The Impact of the Retirement Slowdown on the U.S. Youth Labor Market*

Paul Mohnen†
University of Michigan

June 29, 2019

Abstract

Employment among older Americans has sharply risen since the mid-1990s, particularly in high-skill jobs. How has this labor-supply increase affected other participants in the labor market, and new entrants in particular? Exploiting cross-commuting zone differences in age composition among the old, primarily driven by historical birth patterns, this paper explores the impact of retirement trends on youth employment outcomes between 1980 and 2017. I find that in commuting zones where fewer older workers retire due to the initial age structure, the share of younger workers in high-skill jobs declines while the share of younger workers in low-skill jobs rises. Occupational downgrading further manifests itself through a rise in the share of younger workers who have higher educational attainment than their job typically requires and declining youth wages. The young partly adjust to deteriorating labor market prospects via greater school attendance and net out-migration. Together, the results suggest that the retirement slowdown has contributed to stagnant early career outcomes in recent decades, explaining 30 percent of the rise in the share of younger workers in low-skill jobs between 1980 and 2017.

JEL: J11, J21, J24, J26

*I wish to thank Matthias Doepke, Jon Guryan, Lee Lockwood and Matt Notowidigdo for their guidance throughout this project. For helpful comments and discussions, I thank Martha Bailey, Lori Beaman, Dan Fetter, Ben Friedrich, Sasha Indarte, Seema Jayachandran, Cynthia Kinnan, Shariq Mohammed, Mel Stephens, as well as seminar participants at the Federal Reserve Bank of Dallas, Northwestern University, Stockholm University, University of Michigan, and Washington University in St. Louis. I gratefully acknowledge financial support from the Alfred P. Sloan Foundation Pre-Doctoral Fellowship on the Economics of an Aging Workforce, awarded through the NBER.

†Population Studies Center, University of Michigan (e-mail: mohnen@umich.edu).

1 Introduction

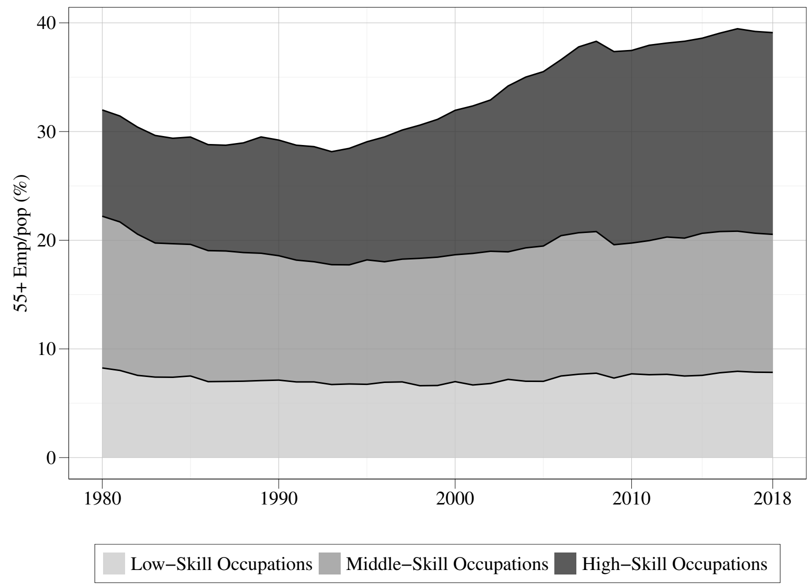
One of the most striking developments in the U.S. labor market in recent decades has been the sharp rise in the labor supply of older Americans. As Figure 1 shows, the share of Americans aged 55+ that are employed has increased from 30 to 40 percent since the mid-1990s. This slowdown in retirements is generally attributed to a combination of greater financial incentives to work longer—due to changes in Social Security, a transition from defined-benefit to defined-contribution pension plans, and rising life expectancy—as well as a greater capacity to work longer, thanks to a shift away from physically demanding jobs and improvements in late-life health (Coile, 2018). Figure 1 also illustrates a lesser-known aspect of retirement trends: older workers are increasingly concentrated in high-skill jobs such as managerial and professional jobs, which is closely linked to the rise in the educational attainment of older generations (Burtless, 2013; Goldin and Katz, 2016).[1]

At the same time, there is mounting evidence that the youth labor market has stagnated in recent years. Beaudry et al. (2014) shows that college graduates who entered the labor market after 2000 had a lower probability of being employed in high-skill cognitive occupations and had flatter wage profiles than previous cohorts. Abel et al. (2014) documents how young college graduates are increasingly employed in low-paying jobs which do not require a college degree. Figure 2 plots changes in occupation group-specific employment shares between 1980 and 2017 among young adults (22-30), for the group as a whole and separately for those with and without a college degree. While younger workers have made some gains in high-skill occupations, this can entirely be attributed to a rise in college attainment. The share of college-educated younger workers employed in high-skill jobs has actually gone *down* since 1980. Younger workers are increasingly starting their career in low-skill jobs such as retail and personal services, particularly the non-college-educated.

Motivated by these facts, this paper explores the following question: To what extent has the rise in the labor supply of older Americans affected job prospects of younger Americans in their 20s in recent decades? To answer this question, I compare the evolution of youth employment outcomes across U.S. commuting zones, which have experienced differential changes in the 55+ employment rate over the period 1980-2017. Estimating the causal effect of retirements on other labor market participants is inherently challenging because unobservable shifts in local labor demand tend to push outcomes of all workers in the same

[1] The share of Americans aged 55 or older with a college degree has gone from 10 to 30 percent between 1980 and 2017.

Figure 1: 55+ Employment Rate Decomposed by Occupation Groups, 1980-2018



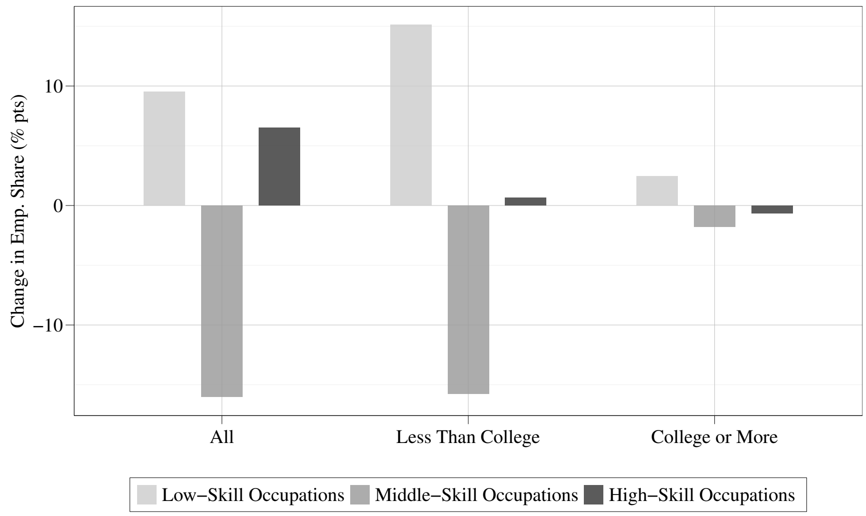
Notes: This graph plots the 55+ employment-to-population ratio, decomposed into occupation groups. Low-skill occupations include agriculture, food/maintenance, personal services and sales (retail/misc). Middle-skill occupations include operators/laborers, office/clerical, production and protective services. High-skill occupations include sales (finance/business), technicians, professionals and managers.

Source: 1980-2018 Annual Social and Economic Supplement of the Current Population Survey (Flood et al., 2018).

direction, resulting in a mechanical relationship between changes in the 55+ employment rate and changes in youth employment outcomes.

To address this empirical challenge, I employ an instrumental variables approach which relies on geographic variation in age composition *among* the old to predict retirement trends. Specifically, I construct a Bartik-style instrument by interacting the initial commuting zone-level 45+ age distribution with 10-year retirement rates by age at the national level. The instrument derives its predictive power from the fact that Americans tend to exit the labor force at specific ages, typically in their 60s. As a result, commuting zones with an above-average proportion of soon-to-be-retired individuals tend to experience a relative decline in their 55+ employment rate over the next 10 years. To support the validity of the instrument, I show that a substantial fraction of the variation in 45+ age composition can be explained by past birth patterns. This bolsters the notion that the variation underlying the instrument is pre-determined, so that 2SLS estimates identify the causal effect of retirement trends on youth employment outcomes.

Figure 2: Change in Occupational Composition Among the Young (22-30), 1980-2017



Notes: This graph plots changes in occupation group-specific employment shares between 1980 and 2017, for different subgroups of young adults (x-axis). Skill groups are defined as in Figure 1.

Source: 1980 Census, 2016-2017 American Community Surveys.

The main finding of this paper is that fewer retirements have a negative impact on the young, not so much in terms of employment, but rather in terms of job quality and wages. In commuting zones where fewer older workers retire due to the initial age structure, the occupational distribution among younger workers shifts away from high-skill jobs towards low-skill jobs. A one percentage point increase in the 55+ employment rate leads to a 0.6 percentage point decline in the share of younger workers employed in high-skill jobs and a 0.5 percentage point rise in the share of younger workers employed in low-skill jobs. This pattern of occupational downgrading further manifests itself through a 0.7 percentage point rise in the share of younger workers that are employed in jobs for which they are overeducated, in the sense that their educational attainment exceeds what is typically required for their job. A one percentage point increase in the 55+ employment rate also leads to a 3.3 percent decline in youth wages over 10 years. In response to deteriorating labor market prospects, young adults adjust in two important ways: they stay in school longer and leave or avoid commuting zones where fewer workers retire. Teenagers (16-21) and prime-aged individuals (31-44) are also adversely affected, though to varying extents and along different margins.

The contribution of this paper is twofold. First, using a novel empirical strategy, I shed new light on how changes in the labor supply of the old can affect youth employment outcomes. On the one hand, studies that have exploited time series or state-level variation have found little evidence that the old "crowd out" the young (Gruber and Wise, 2010; Munnell and Wu, 2012). On the other hand, studies that have examined reforms raising the retirement age in European countries, which differentially affected firms based on the composition of their workforce, provide strong evidence that delayed retirements have a negative effect on youth hiring at the firm level (Martins et al., 2009; Boeri et al., 2016; Bovini and Paradisi, 2018). Recent work shows that delayed retirements also have a negative effect on promotion opportunities within firms (Bianchi et al., 2018).

While a firm-level perspective allows us to study within-firm dynamics and exploit plausibly-exogenous differences across firms, this approach has several drawbacks. Firm-level studies cannot capture what happens to the labor market as a whole since they are silent on what happens to workers who are laid off or workers who are not hired. They also ignore job creation at new firms and job destruction at dying firms since they implicitly compare existing, surviving firms. Lastly, time horizons tend to be shorter given the recency of these policy changes, whereas labor markets typically take time to fully adjust.

My paper strikes a balance between a micro and macro perspective by using local labor markets as the unit of analysis (thereby accounting for local general equilibrium effects), studying 10-year changes over four decades, and isolating variation in retirement trends due to regional differences in age composition.[2] Another key distinction between my paper and existing studies is the emphasis on the skill dimension. Considering the skill-biased nature of retirement trends is essential to understanding their consequences, much in the same way that low-skill immigration and high-skill immigration have very different implications. Correspondingly, the effects on younger workers may show up more clearly in the types of jobs that they hold rather than employment levels, which has been the primary focus of the prior literature.

The second contribution of this paper is to provide a new explanation for the stagnation in youth labor market outcomes. While the misfortunes of young Americans in recent years have been well-documented, much less is known about the underlying causes. Worsening prospects for those with lower levels of education is perhaps unsurprising, but stagnant outcomes for college graduates is somewhat harder to explain. One exception is Beaudry et al. (2016), which argues that a reversal in the demand for cognitive skills driven by trends

[2]A related study is Bertoni and Brunello (2017), which exploits regional differences in age composition (in a different way) to show that delayed retirements induced by changes in the retirement age in Italy have had a negative impact of youth employment.

in information technology took place in the U.S. around 2000, subsequently reducing the demand for high-skill workers. One can view the retirement slowdown as a complementary labor supply-side explanation. My estimates imply that the retirement slowdown can account for 30 percent of the rise in the share of younger workers in low-skill jobs between 1980 and 2017. Alternatively, absent the retirement slowdown, the share of younger workers in high-skill jobs would have been 8 percent higher than it was in 2017.

These findings have important policy implications. To address imbalances in pay-as-you-go pension systems due to aging populations, many countries are encouraging older workers to work longer, notably by raising the retirement age. It is therefore essential for policy makers to understand what greater labor supply at older ages implies for younger generations, whose burden these policies are supposedly designed to ease.

2 Conceptual Framework

In this section, I present a model of the labor market to illustrate how a skill-biased labor-supply increase among the old can lead to occupational downgrading among the young. On the labor demand side, the model features a production function combining capital and four types of labor differentiated by age and skill. On the labor supply side, I allow for Roy-style occupational choice. In the context of the model, one can interpret the recent retirement slowdown as an increase in the labor supply of older workers concentrated in high-skill jobs. Assuming younger and older workers are more substitutable within skill types than low-skill and high-skill labor—which is consistent with the empirical estimates in the literature (e.g. Card and Lemieux, 2001)—I will show that youth high-skill wages must fall relative to youth low-skill wages. In turn, the change in relative wages prompts marginal-ability younger workers to reallocate from high-skill jobs towards low-skill jobs until equilibrium is restored. This central prediction will provide a rationale for the empirical patterns I document in Section 4.

Firm Production

Consider a representative firm combining capital K and labor L according to a Cobb-Douglas production function to produce a good Q:

$$Q = AL^{1-\alpha}K^{\alpha} \tag{1}$$

where $\alpha \in (0,1)$ and A is total factor productivity. Labor can be decomposed into two types, low-skill (L_L) and high-skill (L_H), which I will also refer to as jobs throughout this section. These jobs can be performed by two types of workers, young (L_{Ly}, L_{Hy}) or old (L_{Lo}, L_{Ho}). The different labor inputs are aggregated according to a nested constant elasticity of substitution (CES) structure, similar to Card and Lemieux (2001):

$$L = [\theta_L L_L^{\beta} + \theta_H L_H^{\beta}]^{1/\beta} \tag{2}$$

$$L_L = [\theta_{Ly} L_{Ly}^{\gamma} + \theta_{Lo} L_{Lo}^{\gamma}]^{1/\gamma} \quad \text{and} \quad L_H = [\theta_{Hy} L_{Hy}^{\gamma} + \theta_{Ho} L_{Ho}^{\gamma}]^{1/\gamma} \tag{3}$$

where $\theta_L + \theta_H = 1$ and $\theta_{jy} + \theta_{jo} = 1,\ j \in \{L, H\}$. The key parameters of the model are $\beta \leqslant 1$ and $\gamma \leqslant 1$, which respectively capture the degree of substitution between low-skill and high-skill labor, and between younger and older workers within skill types. Higher values of β and γ imply greater substitutability between inputs. The firm optimally chooses labor inputs and capital to maximize profits, taking the output price p, wages w_{jk} and the rental rate of capital r as given:

$$\max_{(K, L_{jk})} AL^{1-\alpha}K^{\alpha} - rK - \sum_{j\in\{L,H\}} \sum_{k\in\{y,o\}} w_{jk} L_{jk} \tag{4}$$

where the output price has been normalized to 1 without loss of generality.

Occupational Choice and Capital Supply

On the labor supply side, younger and older workers either have low or high levels of education. Denote their labor supply by $(L_y^{\ell}, L_y^{h}, L_o^{\ell}, L_o^{h})$, where the superscripts ℓ and h denote education types. The distinction between skill types and education types implies that the mapping between them is not one-to-one. In particular, I assume that high-education type workers can perform both low-skill and high-skill jobs, whereas low-education type workers are confined to low-skill jobs. Moreover, high-education type workers are endowed with heterogeneous abilities to perform high-skill jobs relative to low-skill jobs. Let u and z respectively denote the relative ability parameters of younger and older workers (in terms of relative efficiency units), distributed according to the cumulative distribution functions $F(u)$ and $G(z)$. Therefore, a younger worker with ability u can either earn $w_{Hy} \cdot u$ in a high-skill job or w_{Ly} in a low-skill job, and the choice is governed by whether or not her ability u exceeds the threshold u^* defined by the following indifference condition:

$$w_{Ly} = u^* \cdot w_{Hy} \tag{5}$$

If her ability is higher than u^*, she will choose to work in a high-skill job; if it is lower than u^*, she will choose to work in a low-skill job. This type of self-selection based on comparative advantage is a common feature in task-based models of the labor market (e.g., Autor et al., 2003).

To simplify the exposition, assume that the ability threshold for high-education type older workers is fixed at $\overline{z}$, i.e. they no longer respond to changes in relative wages, perhaps due to unobserved occupational mobility costs.[3] As a result, a fraction $F(u^*)$ of high-education type younger workers and a fraction $G(\overline{z})$ of high-education type older workers supply their labor in low-skill jobs, and the remaining fractions $1 - F(u^*)$ and $1 - G(\overline{z})$ supply their labor in high-skill jobs. I make two final simplifying assumptions: (1) education types are perfect substitutes in low-skill jobs, and (2) all workers supply their labor inelastically. This yields the following labor supply equations:

$$L_{Ly} = L_y^\ell + F(u^*) \cdot L_y^h \quad \text{and} \quad L_{Hy} = \left\{ \int_{u^*}^{\infty} u \cdot f(u) \cdot du \right\} \cdot L_y^h \tag{6}$$

$$L_{Lo} = L_o^\ell + G(\overline{z}) \cdot L_o^h \quad \text{and} \quad L_{Ho} = \left\{ \int_{\overline{z}}^{\infty} z \cdot g(z) \cdot dz \right\} \cdot L_o^h \tag{7}$$

The inelastic labor supply assumption implies that the only labor supply response to a change in wages is the self-selection response among high-education type younger workers, which is embedded in the cutoff u^*. To close the model, I follow Dustmann et al. (2017) and assume that capital is supplied according to $r = K^\lambda$ where $\lambda \geqslant 0$.

Comparative Statics: Skill-Biased Labor-Supply Increase Among the Old

Consider an increase in the labor supply of the old concentrated in high-skill jobs. In the context of the model, this is equivalent to assuming the increase in the labor supply of older workers $(d \log L_o^\ell, d \log L_o^h)$ satisfies the following condition:

$$s_{Ho} \cdot d \log L_o^h > s_{Lo} \cdot (s_o^h \cdot d \log L_o^h + s_o^\ell \cdot d \log L_o^\ell) \tag{8}$$

[3]This is consistent with evidence showing that occupational mobility rates tend to be relatively low at older ages (Kambourov and Manovskii, 2008). Shutting down self-selection among older workers is not strictly necessary and can be relaxed with some minor additional assumptions.

The left-hand side of (8) is the *effective* labor-supply increase of older workers in high-skill jobs, expressed as the initial share of older workers in high-skill jobs $s_{Ho} = (\theta_{Ho} L_{Ho}^{\gamma})^{1/\gamma}/L_H$ times the growth in the labor supply of high-education type older workers. Similarly, the right-hand side of (8) is the effective labor-supply increase of older workers in low-skill jobs, given by the weighted average of the growth in the labor supply of low and high-education type older workers ($s_o^h + s_o^\ell = 1$ denotes the initial mix of education types in low-skill jobs), scaled by the initial share of older workers in low-skill jobs $s_{Lo} = (\theta_{Lo} L_{Lo}^{\gamma})^{1/\gamma}/L_L$. Letting $d\log L_o^\ell = \delta \cdot d\log L_o^h$ without loss of generality, condition (8) can be restated more succinctly as $s_{Ho} > s_{Lo}\widetilde{\delta}$ where $\widetilde{\delta} = (s_o^h + s_o^\ell \delta)$.

How do equilibrium wages (w_{Ly}, w_{Hy}) and the occupational composition (L_{Ly}, L_{Hy}) of younger workers change in response? To understand what drives changes in the wages of younger workers, consider the totally differentiated first-order conditions for L_{Hy} and L_{Ly} in (4), where the first-order condition for K has already been combined with the capital supply equation and substituted in (see Online Appendix D for details):

$$d\log w_{Hy} = \varphi \cdot d\log L + (\beta - 1) \cdot (d\log L_H - d\log L) + (\gamma - 1) \cdot (d\log L_{Hy} - d\log L_H) \tag{9}$$

$$d\log w_{Ly} = \varphi \cdot d\log L + (\beta - 1) \cdot (d\log L_L - d\log L) + (\gamma - 1) \cdot (d\log L_{Ly} - d\log L_L) \tag{10}$$

where $\varphi = -\alpha\lambda/(1-\alpha+\lambda)$. These equations capture firm optimality on the labor demand side and neatly illustrate the forces at work. The first term captures the complementarity between labor and capital: unless capital is fully elastic ($\lambda = 0$), all wages must go down in response to an overall increase in labor since labor and capital are q-complements under the Cobb-Douglas assumption. The second term captures the complementarity between low-skill and high-skill labor: assuming imperfect substitutability between skill types ($\beta < 1$), a labor-supply increase "biased" towards high-skill jobs has a positive effect on low-skill wages and a negative effect on high-skill wages since skill types are q-complements under the CES assumption. The greater the substitutability between skill types, the smaller the magnitude of this effect. Similarly, the third term captures the complementarity between younger and older workers within skill types: assuming imperfect substitutability between age types ($\gamma < 1$), an increase in the supply of older workers has a positive effect on the wages of younger workers. However, because the labor-supply increase is more pronounced in high-skill jobs, the positive effect on youth high-skill wages is stronger than the positive effect on youth low-skill wages. Note that the skill complementarity and age complementarity effects disappear if (1) the inputs are perfect substitutes ($\beta = \gamma = 1$), or if (2) the labor supply shock is skill-neutral ($d \log L_H = d \log L_L$) and age-neutral ($d \log L_{gy} = d \log L_{go}$). In other words, changes in wages in this model are induced by a combination of imperfect substitutability between inputs and non-neutral labor supply shocks.

To obtain the equilibrium change in wages, we have to take into account the occupational choice response of high-education type younger workers, which will have an indirect effect on wages. This response is summarized in the following equation, obtained by totally differentiating the threshold condition (5):

$$d \log u^* = d \log w_{Ly} - d \log w_{Hy} \tag{11}$$

What matters is the change in *relative* wages, which hinges on whether the skill complementarity effect dominates the age complementarity effect or vice-versa, since they exert opposite pressure on the cutoff u^* (the capital-labor effect cancels out). It turns out that the skill complementarity effect dominates as long as younger and older workers are more substitutable within skill types than skill types themselves, i.e. $\gamma > \beta$. In that case, the decline in high-skill wages relative to low-skill wages prompts high-education type younger workers to reallocate away from high-skill jobs towards low-skill jobs. This self-selection response, driven by marginal workers in the ability distribution, effectively dampens the change in relative wages. To see this formally, the following equation gives the equilibrium change in relative youth wages:

$$d \log w_{Ly} - d \log w_{Hy} = \frac{(\gamma - \beta) \cdot (s_{Ho} - s_{Lo}\widetilde{\delta})}{1 - (\beta - 1) \cdot \eta_u C_2 - (\gamma - 1) \cdot \eta_u C_3} \cdot d \log L_o^h \tag{12}$$

where $\eta_u > 0$ captures the elasticity of the cumulative distribution function $F(\cdot)$ around the initial threshold u^*, and $C_2 > 0$ and $C_3 > 0$ are just functions of the model parameters and initial labor shares (see Online Appendix D for exact definitions). The numerator captures the direct effect of the labor supply shock via firm optimality, whereas the denominator captures the indirect effect via self-selection among younger workers. Under the premise of condition (8) and $\gamma > \beta$, the numerator will be strictly positive and the threshold u^* will go up.[4] The arguments in this subsection are summarized in the following proposition:

[4]The reallocation of older workers towards low-skill jobs, which I have ignored for simplicity, constitutes

Proposition 1. *Consider an increase in the labor supply of older workers satisfying condition (8). If younger and older workers are more substitutable within skill types than high-skill and low-skill labor, i.e. $\gamma > \beta$, then this leads to the following:*

1. *Decline in the share of younger workers in high-skill jobs and rise in the share of younger workers in low-skill jobs:*

$$d \log L_{Hy} < 0 \quad \text{and} \quad d \log L_{Ly} > 0$$

2. *Rise in the share of younger workers with high levels of education in low-skill jobs:*

$$d \log u^* > 0$$

3. *Decline in youth high-skill wages relative to youth low-skill wages:*

$$d \log w_{Hy} < d \log w_{Ly}$$

Proof. See Online Appendix D. □

In summary, the conceptual framework laid out in this section illustrates how an increase in the labor supply of older workers concentrated in high-skill jobs can result in occupational downgrading among the young. The empirical strategy, which I now turn to, essentially compares local labor markets which have experienced differential increases in the labor supply of the old. In Section 4, I will show that in places where fewer older workers retire: (1) the share of younger workers in high-skill jobs declines while the share of younger workers in low-skill jobs rises, (2) the share of younger workers that are "overeducated" for their job rises, and (3) wages of younger workers in high-skill jobs decline by more than wages of younger workers in low-skill jobs, consistent with Proposition 1.

---

another dampening effect since it essentially attenuates the skill-biasedness of the original labor supply shock. Assuming either that the original labor-supply increase is sufficiently skill-biased or that the mass of older workers around the initial ability threshold z^* is not too large is sufficient for the intuition described above to go through.

3 Empirical Strategy

3.1 Data

The main data sources used in the empirical analysis are the 1980, 1990 and 2000 U.S. Censuses 5% samples, as well as the 2006, 2007, 2016 and 2017 American Community Surveys (ACS) 1% samples (Ruggles et al., 2018). I pool the 2006-2007 and 2016-2017 ACS to get a better snapshot of local labor markets in 2007 and 2017. The Census and ACS allow me to measure a wide array of employment outcomes at the local labor market level for various demographic groups. While I primarily focus on young adults aged 22 to 30, I also show how retirement trends affect teenagers (16-21) and the prime-aged (31-44). I exclude from the sample individuals confined to institutional group quarters and individuals on active military duty. All outcomes are constructed using Census sampling weights.

I approximate local labor markets using the concept of commuting zones (CZ) . Commuting zones are 741 clusters of counties characterized by strong commuting ties within CZs and weak commuting ties across CZs (Tolbert and Sizer, 1996). I drop Alaska and Hawaii and focus on the continental U.S., resulting in a total of 722 CZs. Since CZs are not directly identifiable in the Census, I follow standard practice and assign individuals living in areas that overlap with multiple CZs to each of those CZs with weights that add up to one and reflect how an area's population is distributed across those CZs (see Online Appendix A.1 for details).

In order to study changes in occupational structure over multiple decades, I use the time-consistent classification scheme developed by Dorn (2009). It distinguishes between 330 individual occupations which I organize into 12 occupation groups following Autor (2015).

3.2 Empirical Specification

The empirical strategy in this paper consists in comparing the evolution of youth employment outcomes across commuting zones, some of which have experienced greater increases in the labor supply of the old than others over the period spanning 1980 to 2017.[5] I measure changes in the labor supply of the old using changes in the 55+ employment rate. Although

[5]Dustmann et al. (2016) refers to this method of estimating the effect of labor supply shocks as the "pure spatial" approach. By not classifying older workers into education or occupation cells, this approach recovers the total impact of changes in the labor supply of the old, which takes into account imperfect substitutability between capital and labor, and between different labor types (low-skill vs. high-skill, young vs. old).

older workers are often defined as aged 55-64, I include people aged 65+ given that working past 65 has become increasingly common. Online Appendix Figure 1 shows that changes in the 55+ employment rate exhibit a substantial amount of variation, both across CZs and across periods. For the period 2007-2017, the distribution ranges from -7.3 percentage points to 8.1 percentage points, and the interquartile range is 3.5 percentage points. Let c denote commuting zones and t denote time periods. The main regression specification pools first-differences across four time periods (1980-1990, 1990-2000, 2000-2007, 2007-2017), controlling for period fixed effects and start-of-period CZ characteristics:[6]

$$\Delta\, y_{ct} = \alpha_t + \beta \cdot \Delta \text{ emp/pop}^{55+}_{ct} + \Gamma \cdot \text{CZ controls}_{c,t-1} + \varepsilon_{ct} \tag{13}$$

where y_{ct} is some youth employment outcome of interest. The CZ controls include the employment share of manufacturing, the employment share of routine occupations, an index which measures the extent to which occupations are susceptible to offshoring, the population share of immigrants, the unemployment rate, the female employment rate, as well as demographic composition in terms of age, gender, race and education.[7]

The main coefficient of interest, β, denotes the effect of a one percentage point increase in the local 55+ employment rate on changes in youth employment outcomes over 10 years. The ordinary least squares (OLS) estimate of β is likely to be biased for two reasons. First, changes in the 55+ employment rate not only capture flows from employment to inactivity (i.e. retirements), but also flows between employment and unemployment (i.e. hires and separations). This is problematic because hires, layoffs and voluntary quits all tend to be strongly correlated with the state of the local economy, which also affects younger workers. Put differently, in regions where the economy is booming (slumping), firms tend to hire (lay off) workers of all age groups resulting in a mechanical relationship between changes in the 55+ employment rate and changes in youth employment outcomes.

Second, retirement decisions can themselves be influenced by the state of the local economy. Coile and Levine (2007, 2011) finds that the retirement propensity of individuals eligible for Social Security rises during downturns, particularly among less educated workers. On the other hand, Goda et al. (2011) argues that asset losses during the Great Recession induced some individuals to delay their retirement plans. Either way, the sensi-

[6]Following Autor et al. (2013), first-differences for the period 2000-2007 are scaled by 10/7, so that outcomes are implicitly measured in terms of 10 $\times$ mean annual changes for comparability across periods.

[7]Routine occupations are defined as in Autor and Dorn (2013). The full list of controls along with summary statistics is given in Online Appendix Table 1.

tivity of retirement flows to local economic conditions reinforces the notion that changes in the 55+ employment rate may not only reflect labor supply-side variation, but also labor demand-side variation.

3.3 IV Strategy: Local Age Composition Among the Old

To address this endogeneity, I employ an instrumental variables (IV) approach. The idea is that, since older Americans tend to exit the labor force at specific ages, it is possible to predict what fraction of people will retire in a given commuting zone over the next 10 years simply based on their initial age composition. As long as age composition *among the old* is uncorrelated with local labor demand conditions, exploiting this variation to instrument for changes in the 55+ employment rate will isolate the causal effect of retirement trends.

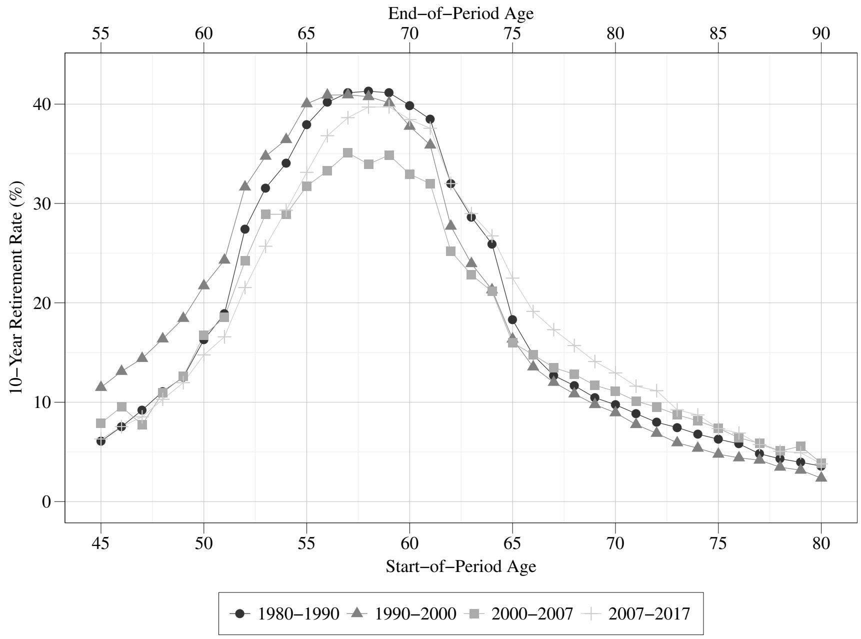
To see how the propensity to retire varies over the life cycle, Figure 3 plots 10-year retirement rates by age at the national level, defined as the difference between the employment rate of a birth cohort at the beginning of the period and the employment rate of the same birth cohort 10 years later. For example, the 10-year retirement rate of 45 year olds in 1990 is equal to the employment rate of 45 year olds in 1990 minus the employment rate of 55 year olds in 2000.[8] In other words, it captures the proportion of 45 year olds in 1990 who have retired at some point between 1990 and 2000. Two features stand out. First, the overall bell shape peaking between the ages of 55 and 60 reflects the fact that most Americans retire in their 60s. Conversely, the tails imply that relatively few people retire by the time they reach their late 50s while people in their late 60s or beyond have already retired for the most part. Second, there are noticeable discontinuities at ages 52, 55, 62 and 65, which are tied to eligibility for Social Security and Medicare.[9]

The implication of these empirical regularities is that one can exploit cross-sectional differences in the age composition among the old to predict future retirement trends, and thereby isolate labor supply-side variation in changes in the 55+ employment rate. I construct a Bartik-style instrument, which I will refer to as "predicted retirement intensity," by interacting start-of-period CZ-specific 45+ age shares with 10-year national retirement rates by age. Formally, predicted retirement intensity in commuting zone c for period t is

[8]For the period 2000-2007, 7-year retirement rates are converted into 10-year equivalents based on the 2000 employment rate-by-age profile. Specifically, the age-specific scaling factors are the ratio of the relevant 10-year and 7-year "retirement rates" according to this profile. These factors range from 3 to 1.2 for 45 and 59 year olds respectively, implying that naively scaling by 10/7 would be a poor approximation.

[9]62 is the earliest age one can claim Social Security benefits, while 65 is the universal eligibility age for Medicare.

Figure 3: 10-Year Retirement Rates by Age, 1980-2017



Notes: The 10-year retirement rate of a birth cohort (start-of-period age $\times$ year) is defined as the start-of-period employment rate of this cohort minus the end-of-period employment rate of the same cohort at the national level.

defined as:

$$\widetilde{\text{PRI}}_{ct}^{45+} = \sum_{a=45}^{80} \frac{\text{pop}_{c,t-10}^{a}}{\text{pop}_{c,t-10}^{45\text{-}80}} \times \left(\text{emp/pop}_{(-c),t-10}^{a} - \text{emp/pop}_{(-c),t}^{a+10}\right) \tag{14}$$

where emp/pop$_{(-c)t}^{a}$ are national employment rates by age a, excluding the commuting zone under consideration to avoid any mechanical correlation in the first-stage relationship.[10] The shape of the 45+ age distribution exhibits a fair amount of variation across commuting zones, as shown in Online Appendix Figure 2. For the period 2007-2017, the distribution of predicted retirement intensity ranges from 18.8 percentage points to 21.8 percentage points, and the interquartile range is 0.7 percentage points. Note that, unlike local industry composition or the spatial distribution of immigrants by country of origin (which underlie other common Bartik IV strategies), age distributions are constantly shifting so that whether an area is characterized by above or below-average predicted retirement intensity naturally varies over time.

[10] I truncate the 45+ age distribution at 80 since age is truncated at 90 in the Census.

3.4 Understanding Variation in Age Composition Among the Old

As argued in Goldsmith-Pinkham et al. (2018), the identifying assumption required for the validity of Bartik-style IV strategies depends on what types of asymptotics are most appropriate given the empirical setting. This paper most naturally falls into the case of locations going to infinity while periods and Bartik share categories are fixed (722 CZs, 4 periods, 36 age categories). In that scenario, the validity of the IV approach hinges on the exogeneity of the initial 45+ age distribution. More specifically, given that the Bartik IV estimator is numerically equivalent to a GMM estimator using individual age shares as instruments and a weight matrix which is a function of 10-year retirement rates by age, the implicit assumption is that the *individual* 45+ age shares are all valid instruments. To assess the plausibility of this identifying assumption this section explores two related questions: (1) which age shares "matter" the most in terms of driving the estimates? (2) what drives cross-sectional variation in age composition?

To answer the first question, I draw from the insights in Goldsmith-Pinkham et al. (2018). The Bartik IV estimator can be decomposed into a weighted sum of just-identified IV estimators using individual age shares as instruments. The weights—referred to as "Rotemberg weights"—can be positive or negative, sum to one, and capture how sensitive the overidentified estimate of β is to endogeneity of any of the age shares. Appendix Figure A.1 plots the Rotemberg weights for each age share.[11] Interestingly, the pattern in this figure mirrors the pattern in Figure 3, with the five age shares for 55-59 having the largest weights. This can be explained by the fact that Rotemberg weights are a direct function of 10-year retirement rates by age, though it is not always the case that the growth rate component dominates (see the examples in Goldsmith-Pinkham et al., 2018). These weights shed light on the identifying variation: they imply that 2SLS estimates using predicted retirement intensity as an instrument are essentially comparing commuting zones with an above vs. below-average fraction of people with the highest propensity to retire over the next 10 years. This naturally leads to the next question of whether places with different initial 45+ age distributions, and different initial shares of 55-59 year olds in particular, are valid counterfactuals for one another if the goal is to estimate the impact of retirement trends on youth labor market outcomes.

[11] There are technically 36 $\times$ 4 Rotemberg weights (for each age $\times$ period), which I have summed up over periods by age for expositional purposes. Also note that these weights were estimated using 10-year retirement rates by age that do not vary across CZs, since the Rotemberg decomposition only holds for national growth rates.

By definition, cross-sectional variation in age composition can come from three sources: (1) patterns in birth rates, (2) patterns in migration rates, and (3) patterns in mortality rates. Birth rates in the distant past are plausibly exogenous to current local labor market conditions. On the other hand, migration and mortality patterns could potentially be correlated with the state of the local economy. For example, industrial decline in some areas might simultaneously lead to poor youth employment outcomes and rapid aging as the working-age population gradually out-migrates over time. Given that a large initial share of elderly implies low predicted retirement intensity, this could lead us to overstate the (negative) impact of an increase in the 55+ employment rate. Therefore, an important consideration is how much variation in age composition can be explained by past birth rates alone.[12]

As an intermediate step, Panels A and B of Appendix Table A.2 try to predict population counts by age $a \in \{45, \cdots, 80\}$, CZ c and year $t \in \{1980, 1990, 2000, 2007\}$ using the lagged age structure in 1980. For example, the number of people aged 60 in a CZ in 2000 is predicted using the number of people aged 40 in the same CZ in 1980, adjusting for mortality. Population counts by age at the county level in 1980 come from the Census Bureau's Intercensal Population Counts and are "projected forward" using life tables from the Centers for Disease Control and Prevention (see Online Appendix A.2 for details). Panel A regresses actual population counts on predicted population counts separately by year in columns 1-4, and then pooling years together in the remaining columns with various fixed effects (age categories and CZs are pooled in all columns). Panel B shows analogous regressions where age counts are replaced with corresponding 45+ age shares.

The 1980 age structure is strongly predictive of future age structure, with R-squares in the 0.96-0.98 range in Panel A. Age shares are somewhat harder to predict because it involves correctly predicting both the numerator and denominator, but R-squares in Panel B are nevertheless in the neighborhood of 0.7-0.8 depending on the specification. Panels C and D go one step further and try to predict 45+ age counts and shares using data on historical births by county (Bailey et al., 2018). In this case, the number of people aged 60 in a CZ in 2000 is predicted using the number of people born in 1940 in the same CZ, again adjusting for mortality. Because coverage is incomplete in the first half of the 20th century, these regressions cover a subset of age categories and a subset of CZs depending

[12]Goldsmith-Pinkham et al. (2018) recommends correlating the Bartik IV as well as the top 5 Rotemberg weight shares with observable characteristics. Online Appendix Tables 2 and 3 show that the initial share of soon-to-be-retired people is not correlated with industrial or occupational composition, but is correlated with demographic composition, the female employment rate, the unemployment rate, and the population share of immigrants (which are controlled for in the regressions).

on the year. Remarkably, historical birth patterns are also strongly predictive of future age structure. The R-squared in the preferred specification pooling all years and without any fixed effects in column 5 is 0.7 in Panel A and 0.6 in Panel B.

These findings imply that much of the variation in 45+ age composition can be traced back to past birth patterns which are arguably orthogonal to current labor market conditions, lending support to the validity of the IV strategy. Although I proceed with the Bartik IV defined in (14) for the baseline 2SLS results, Section 4.5 shows that the results are robust to: (1) replacing actual initial 45+ age shares in the definition of predicted retirement intensity with predicted age shares based on 1980 age structure or historical birth rates, (2) directly exploiting the initial share of the 45+ population aged 55-59 as an instrument, and (3) exploiting initial 45+ age shares as separate instruments in a GMM estimation procedure.

Before moving on to the empirical analysis, I briefly discuss some remaining threats to identification. To address concerns that areas with different age structures are trending differentially, I later show that the results are robust to flexibly controlling for regional time trends (state or commuting zone-specific). Another potential concern is that age composition among the old could be correlated with age composition among the young via fertility patterns. This could potentially bias the estimates as it may affect both the size and the average experience of younger cohorts. The cohort size concern is alleviated by the fact that I control for the shape of the *overall* age distribution (population share of 16-21 vs. 22-30 vs. 31-44 vs. 45+ year olds), while I address the age composition concern in two different ways: (1) by explicitly adjusting youth outcomes for observable composition (incl. age), and (2) presenting results for 5-year age groups.

A final concern is that, even if local age composition is truly exogenous, it could potentially affect labor demand for younger workers via consumption patterns by age. The types of goods and services that people consume change over the life cycle, which may in turn affect the demand for workers across different sectors. In other words, do younger workers end up in retail jobs because of skill-biased retirement trends, or because of rising consumer demand? The consumption story would seem to require wages in low-skill jobs to increase, but in Section 4.3 I show that the opposite occurs. In the context of the model, this can be rationalized by imperfect substitutability between capital and labor and the notion that the supply of capital is not perfectly elastic, favoring the labor supply story.

4 Results

In this section, I show that fewer retirements have a negative impact on young adults (22-30) in terms of occupational composition and wages—and to a lesser extent employment—using the instrumental variables approach described in Section 3. I then document two ways in which the young adjust to declining labor market prospects: greater school attendance and net out-migration. Lastly, I subject the main findings to a series of robustness checks.

4.1 Employment, Unemployment and Labor Force Participation

Table 1 shows the effect of retirement trends on youth employment, unemployment and labor force participation, all measured in 10-year changes as a share of the youth population. Throughout the analysis, observations are weighted by the start-of-period CZ share of national population to lend more weight to larger commuting zones, and standard errors are clustered at the state level to allow for within-state correlation in the error terms, both across CZs and over time.

The OLS estimates in Panel A imply that increases in the 55+ employment rate have a positive effect on youth employment. For example, a one percentage point increase in the 55+ employment rate is associated with a 0.34 percentage point increase in the youth employment rate and a corresponding decline in youth unemployment and non-labor force participation, all statistically significant at the 1 percent level. Youth employment also shifts from part-time to full-time jobs, where part-time jobs are defined as working fewer than 35 hours a week. As discussed in Section 3, OLS estimates are likely biased towards finding a positive relationship between changes in employment among the old and young due to unobservable labor demand shifts.

Panel B instruments for changes in the 55+ employment using predicted retirement intensity based on the initial 45+ age distribution. The first-stage results are shown in Panel A of Appendix Table A.1, separately by period in columns 1-4 and pooling them together in column 5. The instrument has significant explanatory power, with all F-statistics large enough that weak instruments is not a concern. In terms of magnitude, a one percentage point increase in the share of 45+ year olds predicted to retire over the next 10 years is associated with a 1.3 percentage point decline in the 55+ employment rate on average.[13] In contrast to the OLS estimates, the 2SLS estimates in Panel B of Table 1 imply that

[13] The first-stage coefficient would be closer to one if the dependent variable was the start-of-period 45+ employment rate minus the end-of-period 55+ employment rate.

Table 1: The Effect of Retirement Trends on Youth Employment, Unemployment and Labor Force Participation: OLS and 2SLS Estimates

	Dependent variable: Youth outcome (22-30)				
	Δ Emp/pop				
	All	Part-time	Full-time	Δ Unemp/pop	Δ Out of labor force/pop
	(1)	(2)	(3)	(4)	(5)
Panel A: OLS estimates					
Δ Emp/pop (55+)	0.341***	-0.172***	0.512***	-0.120***	-0.221***
	(0.052)	(0.041)	(0.082)	(0.032)	(0.042)
Panel B: 2SLS estimates					
Δ Emp/pop (55+)	-0.232	0.750***	-0.983***	0.189*	0.043
	(0.246)	(0.194)	(0.305)	(0.103)	(0.202)

Notes: $N = 2,888$ (722 CZs $\times$ 4 time periods). All regressions include period fixed effects and start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

increases in the 55+ employment rate have a *negative* effect on youth employment, if anything. Specifically, a one percentage point increase in the 55+ employment rate leads to a statistically insignificant 0.23 percentage point decline in youth employment and a 0.19 percentage point increase in youth unemployment, statistically significant at the 10 percent level. Moreover, the small effect on youth employment masks a simultaneous decline in full-time employment and rise in part-time employment among the young.

Appendix Table A.3 splits the 2SLS results for the young (22-30) by gender and education (college vs. non-college), and shows corresponding results for teenagers (16-21) and the prime-aged (31-44). While the patterns are similar across genders, the negative employment effect is concentrated among college graduates, who experience a 0.35 percentage point decline in their employment rate in response to 1 percentage point increase in the 55+ employment rate. There are also large differences across age groups. While the prime-aged are mostly unaffected, teenagers experience an employment decline on the order of 0.8 percentage points. Interestingly, this decline is offset by an increase in non-labor force participation rather than an increase in unemployment. I will later show that this reflects an increase in the share of teenagers attending school.

4.2 Occupational Composition

Table 2 shows the impact of retirement trends on changes in the share of younger workers employed in low-skill, middle-skill and high-skill occupations. Low-skill occupations include jobs in agriculture, food preparation, retail sales and personal services. Middle-skill occupations include operators and laborers, administrative jobs, production jobs, and protective services (e.g. firemen). High-skill jobs include technicians (e.g. air traffic controllers), jobs in finance and real estate, professionals, and managers. These skill categories respectively account for roughly 20, 45 and 35 percent of the U.S. workforce.[14]

The OLS estimates in columns 1-3 of Panel A imply that in commuting zones where the 55+ employment rate goes up, youth occupational composition shifts away from low-skill and high-skill occupations towards middle-skill occupations. To assess whether or not that represents an improvement on average, column 4 examines changes in mean occupational wage premiums. These premiums are obtained by regressing log hourly wages on occupation fixed effects while flexibly controlling for observable characteristics using the sample of full-time workers aged 25 to 54 in the 2000 Census.[15] The resulting occupation fixed effects are then extracted and used to measure changes in the "average" job held by younger workers in terms of mean hourly wages (net of observables). The mean occupational wage premium among younger workers goes up by 0.06 log points in response to a one percentage point increase in the 55+ employment rate. Therefore, OLS estimates indicate that changes in job quality among younger workers are positively correlated with changes in the 55+ employment rate, which again likely reflects unobservable labor demand shifts.

In contrast, the 2SLS estimates in Panel B imply that youth occupational composition *deteriorates* in commuting zones where fewer older workers retire due to the initial 45+ age distribution. A one percentage point increase in the 55+ employment rate reduces the share of younger workers employed in high-skill jobs by 0.58 percentage points and raises the share of young employed in low-skill jobs by 0.41 percentage points. The coefficient on middle-skill employment is positive but not statistically significant. To get a better sense of the magnitude of these effects, going from the 25th to the 75th percentile commuting zone in terms of the change in the 55+ employment rate leads to a 3 percentage point decline in the youth high-skill employment share and a 2 percentage point increase in the youth low-

[14]Online Appendix Table 4 documents employment shares and mean hourly wages in 2000 for the five most common occupations in each occupation group.

[15]The controls for observable characteristics include fixed effects for gender, race, education, potential experience (defined as age minus years of education minus 6), and state of residence.

Table 2: The Effect of Retirement Trends on Youth Occupational Composition: OLS and 2SLS Estimates

	Dependent variable: Youth outcome (22-30)			
	Δ Employment share			
	Low-skill occupations	Middle-skill occupations	High-skill occupations	Δ Mean occ. wage premium
	(1)	(2)	(3)	(4)
Panel A: OLS Estimates				
Δ Emp/pop (55+)	-0.252***	0.364***	-0.112*	0.062**
	(0.042)	(0.071)	(0.061)	(0.024)
Panel B: 2SLS Estimates				
Δ Emp/pop (55+)	0.410***	0.167	-0.577***	-0.511***
	(0.157)	(0.205)	(0.157)	(0.126)

Notes: $N = 2,888$ (722 CZs $\times$ 4 time periods). All regressions include period fixed effects and start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

skill employment share, relative to national means of 37 percent and 27 percent respectively in 2017.[16] Consistent with the notion that younger workers downgrade to lower skill jobs, the 2SLS estimate in column 4 shows a 0.51 log points decline in the mean occupational wage premium.

Appendix Figure A.2 decomposes the 2SLS estimates from Table 2 at the occupation group level. It shows that the decline in high-skill jobs among young adults is primarily driven by managerial jobs (and to a lesser extent jobs in finance/real estate and technicians), while the increase in low-skill jobs is roughly evenly spread across food preparation, personal services and retail jobs. Note that the statistically insignificant effect for middle-skill occupations masks a reallocation from production jobs to operators/laborers, which pay nearly 20 percent less in terms of mean hourly wages. Appendix Table A.4 reveals that the increase in low-skill employment is concentrated among individuals without a college degree, while the decrease in high-skill employment is most pronounced among college grad-

[16] To ensure this finding does not hinge on the specific way in which I aggregated occupations, Online Appendix Table 7 shows results using an alternative method. Following Autor and Dorn (2013), I rank the 330 individual occupations according to mean hourly wages in 1980 and combine them into three equal-sized “skill terciles,” each containing a third of total employment in 1980. The 2SLS estimates using this alternative grouping of occupations are very similar.

uates. Occupational downgrading is also more pronounced among young female workers than young male workers. Interestingly, the patterns for teenagers are similar to the ones for young adults without a college degree, while prime-aged workers mostly downgrade from high-skill to middle-skill jobs.

Another way to uncover occupational downgrading among the young is to measure changes in the share of younger workers that are "overeducated," in the sense that their education attainment exceeds what is typically required for their job. To construct this outcome, I first categorize occupations into those that require a high school degree or less, those that require some college education (e.g. an Associate's degree), and those that require a 4-year college degree or more. One option is to follow Abel et al. (2014) and exploit job descriptions from the Department of Labor's Occupational Information Network (O*NET) which contains data on educational requirements (see Online Appendix A.3 for details). An alternative approach, following Clark et al. (2016), is to assign the most common education level observed in the data.[17] I construct two separate overeducation measures using this last approach: one based on the modal education level in 2000 and another where the modal education level is allowed to vary over time. Overeducation is then defined as one of two instances: (1) having a college degree or more and being employed in an occupation that does not require one, or (2) having some college education and being employed in an occupation that only requires a high school degree or less.

Table 3 shows the impact of changes in the 55+ employment rate on the share of younger workers with some education beyond high school that are overeducated. While the OLS estimates in Panel A are small and insignificant, the 2SLS estimates in Panel B are large and statistically significant across the board. They imply that a one percentage point increase in the 55+ employment rate leads to a 0.7-0.9 percentage point rise in the share of overeducated younger workers. For comparison, the national share of overeducated younger workers was around 30 percent in 2017 according to O*NET requirements, and 47 percent according to modal education levels in the 2000 Census (see Online Appendix Table 6). Online Appendix Table 9 shows that overeducation rises among both college and non-college-educated younger workers.

The pattern of occupational downgrading among the young documented in this section is consistent with the first two predictions of Proposition 1. Recall that these predictions are valid under two assumptions. The first assumption is that younger and older workers are

[17]Online Appendix Table 5 summarizes educational requirements by occupation group. As expected, occupations at the upper end of the spectrum tend to have higher educational requirements.

Table 3: The Effect of Retirement Trends on Youth Overeducated Employment: OLS and 2SLS Estimates

	Dependent variable: Δ Share workers "overeducated" (22-30)		
	Educational requirement in O*NET database	Modal education level in 2000 Census	Modal education level in Census (by year)
	(1)	(2)	(3)
Panel A: OLS Estimates			
Δ Emp/pop (55+)	0.140***	0.097	0.031
	(0.053)	(0.061)	(0.085)
Panel B: 2SLS Estimates			
Δ Emp/pop (55+)	0.737***	0.789***	0.945***
	(0.181)	(0.226)	(0.255)

Notes: $N = 2,888$ (722 CZs $\times$ 4 time periods). All regressions include period fixed effects and start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

more substitutable within skill types low-skill and high-skill workers. Card and Lemieux (2001) provides the most relevant empirical evidence on the matter. Using Current Population Survey data from 1970 to 1997, they estimate an elasticity of substitution between age types within skill types $1/(1-\gamma)$ in the 4-6 range, and an elasticity of substitution between skill types $1/(1-\beta)$ in the 2-2.5 range. This implies a value of γ between 0.75 and 0.83, and a value of β between 0.2 and 0.5, which is in line with the premise of Proposition 1.

The second assumption is that retirement trends are biased towards high-skill jobs. While this is certainly true at the national level, the extent to which retirement trends are skill-biased likely varies across commuting zones. One corollary of Proposition 1 is that the extent of occupational downgrading among the young is directly related to the skill-biasedness of retirement trends. Online Appendix Table 8 tests this prediction by separately estimating the effect of changes in employment among older college-educated vs. non-college-educated individuals. To do so, I decompose changes in the 55+ employment rate into two additive components corresponding to the contribution of each education group. I then estimate the effect of these two components separately using two instruments defined as in (14), except that age shares are replaced with age-by-education group shares, and 10-year retirement rates by age are education group-specific. The 2SLS estimates show that an increase in the employment of college-educated older workers has a more negative effect than an equally large increase in the employment of non-college-educated older workers, which makes intuitive sense given that college-educated older workers are more likely to work in high-skill jobs. The conceptual framework from Section 2 therefore provides a coherent explanation for the occupational patterns observed in the data.

4.3 Wages

Table 4 shows the impact of retirement trends on changes in mean log hourly wages of younger workers.[18] Column 1 pools all occupations together while columns 2-4 examine wages of workers employed in low-skill, middle-skill and high-skill occupations separately. The OLS estimates in Panel A are all positive and statistically significant. Combined with the positive effect on youth employment in Panel A of Table 1, this is yet another sign that changes in the 55+ employment rate likely capture shifts in labor demand. In the remainder of the analysis, I only discuss 2SLS estimates which rely on variation in age composition.

The baseline estimate in column 1 of Panel B implies that wages of younger workers decline by 3.3 percent in response to a one percentage point increase in the 55+ employment rate. How much of this decline mechanically reflects younger workers downgrading to lower-paying jobs? The 2SLS estimate for the mean occupational wage premium suggests only about 15 percent. Coming back to the model, declining wages in response to an increase in total labor supply is consistent with the notion that capital is not perfectly elastic at the commuting zone level. Proposition 1 also makes the following wage prediction: youth high-skill wages should decline relative to youth low-skill wages. However, this statement applies to wages *per efficiency unit*. The average wage among younger workers in high-skill jobs, which is what we observe in the data, depends on the latent ability distribution:

$$\overline{w_{Hy}} = \int_{u^*}^{\infty} u \cdot w_{Hy} \cdot f(u) \cdot du = w_{Hy} \cdot E(u|u > u^*) \tag{15}$$

Totally differentiating (15) yields:

$$d \log \overline{w_{Hy}} = d \log w_{Hy} + \eta_E \cdot d \log u^* \tag{16}$$

[18]Wage measures exclude the self-employed and are averaged using labor supply weights (Census sampling weights multiplied by annual hours worked). See Online Appendix A.4 for additional details.

Table 4: The Effect of Retirement Trends on Youth Wages: OLS and 2SLS Estimates

	Dependent variable: Δ Log wage (22-30)			
	All occupations	Low-skill occupations	Middle-skill occupations	High-skill occupations
	(1)	(2)	(3)	(4)
Panel A: OLS Estimates				
Δ Emp/pop (55+)	0.930***	0.974***	1.116***	0.592***
	(0.143)	(0.159)	(0.157)	(0.137)
Panel B: 2SLS Estimates				
Δ Emp/pop (55+)	-3.307***	-3.256***	-2.836***	-3.805***
	(0.707)	(0.754)	(0.688)	(0.705)

Notes: $N = 2,888$ (722 CZs $\times$ 4 time periods). All regressions include period fixed effects and start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

where $\eta_E > 0$ is the elasticity of $E(u|u > u^*)$ around the initial ability threshold u^*. The first term on the right-hand side of (16) is negative under the premise of Proposition 1. On the other hand, the second term is positive since $d \log u^* > 0$. Intuitively, it captures the fact that average ability among younger workers who remain in high-skill jobs goes up due to self-selection (recall that marginal ability workers optimally reallocate towards low-skill jobs). Therefore, it is unclear whether we should observe a greater decline in high-skill youth wages than low-skill youth wages. While I cannot statistically reject the null hypotheses that the estimates in columns 2-4 are equal, wages of younger workers in high-skill jobs decline by 3.8 percent relative to wage declines of 3.3 percent and 2.8 percent for younger workers in low-skill and middle-skill jobs respectively.

Online Appendix Table 10 documents heterogeneity in the wage effects across demographic groups. Average wage declines hover around 3 percent for every percentage point increase in the 55+ employment rate, with the exception of prime-aged workers who experience only a 1.3 percent decline. The results by age group discussed so far resemble a "job ladder," in which older age groups are less affected by declines in retirements than younger age groups. While the model only featured two age groups, this goes somewhat counter to what one would expect under competitive labor markets. If prime-aged workers are closer substitutes for older workers than younger ones, which should be the case if accumulated experience is the primary difference between age groups, frictionless models of the labor market would predict larger wage declines for prime-aged workers in response to an increase in the labor supply of the old. If wages of prime-aged workers exhibit rigidities, as in Dustmann et al. (2017), then labor market clearing would require stronger disemployment or occupational downgrading effects. However, the results in the previous subsections have shown that prime-aged workers are relatively unaffected along other dimensions as well. The implies that real-world labor markets are not perfectly competitive, and that one would need to add some type of friction to the model in Section 2 in order to rationalize the patterns by age group.[19]

4.4 Adjustment Margins: School Attendance & Internal Migration

Past studies have shown that college attendance among the young tends to rise during downturns as the opportunity cost of going to school falls. Betts and McFarland (1995) finds a positive relationship between community college enrollment and the unemployment rate. Charles et al. (2018) shows that the housing boom of the 2000s reduced enrollment at 2-year colleges as labor markets prospects improved. Given the results so far, one may wonder whether the option to go back to (or remain in) school similarly serves as an adjustment mechanism in response to rising labor supply among the old. In Appendix Table A.5, I estimate the effect of retirement trends on school attendance. Column 1 implies that the share of young adults attending school increases by 0.59 percentage points in response to a one percentage point increase in the 55+ employment rate. School attendance also rises significantly among teenagers, consistent with the large negative employment effect documented earlier. In contrast, there is no discernible effect among the primed-aged; school attendance is probably not an important adjustment mechanism for people already in their 30s or 40s, and they are less affected to begin with.

There are two ways to interpret this finding. First, it can be viewed as further corroborating evidence that youth labor market prospects deteriorate in commuting zones where fewer older workers retire. Second, to the extent that school attendance raises individuals' future earnings potential, higher educational attainment could potentially mitigate/offset the immediate labor market consequences of increases in the labor supply of the old, a point which I return to in Section 5.

Another way in which young adults can adjust is migration across commuting zones, particularly since they exhibit the highest mobility rate among all age groups (Molloy et al.,

[19]One possibility is that firms find it easier to adjust wages of new workers, and that seniority rules or firm-specific human capital shield incumbent workers from job loss.

2014). Appendix Table A.6 shows the effect of retirement trends on population growth. I find strong evidence of net out-migration among the young: a one percentage point increase in the 55+ employment rate leads to a 3.8 percent contraction in the youth population over 10 years. Although I cannot determine whether this reflects greater out-migration or reduced in-migration, recent studies suggest that reduced in-migration probably plays an important role (Monras, 2017; Yagan, forthcoming). The fact that college graduates appear to be most responsive in terms of geographical mobility is consistent with similar findings in the literature (Bound and Holzer, 2000; Wozniak, 2010; Notowidigdo, forthcoming). In contrast, there is no mobility response among teenagers and the prime-aged.[20]

4.5 Robustness Checks

Isolating Variation in 1980 Age Structure or Historical Birth Patterns

The baseline instrument exploits the start-of-period 45+ age distribution in each commuting zone. Although I showed in Section 3.4 that most of the variation in age composition can be explained by plausibly exogenous variation in past age structure or historical births, one might worry that some of the residual variation reflects endogenous migration or mortality patterns. I now show that the results are robust to solely relying on variation in 1980 age structure or historical births by constructing two alternative instruments in which actual age shares in (14) are replaced with corresponding predicted age shares from Section 3.4.

Table 5 displays 2SLS estimates using these alternative instruments for the main outcomes of interest. Panel A reproduces the baseline results for ease of comparison. The results based on 1980 age structure in Panel B are slightly larger in magnitude but otherwise similar, except that occupational downgrading among the young is more skewed towards middle-skill jobs. Note that using predicted age shares naturally results in a loss of power, with the first-stage F-stat dropping from 112.3 to 61.3. Exploiting historical births additionally leads to a loss of sample size from 2,888 to 1,202 given that the data does not go back far enough to predict 45+ age shares in 1980, and 1990 for nearly all commuting zones (the first-stage F-stat further drops to 23.5).[21]

Panel C shows the baseline estimates for the subset of CZ-periods for which the birth

[20] Online Appendix Table 11 explores three additional adjustment margins: marital status, fertility and living arrangements. An interesting finding is that rentership goes up among all demographic groups, except teenagers who are more likely to live with their parents.

[21] The birth instrument is based on 45-75 rather than 45-80 age shares to retain as many CZs as possible. Online Appendix Figures 3 and 4 illustrate the variation in these two alternative instruments.

Table 5: Alternative Instruments Based on 1980 Age Structure or Historical Births: 2SLS Estimates

	Dependent variable: Youth outcome (22-30)						
		Δ Employment share					
	Δ Unemp/ pop	Low-skill occupations	Middle-skill occupations	High-skill occupations	Δ Mean occupational wage premium	Δ Share workers ”overeducated” (O*NET)	Δ Log wage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Baseline instrument (First-stage F-stat = 112.26)							
Δ Emp/pop (55+)	0.189*	0.410***	0.167	-0.577***	-0.511***	0.737***	-3.307***
	(0.103)	(0.157)	(0.205)	(0.157)	(0.126)	(0.181)	(0.707)
Panel B: Exploit 1980 age composition (First-stage F-stat = 61.28)							
Δ Emp/pop (55+)	0.330**	0.395*	0.737***	-1.132***	-0.731***	0.941***	-4.172***
	(0.157)	(0.219)	(0.258)	(0.258)	(0.183)	(0.233)	(0.962)
Panel C: Baseline instrument: subset of CZ-periods with non-missing historical birth instrument (First-stage F-stat = 29.73)							
Δ Emp/pop (55+)	0.218	0.517	-0.129	-0.389**	-0.360*	0.173	-2.139***
	(0.187)	(0.378)	(0.359)	(0.191)	(0.192)	(0.190)	(0.750)
Panel D: Exploit historical births (First-stage F-stat = 23.5)							
Δ Emp/pop (55+)	-0.166	0.091	0.895***	-0.986***	-0.368*	0.280**	-0.889
	(0.133)	(0.413)	(0.312)	(0.248)	(0.206)	(0.119)	(1.091)

Notes: $N = 2,888$ (722 CZs $\times$ 4 time periods) in Panels A and B, $N = 1,202$ in Panels C and D. All regressions include period fixed effects and start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

instrument can be computed. Relative to the estimates in Panel A, the estimates in Panel C are slightly smaller in magnitude and more imprecise, but the patterns are qualitatively similar. The corresponding results in Panel D using the birth instrument are somewhat larger in magnitude (except for the unemployment and wage coefficients which are statistically insignificant), but similarly show that younger workers are less likely to be employed in high-skill jobs and more likely to be overeducated in commuting zones where fewer older workers retire. Overall, I view these results as evidence that the variation in initial 45+ age composition underlying the main findings is largely pre-determined.

Adjusting Outcomes for Changes in Demographic Composition

In light of the migration results, particularly the fact that young college graduates reallocate away from CZs where fewer older workers retire, one legitimate concern is that changes in average youth outcomes reflect changes in the composition of the youth population. In other words, does occupational downgrading among the young simply reflect a decline in the share of college graduates? The answer to this question is yes and no. Because college graduates are more likely to be employed in high-skill jobs, some of the decline can be attributed to a shift in the educational composition of the young. However, the results by education group in Appendix Table A.4 showed that *both* education groups experience occupational downgrading, implying that the overall effect is not purely mechanical.

To probe this point, I generate "composition-adjusted" outcomes using the two-step procedure in Shapiro (2006). First, using individual-level Census/ACS data, I regress the analog of each outcome (e.g. an indicator for being employed in a high-skill job) on a comprehensive set of individual controls (gender, race, education and potential experience fixed effects) as well as CZ fixed effects, separately by year. I then extract the estimated year-specific CZ fixed effects and take first-differences to obtain changes in average outcomes that are not mechanically driven by changes in the local demographic composition (see Online Appendix A.5 for additional details). Note that this procedure can only account for changes in terms of *observable* characteristics.

The 2SLS estimates for the composition-adjusted outcomes are displayed in Appendix Table A.7. The coefficients are around 10-20 percent smaller in absolute terms than the corresponding estimates in Tables 1-4, consistent with the notion that composition does play a role, but the main findings are otherwise unchanged.

Additional Robustness Checks

While the empirical strategy eliminates level differences across commuting zones, one possible concern is that CZs with different age structures may be trending differentially. In Panel A of Online Appendix Table 12, I allow for state-specific time trends by augmenting the baseline specification (13) with state fixed effects. The resulting estimates are very similar to the baseline estimates. Panel B goes further and allows for commuting zone-specific time trends, thereby only exploiting within-CZ variation in predicted retirement intensity over time. Although the loss of power leads to larger standard errors (the first-stage F-stat drops to 16.3), there is no significant change in the magnitude of the coefficients.

The baseline specification controls for the initial share of workers that are employed in manufacturing and routine occupations to address the fact that CZs may have been differentially exposed to the secular decline of manufacturing and the rise of automation. More generally, there could be other industry or occupation-specific trends that I am not accounting for. Panel C of Online Appendix Table 12 shows that the results are robust to fully controlling for initial differences in terms of industrial/occupational composition.

Online Appendix Table 13 evaluates the robustness of the main findings to alternative sample restrictions. Given the school attendance results, one might be worried that the findings partly reflect the fact that students are more likely to work in part-time, low-paying jobs than non-students. Panel A therefore excludes students from the sample. While composition-adjusted outcomes cannot account for changes in the underlying youth population in terms of unobservables, one way to mitigate the impact of net migration across commuting zones is to exclude individuals who have moved or are likely to have moved in the recent past. Panels B and C respectively drop from the sample people residing in a different state than their state of birth and people who recently migrated from another state (where "recent" means within the last 5 years in the Census and within the last year in the ACS). Lastly, Panel D omits the period 2007-2017 from the sample, thereby abstracting from the Great Recession and its aftermath. The main findings are remarkably stable across all panels. Online Appendix Figure 6 plots 2SLS estimates by 5-year age groups. While there are clear differences across age groups, as emphasized already, the main findings do not hinge on the exact age cutoffs used to define young adults.

Motivated by the finding in Section 3.4 that the key variation driving the results is the initial share of the 45+ population aged 55-59, Panel A of Online Appendix Table 14 directly uses this variable as an instrument. Panel B follows the recommendation in Goldsmith-Pinkham et al. (2018) and uses individual 45+ age shares as separate instruments in an overidentified LIML estimation procedure. While the coefficients are slightly smaller in magnitude in both panels, the main findings are unchanged. This shows that the exact way in which one chooses to exploit variation in initial 45+ age composition does not really matter, which is reassuring. In addition, the overidentification tests in Panel B show that for all main outcomes, I cannot reject the null hypothesis that the overidentifying restrictions are valid.

To alleviate any concerns that the results might be driven by specific parts of the country, Online Appendix Table 15 shows that the results are robust to excluding Census divisions one-by-one. While commuting zones are the standard way to define U.S. local labor markets, Online Appendix Table 16 uses states instead. As before, the OLS estimates in Panel A show that changes in the 55+ employment rate are positively correlated with changes in youth outcomes. In contrast, the 2SLS estimates in Panel B, based on an analogous definition of the predicted retirement intensity instrument, show that an increase in the 55+ employment has a negative impact on youth labor market outcomes, consistent with the CZ-level results.[22]

5 Discussion

Overall, the findings in the previous section indicate that younger workers get "pushed" down the job ladder in places where fewer older workers retire. Going back to the original motivation of the paper, this suggests that the slowdown in retirements since the mid-1990s has likely contributed to deteriorating youth labor market prospects, especially given that older workers are increasingly concentrated at the top of the job ladder. A back-of-the-envelope calculation helps put these trends into perspective. Between 1980 and 2017, the 55+ employment rate rose by 6.4 percentage points. Over the same period, the share of younger workers in low-skill jobs rose by 9.5 percentage points while the share of younger workers in high-skill jobs rose by 6.5 percentage points. Using the preferred composition-adjusted 2SLS estimates from Appendix Table A.7, this implies that the retirement slowdown can account for 30 percent of the aggregate rise in youth low-skill employment between 1980 and 2017 . Alternatively, had the 55+ employment rate had remained at its 1980 level, youth employment in high-skill occupations would have risen by 9.4 rather than 6.5 percentage points between 1980 and 2017, a difference of 2.9 percentage points relative to a baseline level of 36.9 percent in 2017. Of course, these calculations ignore general equilibrium effects, which are to some extent absorbed in the aggregate trend, so these estimates should be interpreted with some caution.

This provides a novel explanation for the recent struggles of young Americans, particularly those with higher levels of education. Unlike individuals with lower levels of education, their woes cannot easily be explained by forces such as globalization or automation. The labor supply-side hypothesis proposed here does not preclude a role for labor demand factors. Notably, Beaudry et al. (2016) argues that the rise in IT productivity over the 1990s followed by a slowdown after 2000 can explain the "Great Reversal" in the demand for cognitive skills which occurred over this period. It is possible that rising demand in high-skill

[22]For power reasons, the state-level instrument is based on national retirement rates by age (not leave-out).

jobs due to the IT revolution outpaced declining demand due to the skill-biased retirement slowdown during the 1990s, and that the latter became more prominent in the 2000s as IT technologies reached maturity and overall labor market conditions stagnated.[23] However, regardless of the underlying aggregate forces, the empirical strategy in this paper isolates the impact of older workers' labor supply.[24]

Poor initial job prospects matter because they can have lasting effects. Numerous studies have documented long-term "scars" associated with graduating from college during a recession (Kahn, 2010; Oreopoulos et al., 2012; Altonji et al., 2016). Recent work by Schwandt and von Wachter (2018) shows that the adverse effects of poor initial conditions extend to individuals without college degrees as well. Using data on individual earnings histories, Guvenen et al. (2017) finds that early career outcomes are an important determinant of cross-cohort and within-cohort patterns in lifetime income inequality.

Therefore, one key question is to what extent individuals entering the labor market at times and in places where fewer older workers retire are able to recover over time, particularly given the school attendance results. Appendix Table A.8 provides some suggestive evidence on the long-term effects of retirement trends by examining changes in *cohort-specific* outcomes. For this exercise, I restrict the sample to individuals residing in their state of birth to abstract away from internal migration as much as possible. Panel A reproduces the results from Panel B of Online Appendix Table 11, where outcomes of people aged 22-30 today are compared to outcomes of people aged 22-30 ten years later. Alternatively, we can follow the same cohort over time and compare outcomes of people aged 22-30 today to outcomes of people aged 32-40 ten years later. The resulting estimates in Panel B reveal that the effects on occupational composition are strongly persistent over time. After 10 years, young adults in commuting zones where fewer workers retire are still significantly less likely to be employed in high-skill jobs than their more fortunate peers, though they are more evenly spread across low-skill and middle-skill jobs. This is reflected in the effects on the mean occupational wage premium and the share of overeducated workers, which are about half as large as the baseline estimates. The wage impact is about a quarter of the size of the baseline effect, but still statistically significant. While this evidence is merely suggestive, it is consistent with the notion that catch-up is imperfect.

[23] It is interesting to note that the employment of older workers in high-skill jobs experienced no reversal after 2000.

[24] Another natural explanation for diverging outcomes between the young and old are increasing returns to experience. However, Jeong et al. (2015) finds little evidence to support the presence of such labor demand shifts.

The findings in this paper have important implications in the context of retirement age policy. As is well-known, population aging is putting enormous pressure on pay-as-you-go pension schemes, in which the current generation of workers supports the current generation of retirees through payroll taxes.[25] To address this problem, policymakers have overwhelmingly opted to try to expand the size of the labor force relative to the size of the retired population by raising the age at which individuals are eligible for partial or full retirement benefits and discouraging early retirements.[26] Indeed, many European countries (e.g. France, Germany, Spain, U.K.) as well as the U.S. are gradually raising their retirement age to 67 or 68.

While the fiscal benefits of these policies are evident, potential costs, if any, are less clear. One concern that is often brought up is the potential crowding-out of younger workers. A common view among the public and some policymakers is that retirements directly affect the number of jobs available for the young, an example of the "lump-of-labor" fallacy. This kind of zero-sum view of the labor market has been widely rejected by economists (Börsch-Supan, 2013). As mentioned in the introduction, studies for the U.S. have found little evidence that the old crowd out the young (Gruber and Wise, 2010; Munnell and Wu, 2012). In light of this evidence, the consensus in policy discussions seems to be that encouraging people to work longer will not have any repercussions for younger generations (United States Government Accountability Office, 2012; The PEW Charitable Trusts, 2012; Carnevale et al., 2013). The results in this paper, together with recent firm-level evidence (e.g. Bianchi et al., 2018), suggest that we should reassess the current view and not only consider how retirements affect employment but also career advancement opportunities.

6 Conclusion

Since the mid-1990s, older Americans have been working increasingly longer, especially those in high-skill jobs. This paper investigates how the retirement slowdown has affected the job prospects of younger Americans by comparing the evolution of youth employment

[25]The demographics are slightly more favorable in the U.S. than in other developed countries thanks to higher inflows of immigrants (who tend to be of working age) and higher fertility rates. Nevertheless, the Social Security Administration projects that the Trust Fund's reserves will be depleted by 2034 (OASDI Board of Trustees, 2016).

[26]In the U.S., complementary measures include the elimination of the Social Security earnings test for individuals who have reached the normal retirement age and delayed retirement credits, which compensate individuals who claim Social Security benefits past their normal retirement age (up to age 70).

outcomes across U.S. commuting zones over the period 1980-2017. I isolate plausibly exogenous variation in retirement patterns by exploiting cross-sectional differences in the age composition of the old, which naturally generate variation in the size of the soon-to-be-retired population and are primarily driven by past birth patterns.

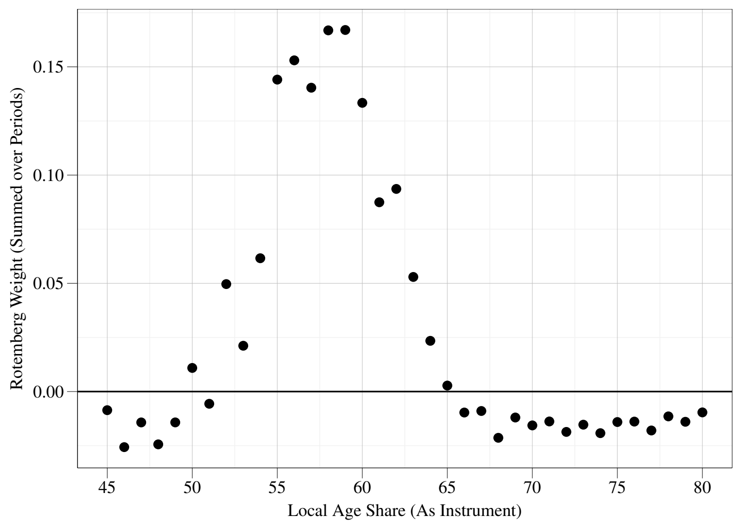
The main finding is that fewer retirements lead to occupational downgrading among the young. In commuting zones where fewer older workers retire due to the initial age structure, the share of younger workers employed in high-skill jobs declines and the share of younger workers employed in low-skill jobs rises. Moreover, the share of younger workers whose educational attainment exceeds what is typically required for their job rises and youth wages decline. I show that the young partly adjust to deteriorating labor market prospects via greater school attendance and net out-migration, both of which have been found to be important adjustment mechanisms in other contexts. While this paper mostly focuses on young adults aged 22 to 30, teenagers and prime-aged individuals are shown to be adversely affected as well, though along different margins and to varying extents.

Overall, the findings suggest that retirement trends have contributed to stagnant youth labor market outcomes in recent decades. In particular, the estimates imply that the retirement slowdown can explain 30 percent of the rise in the share of younger workers in low-skill jobs between 1980 and 2017. Alternatively, absent the retirement slowdown, the share of younger workers in high-skill jobs would have been 8 percent higher in 2017. This provides a novel explanation for the declining fortunes of the young, particularly the college-educated. Whether or not we should be concerned by deteriorating early career outcomes hinges on individuals' ability to catch up over time. Suggestive evidence points to the presence of adverse long-term effects.

Looking ahead, a combination of health improvements, rising life expectancy, and a policy shift toward later retirements implies that the old will likely keep working longer, not just in the U.S. but around the world. This paper offers new evidence on how this structural shift could affect labor markets, and younger generations in particular.

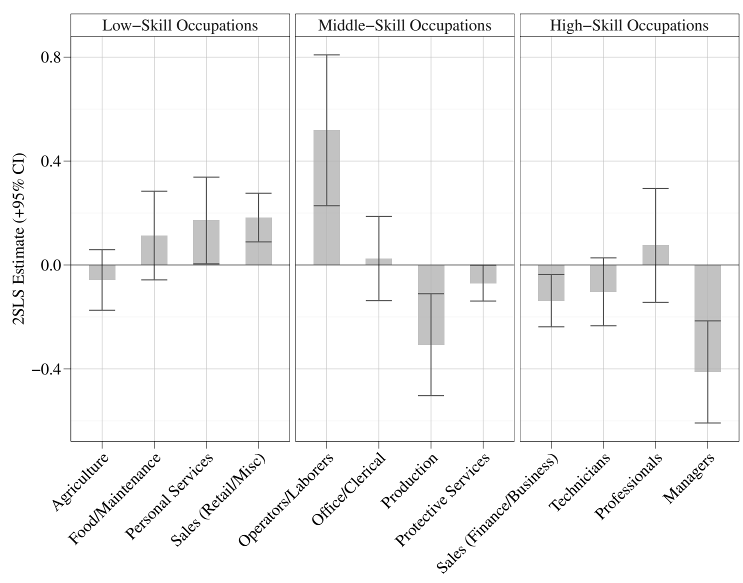
Appendix

Figure A.1: Rotemberg Weights, Summed Over Periods



Notes: This figure plots Rotemberg weights for each age share, where weights were summed over the four periods in the analysis. See Goldsmith-Pinkham et al. (2018) for definition of Rotemberg weights.

Figure A.2: Occupation Group-Specific Effects: 2SLS Estimates



Notes: Each bar represents the coefficient corresponding to the change in the 55+ employment rate from a separate 2SLS regression (baseline specification with period fixed effects and CZ controls), where the dependent variable is the change in the share of younger workers (22-30) employed in a particular occupation group (x-axis). The error bars represent the corresponding 95% confidence intervals.

Table A.1: 2SLS: First-Stage Results

	Dependent variable: Δ Emp/pop (55+)						
	1980-1990	1990-2000	2000-2007	2007-2017	1980-2017	1980-2017	1990-2017
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Baseline IV							
Predicted retirement intensity (45+)	-1.274***	-1.536***	-2.047***	-1.879***	-1.284***		
	(0.246)	(0.192)	(0.564)	(0.314)	(0.121)		
Panel B: Exploit 1980 age composition							
Predicted retirement intensity (45+)						-0.942***	
						(0.120)	
Panel C: Exploit historical births							
Predicted retirement intensity (45+)							-0.403***
							(0.083)
F-stat	26.8	64.15	13.18	35.72	112.26	61.28	23.5
Period fixed effects					✓	✓	✓
Observations	722	722	722	722	2,888	2,888	1,208

Notes: All regressions include start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table A.2: Predicting 45+ Population Counts and Shares Using 1980 Age Structure or Historical Births, 1980-2007

	Period						
	1980	1990	2000	2007	1980-2007	1980-2007	1980-2007
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Predicting population counts/shares using 1980 age structure						
Panel A: Dependent variable: population count							
Predicted population count	0.994***	1.041***	1.050***	1.107***	1.059***	1.012***	0.979***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.998	0.988	0.976	0.962	0.974	0.984	0.992
Age range in sample	45-80	45-80	45-80	45-80	45-80	45-80	45-80
Observations (age × CZ × year)	25,992	25,992	25,992	25,992	103,968	103,968	103,968
Panel B: Dependent variable: population share (among those aged 45-80)							
Predicted population share	1.015***	0.736***	0.714***	0.665***	0.729***	0.608***	0.552***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.004)
R^2	0.822	0.728	0.858	0.771	0.784	0.797	0.817
Age range in sample	45-80	45-80	45-80	45-80	45-80	45-80	45-80
Observations (age × CZ × year)	25,992	25,992	25,992	25,992	103,968	103,968	103,968
	Predicting population counts/shares using historical births						
Panel C: Dependent variable: population count							
Predicted population count	1.564***	1.485***	1.233***	1.181***	1.255***	0.733***	0.771***
	(0.013)	(0.009)	(0.005)	(0.004)	(0.003)	(0.002)	(0.002)
R^2	0.587	0.640	0.737	0.791	0.718	0.959	0.968
Age range in sample	45-65	45-75	45-80	45-80	45-80	45-80	45-80
Observations (age × CZ × year)	9,888	17,107	23,279	25,406	75,680	75,680	75,680
Panel D: Dependent variable: population share (among those aged 45-75)							
Predicted population share	—	0.306***	0.536***	0.607***	0.562***	0.159***	0.094***
		(0.008)	(0.003)	(0.004)	(0.002)	(0.004)	(0.003)
R^2	—	0.352	0.676	0.588	0.606	0.742	0.789
Age range in sample	—	45-75	45-75	45-75	45-75	45-75	45-75
Observations (age × CZ × year)	—	2,852	14,596	20,445	37,893	37,893	37,893
Constant	✓	✓	✓	✓	✓		
Year FEs						✓	
Age FEs						✓	
CZ FEs						✓	
Year × age FEs							✓
Year × CZ FEs							✓
CZ × age FEs							✓

Notes: See Online Appendix A.2 for details on constructing predicted population counts/shares. Robust standard errors in parentheses. *** 1%, ** 5%, * 10% significance.

Source: 1980, 1990, 2000 Censuses, 2006-2007 ACS, 1980 Intercensal County Population Counts, Bailey et al. (2018).

Table A.3: The Effect of Retirement Trends on Employment, Unemployment and Labor Force Participation: Heterogeneity of 2SLS Estimates by Age, Gender and Education

	Dependent variable:				
	Δ Emp/pop				
	All	Part-time	Full-time	Δ Unemp/pop	Δ Out of labor force/pop
	(1)	(2)	(3)	(4)	(5)
Panel A: Young (22-30) $\times$ gender					
Male	-0.131	0.695***	-0.826**	0.076	0.054
	(0.229)	(0.182)	(0.349)	(0.116)	(0.158)
Female	-0.080	0.851***	-0.931***	0.212**	-0.132
	(0.324)	(0.205)	(0.302)	(0.090)	(0.314)
Panel B: Young (22-30) $\times$ education groups					
Less than college	0.019	0.812***	-0.794***	0.094	-0.113
	(0.231)	(0.182)	(0.269)	(0.106)	(0.211)
College or more	-0.350**	0.742***	-1.093***	0.211***	0.140
	(0.173)	(0.234)	(0.241)	(0.075)	(0.171)
Panel C: Other age groups					
Teenagers (16-21)	-0.788***	0.260*	-1.048***	0.183*	0.605***
	(0.194)	(0.146)	(0.209)	(0.109)	(0.162)
Prime-aged (31-44)	0.023	0.187**	-0.164	0.028	-0.051
	(0.187)	(0.082)	(0.164)	(0.041)	(0.183)

Notes: $N = 2,888$ (722 CZs $\times$ 4 time periods). All regressions include period fixed effects and start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table A.4: The Effect of Retirement Trends on Occupational Composition: Heterogeneity of 2SLS Estimates by Age, Gender and Education

	Dependent variable:			
	Δ Employment share			
	Low-skill occupations	Middle-skill occupations	High-skill occupations	Δ Mean occ. wage premium
	(1)	(2)	(3)	(4)
Panel A: Young (22-30) $\times$ gender				
Male	0.231	0.197	-0.428**	-0.411***
	(0.154)	(0.283)	(0.194)	(0.104)
Female	0.800***	0.037	-0.837***	-0.635***
	(0.209)	(0.171)	(0.192)	(0.129)
Panel B: Young (22-30) $\times$ education groups				
Less than college	0.532**	-0.235	-0.297**	-0.368***
	(0.210)	(0.230)	(0.138)	(0.105)
College or more	0.183	0.272	-0.455**	-0.519***
	(0.151)	(0.168)	(0.226)	(0.141)
Panel C: Other age groups				
Teenagers (16-21)	0.463**	-0.180	-0.283**	-0.281**
	(0.230)	(0.176)	(0.127)	(0.117)
Prime-aged (31-44)	-0.123	0.410**	-0.287**	-0.129**
	(0.089)	(0.167)	(0.134)	(0.063)

Notes: $N = 2,888$ (722 CZs $\times$ 4 time periods). All regressions include period fixed effects and start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table A.5: The Effect of Retirement Trends on School Attendance: 2SLS Estimates

	Dependent variable: Δ Share attending school						
	Young (22-30)						
	All	Male	Female	Less than college	College or more	Teenagers (16-21)	Prime-aged (31-44)
	(1)	(2)	(3)	(4)	(6)	(7)	(8)
Δ Emp/pop (55+)	0.588***	0.545***	0.658***	0.689***	0.519**	1.080***	0.128
	(0.202)	(0.183)	(0.175)	(0.178)	(0.203)	(0.209)	(0.079)

Notes: $N = 2,888$ (722 CZs $\times$ 4 time periods). All regressions include period fixed effects and start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table A.6: The Effect of Retirement Trends on Population Growth: 2SLS Estimates

	Dependent variable: Δ $\text{Pop}_t/\text{pop}_{t-1}$						
	Young (22-30)						
	All	Male	Female	Less than college	College or more	Teenagers (16-21)	Prime-aged (31-44)
	(1)	(2)	(3)	(4)	(6)	(7)	(8)
Δ Emp/pop (55+)	-3.806***	-3.578***	-2.934***	-2.671***	-6.471***	0.263	-0.666
	(1.081)	(1.118)	(0.982)	(0.939)	(1.699)	(0.841)	(1.003)

Notes: $N = 2,888$ (722 CZs $\times$ 4 time periods). All regressions include period fixed effects and start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table A.7: Adjusting for Changes in Demographic Composition: 2SLS Estimates

	Dependent variable: Youth outcome (22-30)						
		Δ Employment share					
	Δ Unemp/ pop	Low-skill occupations	Middle-skill occupations	High-skill occupations	Δ Mean occupational wage premium	Δ Share workers "overeducated" (O*NET)	Δ Log wage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Emp/pop (55+)	0.106	0.454**	0.000	-0.454***	-0.438***	0.540***	-3.090***
	(0.090)	(0.201)	(0.182)	(0.160)	(0.118)	(0.172)	(0.761)
Observations	2,888	2,886	2,886	2,886	2,886	2,879	2,888

Notes: See Online Appendix A.5 for details on constructing composition-adjusted outcomes. All regressions include period fixed effects and start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table A.8: The Effect of Retirement Trends on Cohort-Specific Outcomes: 2SLS Estimates

	Dependent variable: Youth outcome (22-30)						
		Δ Employment share					
	Δ Unemp/ pop	Low-skill occupations	Middle-skill occupations	High-skill occupations	Δ Mean occupational wage premium	Δ Share workers "overeducated" (O*NET)	Δ Log wage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Average outcomes of 22-30 today vs. 22-30 ten years later							
Δ Emp/pop (55+)	0.069	0.581**	0.143	-0.724***	-0.501***	0.801***	-3.382***
	(0.097)	(0.255)	(0.232)	(0.175)	(0.142)	(0.218)	(0.820)
Panel B: Average outcomes of 22-30 today vs. 32-40 ten years later							
Δ Emp/pop (55+)	-0.006	0.375**	0.464**	-0.839***	-0.227***	0.528***	-0.848***
	(0.080)	(0.149)	(0.211)	(0.201)	(0.074)	(0.180)	(0.222)

Notes: $N = 2,888$ (722 CZs $\times$ 4 time periods). Sample excludes individuals born out-of-state. All regressions include period fixed effects and start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). For the 2000-2007 period, outcomes of people aged 22-30 in 2000 are compared to outcomes of people aged 29-37 in 2007, and these 7-year cohort-specific changes are scaled by 10/7. Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

References

Abel, Jaison R., Richard Deitz, and Yaquin Su, "Are Recent College Graduates Finding Good Jobs?," *Current Issues in Economics and Finance*, 2014, *20.*

Altonji, Joseph G., Lisa B. Kahn, and Jamin D. Speer, "Cashier or Consultant? Entry Labor Market Conditions, Field of Study, and Career Success," *Journal of Labor Economics*, 2016, *34* (S1), S361–S401.

Autor, David H., "Why Are There Still So Many Jobs? The History and Future of Workplace Automation," *Journal of Economic Perspectives*, 2015, *29* (3), 3–30.

_ and David Dorn, "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market," *American Economic Review*, 2013, *103* (5), 1553–1597.

_ , _ , and Gordon H. Hanson, "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, October 2013, *103* (6), 2121–2168.

_ , Frank Levy, and Richard J. Murnane, "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics*, 2003, pp. 1279–1333.

Bailey, Martha, Karen Clay, Price Fishback, Michael R. Haines, Shawn Kantor, Edson Severnini, and Anna Wentz, *U.S. County-Level Natality and Mortality Data, 1915-2007 [dataset]* ICPSR36603-v2, Ann Arbor, MI: Inter-university Consortium for Political and Social Research, 2018.

Beaudry, Paul, David A. Green, and Benjamin M. Sand, "The Declining Fortunes of the Young since 2000," *American Economic Review*, May 2014, *104* (5), 381–386.

_ , _ , and _ , "The Great Reversal in the Demand for Skill and Cognitive Tasks," *Journal of Labor Economics*, 2016, *34* (S1), S199–S247.

Bertoni, Marco and Giorgio Brunello, "Does A Higher Retirement Age Reduce Youth Employment?," Working paper 2017.

Betts, Julian R. and Laurel L. McFarland, "Safe Port in a Storm: The Impact of Labor Market Conditions on Community College Enrollments," *Journal of Human Resources*, 1995, *30* (4), 741–765.

Bianchi, Nicola, Giulia Bovini, Jin Li, Matteo Paradisi, and Michael Powell, "Chains of Opportunity Revisited," Working paper 2018.

Boeri, Tito, Pietro Garibaldi, and Espen Moen, "A Clash of Generations? Increase in Retirement Age and Labor Demand for Youth," WorkINPS Papers 1, Instituto Nazionale Previdenza Sociale July 2016.

Börsch-Supan, Axel, "Myths, Scientific Evidence and Economic Policy in an Aging World," *The Journal of the Economics of Ageing*, 2013, *1*, 3–15.

Bound, John and Harry J. Holzer, "Demand Shifts, Population Adjustments, and Labor Market Outcomes During the 1980s," *Journal of Labor Economics*, 2000, *18* (1), 20–54.

Bovini, Giula and Matteo Paradisi, "Labor Substitutability and the Impact of Raising the Retirement Age," Working paper 2018.

Burtless, Gary, "The Impact of Population Aging and Delayed Retirement on Workforce Productivity," Working Paper 2013–11, Center for Retirement Research at Boston College 2013.

Card, David and Thomas Lemieux, "Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis," *The Quarterly Journal of Economics*, 2001, *116* (2), 705–746.

Carnevale, Anthony P., Andrew R. Hanson, and Artem Gulish, "Failure to Launch: Structural Shift and the New Lost Generation," *Georgetown University Center on Education and the Workforce*, 2013.

Charles, Kerwin Kofi, Erik Hurst, and Matthew J. Notowidigdo, "Housing Booms and Busts, Labor Market Opportunities, and College Attendance," *American Economic Review*, 2018, *108* (10), 2947–94.

Clark, Brian, Clément Joubert, and Arnaud Maurel, "The Career Prospects of Overeducated Americans," Working paper 2016.

Coile, Courtney C., "Working Longer in the U.S.: Trends and Explanations," Working Paper 24576, National Bureau of Economic Research 2018.

_ and Phillip B. Levine, "Labor Market Shocks and Retirement: Do Government Programs Matter?," *Journal of Public Economics*, November 2007, *91* (10), 1902–1919.

_ and _ , "Recessions, Retirement, and Social Security," *American Economic Review*, May 2011, *101* (3), 23–28.

Dorn, David, "Essays on Inequality, Spatial Interaction, and the Demand For Skills." Dissertation no. 3613, University of St. Gallen 2009.

Dustmann, Christian, Uta Schönberg, and Jan Stuhler, "The Impact of Immigration: Why Do Studies Reach Such Different Results?," *The Journal of Economic Perspectives*, 2016, *30* (4), 31–56.

_ , _ , and _ , "Labor Supply Shocks, Native Wages, and the Adjustment of Local Employment," *The Quarterly Journal of Economics*, 2017, *132* (1), 435–483.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, and J. Robert Warren, *Integrated Public Use Microdata Series, Current Population Survey: Version 6.0 [dataset]*, Minneapolis, MN: IPUMS, 2018. https://doi.org/10.18128/D030.V6.0.

Goda, Gopi Shah, John B. Shoven, and Sita Nataraj Slavov, "What Explains Changes in Retirement Plans during the Great Recession?," *American Economic Review*, May 2011, *101* (3), 29–34.

Goldin, Claudia and Lawrence F. Katz, "Women Working Longer: Facts and Some Explanations," Working Paper 22607, National Bureau of Economic Research September 2016.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, "Bartik Instruments: What, When, Why, and How?," Working paper 2018.

Gruber, Jonathan and David A. Wise, *Social Security Programs and Retirement around the World: The Relationship to Youth Employment*, University of Chicago Press, 2010.

Guvenen, Fatih, Greg Kaplan, Jae Song, and Justin Weidner, "Lifetime Income in the United States over Six Decades," Working Paper 23371, National Bureau of Economic Research 2017.

Jeong, Hyeok, Yong Kim, and Iourii Manovskii, "The Price of Experience," *American Economic Review*, 2015, *105* (2), 784–815.

Kahn, Lisa B., "The Long-Term Labor Market Consequences of Graduating from College in a Bad Economy," *Labour Economics*, 2010, *17* (2), 303–316.

Kambourov, Gueorgui and Iourii Manovskii, "Rising Occupational and Industry Mobility in the United States: 1968–97," *International Economic Review*, 2008, *49* (1), 41–79.

Martins, Pedro S., Álvaro A. Novo, and Pedro Portugal, "Increasing the Legal Retirement Age: The Impact on Wages, Worker Flows and Firm Performance," IZA Discussion Papers 4187, Institute for the Study of Labor (IZA) 2009.

Molloy, Raven, Christopher L. Smith, and Abigail Wozniak, "Declining Migration Within the U.S.: The Role of the Labor Market," Working Paper 20065, National Bureau of Economic Research 2014.

Monras, Joan, "Economic Shocks and Internal Migration," Working paper 2017.

Munnell, Alicia H. and Rebecca A. Wu, "Will Delayed Retirement by the Baby Boomers Lead to Higher Unemployment Among Younger Workers?," Working Paper 2012–22, Center for Retirement Research at Boston College 2012.

Notowidigdo, Matthew J., "The Incidence of Local Labor Demand Shocks," *Journal of Labor Economics*, forthcoming.

OASDI Board of Trustees, "The 2016 Annual Report of the Board of Trustees of the Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds," Annual Report, Social Security Administration 2016.

Oreopoulos, Philip, Till von Wachter, and Andrew Heisz, "The Short-and Long-Term Career Effects of Graduating in a Recession," *American Economic Journal: Applied Economics*, 2012, *4* (1), 1–29.

Ruggles, Steven, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas, and Matthew Sobek, *IPUMS USA: Version 8.0 [dataset]*, Minneapolis, MN: IPUMS, 2018. https://doi.org/10.18128/D010.V8.0.

Schwandt, Hannes and Till von Wachter, "Unlucky Cohorts: Estimating the Long-Term Effects of Entering the Labor Market in a Recession in Large Cross-Sectional Data Sets," Working Paper 25141, National Bureau of Economic Research 2018.

Shapiro, Jesse M., "Smart Cities: Quality of Life, Productivity, and the Growth Effects of Human Capital," *The Review of Economics and Statistics*, May 2006, *88* (2), 324–335.

The PEW Charitable Trusts, "When Baby Boomers Delay Retirement, Do Younger Workers Suffer?," Issue Brief September 2012.

Tolbert, Charles M. and Molly Sizer, "US Commuting Zones and Labor Market Areas: A 1990 Update," Staff Paper no. AGES–9614, U.S. Department of Agriculture, Economic Research Service 1996.

United States Government Accountability Office, "Unemployed Older Workers: Many Experience Challenges Regaining Employment and Face Reduced Retirement Security," Report to the Chairman, Special Committee on Aging, U.S. Senate April 2012.

Wozniak, Abigail, "Are College Graduates More Responsive to Distant Labor Market Opportunities?," *Journal of Human Resources*, 2010, *45* (4), 944–970.

Yagan, Danny, "Employment 'Hysteresis' from the Great Recession," *Journal of Political Economy*, forthcoming.

The Impact of the Retirement Slowdown on the U.S. Youth Labor Market: Online Appendix

Paul Mohnen

June 29, 2019

A Data Appendix

A.1 Mapping Census/ACS Geography to Commuting Zones

The smallest geographic unit available in the Census and ACS varies by year. In the 1980 Census, so-called county groups—typically metropolitan areas plus surrounding counties—are identifiable. Since 1990, the most disaggregated geographic unit reported in the Census/ACS are Public Use Microdata Areas (PUMA), which are subareas comprising between 100,000 and 200,000 residents. When a county group or PUMA overlaps with multiple CZs, individuals in those areas (roughly one in two individuals) are assigned to each of those CZs with weights that add up to one. These weights are based on how the county group/PUMA population is distributed across CZs, and implicitly assume individuals have been sampled at random. For instance, if a PUMA overlaps with two CZs and its population is equally split between them, individuals in this PUMA are assigned to both CZs with half weights. As a result, they will contribute to aggregate outcomes in both locations. County groups and PUMAs were mapped to CZs using crosswalks made available by David Dorn on his website.[1]

A.2 Predicting Age Counts and Shares Using 1980 Age Structure or Historical Births

County population counts by 5-year age groups in 1980 come from the Intercensal Population Counts published by the Census Bureau. The data is first interpolated at the county level to obtain population counts by age, which are then aggregated at the commuting zone level. Population counts are projected forward in time using life tables from the Centers for Disease Control and Prevention (CDC). For example, to predict the number of individuals aged 60 in 2000 in a particular CZ, the number of individuals aged 40 in 1980 in that CZ is multiplied by the survival rate to age 60 divided by the survival rate to age 40 for the cohort of individuals born in 1940 (i.e. the cohort-specific probability of reaching age 60 conditional on reaching age 40).[2] To predict the share of individuals aged 60 among those aged 45-80 in 2000 in a particular CZ, I project the number of individuals aged 25-60 in 1980 in that CZ forward to 2000 and compute the corresponding predicted share.

[1] http://ddorn.net/data.htm.

[2] Life tables from the CDC are given at 5-year age intervals (i.e. 1, 5, 10, etc...) and for birth cohorts at decade intervals (1910, 1920, etc...). I interpolate survival rates within cohort across ages and within age across cohorts to obtain the full spectrum of values.

Historical birth counts by county between 1915 and 1972 come from Bailey et al. (2018). Few counties are represented in the data early on, but coverage gradually improves over time. The data is first aggregated at the year $\times$ CZ level, and then similarly projected forward using life tables from the CDC. For example, to predict the number of individuals aged 60 in 2000 in a particular CZ, the number of individuals born in that CZ in 1940 is multiplied by the cohort-specific survival rate to age 60. To predict the share of individuals aged 60 among those aged 45-80 in 2000 in a particular CZ, I project birth counts between 1920 and 1955 in that CZ forward to 2000 and compute the corresponding predicted share.

A.3 Assigning Education Levels to Occupations using O*NET

I first assign a required level of education to each occupation using descriptions from the U.S. Department of Labor's Occupational Information Network (O*NET). O*NET uses its own variant of the Standard Occupational Classification to identify over 1,000 detailed occupations. For each occupation, O*NET surveys incumbent workers and occupational experts to understand the nature of the job, and among others includes a question on educational requirements. However, rather than a unique education level, O*NET reports the fraction of respondents who believe an occupation requires one of (up to) 12 education levels (e.g. 34% Bachelor's degree and 11% Associate's degree).[3] I assign the education level with the highest response rate to every O*NET occupation. I then match each of the 330 Census occupations to the set of corresponding O*NET occupations using crosswalks published by the Bureau of Labor Statistics (one-to-many matching). When a Census occupation corresponds to multiple O*NET occupations with different educational requirements, I assign the highest education level to that occupation.

A.4 Constructing Mean Hourly Wages

Hourly wages are computed by dividing annual wage income by the product of weeks worked last year and usual hours worked per week.[4] Weeks worked last year is reported in intervals in the 2016-2017 ACS. For those years, I impute weeks worked by interval

[3]The 12 education levels in O*NET are: "Less than high school diploma," "High school diploma or equivalent," "Post-secondary certificate," "Some college, no degree," "Associate's degree," "Bachelor's degree," "Post-baccalaureate certificate," "Master's degree," "Post-master's certificate," "Professional degree," "Doctoral degree," and "Post-doctoral training."

[4]The reference period for income in the Census is the previous calendar year, while in the ACS the reference period is the past 12 months.

category using mean weeks worked in the 2000 Census for 120 gender $\times$ age $\times$ education cells. In the Census/ACS, top-coded wage incomes are automatically replaced by the state median value above the threshold, except in 1980. For that year, I multiply top-coded incomes by 1.5, following Autor and Dorn (2013). Nominal wages are then converted into 2016 dollars using the Personal Consumption Expenditures chain-type price index published by the Bureau of Economic Analysis. Finally, I censor the distribution of real wages at the top and bottom percentiles separately by year to neutralize the influence of outliers. All wage measures exclude self-employed workers, and wages are averaged using labor supply weights, defined as Census sampling weights multiplied by annual hours worked, following Autor (2015).

A.5 Constructing Composition-Adjusted Changes

The procedure described here follows Shapiro (2006) and Albouy (2016). To generate composition-adjusted outcomes, I first run the following OLS regression using individual-level Census data, separately by year:

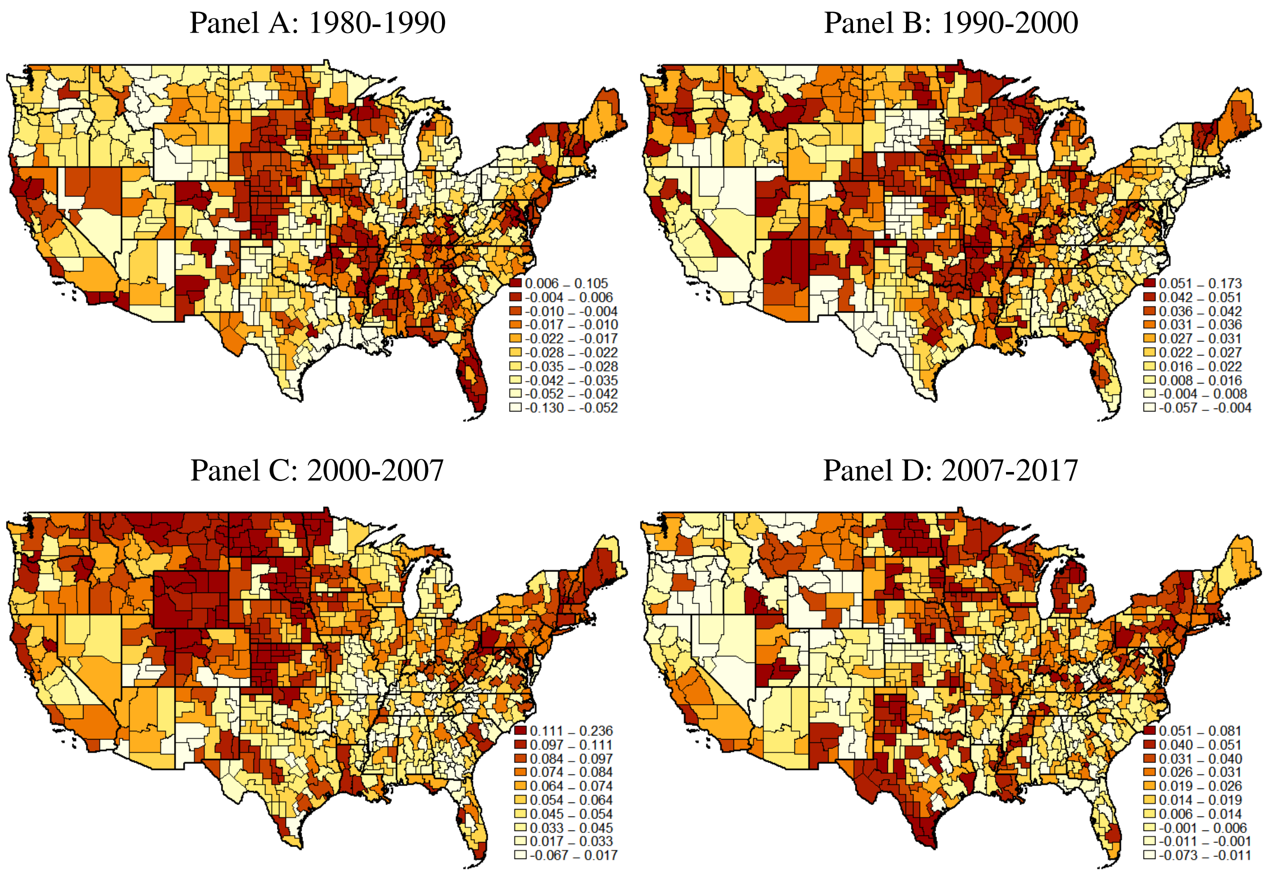
$$y_{ict} = \alpha_{ct} + X'_{it} \cdot \Gamma_t + \varepsilon_{ict} \tag{1}$$

where y_{ict} is the individual-level analog of some outcome of interest (e.g. an indicator for being employed, corresponding to the employment rate), α_{ct} are CZ fixed effects, and X'_{it} is a set of demographic controls, including gender, race (white, Hispanic, Black, Asian, other non-white), education (less than high school, high school graduate, some college, college graduate, greater than college) and potential experience fixed effects. Observations are weighted using Census sampling weights. The baseline sample consists of all individuals aged 22-30, and the sample is further restricted to workers, workers with some college education and individuals with positive wages (excluding the self-employed) when the outcomes of interest are employment shares by occupation group, the share of workers that are overeducated and mean log hourly wages, respectively. The estimated CZ fixed effects $\widehat{\alpha_{ct}}$ are then used to compute CZ-specific changes $\Delta\ \widehat{\alpha_{ct}}$ that are not mechanically driven by changes in local demographic composition.

Note that to make this regression implementable, every individual needs to be assigned to a unique commuting zone. In the same way that individuals in some areas are assigned to multiple CZs with probabilistic weights in order to construct CZ-level outcomes, here I randomly assign them to one of those CZs using the same probabilities.

B Appendix Figures

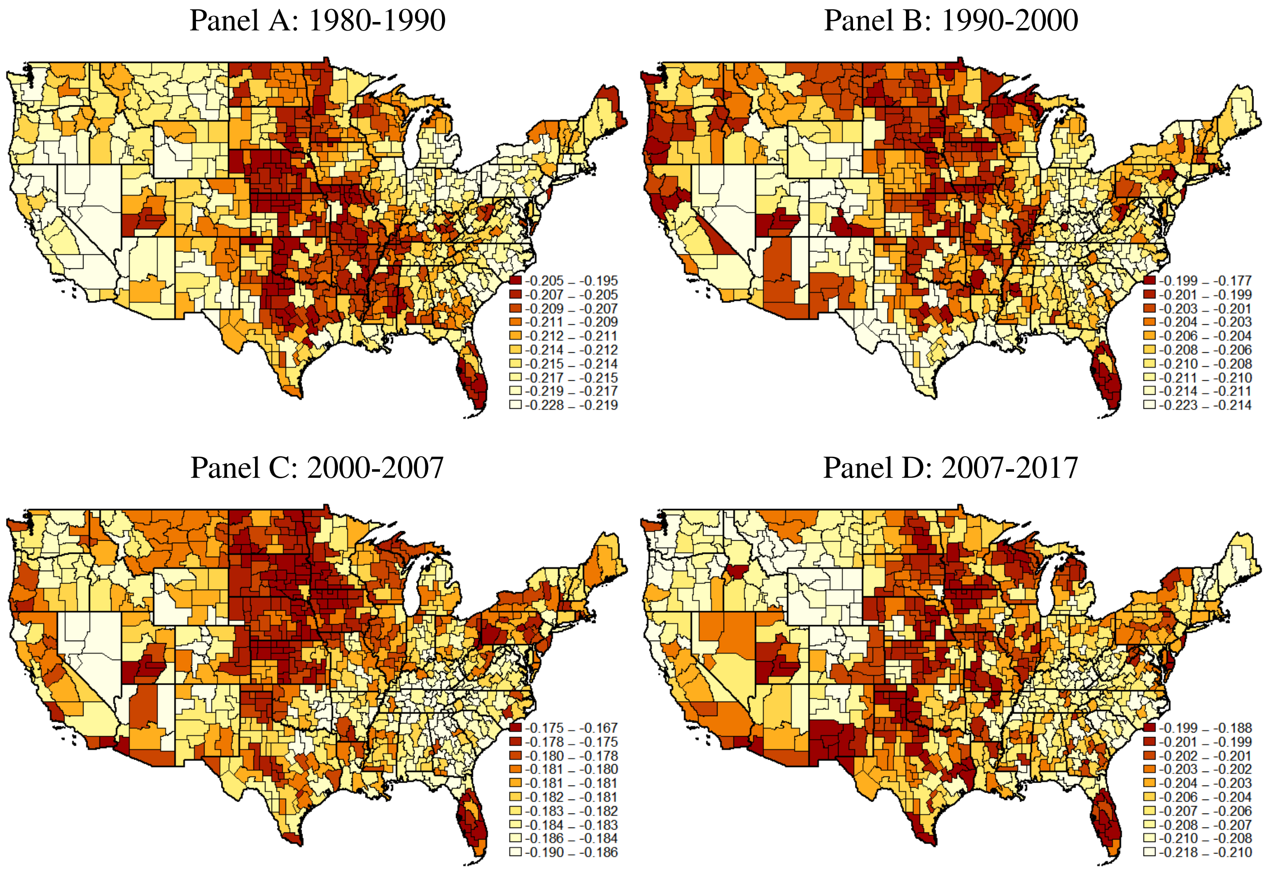
Figure 1: Change in 55+ Employment Rate by Commuting Zone, 1980-2017



Notes: CZs are color-coded by decile bin, separately by period. Dark CZs are characterized by above-average increases in 55+ employment rates.

Source: 1980, 1990, 2000 Censuses, 2006-2007 and 2016-2017 American Community Surveys.

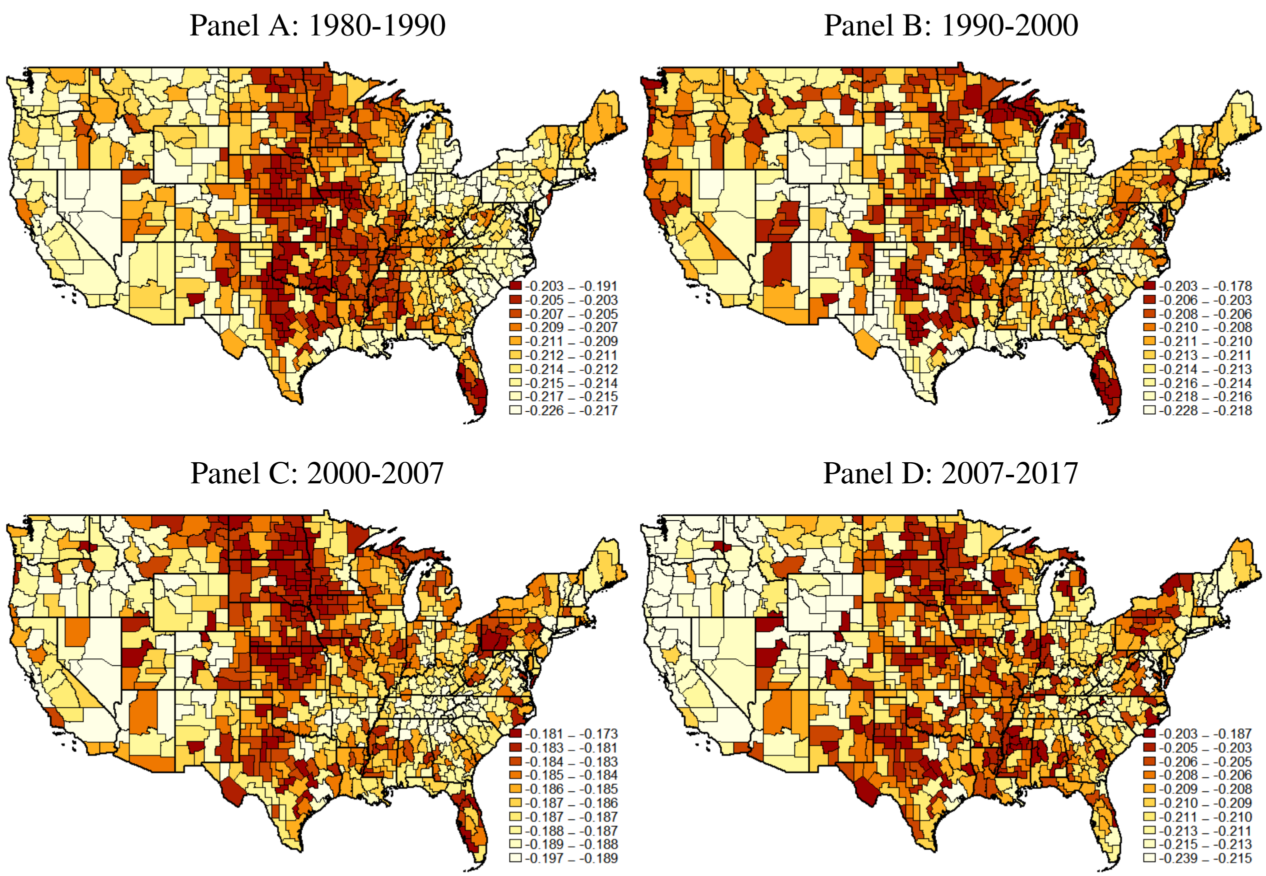
Figure 2: Predicted Retirement Intensity by Commuting Zone Based on Start-of-Period Age Distribution, 1980-2017



Notes: CZs are color-coded by decile bin, separately by period. The sign of predicted retirement intensity is inverted in this graph, so that dark CZs are characterized by below-average predicted retirement intensity.

Source: 1980, 1990, 2000 Censuses, 2006-2007 and 2016-2017 American Community Surveys.

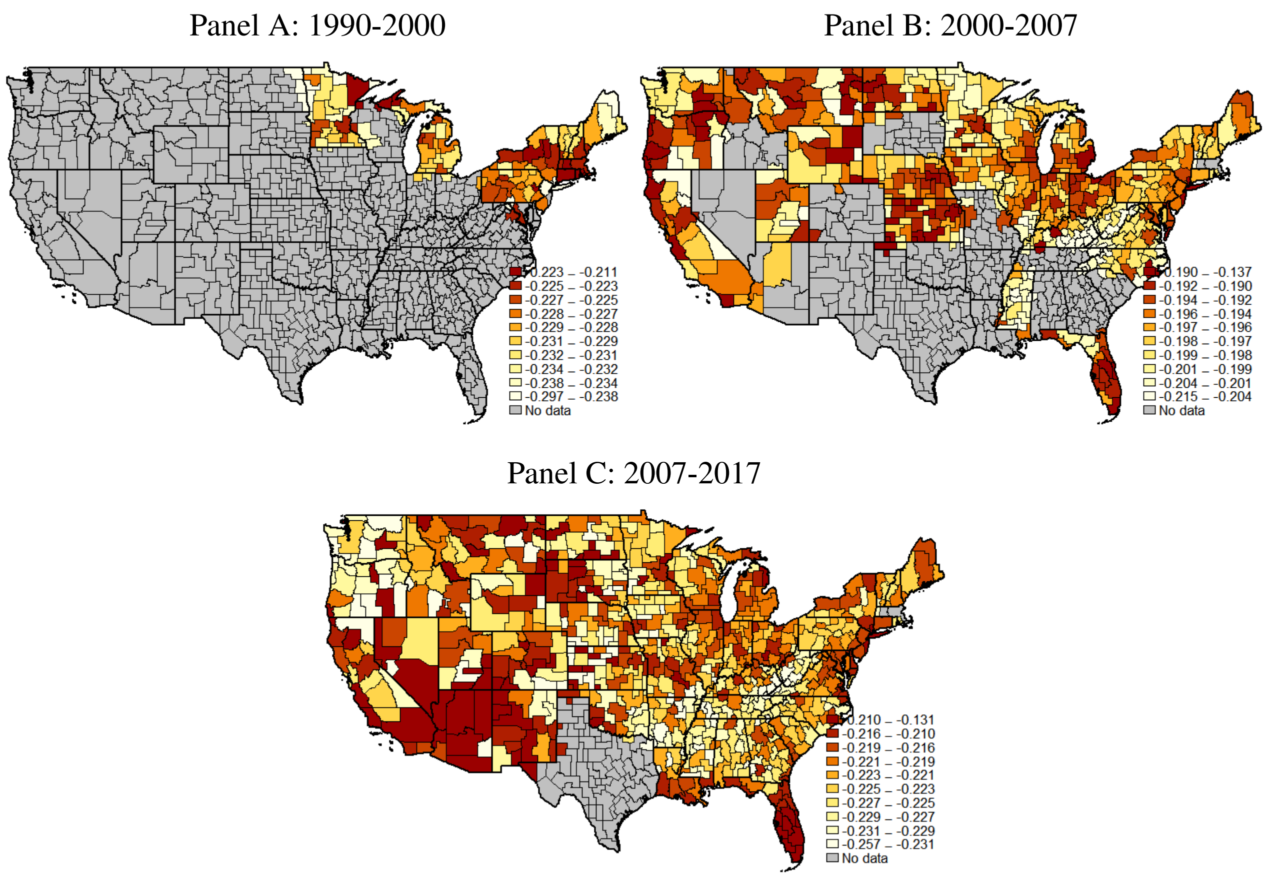
Figure 3: Predicted Retirement Intensity by Commuting Zone Based on 1980 Age Distribution, 1980-2017



Notes: CZs are color-coded by decile bin, separately by period. The sign of predicted retirement intensity is inverted in this graph, so that dark CZs are characterized by below-average predicted retirement intensity.

Source: 1980, 1990, 2000 Censuses, 2006-2007 and 2016-2017 American Community Surveys, 1980 Intercensal County Population Counts.

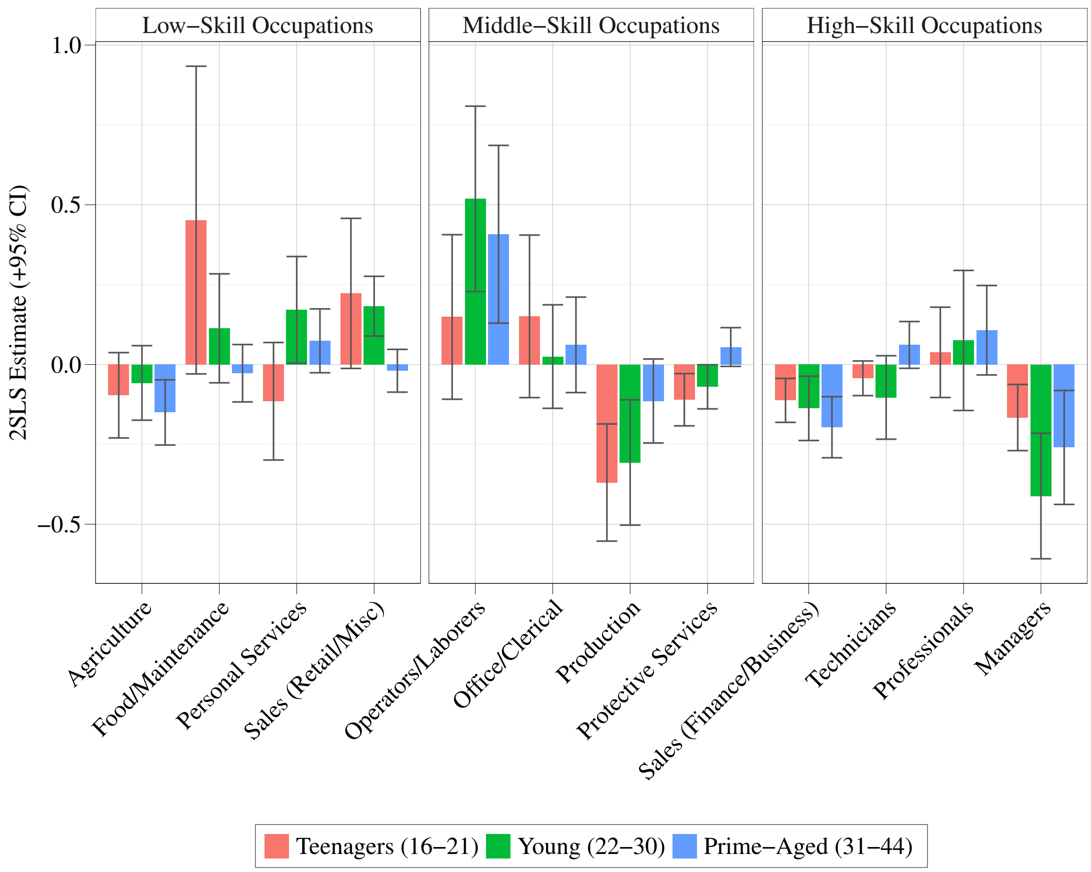
Figure 4: Predicted Retirement Intensity by Commuting Zone Based on Historical Births, 1990-2017



Notes: CZs are color-coded by decile bin, separately by period. The sign of predicted retirement intensity is inverted in this graph, so that dark CZs are characterized by below-average predicted retirement intensity.

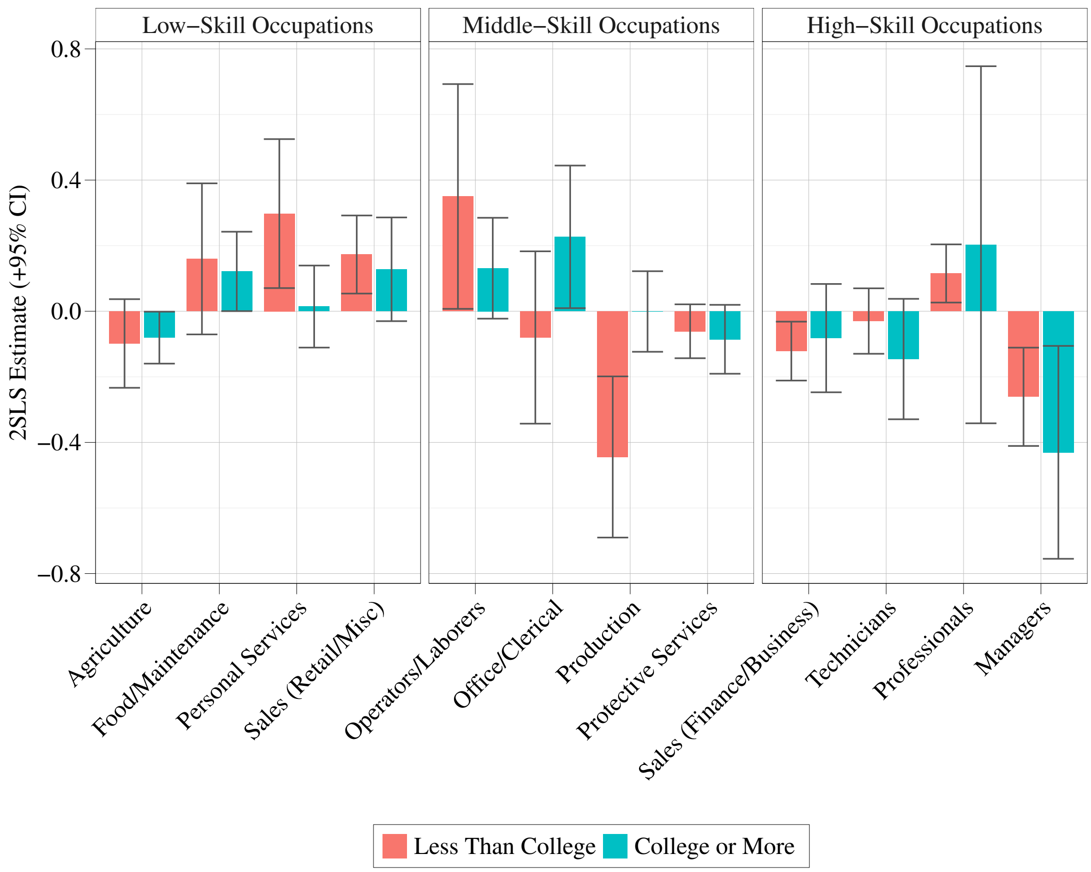
Source: 1980, 1990, 2000 Censuses, 2006-2007 and 2016-2017 American Community Surveys, Bailey et al. (2018).

Figure 5: Occupation Group-Specific Effects by Age Group: 2SLS Estimates



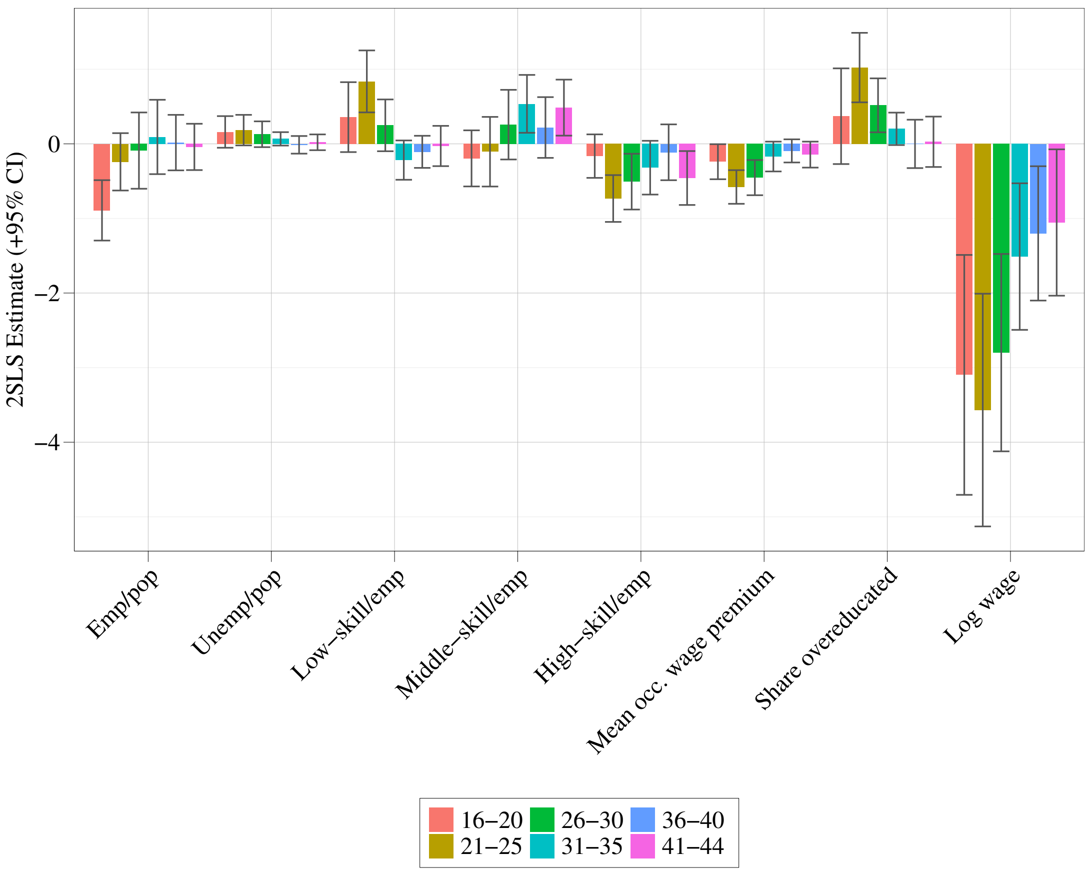
Notes: Each bar represents the coefficient corresponding to the change in the 55+ employment rate from a separate 2SLS regression (baseline specification with period fixed effects and CZ controls), where the dependent variable is the change in employment share for a particular occupation group (x-axis) and age group (legend). The error bars represent the corresponding 95% confidence intervals.

Figure 6: Occupation Group-Specific Effects by Education Group Among the Young (22-30): 2SLS Estimates



Notes: Each bar represents the coefficient corresponding to the change in the 55+ employment rate from a separate 2SLS regression (baseline specification with period fixed effects and CZ controls), where the dependent variable is the change in employment share for a particular occupation group (x-axis) and education group (legend). The error bars represent the corresponding 95% confidence intervals.

Figure 7: Main Results by 5-Year Age Groups: 2SLS Estimates



Notes: Each bar represents the coefficient corresponding to the change in the 55+ employment rate from a separate 2SLS regression (baseline specification with period fixed effects and CZ controls), where the dependent variable is indicated on the x-axis, separately by 5-year age group (legend). The error bars represent the corresponding 95% confidence intervals.

C Appendix Tables

Table 1: Mean and Standard Deviation of CZ Controls, 1980-2017

	1980	1990	2000	2007	2017
Manufacturing employment share	0.225	0.178	0.148	0.121	0.104
	[0.081]	[0.065]	[0.059]	[0.051]	[0.046]
Employment share of routine occupations	0.332	0.324	0.316	0.301	0.279
	[0.036]	[0.026]	[0.021]	[0.019]	[0.016]
Mean offshoring index	0.071	0.064	0.04	0.007	-0.01
	[0.081]	[0.079]	[0.088]	[0.087]	[0.086]
Female employment rate	0.472	0.54	0.549	0.556	0.556
	[0.053]	[0.055]	[0.051]	[0.044]	[0.047]
Immigrant population share	0.074	0.095	0.133	0.152	0.164
	[0.071]	[0.099]	[0.123]	[0.127]	[0.124]
Unemployment rate	0.065	0.064	0.058	0.064	0.055
	[0.02]	[0.016]	[0.015]	[0.013]	[0.012]
Age 22-30 population share	0.208	0.191	0.158	0.154	0.155
	[0.022]	[0.022]	[0.022]	[0.018]	[0.018]
Age 31-44 population share	0.233	0.289	0.286	0.252	0.224
	[0.019]	[0.022]	[0.023]	[0.025]	[0.024]
Age 45+ population share	0.41	0.406	0.446	0.482	0.519
	[0.044]	[0.044]	[0.045]	[0.04]	[0.043]
Female population share	0.529	0.525	0.521	0.517	0.517
	[0.01]	[0.01]	[0.01]	[0.01]	[0.008]
Hispanic population share	0.052	0.042	0.055	0.071	0.106
	[0.083]	[0.068]	[0.078]	[0.089]	[0.116]
Black population share	0.106	0.109	0.111	0.115	0.122
	[0.091]	[0.091]	[0.094]	[0.096]	[0.097]
Asian population share	0.014	0.026	0.037	0.045	0.057
	[0.018]	[0.032]	[0.041]	[0.047]	[0.055]
Other non-whites population share	0.009	0.041	0.077	0.078	0.077
	[0.019]	[0.052]	[0.07]	[0.067]	[0.059]
Some college-educated population share	0.2	0.258	0.279	0.278	0.3
	[0.043]	[0.043]	[0.036]	[0.034]	[0.037]
College-educated population share	0.138	0.181	0.217	0.242	0.285
	[0.038]	[0.053]	[0.063]	[0.067]	[0.076]
Number of commuting zones	722	722	722	722	722

Notes: All outcomes are based on the population aged 16+. Means and standard deviations (in brackets) are weighted by CZ population.

Table 2: Correlating Predicted Retirement Intensity with Start-of-Period CZ Characteristics, 1980-2017

Dependent variable: Predicted retirement intensity (45+)							
Panel A: Industry composition		*Panel B: Occupational composition*		*Panel C: Demographic composition*		*Panel D: Labor market variables*	
Mining/emp	0.087	Food prep/emp	-0.059	Age 22-30/pop	0.060*	Routine occ./emp	-0.002
	(0.059)		(0.064)		(0.033)		(0.014)
Construction/emp	0.060	Personal svc/emp	-0.108	Age 31-44/pop	0.051***	Offshoring index	0.001
	(0.067)		(0.076)		(0.015)		(0.005)
Manufacturing/emp	0.096	Sales (Retail/Misc)/emp	-0.144**	Age 45+/pop	0.003	Emp/pop (female)	0.022***
	(0.059)		(0.073)		(0.024)		(0.008)
Transportation/emp	0.113**	Operators/emp	-0.080	Female/pop	-0.029	Immigrants/pop	-0.010**
	(0.057)		(0.071)		(0.030)		(0.005)
Wholesale/emp	0.087	Office/emp	-0.025	Hispanic/pop	0.005	Unemployment rate	0.076***
	(0.063)		(0.070)		(0.003)		(0.020)
Retail/emp	0.090	Production/emp	-0.025	Black/pop	0.006*		
	(0.055)		(0.069)		(0.003)		
Finance/emp	0.052	Protective svc/emp	-0.041	Asian/pop	0.015**		
	(0.065)		(0.060)		(0.007)		
Business svc/emp	0.074	Sales (Finance/Business)/emp	-0.088	Other non-white/pop	0.000		
	(0.059)		(0.084)		(0.006)		
Personal svc/emp	0.120*	Technicians/emp	-0.114	Some college/pop	-0.014**		
	(0.067)		(0.070)		(0.005)		
Entertainment/emp	0.113**	Professionals/emp	-0.010	$\geqslant$ College/pop	0.004		
	(0.053)		(0.069)		(0.011)		
Professional svc/emp	0.064	Managers/emp	-0.096	Pop/1,000	0.000		
	(0.055)		(0.072)		(0.000)		
Public admin/emp	0.111*						
	(0.061)						
$R^2 = 0.937$				R^2 (net of period FEs) $= 0.500$			

Notes: $N = 2,888$ (722 CZs $\times$ 4 time periods). All regressions include period fixed effects. Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table 3: Correlating Start-of-Period Share of 45+ Population Aged 55-59 with Start-of-Period CZ Characteristics, 1980-2017

Dependent variable: Initial share of 45+ population aged 55-59							
Panel A: Industry composition		*Panel B: Occupational composition*		*Panel C: Demographic composition*		*Panel D: Labor market variables*	
Mining/emp	0.110	Food prep/emp	-0.061	Age 22-30/pop	0.049	Routine occ./emp	0.018
	(0.137)		(0.135)		(0.057)		(0.027)
Construction/emp	0.011	Personal svc/emp	-0.154	Age 31-44/pop	0.050*	Offshoring index	0.005
	(0.135)		(0.181)		(0.030)		(0.010)
Manufacturing/emp	0.125	Sales (Retail/Misc)/emp	-0.192	Age 45+/pop	-0.008	Emp/pop (female)	0.048***
	(0.137)		(0.160)		(0.040)		(0.017)
Transportation/emp	0.183	Operators/emp	-0.117	Female/pop	-0.071*	Immigrants/pop	-0.022**
	(0.136)		(0.153)		(0.042)		(0.009)
Wholesale/emp	0.088	Office/emp	-0.061	Hispanic/pop	0.015**	Unemployment rate	0.131***
	(0.159)		(0.161)		(0.008)		(0.031)
Retail/emp	0.132	Production/emp	0.038	Black/pop	0.011**		
	(0.126)		(0.149)		(0.005)		
Finance/emp	0.069	Protective svc/emp	-0.109	Asian/pop	0.023*		
	(0.152)		(0.144)		(0.013)		
Business svc/emp	0.131	Sales (Finance/Business)/emp	-0.188	Other non-white/pop	-0.004		
	(0.155)		(0.162)		(0.011)		
Personal svc/emp	0.113	Technicians/emp	-0.178	Some college/pop	-0.025***		
	(0.161)		(0.155)		(0.009)		
Entertainment/emp	0.205	Professionals/emp	0.008	$\geqslant$ College/pop	0.019		
	(0.136)		(0.136)		(0.024)		
Professional svc/emp	0.076	Managers/emp	-0.127	Pop/1,000	0.000		
	(0.129)		(0.155)		(0.000)		
Public admin/emp	0.154						
	(0.144)						
$R^2 = 0.829$				R^2 (net of period FEs) $= 0.412$			

Notes: $N = 2,888$ (722 CZs $\times$ 4 time periods). All regressions include period fixed effects. Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table 4: Employment Share and Mean Hourly Wage by Major Occupation, 2000

	Employment share (%)			Mean wage (2016$)		
Top 5 occupations by occupation group	22-30	31-54	55+	22-30	31-54	55+
Panel A: Low-skill occupations						
Agriculture (5/8)	1.21	1.24	2.46	11.26	14.17	15.54
Farm workers	0.65	0.40	0.56	10.30	11.91	13.16
Farmers (owners and tenants)	0.15	0.39	1.32	—	—	—
Farm managers	0.10	0.15	0.28	13.81	19.52	23.42
Animal caretakers, except farm	0.12	0.10	0.09	12.15	14.57	15.29
Timber, logging, and forestry workers	0.13	0.13	0.12	13.79	17.75	19.35
Food/Maintenance (5/11)	7.80	5.26	6.22	12.12	14.46	15.26
Cooks, variously defined	1.61	1.11	1.09	11.56	13.07	13.63
Janitors	0.99	1.36	2.32	12.84	15.77	16.45
Waiter/waitress	1.94	0.64	0.41	12.01	12.96	13.49
Misc food prep workers	0.81	0.51	0.74	10.94	12.51	13.05
Gardeners and groundskeepers	0.86	0.58	0.61	12.28	15.34	15.57
Personal Services (5/16)	6.07	5.23	6.30	12.96	15.40	15.34
Health and nursing aides	2.27	1.92	2.21	12.93	15.25	15.48
Child care workers	1.16	0.83	1.09	11.00	12.60	12.85
Housekeepers, maids, butlers, stewards, and lodging quarters cleaners	0.66	0.87	1.20	10.48	12.17	13.26
Hairdressers and cosmetologists	0.71	0.62	0.53	13.42	14.74	15.07
Recreation facility attendants	0.21	0.15	0.24	15.88	20.62	18.69
Sales (Retail/Misc) (5/5)	6.83	5.15	7.28	16.52	24.96	21.99
Retail sales clerks	3.34	2.47	3.90	17.08	24.97	20.80
Cashiers	2.04	1.11	1.43	11.57	14.07	14.42
Salespersons, n.e.c.	1.30	1.43	1.63	21.68	32.48	31.37
Door-to-door sales, street sales, and news vendors	0.12	0.12	0.21	14.96	17.96	18.14
Sales demonstrators / promoters / models	0.03	0.02	0.12	21.92	24.23	16.02
Panel B: Middle-skill occupations						
Operators/Laborers (5/61)	13.24	12.43	11.84	15.19	19.11	20.00
Truck, delivery, and tractor drivers	2.67	2.89	3.05	15.54	19.30	20.07
Laborers and freight, stock and material handlers, n.e.c.	1.59	1.11	0.93	14.40	18.27	18.98
Assemblers of electrical equipment	1.33	1.17	0.95	15.27	18.41	19.38
Machine operators, n.e.c.	1.14	1.06	0.78	15.35	19.20	19.81
Construction laborers	1.24	0.84	0.53	15.37	19.55	21.04
Office/Clerical (5/40)	15.93	14.61	15.73	15.18	19.16	19.64
Secretaries and stenographers	2.39	3.03	3.59	15.49	18.74	19.70
Customer service reps, investigators and adjusters, except insurance	2.40	1.40	0.93	15.94	20.77	20.79
Bookkeepers and accounting and auditing clerks	1.11	1.35	1.82	15.56	18.46	18.99
General office clerks	1.02	0.95	1.31	14.32	17.79	18.35
Stock and inventory clerks	1.04	0.72	0.75	13.53	17.05	18.21

Notes: See Online Appendix A.4 for details on constructing wages.

Table 4 (cont.): Employment Share and Mean Hourly Wage by Major Occupation, 2000

	Employment share (%)			Mean wage (2016$)		
Top 5 occupations by occupation group	22-30	31-54	55+	22-30	31-54	55+
Panel B: Middle-skill occupations (cont.)						
Production (5/68)	11.38	12.28	9.68	17.17	23.28	25.50
Carpenters	1.20	1.08	0.72	16.26	20.93	23.21
Production supervisors or foremen	0.70	1.20	0.96	18.86	25.22	29.21
Automobile mechanics	0.88	0.79	0.55	16.21	20.65	21.31
Supervisors of construction work	0.49	0.86	0.67	20.42	26.81	30.71
Mechanics and repairers, n.e.c.	0.51	0.62	0.67	16.28	21.36	22.03
Protective Services (5/7)	2.14	2.02	1.92	18.60	25.71	22.10
Police, detectives, and private investigators	0.77	0.75	0.29	22.27	30.46	30.75
Guards, watchmen, doorkeepers	0.66	0.48	1.07	14.80	19.40	17.85
Other law enforcement: sheriffs, bailiffs, correctional institution officers	0.39	0.36	0.20	18.24	23.73	23.68
Fire fighting, prevention, and inspection	0.22	0.30	0.09	18.30	26.39	29.09
Supervisors of guards	0.05	0.07	0.10	17.08	25.03	26.92
Panel C: High-skill occupations						
Sales (Finance/Business) (5/6)	4.01	4.54	5.13	19.86	29.97	31.22
Supervisors and proprietors of sales jobs	2.83	3.05	2.77	17.61	26.01	27.59
Real estate sales occupations	0.26	0.58	1.34	22.33	34.28	30.60
Insurance sales occupations	0.29	0.41	0.60	20.18	33.14	35.88
Financial services sales occupations	0.40	0.30	0.24	32.72	57.90	60.44
Advertising and related sales jobs	0.21	0.16	0.15	22.90	34.29	31.29
Technicians (5/19)	4.37	4.03	2.47	22.79	30.32	31.36
Computer software developers	1.41	1.18	0.45	31.54	40.72	43.03
Licensed practical nurses	0.39	0.50	0.48	16.67	19.49	20.97
Legal assistants, paralegals, legal support, etc	0.50	0.40	0.29	19.69	25.15	27.07
Engineering technicians, n.e.c.	0.31	0.38	0.27	19.55	26.61	30.21
Clinical laboratory technologies and technicians	0.27	0.25	0.16	17.38	24.37	27.19
Professionals (5/67)	15.64	17.21	16.04	21.85	32.75	36.85
Primary school teachers	2.46	2.68	2.35	19.61	27.30	32.48
Registered nurses	1.23	2.16	1.61	24.39	29.80	30.89
Computer systems analysts and computer scientists	1.83	1.37	0.53	25.51	34.52	39.17
Subject instructors (college)	0.87	0.83	1.44	16.65	30.39	40.99
Lawyers and judges	0.47	0.86	0.90	33.14	56.63	67.78
Managers (5/22)	11.36	16.00	14.93	22.29	35.97	40.46
Managers and administrators, n.e.c.	3.16	5.16	4.36	21.55	36.18	41.67
Accountants and auditors	1.55	1.51	1.37	22.90	31.19	31.67
Office supervisors	1.09	1.50	1.22	17.76	23.98	25.91
Managers and specialists in marketing, advertising, and public relations	1.14	1.18	0.75	25.07	41.85	44.04
Chief executives and public administrators, legislators	0.20	1.04	1.59	35.15	65.94	70.52

Notes: See Online Appendix A.4 for details on constructing wages.

Table 5: Occupation Group Characteristics

Occupation	Routine	Mean offshoring score	Tradable	Mean occ. wage premium	O*NET educational requirement: High school degree or less	O*NET educational requirement: Post-high school degree	O*NET educational requirement: College degree or more	Modal education level in 2000 Census: High school degree or less	Modal education level in 2000 Census: Some college	Modal education level in 2000 Census: College degree or more	Total
Agriculture	0	-0.02	3	1.91	5	0	3	8	0	0	8
Food/Maintenance	2	-0.19	7	1.89	9	2	0	11	0	0	11
Personal Services	5	-0.12	7	1.97	6	5	5	11	5	0	16
Sales (Retail/Misc)	1	1.14	4	2.11	3	0	2	4	0	1	5
Operators/Laborers	27.04	0.17	31	2.12	56	5	0	61	0	0	61
Office/Clerical	34	1.13	35	2.13	25	6	9	13	26	1	40
Production	16	-0.68	16	2.23	45	23	0	58	10	0	68
Protective Services	1	-1.03	2	2.16	3	0	4	3	4	0	7
Sales (Finance/Business)	4	0.11	3	2.45	0	0	6	0	2	4	6
Technicians	5	-0.03	9	2.36	1	6	12	1	14	4	19
Professionals	15	-0.07	35	2.34	2	2	63	1	5	61	67
Managers	6	0.29	13	2.41	0	1	21	1	6	15	22
Total	116.04	0.02	165	2.21	155	50	125	172	72	86	330

Notes: Following Autor and Dorn (2013), routine occupations are defined as the top third of occupations in terms of 1980 employment share, ranked according to an index of task content ($\log \text{routine} - \log \text{manual} - \log \text{abstract}$). Offshoring scores come from Firpo et al. (2011), and measure the extent to which occupations are susceptible to offshoring based on task content (face-to-face contact, on-site support). Tradable occupations are defined as above-median based on offshoring scores. See Online Appendix A.3 for details on O*NET educational requirements.

Table 6: Descriptive Statistics by Age Group, 1980-2017

	1980			1990			2000			2007			2017		
	22-30	31-54	55+	22-30	31-54	55+	22-30	31-54	55+	22-30	31-54	55+	22-30	31-54	55+
Panel A: Employment, unemployment and labor force participation (in population shares)															
Employed	0.730	0.738	0.319	0.767	0.795	0.294	0.746	0.772	0.312	0.757	0.784	0.363	0.768	0.790	0.383
Employed: part-time	0.113	0.110	0.078	0.133	0.116	0.083	0.137	0.106	0.088	0.138	0.099	0.089	0.171	0.108	0.092
Employed: full-time	0.617	0.628	0.241	0.634	0.679	0.211	0.609	0.667	0.223	0.619	0.685	0.274	0.597	0.682	0.291
Unemployed	0.060	0.035	0.015	0.060	0.039	0.013	0.053	0.033	0.013	0.064	0.039	0.014	0.058	0.036	0.014
Not in labor force	0.211	0.227	0.666	0.173	0.166	0.693	0.201	0.195	0.675	0.179	0.177	0.623	0.174	0.174	0.602
Panel B: Occupational composition (in employment shares)															
Low-skill occupations	0.178	0.172	0.257	0.206	0.165	0.243	0.219	0.169	0.223	0.252	0.182	0.207	0.273	0.190	0.201
Middle-skill occupations	0.519	0.478	0.449	0.470	0.429	0.410	0.427	0.413	0.392	0.411	0.392	0.365	0.358	0.352	0.357
High-skill occupations	0.304	0.350	0.294	0.325	0.406	0.348	0.354	0.418	0.386	0.338	0.426	0.429	0.369	0.458	0.442
Panel C: "Overeducated" employment (in employment shares of individuals with some post-secondary education)															
O*NET	0.305	0.208	0.206	0.298	0.226	0.211	0.264	0.217	0.213	0.278	0.211	0.212	0.286	0.209	0.222
Census: 2000 basis	0.404	0.291	0.288	0.402	0.319	0.310	0.398	0.328	0.330	0.440	0.334	0.338	0.469	0.346	0.349
Census: Yearly basis	0.648	0.560	0.574	0.516	0.422	0.409	0.398	0.328	0.330	0.439	0.335	0.332	0.364	0.277	0.275
Panel D: Educational attainment (in population shares)															
Attending school	0.126	0.041	0.009	0.168	0.066	0.016	0.183	0.053	0.012	0.198	0.049	0.010	0.202	0.046	0.009
Less than college	0.801	0.810	0.904	0.791	0.753	0.870	0.751	0.725	0.814	0.742	0.703	0.758	0.683	0.654	0.717
College or more	0.199	0.190	0.096	0.209	0.247	0.130	0.249	0.275	0.186	0.258	0.297	0.242	0.317	0.346	0.283
Panel E: Mean log wages (in 2016$)															
Mean occupational wage premium	2.18	2.21	2.17	2.18	2.22	2.18	2.18	2.22	2.19	2.16	2.22	2.21	2.16	2.22	2.21
All occupations	2.64	2.90	2.82	2.63	2.94	2.88	2.71	3.03	3.02	2.68	3.06	3.06	2.67	3.08	3.11
Low-skill occupations	2.37	2.50	2.40	2.36	2.55	2.47	2.44	2.66	2.61	2.39	2.64	2.61	2.36	2.62	2.64
Middle-skill occupations	2.64	2.84	2.81	2.59	2.83	2.80	2.64	2.89	2.88	2.62	2.88	2.88	2.58	2.87	2.91
High-skill occupations	2.78	3.14	3.14	2.83	3.19	3.22	2.94	3.31	3.36	2.95	3.37	3.42	2.94	3.39	3.47

Notes: Part-time employment is defined as working fewer than 35 hours a week. See Online Appendix Table 4 for definition of low-skill, middle-skill and high-skill jobs. Overeducated workers are defined as: (1) workers with at least a 4-year college degree employed in occupations which typically do not require one, or (2) workers with some post-secondary education (e.g. Associate's degree) employed in occupations which typically only require a high school degree or less. See Online Appendix A.3 and A.4 for details on assigning education levels to occupations and constructing wages.

Table 7: The Effect of Retirement Trends on Youth Occupational Composition (Skill Terciles): 2SLS Estimates

	Dependent variable: Δ Employment share (22-30)		
	Bottom tercile of 1980 skill distribution	Middle tercile of 1980 skill distribution	Top tercile of 1980 skill distribution
	(1)	(2)	(3)
Δ Emp/pop (55+)	0.579***	0.167	-0.734***
	(0.181)	(0.166)	(0.185)

Notes: $N = 2,888$ (722 CZs $\times$ 4 time periods). All regressions include period fixed effects and start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table 8: The Effect of Education Group-Specific Retirement Trends on Youth Occupational Composition: 2SLS Estimates

	Dependent variable: Youth outcome (22-30)				
	Δ Employment share				
	Low-skill occupations	Middle-skill occupations	High-skill occupations	Δ Mean occupational wage premium	Δ Share workers overeducated (O*NET)
	(1)	(2)	(3)	(4)	(5)
Δ Emp/pop (55+) (less than college)	0.326*	0.028	-0.354	-0.425***	0.618***
	(0.177)	(0.267)	(0.219)	(0.156)	(0.219)
Δ Emp/pop (55+) (college or more)	0.586**	0.555**	-1.141***	-0.777***	0.918***
	(0.281)	(0.283)	(0.351)	(0.219)	(0.302)

Notes: $N = 2,888$ (722 CZs $\times$ 4 time periods). See text for details on main explanatory variables and corresponding instruments. All regressions include period fixed effects and start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. Kleibergen-Paap rk Wald F-stat = 59.64. *** 1%, ** 5%, * 10% significance.

Table 9: The Effect of Retirement Trends on Overeducated Employment: Heterogeneity of 2SLS Estimates by Age, Gender and Education

	Dependent variable: Δ Share workers "overeducated"		
	Educational requirement in O*NET database	Modal education level in 2000 Census	Modal education level in Census (by year)
	(1)	(2)	(3)
Panel A: Young (22-30) × gender			
Male	0.632**	0.796***	0.675***
	(0.280)	(0.252)	(0.227)
Female	0.853***	1.092***	1.237***
	(0.177)	(0.251)	(0.313)
Panel B: Young (22-30) × education groups			
Less than college	0.539***	1.112***	1.328***
	(0.209)	(0.282)	(0.315)
College or more	0.562***	0.407*	0.335
	(0.199)	(0.222)	(0.228)
Panel C: Other age groups			
Teenagers (16-21)	0.479	1.031***	0.843**
	(0.332)	(0.355)	(0.337)
Prime-aged (31-44)	0.063	-0.141	-0.220
	(0.106)	(0.126)	(0.206)

Notes: $N = 2,888$ (722 CZs × 4 time periods). All regressions include period fixed effects and start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table 10: The Effect of Retirement Trends on Wages: Heterogeneity of 2SLS Estimates by Age, Gender and Education

	Dependent variable: Δ Log wage			
	All occupations	Low-skill occupations	Middle-skill occupations	High-skill occupations
	(1)	(2)	(3)	(4)
Panel A: Young (22-30) $\times$ gender				
Male	-2.875***	-2.271***	-2.666***	-3.389***
	(0.678)	(0.807)	(0.702)	(0.638)
Female	-3.428***	-3.476***	-2.583***	-3.604***
	(0.715)	(0.762)	(0.666)	(0.664)
Panel B: Young (22-30) $\times$ education groups				
Less than college	-2.875***	-2.825***	-2.617***	-3.459***
	(0.714)	(0.677)	(0.706)	(0.696)
College or more	-3.102***	-2.757**	-3.103***	-3.037***
	(0.647)	(1.133)	(0.702)	(0.629)
Panel C: Other age groups				
Teenagers (16-21)	-3.226***	-2.427***	-3.532***	-4.511***
	(0.823)	(0.655)	(0.904)	(1.106)
Prime-aged (31-44)	-1.278***	-1.750***	-1.413***	-1.284***
	(0.454)	(0.620)	(0.464)	(0.442)

Notes: $N = 2,888$ (722 CZs $\times$ 4 time periods), except row 4 column 2 ($N = 2,882$) and row 5 column 4 ($N = 2,870$). All regressions include period fixed effects and start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table 11: The Effect of Retirement Trends on Marital Status, Fertility, and Living Arrangements: 2SLS Estimates

	Dependent variable: Δ Non-labor market outcome			
	Married/ pop	Have at least 1 child living in household/ pop	Living with parent(s) as dependent/ pop	Renting as head of household/ pop
	(1)	(2)	(3)	(4)
Panel A: Young (22-30)				
All	-0.039	0.327	0.031	1.309***
	(0.261)	(0.210)	(0.314)	(0.454)
Panel B: Young (22-30) $\times$ gender				
Male	-0.237	0.003	0.397	0.830**
	(0.161)	(0.165)	(0.379)	(0.403)
Female	-0.461***	0.234	0.015	1.241***
	(0.170)	(0.213)	(0.233)	(0.432)
Panel C: Young (22-30) $\times$ education groups				
Less than college	-0.471***	0.139	0.151	1.078***
	(0.171)	(0.177)	(0.297)	(0.399)
College or more	-0.198	-0.351*	0.382	1.411***
	(0.249)	(0.210)	(0.330)	(0.472)
Panel D: Other age groups				
Teenagers (16-21)	-0.214**	-0.196**	1.273***	-0.021
	(0.097)	(0.083)	(0.189)	(0.097)
Prime-aged (31-44)	-0.296**	0.235	-0.238**	0.633**
	(0.144)	(0.151)	(0.097)	(0.252)

Notes: $N = 2,888$ (722 CZs $\times$ 4 time periods). All regressions include period fixed effects and start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table 12: Alternative Sets of Controls: 2SLS Estimates

	Dependent variable: Youth outcome (22-30)						
		Δ Employment share					
	Δ Unemp/ pop	Low-skill occupations	Middle-skill occupations	High-skill occupations	Δ Mean occupational wage premium	Δ Share workers "overeducated" (O*NET)	Δ Log wage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: State fixed effects (First-stage F-stat = 82.33)							
Δ Emp/pop (55+)	0.192	0.459***	0.038	-0.497***	-0.518***	0.603***	-3.265***
	(0.123)	(0.165)	(0.220)	(0.165)	(0.135)	(0.193)	(0.818)
Panel B: CZ fixed effects (First-stage F-stat = 16.32)							
Δ Emp/pop (55+)	0.176	0.568	-0.067	-0.501*	-0.615**	0.401	-3.705**
	(0.265)	(0.414)	(0.353)	(0.275)	(0.274)	(0.283)	(1.658)
Panel C: Full industry and occupation group shares (First-stage F-stat = 63.46)							
Δ Emp/pop (55+)	0.301**	0.669***	-0.210	-0.459***	-0.513***	0.479***	-3.332***
	(0.128)	(0.210)	(0.221)	(0.144)	(0.124)	(0.183)	(0.743)

Notes: $N = 2,888$ (722 CZs $\times$ 4 time periods). All regressions include period fixed effects and the baseline set of start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Panel A additionally includes state fixed effects. Panel B additionally includes CZ fixed effects. Panel C additionally controls for initial employment shares in 13 broad industry groups (agriculture, mining, construction, manufacturing, transportation/communications/utilities, wholesale trade, retail trade, finance/insurance/real estate, business and repair services, personal services, entertainment and recreation services, professional services, and public administration) and 12 broad occupational groups (see Online Appendix Table 5). Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table 13: Alternative Sample Restrictions: 2SLS Estimates

	Dependent variable: Youth outcome (22-30)						
		Δ Employment share					
	Δ Unemp/ pop	Low-skill occupations	Middle-skill occupations	High-skill occupations	Δ Mean occupational wage premium	Δ Share workers "overeducated" (O*NET)	Δ Log wage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Exclude students (First-stage F-stat = 112.26)							
Δ Emp/pop (55+)	0.168	0.465***	0.138	-0.603***	-0.502***	0.661***	-2.924***
	(0.107)	(0.160)	(0.222)	(0.178)	(0.107)	(0.198)	(0.692)
Panel B: Exclude those born out-of-state (First-stage F-stat = 112.26)							
Δ Emp/pop (55+)	0.069	0.581**	0.143	-0.724***	-0.501***	0.801***	-3.382***
	(0.097)	(0.255)	(0.232)	(0.175)	(0.142)	(0.218)	(0.820)
Panel C: Exclude recent out-of-state in-migrants (First-stage F-stat = 112.26)							
Δ Emp/pop (55+)	0.100	0.445**	0.166	-0.611***	-0.487***	0.701***	-3.103***
	(0.087)	(0.191)	(0.221)	(0.158)	(0.126)	(0.193)	(0.715)
Panel D: Exclude 2007-2017 period (First-stage F-stat = 47.82)							
Δ Emp/pop (55+)	0.267**	0.381*	0.545**	-0.926***	-0.766***	1.332***	-4.332***
	(0.134)	(0.218)	(0.244)	(0.267)	(0.197)	(0.313)	(1.101)

Notes: $N = 2,888$ (722 CZs × 4 time periods), except Panel D ($N = 2,166$). The restrictions in Panels A, B and C are applied to the sample of young adults (22-30) used to construct the dependent variables. All regressions include period fixed effects and start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table 14: Alternative Instruments: 2SLS/LIML Estimates

	Dependent variable: Youth outcome (22-30)						
		Δ Employment share					
	Δ Unemp/ pop	Low-skill occupations	Middle-skill occupations	High-skill occupations	Δ Mean occupational wage premium	Δ Share workers ”overeducated” (O*NET)	Δ Log wage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Exploit start-of-period share of 45+ population aged 55-59 (First-stage F-stat = 108.87)							
Δ Emp/pop (55+)	0.065	0.333**	0.139	-0.472***	-0.349***	0.449***	-2.003***
	(0.074)	(0.146)	(0.184)	(0.101)	(0.096)	(0.173)	(0.586)
Panel B: Exploit start-of-period 45+ age shares as separate instruments in LIML estimation (Kleibergen-Paap rk Wald F-stat = 21.91)							
Δ Emp/pop (55+)	0.126*	0.315**	0.171	-0.447***	-0.371***	0.373***	-1.805***
	(0.071)	(0.140)	(0.170)	(0.110)	(0.081)	(0.142)	(0.586)
Overiden. test (p-value)	0.261	0.221	0.454	0.393	0.186	0.663	0.443

Notes: $N = 2,888$ (722 CZs $\times$ 4 time periods). All regressions include period fixed effects and start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period CZ share of national population. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table 15: Excluding Census Divisions One-by-One: 2SLS Estimates

	Excluded Census division								
	New England	Middle Atlantic	East North Central	West North Central	South Atlantic	East South Central	West South Central	Mountain	Pacific
Youth outcome (22-30)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ Unemp/pop	0.220**	0.184	0.118	0.217*	0.215	0.184	0.228***	0.209*	0.145
	(0.103)	(0.118)	(0.104)	(0.113)	(0.162)	(0.118)	(0.085)	(0.111)	(0.118)
Δ Low-skill occ./emp	0.360**	0.422**	0.396**	0.409**	0.491*	0.434**	0.410***	0.425***	0.361***
	(0.156)	(0.176)	(0.164)	(0.172)	(0.257)	(0.195)	(0.152)	(0.162)	(0.129)
Δ Middle-skill occ./emp	0.259	0.111	0.123	0.095	0.053	0.183	0.167	0.204	0.231
	(0.204)	(0.231)	(0.216)	(0.210)	(0.308)	(0.260)	(0.193)	(0.220)	(0.165)
Δ High-skill occ./emp	-0.618***	-0.533***	-0.519***	-0.504***	-0.545***	-0.618***	-0.577***	-0.630***	-0.592***
	(0.158)	(0.158)	(0.170)	(0.148)	(0.182)	(0.200)	(0.158)	(0.177)	(0.175)
Δ Mean occ.	-0.476***	-0.432***	-0.492***	-0.483***	-0.585***	-0.544***	-0.525***	-0.558***	-0.534***
wage premium	(0.126)	(0.116)	(0.136)	(0.124)	(0.174)	(0.155)	(0.121)	(0.139)	(0.138)
Δ Share workers	0.782***	0.564***	0.714***	0.659***	0.688***	0.785***	0.777***	0.820***	0.672***
”overeducated” (O*NET)	(0.191)	(0.160)	(0.190)	(0.169)	(0.225)	(0.208)	(0.185)	(0.206)	(0.206)
Δ Log wage	-2.927***	-2.996***	-3.217***	-3.101***	-3.948***	-3.556***	-3.309***	-3.584***	-3.033***
	(0.676)	(0.815)	(0.743)	(0.700)	(1.084)	(0.851)	(0.671)	(0.773)	(0.762)
First-stage F-stat	102.95	68.69	119.09	100.67	40.23	90.52	141.69	98.42	106.63
Observations	2,824	2,780	2,548	2,220	2,464	2,596	2,448	2,512	2,712

Notes: All regressions include period fixed effects and start-of-period CZ controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period CZ share of national population (excluding relevant Census division). Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table 16: State-Level Sample: 2SLS Estimates

	Dependent variable: Youth outcome (22-30)						
		Δ Employment share					
	Δ Unemp/ pop	Low-skill occupations	Middle-skill occupations	High-skill occupations	Δ Mean occupational wage premium	Δ Share workers "overeducated" (O*NET)	Δ Log wage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: OLS estimates							
Δ Emp/pop (55+)	-0.257***	-0.425***	0.345***	-0.037	0.205***	-0.006	1.933***
	(0.055)	(0.088)	(0.116)	(0.095)	(0.055)	(0.098)	(0.310)
Panel B: 2SLS estimates (First-stage F-stat = 14.04)							
Δ Emp/pop (55+)	0.258	0.636	-0.598	-1.071**	-0.778**	1.194**	-5.385**
	(0.247)	(0.438)	(0.499)	(0.452)	(0.340)	(0.489)	(2.327)

Notes: $N = 196$ (49 states $\times$ 4 time periods). All regressions include period fixed effects and start-of-period state controls (manufacturing employment share, employment share of routine occupations, mean offshoring index, female employment rate, population share of immigrants/young (22-30)/prime-aged (31-44)/old (45+)/females/Blacks/Asians/other non-whites/some college-educated/college-educated). Observations are weighted by start-of-period state share of national population. Robust standard errors in parentheses. *** 1%, ** 5%, * 10% significance.

D Theory Appendix

Proof of Proposition 1. The proof proceeds in three steps: (1) derive the labor demand equations on the firm side (net of capital), (2) derive the labor supply equations on the worker side, and (3) combine them to obtain the equilibrium wage response, which in turn determines the equilibrium occupational choice response.

Labor Demand Equations

Start by totally differentiating the capital supply equation:

$$d \log r = \lambda \cdot d \log K \tag{D.1}$$

Next, totally differentiate the first-order condition for K in equation (4) and substitute for $d \log r$ using equation (D.1):

$$d \log K = \frac{1-\alpha}{1-\alpha+\lambda} d \log L \tag{D.2}$$

Totally differentiate the first-order condition for L_{jk} in equation (4) and substitute for $d \log K$ using equation (D.2) to obtain the net-of-capital labor demand equations:

$$d \log w_{jk} = \varphi \cdot d \log L + (\beta - 1) \cdot (d \log L_j - d \log L) + (\gamma - 1) \cdot (d \log L_{jk} - d \log L_j) \tag{D.3}$$

where $\varphi = -\alpha\lambda/(1-\alpha+\lambda) \leqslant 0$, and the subscripts $j \in \{L, H\}$ and $k \in \{y, o\}$ respectively denote skill types and age types.

Labor Supply Equations

Totally differentiate the CES aggregates (2) and (3):

$$d \log L = s_L \cdot d \log L_L + s_H \cdot d \log L_H \tag{D.4}$$

$$d \log L_j = s_{jy} \cdot d \log L_{jy} + s_{jo} \cdot d \log L_{jo} \tag{D.5}$$

where $s_j \in [0,1]$ and $s_{jk} \in [0,1]$ are initial (effective) labor shares given by:

$$s_j = \frac{\theta_j L_j^\beta}{\theta_L L_L^\beta + \theta_H L_H^\beta} \quad \text{and} \quad s_{jk} = \frac{\theta_{jk} L_{jk}^\gamma}{\theta_{jy} L_{jy}^\gamma + \theta_{jo} L_{jo}^\gamma}$$

Since the labor supply (L_y^ℓ, L_y^h) of younger workers is assumed to stay unchanged, totally differentiating the labor supply equations (6) yields:

$$d\log L_{Ly} = s_y^h \eta_u \cdot d\log u^* \tag{D.6}$$

$$d\log L_{Hy} = -s_u \eta_u \cdot d\log u^* \tag{D.7}$$

where $\eta_u > 0$ is the elasticity of the cumulative distribution function $F(\cdot)$ around the initial ability threshold u^*:

$$\eta_u = \frac{\partial F(u^*)}{\partial u^*} \cdot \frac{u^*}{F(u^*)}$$

$s_y^h \in [0,1]$ is the initial share of youth low-skill labor that can be attributed to high-education types, and $s_u > 0$ is just a scaling factor:

$$s_y^h = \frac{F(u^*) \cdot L_y^h}{L_y^\ell + F(u^*) \cdot L_y^h} \quad \text{and} \quad s_u = \frac{u^* \cdot F(u^*)}{\int_{u^*}^\infty u \cdot f(u) \cdot du}$$

Next, totally differentiate the threshold condition (5) to obtain equation (11), displayed again here for convenience:

$$d\log u^* = d\log w_{Ly} - d\log w_{Hy}$$

This expression can be inserted into equations (D.6)-(D.7) to yield the labor supply equations for youth low-skill and high-skill labor.

We can repeat the same steps for older workers except that, in contrast, their labor supply is assumed to exogenously increase according to $d\log L_o^h \geqslant d\log L_o^\ell > 0$ while $\overline{z}$ is fixed (no self-selection response). Without loss of generality, let $d\log L_o^\ell = \delta \cdot d\log L_o^h$. The labor supply equations for older workers are then given by:

$$d\log L_{Lo} = (s_o^\ell \delta + s_o^h) \cdot d\log L_o^h \tag{D.8}$$

$$d\log L_{Ho} = d\log L_o^h \tag{D.9}$$

where $s_o^\ell + s_o^h = 1$ is the initial mix of education types among older low-skill workers while $s_z > 0$ is just a scaling factor:

$$s_o^\ell = \frac{L_o^\ell}{L_o^\ell + G(\overline{z}) \cdot L_o^h} \quad \text{and} \quad s_o^h = \frac{G(\overline{z}) \cdot L_o^h}{L_o^\ell + G(\overline{z}) \cdot L_o^h} \quad \text{and} \quad s_z = \frac{\overline{z} \cdot G(\overline{z})}{\int_{\overline{z}}^{\infty} z \cdot g(z) \cdot dz}$$

Equilibrium

In a competitive equilibrium, labor supply and labor demand have to be equal. In practice, this amounts to combining the four labor supply and four labor demand equations and solving for wages. Since we have assumed away self-selection among older workers, we only need to combine the two labor demand equations for younger workers with the labor supply equations to understand what happens to youth wages and youth occupational composition. To ease the notation, define the following set of constants:

$$C_0 \equiv s_L s_{Lo} \widetilde{\delta} + s_H s_{Ho} \quad \text{and} \quad C_1 \equiv s_L s_{Ly} s_y^h - s_H s_{Hy} s_u \quad \text{and} \quad C_2 \equiv s_{Ly} s_y^h + s_{Hy} s_u$$

$$C_3 \equiv s_{Lo} s_y^h + s_{Ho} s_u \quad \text{and} \quad C_4 \equiv s_{Ho} - s_{Lo} \widetilde{\delta}$$

where $\widetilde{\delta} \equiv s_o^\ell \delta + s_o^h$. To start, compute the change in high-skill, low-skill and overall labor by substituting the labor supply equations (D.6)-(D.9) into equations (D.4)-(D.5):

$$d\log L_H = -s_{Hy} s_u \eta_u \cdot \big(d\log w_{Ly} - d\log w_{Hy}\big) + s_{Ho} \cdot d\log L_o^h \tag{D.10}$$

$$d\log L_L = s_{Ly} s_y^h \eta_u \cdot \big(d\log w_{Ly} - d\log w_{Hy}\big) + s_{Lo} \widetilde{\delta} \cdot d\log L_o^h \tag{D.11}$$

$$d\log L = \eta_u C_1 \cdot \big(d\log w_{Ly} - d\log w_{Hy}\big) + C_0 \cdot d\log L_o^h \tag{D.12}$$

Next, compute the following set of intermediate expressions:

$$d\log L_H - d\log L = -s_L \eta_u C_2 \cdot \big(d\log w_{Ly} - d\log w_{Hy}\big) + s_L C_4 \cdot d\log L_o^h \tag{D.13}$$

$$d\log L_L - d\log L = s_H \eta_u C_2 \cdot \big(d\log w_{Ly} - d\log w_{Hy}\big) - s_H C_4 \cdot d\log L_o^h \tag{D.14}$$

$$d\log L_{Hy} - d\log L_H = -s_{Ho} s_u \eta_u \cdot \big(d\log w_{Ly} - d\log w_{Hy}\big) - s_{Ho} \cdot d\log L_o^h \tag{D.15}$$

$$d\log L_{Ly} - d\log L_L = s_{Lo} s_y^h \eta_u \cdot \big(d\log w_{Ly} - d\log w_{Hy}\big) - s_{Lo} \widetilde{\delta} \cdot d\log L_o^h \tag{D.16}$$

Substitute equations (D.12)-(D.16) into the first-order conditions (D.3) for L_{Hy} and L_{Ly} to obtain the equilibrium change in youth wages:

$$\begin{aligned} d\log w_{Hy} &= [\varphi \cdot \eta_u C_1 - (\beta - 1) \cdot s_L \eta_u C_2 - (\gamma - 1) \cdot s_{Ho} s_u \eta_u] \cdot \big(d\log w_{Ly} - d\log w_{Hy}\big) \\ &\quad + [\varphi \cdot C_0 + (\beta - 1) \cdot s_L C_4 - (\gamma - 1) \cdot s_{Ho}] \cdot d\log L_o^h \qquad \text{(D.17)} \\ d\log w_{Ly} &= [\varphi \cdot \eta_u C_1 + (\beta - 1) \cdot s_H \eta_u C_2 + (\gamma - 1) \cdot s_{Lo} s_y^h \eta_u] \cdot \big(d\log w_{Ly} - d\log w_{Hy}\big) \\ &\quad + [\varphi \cdot C_0 - (\beta - 1) \cdot s_H C_4 - (\gamma - 1) \cdot s_{Lo} \widetilde{\delta}] \cdot d\log L_o^h \qquad \text{(D.18)} \end{aligned}$$

Finally, subtracting equation (D.17) from equation (D.18) yields the equilibrium change in relative youth wages (equation (12) from Section 2):

$$d\log w_{Ly} - d\log w_{Hy} = \frac{(\gamma - \beta) \cdot C_4}{1 - (\beta - 1) \cdot \eta_u C_2 - (\gamma - 1) \cdot \eta_u C_3} \cdot d\log L_o^h$$

This proves part 3 since the premise of the proposition is that the labor supply increase among the old satisfies $C_4 > 0$ and that age types are more substitutable than skill types, i.e. $\gamma > \beta$. Parts 1 and 2 immediately follow in light of equations (11) and (D.6)-(D.7). $\square$

References

Albouy, David, "What Are Cities Worth? Land Rents, Local Productivity, and the Total Value of Amenities," *Review of Economics and Statistics*, 2016, *98* (3), 477–487.

Autor, David H., "Why Are There Still So Many Jobs? The History and Future of Workplace Automation," *Journal of Economic Perspectives*, 2015, *29* (3), 3–30.

_ **and David Dorn**, "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market," *American Economic Review*, 2013, *103* (5), 1553–1597.

Bailey, Martha, Karen Clay, Price Fishback, Michael R. Haines, Shawn Kantor, Edson Severnini, and Anna Wentz, *U.S. County-Level Natality and Mortality Data, 1915-2007 [dataset]* ICPSR36603-v2, Ann Arbor, MI: Inter-university Consortium for Political and Social Research, 2018.

Firpo, Sergio, Nicole M. Fortin, and Thomas Lemieux, "Occupational Tasks and Changes in the Wage Structure," IZA Discussion Papers 5542, Institute for the Study of Labor (IZA) February 2011.

Shapiro, Jesse M., "Smart Cities: Quality of Life, Productivity, and the Growth Effects of Human Capital," *The Review of Economics and Statistics*, May 2006, *88* (2), 324–335.