy.

To create our sample, we begin with the universe of roughly 6 million public and private firms reporting tax information between 2001 and 2020. Since close to 97% of Canadian firms are either self-employed individuals or small and medium enterprises (ISEDC, 2024), we restrict our analysis to firms with at least 50 employees at any point in time to ensure meaningful variation in workforce characteristics. We further restrict the sample to firm-years with hiring activity (95% of firm-years in our size range), remove observations with negative book equity or leverage ratios exceeding 40, and require complete data for our main variables. Our final sample consists of 136,680 firm-year observations across 16,385 unique firms over 2008-2020.[7] Despite sample restrictions, these firms account for 64% of total employment in the Canadian economy and our sample encompasses nearly 20 million

[7]Our estimation sample spans 2008-2020 due to the five-year lags required to construct our instrument.

unique workers over the sample period, ensuring broad representativeness. Table A.1 in the Appendix documents the complete sample construction process.

Our main variable of interest is the average age of workers hired in a given year, calculated as:

$$\overline{\text{Age}}_{jt}^{\text{hire}} = \frac{1}{N_{jt}^{\text{hire}}} \sum_{i=1}^{N_{jt}^{\text{hire}}} \text{Age}_{ijt}^{\text{hire}},$$

where N_{jt}^{hire} is the number of workers hired by firm j in year t and $\text{Age}_{ijt}^{\text{hire}}$ is the age of newly hired worker i as of December 31.[8] We similarly construct measures for the average age and industry tenure of existing workers, the average age of terminated and quitting workers, and average earnings. Table A.2 in the Appendix provides complete definitions and data sources for all variables.

Our main outcome variable is investment, measured as total tangible investment minus asset sales divided by lagged tangible assets. Tangible investments include net investment in buildings, machinery and equipment, and other tangible assets.[9]

Figure 3 previews the key empirical patterns. Panel A reveals a positive correlation between investment and the average age of newly hired workers: investment rises from approximately 10% to 13% as the average age of new hires increases from 20 to 40 years. In contrast, Panel B shows a strongly negative correlation between investment and the average

[8]In robustness tests, we also use a binary indicator equal to 1 if firm hires workers with average age greater than 32 (the sample median).

[9]Table A.3 shows that our results are robust to alternative investment definitions.

age of existing workers: investment declines from about 20% to 7% as the existing workforce ages from 25 to 50 years.

These contrasting patterns underscore a critical distinction in our analysis. The positive slope in Panel A suggests that strategically hiring older workers may complement capital deepening, while the negative slope in Panel B indicates that firms with aging existing workforces invest less. These are, however, unconditional correlations that conflate endogenous hiring and investment decisions. Our identification strategy in Section 3.2 exploits plausibly exogenous variation in industry-level demographic trends to isolate the causal effect of hiring older workers on investment.

Table 1 presents summary statistics. The average firm is 21 years old with an investment rate of 12%, profitability of 5%, and 68% tangible assets. The average age of existing workers is 36.8 years, while newly hired workers average 32.2 years. Firms in our sample employ an average of 448 workers and hire 138 new workers annually, of which 35% are classified as older (above the median hire age of 32). In the data, older workers earn on average $59,926 Canadian dollars, which corresponds to a wage premium of 95% relative to younger workers. Newly hired workers have 3.6 years of industry experience compared to 6.3 years for existing workers. Workers who are fired or quit average 40.6 and 33.7 years old, respectively.[10] Throughout our analysis, we use multiple age thresholds: 32 (median age of new hires), 36 (median age of existing workers), and 48 (75th percentile of existing workers) depending on

[10]Firm size and hiring averages are skewed by a long right tail. The median firm has 143 employees and hires 44 workers per year. The average net hiring rate is approximately 5% annually.

the specific context.[11]

3.2 Empirical Strategy

To test Prediction 1 that hiring older workers increases investment, we estimate:

$$\text{Investment}_{jt} = \beta_0 + \beta_1 \overline{\text{Age}}^{\text{hire}}_{jt-1} + \mathbf{X}'_{jt-1}\boldsymbol{\beta} + \mu_j + \delta_{pt} + \varepsilon_{jt}, \tag{7}$$

where Investment_{jt} is the investment rate, $\overline{\text{Age}}^{\text{hire}}_{jt-1}$ is the average age of hired workers, $\mathbf{X}_{jt-1}$ includes time-varying firm and worker characteristics, μ_j are firm fixed effects, and δ_{pt} are province-year fixed effects.

As our model shows, hiring and investment decisions are jointly determined in equilibrium, creating endogeneity concerns. Demographic shifts may force firms to hire older workers while simultaneously constraining investment due to shrinking labor markets and reduced growth prospects, generating spurious negative correlations that obscure the productivity benefits of experienced workers.[12]

[11] These thresholds are determined empirically from our sample of workers (which can differ from the firm-level averages presented in Table 1). They are used consistently to define "older workers" in different analyses: 32 for binary treatment specifications (Section 4.2), 36 for constructing the shift-share instrument (Section 3.2), and 48 for robustness tests of alternative age cutoffs (Section 4.2).

[12] In the model, declining L_y reduces investment ($-\frac{\partial k}{\partial l}\frac{\partial l}{\partial L_y} < 0$) while increasing $\frac{L_o}{L_y+L_o}$, creating a negative correlation between workforce age and investment.

Identification Strategy

To isolate causal effects, we exploit a shift-share instrumental variable that interacts firms' initial workforce composition with industry-level demographic trends (Bartik, 1991). The intuition is straightforward: when an industry experiences workforce aging, firms with different initial age compositions will be differentially exposed to these demographic pressures, creating plausibly exogenous variation in hiring patterns. For instance, a firm with an initially old workforce in an aging industry faces stronger pressure to hire younger workers to rebalance its composition, while a firm with an initially young workforce in the same industry can more easily hire older workers.

We calculate the instrument as:

$$\text{Shift-share}_{jt} = \text{Share of older workers}_{j,t-5} \times \Delta\overline{\text{Age}}^{\text{industry}}_{k,t-5:t},$$

where Share of older workers$_{j,t-5}$ is the proportion of workers aged 36+ (the sample median) in firm j five years earlier, and $\Delta\overline{\text{Age}}^{\text{industry}}_{k,t-5:t}$ is the five-year change in average worker age in firm j's industry k (measured at the 2-digit NAICS level). We use five-year rolling windows to construct the instrument, such that our estimation sample covers 2008-2020.[13]

Both instrument components exhibit substantial variation (Table 1, Panel C). The share of older workers ranges from 0.32 to 0.64 (25th-75th percentiles), while five-year industry

[13] For example, to instrument hiring age in 2007 (for outcome year 2008), we use the firm's 2002 workforce composition and the 2002-2007 industry age change. Section 4.2 shows results are robust to 4-digit industries, growth rates instead of levels, and alternative age thresholds.

age shifts range from 0.63 to 1.55 years. Figure 4 shows this variation across industries: the share of older workers varies from 20% to 75%, while industry age shifts vary from 0.5 to 2 years. Crucially, these components are only weakly correlated, providing independent variation that strengthens identification. For example, industries with similar initial age compositions (e.g., Entertainment vs. Agriculture) experience vastly different demographic shifts, while industries with different initial compositions (e.g., Finance vs. Construction) experience similar aging trends.

Our empirical strategy follows Borusyak et al. (2022), where exogenous variation comes from industry shifts rather than firm shares. This is crucial because firm shares may be endogenous—for example, firms with older workforces might reduce investment in anticipation of lower growth opportunities.[14] We instead rely on industry-level demographic trends being exogenous to individual firm decisions. Identification thus exploits cross-sectional variation in firms' exposure to older workers interacted with time-series variation in industry-level demographic changes.[15]

We implement this strategy using two-stage least squares, instrumenting $\overline{\text{Age}}^{\text{hire}}_{jt-1}$ with

[14] Goldsmith-Pinkham et al. (2020) propose an alternative path to causal identification that instead relies on exogenous shares. See Borusyak et al. (2025) for an excellent practical guide that compares both frameworks.

[15] We focus on same-industry demographic shifts rather than cross-industry exposure because firms in our sample primarily hire workers with industry experience: the median firm hires workers with 3 years of industry tenure, and 90% of firms hire workers with at least 1.5 years of industry tenure.

Shift-share$_{jt-1}$:

$$\overline{\text{Age}}^{\text{hire}}_{jt-1} = \alpha_0 + \alpha_1 \text{Shift-share}_{jt-1} + \mathbf{X}'_{jt-1}\boldsymbol{\alpha} + \mu_j + \delta_{pt} + \nu_{jt-1}. \tag{8}$$

Because firms differ in the way their hiring decisions respond to demographic shocks, our empirical setting naturally features heterogeneous treatment effects. In this environment, our two-stage least squares estimates identify a local average treatment effect (LATE): the causal effect of hiring older workers on investment for the subset of firms whose hiring decisions are shifted by the instrument (Angrist and Imbens, 1995). These *complier* firms are those whose hiring age responds to industry demographic shocks; firms with older initial workforces that substitute toward younger hires when experienced labor becomes scarce, and firms with younger initial workforces that substitute toward older hires when demographic aging expands the pool of experienced workers. Under the standard assumptions for shift–share instruments, our IV estimates recover the causal effect of older hiring for these complier firms.[16]

Instrument Validity

For valid identification, the instrument must satisfy relevance and exclusion restrictions. First-stage F-statistics exceed 140, confirming strong relevance (Staiger and Stock, 1997;

[16]These include: (i) relevance of the demographic shock, (ii) exogeneity of industry-level aging trends, (iii) the exclusion restriction that these shocks affect investment only through their impact on hiring age, and (iv) monotonicity in firms' hiring responses.

Andrews et al., 2023). The exclusion restriction requires that industry demographic shifts affect investment only through workforce composition, not other channels. This is plausible because industry-level trends reflect broad macroeconomic forces (retirement patterns, technological change) beyond any single firm's control. With firm fixed effects, identification comes from within-firm variation in hiring age induced by industry trends, isolating the workforce composition channel. Section 4.2 provides extensive validity tests following Borusyak et al. (2022), including pre-trend tests showing future demographic shifts don't predict past outcomes, and falsification tests confirming the instrument doesn't affect predetermined firm characteristics.

4 Results

We present our empirical results in three parts. First, we establish the causal effect of hiring older workers on investment using our shift-share instrumental variable. Second, we demonstrate the robustness of this relationship across alternative instrument constructions and validity tests. Third, we examine heterogeneity in the investment response across capital intensity and initial workforce composition, confirming our model's predictions about when capital deepening effects should be strongest.

4.1 Main Results: Hiring Older Workers and Investment

We test our model's core prediction that hiring older workers increases capital deepening (Prediction 1). The theoretical mechanism operates through capital-labor complementarity: more productive older workers increase the marginal return to capital investment, driving firms to optimally increase their capital stock.

We begin by estimating Equation (7) using OLS. Each specification includes controls for workforce characteristics (average age of current workers, tenure of new and existing workers, turnover patterns) and firm characteristics (profitability, size, tangibility, age), along with firm fixed effects and province-by-year fixed effects that absorb firm-level heterogeneity and time-varying regional economic conditions.[17] These controls ensure we capture the effect of strategically hiring older workers, rather than mechanical effects from workforce turnover, firm-level trends, or regional shocks. Column (1) of Table 2 shows a positive but economically small association between hiring older workers and investment (0.001). This likely reflects downward bias if demographic shifts force firms to hire older workers while simultaneously constraining investment due to shrinking labor markets or reduced growth opportunities.

Our shift-share instrumental variable addresses this endogeneity. The reduced-form estimate in column (2) reveals the demographic pressure channel: firms with older initial workforces in aging industries invest less (-0.011, significant at 1%), while firms with younger

[17]Hiring decisions represent the primary margin through which Canadian firms adjust workforce composition, as employment protection makes firing difficult while firms have limited control over voluntary quits (ESDC, 2019). We control for turnover patterns to ensure our results reflect strategic hiring choices rather than mechanical substitution effects.

initial workforces in aging industries invest more. The first-stage estimate in column (3) shows why: when industries age, firms with older workforces respond by hiring younger workers (-0.523, significant at 1%), while firms with younger workforces hire relatively older workers. This pattern illustrates firms' active workforce rebalancing in response to demographic pressures in that firms facing diminishing returns from additional experienced workers (Prediction 3) strategically rebalance their workforce composition. The Kleibergen-Paap F-statistic of 141.47 confirms strong instrument relevance (Staiger and Stock, 1997; Andrews et al., 2023).

The instrumental variable estimate in column (4) isolates the causal effect of hiring older workers. A one-year increase in the average age of new hires raises investment by 2.2 percentage points—an 18% increase relative to the sample mean. This economically large effect represents substantial capital deepening: firms hiring more experienced workers optimally respond by increasing capital per worker, consistent with the productivity complementarity between experienced labor and physical capital.[18] For perspective, Panel C of Table 1 shows that industry-level age shifts average only 1.19 years over five-year windows, making a one-year hiring age increase economically large given the slow-moving nature of workforce demographics. To contextualize the magnitude further, the average year-to-year change in hiring age is 0.14 years. Applying our coefficient to this typical annual variation implies a 0.3

[18]These findings focus on strategic hiring of older workers rather than constraints of managing an aging existing workforce. Table A.4 shows that having an older existing workforce reduces investment, consistent with Maestas et al. (2023), confirming these represent distinct channels.

percentage point increase in investment, or 2.6% of the sample mean—a more modest but still economically meaningful effect that reflects normal hiring dynamics rather than large discrete shifts in workforce strategy.

To confirm that this investment response reflects genuine productivity improvements rather than financial market frictions or agency problems, we examine direct measures of firm performance. Table 3 demonstrates that hiring older workers significantly increases firm productivity and profitability. Panel A shows that total factor productivity (measured using worker headcount) rises by 0.077 (significant at 1%) for each additional year in average hire age. Panel B confirms this result using full-time equivalent workers (0.073, significant at 1%), addressing concerns about part-time employment composition. Panel C reveals that log sales increase by 0.098 (significant at 1%), indicating that the productivity gains translate directly into revenue growth. These results provide compelling evidence that the mechanism operates through the productivity complementarity channel in our model: experienced workers enhance production efficiency, which in turn justifies higher capital investment. The magnitudes are economically substantial—the TFP increase represents approximately 8% of the sample standard deviation, while the sales effect corresponds to a 10% revenue increase for a one-year age shift.

The investment increase merits careful interpretation. Our IV estimate captures a local average treatment effect (LATE) rather than an average treatment effect for all firms (Angrist and Imbens, 1995). The LATE identifies effects for "compliers", that is firms whose hiring decisions respond to industry demographic shifts interacted with their initial workforce composition. These firms may be particularly sensitive to labor quality changes and thus exhibit stronger investment responses than the average firm. This interpretation aligns with the well-documented pattern that IV estimates often exceed OLS coefficients when addressing endogeneity (Jiang, 2017).

Overall, our results reveal two distinct channels through which workforce aging affects firm investment, resolving the apparent tension between first-stage and second-stage effects. The first-stage estimates capture demographic pressure: when industries age, firms with older initial workforces rebalance toward younger workers due to diminishing returns and labor supply constraints. Since younger workers command lower wages but are also less productive, the reduced form results show that this substitution reduces investment. The IV estimate isolates the productivity effect: hiring older workers increases investment through the capital-labor complementarity mechanism in Equation (4). This confirms Prediction 1: older workers' higher productivity—reflected in their wage premium—creates complementarity with physical capital, leading firms to optimally increase capital deepening when hiring these workers. Critically, the first-stage estimate reflects workforce rebalancing under constraints, while the second-stage effect captures the causal benefit of experienced workers absent such constraints. The OLS estimate conflates these opposing forces (negative demographic pressure and positive productivity effects), explaining its small magnitude. Our IV approach separates these channels, confirming that strategic hiring of older workers drives substantial capital investment, as predicted by our model. Most importantly, the investment increases are accompanied by significant improvements in productivity and profitability (Table 3), confirming the mechanism operates through genuine efficiency gains rather than financial frictions or agency problems.

4.2 Robustness

We conduct extensive robustness and validity tests to ensure our results are not sensitive to specific modeling choices in constructing the shift-share instrument and that our identification strategy credibly isolates causal effects. We first examine alternative instrument constructions and then implement falsification tests following Borusyak et al. (2022).[19]

Alternative Instrument Specifications

Table 4 demonstrates that our results are robust across multiple instrument constructions. Our baseline uses 2-digit NAICS industries and absolute age changes to construct the shift component. Panel A shows similar results using 4-digit NAICS codes (IV estimate: 0.029, F-stat: 57.44), confirming findings are not sensitive to industry aggregation. Panel B uses growth rates rather than levels for demographic shifts (IV estimate: 0.046, F-stat: 60.73), addressing concerns about scale effects across industries with different baseline age structures. Panel C varies the age threshold defining the share component from 36 (median) to 48 (75th

[19]Table A.3 shows additional robustness to excluding regulated industries and using alternative investment definitions.

percentile), yielding an even stronger first stage (F-stat: 97.78) and positive investment effect (0.011), suggesting demographic pressures are particularly pronounced for firms with substantially older workforces.

Most importantly, Panel D addresses concerns about forward-looking firm behavior by isolating only unpredictable demographic shifts. A potential critique of our IV approach is that firms might anticipate demographic shifts and adjust policies in advance, violating the exogeneity assumption. To address this concern, we isolate the unpredictable component of industry age trends by estimating a predictive regression:

$$\Delta\overline{\text{Age}}^{\text{industry}}_{k,t-3:t} = \alpha_0 + \alpha_1 \Delta\overline{\text{Age}}^{\text{industry}}_{k,t-6:t-3} + \varepsilon_{k,t},$$

where past demographic trends predict future changes at the 2-digit NAICS level. We then reconstruct the instrument using only the residuals $\varepsilon_{k,t}$: $\text{Shift-share}^{\text{unpred}}_{jt} = \text{Share of older workers}_{j,t-3} \times \varepsilon_{k,t}$. This modified instrument captures only demographic changes that firms could not reasonably anticipate based on historical patterns.[20]

Panel D of Table 4 shows that our findings remain robust under this stricter identification strategy. The first-stage coefficient (-0.075) confirms that firms with older initial workforces respond to unpredictable industry aging by hiring younger workers. The instrument is weaker by construction (F-stat: 6.59)—removing predictable trends mechanically eliminates most variation, leaving only residual unpredictable shocks. This conservative approach

[20] We use 3-year windows for this test to maximize sample coverage, with estimation beginning in 2010.

deliberately sacrifices statistical power to ensure exogeneity by using only the component of demographic change that firms could not forecast. Critically, the second-stage estimate (0.091) remains positive, significant at 5%, and actually larger than our baseline (0.022). These results demonstrate that our conclusions hold even when using only unpredictable demographic shifts, thereby strengthening the causal interpretation and addressing concerns about forward-looking behavior.

Robustness to Age Threshold Definition

A key modeling choice when constructing the instrument is defining "older workers" using a continuous age measure. While our baseline specification treats age linearly, firms may respond differently when hiring workers substantially above or below typical age thresholds. Table 5 examines whether our results are sensitive to how we define the hiring of older workers by using binary treatment indicators based on different percentiles of the age distribution.

The table reports IV estimates using binary treatments for whether firms hire workers above the 50th (age 32), 75th (age 36), 90th (age 40), 95th (age 43), and 99th (age 48) percentiles. Several patterns emerge. First, all specifications show positive and significant investment responses, confirming our main result is not sensitive to the specific age cutoff. Second, the economic magnitude increases with the percentile threshold: the effect rises from 0.297 at the median to 1.16 at the 99th percentile. This pattern is consistent with our model's prediction of complementarity between worker experience and capital—hiring workers substantially older than average generates stronger investment responses. Third, the first-stage F-statistics remain strong across all specifications (ranging from 17.62 to 89.59), indicating our instrument maintains relevance regardless of age threshold. These results provide two key insights: (1) our findings are robust to discrete rather than continuous age measures, confirming that both marginal and substantial shifts toward older workers increase investment, and (2) the monotonic increase in effect sizes with age thresholds validates our use of a linear age specification, as it captures the average effect across this monotonically increasing relationship. The larger effects at higher percentiles also suggest that firms hiring substantially older workers experience particularly strong productivity complementarities that justify major capital investments.

Validity Tests

We implement two key falsification tests. First, we test for pre-trends. An important concern is that our results might reflect pre-existing trends rather than causal effects. To address this issue, we implement a pre-trend test in which past outcomes are regressed on future realizations of the instrument. If future shocks predict past outcomes, it would suggest our instrument captures long-term trends rather than exogenous variation. We reverse temporal ordering by calculating the shift-share instrument using 2008 demographic shifts and examining investment over 2002-2007. Table 6, Panel A shows that while the first stage remains strong (F-stat: 123.89) with the expected sign reversal (0.874), neither the reduced-form

(0.002) nor IV estimate (0.003) is statistically significant. Future demographic shifts do not predict past investment, ruling out spurious long-run trends.

Second, following Borusyak et al. (2022), we test whether our instrument affects predetermined firm characteristics. A central concern is that our instrument might affect investment through channels other than workforce composition, thereby violating the exclusion restriction and confounding our test of the model's mechanism. Panel B examines firm age, employment levels, and unionization rates—variables that could correlate with investment but should not be causally affected by industry demographic shifts if our exclusion restriction holds. The IV estimates are statistically indistinguishable from zero for all three outcomes (firm age: -0.001; number of workers: 22.83; percent unionized: 0.004), confirming our instrument does not capture unobserved firm-specific trends that might confound our main results through alternative channels.

These tests collectively demonstrate that hiring older workers causally increases firm investment through the capital-labor complementarity mechanism in our model. Our findings are insensitive to instrument construction choices including industry classification (2-digit vs 4-digit NAICS), demographic measurement (levels vs growth rates), treatment definition (continuous vs binary), age thresholds (median vs 75th percentile), and predictability of demographic shifts. The results do not reflect pre-existing trends, operate through workforce composition rather than alternative channels, and are robust to using only unpredictable demographic changes that firms could not anticipate.

4.3 Heterogeneity

Having established that hiring older workers increases capital deepening, we examine when this effect should be strongest. Our model generates two key predictions: the investment response should be weaker in labor-intensive firms where capital plays a smaller production role (Prediction 2) and weaker for firms with initially older workforces due to diminishing marginal returns to experience (Prediction 3).

Labor Intensity

Panel A of Table 7 splits the sample by labor-to-assets ratio (median: 0.44). The results strongly confirm Prediction 2: labor-intensive firms show no significant investment response (coefficient: 0.006, insignificant), while capital-intensive firms exhibit large, significant effects (coefficient: 0.020, significant at 1%). The reduced-form estimates follow the same pattern, with significant negative effects only for capital-intensive firms (-0.020). This confirms the model's mechanism: in capital-intensive firms, the marginal product of capital is more sensitive to labor productivity changes (Equation (4)), creating stronger complementarity between experienced workers and physical capital. Where capital matters less for production, older workers' productivity advantages fail to generate additional capital deepening. Both subsamples maintain strong first stages (F-stats: 14.96 and 94.09), with capital-intensive firms responding more to demographic shifts (-0.585 vs. -0.265).

Initial Workforce Composition

Panel B splits firms by whether over 50% of workers exceed age 36 (the sample median).[21] The results validate Prediction 3: firms with initially younger workforces show nearly three times larger investment responses (0.051) than firms with older workforces (0.014), both significant but economically distinct. This pattern reflects diminishing marginal returns to experience—firms with predominantly older workforces already capture most productivity gains from experience, while firms with younger workforces experience stronger marginal benefits from hiring experienced workers. This is consistent with the concave relationship between older worker share and productivity in Equation (1). First stages remain strong in both subsamples (F-stats: 55.81 and 37.09) with similar magnitudes (-0.490 vs. -0.543).

These cross-sectional patterns provide compelling evidence that capital-labor complementarity drives our results. The investment response to hiring older workers is strongest precisely where the model predicts: in capital-intensive firms and firms with initially younger workforces. Combined with the productivity and profitability results in Table 3, these heterogeneous effects confirm the theoretical mechanism of our model. The fact that investment responses are concentrated among capital-intensive firms, where the complementarity between experienced labor and physical capital is strongest, directly validates Equation (4) in our model. Similarly, the diminishing returns pattern for firms with initially older workforces aligns with the diminishing productivity of older workers (Equation (1)), where marginal

[21] We categorize firms as having a high or low initial share of older workers based on their shares at the start of our sample in 2002.

productivity gains from additional experienced workers decline as the workforce ages. This evidence on investment across sample splits demonstrates that strategic hiring of experienced workers operates through the capital deepening channel emphasized in our theoretical framework.

5 Conclusion

This paper examines how workforce aging affects corporate investment, addressing a fundamental puzzle at the intersection of corporate finance and the economics of aging. More than two decades after Federal Reserve Chairman Alan Greenspan questioned whether aging would constrain or enhance capital investment, we provide the first firm-level evidence that helps understand this tension. We develop a model where firms optimally choose between younger and older workers who differ in productivity and wages. When older workers are more productive—as evidenced by the wage premiums they command—hiring them increases the marginal return to capital through complementarity between experienced labor and physical capital.

Using comprehensive Canadian employer-employee data covering nearly 20 million workers and a shift-share instrumental variable approach, we establish that a one-year increase in the average age of new hires raises investment by 2.2 percentage points. Consistent with theory, effects are concentrated among capital-intensive firms and those with initially younger workforces. Our identification strategy isolates the causal channel: strategic hiring of older workers drives capital deepening through productivity complementarity, distinct from the constraints of managing an aging existing workforce.

Our findings reveal two opposing forces. Declining labor supply constrains aggregate investment—a negative labor supply channel documented in prior research. However, strategic hiring of experienced workers enables capital deepening—a positive workforce aging channel that can offset demographic headwinds at the firm level. This distinction reconciles the tension between macro-level constraints and firm-level investment responses.

The policy implications are clear. For managers, productivity gains from experienced workers justify the higher costs and warrant additional capital investment. For policymakers, workforce aging need not constrain productivity growth if firms leverage the complementarity between experience and physical capital through strategic hiring. Our results demonstrate that firms are not passive victims of demographic change but actively respond as populations age. As global aging accelerates, understanding and facilitating these strategic responses will prove increasingly critical for maintaining economic dynamism.

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Figure 1: **Population and Workforce Aging in Canada.** Panel A shows the average and median age in Canada using the Population Estimates from Statistics Canada, see here. Panel B shows the fraction of workers in each age category in our sample, which relies on the Canadian Employer–Employee Dynamics Database (see Section 3.1).

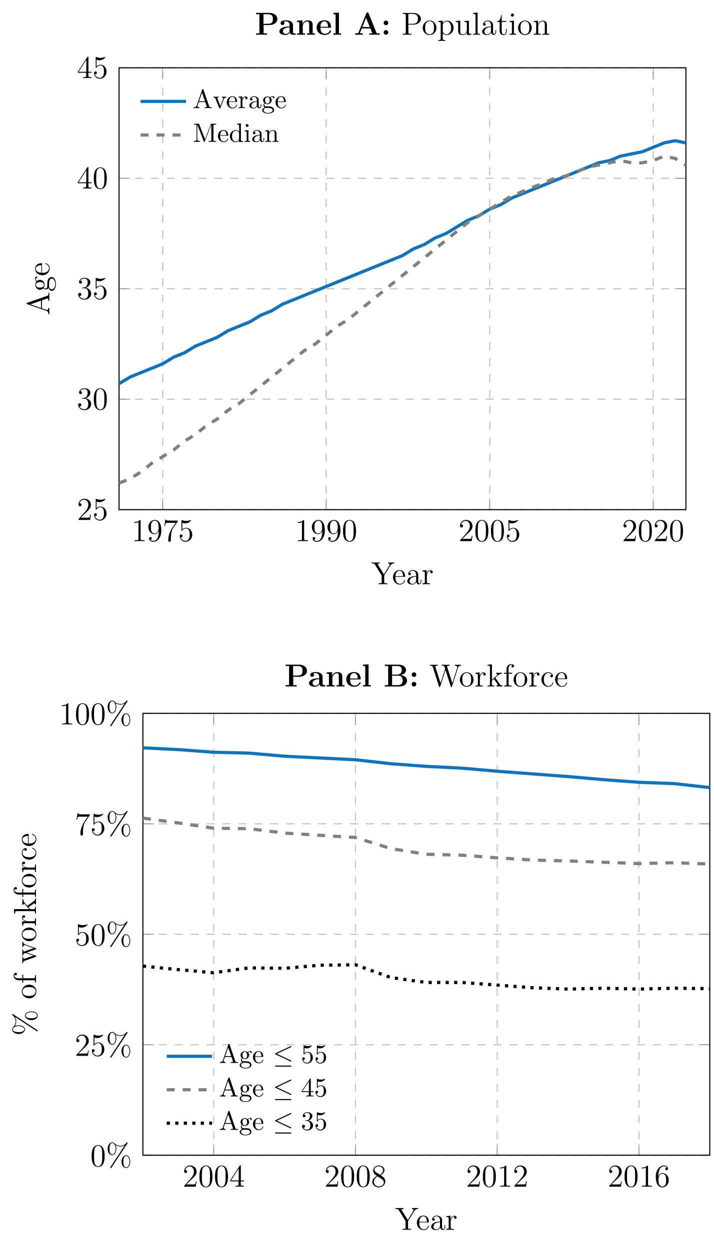

Figure 2: **Impact of Labor Intensity and Worker Composition.** Panel A shows the effect on investment Δ for different labor intensities where we keep $\alpha+\beta = 0.95$ and vary α. Panel B shows the effect on investment Δ as a function of initial workforce composition where we keep $l_o + l_y = 1$ and vary $\frac{l_o}{l_y+l_o}$. We calibrate the model using our data (Section 3.1): $r = 1.63\%$ is the average rate of Canadian 3-month treasury bill over our sample period, $\delta = 12\%$ matches our average investment rate, and $L_y = 49\%$ and $L_o = 51\%$ correspond to the share of young and older workers in our sample. We normalize TFP to 1 and use a Cobb-Douglas labor aggregator $\rho = 0$. Finally, we set $\eta = 0.33$ to match the observed wage premium of 1.95.

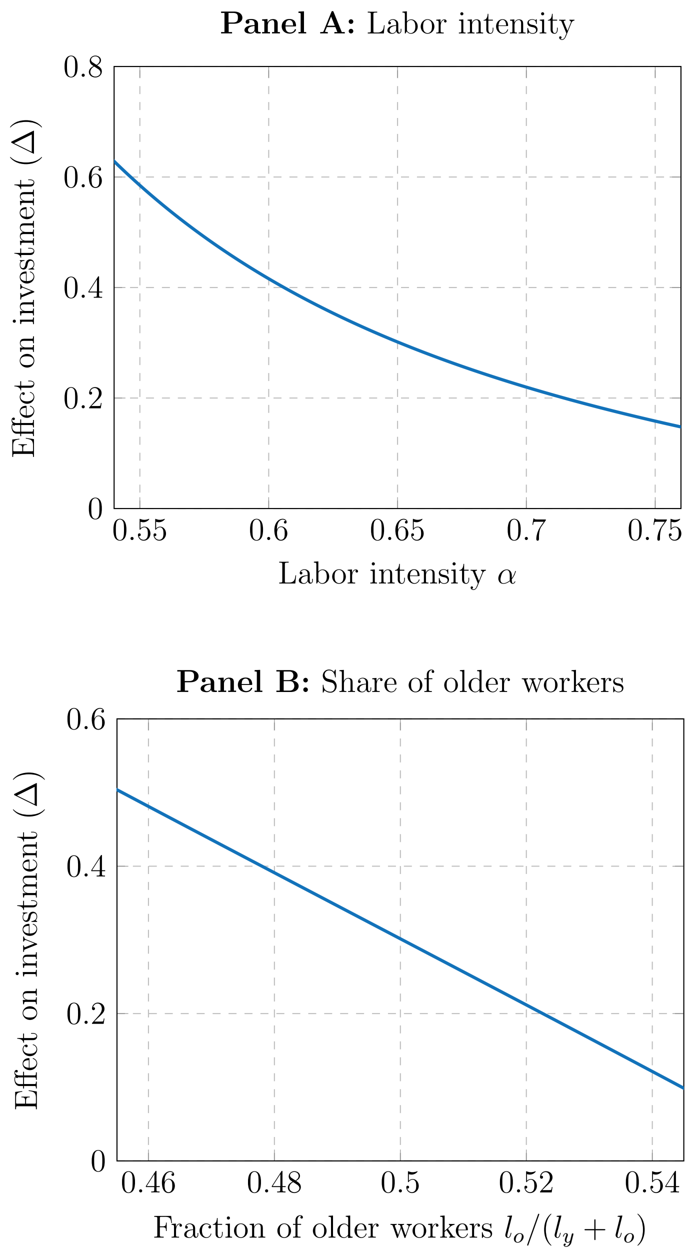

Figure 3: **Investment and Age of New Workers Hired Versus Existing Workers**. Panel A shows a binscatter plot of the average net investment versus age of new workers hired. Panel B shows a binscatter plot of the average net investment versus age of current workers. We control for firm fixed effects in each plot. The sample period is from 2001 to 2020. We provide the definitions of variables in Table A.2.

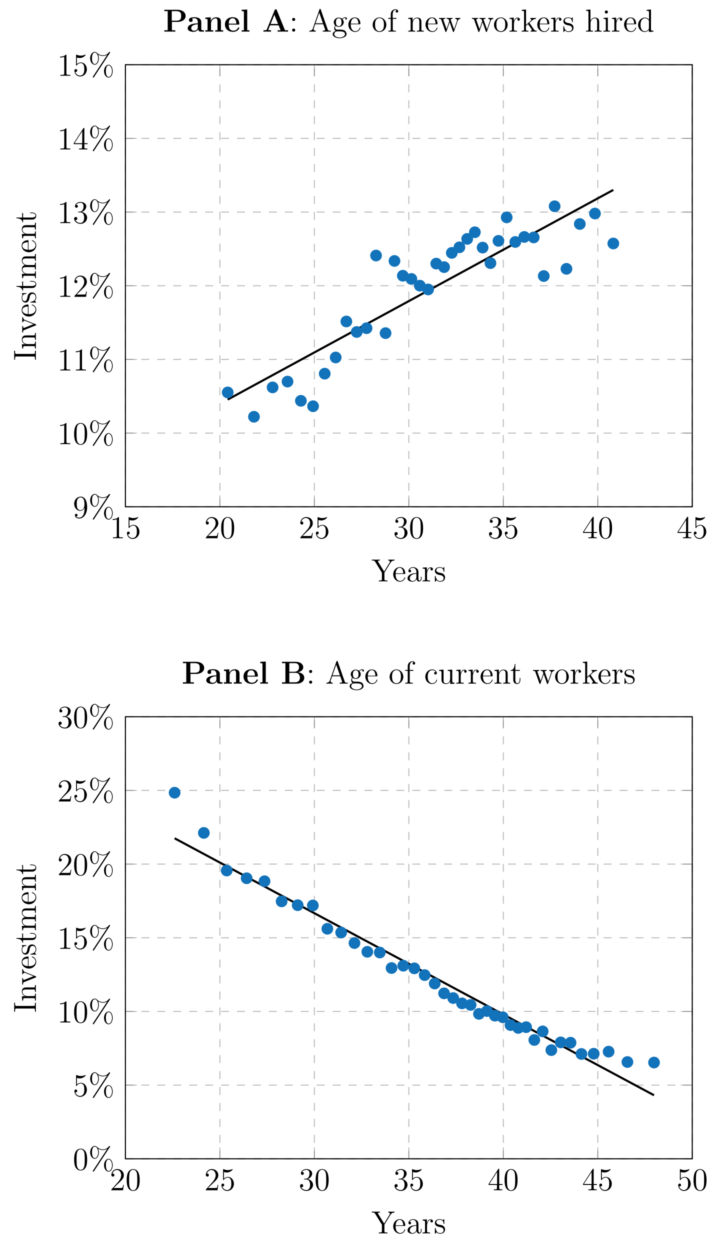

Figure 4: **Shift Versus Share Across Industries**. This plot shows the two components of our instrument: the share (Initial share of older workers) and the shift (5-year absolute change in average worker age). Each variable is calculated as the average within every industry.

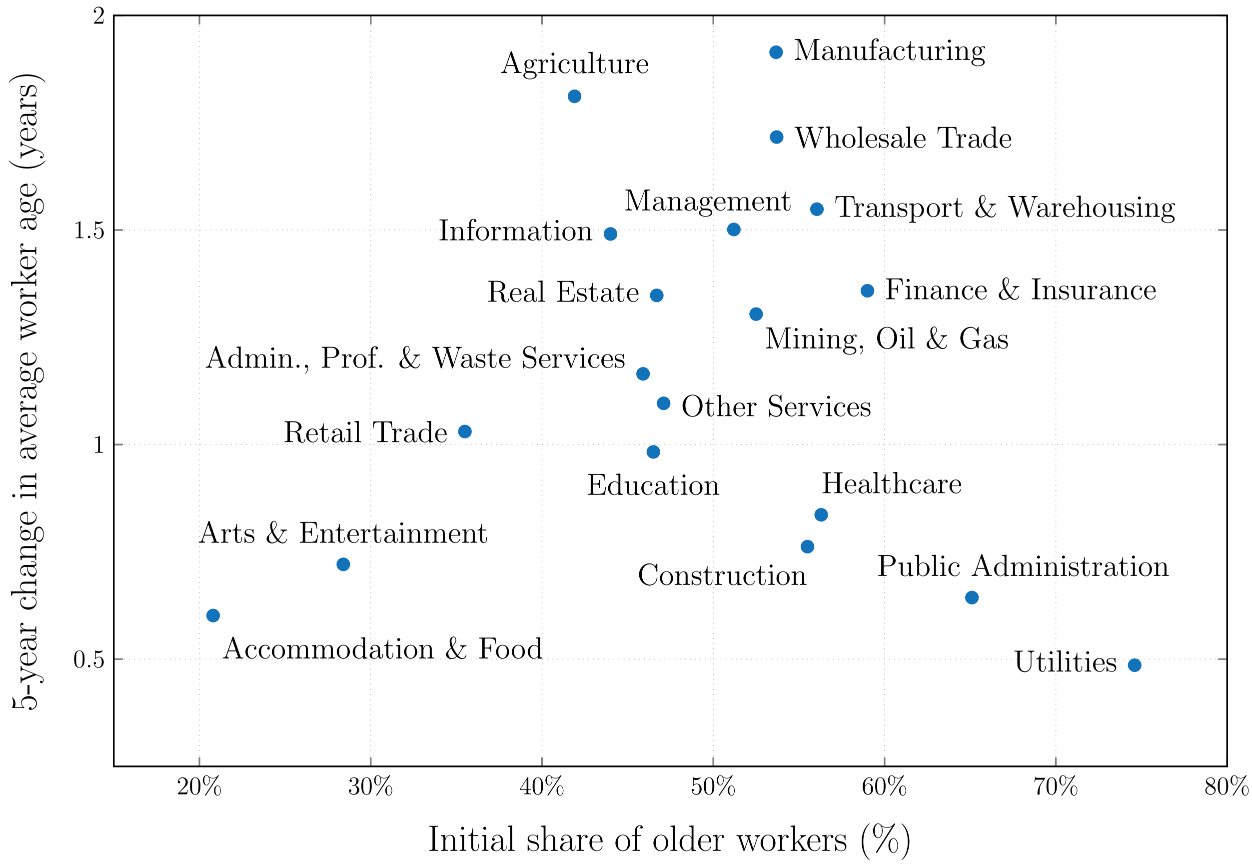

Table 1: **Summary Statistics**. This table presents the summary statistics of sample firms. Panel A documents firm-specific variables. Panel B describes worker-specific variables. The full sample covers 2001-2020 and the estimation sample covers 2008-2020. We winsorize all variables at the 1% and 99% levels. We provide the definitions of variables in Table A.2.

Panel A. Firm characteristics					
	Mean	Std. dev.	P25	P50	P75
Investment	0.12	0.25	0.01	0.05	0.12
Profit margin	0.05	0.07	0.01	0.03	0.06
Log(total assets)	15.96	1.90	14.66	15.81	16.96
Tangibility	0.68	0.58	0.22	0.54	1.00
Leverage	0.16	4.31	-0.50	0.00	0.69
Firm age	21.21	16.40	9.06	17.69	29.02
TFP (headcount)	0.00	0.92	-0.35	0.07	0.50
TFP (full-time)	0.00	1.51	-0.36	0.05	0.48
Panel B. Workforce characteristics					
	Mean	Std. dev.	P25	P50	P75
Age of current workers	36.81	6.81	31.77	37.58	41.86
Total # of current workers	448	2,923	95	143	256
Tenure of current workers	6.32	3.32	3.64	5.54	8.43
Age of new workers hired	32.15	6.20	27.50	32.07	36.35
Total # of new workers hired	138	876	24	44	85
Tenure of new workers hired	3.57	2.35	1.80	2.69	4.49
Indicator for old workers hired	0.35	0.20	0	0	1
Age of fired workers	40.57	10.92	34.10	38.36	45.25
Age of quitting workers	33.70	6.83	28.45	33.43	38.31
Observations	281,765				
Panel C. Shift-share instrument					
	Mean	Std. dev.	P25	P50	P75
Shift-share$_{jt}$	0.60	0.48	0.20	0.49	0.87
Share of older workers$_{j,t-5}$	0.48	0.21	0.32	0.50	0.64
$\Delta\overline{\text{Age}}^{\text{industry}}_{k,t-5:t}$	1.19	0.72	0.63	1.02	1.55
Observations	136,680				

Table 2: **The Causal Effect of Worker Aging on Investment**. This table reports the baseline results of our analysis, see Section 4.1. Column (1) presents the non-instrumented (OLS) effect of the average age of new workers on investment. Column (2) presents the reduced-form (RF) effect of the shift-share instrument on investment. The shift-share instrument interacts the firm's initial share of older workers (aged 36+) with industry-level demographic trends (average change in worker age; Equation (7)). Column (3) presents the first-stage (FS) result, that is the effect of the shift-share instrument on the average age of hired workers (Equation (8)). Column (4) presents the instrumented (IV) effect of the average age of new workers on investment. All specifications include dummies for missing observations of the average age of fired workers and average age of quitting workers. We provide the definitions of variables in Table A.2. Standard errors clustered by firm are in parentheses.

	(1) OLS	(2) RF	(3) FS	(4) IV
Shift-share instrument		-0.011***	-0.523***	
		(0.002)	(0.044)	
Average age of new workers	0.001***			0.022***
	(0.0002)			(0.005)
Worker composition controls	✓	✓	✓	✓
Worker turnover controls	✓	✓	✓	✓
Firm characteristics controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Province×Year FE	✓	✓	✓	✓
F-statistic			141.47	
N	136,680	136,680	136,680	136,680

Table 3: **Productivity Channel.** This table examines the effect of hiring older workers on firm productivity and profitability. Column (1) presents the non-instrumented (OLS) effect of the average age of new workers on investment. Column (2) presents the reduced-form (RF) effect of the shift-share instrument on investment. The shift-share instrument interacts the firm's initial share of older workers (aged 36+) with industry-level demographic trends (average change in worker age; Equation (7)). Column (3) presents the first-stage (FS) result, that is the effect of the shift-share instrument on the average age of hired workers (Equation (8)). Column (4) presents the instrumented (IV) effect of the average age of new workers on investment. All specifications include all controls and fixed-effects from Table 2. Panel A shows the results when total factor productivity (TFP) is calculated using worker headcount as the independent variable. Panel B shows the results when TFP is calculated using full-time equivalent workers. Panel C uses log sales as the dependent variable. TFP is calculated as the residual from regressing log sales on log total assets, log employment (measured using head count or full-time equivalent number of workers), and industry-year fixed effects. We provide the definitions of variables in Table A.2. Standard errors clustered by firm are in parentheses.

	(1) OLS	(2) RF	(3) FS	(4) IV
A. TFP (worker head count)				
Shift-share instrument		-0.0467***	-0.610***	
		(0.007)	(0.045)	
Average age of new workers	0.001***			0.077***
	(0.0004)			(0.013)
F-statistic			181.43	
N	128,280	128,280	128,280	128,280
B. TFP (full-time equivalent workers)				
Shift-share instrument		-0.044***	-0.609***	
		(0.007)	(0.045)	
Average age of new workers	0.001***			0.073***
	(0.0003)			(0.013)
F-statistic			180.31	
N	128,140	128,140	128,140	128,140
C. Log sales				
Shift-share instrument		-0.060***	-0.610***	
		(0.007)	(0.045)	
Average age of new workers	0.003***			0.098***
	(0.0004)			(0.014)
F-statistic			181.43	
N	128,280	128,280	128,280	128,280

Table 4: **Instrument Robustness.** This table reports robustness tests of the main specification of the instrument, see Section 4.2. Column (1) presents the non-instrumented (OLS) effect of the average age of new workers on investment. Column (2) presents the reduced-form (RF) effect of the shift-share instrument on investment. The shift-share instrument interacts the firm's initial share of older workers (aged 36+) with industry-level demographic trends (average change in worker age; Equation (7)). Column (3) presents the first-stage (FS) result, that is the effect of the shift-share instrument on the average age of hired workers (Equation (8)). Column (4) presents the instrumented (IV) effect of the average age of new workers on investment. All specifications include all controls and fixed effects from Table 2. We provide the definitions of variables in Table A.2. Standard errors clustered by firm are in parentheses.

	(1) OLS	(2) RF	(3) FS	(4) IV
A. Industry shift calculated using 4-digit NAICS				
Shift-share instrument		-0.006***	-0.195***	
		(0.001)	(0.026)	
Average age of new workers	0.001***			0.029***
	(0.0002)			(0.008)
F-statistic			57.44	
N	136,675	136,675	136,675	136,675
B. Industry shift calculated using growth rates of workforce age				
Shift-share instrument		-0.009***	-0.196***	
		(0.001)	(0.025)	
Average age of new workers	0.001***			0.046***
	(0.0002)			(0.009)
F-statistic			60.73	
N	136,680	136,680	136,680	136,680
C. Alternative threshold for initial share of old workers (48+)				
Shift-share instrument		-0.009**	-0.836***	
		(0.004)	(0.085)	
Average age of new workers	0.001***			0.011**
	(0.0002)			(0.005)
F-statistic			97.78	
N	136,680	136,680	136,680	136,680
D. Unpredictable industry shift				
Shift-share instrument		-0.007***	-0.075**	
		(0.002)	(0.030)	
Average age of new workers	0.001***			0.091**
	(0.0002)			(0.043)
F-statistic			6.59	
N	128,170	128,170	128,170	128,170

Table 5: **Robustness to Using Binary Age Thresholds.** This table examines the robustness of our results to alternative definitions of "older workers" using binary treatment indicators at different percentiles of the new hires age distribution, see Section 4.2. The shift-share instrument interacts the firm's initial share of older workers with industry-level demographic trends. Each column presents the IV estimate from a specification where the treatment variable is an indicator for hiring workers above the specified age threshold (corresponding to different percentiles: 50th = age 32, 75th = age 36, 90th = age 40, 95th = age 43, 99th = age 48). The dependent variable in all specifications is investment. All specifications include all controls and fixed effects from Table 2. We provide the definitions of variables in Table A.2. Standard errors clustered by firm are in parentheses.

	(1) 50th pct 32+	(2) 75th pct 36+	(3) 90th pct 40+	(4) 95th pct 43+	(5) 99th pct 48+
Hiring older workers dummy	0.297***	0.250***	0.469***	0.592***	1.16***
	(0.071)	(0.059)	(0.127)	(0.166)	(0.376)
F-statistic	67.86	89.59	33.98	29.29	17.62
N	136,680	136,680	136,680	136,680	136,680

Table 6: **Falsification Tests.** This table reports falsification tests of the main specification, see Section 4.2. Column (1) presents the non-instrumented (OLS) effect of the average age of new workers on investment. Column (2) presents the reduced-form (RF) effect of the shift-share instrument on investment. The shift-share instrument interacts the firm's initial share of older workers (aged 36+) with industry-level demographic trends (average change in worker age; Equation (7)). Column (3) presents the first-stage (FS) result, that is the effect of the shift-share instrument on the average age of hired workers (Equation (8)). Column (4) presents the instrumented (IV) effect of the average age of new workers on investment. All specifications include all controls and fixed effects from Table 2 (except for the test for pre-determined firm age in which this variable is not included as a control). We provide the definitions of variables in Table A.2. Standard errors clustered by firm are in parentheses.

	(1) OLS	(2) RF	(3) FS	(4) IV
A. Pre-trend test				
Shift-share instrument		0.002	0.874***	
		(0.006)	(0.078)	
Average age of new workers	0.0002			0.003
	(0.0004)			(0.007)
F-statistic			123.89	
N	61,230	61,230	61,230	61,230
B. Pre-determined outcomes				
		Firm age		
Shift-share instrument		0.0006	-0.523***	
		(0.0008)	(0.044)	
Average age of new workers	-0.00003			-0.001
	(0.00004)			(0.002)
F-stat.			141.47	
Obs.	136,680	136,680	136,680	136,680
		Number of workers		
Shift-share instrument		-11.93	-0.523***	
		(9.53)	(0.044)	
Average age of new workers	0.997**			22.83
	(0.488)			(18.36)
F-stat.			141.47	
Obs.	136,680	136,680	136,680	136,680
		Percent of unionized workers		
Shift-share instrument		-0.002	-0.523***	
		(0.002)	(0.044)	
Average age of new workers	-0.0002***			0.004
	(0.0001)			(0.003)
F-stat.			141.47	
Obs.	136,680	136,680	136,680	136,680

Table 7: **Heterogeneity.** This table reports heterogeneity tests of the main specification across firms with different labor intensity (Panel A) and different initial share of older workers (Panel B), see Section 4.3. Column (1) presents the non-instrumented (OLS) effect of the average age of new workers on investment. Column (2) presents the reduced-form (RF) effect of the shift-share instrument on investment. The shift-share instrument interacts the firm's initial share of older workers (aged 36+) with industry-level demographic trends (average change in worker age; Equation (7)). Column (3) presents the first-stage (FS) result, that is the effect of the shift-share instrument on the average age of hired workers (Equation (8)). Column (4) presents the instrumented (IV) effect of the average age of new workers on investment. All specifications all controls and fixed effects from Table 2. We provide the definitions of variables in Table A.2. Standard errors clustered by firm are in parentheses.

	(1) OLS	(2) RF	(3) FS	(4) IV
A. Labor intensity				
		High labor intensity		
Shift-share instrument		-0.002	-0.265***	
		(0.004)	(0.068)	
Average age of new workers	0.001**			0.006
	(0.0003)			(0.016)
F-statistic			14.96	
N	62,390	62,390	62,390	62,390
		Low labor intensity		
Shift-share instrument		-0.012***	-0.585***	
		(0.003)	(0.060)	
Average age of new workers	0.001***			0.020***
	(0.0003)			(0.006)
F-statistic			94.09	
N	72,530	72,530	72,530	72,530
B. Initial share of older workers				
		High initial share		
Shift-share instrument		-0.007**	-0.490***	
		(0.003)	(0.066)	
Average age of new workers	0.001***			0.014**
	(0.0003)			(0.007)
F-statistic			55.81	
N	49,825	49,825	49,825	49,825
		Low initial share		
Shift-share instrument		-0.027***	-0.543***	
		(0.006)	(0.089)	
Average age of new workers	0.0002			0.051***
	(0.0004)			(0.014)
F-statistic			37.09	
N	49,010	49,010	49,010	49,010

Appendix

Table A.1: **Sample Construction**. This table presents how the number of firms and observations changes with the applications of data filters.

Sample Restriction	Firms	Observations
Population: All firms in NALFM 2001 to 2020	5,865,270	50,000,140
Initial sample: Firms with 50+ employees	57,385	591,530
Drop firms without financial statement data	50,585	492,895
Drop negative EBITDA or LT debt/EBITDA > 40	45,640	432,150
Drop observations with missing lagged variables	41,065	383,965
Drop firms without hiring or missing hire data	36,855	345,340
Drop observations with missing control variables	26,970	281,765
Main shift-share regression sample (2008+)	16,385	136,680

Table A.2: **Definitions of Variables**. This table presents the definitions and sources of variables used throughout the paper.

Variable	Definition	Source
A. Firm characteristics		
Investment	Total tangible net investment divided by lagged total tangible assets	NALFM
Profit margin	Net income after tax treatments divided by total revenue	NALFM
Log(total assets)	Natural logarithm of total assets	NALFM
Tangibility	Total tangible assets divided by total assets	NALFM
Leverage	Net total debt divided by EBITDA	NALFM
Firm age	Number of years since incorporation	NALFM
Labor intensity	Total labor costs divided by total assets	NALFM and T4ROE
TFP (headcount)	Residual from regressing log sales on log total assets, log employment (total number of workers) and industry-year fixed effects	NALFM and T4ROE
TFP (full-time)	Residual from regressing log sales on log total assets, log employment (total number of full-time equivalent workers), and industry-year fixed effects	NALFM and T4ROE
B. Workforce characteristics		
Age of current workers	Average age of all current workers at the firm	T1PMF and T4ROE
Total # of current workers	Total number of workers employed by the firm	T4ROE
Tenure of current workers	Average industry experience of current workers (in years)	T4ROE
Age of new workers hired	Average age of newly hired workers in current year	T1PMF and T4ROE
Total # of new workers hired	Total number of employees hired in current year	T4ROE
Tenure of new workers hired	Average industry experience of newly hired workers (in years)	T4ROE
Indicator for old workers hired	Binary indicator equal to 1 if firm hires workers with average age > 32 (median)	T1PMF and T4ROE
Age of fired workers	Average age of workers terminated by the firm	T1PMF and T4ROE
Age of quitting workers	Average age of workers who voluntarily quit	T1PMF and T4ROE
Percent unionized	Percentage of workers covered by collective bargaining agreements	T4ROE
C. Instrument variables		
Shift-share$_{jt}$	Interaction of firm's initial share of older workers and industry age shift	T1PMF and T4ROE
Share of older workers$_{j,t-5}$	Proportion of workers aged 36+ in firm j five years prior	T1PMF and T4ROE
$\Delta\overline{\text{Age}}^{\text{industry}}_{k,t-5:t}$	Five-year change in average worker age in industry k (2-digit NAICS)	T1PMF and T4ROE
Shift-share$^{\text{unpred}}_{jt}$	Shift-share using residualized (unpredictable) industry age trends	T1PMF and T4ROE

Table A.3: **Additional Robustness Tests.** Column (1) presents the non-instrumented (OLS) effect of the average age of new workers on investment. Column (2) presents the reduced-form (RF) effect of the shift-share instrument on investment. The shift-share instrument interacts the firm's initial share of older workers (aged 36+) with industry-level demographic trends (average change in worker age; Equation (7)). Column (3) presents the first-stage (FS) result, that is the effect of the shift-share instrument on the average age of hired workers (Equation (8)). Column (4) presents the instrumented (IV) effect of the average age of new workers on investment. All specifications include all controls and fixed effects from Table 2. We provide the definitions of variables in Table A.2. Standard errors clustered by firm are in parentheses.

	(1) OLS	(2) RF	(3) FS	(4) IV
A. Excluding regulated industries				
Shift-share instrument		-0.011***	-0.589***	
		(0.003)	(0.045)	
Average age of new workers	0.001***			0.019***
	(0.0002)			(0.005)
F-statistic			168.70	
N	131,540	131,540	131,540	131,540
B. Alternative investment (total investment/total assets)				
Shift-share instrument		-0.007***	-0.523***	
		(0.001)	(0.044)	
Average age of new workers	0.0004***			0.014***
	(0.0001)			(0.002)
F-statistic			141.47	
N	136,680	136,680	136,680	136,680

Table A.4: **Age of Existing Workforce.** This table repeats the analysis from Table 2 but instruments the age of existing workforce rather than age of hired workers. Column (1) presents the non-instrumented (OLS) effect of the average age of new workers on investment. Column (2) presents the reduced-form (RF) effect of the shift-share instrument on investment. The shift-share instrument interacts the firm's initial share of older workers (aged 36+) with industry-level demographic trends (average change in worker age; Equation (7)). Column (3) presents the first-stage (FS) result, that is the effect of the shift-share instrument on the average age of hired workers (Equation (8)). Column (4) presents the instrumented (IV) effect of the average age of new workers on investment. All specifications include all controls and fixed effects from Table 2, except for the average age of existing workforce. We provide the definitions of variables in Table A.2. Standard errors clustered by firm are in parentheses.

	(1) OLS	(2) RF	(3) FS	(4) IV
Shift-share instrument		-0.012***	0.446***	
		(0.002)	(0.027)	
Average age of current workers	-0.001**			-0.026***
	(0.001)			(0.006)
F-statistic			280.88	
N	136,680	136,680	136,680	136,680