Demographic Origins of the Decline in Labor's Share*

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Abstract

Since 1980, the earnings share of older workers has risen in the United States, simultaneous with a historic decline in labor's share of income. We hypothesize that an aging workforce has contributed to the decline in labor's share. We formalize this hypothesis in an on-the-job search model, in which employers of older workers may have substantial monopsony power due to the decline in labor market dynamism that accompanies age. This manifests as a rising wedge between a worker's earnings and marginal product over the life-cycle. We estimate the age profile of these wedges using cross-industry responses of labor shares to changes in the age-distribution of earnings. We find that a sixty year old worker receives half of her marginal product relative to when she was twenty, which, together with recent demographic trends, can account for 59% of the recent decline in the U.S. labor share. Industrial heterogeneity in this age profile is consistent with the monopsony-power mechanism: highly unionized industries exhibit no relationship between age and payroll shares.

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1 Introduction

Since the early 1980s, labor's share of income has fallen in the United States, as well as many countries around the world (Karabarbounis and Neiman [12]). This is in contrast to the historical experience of a stationary distribution of income between factors (Kaldor [11]). The recent downward trend has been historically large – labor's share has fallen by $3.6 - 6.4$ percentage points in the United States and five percentage points globally.[1] This decline has caused concern over the distribution of income between factors (Piketty [21]) and raised questions of how policy makers should respond.

Concurrent with the decline in labor's share, the United States has experienced an unprecedented demographic shift in earnings towards older workers. As shown in Figure 2, the share of earnings accruing to prime age workers has been falling since the 1980's, coincident with the decline in labor's share.[2] Furthermore, the share of earnings accruing to workers near retirement (60+) has doubled since the late 1990s, coinciding with a hastening of the decline in labor's share. As with the decline in labor's share, the U.S. is part of a global trend - many countries have aged during this period, leading to a large increase in the world-wide average age (see Figure 7a).

Established models of frictional matching and on-the-job search provide a microeconomic foundation to link these two trends, mediated by the steep decline in labor market dynamism that comes with age (Bjelland, et al. [7]). We extend Postel-Vinay and Robin's [22] model of earnings and job mobility to include an age-profile of both labor productivity and the arrival rate of outside offers while searching on the job. This model naturally generates monopsony power for employers because workers cannot immediately leave for higher wages. Furthermore, monopsony power is more severe if workers are less able (or willing) to switch jobs (or to generate credible outside offers of employment). Earnings may therefore lag productivity as a worker ages (and becomes less mobile) because the model predicts that raises are generated by competition when a worker receives an outside job offer. We show that this model can generate rising monopsony power for employers as their worker's age and therefore a rising wedge between the worker's marginal product and her earnings. Therefore, a shift of aggregate

[1]The range for the United States depends on how proprietor's income is allocated to factors (Elsby, Hobijn, and Şahin [9]). The global decline of 5% is in the corporate sector, which excludes proprietors (Karabarbounis and Neiman [12]).

[2]The post-2000 rise in earnings share for older workers is largely because they are a larger share of the labor force, but also because older workers' average earnings have grown faster than those of young workers. This is consistent with Beaudry, Green, and Sand [6], who document that early-career earnings growth has declined since 2000.

earnings towards older workers has a negative effect on labor's share.

Motivated by the above theory, we seek to quantify how much of the decline in labor's share can be attributed to aging. An immediate difficulty arises - marginal products are not observable and value added is not measured by age in the national accounts. We therefore develop a framework to estimate age-specific earnings wedges (i.e. the percentage gap between earnings and marginal product) from cross-industry data containing payroll shares and the age-distribution of earnings. Under weak assumptions on production functions and labor market institutions, we can write an industry's labor share as the earnings-share weighted harmonic mean of these age-specific wedges.[3] Intuitively, we infer that earnings wedges rise with age if payroll shares tend to decline whenever the earnings of mature workers rises relative to that of young for reasons that are exogenous to industry-level shocks to factor shares (shocks to relative labor supply, for example).

Our source of identifying variation in the age-distribution of earnings follows the logic of Bartik [5], as implemented by Nakamura and Steinsson [18]. Specifically, we create instruments by projecting moments of the age distribution of earnings for a given industry onto the aggregate. This step is key since labor can relocate across industries and changes in factor shares amount to earnings shocks at the individual level. In response, young workers may decide to switch occupations and industries at different rates than older workers or older workers may decide to retire. Either response would bias our estimates of earnings wedges.

We estimate that workers receive a smaller share of their marginal product as they age (we say that older workers have a larger "earnings wedge", since this represents a wedge between the worker's earnings and marginal product of labor). Importantly, our framework nests the standard assumption of perfectly competitive labor markets, but cross-sectoral movements in labor's share and the age-distribution of earnings indicate an increasing age-profile of earnings wedges. Our estimates imply that the observed increase in earnings accruing to older workers accounts for 59% of the post-1980 decline in labor's share in the United States and 54% of the global decline since 1975.[4]

We provide an alternative to technology-based explanations for the decline in labor's share, which typically generalize the production function(s) while retaining perfect competition in product and factor markets (Karabarbounis and Neiman [12], Koh, San-

[3] See 3 for these assumptions. Essentially, we need to assume that the marginal product of labor is proportional to the average product (as with a Cobb-Douglas production function) and that the age-profile of wedges is constant over time.

[4] The global decline assumes that the U.S. wedges apply internationally.

taeulàlia-Llopis, and Zheng [14], Alvarez-Cuadrado, Long, and Poschke [1], Orak [20]).[5] We are more similar to the literature on concentration in product markets (Autor, et al [2] and Kehrig and Vincent [13]) or labor markets (Azar, et al. [3]), but we are the first to propose a link between demographics and the strength of competition.[6]

In the next section we derive the relationship between labor's share and the age-profile of earnings. We then describe the data used to estimate the age-profile of earnings wedges. We present our baseline estimates, which we then use to perform counterfactual analysis and determine age-profiles of earnings and productivity. We discuss the microeconomic implications of our estimates, show that our estimates are robust, and conclude.

2 Age and Labor's Share in Theory

We extend the model of Postel-Vinay and Robin [22] to include an age-profile of job-to-job flows consistent with the empirical findings of Bjelland, et al. [7] and an age-profile of worker-specific labor productivity to match the empirical age profile of earnings.[7] The stark decline in job-to-job transition rates means that older workers, while receiving higher wages and working at more productive firms, capture a smaller share of their marginal product than do young workers.

The model is in continuous time. There is an exogenous distribution of firms over productivities in the support $[p_{\min}, p_{\max}]$, with CDF $F(p)$ and PDF $f(p)$. Firms use effective labor hours in production, so that a firm of productivity p who employs a worker with z units of effective hours produces pz units of the consumption good.

Workers may be employed or unemployed and of age $a = 0, 1, 2, ...$ Workers age at

[5]These papers are related to an older literature on estimating the elasticity of substitution between capital and labor. León-Ledesma, McAdam, and Willman [15] and Chirinko [8] review the literature and report that the majority estimates of the elasticity of substitution are below one, which aligns with the more recent estimates of Oberfield and Raval [19] and suggests that capital accumulation is unlikely to have reduced the labor share. A notable exception in this literature is Karabarbounis and Neiman [12], who estimate an elasticity substantially above one using cross-country trends in investment prices and labor shares, but Glover and Short [10] argue that their estimate is biased upwards due to omitted variable bias and estimate an elasticity no greater than one using the same data once this bias is corrected.

[6]Our microfoundation for the interaction between age and labor's share rests on monopsony power in bilaterally matched labor markets. However, we show that our aggregate estimates are consistent with a life-cycle extension of Autor, et al's product market model.

[7]Bagger, et al. [4] also extend the Postel-Vinay and Robin [22] model to include a life-cycle profile of productivity, but do not allow for age-specific contact rates. Lentz and Roys [16] extend the model to include both general and match-specific worker training, so that a worker's productivity is endogenous.

exogenous and constant rate α, retire at rate μ_a, and receive offers of employment at rate λ_a while employed and γ_a while unemployed. The effective hours of a worker is given by a sequence $(z_a)_{a=0}^{\infty}$, which is exogenous and deterministic. Finally, workers leave their current employer for unemployment at rate δ_a and receive value U_a from unemployment. We will assume that there is some A such that $\lambda_a = \lambda_A, \gamma_a = \gamma_A, \delta_a = \delta_A, U_a = U_A$ and $z_a = z_A$ for all $a \geq A$.

Matching is random, so that each worker who matches with a potential employer draws from the population distribution $F(p)$. We will assume that U_a is sufficiently low that all unemployed workers accept unemployment when contacted. An employed worker who matches with a firm of productivity p' then reports the meeting to her current employer (with productivity p), and the two firms engage in Bertrand competition. Denoting $p^+ = \max\{p, p'\}$ and $p^- = \min\{p, p'\}$, the worker continues working for whichever has the higher productivity. Her new wage is the larger of her current wage, w, and $\phi_a(p^-, p^+)$ defined from

$$V_a(\phi_a(p^-, p^+), p^+) = V_a(z_a p^-, p^-), \tag{1}$$

which makes her just indifferent between working at the more productive firm and leaving for the less productive firm.[8] The above holds for an employed worker, while an unemployed worker's wage is given by $\phi_a^0(p)$ and solves

$$V_a(\phi_a^0(p)) = U_a. \tag{2}$$

We define the lowest productivity relative to p that elicits a wage change by $q_a(w, p)$ from setting $\phi_a(q_a(w, p), p) = w$. A worker aged a employed at wage w at a firm with productivity p is therefore defined by

$$\begin{aligned}\Big[r + \delta + \alpha + \mu_a + \lambda_a \overline{F}\big(q_a(w, p)\big)\Big] V_a(w, p) = u(w) + \alpha V_{a+1}(w, p) + \delta U_a + \\ \lambda_a \int_{q_a(w,p)}^{p} V_a\big(\phi_a(x, p), p\big) f(x) dx + \lambda_a \int_{p}^{p_{\max}} V_a\big(\phi_a(p, x), x\big) f(x) dx,\end{aligned} \tag{3}$$

[8] We assume that firms cannot pay more than the flow output of their workers, so that the less productive firm would pay $z_a p^-$. This wage would not exhaust the expected discounted profits of the less productive firm, since z_a is weakly growing with time. If we allowed firms to borrow in order to pay up to the annuity value of a worker's expected discounted marginal product, then younger workers would have higher wages (their wages would be even larger than their marginal product) and the model becomes untractable. Since we will find that young workers earn a larger share of their marginal product than do older workers, we expect our results would be strengthened in the more complicated model.

where r is the rate of time preference and $\bar{F}(x) = 1 - F(x)$. Equations (1), (2), (3), and the definition of $q_a(w,p),p) = w$ determine the equilibrium wage policy functions and value functions.

With the above functions in hand, a stationary distribution of workers over age, firm productivity, and wages is derived. First, let M_a denote the measure of workers aged a years. These are determined by fixing M_0 and then setting age $a \geq 1$ outflows equal (aging and retiring) to inflows (aging of $a-1$ workers):

$$(\alpha + \mu_a)M_a = \alpha M_{a-1}, \tag{4}$$

Denote the measure of unemployed workers of each age by $u_a M_a$, where u_a is the unemployment rate. Setting outflows equal to inflows and using the above relationship between M_{a-1} and M_a gives:

$$u_a(\alpha + \mu_a + \gamma_a + \delta_a) = \delta_a + (\alpha + \mu_a)u_{a-1}, \tag{5}$$

$$(1 - u_a)(\alpha + \mu_a + \gamma_a + \delta_a) = \gamma_a + (\alpha + \mu_a)(1 - u_{a-1}). \tag{6}$$

Finally, the distributions of workers over firms and wages is endogenous. Let $L_a(p)$ be the CDF of workers of age a over firm-productivities and $\ell_a(p) = L_a'(p)$. Let $G_a(w|p)$ be the CDF over wages for workers aged a, employed at a firm with productivity p. Then matching inflows and outflows for workers aged $a = 0$ requires

$$\Big[\alpha + \delta_0 + \mu + \lambda_0 \overline{F}\big(q_0(w,p)\big)\Big] G_0(w|p)\ell_0(p) = \left\{\gamma_0 \frac{u_0}{1-u_0} + \lambda_0 \int_{p_{\min}}^{q_0(w,p)} \ell_0(x)dx\right\} f(p), \tag{7}$$

while for workers aged $a \geq 1$ this requires

$$\begin{aligned}\Big[\alpha + \delta_a + \mu_a + \lambda_a \overline{F}\big(q_a(w,p)\big)\Big] G_a(w|p)\ell_a(p) = \alpha \frac{(1-u_{a-1})M_{a-1}}{(1-u_a)M_a} G_{a-1}(w|p)\ell_{a-1}(p) \\ + \left\{\gamma_a \frac{u_a}{1-u_a} + \lambda_a \int_{p_{\min}}^{q_a(w,p)} \ell_a(x)dx\right\} f(p).\end{aligned} \tag{8}$$

We now show that older workers may receive a smaller share of their marginal product as earnings in this model. The example is stylized to maintain analytical tractability and fix ideas for our empirical work, which uses a more flexible reduced form model.

2.1 Illustrative Example

Consider an economy with $A = 1$. Furthermore, assumed that $\lambda_0 > \lambda_1 = 0$, so that older workers do not receive outside offers while employed. Further, assume that $z_1 \geq z_0 = 1$. Under these assumptions, we can write the value functions as

$$V_a(w,p)(r+\mu_1) = u(w) + \delta U_, a \geq 1 \tag{9}$$

$$V_0(w,p)(r+\delta_0+\mu_0+\alpha) = \tag{10}$$

$$u(w) + \delta U_0 + \alpha V_1(w,p) + \frac{\lambda_0}{r+\delta_1+\mu_1}\int_{q_0(w,p)}^{p} u'(x)\overline{F}(x)dx.$$

The definition of $\phi_0(p^-, p^+)$ then yields

$$\log\left(\phi_0(p^-,p^+)\right) = \log(p^-) - \frac{\lambda_0}{r+\alpha+\delta_1+\mu_1}\int_{p^-}^{p^+} \frac{\overline{F}(x)}{x}dx, \tag{11}$$

which mirrors the wage equation in Postel-Vinay & Robin [22].[9] Finally, we will assume that the sequence $(U_a)_{a=0}^{\infty}$ is such that an unemployed worker would accept any job offer, but would extract the entire surplus from the least productive firm.[10] That is, for all a, we set

$$V_a(z_a p_{\min}, p_{\min}) = U_a. \tag{12}$$

The stationary distribution therefore has a support over wages in the set

$$\{z_0 p_{\min}, z_1 p_{\min}\} \cup \{\phi_0(p^-,p^+) | (p^-,p^+) \in [p_{\min}, p_{max}]^2\}.$$

The measure of older workers ($a > 0$) earning a given wage $\phi_0(p^-, p^+)$ will be equal to the measure of young workers with that wage who have since aged, but have not experienced a separation. All older workers who have experienced a separation will earn $z_1 p_{min}$ upon finding a new job. Mathematically, the stationary distribution of workers

[9]Our general model does not admit such a simple representation of ϕ_a when $\lambda_{a+1} > 0$. We therefore solve the entire system of V_a, ϕ_a, q_a for our quantitative analysis.

[10]The value of unemployment could be set strictly lower than this value and workers would still accept any job offer. Some authors set the value of unemployment to zero (Postel-Vinay and Robin [22]), while others set it to the value of least productive firm, as in this example (Bagger, et al [4]). In the quantitative model we will introduce a parameter such that $U_a = \psi V_a(z_a p_{\min}, p_{\min})$.

aged $a \geq 1$ over firms and wages must satisfy

$$M_a(1-u_a)(\mu_a+\delta_a+\alpha)G_a(w|p)\ell_a(p) = \\ M_a u_a \gamma_1 f(p) + \alpha M_{a-1}(1-u_{a-1})G_{a-1}(w|p)\ell_{a-1}(p), \tag{13}$$

which, along with the relationship $(1-u_a)M_a(\delta_a+\mu_a+\alpha) = \gamma_a u_a M_a + \alpha M_{a-1}(1-u_{a-1})$, implies that

$$G_a(w|p)\ell_a(p) = \theta_a f(p) + (1-\theta_a)G_{a-1}(w|p)\ell_{a-1}(p), \tag{14}$$

where $\theta_a = \frac{\gamma_a u_a M_a}{\gamma_a u_a M_a + \alpha(1-u_{a-1})M_{a-1}}$. The average earnings of workers aged $a > 0$ is therefore $E_a[w] = \theta_a z_1 p_{\min} + (1-\theta_a)E_{a-1}[w]$, while the average labor productivity is $E_a[p] = z_a\Bigg[\theta_a\bar{p} + (1-\theta_a)E_{a-1}[p]\Bigg]$, where $\bar{p}$ is the unconditional average productivity of firms. We therefore have a relationship between age and the share of a worker's marginal product that she receives as earnings:

$$\frac{\mathbb{E}_a[w]}{\mathbb{E}_a[p]} = \left\{\psi_a \frac{p_{\min}}{\bar{p}} + (1-\psi_a)\frac{\mathbb{E}_{a-1}[w]}{z_a\mathbb{E}_{a-1}[p]}\right\}, \tag{15}$$

where $\psi_a \equiv \frac{\theta_a z_a \bar{p}}{E_a[p]}$. Equation (15) shows that the average earnings that a worker receives, as a share of her marginal product, is weakly decreasing in age. This is for two reasons. First, holding $z_1 = z_0 = 1$, flows into employment from unemployment leads to a larger and larger share of workers earnings $z_a p_{\min}$. Second, when $z_a > z_{a-1}$, the term $\frac{\mathbb{E}_{a-1}[w]}{z_a\mathbb{E}_{a-1}[p]}$ will shrink further. The model is therefore capable of generating a stationary equilibrium in which the share of a worker's marginal product paid as earnings declines with age. We now ask the model to match the life-cycle profiles of job flows and earnings in order to quantify the slope of this profile.

While stylized, the above example shows that declining job-to-job mobility can generate a rising wedge between a worker's marginal product and her earnings. We use this insight to inform our empirical work below, which treats the wedge as a parameter and the allows for age-independent shocks to labor's share as a residual.

3 Factor-Income Accounting With Wedges

We now provide assumptions on the relationship between earnings, marginal products, and the form of the production function that allow us to estimate the age-profile of earnings wedges. To save notation, we do not index any variable by a cross-sectional unit at this point, but emphasize that the resulting model can be estimated at any level of aggregation for which labor's share and the age-distribution of earnings are available. The goal is to make weak assumptions so that our estimates hold for a large class of structural models of the labor market.[11] We then provide an example of a neoclassical economy for which these assumptions are satisfied and use it to discuss the effect of the earnings-average age on labor share and how to identify earnings wedges.

3.1 Earnings Wedges

We make two assumptions. The first relaxes the assumption of perfect spot markets for labor by introducing earnings wedges to the wage equation. The second allows us to relate the unobservable marginal product of labor to the observable average product.

Assumption 1 *For a worker, ℓ, aged $a = 1, 2, ...A$ years at time t, the wage is given by:*

$$w_{\ell,t} = \left(\omega_a + \varepsilon_t\right)^{-1} \frac{\partial Y_t}{\partial n_{\ell,t}}. \tag{16}$$

The worker's marginal product is $\frac{\partial Y_t}{\partial n_{\ell,t}}$ and we refer to $\omega_a + \varepsilon_t$ as an earnings wedge, since the larger is ω the lower is a worker's earnings relative to her marginal product (note that this model nests both the fully-competitive model when we set $\omega_{a,t} = 1$ for all a and t). We have also assumed that that the worker's age has a time-invariant effect on her wedge, while the time-varying part of the earnings wedge is shared by all workers. We can allow for other worker observables to affect the wedge, though must economize on parameters in practice. Since most of the decline in labor's share in the U.S. coincided with the aging of the baby-boom generation, we explicitly allow for a baby-boom-cohort-specific wedge in Section 6.

Our second assumption is a restriction on the aggregate production function and allows us to relate the marginal product of labor to the average product:

Assumption 2 *For any t in which L_t is the total labor force, the following holds:*

$$\sum_{i=1}^{L_t} \frac{\partial Y_t}{\partial n_{\ell,t}} n_{\ell,t} = \alpha Y_t. \tag{17}$$

This assumption holds for any constant-returns to scale production function during periods when workers from each age group utilize a constant share of the capital stock. It

[11] As we show in Section 8, our reduced form estimates can recover structural parameters even for microeconomic models that violate these assumptions.

holds independently of the allocation of capital across workers if the production function is Cobb-Douglas.

These assumptions are sufficient to derive our estimating equation, which then allows us to estimate relative earnings wedges.[12] The assumptions imply that labor's share is the earnings-share weighted harmonic mean of earnings wedges, plus the age-independent shock ε_t, as shown in Equation 18 below:

$$LS_t^{-1} = \alpha^{-1}\left[\sum_{a=15}^{80} \omega_a \frac{E_{a,t}}{E_t} + \varepsilon_t\right]. \tag{18}$$

Here $E_{a,t}$ is the total earnings of workers aged a (which ranges from 15 to 80 in our data) at t and E_t is aggregate earnings. Equation 18 relates observable labor's share and age-specific earnings shares linearly with respect to the unobservable earnings-wedge parameters.

The logic of identification is straight forward: if we observe an exogenous increase in labor supply for workers aged a, followed by a decline in labor's share of income, then we infer that that age group must receive a smaller share of their marginal product in wages (ω_a is relatively large). The majority of this paper is concerned with estimating these wedges, which requires two additional steps. First, we must model ω_a parsimoniously because of data limitations. Second, we must seek instruments to isolate changes in the age-distribution of earnings that are exogenous to ε_t. We first consider a simple example that clarifies the identification strategy.

3.2 An Example

We use an example to understand identification in our reduced form model. Consider the growth model in discrete and infinite time. The economy consists of two age groups with $a = 1$ representing "immature" and $a = 2$ representing "mature". Total labor supply of each group is exogenously given by $N_{a,t}$, capital is given by the sequence $(K_t)_{t=0}^{\infty}$, and production is given by:

$$Y_t = K_t^{1-\alpha}\Big(Z_{1,t}N_{1,t} + Z_{2,t}N_{2,t}\Big)^{\alpha}, \tag{19}$$

where $Z_{a,t}$ is the relative efficiency of worker aged a's labor. Note that this production function satisfies Assumption 2 by virtue of being Cobb-Douglas in capital and effective

[12]See Section A for the derivation.

labor. Since there are only two age groups, we make Assumption 2 by setting $\varepsilon_t = 0$ and $\omega_1 = 1$ while $\omega_2 \geq 1$. The wage equations satisfy Assumption 1. Denoting $\rho_t = \frac{Z_{2,t}N_{2,t}}{Z_{1,t}N_{1,t}}$ as the relative *effective* labor supply of mature to immature workers, labor's share is given by:

$$\frac{E_t}{Y_t} \;=\; \alpha\left(\frac{1}{1+\rho_t} + \frac{\rho_t}{1+\rho_t}\frac{1}{\omega_2}\right). \tag{20}$$

Equation 20 says that labor's share differs from the output elasticity, α, by a convex combination of $\frac{1}{\omega_1} = 1$ and $\frac{1}{\omega_2} \leq 1$. In addition, the share of earnings accruing to mature workers is given by:

$$\frac{E_{2,t}}{E_t} \;=\; \frac{\frac{1}{\omega_2}\rho_t}{1+\frac{1}{\omega_2}\rho_t}. \tag{21}$$

Now consider an increase in the labor supplied by mature workers. This raises the effective labor of mature workers relative to immature ($\rho_t \uparrow$), which causes a rise in mature workers' earnings share according to Equation 21. At the same time, the convex combination in Equation 20 shifts more weight towards the smaller value $\frac{1}{\omega_2}$, which reduces labor's share. Changes in the relative supply of labor by mature workers therefore cause a negative comovement between their share of aggregate earnings and labor's share.[13]

In practice, we do not observe ρ_t because we do not observe $Z_{a,t}$. Therefore, it is useful to work with the inverse labor's share in Equation 18. Using the fact that $\frac{E_{1,t}}{E_t} = 1 - \frac{E_{2,t}}{E_t}$, Equation 18 simplifies to:

$$\frac{Y_t}{E_t} = \alpha^{-1}\left[1 + \big(\omega_2 - 1\big)\frac{E_{2,t}}{E_t}\right]. \tag{22}$$

A negative correlation between labor's share and mature workers' earnings share directly implies $\alpha^{-1}\omega_2 > 1$.[14] If, on the other hand, mature workers' earnings share and labor's share were uncorrelated then Equation 22 would imply that $\omega_2 = 0$ and the earnings

[13]A similar negative comovement would arise from an increase in $Z_{2,t}$ relative to $Z_{1,t}$. Importantly, along a balanced growth path in which relative productivities and labor supplies are constant, the economy will exhibit a constant labor's share consistent with Kaldor's stylized facts (though labor's share will not equal α).

[14]We have fixed $\omega_1 = 1$ in this example, which need not be true in general. This means that we can only identify the ω_a coefficients up to the multiplicative term α^{-1}. This is enough to perform counterfactuals on aggregate labor's share, though additional restrictions are required to identify α.

wedge would be independent of age.

4 Data

Our measure of aggregate labor share comes from the Bureau of Labor Statistics at the state level, which we then aggregate to compute the national labor share. This has the same dynamics as the index published by the Federal Reserve Bank of St. Louis. We use annual data from the March Current Population Survey to calculate moments of the aggregate age-distribution of earnings (earnings shares and earnings-weighted average age of the labor force).

Our baseline estimation uses sectoral data on payroll shares and the age-distribution of earnings from 1987 to 2011. We separate the economy into 57 industries.[15] Our payroll shares are from Elsby, Hobijn, and Şahin [9]. For earnings shares at the sector level we once again use the March Current Population Survey. We match a worker to the sector in which she is employed and assign her earnings accordingly.[16]

Figure 1 shows the aggregate labor share from 1962 to 2013. From $1962 - 2000$, labor's share has a slight downward trend; as recently as 2000 labor's share was at 0.64, which is essentially the average value through 1980. A turning point occurs in 2000, when labor's share begins to decline and hasn't experienced robust growth since. By the end of the sample, labor's share has fallen from 0.64 to just below 0.58.

At the same time, there have been large shifts in the age composition of earnings. Figure 2 plots our computed earnings shares for five age groups since 1962, normalized by that group's earnings share in 2000. There has been a large increase in the earnings shares of older workers since 2000, with the share of earnings accruing to workers aged 60+ nearly doubling and the earnings share of workers aged $50 - 59$ increasing by over 25%. These shifts have cause the the earnings-weighted average age of the labor force to rise from 38.7 to 44.

[15]We drop two real estate industries in our baseline analysis due to concerns about data quality (extremely lose initial payroll shares), but verify that the results are similar (in fact stronger) if we include all industries.

[16]Our earnings measure excludes business income.

5 Reduced Form Model

We now develop the empirical specifications we use to estimate earnings wedges. We index each industry in our panel by i. Given that our time series extend for $T = 25$ years and there are 66 age groups (from 15 to 80) for which we have earnings, we must restrict how ω_a varies with age. We consider two parameterizations for ω_a, each of which allows us to estimate a single structural parameter. The first assumes that ω_a is linear in age, so that:

$$\omega_a = \Omega_0 + \Omega_1 a. \tag{23}$$

With this specification, Equation 18 simplifies to[17]

$$LS_{i,t}^{-1} = \alpha^{-1}\Big[\Omega_0 + \Omega_1 EAGE_{i,t} + \varepsilon_{i,t}\Big], \tag{24}$$

where the variable $EAGE_{i,t}$ is the average "earnings age" of the labor force, defined as:

$$EAGE_{i,t} \equiv \sum_{a=15}^{80} a \frac{E_{i,a,t}}{E_{i,t}}. \tag{25}$$

We also estimate a specification assuming ω_a varies only across larger age ranges, in which we model earnings wedges as

$$\omega_a = \begin{cases} \Omega_0 & \text{if } a \leq A_0 - 1, \\ \Omega_j & \text{if } A_{j-1} \leq a \leq A_j - 1 \text{ for } j \in \{1, 2..., J\}, \\ \Omega_N & \text{if } j \geq A_N. \end{cases} \tag{26}$$

Under this specification, Equation 18 simplifies to

$$LS_{i,t}^{-1} = \alpha^{-1}\Big[\Omega_0 + \sum_{j=1}^{J} \big(\Omega_j - \Omega_0\big) ES_{i,j,t} + \varepsilon_{i,t}\Big], \tag{27}$$

where the variable $ES_{i,j,t}$ is the share of cross-sectional unit i's total earnings received by members of age group j

$$ES_{i,j,t} \equiv \frac{\sum_{a=A_{j-1}}^{A_j - 1} E_{i,a,t}}{E_{i,t}}. \tag{28}$$

Equations 24 and 27 map into linear reduced form models with residuals given by

[17] We write LS throughout, although this is actually payroll share for the sectoral data.

$\epsilon_{i,t} = \alpha^{-1}\varepsilon_{i,t}$. We are concerned with aggregate trends in average-age and labor's share being shared by all sectors, so we model $\epsilon_{i,t}$ as having a shared aggregate time fixed effect. More importantly, we acknowledge the potential for confounding correlation between the residual and the age distribution of earnings. For example, Autor, et al [2] document a larger decline in labor's share in industries with increasing concentration of sales. If older workers are disproportionately employed in these industries and earnings wedges were constant in age, then ordinary least squares will erroneously estimate that the wedge rises with age.[18] We therefore use national changes in the age-distribution of earnings to create instruments for each sector's earnings-age and age-earnings shares.

5.1 Instruments

Our instruments build upon Bartik [5] and Nakamura and Steinsson [18]. The idea is to create shifts in the supply of labor for each age group that is exogenous shocks to a given industry's factor shares. We fix the age-distribution of earnings shares within a industry to their 1987 values and create a hypothetical distribution for that industry in any later year by applying the national growth rate of earnings for each age group. For each industry, at each date, this gives a hypothetical earnings $E_{i,a,t}$, with which we compute hypothetical earnings-share weighted average age $EAGE^B_{i,t}$ for the linear specification of ω_a and grouped shares $ES^B_{i,j,t}$ for the pooled non-linear specification.

Our preferred specification follows Nakamura and Steinsson [18], in that we allow for industrial heterogeneity in the sensitivity of $EAGE_{i,t}$ to $EAGE^B_{i,t}$ (and likewise $ES_{i,j,t}$ to $ES^B_{i,j,t}$). For our baseline regression, the resulting instruments are generated by estimating

$$\Delta EAGE_{i,t} = a_i + b_i \Delta EAGE^B_{i,t} + \nu^B_{i,t}, \tag{29}$$

and a similar equation for the specification with earnings shares.

6 Estimation Results

We present estimates from different specifications of ω_a and levels of aggregation and the implication of these estimates on labor's share, both in the United States and globally.

[18]The converse may also hold. Suppose that industries with aging labor forces experience a rise in concentration. If older workers have larger earnings wedges then this would cause a decline in labor's share in those industries, even if concentration had no independent effect.

6.1 Pooled Panel Estimates

Our baseline specifications estimate Equations 24 and 27 in first differences from the pooled industrial panel. We report estimates from the linear specification for ω_a as well as a two-group (mature vs immature) specification by setting $A_0 = 49$ and $A_1 = 50$. Therefore, our reduced-form slope coefficients on $\Delta EAGE_{i,t}$ and $\Delta ES_{i,50+,t}$ identify $\alpha^{-1}\Omega_1$ and $\alpha^{-1}(\Omega_1 - \Omega_0)$, respectively. In either case, a positive point estimate implies that older workers have larger earnings wedges and that shifting earnings towards them will reduce labor's share. Table 1 reports estimates for each specification of ω_a with the instruments described above (i.e. with industry-specific sensitivities), with the traditional pooled first-stage (i.e. traditional Bartik specification), as well as OLS. All standard errors are clustered at the industry level. All specifications include year and industry fixed effects.

Table 1: U.S. Pooled Industry Baseline Results

		N.S. Instrument		Bartik	OLS
		(1)	(2)	(3)	(4)
1	EAGE	0.043***	0.030*	0.056	-0.003
		(0.013)	(0.018)	(0.080)	(0.003)
2	Earnings Share of ages 50+	0.737***	1.316***	1.356	-0.027
		(0.217)	(0.487)	(1.816)	(0.081)
	F Stat $\geq$	31.61	38.32	1.18	N/A
	Observations	1320	1320	1320	1320
	Year FE	Yes	Yes	Yes	Yes
	Industry FE	Yes	Yes	Yes	Yes
	Industry Wgts	No	Yes	Yes	Yes

Standard errors clustered at industry level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Our baseline estimates are reported Columns (1) and (2), the only difference being that we weight the regression by industry employment shares in Column (2). The point estimates are positive for both specifications of ω_a, implying that earnings wedges rise with age, and all estimates are significant at the 10% level (typically the 1% level). Furthermore, our instruments are strong by conventional measures, with F Statistics above 30. Throughout the rest of the paper, we refer to the estimate of 0.030 in the linear specification as our baseline and use it for counterfactual analysis.

These estimates identify the slope of the age-profile of wedges up to the output elasticity α and allow us to infer the marginal effect of aging on labor's share. Starting from the average labor's share for the United States since 1987, the linear specification implies that increasing the earnings-weighted average age by one (year) causes a 1.2 percentage point decline in labor's share. The grouped specification implies that labor's share declines by 0.70 percentage points in response to a one percentage point increase in the earnings share of workers aged 50+.[19]

Column (3) of Table 1 estimates each specification by pooling the first stage, i.e. restricting the slope on $\Delta EAGE^B_{i,t}$ and $\Delta ES^B_{i,50+,t}$ to be the same for each industry. The point estimates are very similar to our preferred specification, but standard errors rise dramatically since the first stage becomes much weaker (with F-Stats below 2 for both specifications). Finally, the OLS estimates in Column (4) are effectively zero, consistent with labor mobility in response to industry-level shocks.

6.2 Heterogeneity in the Age Profile

Our baseline estimates assume that aging affects labor's share identically in all industries, but we can allow for heterogeneity across industries. Specifically, we explore the effect of unionization rates on the age-profile of wedges. We expect the bilateral model of wage determination from Section (3) to be less relevant for highly unionized industries in which a large fraction of wages are bargained for workers as a group. We therefore predict a flatter age-profile of earnings wedges in these industries than in those with low unionization rates.

The data strongly confirm the above prediction, as seen in Table (2), which estimates the reduced form slope from Equation (24) on groups of industries split by their unionization rate in 1987. The lowest third had rates below 7.22% and exhibit a very strong relationship between earnings age and payroll shares, with a statistically significant effect that is more than twice the magnitude of our pooled estimate. Moving to higher unionization rates, the middle third looks quite similar to our pooled estimate, while the age-profile of earnings wedges is essentially flat for the most unionized industries.

We now use our baseline point estimate of $\widehat{\alpha^{-1}\Omega_1} = 0.0267$ to quantify the effect on labor's share in the United States. We also calculate the effect of aging on labor's share

[19]The point estimates relate to changes in inverse labor share. The effect on labor's share is then computed around the averages of each variable for this time period. The average of inverse labor's share for the United States since 1987 is 1.626 and the coefficient on EAGE in Column (2) implies an increase of 0.030.

Table 2: By Unionization Rates - Bottom, Middle, and Top Terciles

		Bottom Third Union % $\leq$ 7.2%		Middle Third 7.2% $<$ Union % $<$ 17%		Top Third 17% $\leq$ Union %	
1	EAGE	0.138***	0.075*	0.045***	0.017	-0.011	0.002
		(0.034)	(0.039)	(0.008)	(0.013)	(0.022)	(0.042)
	F Stat	21.41	16.98	25.97	16.70	25.46	23.20
	Observations	456	456	432	432	432	432
	Year FE	Yes	Yes	Yes	Yes	Yes	Yes
	Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
	Industry Wgts	No	Yes	No	Yes	No	Yes

Standard errors clustered at the industry level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

globally, under the assumption that other countries share this coefficient.

7 Counterfactuals

We use our estimates for two counterfactual exercises. In the first, we use the linear ω_a specification to quantify the effect of (earnings-weighted) aging on labor's share in the U.S. In the second, we use the international series on labor's share constructed by Karabarbounis and Neiman [12] and our own series on (GDP-weighted) average age to quantify the effect of aging on the global decline in labor's share.

7.1 Aggregate Aging and Labor's Share in the United States

For the United States, we predict labor's share using our estimates of $\alpha^{-1}\Omega_1$ and the time fixed effects (call them $\hat{\mu}_t$). We normalize the predicted labor's share ($LS_{p,t}$) in 1987 to match the data, then integrate the first-differenced estimates up to a given year t using the earnings-weighted average age of the U.S. labor force:

$$LS_{p,t}^{-1} = LS_{US,1987}^{-1} + \sum_{\tau=1988}^{t} \left(0.0267 \Delta EAGE_{US,\tau} + \hat{\mu}_\tau \right) \tag{30}$$

The predicted and the actual series are plotted in Figure 3. The two align closely through the year 2000, at which point the predicted series rises slightly above the data. After 2000 they both begin a sharp decline. By 2011 the empirical series has fallen by six percentage points and the predicted has fallen by 4.3, so that the predicted change is around 73% of the decline since 1987 (and 78% of the decline since 2000). This difference between the predicted and actual series arises because the aggregate series is labor's share whereas we have used sectoral payroll shares to estimate the model.[20]

In order to assess how much of the decline in labor's share is accounted for by aging, we use the predicted series as our point of reference. That is, we generate the counter-factual series for labor share using our estimates from 2000 onward, keeping earnings-age at it's 2000 value, but aggregating the time fixed effects. We generate the series:

$$LS^{-1}_{cf1,t} = \begin{cases} LS^{-1}_{p,t} & t \leq 2000, \\ LS^{-1}_{p,2000} + \sum_{\tau=2001}^{t} \hat{\mu}_\tau & t \geq 2001. \end{cases} \tag{31}$$

The reciprocal of these two series represent predicted and counter-factual labor share, which are plotted along side realized labor share in Figure 4. The predicted change due to aging alone is therefore the difference between the overall prediction and the counter-factual, which amounts to a 3.5% decline from 1987 to 2011. We therefore estimate that aging (in the earnings-weighted sense) accounts for 59% of the decline in labor's share since 1987 (57% since 2000).

Earnings-age and the earnings share of older workers have risen because the population has aged, older workers have historically high labor force attachment, and the earnings of older workers have grown faster than other groups in recent years. For illustration, we decompose the contribution of each of these factors for the earnings share of 50+ workers in Figure 5. The aging of baby boomers has directly increased the (un-weighted) age of the U.S. population, but there is more to the story. The labor force participation rate of older workers has been rising over time as people retire later and the average earnings of older workers has risen relative to the young.[21] Since labor force participation and earnings-per-worker are endogenous outcomes, we find it useful to consider the effect of an aging *population* in isolation.

To explore the relative importance of population size relative to endogenous labor market variables (participation, employment, earnings), we create a second counterfactual time series for labor share that only accounts for the rising *population shares* of older workers over the post-2000 period. Denoting average earnings of workers aged a

[20]The time fixed effects allow us to match the aggregate payroll share series exactly.

[21]The only endogenous variable that has not risen for this group is the employment-to-labor-force ratio.

in t as $\overline{e}_{a,t}$, we define the counter-factual earnings-age for $t \geq 2001$:

$$AGE_{CF,t} = \sum_{a=15}^{80} \frac{\overline{e}_{a,2000} N_{a,t}}{E_t} a \tag{32}$$

And $AGE_{CF,t} = AGE_{US,t}$ for $t \leq 2000$. Then the population-age counter-factual inverse labor share is:

$$LS^{-1}_{cf2,t} = \begin{cases} LS^{-1}_{US,1987} + \sum_{\tau=1988}^{t} \left(0.0267 \Delta AGE_{US,\tau} + \hat{\mu}_\tau\right), & t \leq 2000 \\ LS^{-1}_{US,1987} + \sum_{\tau=1988}^{t} \left(0.0267 \Delta AGE_{CF,\tau} + \hat{\mu}_\tau\right), & t \geq 2001 \end{cases} \tag{33}$$

Figure 6 shows the counter factual series for labor's share along side our baseline prediction. The counter factual labor's share with only population aging falls by 60% of the total predicted decline, implying that raw aging accounts for 29% of the total decline in labor's share since 1987 (28% since 2000).

7.2 Global Aging and Decline of Labor's Share

The U.S. experience has been shared by many countries, both in terms of the decline in labor's share and in the demographic shift towards older workers. Figure 7a plots (indices) for global labor's share and average age (both GDP weighted) from 1975 to 2012. The labor's share series are derived from data by Karabarbounis and Neiman [12] and exhibits a downward trend over this period, while the average age series shows an upward trend, steepening in the late 1990's.

While we do not have sufficient data to estimate $\alpha^{-1}\Omega_a$ on the cross-country panel, we quantify the effect of aging using our estimate from the U.S.[22] Following our procedure for the U.S., we generate the predicted series for changes in inverse labor's share using changes in average age. Two caveats apply. First, we do not have earnings-weighted average age series, so we use the unweighted average age of each country. Second, we do not have time fixed effects, and cannot compare our prediction with the counter-factual as we did with the U.S.

The predicted series is plotted against the data in Figure 7b. Remarkably, and without intent, the beginning to end decline is matched closely, although that is partly because labor's share was higher in $2010 - 2012$ than in the prior years. Considering

[22] We have also estimated a reduced form regression on the panel of countries. The quantile plot associated with that regression is found in Figure 8.

only the pre-1994 to post-1994 averages, predicted labor share is 3.0 percentage points lower in the second half of the sample than in the first. This accounts for 54% of the observed decline, which was 5.6 percentage points.

In summary, the age-profile of earnings wedges estimate from U.S. sectoral data indicate that aging can account for just over half of the recent decline in labor's share, both in the U.S. and around the world.

8 The Age Profile of Earnings Wedges

Our estimate that $\Omega_1 > 0$ implies that the age-profile of earnings is flatter than that of productivity, but does not allow us to fully describe these profiles because we have not identified the output elasticity (α) or the intercept (Ω_0). We need two more restrictions to construct the age-profile of earnings wedges to recover these parameters, which requires additional theoretical structure. A detailed microeconomic model is beyond the scope of this paper, so we instead normalize the level of labor's share in 1987 to match the data and assume that the present value of life-time earnings for a worker is equal to the present value of her marginal product of labor. We see this as an intuitive deviation from the canonical model in which a worker's earnings are equal to her marginal product in every period.

We generate the required restrictions by first setting predicted inverse labor's share equal to the data in 1987. This gives one restriction:

$$LS_{1987}^{-1} = \alpha^{-1}\Omega_0 + \widehat{\alpha^{-1}\Omega_1} EAGE_{1987},$$

which has two unknowns, α^{-1} and Ω_0. The second restriction imposes that the present value of earnings over a worker's lifetime equals the the present value of her marginal product. Mathematically, this implies

$$\sum_{a=15}^{80}\left(\frac{1+g}{1+r}\right)^a E_{a,1987} = \sum_{a=15}^{80}\left(\frac{1+g}{1+r}\right)^a \frac{\partial Y_{1987}}{\partial N_a}, \tag{34}$$

where g is the economy wide growth rate and r is the risk free interest rate.[23] We set this ratio to 0.96, reflecting an annual risk free rate of 4%. Using Assumption 1 to replace

[23]We assume that the shape of the age-earnings and age-productivity profiles are constant post 1987 for this example.

the unobservable marginal products yields the second restriction:

$$\sum_{a=15}^{80} \left(\frac{1+g}{1+r}\right)^a E_{a,1987} = \sum_{a=15}^{80} \left(\frac{1+g}{1+r}\right)^a \left[\alpha^{-1}\Omega_0 + \widehat{\alpha^{-1}\Omega_1} a E_{a,1987}\right]. \tag{35}$$

Our preferred baseline estimate of $\widehat{\alpha^{-1}\Omega_1} = 0.0267$ implies that $\hat{\alpha} = 0.71, \widehat{\Omega_0 + \varepsilon_{1987}} = 0.21$, and $\hat{\Omega}_1 = 0.0234$.

We then estimate the age-profile of earnings from a Mincer [17] regression for the years $1987-2011$, which allows us to plot the age profile of earnings and productivity in Figure 9. The dashed hump-shaped curve is the age-profile of earnings, which rises by a factor of three from age 25 to 47 and then begins to decline. However, because earnings wedges rise with age, workers capture a smaller and smaller share of their marginal products. This implies that the productivity profile is steeper than the earnings profile, growing by a factor of five, and peaks nearly five years later in life.

9 Robustness

We now consider alternative samples and weighting methods for our baseline panel regression. Tables 4 and 5 present alternative estimates of the linear and two-age group specifications, respectively. For both specification, all of the point estimates are greater than our baseline estimate, and all remain significant.

In our baseline estimates we control for the importance of each sector by weighting sectors by their share of aggregate employment. Row 2 presents results when we estimate the coefficient with equal weights across sectors. The point estimates for both specifications are larger and remain significant. Our concern with the distinct differences in the pay structures and the significantly lower payroll share in the "Financial Services" sector led us to exclude this sector from our baseline estimation. Rows 3 and 4 present estimates when all sectors are included, for both the weighted and un-weighted cases. Including the financial sector results in much larger and significant point estimates when using either of the instruments. Similar to the estimates which exclude the financial sector, the un-weighted estimates are larger than the weighted.

In addition, we consider time series estimates that allow for sectoral heterogeneity in ω_a. The benefit of the pooled specification is it allows for arbitrary aggregate trends, but it comes with a cost because we must assume that all sectors have the same value of $\alpha^{-1}\Omega_1$. We now consider the alternative specification, which allows $\alpha^{-1}\Omega_1$ to vary by sector, by estimating the model from time series variation within each sector. We estimate the model with two age groups, workers under fifty and workers over fifty and allow for a linear trend time trend.

Figure 10 and Table 6 summarize these estimates. We report our estimates of the ratio $\frac{\Omega_0}{\Omega_1}$ in our grouped specification. The figure shows estimates for our eleven sectors as well as U.S. aggregate labor's share and earnings-weighted age.[24] The national point estimate is 0.582, implying that mature workers receive approximately forty percent less of their marginal product relative to immature workers (this estimate is significantly below one). Many sectors have large standard error bands, but the majority of estimates are below one, and the few sectors with point estimates above one have very large standard errors. Overall, the heterogenous parameter estimates are consistent with both the baseline pooled estimates and the national time-series estimate.

10 Conclusion

We have given an account of recent demographic trends in the U.S. and how these changes have appeared in relative earnings. By relaxing the assumption that workers are paid their static marginal product, we have derived a relationship between the age-distribution of earnings and labor's share in income, which holds under weak assumptions and at any level of aggregation for which data on the age-profile of earnings and labor's share are available. We used cross-sectoral variation to estimate the shape of the earnings-wedge profile and found that older workers receive a smaller share of their marginal product than do younger workers. Our estimates imply that just over half of the decline in labor's share can be accounted for by aging, both in the U.S. and around the world.

[24]For the U.S. specification we use the population share of mature workers (again, those over 50) as instruments for this group's earnings share.

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A Derivation of Accounting Equation

This section derives the relationship between labor's share and earnings shares for a more general constant returns to scale production function. That is, output is given by

$$Y_t = F_t\big(K_t, n_{1,t}, ..., n_{I_t,t}\big), \tag{36}$$

with F_t homogeneous of degree one.

We first rearrange the earnings equation to isolate worker ℓ's marginal product: $\frac{\partial Y_t}{\partial n_{\ell,t}} = (\omega_a + \varepsilon_t)e_{\ell,t}$. Notice that the marginal product on the left-hand side is unobservable, as is the wedge term on the right hand side. However, if we define $E_{a,t} \equiv \sum_{\ell=1}^{L_t} e_{\ell,t} n_{\ell,t} \mathbb{I}_{\{age_{\ell,t}=a\}}$ and sum over all of the groups, then we have:

$$Y_t = \frac{\partial Y_t}{\partial K_t} K_t + \sum_{a=15}^{80} \omega_a E_{a,t} + \varepsilon_t \sum_{a=15}^{80} \omega_a E_{a,t} \tag{37}$$

Dividing by $E_t \equiv \sum_{j,t} E_{j,t}$ we arrive at the accounting equation:

$$LS_t^{-1} = \frac{\partial Y_t}{\partial K_t} \frac{K_t}{E_t} + \sum_{a=15}^{80} \omega_a \frac{E_{a,t}}{E_t} + \varepsilon_t \tag{38}$$

This equation simplifies to Equation 18 if production is Cobb-Douglas, since then $\frac{\partial Y_t}{\partial K_t} = (1-\alpha)\frac{Y_t}{K_t}$.

B Figures and Tables

B.1 Figures

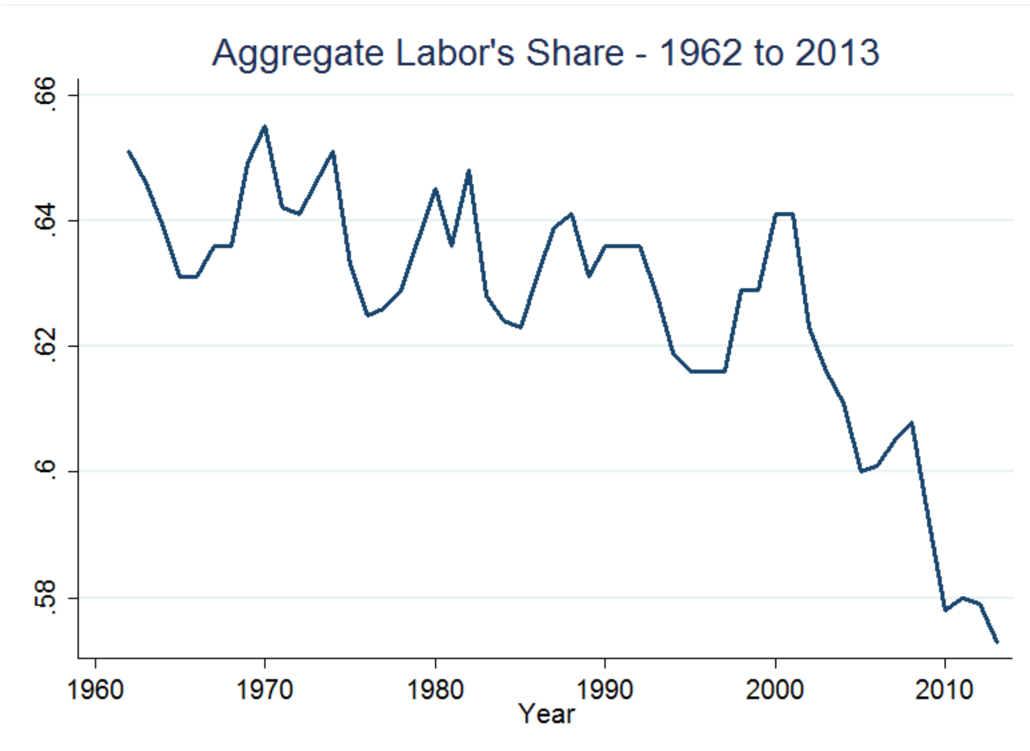


Figure 1: Aggregate Labor Share

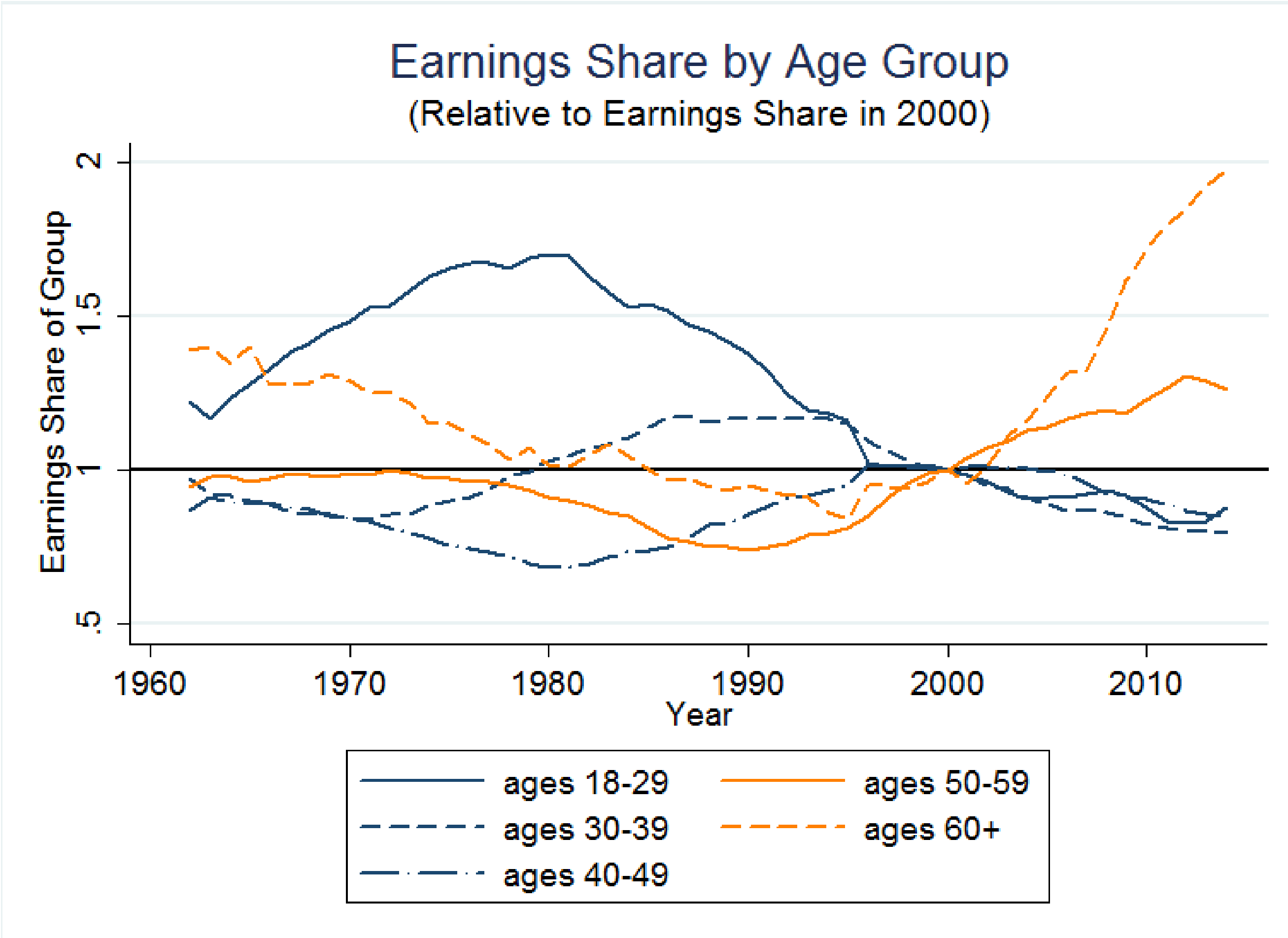


Figure 2: Age Distribution of Earnings Shares

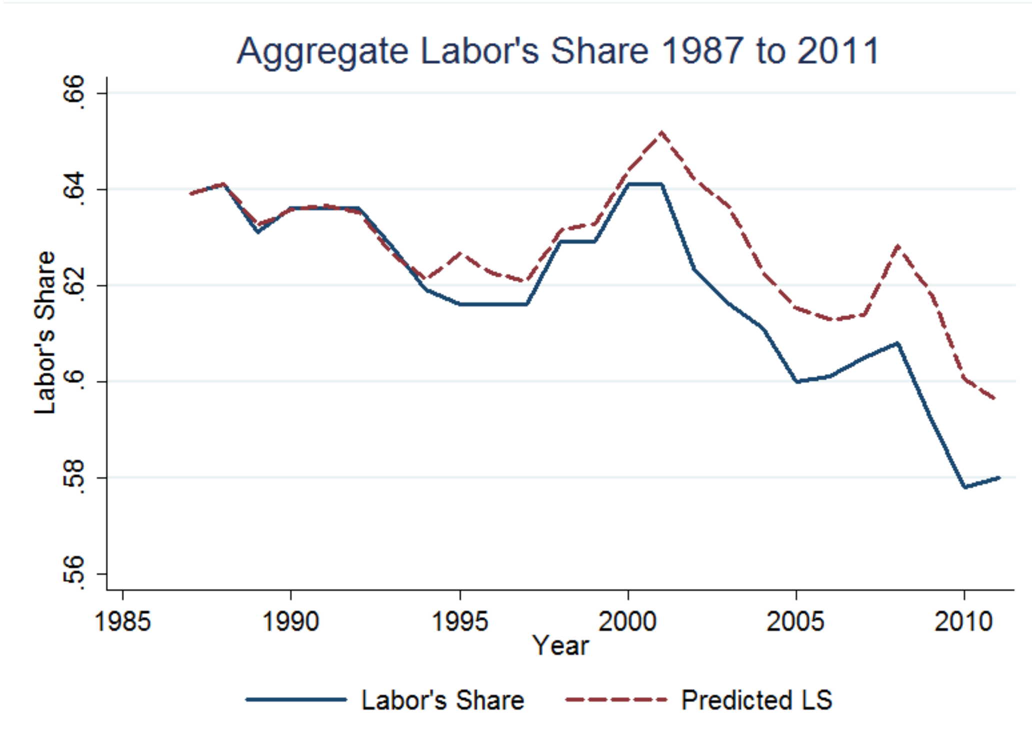


Figure 3: Actual vs Predicted Labor Share

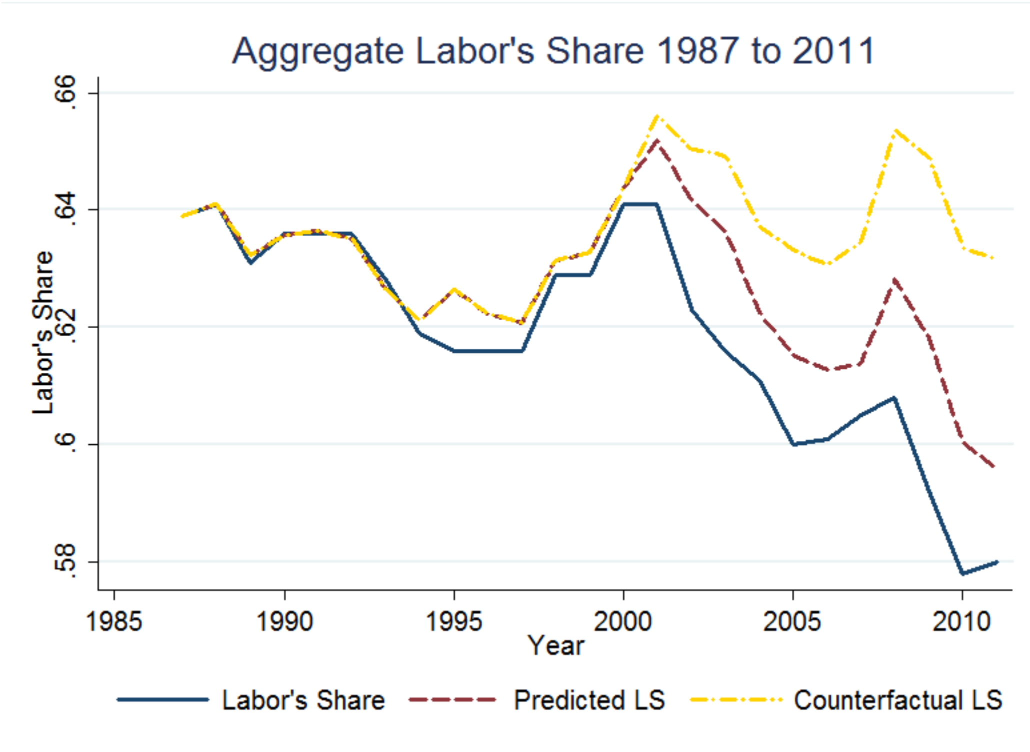


Figure 4: Counterfactual vs Predicted Labor Share

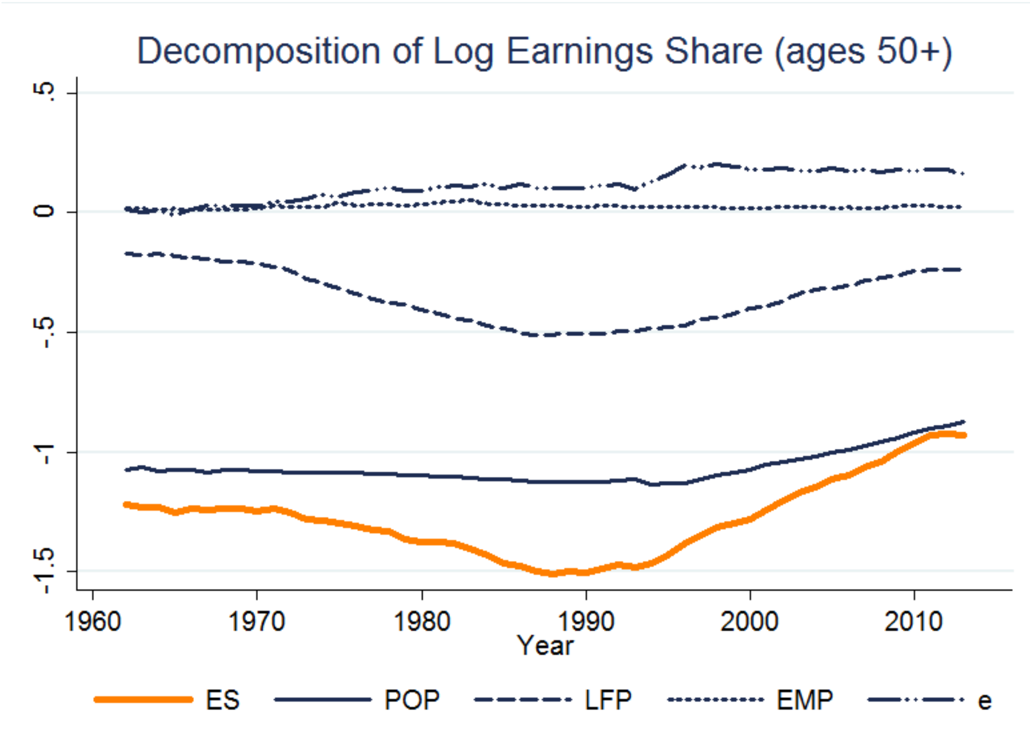


Figure 5: Sources of Rising Earnings Share of 50+

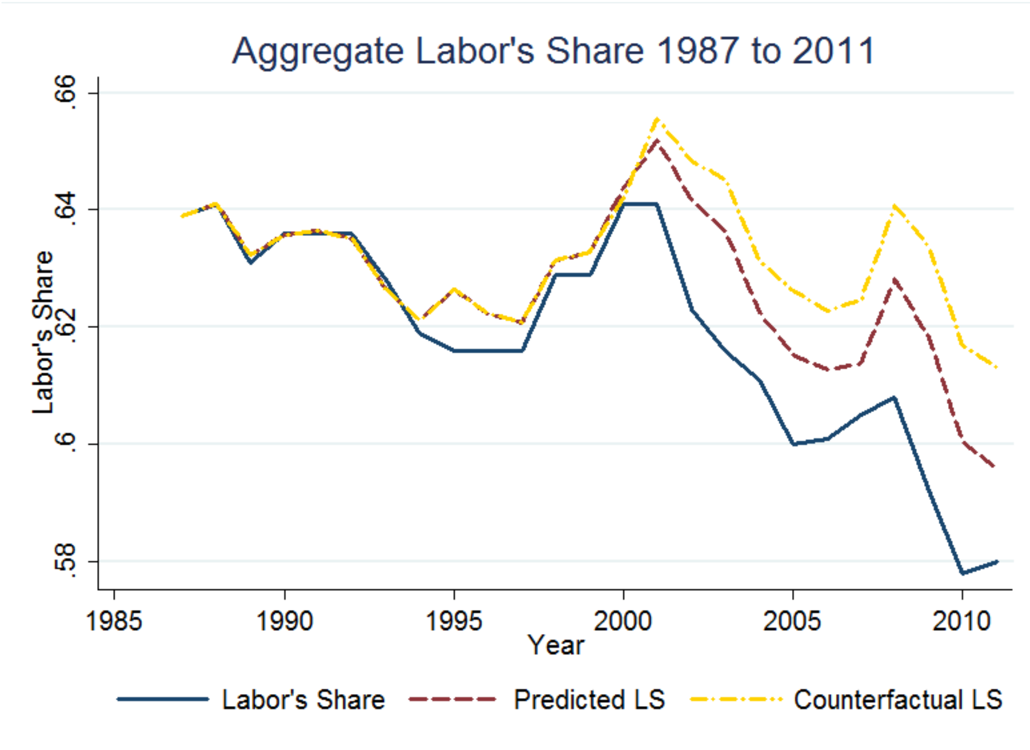
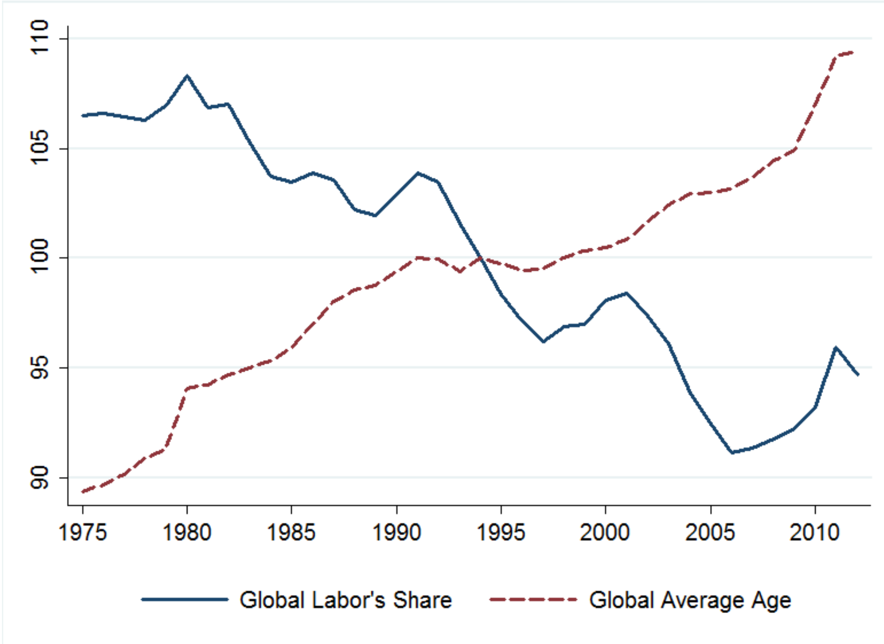
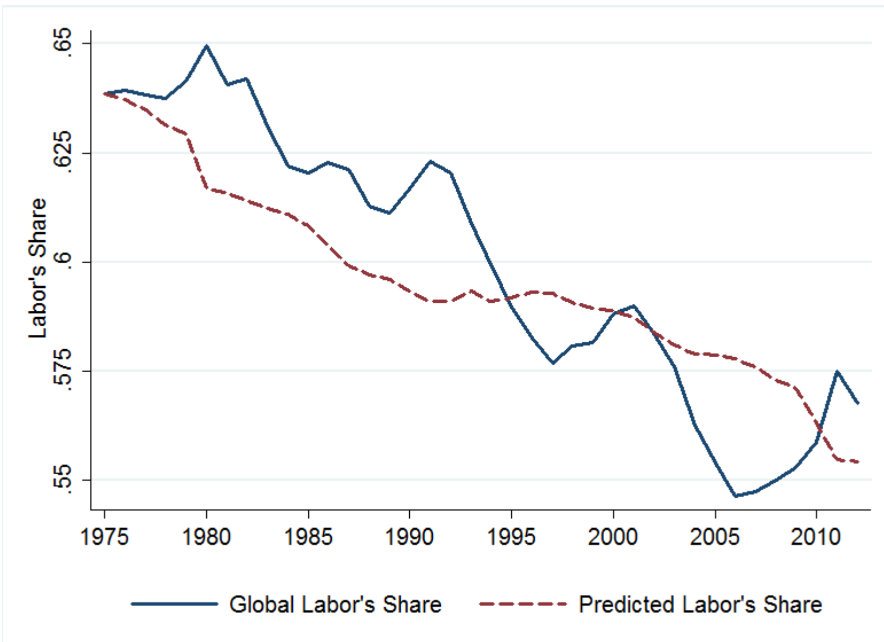


Figure 6: Actual vs Predicted Labor Share



(a)



(b)

Figure 7: Global Aging and Labor's Share: Data and Prediction

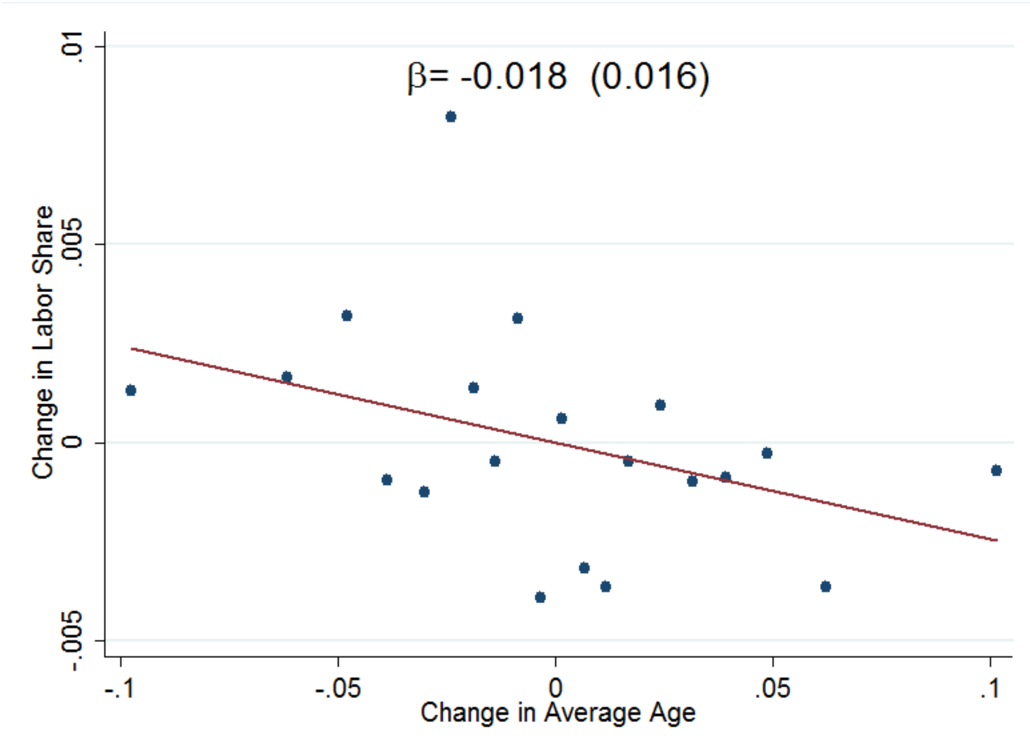


Figure 8: Cross-Country Labor's Share Vs. Age

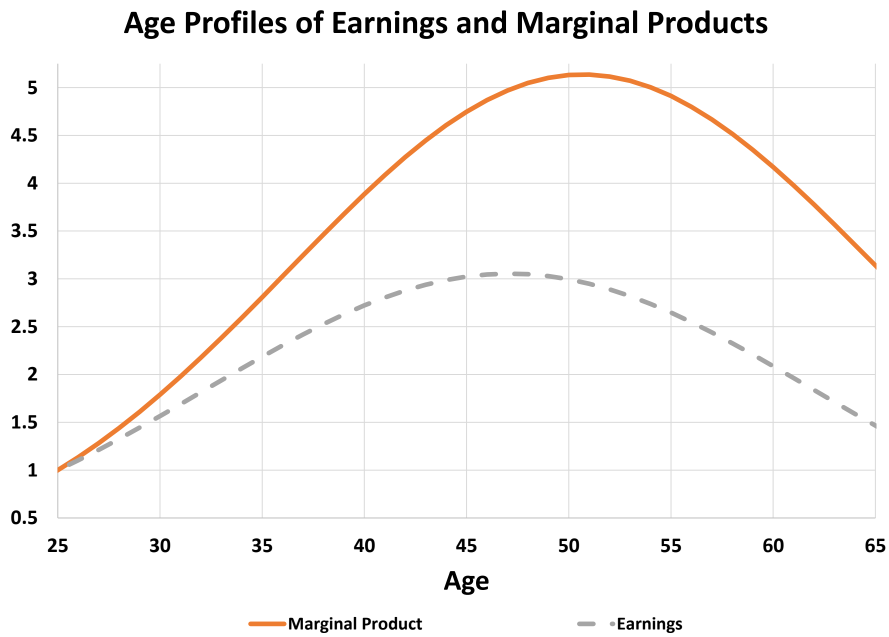


Figure 9: Age Profile of Earnings and Productivity

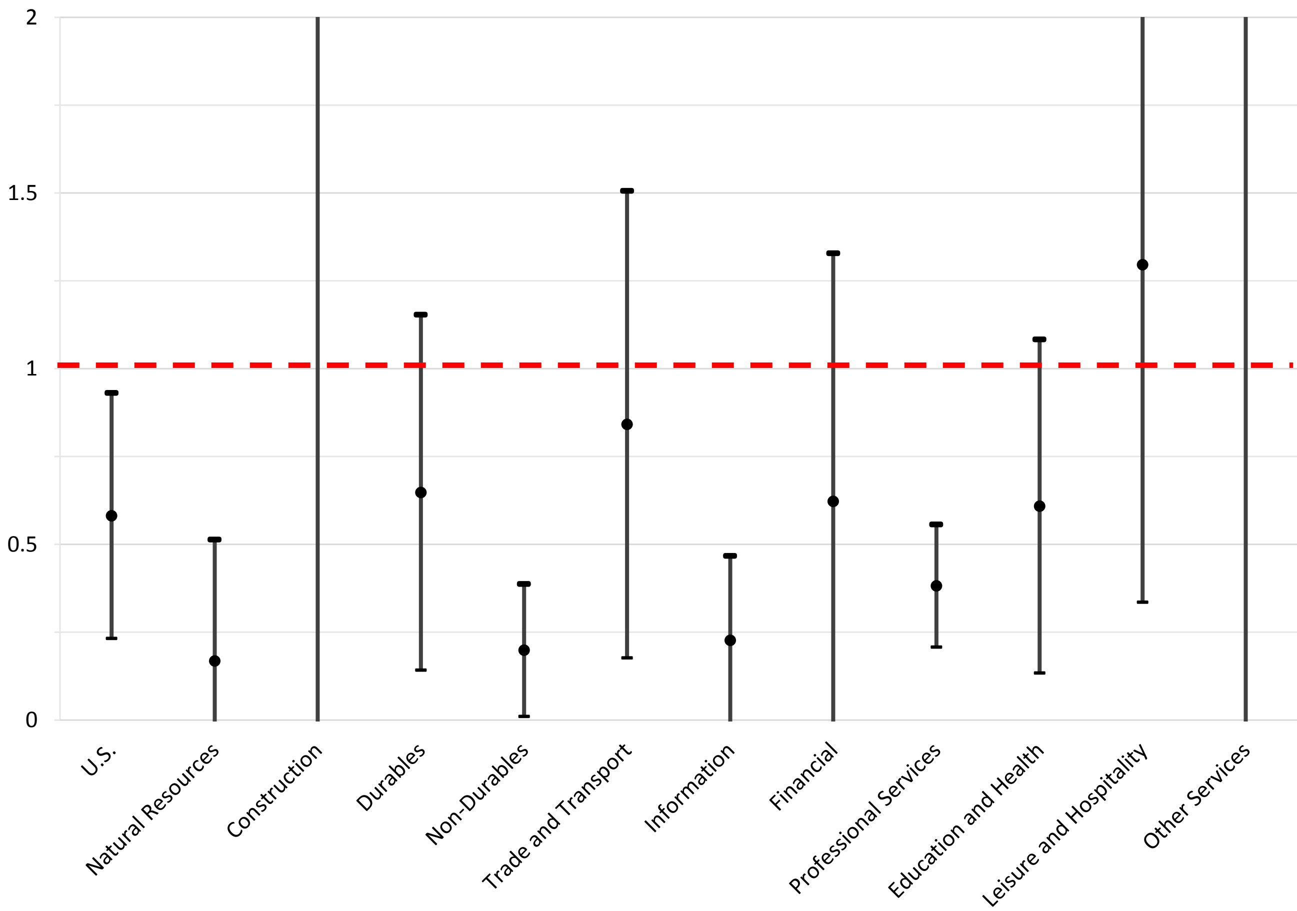


Figure 10: Ratio of Earnings Wedges ($\frac{\hat{\alpha}_{50+}^{-1}}{\hat{\alpha}_{49-}^{-1}}$) Estimates and 90% CI

B.2 Tables

Table 3: Sectors

1	Natural resources and mining
2	Construction
3	Durable goods manufacturing
4	Non-durable goods manufacturing
5	Trade/Transportation and utilities
6	Information
7	Financial activities
8	Professional and business services
9	Education and health services
10	Leisure and hospitality
11	Other services

Table 4: U.S. Pooled Industry Results - EAGE Robustness

			Bartik Instrument		National Instrument		OLS	
		Obs.	(1)	(2)	(3)	(4)	(5)	(6)
1	Baseline	1320	0.0267	0.0295	0.0168	0.0183	-0.00288	-0.00296
			(0.0135)	(0.0164)	(0.0163)	(0.0201)	(0.00305)	(0.00303)
2	Un-weighted	1320	0.0402	0.0429	0.00314	0.00420	-0.00845	-0.00846
			(0.0101)	(0.0127)	(0.0363)	(0.0487)	(0.00297)	(0.00303)
3	All Industries † Weighted	1378	0.0742	0.0817	0.0532	0.0579	-0.00295	-0.00313
			(0.0468)	(0.0523)	(0.0383)	(0.0435)	(0.00296)	(0.00295)
4	All Industries† Un-weighted	1378	0.0485	0.0515	0.0226	0.0230	-0.00744	-0.00761
			(0.0136)	(0.0160)	(0.0357)	(0.0513)	(0.00300)	(0.00303)
	Industry FE		No	Yes	No	Yes	No	Yes

Standard errors clustered at the sectoral level in parentheses

† The Real Estate Industries are included.

Table 5: U.S. Pooled Industry Results - Earnings share of ages 50+ Robustness

			Bartik Instrument		National Instrument		OLS	
		Obs.	(1)	(2)	(3)	(4)	(5)	(6)
1	Baseline	1320	1.010	1.085	0.931	0.995	-0.0242	-0.0265
			(0.323)	(0.348)	(0.300)	(0.338)	(0.0783)	(0.0780)
2	Un-weighted	1320	1.381	1.373	1.155	1.129	-0.128	-0.131
			(0.710)	(0.660)	(0.562)	(0.546)	(0.0755)	(0.0734)
3	All Industries† Weighted	1358	0.843	0.903	0.901	0.954	-0.130	-0.133
			(0.336)	(0.357)	(0.288)	(0.322)	(0.119)	(0.119)
4	All Industries† Un-weighted	1358	0.698	0.668	0.481	0.433	-0.146	-0.150
			(0.599)	(0.573)	(0.412)	(0.390)	(0.0690)	(0.0671)
	Industry FE		No	Yes	No	Yes	No	Yes

Standard errors clustered at the sectoral level in parentheses

† The Real Estate Industries are included.

Table 6: Ratio of Earnings Wedges - $\frac{Mature}{Young}$

		Bartik Instrument		National Instrument	
		Ratio of Wedges	Cragg-Donald F-stat	Ratio of Wedges	Cragg-Donald F-stat
1	U.S.†	0.582 (0.203)	145.6		
2	Forestry, fishing, and related activities	0.891 (0.195)	4.606	0.880 (0.188)	4.801
3	Oil and gas extraction	0.121 (0.302)	1.643	0.124 (0.327)	1.429
4	Mining, except oil and gas	0.237 (0.115)	6.952	0.219 (0.115)	6.403
5	Utilities	0.782 (0.432)	14.460	0.735 (0.411)	12.883
6	Construction	3.870 (2.501)	53.465	4.098 (2.800)	52.491
7	Wood products	0.733 (0.197)	16.782	0.779 (0.218)	16.060
8	Nonmetallic mineral products	-0.706 (0.404)	1.547	-0.728 (0.410)	1.709
9	Primary metals	0.621 (0.562)	7.613	0.725 (0.657)	8.104
10	Fabricated metal products	-8.034 (35.073)	3.822	-8.348 (37.478)	3.912
11	Machinery	0.508 (0.226)	17.418	0.499 (0.221)	17.446
12	Computer and electronic products	0.071 (0.116)	10.229	0.068 (0.116)	9.830
13	Electrical equipment, appliances, and components	6.924 (18.696)	14.802	6.384 (16.039)	14.524
14	Motor vehicles, bodies and trailers, and parts	-0.756 (0.370)	4.428	-0.750 (0.367)	4.259
15	Other transportation equipment	0.285 (0.200)	8.074	0.298 (0.200)	8.643
	Obs.	25		25	

Standard errors in parentheses

† The population share of persons over 49 years of age is used as the instrumental variable for the U.S. aggregate.