The Race between the Supply and Demand for Experience

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July 2016

PRELIMINARY

Abstract: We propose a model in which rising supply of experience reduces experienced workers' relative wages, and also negatively and systematically impacts their labor market participation. We then quasi-experimentally investigate the existence of these effects, using variation across US local labor markets (LLMs) over the last 50 years and instrumenting experience supply by the LLMs' age structures a decade earlier. We find that aging drastically reduces the labor market participation of experienced relative to inexperienced workers; increasing their welfare-, disability-, and especially social security claims. Aging also reduces the (relative) migration of older workers into the aging LLMs. All of these reactions are mainly driven by low-skilled and low-earning workers. Our results imply that the effect of demographic change on the labor market is substantially more severe than previously recognized; it systematically impacts labor market outcomes beyond wages.

Keywords: Employment of Older Workers, Selection Bias, Return to Experience, Aging, Demographic Change
JEL codes: E24, J11, J21, J22, J24, J26, J31

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We wish to thank seminar participants at Aalto, HU Berlin, Bonn, Centre for Economic Performance (LSE), Mannheim, and Uppsala; and participants at the SPP conference on "Occupations, Skills, and the Labor Market" in Mannheim 2016 for very helpful comments on an earlier version entitled "The Race between the Supply and Demand for Experience".

1 Introduction

Many developed economies have experienced a rapid aging of their workforces. In the United States the share of workers above their 40s increased over the last three decades from under a third to over one half. Even aside from the strain on the social security system, this demographic change may have substantial effects on the labor market, notably via changing relative supplies of older and younger (or experienced and inexperienced) workers. In particular, if experience is a skill valued by the labor market, its price, the return to experience, should reflect the relative scarcity. At the same time, a higher supply of experience may affect the incentives or the opportunities of experienced workers to participate in the labor market.

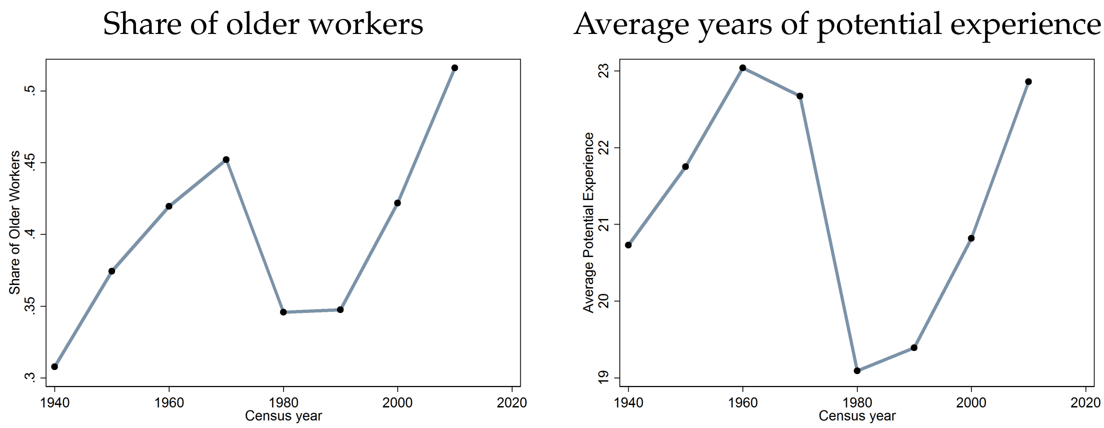


Figure 1: Share of older workers and average years of potential experience in the U.S. (1940–2010)

The left panel shows the share of 'Younger', age 18 to 42, to 'older', age 43 to 65, workers. The right panel shows the average years of potential experience, computed as age minus years of schooling minus six.

Previous research that has studied how the return to experience is affected by changing supply found a varying strength of this channel. Relating the observed wages of experienced versus inexperienced workers to their relative employment, the seminal paper by Katz and Murphy (1992) estimated over 1963–1987 an elasticity of substitution around three. The recent study by Jeong, Kim, and Manovskii (2015) obtained a substantially smaller elasticity, and also a strong contribution of supply in accounting for the return to experience. Other examples include Welch (1979), Freeman (1979), and Caselli (2015).[1]

In this paper, we take a different approach, examining experienced workers' relative wages and employment rates at the same time. If prices do not fully vary with relative scarcity, or if workers' labor supply is upward-sloping, aging may lead to lower employment rates of older workers. We find that, indeed, relative employment rates of experienced workers strongly fall when they become abundant, and that this mainly affects lower-skilled and lower-earning individuals. The finding that demographic change not only has effects on relative wages, but also on employment rates, is new to the literature and a key contribution of our paper. It also raises flags that studies trying to estimate the elasticity of substitution between experience and inexperience inputs in production might need to take selection effects into account. Ignoring that observed wages are potentially biased by systematic selection, might overstate the substitutability between experienced and inexperienced workers.

Furthermore, we document that demographic change has significant and substantial effects on the likelihood that a worker –with given years of experience– is a claimant on a welfare, disability, or social security program. We find that a higher supply of experience, increases program claims of more experienced workers compared to inexperienced workers, suggesting one channel through which demographic change not only lowers relative wages but also employment rates. Similarly we find a negative effect on in-migration.

We also empirically improve upon the existing literature by exploiting the differential aging of local labor markets in the US over the last 50 years in order to causally identify the effect of demographic change. We employ an instrumental variables strategy, which uses the fact that current demographic changes are largely determined by the age structure a decade earlier, and that the aggregate educational attainment can be used to predict the change at the local labor market (henceforth LLM) level (a shift-share IV). Hence, we can extract plausibly exogenous variation in potential experience using the predicted age structure from earlier years (adjusting for changes in education). We flexibly capture aggregate changes in labor demand (e.g., technology) that

[1]The early works by Welch (1979) and Freeman (1979) did not account for changes in labor demand. Caselli (2015) finds that technological change has been biased in favor of experience. Card and Lemieux (2001) is also related.

are experience-biased, and changes in participation rates of different experience levels, by time fixed effects.[2] Changes in these variables that vary across LLM-years are removed by the instrumental variable and any level differences across local labor markets are absorbed by LLM fixed effects.[3]

Using data from the US decennial census and the American Community Survey (ACS), we first define LLMs by the 722 commuting zones used in Autor and Dorn (2012) and Autor, Dorn, and Hansen (2013), and then also explore a version in which LLMs are the 51 states. Our estimation sample is decennial from 1980 to 2010 for the commuting zones and from 1960 to 2010 for the US states. In line with Autor, Dorn, and coauthors, we treat LLMs as sub-economies for which we can observe market equilibrium outcomes in different points in time.

For our theoretical framework we adopt the recent model of Jeong, Kim, and Manovskii (2015), the demand side of which combines units of experienced and inexperienced labor using a constant elasticity of substitution (CES) production function. On the supply side, the model allows for individual-level wage equations, to be aggregated to overall experience and inexperienced inputs.[4] The key strength of this approach is that the estimated price of experience can be cleaned of confounding wage determinants such as education, race, or gender. It also yields one single price of experience that is determined by supply and demand in the (local) labor market.[5]

We extend this model by adding an employment decision. In particular, an individual-level reservation wage is introduced, which depends on demographic and skill characteristics as well as experience (or age conditional on education). Workers decide to be employed when their labor market earnings exceed the reservation wage.

Our extended Jeong, Kim, and Manovskii (2015) model on the LLM level prescribes a three-step empirical approach. For each LLM in each year, we run individual-level wage and employment regressions in order to identify the price of experience and the

[2]Equivalently, we can compute the mean demand for experience in the U.S. in each period by averaging our estimated demand level for each individual LLM.

[3]Our strategy is related to how Ciccone and Peri (2005) account for demand effects in their study of the elasticity of substitution between educational groups.

[4]To simplify the estimation, we make one approximation in the Jeong et al. wage equation, see section 2.2.

[5]The Jeong, Kim, and Manovskii (2015) setup also improves statistical power, as it allows to use the fine-grained variation in different years of potential experience in the individual wage regression.

relative employment rates of experienced workers. We explore two versions of these regressions. The first one is linear in years of potential experience and provides the linear wage return to experience (the change in wages due to one more year of experience) and the employment gradient of experience (the change in the fulltime employment rate due to one more year of experience), respectively. The other version uses an experience indicator for individuals with twenty or more years of experience and thus identifies (according to this definition) experienced workers' relative wages and employment rates. We use the terms employment gradient of experience and relative employment of experienced workers largely interchangeably in the following.

The second step of our empirical analysis relates these relative wages and employment rates to the relative experienced labor inputs, generated by computing average years of potential experience or the share of experienced workers, respectively, in the panel of LLMs. Since relative experience inputs may be driven by demand as well as supply across LLMs, we instrument experience supply using the predicted age structure (adjusted by aggregate changes in education) of the LLM from ten years earlier. This last step of the empirical approach also accounts for measurement error in LLM-year-level variables that are due to sampling variation as well as endogenous responses in migration across LLMs.[6]

We find that aging has a substantial negative effect on experienced workers' *observed* relative wages within the range of previous estimates using time series data (e.g., Katz and Murphy, 1992; Jeong, Kim, and Manovskii, 2015; Caselli, 2015).[7] But we also identify a novel and strong effect of demographic change on employment. In LLM-years where they are more abundant, experienced workers have drastically lower probability of working (full-time and part-time), higher likeliness of having exited the labor force, and of claiming disability-, welfare-, or social security benefits compared with inexperienced workers.

We next examine which are the skill groups that react strongest to this "own-abundance shock". Examining the effect by workers' education levels and predicted earnings according to skill proxies yields suggestive evidence that it is rather the low-

[6]Standard errors are bootstrapped in order to account for the multilevel nature of our approach.

[7]Rising time fixed effects in the wage regression also support Caselli (2015)'s finding that aggregate technological change may have been experience-biased.

skill workers that are affected. This evidence of a negative selection becomes strong when we use actual earnings from last year for workers' labor force status in the current year and current earnings of workers who migrated into the LLM during the last five years. These finding not only indicate that low-skill workers are most severely affected by own-abundance demographic shocks of their age group, but also that previous estimates of the elasticity of substitution in production between experience inputs may have been attenuated by a selection bias in observed wages.

Our results are robust to using either commuting zones or states as LLMs and to different instrumental variables, to estimation in first differences instead of LLM fixed effects, to weighting individual workers according to their efficiency units of skill, or not, when computing LLM-level supply, and using the subsample of males only. We use two definitions of experience input, one fine-grained where a worker's experience rises linear in age conditional on education, and one where workers are considered inexperienced when they are below the median in the overall sample (less than 20 years) and experienced when they are weakly above. Two additional instruments, one which predicts the age structure from two decades earlier and one which exclusively exploits the effect of the baby boom, are also explored. In the choice regressions, a linear probability and a probit model yield the same results. Endogenous migration of workers across LLMs is an outcome that supports the hypothesized economic mechanism, not a confounder for our analysis.

A limitation of the census data is that it does not provide actual labor market experience. One can construct a measure of potential experience, but it is not possible to distinguish between age and potential experience conditional on education. However, this is not a severe problem for our analysis because we are interested in the effect of demographic change on the labor market, whether this comes from imperfect substitutability of old and young workers or of experienced and inexperienced labor inputs.

The paper continues as follows. The next section presents the economic model and derives implications of demographic change for relative wages and participation rates. Section 3 discusses the data and the empirical strategy. Section 4 estimates the effect of aging on the relative fulltime employment and observed wages of experienced individuals. In Section 5 the relative overall employment effect, unemployment, and labor force participation, as well as disability-, welfare-, and social security claims are examined. Then we split the analysis by skill and earnings groups, and examine the effect on (skill-biased) in-migration. Section 6 asses how much of the aggregate evolution of experienced workers' relative participation rates and wages over the last decades are due to supply changes. The final section concludes.

2 Economic Model

2.1 Aggregate Level: Production

Our starting point is to assume that production can be described by a CES production function.

$$Y = A\left(I^{\frac{\varepsilon-1}{\varepsilon}} + \delta E^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{1}$$

where I is inexperienced labor and E experienced labor input, δ technology augmenting skilled labor, and A a neutral technology parameter augmenting both factors, which reflects both total factor productivity and any other input to production. The parameter ε is the elasticity of substitution between the two inputs. The marginal products of inexperienced and experienced labor are given by

$$\begin{aligned} MPI &= A\left(I^{\frac{\varepsilon-1}{\varepsilon}} + \delta E^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{1}{\varepsilon-1}} I^{-\frac{1}{\varepsilon}} \\ MPE &= A\left(I^{\frac{\varepsilon-1}{\varepsilon}} + \delta E^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{1}{\varepsilon-1}} \delta E^{-\frac{1}{\varepsilon}} \end{aligned}$$

Since competitive firms' cost minimization implies that each type of labor's marginal products are equalized to their factor prices, the experience price is given by

$$p = \frac{MPE}{MPI} = \delta\left(\frac{E}{I}\right)^{-\frac{1}{\varepsilon}} \tag{2}$$

which is negatively related to the average experience per worker in each LLM-year. The relationship between the experience price and the relative supplies is linear in logs

$$\log(p) = \log(\delta) - \frac{1}{\varepsilon}\log\left(\frac{E}{I}\right) \tag{3}$$

As mentioned in the introduction, we present alternative empirical frameworks, which differ in the specification of I, E, and thus of p. The first specification obtains the return to experience in a reduced form linear wage regression and relates it to the average potential experience in each LLM-year. This modeling strategy is one of the key advantages of Jeong, Kim, and Manovskii's paper relative to Katz and Murphy (1992) or Card and Lemieux (2001), as it does not rely on assigning individual workers into discrete skill groups, but uses fine-grained information about workers' relative supply of experience skill. As a robustness check, we also show results for a specification that assigns workers into discrete experience groups.

2.2 Individual Level: Labor Supply

Our preferred worker-level wage function is inspired by the model of Jeong, Kim, and Manovskii (2015). A worker j supplies units of inexperienced ('raw') labor as well as their experience skill e_j (in years of experience). Denoting the price of experience by p, workers potential wages are

$$\log(w_j) = p\, e_j + \alpha_1 + \beta_1 x_j + u_j, \tag{4}$$

where x_j is a vector of observable productive characteristics (such as education, race, gender), for which we control to identify an unconfounded price p, and u_j is an unobserved individual-specific component.[8] Workers idiosyncratic productivity is therefore $\tilde{z}_j = \beta_1 x_j + u_j$.

To model the participation decision, we assume for workers' reservation wages

$$\log(r_j) = \gamma e_j + \alpha_2 + \beta_2 x_j + v_j \tag{5}$$

which allows for the reservation wage to depend on workers' characteristics x_j and experience e_j (or age conditional on education), where the coefficient γ could take any

[8]This specification of the wage function is a simplification and approximation of the setup in model of Jeong, Kim, and Manovskii (2015). There workers supply both raw labor, earning w^i and experience labor, earning w^E per unit. This implies $\log(w_j) = \log(1 + p\, e_j) + \log(w^i) + \beta_{lt} x_j + u_j$ with $p = \frac{w^E}{w^I}$. When approximating $\log(1 + p\, e_j) \approx p\, e_j$, which is a good approximation when p is small (which we find in our empirical analysis), our specification 4 follows.

sign. A worker j participates in the labour market if the following inequality holds

$$\underbrace{\alpha_1 - \alpha_2 + (\beta_1 - \beta_2)x_j + (u_j - v_j)}_{=z_j} > \underbrace{-(p-\gamma)e_j}_{\underline{\mathbf{Z}}(e_j,p)} \tag{6}$$

This inequality implies that workers participate only if the payoff from working z_j (the left hand side) exceeds a cutoff given by the right hand side. In general, the participation cutoff $\underline{\mathbf{z}}(e_j, p) = -(p-\gamma)e_j$ depends on a worker's experience (e_j) and the experience price (p). If $p > \gamma$ (which is an empirical question and is in line with the findings in our data), the cutoff falls in experience and more experienced have a higher participation rate (assuming that the distribution of z_j is identical for all e). Note that $\frac{\partial \underline{\mathbf{Z}}(e,p)}{\partial p} = -e < 0$, $\frac{\partial \underline{\mathbf{Z}}(e,p)}{\partial e} = -(p-\gamma) < 0$ if $p > \gamma$, and $\frac{\partial^2 \underline{\mathbf{Z}}(e,p)}{\partial e \partial p} = -1 < 0$, implying that more experienced workers are impacted more strongly by changes in p. This leads to

Proposition 1. *The participation cutoff of more experienced workers reacts more strongly to changes in the price of experience.*

The participation rate for workers with e experience years is given by the fraction of workers whose payoff from working exceeds the participation cutoff and is given by

$$R(e,p) = 1 - F^z(\underline{\mathbf{z}}(e,p)) \tag{7}$$

where F^z is the cumulative distribution function of z.

The participation rate at any experience level $e > 0$ depends positively on the experience price p. To establish how the participation rates change differentially across workers with different years of experiences, we investigate the cross-derivative of (7) with respect to p and e. Using Proposition 1 and denoting the density function of z by $f^z = \frac{F^z}{\partial z}$, the properties of the model-implied participation rate are $\frac{\partial R(e,p)}{\partial p} = -f^z(\underline{\mathbf{z}}(e,p))\frac{\partial \underline{\mathbf{Z}}(e,p)}{\partial p} > 0$, $\frac{\partial R(e,p)}{\partial e} = -f^z(\underline{\mathbf{z}}(e,p))\frac{\partial \underline{\mathbf{Z}}(e,p)}{\partial e} > 0$ if $p > \gamma$, and the cross-derivative is given by

$$
\begin{aligned}
\frac{\partial^2 R(e,p)}{\partial e \partial p} &= -\left(f^z(\underline{\mathbf{z}}(e,p)) \frac{\partial^2 \underline{\mathbf{z}}(e,p)}{\partial e \partial p} + \frac{\partial f^z(\underline{\mathbf{z}}(e,p))}{\partial \underline{\mathbf{z}}(e,p)} \frac{\partial \underline{\mathbf{z}}(e,p)}{\partial e} \frac{\partial \underline{\mathbf{z}}(e,p)}{\partial p} \right) \\
&= -f^z(\underline{\mathbf{z}}(e,p)) \left(\frac{\partial^2 \underline{\mathbf{z}}(e,p)}{\partial e \partial p} + \frac{\frac{\partial f^z(\underline{\mathbf{Z}}(e,p))}{\partial \underline{\mathbf{Z}}(e,p)}}{f^z(\underline{\mathbf{z}}(e,p))} \frac{\partial \underline{\mathbf{z}}(e,p)}{\partial e} \frac{\partial \underline{\mathbf{z}}(e,p)}{\partial p} \right) \\
&= -f^z(\underline{\mathbf{z}}(e,p)) \left(-1 + \frac{\frac{\partial f^z(\underline{\mathbf{Z}}(e,p))}{\partial \underline{\mathbf{Z}}(e,p)}}{f^z(\underline{\mathbf{z}}(e,p))} (p-\gamma) e \right) \\
&= f^z(\underline{\mathbf{z}}(e,p)) \left(1 + \frac{\partial f^z(\underline{\mathbf{z}}(e,p))}{\partial \underline{\mathbf{z}}(e,p)} \frac{\underline{\mathbf{z}}(e,p)}{f^z(\underline{\mathbf{z}}(e,p))} \right)
\end{aligned}
$$

where the last two equalities make use of the definition of the $\underline{\mathbf{z}}(e,p)$-cutoff. The sign of the cross-derivative is in general ambiguous, but in most situations likely to be positive, which would imply that the participation rates of more experienced workers react more strongly to changes in the experience price than of inexperienced workers. Typically, experienced workers react more strongly to price changes as their cutoff-skill changes by more than the inexperienced workers', as established in Proposition 1. This is the first term in the cross-derivative above. The second term captures how a given change in the cutoffs feeds on to changes in relative participation. For an arbitrary class of distributions, one can construct examples where a small change in the cutoff of inexperienced workers leads to a larger change in their participation rates than a larger change in the participation cutoff of more experienced workers at a different point of the density function does. Yet, for some classes of distributions it is always true, and for many other distributions it is likely that at many points $\frac{\partial^2 R(e,p)}{\partial e \partial p} > 0$. A sufficient condition for this is $\frac{\partial f^z(\underline{\mathbf{Z}})}{\partial \underline{\mathbf{Z}}} \frac{\underline{\mathbf{Z}}}{f^z(\underline{\mathbf{Z}})} > -1$, i.e. that the elasticity of the density function is not smaller than minus one.[9] In this case, following a change in the price of experience, the participation rate of more experienced workers reacts stronger than of less experienced workers.

Proposition 2. *More of the experienced workers than of the inexperienced workers react to changes in the experience price, if the z-density function has an elasticity larger than minus*

[9]An example for a distribution for which this condition is satisfied at any points is the uniform distribution; if $z \sim U[a,b]$, $\frac{\partial f^z(z)}{\partial z} \frac{z}{f^z(z)} = 0$ and $\frac{\partial^2 R(e,p)}{\partial e \partial p} > 0$ at any z. For the normal distribution, there is an open interval of points for which the elasticity is less than one. For instance, if $z \sim N[0,1]$, then $\frac{\partial f^z(z)}{\partial z} \frac{z}{f^z(z)} = -\frac{1}{2} z^2$ and $\frac{\partial^2 R(e,p)}{\partial e \partial p} > 0$ for $z^2 < 2$ (which has probability 0.843%).

one.

Next, we establish that changes in the price of experience systematically alters the pool of workers participating. When the price of experience participation-cutoff $\underline{z}(e,p)$ increases, the observed mean z_j conditional on participating decreases at any given years of experience. If the workers' payoff from working z_j mainly reflect skills, i.e. if $\beta_2 x_j + v_j \approx const.$, this lowers the mean skill of participating workers. Conditional on participating, the mean z_j of workers with e years experiences is given by

$$E[z(e)|z_j > \underline{z}(e,p)] = \frac{1}{\int_{\underline{Z}(e,p)}^{\infty} f^z(z_j)dz_j} \int_{\underline{Z}(e,p)}^{\infty} z_j f^z(z_j)dz_j = \frac{\int_{\underline{Z}(e,p)}^{\infty} z_j f^z(z_j)dz_j}{1 - F^z(\underline{z}(e,p))}$$

A fall in the price of experience p increases the participation cutoff $\underline{z}(e,p)$ at any level $e > 0$. The impact on mean z_j conditional on participating is therefore given by $\frac{\partial E[z(e)|z_j > \underline{Z}(e,p)]}{\partial \underline{Z}(e,p)}$, which can be shown to positive, [10] implying the following proposition:

Proposition 3. *If z_j is mainly a positive function of skill ($\beta_2 x_j + v_j \approx const$), low-skill workers react more strongly to changes in the price of experience.*

To summarize, a fall in the return to experience (p) increases the participation cutoff ($\underline{z}(e,p)$) and reduces the participation rate ($R(e,p)$) at any years of experience. Since the participation cutoff of more experiened workers is impacted more, it is likely that their participation rates react stronger. Moreover, since the change in participation is systematic, the fall in the return to experience increases the mean skill of workers who continue to participate (($E[z(e)|z_j > \underline{z}(e,p)]$).

[10] The derivative is given by

$$\begin{aligned}\frac{\partial E[z(e)|z_j > \underline{z}(e,p)]}{\partial \underline{z}(e,p)} &= \frac{-\underline{z}(e,p) f^z(\underline{z}(e,p))(1 - F^z(\underline{z}(e,p))) + \int_{\underline{Z}(e,p)}^{\infty} z_j f^z(z_j)dz_j f^z(\underline{z}(e,p)))}{(1 - F^z(\underline{z}(e,p)))^2} \\ &= \frac{f^z(\underline{z}(e,p))}{(1 - F^z(\underline{z}(e,p)))^2} \frac{1}{\underline{z}(e,p)} \left[\int_{\underline{Z}(e,p)}^{\infty} \frac{z_j}{\underline{z}(e,p)} f^z(z_j)dz_j - (1 - F^z(\underline{z}(e,p)) \right]\end{aligned}$$

The first factor is clearly positive. Also the second factor, given by the square brackets is positive, since $\int_{\underline{Z}(e,p)}^{\infty} \frac{z_j}{\underline{Z}(e,p)} f^z(z_j)dz_j > \int_{\underline{Z}(e,p)}^{\infty} f^z(z_j)dz_j = (1 - F^z(\underline{z}(e,p))$. As a consequence, $\frac{\partial E[z(e)|z_j > \underline{Z}(e,p)]}{\partial \underline{Z}(e,p)} > 0$.

2.3 Equilibrium and Demographic Change

The relative supply of the experience skill of participating workers is given by

$$\frac{E}{I} = \frac{\sum_j e_j \tilde{z}_j f_j}{\sum_j \tilde{z}_j f_j} \tag{8}$$

where $\tilde{z}_j$ are some individual level weights. In our preferred empirical specification, these consist of individuals' observed productive characteristics $\exp(\beta x_j)$, following Jeong, Kim, and Manovskii (2015). An alternative formulation is to set $\tilde{z}_j = 1$ such that $\frac{E}{I}$ is the simple average of experience.

To illustrate the effects of demographic change, we work with this simpler formulation, where the equilibrium relative supply of experience skill is average experience weighted by participation rates $R(e, p)$. Assuming only workers with 0 to 45 years of experience participate, it can be written as

$$\frac{E(p)}{I(p)} = \frac{\sum_{e=0}^{45} n(e) e R(e, p)}{\sum_{e=0}^{45} n(e) R(e, p)} \tag{9}$$

where $n(e)$ is the number of workers with e years of experience.

Potential supply, the supply if all workers participated is given by $\frac{\tilde{E}}{\tilde{I}} = \frac{\sum_{e=0} n(e)e}{\sum_{e=0} n(e)}$. Demographic changes are shifts in the group sizes of workers with different years of experiences. These changes in potential supply have in equilibrium effects on the experience price and supply. As illustrated in Figure 2, when due to ageing the supply of experience increases, the supply curve shifts out. In equilibrium this leads to fall in the experience price and a reduction in the relative participation of experienced workers, which is a leftward movement along the new supply curve.

To see the shift of the supply curve due to demographic change formally, define the actual relative experience supply at price p as $S(p) = \frac{E(p)}{I(p)} = \frac{\sum_{e=0}^{45} n(e) e R(e,p)}{\sum_{e=0}^{45} n(e) R(e,p)}$ and log-linearize allowing for changes in the age structure ($n(e)$). Holding the price constant, $\widehat{S} = \Delta \log(S)$, (roughly) the percentage change in S is given by

$$\widehat{S} = \sum_{e=0}^{45} \underbrace{\left(\frac{n(e) e R(e, p)}{E} - \frac{n(e) R(e, p)}{I} \right)}_{\Omega(e)} \widehat{n(e)}$$

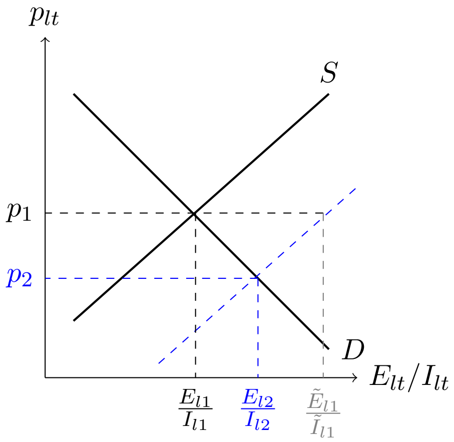


Figure 2: Slope of the relative labor supply curve of experience
An increase in the experience supply shifts the supply curve to the right (to the dashed line). The resulting fall in the price of experience reduces the quantity along the new supply curve (from $\frac{\tilde{E}_1}{\tilde{I}_1}$ to $\frac{E_2}{I_2}$), reflecting a reduction in participation.

where $\widehat{n(e)} = \Delta\log(n(e))$, (approximately) the percentage change in $n(e)$).

Defining $\Omega(e) = \frac{n(e)eR(e,p)}{E} - \frac{n(e)R(e,p)}{I}$, it is straightforward that an increase of the number of workers with $\tilde{e}$ years leads to a larger supply at a given price if $\Omega(\tilde{e}) > 0$, which occurs when $\tilde{e} > \frac{E}{I}$. Hence, when the share of workers with more than the average years of experiences increases, the supply curve shifts to the right. Conversely, when the share of workers with less than the average years of experiences increases, the supply curve shifts to the left.

Market clearing requires that in response to larger supply, the price of experience falls since the demand curve (3) is downward-sloping. A log-linearization gives

$$\widehat{D} = -\varepsilon\widehat{p}$$

where $\widehat{D} = \Delta\log(D)$ and $\widehat{p} = \Delta\log(p)$.

Log-linearizing of the relative supply (9) allowing for changes in the sizes of demographic groups as well as in the experience price gives

$$\widehat{S} = \underbrace{\sum_{e=0}^{45}\Omega(e)\widehat{n(e)}}_{\text{potential rel supply change}} \quad \underbrace{-\sum_{e=0}^{45}\Omega(e)\frac{p}{R(e,p)}\frac{\partial R(e,p)}{\partial p}\widehat{p}}_{\text{particpation change}}$$

The first term reflects by how much supply changes due to demographic change at a constant price, whereas the second term by how much supply changes due to the induced price adjustment. When the experience price falls, participation is reduced, especially amongst more experienced workers, as established in Proposition 2, and as a consequence the quantity supplied falls (along the supply curve).

In equilibrium, the change in demand has to equal the change in supply, i.e. $\widehat{D} = \widehat{S}$. Following an increase in potential supply due to demographic change, given by $\sum_{e=0}^{45} \Omega(e)\widehat{n(e)} > 0$, the market clearing price falls,

$$\widehat{p} = -\frac{\sum_{e=0}^{45} \Omega(e)\widehat{n(e)}}{\epsilon + \sum_{e=0}^{45} \Omega(e)\frac{p}{R(e,p)}\frac{\partial R(e,p)}{\partial p}} < 0$$

and the equilibrium supply change is

$$\widehat{S} = \frac{\varepsilon \ \sum_{e=0}^{45} \Omega(e)\widehat{n(e)}}{\epsilon + \sum_{e=0}^{45} \Omega(e)\frac{p}{R(e,p)}\frac{\partial R(e,p)}{\partial p}}$$

which is $0 < \widehat{S} < \sum_{e=0}^{45} \Omega(e)\widehat{n(e)}$. This means that following an increase in potential supply due to aging of the workforce, actual supply increases in equilibrium, but by less than potential supply since relative participation rate of more experienced workers falls.

The properties of relative experience supply and the equilibrium effects of demographic change are summarized in proposition 4.

Proposition 4. *Properties of relative experience supply and the equilibrium effects of demographic change:*

- *A shift in potential supply shifts the relative experience supply curve (at a constant price).*
- *An increase in the price increases relative experience supply under reasonable conditions (holding constant potential supply).*
- *In equilibrium, higher potential supply decreases the experience price and thus increases actual supply by less than 1:1.*

3 Data and Empirical Strategy

In this section we describe how we apply the model described in the previous section to local labor markets. Our starting point is to assume that workers' participation decisions and production occur at the LLM level. In a further application we also explore implications for worker migration across local labor markets.

3.1 Data

We use data from the US Census of 1940, 1950, 1960, 1970, 1980, 1990, 2000 and the American Community Survey (ACS) of 2010, which we access from IPUMS-USA, provided by Ruggles, Alexander, Genadek, Goeken, Schroeder, and Sobek (2010).[11]

We construct a sample of the working age population 16–65 in the census/ACS years 1960 to 2010. We translate the consistent education variable in the census/ACS into years of school in order to compute the number of years of potential labor market experience.[12] In particular, we define potential experience as an individual's age minus years of schooling minus six. It is censored below at zero and above at 45 years. As in Jeong, Kim, and Manovskii (2015), we construct an indicator that divides individuals into "high-school" workers with 12 or less years of schooling and "college" workers with more than 12 years of schooling.

We also construct fulltime employed variable of employees in non-farm, non-military occupations aged 16 to 65. They work at least 40 weeks per year, 35 hours per week and they report a positive salary income for the previous year. We compute an estimate of hourly equivalent wages by dividing the salary income by 35 hours and 40 weeks.[13]

Table 1 lists some summary statistics for the sample of individuals aged 16–65 that

[11]For the censuses of 1940, 1950, and 1960 this is the one percent sample, for the 1980, 1990 and 2000 census the five percent samples, and for the 2010 ACS the one percent sample. For the 1970 census we use the two one percent metro samples in our analysis on the commuting zone level and the two state samples in our analysis on the state level. We also checked for the robustness of our results to the Great Recession using the 2007 ACS instead of the 2010 version.

[12]Education codes below grade nine are given in intervals. We code "Nursery up to grade 4" as three years of schooling and "Grade 5, 6, 7, or 8" as seven years.

[13]We cannot compute the exact hourly wage for the 1960 and 1970 censuses as they only provide intervals for the weeks and hours worked. Alternatively, using the midpoint of the intervals and then dividing the salary income by hours and weeks yields very similar results.

are in our regression sample.[14] We do include females in our analysis, as their experience supply matters for the general equilibrium effect that we are after, but our main results are robust to excluding females.

Table 1: Summary Statistics for Population Aged 16–65

	Log(Wage)	Fulltime	Age	Pot Exper	Yrs Educ	Female
1960						
mean	0.50	0.33	38.4	21.8	10.3	0.51
sd	1.21	0.47	13.8	14.3	3.1	0.50
1970						
mean	0.93	0.36	37.6	20.2	11.2	0.52
sd	1.22	0.48	14.5	14.9	2.9	0.50
1980						
mean	1.61	0.43	36.6	18.4	12.0	0.51
sd	1.22	0.49	14.4	14.6	2.7	0.50
1990						
mean	2.20	0.47	37.3	18.6	12.6	0.51
sd	1.22	0.50	13.4	13.4	2.4	0.50
2000						
mean	2.62	0.49	38.5	19.6	12.7	0.50
sd	1.17	0.50	13.3	13.1	2.3	0.50
2010						
mean	2.79	0.44	39.8	20.8	13.0	0.50
sd	1.26	0.50	14.2	14.0	2.3	0.50
Total						
mean	2.00	0.43	38.1	19.8	12.2	0.51
sd	1.45	0.49	14.0	14.0	2.7	0.50
N	10316637					

The 1940 and 1950 censuses are not used for our wage regressions, but they are used to construct our instrument for experience.[15] This is based on predicting the current age structure of a given local labor market using the censuses ten (twenty) years earlier. We also cannot use the 1970 census for the wage regressions when we do our analysis on the commuting zone level as opposed to the state level. The reason is that county group information, which is necessary for constructing the Autor and Dorn (2012) commuting zones, is not available in 1960 (so we cannot construct our instrument for 1970).

Therefore, our commuting zone analysis begins in 1980; just when the baby boom cohorts start entering the labor market and pushing down the age of the workforce.

[14]Table 12 of the appendix shows these summary statistics for fulltime workers aged 16–65.

[15]The weeks worked variable in 1950 has many unexplained missing values. Including or excluding the workers with missing weeks either leads to implausibly high or low average wages.

The state level analysis begins two decades earlier than that, a period when the average work force age was still rising. Table 1 shows that there are more than ten million individual observations underlying the state level analysis (more than 4.3 million full-time workers, Table 12).[16]

3.2 Empirical Strategy

Our empirical analysis is on the LLM-year level and consists of three steps: a choice or wage regression on the individual level, the relationship between the supply of experience and the coefficient from the individual on the LLM level, and instrumentation of the supply of experience. The first two steps are similar to Jeong, Kim, and Manovskii (2015) and the analysis of the "canonical model" more generally (e.g., Acemoglu and Autor, 2011), but importantly they include an estimation of relative participation choices in addition to relative wages. The third step is our approach to disentangle supply from demand effects in the panel of local labor markets that we construct.

$$F_{jlt} = \alpha_{jlt} + r_{lt}e_{jlt} + \beta_{lt}x_{jlt} + u_{jlt} \tag{10}$$

We first run in each LLM-year[17] the linear choice regression given in (10), which is the empirical implementation of (6). Here, the outcome F_{jlt} is an indicator for working full-time. The main regressor of e_{jlt} interest is either linear potential experience in years or a dummy for being experienced ($e_{jlt} \geq 20$) versus inexperienced ($e_{jlt} < 20$). We include x_{jlt} to control for other factors that differ by experience and may influence full-time participation to obtain this relationship cleaned of observable confounders. In line with the recent paper by Jeong, Kim, and Manovskii (2015) we include years of schooling, sex, and race.[18] u_{jlt} is the regression error, that is, the individual-specific deviation from the conditional mean. Our baseline specification for the choice regression

[16]In the communting zone analysis without the 1960 and 1970 censuses, these numbers are 6.8 million and 3.1 million, respectively.

[17]On the commuting zone level, there are 722 LLMs per year in 1980–2010, on the state level there are 51 LLMs per year in 1960–2010. In the year 1970, locational information is not available for seven states.

[18]In Section 5 we study the effect of increasing average experience on employment by observable skills. There we construct the participation-experience gradient by education or (predicted) earnings groups.

is a linear probability model, but in the Appendix we show that the results are similar in a Probit specification.

We interpret the coefficient r_{lt} as the experience-participation gradient for e_{jlt} as linear potential experience and as the relative full-time participation rate of experienced workers for e_{jlt} as the experienced dummy, respectively. Alternatively, when we run equation (10) as a Mincer wage regression, replacing F_{jlt} with the log wage $\log(w_{jlt})$, r_{lt} is simply the return to experience.

Note that choice estimation of equation (10) is more general than our economic model. It summarizes the empirical relationship between experience supply and experienced workers' employment, whether this is mediated via the price of experience in a competitive factor market or whether there are some rigidities and firms are for example unwilling to hire or retain experienced workers at the going wage rate. Our empirical findings below support the competitive model of Section 2, as we find no effect on unemployment, a strong effect on labor force participation, and a substantial effect on the price of experience.

Estimating (10) in each LLM-year gives us a panel of local experience supplies, experience-participation gradients and returns to experience . The main advantage of using this setup linear in potential experience, compared to grouping workers into discrete "experienced" and "unexperienced" groups (e.g., Card and Lemieux, 2001; Caselli, 2015), is that it uses the fine-grained "within-group" variation in workers' supply of years of experience.

As a robustness check, we estimate the model in the dummy specification where workers can only provide either experienced or inexperienced labor inputs. Compared to simply computing average wages for experienced and inexperienced workers (e.g., Caselli, 2015), employing the modified individual-level wage equations has the advantage that via the control variables $\beta_{lt}x_{jlt}$ one can remove the confounding effects of other productive characteristics that potentially differ between experienced and inexperienced workers.

In the second stage of our analysis, we relate the relative participation rate of experienced workers r_{lt} to the relative supply of experience $\frac{E_{lt}}{I_{lt}}$ in our panel of local labor markets:

$$r_{lt} = \eta \left(\frac{E_{lt}}{I_{lt}} \right) + D_l + D_t + error_{lt} \tag{11}$$

We specify $\frac{E_{lt}}{I_{lt}}$ to be the average years of potential experience in LLM-year lt or the share of experience workers, according to the respective definition of e_{jlt}.[19] We use the average experience of actual full-time employment, and not of the working age population, in the regression because in the economic model (see Figure 2 or Section 2.1) this determines the relative marginal products and thus the market price of experience. We also explore a log-log version of equation (11), which is closer to the classic Katz-Murphy regression.

The fixed effects in equation (11) D_l flexibly control for time-invariant differences in relative full-time participation (or wages) of experienced workers across locations, while the D_ts control for aggregate changes in these variables over time (e.g., due to experience-biased changes in labor demand or trends in early early retirement behavior which might be due to policies).[20]

However, there are likely to exist changes in the demand for experience that vary across LLM-years. Therefore, in the third step of our analysis, we design an empirical strategy to extract changes in local supply from changes in demand. As we are exploiting in our fixed effect regression (11) the variation across local labor markets, what is needed is to predict the differential supplies of experience skills across LLMs. In the construction of the instrument we can therefore make use of a shift-share strategy, which we rely on for education, as well as of the age structure observed in the previous census. For each LLM, we use the $t-1$ predicted age structure of the working age population along with the (at the aggregate level observed) years of education in t (by age and gender) to instrument for the LLM's relative supply of experience skill in year t. We also explore one version of the instrument in which we adjust the predicted relative supply of experience skill for LLM l in year t using the aggregated age-gender-education-specific full-time employment rates. We bootstrap steps 1–3 to-

[19]Weighting every individual equally or by their effective labor input $\beta_{lt} x_{jlt}$, as in Jeong, Kim, and Manovskii, when computing the averages, does not affect the results.

[20]Although this removes a substantial portion (90–95 %) of the variation of experience in the panel, there is still enough variation left to identify our model. For example, see the differential aging of LLMs (states) in Figures 6.

gether 50 times in order to obtain the correct standard errors.

Our instrument is exogenous if, controlling for permanent differences across LLMs D_l and aggregate differences across years D_t, the age structure in a given LLM in $t-1$ is not affected by the relative demand for experience skill in t. If it were to some extent affected by the demand for experience in t, our instrument would not fully succeed in extracting variations in experience on the LLM level that are due to changes in supply. Thus it would underestimate the effect on relative wages and employment rates, and overstate the elasticity of substitution in demand.

For validity of the instrument, we also need that a first stage exists and that the exclusion restriction holds. The exclusion restriction states that the age structure in $t-1$ does not affect the skill price in t other than through its effect on the supply of skill in t. We control for average education in our IV second-stage, as changes in an LLMs age structure may come with changes in educational attainment. In Appendix Table 16 we explore instrumenting with a two-decades lag $t-2$ and an alternative instrument, which exclusively exploits the effect of the baby boom across LLMs.

Assuming that our instrumental variables strategy is valid, it provides identification of the price elasticity of demand and of workers' employment response in what may be interpreted as a simultaneous equations model of the market of experience skill. This reasoning is illustrated in Figure 2. In LLM 1, demographic change shifts the relative supply of experience to the right. While the previous literature assumed that labor supply by experience is inelastic (the relative participation rate of experienced workers is unaffected by their relative abundance) and thus vertical, our empirical results below show that it is indeed upward-sloping as sketched in the figure.[21] Therefore, as derived in Section 2.3 and summarized in Proposition 4, the relative input of experienced workers rises by less than the shift in the supply curve ($\frac{E_{l2}}{I_{l2}}$ instead of $\frac{\tilde{E}_{l2}}{\tilde{I}_{l2}}$) and also the effect on the new equilibrium price p_{lt} is weaker.

Demographic change may therefore have real relative employment effects, but also general equilibrium participation effects that attenuate it but at the same time affect individuals' lives beyond declining wage rates. This reasoning does not per se have

[21] We do not focus on the intensive margin of labor supply as the Census prior to 1980 did not include detailed information on hours worked, but only brackets. We also find strong effects on the extensive margin.

implications about the correctness of existing estimates of the slope of demand in Figure 2, and one could even combine the price and the participation response to obtain a relative elasticity of labor supply of experienced workers. However, as we show below and in line with Proposition 3, the individuals on the participation margin do not appear to correspond to the average worker, and thus prices as well as estimates of the substitution elasticity may be selection-biased.

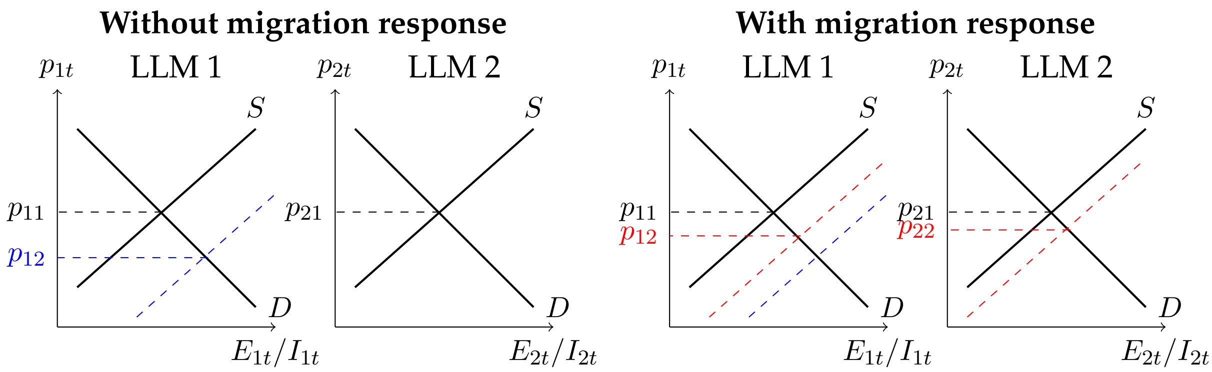


Figure 3: Effect of relative experience supply shock in LLM 1

Finally, note that our identification strategy is robust to an employment response that runs in a third dimension of the demand and supply diagram. Figure 3 illustrates an endogenous migration response of rising relative migration of experienced workers from LLM 1, which was hit by an aging shock, to LLM 2. The original shock in LLM 1 moves the relative supply of experience down to the blue dashed line, which goes in hand with a substantial decline in the relative price of experience. In response, some relatively experienced individuals may decide to move to LLM 2, increasing the supply of experience there and reducing it in LLM 1. Nonetheless, the red line shifts further out in LLM 1 than LLM 2 and our empirical strategy identifies the slope of the demand curve from that difference. As long as this does not perfectly smoothen out all of the original change in experience supply, endogenous migration is therefore not a concern, but an additional outcome of interest. In fact, in Section 5 we find a negative effect of rising experience on the in-migration of experienced workers.

4 Aging's Effect on Relative Full-Time Participation and Observed Wages

We show estimation results of the effect of aging on the relative labor market participation for experienced workers and on the return to experience according to observed wages. Our baseline results are for commuting zones (czones) as the local labor market level, but we also report results at the state level as a comparison and robustness check.

4.1 Variation in the LLM-Year Panel

Figure 6 in the appendix plots the variation in average age across states, which allows for a longer time dimension, and over time. The fixed effects in our second-stage regression (11) remove time-invariant differences across LLM and aggregate changes over time, which admittedly makes up a large part (90–95 percent) of the variation in age and potential experience in the czone and the state panel. Nonetheless, one can also visually infer from the figure that substantial differences that run across LLM-years, and which are particularly informative for identification, remain.

There are several sources from which these differences may originate. First, rural and urban areas had historically different fertility rates, which fluctuated or changed over time together with urban to rural migration of mostly young workers. The 1950s and 1960s were an especially transformational period, with cultural norms with respect to family shifting first in the coastal urban centers and then later in the rural interior. This went in hand with variation in birth control and abortion legislation as well as anti-obscenity laws, which persisted until the mid-1960s (Bailey 2010, Bronson and Mazzocco 2013).[22] Our fixed effects strategy aims to remove variation in experience across years or local labor markets that are due to demand, any other variation that is due such supply factors would be informative.

Table 2 reports the results collected from the individual-level regression (10) as well as other information for our LLM-year panel on the czone level (the corresponding

[22] Also note that earlier differences in birth-, migration-, or mortality rates have persistent effects on (cycles in) the age structure, even across multiple generations.

Table 2: Descriptives for the Czone Panel

	Fullt	Fgrad x100	Wage	Rtrn x100	Sh Expd	Avg Exper	Yrs Educ	Female
1980								
mean	0.08	0.37	0.27	1.28	0.44	19.3	12.4	0.38
sd	0.04	0.14	0.04	0.21	0.04	1.1	0.4	0.03
1990								
mean	0.06	0.28	0.27	1.49	0.44	19.1	13.0	0.42
sd	0.04	0.16	0.05	0.24	0.03	0.8	0.4	0.03
2000								
mean	0.06	0.28	0.26	1.44	0.52	20.5	13.2	0.43
sd	0.03	0.15	0.04	0.20	0.03	0.8	0.4	0.02
2010								
mean	0.09	0.34	0.31	1.50	0.57	22.2	13.5	0.46
sd	0.03	0.12	0.04	0.20	0.04	0.9	0.4	0.02
Total								
mean	0.07	0.32	0.28	1.44	0.50	20.4	13.1	0.43
sd	0.04	0.15	0.05	0.23	0.07	1.6	0.5	0.04
N	2888							

For each year, the table shows mean and standard deviations of the variation across LLMs for the variables named in the top row. The first four columns are r_{lt} coefficients from regression (10). Column 1 shows the relative fulltime employment rate of experienced workers (minus 1), Column 2 the linear experience gradient of fulltime employment (times 100), Column 3 the relative wage of experienced workers (minus 1), and Column 4 the linear wage return to experience (times 100). Columns 5 and 6 show the two measures of the supply of experience, the share of experienced workers and the average experience, respectively. The last two columns report the average years of education and the share of females among fulltime workers.

information on the state level is in Appendix Table 14). For each year, the table reports mean and standard deviations of the variation across LLMs for the variables named in the top row. Column 1 shows the relative full-time employment rate of experienced versus inexperienced workers, when e_{jlt} is a dummy in regression (10), and column 2 the experience gradient of full-time employment (multiplied by 100), when e_{jlt} is potential experience in years. Columns 3 and 4 show the respective relative observed wage of experienced workers and the return to years of potential experience. The share of experienced workers and the average years of potential experience among the full-time workers are reported in columns 5 and 6. The last two columns show the average years of education and the share of females for this group.

Appendix Table 14 shows the corresponding information for the state panel starting in 1960. The means are very similar, but the standard deviations (especially within year) are unsurprisingly smaller. Overall there are 2,888 observations in the czone panel and 304 observations in the state panel. The means in the tables reveal that over 1980–2005 fulltime employment gradient first dropped and then recovered, the price of experience increased by 44%, and the experience supply first decreased over

1970–1990 (due to baby boomers entering the labor market) and then increased quite considerably (due to aging).

4.2 Estimation Results

Table 3 reports the relationship of the supply of experience with the relative participation rate of experienced workers when the second stage equation (11) is estimated by OLS.

Table 3: Supply and Relative Full-Time Participation of Experienced Workers' (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Fgrad x100	Fgrad x100	Log Fgrad	Fullt	Fgrad x100	Fgrad x100	Log Fgrad	Fullt
Exper	0.06***	0.05***			0.02**	0.02**		
	(0.00)	(0.00)			(0.01)	(0.01)		
Yrs Educ		-0.10***				-0.01		
		(0.01)				(0.02)		
Log Exp			3.76***				1.50	
			(0.33)				(0.97)	
Sh Expd				0.58***				0.33***
				(0.02)				(0.06)
Observations	2888	2888	2632	2888	304	304	303	304
R^2	0.79	0.80	0.65	0.81	0.86	0.86	0.69	0.90
Fixed Effects	czone+year	czone+year	czone+year	czone+year	state+year	state+year	state+year	state+year
Weight	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght
Sample	>=1980	>=1980	>=1980	>=1980	>=1960	>=1960	>=1960	>=1980

The table reports results from the second-stage estimation (11) using OLS. Dependent and independent variables are constructed from regression (10) in each LLM-year using an individual's full-time participation dummy as the dependent variable. Columns (1) to (4) show OLS estimates for the panel of commuting zones over 1980–2010, columns (5) to (8) for states over 1960–2010. Standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.

In the first column of Table 3 average potential experience and the full-time participation gradient with respect to potential experience covary positively across the panel of commuting zones. This relationship does not change when we control for average years of education, which might change with an aging workforce.[23] The log-log specification of column (3) indicates a (qualitatively) similar relationship, though the interpretation changes and we lose some observations because the estimated full-time participation gradient is not positive in all czone-years. Column (4) repeats the exercise with a discrete assignment of workers into experienced and inexperienced groups and the (cleaned for confounders, see regression (10)) relative full-time participation

[23]More educated czone-years have lower relative full-time employment rates of experienced workers in column 2. For the state level this relationship is not as clear (column 6).

rate between the groups.[24] We see that a one percentage point increase in the share experienced workers is associated with a .5 percentage point increase of the relative employment rate of experienced workers.

Columns (5) to (8) conduct the corresponding analysis on the state level. There is no systematic relationship between experience supply and full-time participation gradient of experience detectable on this level.

Table 15 in the Appendix reports the corresponding estimates to Table 3 for the return to experience and the relative earnings of experienced workers according to observed earnings. Contrary to the full-time participation gradient, the return to experience is negatively correlated with average potential experience across LLM-years in columns (1)–(3) and (5)–(6), while the relative wage of experienced workers is positively related to the share of experienced workers (columns 4 and 8).

The pictures that Tables 3 and 15 paint about the relationship between supply of experience and labor market opportunities of experienced workers is mixed. This is not surprising, as the in the OLS it is not clear whether changes in the experiencedness of LLMs occur because of shocks to supply of- or demand for such workers. We therefore use our instrumental variables strategy in the following in order to extract variation in this variable that is solely due to supply.

Table 4: Regression of Experience onto Predicted Supply of Experience from 10 Years Prior (IV First-Stage)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Exper	Exper	Log Exp	Sh Expd	Exper	Exper	Log Exp	Sh Expd
Pred Exper	0.48***	0.57***		0.01***	0.51***	0.65***		0.02***
	(0.03)	(0.03)		(0.00)	(0.05)	(0.05)		(0.00)
Yrs Educ		-1.03***				-0.82***		
		(0.08)				(0.12)		
Log Pred Exper			0.49***				0.53***	
			(0.03)				(0.05)	
Observations	2888	2888	2888	2888	304	304	304	304
R^2	0.91	0.92	0.91	0.91	0.96	0.96	0.96	0.96
Fixed Effects	czone+year	czone+year	czone+year	czone+year	state+year	state+year	state+year	state+year
Weight	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght
Sample	>=1980	>=1980	>=1980	>=1980	>=1960	>=1960	>=1960	>=1980

The table reports the regression of average experience of full-time workers onto the predicted supply of experienced workers from the census 10 years prior. Columns (1) to (4) show estimates for the panel of commuting zones over 1980–2010, columns (5) to (8) for states over 1960–2010. Columns (4) and (8) have the share of experienced workers as a dependent variable, the others average potential experience in that LLM-year. Standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.

[24]We used the same cutoff as Caselli (2015), with the median and the mean of potential experience in his as well as our dataset at around 20 years.

Table 4 reports the first stage from this IV regression. The coefficients of average experience (columns 1–3 and 5–7) and the share of experienced workers (columns 4 and 8) on predicted average experience from the census 10 years earlier are highly significant, even conditional on LLM and year fixed effects. Unreported F-statistics are all above 100 for average potential experience as the dependent variable and above 40 for the share of experienced workers. Because it is more fine-grained and statistically more powerful, in columns (4) and (8) we also use predicted average experience as the instrument instead of the predicted share of experienced workers. However, our estimation results are qualitatively similar when use the latter.

The coefficient of the first-stage is large in value, but smaller than one in columns (1)–(3) and (6)–(8) of Table 4. We would expect this to be the case when the instrument removes changes in experience across LLMs that are due to demand shocks (and go in hand with rising returns to experience). In that sense the identification strategy seems to work. Moreover, it corrects for measurement error due to sampling variation. Since our census data are a 1, 2, or 5 percent subsamples of the population, the supply of experience variables that we compute on the detailed LLM level may be measured with error.[25] However, because the instrument is constructed from an earlier cross-section, the measurement errors in the regressor and IV are uncorrelated. This removes potential attenuation bias in our estimates.

An additional reason why we expect the first-stage coefficients to be below one are endogenous participation and migration decisions. In fact, we find below that there is a negative effect of rising experience on the labor market participation and the in-migration of experienced versus inexperienced workers.[26]

Table 5 reports the IV result of the effect of experience supply on the relative full-time participation of experienced workers. All the relationships from the OLS turn around and become more negative, as one would expect when the variation that is due to demand shocks is removed by the instrument. The relationship between average potential experience and the share of experienced workers with the experience

[25]Even though we have several millions of observations in our individual level regressions (10), the census data are at most 5 percent samples and especially for some czone-years cell sizes are not that large (minimum on the czone level is 564, maximum is 115,201 observations)

[26]Of course, if the participation or the migration response were perfect, we would not get any first stage at all.

Table 5: Supply and Relative Full-Time Participation of Experienced Workers' (IV)

	(1) Fgrad x100	(2) Fgrad x100	(3) Log Fgrad	(4) Fullt	(5) Fgrad x100	(6) Fgrad x100	(7) Log Fgrad	(8) Fullt
Exper	-0.10***	-0.06***			-0.06***	-0.05***		
	(0.01)	(0.01)			(0.02)	(0.01)		
Yrs Educ		-0.19***				-0.03		
		(0.01)				(0.02)		
Log Exp			-8.50***				-4.31***	
			(1.08)				(1.57)	
Sh Expd				-0.46***				-0.28***
				(0.10)				(0.11)
Observations	2888	2888	2632	2888	304	304	303	304
R^2	0.53	0.66	0.39	0.50	0.81	0.82	0.65	0.84
Fixed Effects	czone+year	czone+year	czone+year	czone+year	state+year	state+year	state+year	state+year
Weight	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght
Sample	>=1980	>=1980	>=1980	>=1980	>=1960	>=1960	>=1960	>=1960

The table reports results from the second-stage estimation (11) using predicted potential experience from the census 10 years prior as an IV. Dependent and independent variables are constructed from regression (10) in each LLM-year using an individual's full-time participation as the dependent variable. Columns (1) to (4) show IV estimates for the panel of commuting zones over 1980–2010, columns (5) to (8) for states over 1960–2010. Standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.

gradient of full-time participation and the relative participation rate of experienced workers, respectively, is now strongly negative and highly significant. That is, column one implies that a one year (5/8 of a standard deviation) increase in a local labor market's average experience leads to a .1 percent lower full-time experience gradient in that LLM (a roughly 30% decline from the average of .32 and 2/3 of a standard deviation across czones, see Table 2). A ten percentage point higher share of experienced workers (10/7 of a standard deviation) leads to a .046 lower relative full-time employment rate of experienced workers (mean .07, standard deviation .04). The effects on the state level are quantitatively smaller (compare columns (5)–(8) to Table 2), but overall these relationships are significant, economically as well as statistically.

Appendix Table 18 provides the results for the instrumental variables estimation on the LLM-year level when the individual-level choice regressions are run using a probit model instead of an LPM. The resulting parameter on potential experience constitutes the structural $p_{lt} - \gamma_{lt}$ if we are willing to assume that the error components in the potential and the reservation log wage equations (4) and (5) are normally distributed. Descriptive statistics on the panel of czones for variables that differ due to the probit choice regression are reported in Appendix Table 17. We see that the results are qualitatively the same when we use the probit model on the individual level as when we use the LPM. Quantitatively, a one standard deviation change in average potential experience also has a similar effect in terms of standard deviations of the $p_{lt} - \gamma_{lt}$ parameter as it has on the full-time gradient of experience in Table 5 (compare Appendix Table 17).[27]

Appendix Table 16 provides a further robustness check of this result.[28] In Table 16 we use a 20 year lagged instrument instead of our ten year lag in the main text. In the case of czones, this leaves our analysis with the years 1990, 2000, and 2010, because we cannot construct a 20 year IV for 1980 (no information on czones in 1960).[29] Using LLM fixed effects, this is therefore a demanding specification in columns (1) to (4) and the first-stage coefficient of the IV declines (unreported). However, the effect qualitatively persists in three out of four cases. On the state level, the effect qualitatively persists in all specifications, remaining significant at the five percent level in columns (5) and (6). Thus, while the relationship between the supply of experience and full-time participation weakens to around half its size across all specifications, Table 16 indicates that it persists with this different IV.

Table 6 provides the same instrumental variables regressions as Table 5 with relative observed wages and the return to experience as the outcome variable. Again, the relationship becomes more negative with the IV compared to the OLS, which suggests that the former is in fact able to remove variation in average experience and the outcome variable that is due changing demand for experience. That higher experience supply goes in hand with a lower return to experience is economically sensible if experienced and inexperienced workers are imperfect substitutes. The effect of experience supply on experienced workers' fulltime employment is strongly negative in all spec-

[27]The interpretation of the coefficients from the individual-level LPM and the probit regressions differ. The LPM coefficient is the average marginal effect of another year of experience on fulltime participation discussed above. The probit coefficient is the structural $p_{lt} - \gamma_{lt}$ when the error terms in the potential and the reservation log wage equations are normally distributed. The marginal effect of another year of experience on fulltime participation is not constant and would have to be examined at specific values of the individual-level covariates. The coefficients on average potential experience in regressions on the LLM-year in Tables 5 and 18 have the according different interpretations.

[28]For the main results we weight observations by the lagged (in order to prevent endogeneity) actual population size of each LLM-year according to their summed sample weights. Our results persist almost perfectly when we use only the number of underlying sample observations or when we scale all weights so that every census year gets equal overall weight. As in Jeong, Kim, and Manovskii (2015), we compute average potential experience and the share of experienced workers weighted by their observed skill proxies $\beta_{lt}x_{jlt}$ from regression (10) with wages as a dependent variable, but the results do not depend on this.

[29]We also cannot instrument for individuals aged 16–19, as they are not yet born 20 years earlier.

Table 6: Supply and Observed Relative Wages of Experienced Workers' (IV)

	(1) Rtrn x100	(2) Rtrn x100	(3) Log Rtrn	(4) Wage	(5) Rtrn x100	(6) Rtrn x100	(7) Log Rtrn	(8) Wage
Exper	-0.08***	-0.10***			-0.05**	-0.06***		
	(0.02)	(0.01)			(0.03)	(0.02)		
Yrs Educ		0.08***				0.01		
		(0.02)				(0.03)		
Log Exp			-1.28***				-0.62	
			(0.26)				(0.44)	
Sh Expd				-0.17				-0.22
				(0.12)				(0.15)
Observations	2888	2888	2888	2888	304	304	304	304
R^2	0.61	0.61	0.59	0.55	0.89	0.89	0.89	0.85
Fixed Effects	czone+year	czone+year	czone+year	czone+year	state+year	state+year	state+year	state+year
Weight	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght
Sample	>=1980	>=1980	>=1980	>=1980	>=1960	>=1960	>=1960	>=1980

The table reports results from the second-stage estimation (11) using predicted potential experience from the census 10 years prior as an IV. Dependent and independent variables are constructed from regression (10) in each LLM-year using an individual's observed wage as the dependent variable. Columns (1) to (4) show IV estimates for the panel of commuting zones over 1980–2010, columns (5) to (8) for states over 1960–2010. Standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.

ifications, though again stronger on the czone than on the state level. For example, in the first column of Table 6, a one year higher average experience (5/8 of a standard deviation, see Table 2) leads to a .08 percent lower return to experience (1/3 of a standard deviation).This is in line with a substantial general equilibrium effect of supply on the price of experience, which, given upward-sloping labor supply, translates into a strong negative effect on labor market participation of older workers.

5 Type of Responses and Effect by Skill Groups

We study the components of the full-time employment rate response by analyzing the effect on overall employment (whether part-time or full-time), labor force participation, unemployment, as well as welfare-, disability-, and social security claims. We then examine which skill groups are most affected by using education and observed wages, and by analyzing migration across LLMs.

5.1 Effect on Employment Statuses and Program Claims

In Table 7 we investigate the effect of experience supply on non-employment (neither full-time nor part-time), and split this up into being unemployed or not in the labor force. We do not estimate the log-log specification because the experience gradients for

Table 7: Effect on Experienced Unemployment and Labor Force Participation (IV)

	(1) noEmp-gr	(2) Unem-gr	(3) noLF-gr	(4) noLF-rel	(5) noEmp-gr	(6) Unem-gr	(7) noLF-gr	(8) noLF-rel
Exper	0.15***	-0.01**	0.16***		0.15***	-0.02***	0.17***	
	(0.01)	(0.00)	(0.02)		(0.03)	(0.01)	(0.03)	
Sh Expd				0.94***				1.02***
				(0.12)				(0.17)
Observations	2888	2888	2888	2888	304	304	304	304
R^2	0.53	0.53	0.56	0.39	0.78	0.79	0.81	0.83
Fixed Effects	czone+year	czone+year	czone+year	czone+year	state+year	state+year	state+year	state+year
Weight	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght
Sample	>=1980	>=1980	>=1980	>=1980	>=1960	>=1960	>=1960	>=1960

The table reports results from the second-stage estimation (11) using predicted potential experience from the census 10 years prior as an IV. The outcome variable is 100x the employment (full-time or part-time) employment gradient, unemployment, and labor force non-participation gradient of potential experience, and the relative labor force non-participation rate of the discrete group of experienced workers. Columns (1) to (4) show IV estimates for the panel of commuting zones over 1980–2010, columns (5) to (8) for states over 1960–2010. Standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.

non-employment and being unemployed are negative in most LLM-years, so the log is not defined. The effects on non-employment on both the czone and the state level are about fifty percent stronger in levels than for full-time employment on the czone level. In terms of standard deviations, they are comparable (a 1.6 years = 1 stdev increase in average experience reduces the relative employment gradient by .24 = 1.2 stdev; see Tables 2 and 13). This implies that experienced workers also substantially reduce their part-time labor supply when they become more abundant.

Splitting the estimates up into the effect on unemployment and non-participation in columns (2)–(3) and (6)–(7), shows that all of the effect is on labor force participation rather than unemployment. Unemployment of experienced workers actually slightly falls when they become abundant. This is in line with our interpretation below of lower equilibrium wage offers for experienced workers that make it worthwhile not to work, and with early retirement schemes that may attract experienced workers into non-participation.

Columns (4) and (8) of Table 7 report the effect on the relative employment rate for discrete groups of inexperienced (19 years of experience or less) and experienced (20 years of experience or more) workers. The effect on non-labor force participation for the czone is around twice as large and close to one, implying that a one percentage point increase in the share of experienced workers (i.e., 1/7 of a standard deviation) decreases their relative labor force participation by one percentage point (i.e., 1/4 of a standard deviation).

Table 8: Effect on Disability, Welfare, and Social Security Claims (IV)

	(1) Disab-gr	(2) Welf-gr	(3) SoSec-gr	(4) Migr-gr	(5) Disab-gr	(6) Welf-gr	(7) SoSec-gr	(8) Migr-gr
Exper	0.02***	0.01***	0.07***	-0.09***	0.02*	-0.01	0.07***	-0.06***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)
Observations	2888	2888	2888	2888	255	255	255	304
R^2	0.84	0.37	0.75	0.78	0.92	0.50	0.86	0.82
Fixed Effects	czone+year	czone+year	czone+year	czone+year	state+year	state+year	state+year	state+year
Weight	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght
Sample	>=1980	>=1980	>=1980	>=1980	>=1960	>=1960	>=1960	>=1960

The table reports results from the second-stage estimation (11) using predicted potential experience from the census 10 years prior as an IV. The outcome variable is 100x the disability, welfare, social security, and in-migration gradient of potential experience. Columns (1) to (4) show IV estimates for the panel of commuting zones over 1980–2010, columns (5) to (8) for states over 1960–2010. Standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.

Next, Table 8 investigates what exactly are the constituting components of these responses. Columns (1)–(3) and (5)–(7) show that relative disability-, welfare-, and especially strongly social security claims rise when experience supply increases.[30] In terms of size, a one standard deviation (1.6 years) increase in average experience raises the experience gradient of disability claims by one fourth of a standard deviation (.03), and it raises social security claims by almost a standard deviation (.1). Thus, experienced workers seem to at least partly leave the labor market via claiming retirement benefits (social security) when they can, and otherwise file for disability or outright depend on welfare.

Finally, in columns (4) and (8) of Table 8 we report the relative in-migration gradient into the respective LLM of experienced workers. The effect on this variable is in the direction that we predicted in Figure 3, that is, there is a lower inflow of experienced workers into LLMs that are relatively experience-abundant. Quantitatively, this effect is also substantial: a one standard deviation (1.6 years) increase in average experience leads to a ca 2/3 of a standard deviation (.15) lower experience gradient of in-migration.

[30] Information on disability, welfare, and social security claims are not available in 1960, which reduces the number of observations on the state level. We also harmonized somewhat different definitions of disability and migration for 2010 with the previous years. As one would expect given the US retirement rules, the share of people who report claiming social security in the data trebles to 32 percent from age 61 to 62 and then increases rapidly to 67 percent at age 65.

5.2 Effect on Participation and Migration by Skill Group

The economic model of Section 2 predicts that the response in workers' participation decision due to demographic change should be systematic in the sense that those workers with the lowest overall rent of participating should be the first to leave when their experience group becomes abundant. These rents should be determined by skills (via potential wages) and by preferences for working (via reservation wages), and different observable skill proxies may at the same time be related to the preferences for working. We explore in this section whether participation is systematic in observable skill proxies and actual wages, and find some evidence for the latter.

Table 9: Effect on Labor Force Participation by Education Groups (IV)

	(1) nLF 1	(2) nLF 2	(3) nLF 3	(4) nLF 4	(5) nLF 1	(6) nLF 2	(7) nLF 3	(8) nLF 4
Exper	0.20**	0.10**	0.15**	-0.01	0.16**	0.14***	0.19***	0.14***
	(0.10)	(0.04)	(0.06)	(0.03)	(0.07)	(0.04)	(0.05)	(0.04)
Observations	2888	2888	2888	2888	304	304	304	304
R^2	0.56	0.69	0.62	0.64	0.69	0.82	0.81	0.87
Fixed Effects	czone+year	czone+year	czone+year	czone+year	state+year	state+year	state+year	state+year
Weight	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght
Sample	>=1980	>=1980	>=1980	>=1980	>=1960	>=1960	>=1960	>=1960

The table reports results from the second-stage estimation (11) using predicted potential experience from the census 10 years prior as an IV by education group. The first and fifth column report the effect on 100 times the experience-labor force participation gradient of dropouts, the (2) and (6) on highschool graduates, (3) and (7) on individuals with some college, and (4) and (8) on four-year college degrees or more. Standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.

Table 9 reports the effect of increasing average experience in an LLM on the full-time participation gradient of experience by education groups: columns (1) and (5) are dropouts for czones and states, respectively, (2) and (6) are highschool graduates, (3) and (7) attended some college, and (4) and (8) attained a four-year college degree or more. On the czone level it appears that the effect of aging on older workers' relative participation is strongest for the least-skilled workers and non-existent for college graduates. However, on the state level such a difference of the effect by skill does not become apparent. When we construct predicted earnings quartiles from a wage regression using education groups, gender, and race dummies, we also find no clearly declining or rising effects on participation by skill (unreported).

It is theoretically not clear that lower-educated workers should be more likely at the margin of participating than higher-educated workers, even if the marginal participant is lower-skilled than labor force participants overall and higher-skilled than

Table 10: Effect on Labor Force Participation by Last Year's Earnings Groups (IV)

	(1) nLF 1	(2) nLF 2	(3) nLF 3	(4) nLF 4	(5) nLF 1	(6) nLF 2	(7) nLF 3	(8) nLF 4
Exper	0.12**	0.03	0.04***	0.01	0.16***	0.05*	-0.02	0.05***
	(0.05)	(0.03)	(0.01)	(0.01)	(0.04)	(0.03)	(0.01)	(0.01)
Observations	2888	2888	2888	2888	304	304	304	304
R^2	0.64	0.69	0.35	0.41	0.85	0.92	0.84	0.81
Fixed Effects	czone+year	czone+year	czone+year	czone+year	state+year	state+year	state+year	state+year
Weight	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght
Sample	>=1980	>=1980	>=1980	>=1980	>=1960	>=1960	>=1960	>=1960

The table reports results from the second-stage estimation (11) using predicted potential experience from the census 10 years prior as an IV by last year's earnings group. The first and fifth column report the effect on 100 times the experience-labor force participation gradient of workers who have no earnings in the previous year. Columns (2)–(4) and (6)–(8) report the effect on previous year's earnings terciles. Standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.

non-participants overall. Table 10 therefore considers workers' decision to work in the current year by earnings groups in the previous year. This is possible with the labor force participation variable in the census, because it is asked for the current year while wages are constructed from earnings and hours from the previous year. But it is not possible using our fulltime work indicator, which employs information from the current as well as the past year. This is why we focus on labor force participation instead of fulltime work in Tables 9 and 10.

We see in Table 10 that the bulk of the non-participation effect is driven by individuals who did not have any earnings in the preceding year (columns 1 and 5), while the effect on the terciles of actual earnings is much lower. If not having earned last year is a proxy for possessing less of the relevant skills, this suggests that aging effects lower-skilled workers' participation more than higher-skilled workers. More generally, the effect on participation is systematic in the sense that rather previously inactive workers become less likely to enter the labor force than previously active workers becoming inactive.[31]

Another variable where we can construct skills according to actual earnings is migration. We observe the wages of fulltime-employed workers who migrated into the current LLM during the last five years. Table 11 reports the results by earnings quartile. We see on the czone as well as on the state level, the relative in-migration of low-earnings experienced workers declines when the LLM experiences an aging shock.

[31] Accordingly, Dustmann, Schönberg, and Stuhler (2015) find that a migration shock from Eastern Europe mostly reduces previously not employed German workers' transitions into employment rather than increasing transition rates out of employment.

Table 11: Effect on In-Migration by Actual Fulltime Earnings (IV)

	(1) Migr 1	(2) Migr 2	(3) Migr 3	(4) Migr 4	(5) Migr 1	(6) Migr 2	(7) Migr 3	(8) Migr 4
Exper	-0.15***	-0.08*	-0.05	-0.04	-0.13***	-0.05	-0.03	0.07*
	(0.05)	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)
Observations	2888	2888	2888	2888	304	304	304	304
R^2	0.42	0.56	0.61	0.61	0.60	0.76	0.80	0.85
Fixed Effects	czone+year	czone+year	czone+year	czone+year	state+year	state+year	state+year	state+year
Weight	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght
Sample	>=1980	>=1980	>=1980	>=1980	>=1960	>=1960	>=1960	>=1960

The table reports results from the second-stage estimation (11) using predicted potential experience from the census 10 years prior as an IV by in-migrants' actual fulltime earnings. Columns (1)–(4) and (5)–(8) report the effect on 100 times the experience-in-migration gradient by quartile of actual fulltime earnings. Standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.

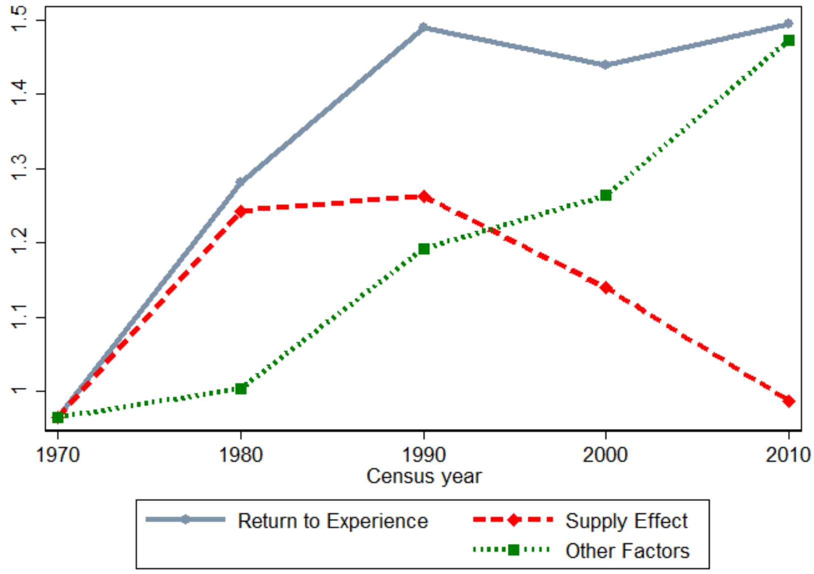
Although mostly suggestive, the evidence presented in this section is consistent with the theoretical prediction that the participation response to demographic change should be systematic, and that it may be biased toward lower-skilled workers. This may imply that the elasticity of substitutions estimated from observed wages of experienced versus inexperienced worker, even conditional on control variables, could be biased by self-selection into employment.

6 The Race between the Supply and Demand for Experience

This final section uses our estimates in order to assess the contribution of demographic change to the aggregate trends in the experience gradient of fulltime work and the wage return to experience over the last fifty years. From regression (11), the supply effect on the respective outcome is given by $\eta\left(\frac{E_{lt}}{I_{lt}}\right)$, and the demand or other effects by $D_l + D_t$. The latter may capture biases in technology towards experience, but also changing preferences and policies that affect the relative incentives to work or the relative pay of experienced individuals.

Figures 4 and 5 depict these contributions for the data and estimates from the commuting zone panel (results for the state panel are in Appendix Figures 7 and 8). The solid lines in both figures represent the evolution of the wage return to experience and the experience gradient of fulltime work from 1970 to 2010, respectively. During the first 20 years of the sample, the wage return to experience rises strongly, while the experience-participation gradient (i.e., the relative participation rate of experienced workers) declines. After that, relative participation and wages of experienced workers are approximately flat.

Figure 4: The Aggregate Wage Return to Experience (Czone Estimates, 1970–2010)

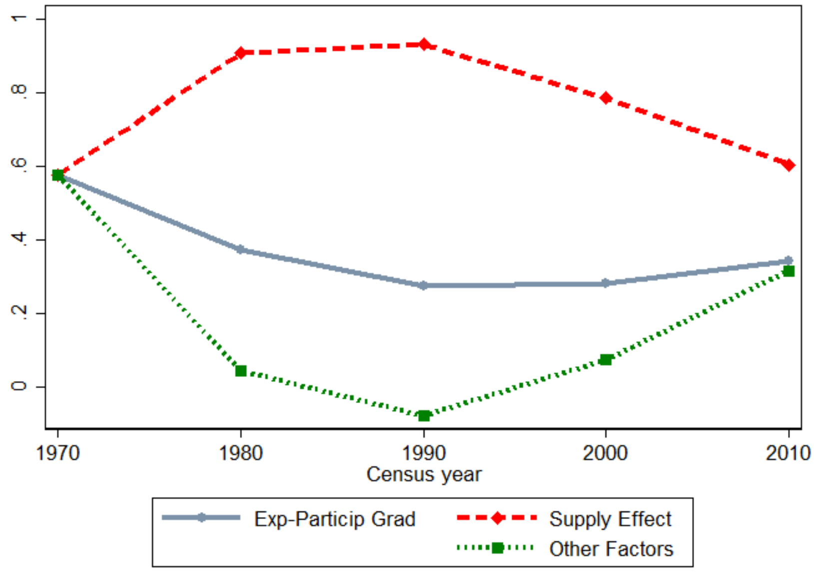


Supply effect and other factors (including demand) using the IV estimates for the panel of commuting zones (Column one of Table 6).

The first two decades in Figures 4 and 5 underline why it is difficult to evaluate the effect of demographic change on either relative wages or participation rates in aggregate data alone. That is, in a demand and supply model, experienced workers' relative wages as well as their participation rates should rise at the same time when they become more productive (demand shock) and they should fall when they become more abundant (supply shock; as we have verified above). The strongly rising wages and the falling participation rates of experienced workers during the 1970s and 1980s must therefore stem from other factors than only supply and demand. These may include early retirement and disability policies, a changing (distribution of) private wealth accumulation and preferences for working, or labor market entry of women and minorities.[32] In addition, (cyclical) changes in overall labor force participation and unem-

[32]For example, there was a falling and then a rising access to- and attractiveness of disability programs during the 1970 to 1990s as discussed in Autor and Duggan (2003). Another study by Autor, Duggan, Greenberg, and Lyle (2016) shows a large effect of disability eligibility for Vietnam era veterans in 2001. In Figure 2 above, such factors, which affect different age groups differently, constitute

Figure 5: The Aggr. Participation Gradient of Experience (Czone Estimates, 1970–2010)



Supply effect and other factors (including demand) using the IV estimates for the panel of commuting zones (Column one of Table 5).

ployment may also affect the relative shares of older and younger workers in (fulltime) employment.

Our identification strategy therefore exploits the local labor market level in order to clean the effect of aging supply from other aggregate factors (using year fixed effects D_t), local factors (using LLM fixed effects D_l), and from changes that vary across locations and time (using predicted experience as an instrument for supply). The red dashed lines in Figures 4 and 5 depict the resulting effect of aging supply on experienced workers' relative wages and fulltime participation rates.[33] The dotted green lines depict the residual, that is, all the other factors, including demand for experience, which have driven the return to- and the participation gradient of experience.

We see in both figures that the effects of experience supply on relative wages as well as on relative participation rates point in the same direction. That is, they are a force for raising both variables during the 1970s and 1980s and a force for lowering

(potentially simultaneous) shifts of the supply and demand curves for relative experience that are different from shifts that are due to demographic change.

[33]We use the results from the level-level regression equation (11) instead of the theoretically-implied log-log regressions, because the experience participation gradient is negative (and the log not defined) in a substantial number of LLM-years. The assumption for aggregating these results by simple averaging, which we maintain throughout the paper, is that production takes place on the level of the local labor market.

them during the 1990s and 2000s. This is in line with our theoretical reasoning and the demand and supply model of Section 2. Moreover, the effect is quantitatively strong in the sense that the effect of supply is varying to a similar extent as the actual change in the respective outcome variable (the grey solid line) in both diagrams.

We now focus on Figure 4. In the 1970s, as in Jeong, Kim, and Manovskii (2015), the supply effect is positive and it explains most of the rising wage return to experience during this decade. However, since 1980 the positive contribution of other factors on the price of experience has much accelerated. Most of the long-run increase in the price of experience is due to this other effect since 1980, which is in line with Katz and Murphy (1992)'s findings who interpret it as demand for experience.

It is also consistent with the recent result of Caselli (2015) who argues using time series data that technological progress has been experienced-biased. With our flexible estimation approach, we unveil that such purported experience-biased demand was particularly strong during the 1980s, when it raised the return to experience substantially. It was also particularly strong during the 2000s, otherwise the return to experience would have actually fallen in the last two sample decades because of demographic change.

In Figure 5 we see that the due to the baby boom and the entry of many young workers into the labor market, the relative participation rates of experienced workers should have risen during the 1970s and 1980s (dashed red line). However, it appears that other factors, which may include policy changes or preferences for working, have reduced the aggregate participation gradient of experience even more strongly (e.g., more lenient access to disability benefits after 1984; see Autor and Duggan, 2003).

Conversely, during the 1990s and 2000s, when they were pushed down by an aging work force, other factors held constant experienced workers' relative fulltime participation rates. Consistent with the discussion of Figure 4, these other factors may include relative demand and experience-biased technical change as well as policies that have raised the incentives to extend working lives.[34]

Overall, it seems that demographic change has had a substantial effect on aggregate

[34] Note that despite more positive trends in overall than in male fulltime participation rates, the trends in the experience gradient of fulltime participation depicted for both genders in Figure 5 is qualitatively similar for males only.

relative wages and participation rates of experienced workers when it is cleaned of other important factors that may have affected these variables on an economy-wide level. Some of these factors could in fact be a response to demographic change, such as early retirement programs in the 1970s and 1980s and their phasing out during the decades after that (e.g., Lee, 2016), or technological change on the aggregate as in Acemoglu (1998). Our estimation approach uncovers only the supply effect, but we think this is a necessary first step for understanding the interplay between all these variables.

7 Conclusion

In this paper we re-open the debate about the impact of demographic change on the labor market. Exploiting the differential aging of local labor markets in the US over the past 50 years, we estimate the effect of changes in the supply of experienced workers on the return to experience and on experienced workers' labor force participation. Our empirical strategy, using local labor market panel data and establishing causal (local) supply effects through instrumental variables, allows us to disentangle the contribution of supply from demand for experience as well as other factors that may have influenced experienced workers' relative wages and employment rates.

We find that a rise of experience supply across local labor markets (commuting zones or US states) decreases the return to experience, echoing previous literature. However, we also find that it lowers the relative employment rates of experienced workers. We further show that a rise in the supply of experiences increases experienced worker's claim rates on welfare, disability, and social security programs, and lowers their in-migration from another LLM. Moreover, we document that these effects are not uniform across education or earnings groups, but stronger for low-skilled workers. This suggests that previous estimates of the elasticity of substitution in production between experience inputs might have been attenuated by a selection bias in observed wages.

On the aggregate level, over the last five decades the return to experience was negatively affected by the rising supply of experienced workers, but also positively by rising demand, especially since 1980. This suggests that technological change has been biased towards experience skill. We therefore expect that, when the United States labor force rejuvenates from 2025 onward, the returns to experience skill will rise strongly.

Our results also have implications for the desirability of recent policies that phase out early retirement schemes or raise the retirement age in the face of demographic change. On the individual level, being pressured to work in times when they are abundant may be particularly costly to experienced workers, in terms of wages as well as of non-pecuniary job aspects.[35] Additionally participating older workers also have a negative externality on the wages of their peers. On the aggregate level, the effect on overall output is rather small when additional experienced workers crowd into a labor market that employs already many experienced workers. Therefore, in the present situation, outright cuts in retirement benefits (along with raising workers' social security contributions) may be the more attractive policy to stem the rising old-age-dependency ratio, compared to incentivizing longer working lives.[36]

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[35] We expect that experienced workers' hierarchical positions, appreciation by their bosses and coworkers, as well as employer provided benefits such as health insurance may also be adversely affected.

[36] The current influx of young migrants into countries such as Germany may also constitute an opportunity to balance the experience composition of the labor force.

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Appendix

A Additional Figures and Tables

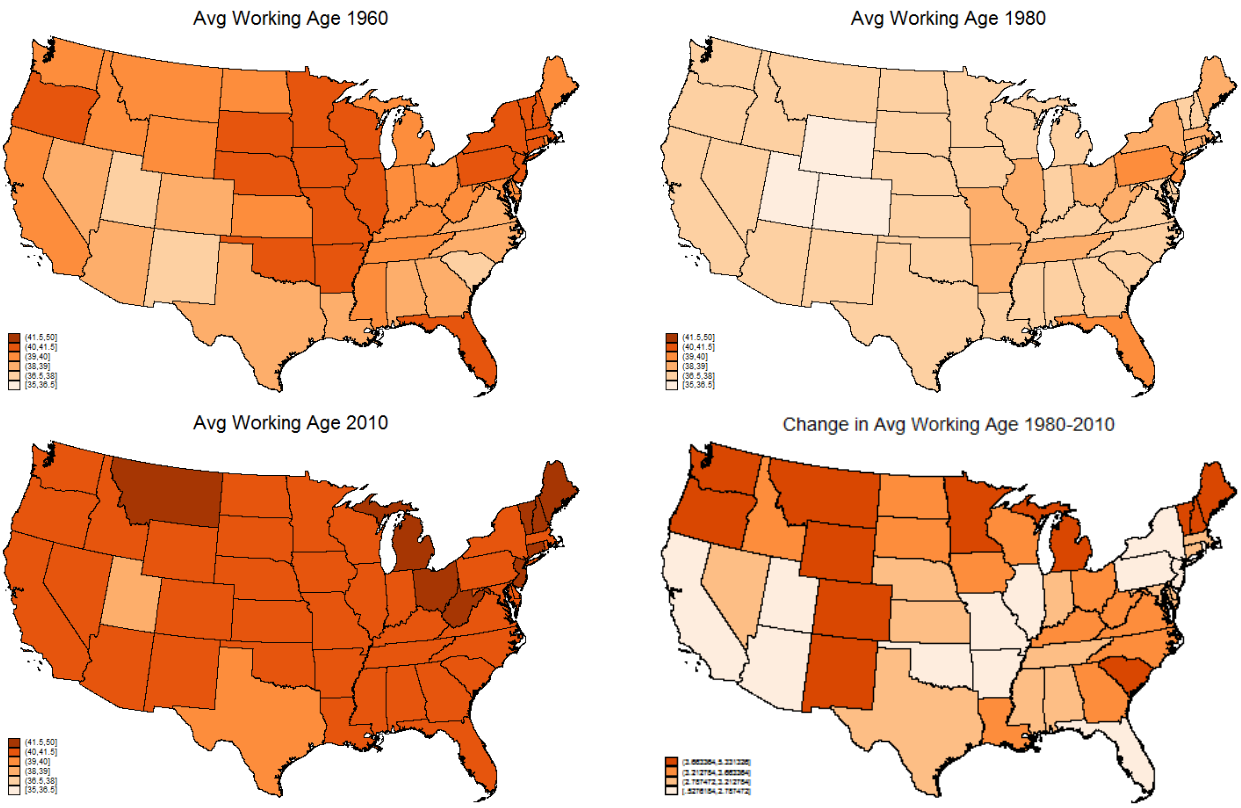
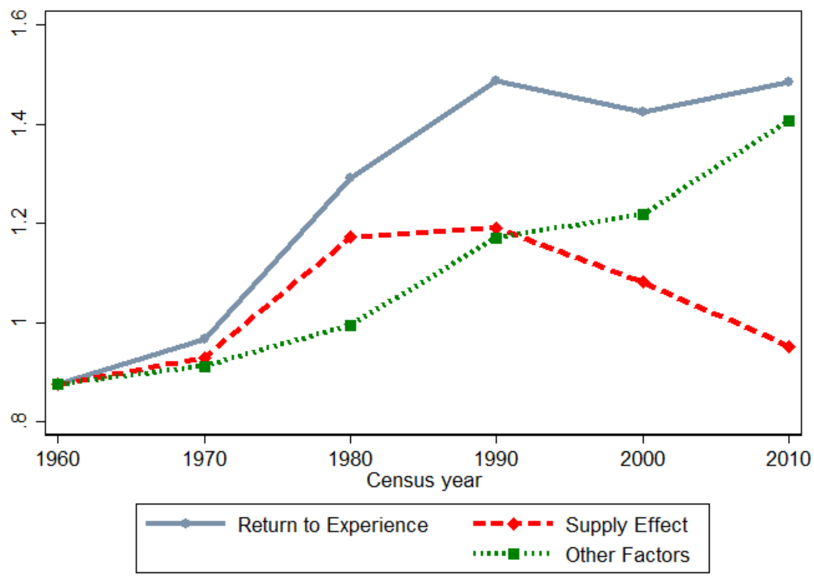


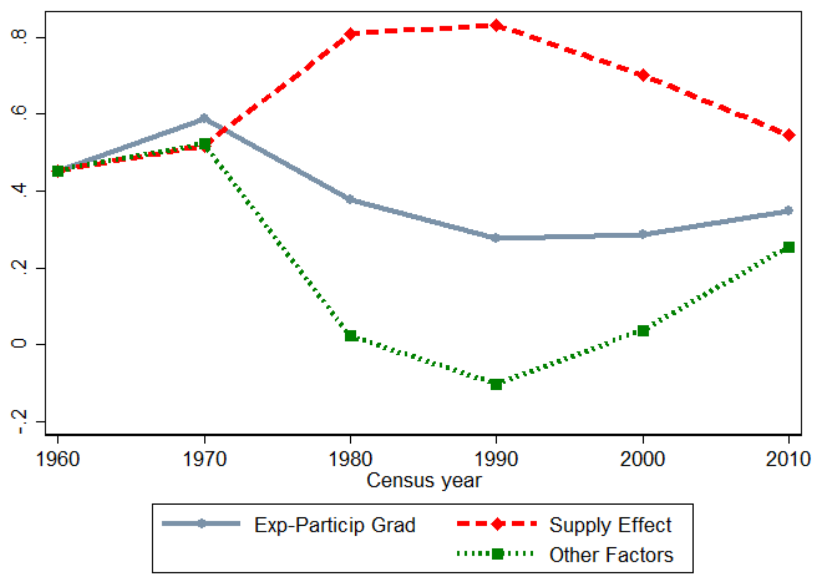
Figure 6: The distribution of average working age across US states and time

Figure 7: The Aggregate Wage Return to Experience (State Estimates, 1960–2010)



Supply effect and other factors (including demand) using the IV estimates for the panel of states zones (Column five of Table 6).

Figure 8: The Aggregate Participation Gradient of Experience (State Estimates, 1960–2010)



Supply effect and other factors (including demand) using the IV estimates for the panel of states (Column five of Table 5).

Table 12: Summary Statistics for Full-time Workers Aged 16–65

	Log(Wage)	Age	Pot Exper	Yrs Educ	Female
1980					
mean	2.16	37.7	19.3	12.3	0.37
sd	0.68	12.5	13.0	2.6	0.48
1990					
mean	2.72	38.3	19.2	12.9	0.42
sd	0.63	11.2	11.5	2.2	0.49
2000					
mean	3.06	39.9	20.6	13.1	0.43
sd	0.65	11.1	11.2	2.1	0.50
2010					
mean	3.32	42.0	22.4	13.5	0.46
sd	0.69	11.8	11.9	2.1	0.50
Total					
mean	2.86	39.6	20.5	13.0	0.42
sd	0.79	11.7	11.9	2.3	0.49
N	4438673				

Table 13: Descriptives for the Czone Panel (Additional Variables)

	NEmp x100	Unemp x100	NLF x100	Rel NLF	Disab x100	Welf x100	SocSec x100	Migr x100
1980								
mean	-0.08	-0.12	0.05	0.00	0.41	-0.01	0.46	-0.44
sd	0.17	0.04	0.17	0.04	0.09	0.03	0.09	0.21
1990								
mean	0.04	-0.13	0.17	0.02	0.38	0.00	0.50	-0.47
sd	0.18	0.04	0.17	0.04	0.08	0.04	0.10	0.20
2000								
mean	0.03	-0.13	0.16	0.01	0.21	-0.01	0.46	-0.53
sd	0.17	0.04	0.17	0.03	0.07	0.02	0.11	0.20
2010								
mean	-0.13	-0.13	-0.00	-0.01	0.39	-0.00	0.49	-0.16
sd	0.16	0.06	0.19	0.04	0.11	0.02	0.13	0.08
Total								
mean	-0.04	-0.13	0.09	0.01	0.35	-0.00	0.48	-0.38
sd	0.19	0.05	0.19	0.04	0.12	0.03	0.11	0.23
N	2888							

For each year, the table shows mean and standard deviations of the variation across LLMs for the variables named in the top row.

Table 14: Descriptives for the State Panel

	Fullt	Fgrad x100	Wage	Rtrn x100	Sh Expd	Avg Exper	Yrs Educ	Female
1960								
mean	0.11	0.45	0.18	0.88	0.58	23.1	10.7	0.27
sd	0.02	0.08	0.03	0.14	0.02	0.7	0.5	0.03
1970								
mean	0.14	0.59	0.21	0.97	0.56	22.4	11.5	0.31
sd	0.02	0.08	0.02	0.13	0.02	0.7	0.4	0.02
1980								
mean	0.09	0.38	0.27	1.29	0.44	19.3	12.5	0.38
sd	0.03	0.11	0.03	0.13	0.03	0.9	0.3	0.02
1990								
mean	0.06	0.28	0.27	1.49	0.44	19.0	13.1	0.42
sd	0.02	0.10	0.03	0.16	0.02	0.5	0.2	0.02
2000								
mean	0.06	0.29	0.26	1.42	0.52	20.4	13.2	0.43
sd	0.02	0.09	0.02	0.11	0.02	0.5	0.2	0.02
2010								
mean	0.09	0.35	0.31	1.48	0.57	22.1	13.6	0.46
sd	0.02	0.07	0.03	0.12	0.02	0.6	0.2	0.02
Total								
mean	0.09	0.37	0.26	1.30	0.52	21.0	12.6	0.39
sd	0.03	0.13	0.05	0.27	0.06	1.6	1.0	0.07
N	304							

For each year, the table shows mean and standard deviations of the variation across LLMs for the variables named in the top row. The first four columns are r_{lt} coefficients from regression (10). Column 1 shows the relative fulltime employment rate of experienced workers (minus 1), Column 2 the linear experience gradient of fulltime employment (times 100), Column 3 the relative wage of experienced workers (minus 1), and Column 4 the linear wage return to experience (times 100). Columns 5 and 6 show the two measures of the supply of experience, the share of experienced workers and the average experience, respectively. The last two columns report the average years of education and the share of females among fulltime workers.

Table 15: Supply and Observed Relative Wages of Experienced Workers' (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Rtrn x100	Rtrn x100	Log Rtrn	Wage	Rtrn x100	Rtrn x100	Log Rtrn	Wage
Exper	-0.03***	-0.02***			-0.03	-0.02		
	(0.01)	(0.01)			(0.02)	(0.02)		
Yrs Educ		0.13***				0.01		
		(0.02)				(0.03)		
Log Exp			-0.49***				-0.35	
			(0.10)				(0.29)	
Sh Expd				0.17***				0.13
				(0.03)				(0.09)
Observations	2888	2888	2888	2888	304	304	304	304
R^2	0.62	0.63	0.60	0.57	0.89	0.89	0.89	0.86
Fixed Effects	czone+year	czone+year	czone+year	czone+year	state+year	state+year	state+year	state+year
Weight	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght
Sample	>=1980	>=1980	>=1980	>=1980	>=1960	>=1960	>=1960	>=1980

The table reports results from the second-stage estimation (11) using OLS. Dependent and independent variables are constructed from regression (10) in each LLM-year using an individual's observed wage as the dependent variable. Columns (1) to (4) show OLS estimates for the panel of commuting zones over 1980–2010, columns (5) to (8) for states over 1960–2010. Standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.

Table 16: Supply and Relative Full-Time Participation of Experienced Workers' (IV, 20 years)

	(1) Fgrad x100	(2) Fgrad x100	(3) Log Fgrad	(4) Fullt	(5) Fgrad x100	(6) Fgrad x100	(7) Log Fgrad	(8) Fullt
Exper	-0.05**	-0.01			-0.05**	-0.04**		
	(0.02)	(0.02)			(0.02)	(0.02)		
Yrs Educ		-0.14***				-0.03		
		(0.02)				(0.02)		
Log Exp			-7.91***				-2.90	
			(2.44)				(2.17)	
Sh Expd				-0.25				-0.19
				(0.18)				(0.14)
Observations	2166	2166	1945	2166	302	302	301	302
R^2	0.73	0.78	0.56	0.67	0.82	0.84	0.66	0.86
Fixed Effects	czone+year	czone+year	czone+year	czone+year	state+year	state+year	state+year	state+year
Weight	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght
Sample	>=1990	>=1990	>=1990	>=1990	>=1960	>=1960	>=1960	>=1960

The table reports results from the second-stage estimation (11) using predicted potential experience from the census 20 years prior as an IV. Dependent and independent variables are constructed from regression (10) in each LLM-year using an individual's full-time participation as the dependent variable. Columns (1) to (4) show IV estimates for the panel of commuting zones over 1980–2010, columns (5) to (8) for states over 1960–2010. Standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.

Table 17: Descriptives for the Czone Panel (Probit Choice Regression)

	Fullt	Fgrad	NEmp	Unemp	NLF	Rel NLF	Disab	Welf	SocSec	Migr
1980										
mean	0.23	1.04	-0.24	-1.41	0.12	0.00	2.62	-0.10	3.30	-1.87
sd	0.10	0.40	0.49	0.40	0.52	0.13	0.37	0.45	0.50	0.64
1990										
mean	0.15	0.75	0.11	-1.40	0.52	0.08	2.44	0.01	4.51	-1.95
sd	0.10	0.43	0.52	0.41	0.54	0.12	0.35	0.46	0.62	0.68
2000										
mean	0.16	0.75	0.10	-1.51	0.50	0.05	1.07	-0.14	4.84	-2.05
sd	0.09	0.42	0.50	0.48	0.52	0.11	0.33	0.47	0.60	0.71
2010										
mean	0.23	0.95	-0.33	-0.87	0.02	-0.04	2.30	-0.02	4.96	-1.80
sd	0.08	0.35	0.45	0.41	0.57	0.12	0.33	0.50	0.62	0.77
Total										
mean	0.20	0.87	-0.09	-1.27	0.29	0.02	2.07	-0.06	4.49	-1.91
sd	0.10	0.42	0.53	0.50	0.59	0.13	0.70	0.48	0.85	0.71
N	2888									

For each year, the table shows mean and standard deviations of the variation across LLMs for the variables named in the top row. Every variable, except Fullt and Rel NLF, are multiplied by 100.

Table 18: Supply and Relative Full-Time Participation of Experienced Workers' (IV; Probit Individual Choice Regression)

	(1) Fgrad x100	(2) Fgrad x100	(3) Log Fgrad	(4) Fullt	(5) Fgrad x100	(6) Fgrad x100	(7) Log Fgrad	(8) Fullt
Exper	-0.30***	-0.19***			-0.34***	-0.28***		
	(0.04)	(0.03)			(0.08)	(0.06)		
Yrs Educ		-0.58***				-0.11*		
		(0.04)				(0.06)		
Log Exp			-9.42***				-7.72***	
			(1.25)				(2.64)	
Sh Expd				-1.26***				-1.09***
				(0.27)				(0.32)
Observations	2888	2888	2614	2888	304	304	303	304
R^2	0.49	0.65	0.35	0.50	0.78	0.80	0.61	0.86
Fixed Effects	czone+year	czone+year	czone+year	czone+year	state+year	state+year	state+year	state+year
Weight	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght
Sample	>=1980	>=1980	>=1980	>=1980	>=1960	>=1960	>=1960	>=1960

The table reports results from the second-stage estimation (11) using predicted potential experience from the census 10 years prior as an IV. Dependent and independent variables are constructed from regression (10) in each LLM-year using a probit choice regression with an individual's full-time participation as the dependent variable. Columns (1) to (4) show IV estimates for the panel of commuting zones over 1980–2010, columns (5) to (8) for states over 1960–2010. Standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.

Table 19: Effect on Experienced Unemployment and Labor Force Participation (IV; Probit Individual Choice Regression)

	(1) noEmp-gr	(2) Unem-gr	(3) noLF-gr	(4) noLF-rel	(5) noEmp-gr	(6) Unem-gr	(7) noLF-gr	(8) noLF-rel
Exper	0.45***	-0.02	0.53***		0.61***	-0.24***	0.72***	
	(0.05)	(0.04)	(0.05)		(0.12)	(0.08)	(0.14)	
Sh Expd				3.26***				4.50***
				(0.44)				(0.93)
Observations	2888	2869	2888	2888	304	304	304	304
R^2	0.50	0.64	0.51	0.36	0.75	0.76	0.78	0.80
Fixed Effects	czone+year	czone+year	czone+year	czone+year	state+year	state+year	state+year	state+year
Weight	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght	lsizewght
Sample	>=1980	>=1980	>=1980	>=1980	>=1960	>=1960	>=1960	>=1960

The table reports results from the second-stage estimation (11) using predicted potential experience from the census 10 years prior as an IV. The outcome variable is 100x the employment (full-time or part-time) employment gradient, unemployment, and labor force non-participation gradient of potential experience, and the relative labor force non-participation rate of the discrete group of experienced workers. Columns (1) to (4) show IV estimates for the panel of commuting zones over 1980–2010, columns (5) to (8) for states over 1960–2010. Standard errors in parentheses: * p<0.1, ** p<0.05, *** p<0.01.