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Keywords: Demographic Change, Employment of Experienced Workers, Return to Experience

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This paper studies the impact of demographic change on experienced workers' relative wages and employment rates. We investigate empirical predictions from a framework of supply and demand for experience skill, using variation across U.S. local labor markets (LLMs) over the last decades and instrumenting experience skill supply by the LLMs' age structures a decade earlier. We find that aging substantially reduces experienced workers' relative wages and full-time employment rates, and also their labor market participation rates. Our results imply that the effect of demographic change on labor markets might be more severe than previously recognized, as it reaches beyond wages.

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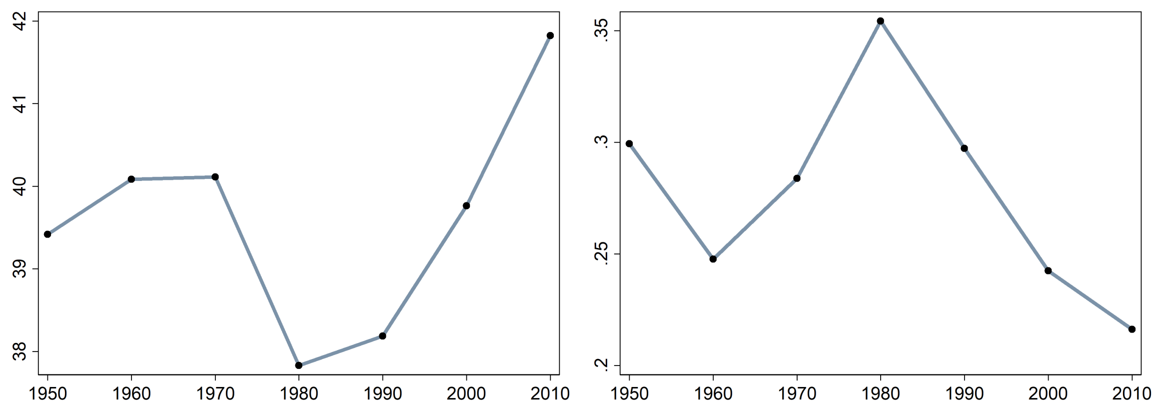
1 Introduction

Recently, many developed economies have experienced a rapid aging of their workforces. In the United States the average age of the full-time employed workers increased from around 38 in 1980 to almost 42 years in 2010, while the share of young workers age thirty and below dropped from a peak of 35.4 percent to 21.6 percent (see Figure 1). Such demographic change has substantial effects on the labor market by changing the relative supplies of young versus older (inexperienced versus experienced) workers, and thereby on their relative wages (e.g. Welch, 1979; Katz and Murphy, 1992; Jeong, Kim, and Manovskii, 2015). But, if labor supply is not completely inelastic, demographic change might also affect the fraction of experienced workers who are in employment. This would signify that the overall impact on labor market outcomes of experienced versus inexperienced individuals reaches beyond what can be seen in wages alone.

Figure 1: Workers' Age and Share of Young Workers in the U.S. (1950–2010)

(a) Average full-time workforce age

(b) Share of young full-time workers



The left panel shows the mean age of all full-time workers aged 16 to 65. The right panel shows the corresponding share of 'young', defined as age 16 to 30, among full-time workers.

In this paper we study both the effect of demographic change on relative wages as well as on relative employment rates of experienced workers. A framework of experience skill supply and demand yields empirical predictions for the impact on each of these margins, which we investigate in U.S. Census data. We find that increased experience supply not only reduces experienced workers' relative wages, but also the relative fraction of experienced individuals in employment compared to inexperienced individuals.

These results are potentially very important for evaluating the consequences of demographic change, as they highlight that (experienced) workers' participation rates should not be viewed as constants nor as following secular trends alone. Instead our findings imply that a more abundant group has a lower relative employment rate, suggesting that aging affects labor market inequality across generations.

Our second contribution is empirical. It is difficult to study the effect of demographic change on experienced workers' relative wages and especially employment rates in aggregate data, since important other variables (including technology, policy, and society) change at the same time. We therefore devise a quasi-experimental identification strategy based on the differential aging of local labor markets. We construct an instrumental variable for local experience, which exploits the largely predetermined age structure and which allows us to estimate the causal effects of experience supply.

We estimate workers' accumulation of experience skill from the average life-cycle wage profile. The relative wages of more experience-skilled workers are measured as the returns in a Mincer regression to this experience skill. We also measure the relative employment rates in a regression of individuals' (binary) employment indicator onto their experience skill. The resulting slope coefficient is the "employment gradient" of experience skill.[1] This and the wage return are obtained through a regression as it allows us to control for (otherwise potentially confounding) individual observable characteristics, such as education, race, or gender. This is the key strength of the measurement approach in Jeong, Kim, and Manovskii (2015), which we adopt.

Also as in Jeong, Kim, and Manovskii (2015), in our framework all workers supply both raw labor and experience skill (in varying amounts) and the overall supplies of experienced and raw labor inputs can be aggregated from individual-level wage equations. We apply this measurement framework to the local labor market level and additionally examine an employment decision. Consistent with Jeong, Kim, and Manovskii (2015) throughout, we control for the same observable characteristics in the estimation of the experience skill accumulation profile itself.

Unlike most previous studies of the impact of demographic change, we implement

[1] In the following we use the terms wage return to experience (in the model this will be the "price of experience skill") and relative wage of experienced workers largely interchangeably, and similarly the terms employment gradient of experience and relative employment rates of experienced workers.

our empirical analysis at the local level in order to quasi-experimentally study these supply effects. Using data from the U.S. decennial census and the American Community Survey (ACS), we define local labor markets (LLMs) as U.S. states (e.g. as in Blanchard and Katz, 1992). We then also explore a version in which LLMs are the 722 commuting zones of the contiguous United States (Autor and Dorn, 2012; Autor, Dorn, and Hanson, 2013). Our estimation sample is decennial from 1960 to 2010 for the U.S. states, whereas due to data limitations it is only from 1980 to 2010 for the commuting zones. In line with a long-standing literature in regional economics (e.g., Blanchard and Katz, 1992) and with Autor, Dorn, and coauthors we treat LLMs as sub-economies for which we can observe market equilibrium outcomes in different points in time.

The key advantage of the large-scale census data is that we can exploit the differential aging of local labor markets over the last 50 years, in order to causally identify the effect of changing relative supply of experience skill. This variation in the local age structure, and thus in the experience supply, stems from a variety of factors, such as differences in fertility and mortality rates, but also due to migration patterns. The instrumental variable strategy that we employ uses the fact that current demographic changes are largely determined by the age structure a decade earlier, and that aggregate educational attainment can be used to predict the change at the local labor market level (a shift-share IV). Hence, we can extract plausibly exogenous variation in experience skill using the predicted age structure from earlier years (adjusting for aggregate changes in education). We flexibly capture aggregate changes in labor demand (e.g. technology) that might be experience-biased (see Caselli, 2015), in policies or in other factors, by time fixed effects. Our instrument then exploits changes in local experience skill that are driven exclusively by supply while any level differences across local labor markets are absorbed by LLM fixed effects.

Our empirical framework, including the adaptation of Jeong, Kim, and Manovskii (2015) for the employment margin and to the local labor market level, prescribes a multi-step empirical approach. First, we estimate the experience skill accumulation profile. We then construct individuals' experience skill, and run for each LLM in each year individual-level wage and employment choice regressions on experience skill to identify the wage return and the employment gradient of experience. The next step of our empirical analysis relates these relative wages and employment rates in the panel of LLMs to the relative experienced labor inputs, computed as the local market's average experience skill. Since changes in relative experience skill may be driven by demand as well as supply across LLMs, we instrument it using the predicted age structure (adjusted by aggregate changes in education) of the LLM from ten years earlier. This IV approach also accounts for measurement error in LLM-year-level relative experience skill that is due to sampling variation.

Our estimated experience skill is a function of individuals' years of age post education and as such it is a measure of "life skills". We allow these life skills to accumulate non-linearly (or flexibly) over the life-cycle. That the accumulation profile turns out to be concave over the life-cycle is plausible, and it implies that in particular the number of young versus middle-aged or old workers matters for the overall relative supply of experience skill in a market. Therefore, demographic change of the workforce is very important for the relative scarcity of experience skill compared to raw labor. While we adopt important aspects of the measurement approach of Jeong, Kim, and Manovskii (2015), we have a notion of life experience skill and a focus on aging of local labor markets, and as such study a different phenomenon.

We estimate the effect of demographic change on relative wages and on relative employment rates of experienced workers separately. We do this to identify our novel employment margin independent of any particular wage change estimates, assumptions about labor supply elasticities or in fact a particular economic framework. For example, not all employment changes need be due to wage changes but in addition may occur (or be reinforced) through further mechanisms, such as peer (age-group) effects on labor market participation. While we pay special attention to correct measurement of wage returns (i.e. by using the Jeong, Kim, and Manovskii approach and focusing on a wage sample of only full-time workers), it remains cleanest to directly relate experience-skilled workers' employment responses to their relative supply in the market (where our IV strategy also alleviates potential measurement error biases).

Our estimates at the state level imply that when the relative experience skill in a local market increases by one log point it reduces the wage return by 4.12 log points. We illustrate how this compresses the life-cycle wage profile. For instance, starting at the mean return, this lowers the cross-sectional wage difference between workers with twenty-five years of potential experience compared to workers with zero years from

130% to 122%. At the same time, a market's relative experience skill supply impacts the relative labor force participation and full-time employment rates of more experienced workers. For instance, while on average the full-time gradient in experience skill is 4%, a one log point increase in relative experience supply decreases it by 0.22 percentage points, i.e., by 5.6% relative to the mean. These effects are statistically significant, robust to alternative specifications, and in line with our supply and demand framework. The effects on the full-time employment and labor force participation gradients are a new empirical finding and potentially important, as discussed above.

Our paper contributes to a literature studying the effect of demographic change on labor market outcomes. While Shimer (2001) analyzes age-specific unemployment rates, this literature typically focuses on (relative) wages, such as Katz and Murphy (1992), Card and Lemieux (2001), Jeong, Kim, and Manovskii (2015), and Caselli (2015), but also early works by Welch (1979) and Freeman (1979) which analyzed the effects of cohort size.[2] In line with these papers, we find that rising relative experience supply leads to falling relative wages of experience-skilled individuals. But we newly establish that it at the same time reduces the relative employment and labor force participation rates of this group. We also use a quasi-experimental identification strategy based on local labor markets in order to disentangle experience supply effects from demand or other potential confounders. Unlike most of the literature, which allocates workers based on their experience into discrete groups, we follow Jeong, Kim, and Manovskii (2015) and treat workers' supply of experience skill as continuous.[3] As mentioned above, the key advantage of this approach is that it can account for other productive characteristics that might vary with experience skill (see Section 3.2).

The paper continues as follows. The next section presents our supply and demand framework and develops implications of demographic change for relative wages and employment rates. Section 3 discusses the data and explains the empirical strategy

[2]More broadly, we contribute to a growing literature that documents the importance of demographic change. For example, a number of recent papers emphasize the effect of aging on slowing firm dynamics and the U.S. start-up deficit (Bornstein, 2019; Engbom, 2019; Hopenhayn, Neira, and Singhania, 2018; Karahan, Pugsley, and Şahin, 2019; Peters and Walsh, 2019).

[3]Had we grouped workers based on their experience into N discrete groups, we would need to analyze $N(N-1)/2$ relative wages and relative employment rates, as opposed to one experience price and one gradient per LLM-year. The Jeong, Kim, and Manovskii (2015) setup also improves statistical power compared to grouping workers into discrete experience bins, as it uses the full variation of experience in the individual-level wage and choice regressions as explained below.

in detail. Section 4 presents the main estimation results for relative employment and wages as well as important robustness checks and results for additional employment-related outcomes. The final section concludes.

2 A Supply and Demand Framework

Following Jeong, Kim, and Manovskii (2015), 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 relative efficiency of experience (due to experience-augmenting technology), 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:

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

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 supply of experience relative to inexperienced labor. The relationship between the price of experience and the relative supply is linear in logs

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

We follow Jeong, Kim, and Manovskii (2015) further in assuming that each worker supplies both raw labor and their experience skills in the market. A worker's total wage is thus composed of the pay for both of these inputs. Due to (2), it can be described as a function of the return on their raw labor, the experience price, and the amount of their experience skill. We assume that individuals accumulate experience skill once they completed their education, and allow for this skill accumulation to have non-constant returns. As we describe in more detail in section 3.2, we will in our empirical analysis specify a polynomial in potential experience whose coefficients we estimate against log wages. In our framework, individuals accumulate a 'life experience' skill as it is a function of individuals' years of age post education only. When this skill profile is multiplied with the experience price it traces out the profile of log wages against potential experience (whereas the raw labor return is reflected in the profile's intercept). The experience price p therefore captures how this skill is valued in the market. According to equation (3), it depends negatively on the amount of experience skill supplied relative to inexperienced labor, $\frac{E}{I}$. When assuming that all workers supply one unit of raw labor, thus contributing to the I input, but vary in their contribution to the E input to production, $\frac{E}{I}$ reflects the amount of experience skill per worker.

The experience price is determined in the market by supply and demand. Above we described already the demand from the firm side of the economy. The relative supply of the experience skill of employed workers is given by

$$\frac{E}{I} = \frac{\sum_j e_j z_j f_j}{\sum_j z_j f_j}, \tag{4}$$

where f_j is an indicator for individual j being employed, e_j the amount of experience skill they posses, and z_j are some individual-level weights such that more productive workers simultaneously contribute more to the market's E and I inputs.[4]

To illustrate the equilibrium effects of demographic change, we work with a simpler formulation with $z_j = 1$ such that $\frac{E}{I}$ is the simple average of experience. In this case the equilibrium relative supply of experience skill is the average experience skill weighted by experience-specific employment rates $\overline{R}(e, p)$. These employment rates in general might vary with the amount of experiences skill e a group of workers has and

[4] Jeong, Kim, and Manovskii (2015) show that in their framework, where a worker's wage is the sum of remuneration for their raw labor and their experience, aggregating from the micro data to the macro level is consistent when weighting both labor inputs by the effects of other productive characteristics.

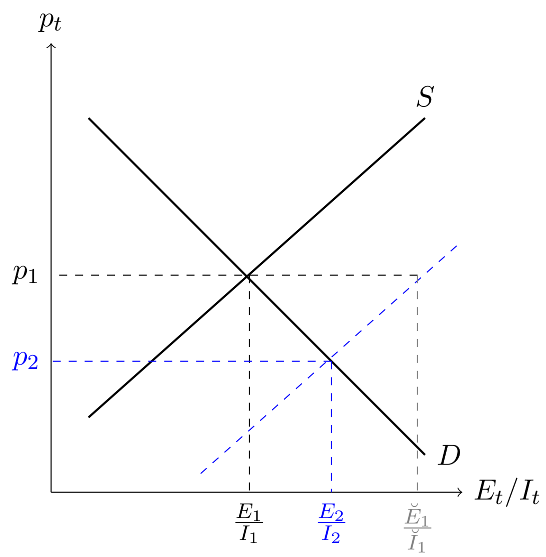
with the experience skill price p. The relative experience supply can be written as

$$\frac{E(p)}{I(p)} = \frac{\sum_e n(e)e\overline{R}(e,p)}{\sum_e n(e)\overline{R}(e,p)} \tag{5}$$

where $n(e)$ is the number of individuals with e units of experience skill and we sum over all possible values of e.

Potential supply, the supply if everyone participated, is given by $\frac{\breve{E}}{\breve{I}} = \frac{\sum_e n(e)e}{\sum_e n(e)}$. Demographic changes are shifts in the relative group sizes of individuals with different units of experience skills. These changes in potential supply have in equilibrium effects on the experience price and supply. When due to aging the supply of experience increases, the supply curve shifts out, as illustrated in Figure 2. Assuming that the relative supply is upward sloping, this leads in equilibrium to a lower experience price and a reduction in the relative employment rate of experienced individuals, which is a leftward movement along the shifted supply curve.

Figure 2: A shift of the relative labor supply curve of experience skill



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 $\frac{\breve{E}_1}{\breve{I}_1}$ to $\frac{E_2}{I_2}$), reflecting a reduction in the relative employment rate of more experienced workers.

To see the shift of the supply curve due to demographic change formally, define the actual relative experience skill supply at price p as $S(p) = \frac{E(p)}{I(p)} = \frac{\sum_e n(e)e\overline{R}(e,p)}{\sum_e n(e)\overline{R}(e,p)}$ and log-linearize allowing for changes in $n(e)$, the number of individuals supplying e units of experience. Holding the price, and thus the employment rates for each group of individuals, constant, $\widehat{S} = \Delta \ln(S)$, (roughly) the percentage change in relative supply, is given by

$$\widehat{S} = \sum_e \underbrace{\left(\frac{n(e)e\overline{R}(e,p)}{E} - \frac{n(e)\overline{R}(e,p)}{I} \right)}_{\Omega(e)} \widehat{n(e)}$$

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

Defining $\Omega(e) = \frac{n(e)e\overline{R}(e,p)}{E} - \frac{n(e)\overline{R}(e,p)}{I}$ (which intuitively captures how experienced workers with e units are relative to the market's average experience skill), it is straightforward to see that an increase of the number of workers with $\check{e}$ experience skills leads to a larger experience skill supply at a given price if $\Omega(\check{e}) > 0$, which occurs when $\check{e} > \frac{E}{I}$. Hence, when the share of workers with experience skills above the current average increases (which implies that average experience skill rises), the supply curve shifts to the right. Conversely, when the share of workers with less than average experiences increases, the supply curve shifts to the left.

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

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

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

Log-linearizing of the relative supply (5) allowing for changes in the sizes of demographic groups as well as in the experience price gives

$$\widehat{S} = \underbrace{\sum_e \Omega(e)\widehat{n(e)}}_{\text{potential rel supply change}} + \underbrace{\sum_e \Omega(e) \frac{p}{\overline{R}(e,p)} \frac{\partial \overline{R}(e,p)}{\partial p} \widehat{p}}_{\text{rel employment rate change}}.$$

The first term captures by how much supply changes due to demographic change at a constant price, which is a *shift* in the supply curve. The second term reflects that induced price adjustments affect employment and thereby the quantity supplied as movements *along* the supply curve. Under the assumption of $\sum_e \Omega(e) \frac{p}{\overline{R}(e,p)} \frac{\partial \overline{R}(e,p)}{\partial p} > 0$, the relative supply of experience is upward sloping in p. This could reflect that more experienced workers respond more strongly in their participation decision to changes in the experience price, which is one of the outcomes studied in our empirical analysis.

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 $\sum_e \Omega(e)\widehat{n(e)} > 0$, the market clearing price falls, as

$$\widehat{p} = -\frac{\sum_e \Omega(e)\widehat{n(e)}}{\varepsilon + \sum_e \Omega(e) \frac{p}{\overline{R}(e,p)} \frac{\partial \overline{R}(e,p)}{\partial p}} < 0 \tag{6}$$

and the equilibrium supply change is

$$\widehat{S} = \frac{\varepsilon \ \sum_e \Omega(e)\widehat{n(e)}}{\varepsilon + \sum_e \Omega(e) \frac{p}{\overline{R}(e,p)} \frac{\partial \overline{R}(e,p)}{\partial p}}, \tag{7}$$

which is $0 < \widehat{S} < \sum_e \Omega(e)\widehat{n(e)}$. This means that following an increase in potential supply due to aging of the workforce (in Figure 2 the rightward shift in the supply curve), actual supply increases in equilibrium (from $\frac{E_1}{I_1}$ to $\frac{E_2}{I_2}$), but by less than potential supply since the relative employment rate of more experienced workers falls. This change in relative employment rates is the leftward movement along the new supply curve that occurs as the experience price declines (illustrated in the figure as the change from $\frac{\check{E}_1}{\check{I}_1}$ to $\frac{E_2}{I_2}$ as p_1 decreases to p_2)

The equilibrium effects of demographic change are summarized as follows. Assuming an upward sloping supply curve for relative experience, higher potential supply in equilibrium (i) decreases the experience price, which (ii) lowers the relative employment rate of experienced workers, and thus (iii) increases actual supply by less than one to one.

3 Data and Empirical Strategy

This section describes how we apply the model in the previous section to local labor markets (LLMs). Our starting point is to assume that workers' employment decisions and production occur at the LLM level. We are applying the framework of the previous section to the local level, allowing for differences in technologies across locations, both in terms of neutral technology A and experience-biased technology δ. Such technology differences in the production function (1) could for instance reflect that the various local economies produce different goods or use different intermediate inputs. In a further application we also explore implications for worker migration across LLMs.

3.1 Micro-Level Data

We use data from the U.S. Census of 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).[5] These data are large scale and thereby allow a good representation of individuals in all LLM-years. This is critical for our empirical analysis based on local labor markets.

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 schooling in order to compute the number of years of potential labor market experience.[6] 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. Following 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.

Earnings in the Census are reported for the previous year and in the ACS for the period of the past 12 months. To construct hourly wages, information on hours worked over the same period is needed. However, the availability of hours data differs across census years. In particular, prior to 1980 there is no information on usual hours worked per week, while hours and weeks worked last year are only available as intervals. Similar to Katz and Murphy (1992) or Katz and Autor (1999), we therefore restrict attention to wages of only full-time workers. For these workers we compute an hourly equiv-

[5] For the 1950 and 1960 census this is the 1% sample, for the 1980, 1990 and 2000 census the 5% sample, and for the 2010 ACS the 1% sample. For the 1970 census we use the two state samples in our analysis at the state level and the two 1% metro samples for the commuting zone analysis. We checked the robustness of our results to the Great Recession using the 2007 ACS instead of the 2010 ACS.

[6] 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.

alent wage by dividing their full salary income last year by 35 hours and 40 weeks.[7] The advantage of this calculation of wages is that it is relatively precise, as it includes only rather similar (full-time) workers and does not introduce noise from additional assumptions about hours and weeks worked. Accordingly we define an indicator variable for full-time full-year employment (in non-farm, non-military occupations) in the previous year, based on whether respondents worked at least 40 weeks, 35 hours per week and had a positive labor income. In our main empirical analysis of Section 4.1 we study how wages, full-time employment as defined here, and labor force participation are affected by demographic change. Note, given the definitions in the census, wages and the full-time indicator refer to the previous year, whereas the labor force status is based on a variable on employment status that refers to the point in time when the respondent completes the questionnaire.

Table E.1 in the Appendix lists summary statistics for the sample of individuals aged 16–65 that are in our regression sample. The top panel shows the population and the bottom panel full-time workers only. We do include females in our analysis, as their experience supply matters for the equilibrium effect that we are after, but our main results are robust to excluding females or to also including part-time workers in our measure of experience supply (see Section 4.2.2).

The 1950 census data are not used for our wage and choice regressions, but they are used to construct our instrument for relative supply of experience skill.[8] This is based on predicting the current age structure of a given local labor market using the censuses ten years earlier. We cannot use the 1960 or 1970 census for the outcome regressions either when we do our analysis on the commuting zone (czone) 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).[9]

[7] Since usual hours last year is not available prior to the 1980 Census, in earlier years we use an interval of hours worked last week as a proxy. In the 1960 and 1970 Census we also do not know the exact number of weeks worked last year but only an interval. We deem individuals to work full-time if their hours worked were at least in the 35–39 hours bracket and their weeks worked in the 40–47 weeks bracket or higher.

[8] 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.

[9] Several county groups (censuses 1970 and 1980) and public use microdata areas (1990, 2000, and 2010) belong to multiple commuting zones. We use weights ('afactor') available on David Dorn's website to probabilistically assign every individual in those geographic units to the respective czones.

Hence, our czone analysis begins in 1980; just when the baby boom cohorts start entering the labor market and pushing down the workforce age. The state analysis begins two decades earlier than that, at a time when the average workforce age was still rising. Appendix Table E.1 shows there are more than ten million individual observations underlying the state level analysis (and more than 4.3 million full-time workers).[10]

3.2 Empirical Strategy

The framework of Section 2 under the assumption of upward sloping relative experience supply leads to three empirical predictions that we can examine in the data (now in the order that they will be tested):

Empirical Prediction 1. *Demographic change that raises the potential supply of relative experience increases the actually observed supply, but under-proportionally.*

Empirical Prediction 2. *Higher relative experience supply lowers the relative employment rate of experienced workers.*

Empirical Prediction 3. *Higher relative experience supply lowers the wage return to experience.*

Since these are predictions about market equilibrium outcomes, we use an empirical setup where one can arguably observe sufficiently many such equilibria as well as account for confounding factors. In particular, we examine Predictions 1–3 in LLMs in the U.S. at a frequency of one decade. We use year and LLM fixed effects in order to control for aggregate differences across time and time-invariant differences across locations in the employment gradients and the wage returns to experience. We further use an IV strategy based on predicting current relative experience skill from earlier age structure to isolate the relevant changes in local experience supply.

Our empirical analysis consists of multiple steps. In a first step we obtain the experience skill accumulation profile through averaging estimates from Mincer wage regressions by local labor market and year that control for other productive characteristics. This profile captures how individuals accumulate experience throughout their

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

lives and this skill accumulation is a law of nature that is invariant across markets, time and space in our application. As we do not use actual but potential experience, different to Jeong, Kim, and Manovskii (2015), in our context this is the accumulation of a 'life' experience skill based on years of age post education. Equipped with this experience skill profile, we then run individual-level employment choice and Mincer wage regressions from which we obtain employment gradients in experience and experience skill prices, again by LLM-year and as in Jeong, Kim, and Manovskii (2015) controlling for observable characteristics. This gives us a local labor market panel where we can study the effects of changes in the relative supply of experience skill on the experience price and the employment gradient, using instrumental variables that we construct in a final step.[11] Throughout we cluster standard errors on state to account for serial correlation within LLMs as well as for spatial correlation across czones within states. To take account of the multi-step estimation procedure, we have also bootstrapped the estimation of the skill accumulation profile, individual-level regressions, and IV second-stage steps together, again clustering standard errors at the state level.[12] This tended to result in slightly lower standard errors. We like to err on the conservative side and therefore report the analytical standard errors in the paper.

In the following we explain in detail our empirical strategy.

3.2.1 Identification of experience skill

Our identification for workers' experience skills takes into account that these may be concave over the life cycle and that prices for experience skills, which may stretch or condense measured life-cycle wage profiles, vary across markets. We therefore first run in each state and year a Mincer wage regression for full-time workers on a polynomial of order K in potential experience (potexp) and further controls (x):

$$\ln w_{jlt} = \sum_{k=1}^{K} \beta_{klt} \mathrm{potexp}_j^k + x_j \gamma_{lt} + \mathrm{error}_{jlt} \tag{8}$$

[11]We use this multi-step approach because of its transparency as well as computational reasons. We need to know the experience skill accumulation profile not only in order to run the individual-level employment choice and wage regressions, but also to construct the experience supply and its instrument in each market.

[12]We used 199 replications. Since the czones use the accumulation profile from the state level, this step was left out from the czone bootstrap iterations.

where j is the worker in local labor market l in year t. In practice, we set $K = 4$, following the recommendation in Lemieux (2006)'s review article who finds that a fourth order polynomial fits the life-cycle component in the Mincer equation well. As Lemieux (2006) further recommends a quadratic in schooling we include this in x (we also interact it with a college dummy to fully capture returns to years of education for college and non-college workers), besides male and black indicator variables, following Jeong, Kim, and Manovskii (2015). This flexible specification provides a good fit to the (conditional) life-cycle earnings profiles, which we verify below.

The estimated coefficients $\beta_{1lt}, \beta_{2lt}, \beta_{3lt}, \beta_{4lt}$ of regressions (8) describe the product of the market-level price per unit of experience skill and the coefficients of the underlying experience skill accumulation. Normalizing the linear coefficient of experience skill accumulation to one, we back out the higher order skill accumulation coefficients terms from the ratios of estimated coefficients relative to the linear coefficient. That is, we assume that wages and the accumulation of experience skill are described by

$$\begin{aligned} \ln w_{jlt} &= p_{lt} e_j + x_j \gamma_{lt} + \text{error}_{jlt} \\ e_j &= \lambda_1 \text{potexp}_j + \lambda_2 \text{potexp}_j^2 + \lambda_3 \text{potexp}_j^3 + \lambda_4 \text{potexp}_j^4 \end{aligned} \tag{9}$$

Under standard assumptions, the least squares coefficient from regression (8) converge to $\hat{\beta}_{klt} \xrightarrow{p} p_{lt}\lambda_k$ as the number of observations n_{lt} in the lt-th market go to infinity. From this, their ratio is also a consistent estimate of $\frac{\hat{\beta}_{2lt}}{\hat{\beta}_{1lt}} \xrightarrow{p} \frac{\lambda_2}{\lambda_1}$. Averaging over all markets we get $\frac{1}{N_{lt}} \sum_{lt}^{N_{lt}} \frac{\hat{\beta}_{klt}}{\hat{\beta}_{1lt}} \xrightarrow{p} \frac{\lambda_k}{\lambda_1}$, which follows directly under the assumption that the number of markets N_{lt} is bounded (and can also be shown under additional assumptions for the case that $N_{lt} \to \infty$).[13]

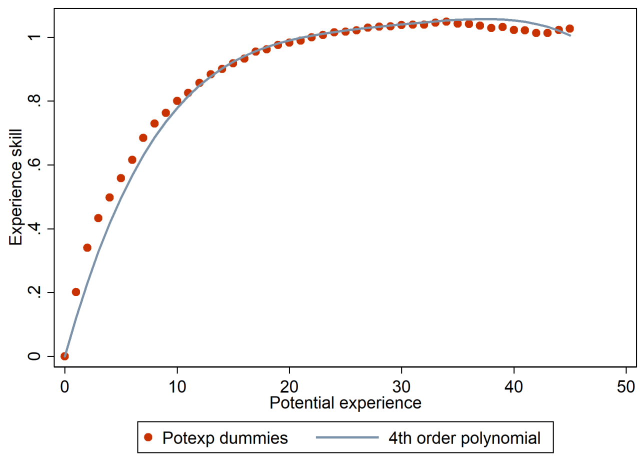
From regression (8) we can therefore consistently estimate the concavity of life-cycle profiles to construct a normalized experience skill

$$\tilde{e_j} = \text{potexp}_j + \frac{\lambda_2}{\lambda_1}\text{potexp}_j^2 + \frac{\lambda_3}{\lambda_1}\text{potexp}_j^3 + \frac{\lambda_4}{\lambda_1}\text{potexp}_j^4. \tag{10}$$

[13] In our empirical estimation we weight (9) by the underlying number of observations ($weight_j = \frac{n_j}{\sum_{j \in J} n_j}$), since in larger markets the β_{klt} and thus relative λ_k parameters are estimated more precisely, but the results are essentially the same when not weighting. This is because the λ-profiles are very similar across markets, consistent with our invariant specification of experience skill e_j in (9) and the Jeong, Kim, and Manovskii (2015) model more generally.

This $\tilde{e_j}$ is a normalized version of e_j from Equation (9) that is sufficient for our purposes. It can be used to correctly estimate prices $\tilde{p}_{lt} = p_{lt}\lambda_1$ in regression (12) below up to the constant scaling factor λ_1. That is, the relative prices between any two markets $\frac{\tilde{p}_{lt}}{\tilde{p}_{l't'}} = \frac{p_{lt}}{p_{l't'}}$ are correctly identified. The same holds for relative employment gradients in regression (11) below, where $\tilde{g}_{lt} = g_{lt}\lambda_1$ when using the normalized experience skill $\tilde{e_j}$ as a regressor. The scaling factor in $\tilde{e_j}$ affects only the units of measurement. In specifications with experience skill in logs –our main estimation in the LLM-year panel, see (13) below– it only affects the regression intercept. In level-specifications –as in micro-data regressions (11) and (12)– it rescales the slope coefficient of $\tilde{e_j}$ but leaves the size of normalized effects (the fraction of outcome variation explained by one standard deviation of $\tilde{e_j}$) unaffected.

Figure 3: Estimated experience skill profile, non-parametric and 4th order polynomial



Notes: The solid blue line represents the estimated curvature of the experience skill profile using the fourth order polynomial in (9). The red dots depict the nonparametric skill profile using potential experience dummies as described in the text. For this figure both profiles are normalized to one at $\text{potexp} = 22$.
Sample: State panel over 1960–2010.

We implement this procedure using states as local labor markets and using data from 1960–2010. We use the same profile when studying outcomes at the commuting zone level.[14] Figure 3 shows the resulting normalized experience-skill profile. It is

[14]We use the same estimated experience skill profile for multiple reasons. First, we think of this life experience skill accumulation as a law of nature that is invariant across time and space. Second, using the very same coefficients eases comparison of results across the state and czone panels, as it ensures that the profiles are based on the same normalization, i.e. that experience skill is measured in the same units. Third, estimating at the czone level is somewhat more noisy as in some czone-year cells there are very few observations for certain specific potential experience values. Reassuringly, results were the same when we instead estimated separate profiles for czones.

mostly increasing in potential experience potexp, but indeed (very) concave. This is depicted in the solid gray-blue line. To illustrate the goodness of fit of the 4th order polynomial, we compare this profile to a non-parametric version of regression equation (8) with flexible dummies for every level of potential experience, which are integers running from 0 to 45 years in our data: $\ln w_{jlt} = \sum_{k=0}^{45} \beta_{klt}^{np} \mathbb{1}\left[\mathrm{potexp}_j = k\right] + x_j \gamma_{lt} + \mathrm{error}_{jlt}$. This is depicted as the red dots in Figure 3. Notice that due to the normalization (10) one cannot interpret the level of either of these profiles (any linear transformation of $\widetilde{e}_j$ is equivalent for our purposes, as explained above). In the figure we have in fact re-scaled $\widetilde{e}_j$ to make it comparable to the non-parametric profile, which itself is normalized to exactly one at $\mathrm{potexp} = 22$.[15]

What we instead need to focus on in Figure 3 is the curvature of the skill profiles. In general both profiles are very concave and very similar. This is consistent with Lemieux (2006)'s recommendation for using the 4th order polynomial. If there is any difference, then that the nonparametric profile is even more curved in the sense that it is slightly steeper in the early years and accordingly flatter in the later years. The difference is however small and there are several advantages of the 4th order polynomial over the nonparametric specification,[16] which is why we employ specification (9) for our baseline experience skill estimation. We show below (i.e. Table E.2) that all our main results are the same when using the nonparametric experience skill profile.

3.2.2 Measurement of prices and employment gradients of experience skill

Given the experience skill $\widetilde{e}_j$ constructed from (10), we run individual-level employment choice and Mincer wage regressions *within* each LLM-year of the form:

$$f_{jlt} = \alpha_{lt}^g + \tilde{g}_{lt} \widehat{\widetilde{e}_{jlt}} + \beta_{lt}^g x_{jlt} + u_{jlt}^g \tag{11}$$

[15]We first estimate the nonparametric profile separately by market as in regression (8). Parallel to equation (10), we then divide all $\hat{\beta}_{klt}^{np}$ by the $\hat{\beta}_{22lt}^{np}$ coefficient in the middle of the potential experience range to cancel out the experience price (using other ks for the normalization yields very similar results). We obtain our final estimate by averaging $\frac{1}{N_{lt}} \sum_{lt}^{N_{lt}} \frac{\hat{\beta}_{klt}^{np}}{\hat{\beta}_{22lt}^{np}} \xrightarrow{p} \frac{\lambda_k^{np}}{\lambda_{22}^{np}}$ for all k.

[16]The polynomial is a parametric way of estimating the skill accumulation and as such utilizes information of all observations to fit the overall profile. In contrast, the nonparametric approach fits each point separately only based on workers with that amount of potential experience. The polynomial is relatively smooth by construction since a continuous function is fitted, and only 3 instead of 44 relative λ-parameters need to be estimated. Using the polynomial is also consistent with a long literature using Mincer regressions (referenced e.g. in Lemieux, 2006).

$$\ln(w_{jlt}) = \alpha^p_{lt} + \tilde{p}_{lt}\widehat{\widetilde{e_{jlt}}} + \beta^p_{lt} x_{jlt} + u^p_{jlt}, \tag{12}$$

where l again indexes the local labor market and t time, f_{jlt} is an indicator for being employed full-time or alternatively in the labor force, and a full-time employee's wage is w_{jlt}.[17] This specification of the wage function (12) is a simplification and approximation of the setup of Jeong, Kim, and Manovskii (2015).[18] The employment choice as a function of experience skill can be derived from a standard reservation wage model of labor supply, which we describe in Appendix A. We implement equation (11) with a linear probability regression. Note that these choice and wage regressions relate to Empirical Predictions 2 and 3, respectively.

The main regressor of interest is $\widehat{\widetilde{e_{jlt}}}$ that we construct according to (10) based on the estimates of regression (8) as described above. In line with the key strength of the framework developed by Jeong, Kim, and Manovskii (2015), we include x_{jlt} to control for other factors (non-experience skills or in (11) preferences for working) that differ by experience and may influence employment or wages to obtain these relationships cleaned of observable confounders. The controls we include are the same as in the estimation of the experience skill accumulation profile (8). u^g_{jlt} and u^p_{jlt} are the regression errors, that is, the individual-specific deviations from their conditional means.

We interpret the coefficients $\tilde{g}_{lt}$ as the experience-employment gradients and $\tilde{p}_{lt}$ as the wage returns to experience skill that prevail in LLM l in time t. The $\tilde{g}_{lt}$-gradients capture by how much the full-time employment and the labor force participation (LFP) rates vary with experience. In particular they describe by how much an individual's probability of employment rises with an extra unit of experience skill. The returns to experience captures by how much log wages change with experience skill.

To note is that we estimate the wage returns to experience skill in (12) as well as the experience skill accumulation (8) in the subsample of full-time workers only. We

[17]We now make the l, t subscripts also on $\widetilde{e_{jlt}}$ and $\widetilde{x_{jlt}}$ explicit, whereas before we had not written those out in order to ease notation.

[18]There, workers supply both raw labor, earning w^I, and experience labor, earning w^E per unit. This implies

$$\ln(w_j) = \ln(1 + p\, e_j) + \ln(w^I) + \beta_1 x_j + u_j$$

with $p = \frac{w^E}{w^I}$ and raw labor normalized to 1 conditional on x_j, since in our analysis we do not distinguish between age and experience skill conditional on education. When approximating $\ln(1 + p\, e_j) \approx p\, e_j$, our specification (12) follows. As a robustness check, we also estimate the "structural" wage equation in Appendix B which gives very similar results.

use this "wage sample", in the terminology of Katz and Murphy (1992), to obtain a clean measurement of the price of experience avoiding any measurement issues with working hours (or potential wage penalties) for part-time employees. We also want to avoid any differential selection by skill into the labor force more broadly. In fact, in Appendix D we explore effects by various skill groupings. We do not find much evidence in terms of differential effects on full-time employment, yet some on labor force participation, suggesting the wage rate measurement using part-time workers might be confounded by selection effects, which reinforces our choice to estimate (8) and (12) in the subsample of full-time workers only.

Another strength of the empirical formulation in (11) and (12) is that it results (for each LLM-year) in *one* estimated (full-time or LFP) gradient and *one* return that describe how employment and wages vary across workers with different experience skill. This allows us to construct a panel of gradients and returns, which we can then use to study the effects of demographic change on market-wide relative employment rates and wages. To make this feasible, we rely in the regressions (11) and (12) on the linearity in $\widetilde{e_{jlt}}$. But do note that concavity of the life-cycle earning profiles is taken into account as we estimate the skill accumulation profile flexibly as a polynomial in potential experience. The relationship that we impose in (12) is such that the experience price $\tilde{p}_{lt}$ stretches or compresses the wage profiles proportionally to $\widetilde{e_{jlt}}$.

In our main specification $\widetilde{e_{jlt}}$ is a worker's experience skill estimated as described in equation (10). In a robustness check we study the effects of experience supply by 5-year potential experience bins,[19] finding that effects on relative wages and employment are indeed more negative for bins with higher experience skill, yet not linear in potential experience. This is consistent with the experience skill accumulation shown in Figure 3, which virtually stops rising after about 25 years of potential experience. These results indicate that the polynomial of experience skill accumulation is well suited to capture the effects not only on relative wages but also on relative employment. Our preferred setup is therefore the one based on the continuous experience skill function, following again Jeong, Kim, and Manovskii (2015), which also uses the full variation in workers' potential experience.

[19]In their study, Card and Lemieux (2001) use 5-year age bins while Caselli (2015) makes a binary split into experienced ($\mathrm{potexp}_j \geq 20$) and inexperienced ($\mathrm{potexp}_j < 20$) workers.

3.2.3 Panel estimation with instrumental variables

Estimating Equations (11) and (12) in each LLM-year gives us a panel of local employment gradients and of wage returns to experience. We also construct a panel of local relative supplies of experience skill by computing Equation (4), $\widehat{\frac{E_{lt}}{I_{lt}}} = \frac{\sum_{j\epsilon\{l,t\}} \widehat{e_{jlt}}\widehat{z_{jlt}} f_{jlt}}{\sum_{j\epsilon\{l,t\}} \widehat{z_{jlt}} f_{jlt}}$, with observed individual productivity weights $\widehat{z_{jlt}} = \widehat{\beta^p_{lt}} x_{jlt}$ and f_{jlt} being the full-time employment indicator. Applying the effect of non-experience productive characteristics as weights follows Jeong, Kim, and Manovskii (2015), who show that this gives in their framework consistent aggregation from the micro to the market level. In this setup, workers are remunerated in the market for supplying both their raw labor and their experience skills. As the other productive characteristics augment both of these inputs, weighting with their effects when summing over all workers gives the market aggregate quantity $\widehat{\frac{E_{lt}}{I_{lt}}}$.

We then relate the experience-employment gradient and the wage return to experience to the relative supply of experience $\widehat{\frac{E_{lt}}{I_{lt}}}$ in our panel of local labor markets:[20]

$$\text{outcome}_{lt} = \eta \ln\left(\widehat{\frac{E_{lt}}{I_{lt}}}\right) + D_l + D_t + \text{error}_{lt}, \tag{13}$$

where outcome_{lt} is either $\widehat{g_{lt}}$ or $\ln(\widehat{p_{lt}})$, estimated earlier. In line with the theoretical relationship (3), our preferred specification for the experience price is in log-log form. For the employment gradient, our baseline specification is in levels of $\widehat{g_{lt}}$ as a priori it is not clear whether these outcomes are positive or not (since it depends on the effect on wages vs. reservation wages). We also explore for the employment gradients a version with the experience supply regressor specified in levels, instead of logs, and a level-level specification for the experience price.

We use the relative experience skill supply of full-time workers for the regression (13), and not of the working age population, because in the economic model the actual supplies determine the relative marginal product and thus the market price of experience. We also construct any further controls in the LLM-year panel among the

[20]Observations in micro-level regressions (11) and (12) are weighted by the individual workers' sampling weights. Observations in regression (13) are weighted by the relative size (share of summed individual weights) of the LLM in the respective preceding census. We also show unweighted results for regression (13).

workers in full-time employment (e.g. average years of education described below). In a robustness check, we further include the experience skill of part-time and temporary workers in our experience supply measure. The fixed effects D_l flexibly control for time-invariant differences in relative employment 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 retirement behavior which might be due to policies).

However, it is likely that changes in the demand for experience skill exist which vary across LLM-years. For example, in one local labor market the demand for experienced workers might increase, leading through market adjustments also to an increase in (local) experience skill, e.g. via changes in participation or migration. In particular, as individuals can easily move between local markets, endogenous migration responses within the U.S. may be quite substantial (and below we do find evidence of substantial migration across LLMs due to experience skill supply). Therefore, in our main analysis we address this potential endogeneity problem and design an empirical strategy to disentangle changes in local supply of experience from changes in experience due to demand or other factors. Our approach is based on the predicted (in the absence of local shocks) supply of experience in each LLM-year. As we are exploiting in our fixed effect regression (13) the variation across local labor markets, what is needed is to project the differential supplies of experience skill across LLMs and years. This prediction is first and foremost based on the age structure (by year and LLM), which is predetermined and observed in the previous census. Since we want to project the relative supply of experience skill, we refine the prediction from aging with changes in years of education in the aggregate data (by year, age and gender).

Specifically, we want to predict the supply of experience skill per worker aged 16 to 65 in LLM l and year t. To do this we use the micro data on all individuals observed in the previous decennial census, i.e. in $t-10$, where the relevant age groups are the 6 to 55 year old, as these individuals will form the working-age population in t if they do not migrate (e.g. due to local shocks). We project their potential experience for year t after they would have aged by ten years and would have acquired education according to the age- and gender-specific national education attainment rates in t. We then compute each individual's experience skill and aggregate to obtain the LLM's predicted experience supply in t. These steps can be summarized by the following equation describing the construction of the predicted supply of experience skill per worker in LLM l and year t:

$$\left(\frac{E_{lt}}{I_{lt}}\right)^{IV} = \frac{1}{\sum_j \omega_{jlt-10}} \sum_j \omega_{jlt-10} \cdot \left(\sum_{k=1}^{4} \frac{\widehat{\lambda_k}}{\lambda_1} \left[(\text{age}_{jlt-10} + 10) - \widehat{\text{educ}_{jt}} - 6\right]^k\right) \tag{14}$$

$$\text{for all } j \text{ observed in } l \text{ at } t-10 \text{ with } 6 \leq \text{age}_{jlt-10} \leq 55,$$

where ω_{jlt} denote individual level sampling weights, age_{jlt} the age of individual j in LLM l and year t, and $\widehat{\text{educ}_{jt}}$ is the educational attainment predicted from national rates for j in year t given their gender and age. The summation in parentheses enters the worker's predicted potential experience $\widehat{\text{potexp}}_{jt} = \left[(\text{age}_{jlt-10} + 10) - \widehat{\text{educ}_{jt}} - 6\right]$ into the definition of normalized experience skill (10). As the construction of the instrument $\left(\frac{E_{lt}}{I_{lt}}\right)^{IV}$ is based on the micro data, it makes use of the entire distribution of (in 10 years' time working-age) individuals' age.[21] In practice, if a local labor market has many young individuals in $t-10$, of whom some may not have entered the labor market yet, it is predicted to exhibit relatively low experience supply in t; vice versa, an LLM with many middle-aged and older individuals up to age 55 in $t-10$ is predicted to have a relatively high experience supply in t.

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 $t-10$ 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 at the LLM level that are due to changes in supply. In this case, we would expect η from Equation (13) to be over-estimated (under-estimated in absolute value), as demand shocks work in the opposite direction of the predicted negative relationship of experience supply with $\tilde{g}_{lt}$ and $\tilde{p}_{lt}$. As a robustness check in section 4.2.1, we also construct the instrument based on the age structure in $t-20$. If there were any endogeneity due to the demand for experience left, this alternative 20-year IV should be less affected by this than the baseline 10-year instrument and

[21] A number of recent papers study demographic change in relation to firm dynamics and the startup deficit. These typically focus on past birth rates across U.S. states to instrument for aging or labor supply growth (e.g., Engbom, 2019; Karahan, Pugsley, and Şahin, 2019). One exception is Bornstein (2019), who uses the full ten year lagged age structure as we do.

therefore arguably yield stronger (in absolute value) results. However, our estimates in Table E.7 suggest that this is not the case.

For validity of the instrument, we further need that a first stage exists and that the exclusion restriction holds. The first stage sheds some light on Empirical Prediction 1, as it is the regression of actual relative experience skill supply on our instrument of potential supply.[22] The exclusion restriction states that the age structure in $t - 10$ does not affect the relative employment or price of experience in t other than through its effect on the supply of experience skill in t. As one of our main specifications, we therefore control for average years of education in the IV estimation, since changes in a local labor market's age structure may come with changes in educational attainment. In robustness checks, we further include additional demographic characteristics of the LLM as well as the employment structure in terms of (broad) industries and occupations. We also control for state$\times$year interaction in our estimation at the czone level to rule out that any state (or federal) policy changes in response to aging affect employment decisions or wages rather than the changing supply of experience skill. Note, the model-consistent construction of the instrument in (14) reduces the possibility that variation in the variables used for the prediction may directly affect the outcome via channels other than experience supply. This approach also strengthens the first stage.

Assuming that our empirical identification 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 for experience skill. This reasoning is illustrated in Figure 2: 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 employment rate of experience-skilled 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.[23] Therefore, as derived in Section 2, the actual input of experience-skilled workers rises by less than the shift in the supply curve ($\frac{E_{l2}}{I_{l2}}$ instead of $\frac{\breve{E}_{l2}}{\breve{I}_{l2}}$) and also the effect on the

[22]This estimation may be downward-biased due to measurement error in potential supply. Therefore, our main test is the direct effect on relative participation rates (i.e. the instrumented Equation (13) for the employment gradient), implied by Empirical Prediction 2, which constitute the difference between actual experience of workers and of the population that underlies Empirical Prediction 1.

[23]We do not focus on the intensive margin of labor supply as censuses prior to 1980 only include information on hours worked in broad brackets. We also find strong effects on the extensive margin.

new equilibrium price p_2 is weaker. Demographic change hence may have equilibrium participation effects that attenuate the overall effect on employment and affect individuals' lives beyond declining wage rates.

Note, our identification strategy is robust to an employment response that runs in a third dimension of the demand and supply diagram. As long as it does not perfectly smoothen out all of the original changes in experience supply, for instance endogenous migration is not a concern, but an additional outcome of interest (see Appendix Figure E.1 for illustration). In fact, Section 4.3 reports evidence for a negative effect of rising experience on the relative in-migration of experience-skilled workers into a LLM.

3.3 Variation in the Local Labor Market-Year Panel

Appendix Figure E.2 plots the local variation in average age of full-time workers across the contiguous U.S. for the years 1970, 1990, and 2010.[24] The fixed effects in our second-stage regression (13) remove time-invariant differences across LLMs and aggregate changes over time, which make up a large part (90–95 percent) of the variation in age in the state and the czone panel. Still, significant differences in aging remain which run across LLM-years and which are particularly informative for identification.[25]

The top panel of Table 1 reports the results collected from the individual-level regressions as well as other information for our LLM-year panel at the state level. For each year, the table reports mean and standard deviations of the variation across LLMs for the variables named in the top row. Columns 1 and 2 show the full-time employment and labor force participation gradients in experience skill (multiplied by 100), obtained from estimating (11), and column 3 the wage return to experience skill (times 100) from (12).[26] The last four columns show for full-time workers statistics on relative supply of experience skill (as computed in Section 3.2), average age and years of education, and the share of females. The bottom panel of Table 1 shows the corresponding

[24]The borders drawn into Figure E.2 are for counties in 1990, which can be aggregated to states or czones. The age variation colored into the map is for the 722 czones.

[25]There are 50 states plus the District of Columbia per year in 1960–2010 but, since Alaska and Hawaii only became states in 1959, our IV estimates have 49 states for the year 1960. Therefore we run 304 separate regressions (11) and (12) each at the state level (304 state-year observations overall). At the commuting zone level, there are 722 LLMs per year in 1980–2010 (2,888 czone-year observations overall).

[26]Recall that experience skills, and thus gradients and returns, are subject to the normalization discussed in Section 3.2 but, since this is a common normalization, they can be compared across markets.

Table 1: Descriptive Statistics for the State and Commuting Zone Panels

	FTgrad x100	LFgrad x100	Rtrn x100	Rel.Exper	Avg Age	Yrs Educ	Female
State Panel							
1960							
mean	4.00	2.85	8.44	7.05	40.1	10.7	0.27
sd	0.43	0.61	0.87	0.08	0.8	0.5	0.03
1970							
mean	4.49	2.75	8.90	6.84	40.1	11.5	0.31
sd	0.40	0.58	0.72	0.07	0.7	0.4	0.02
1980							
mean	3.78	1.37	9.54	6.47	37.9	12.5	0.38
sd	0.52	0.68	0.72	0.09	0.9	0.3	0.02
1990							
mean	3.90	1.30	10.78	6.74	38.2	13.1	0.42
sd	0.41	0.53	0.91	0.06	0.5	0.2	0.02
2000							
mean	3.93	0.85	10.59	6.96	39.8	13.2	0.43
sd	0.33	0.50	0.71	0.07	0.5	0.2	0.02
2010							
mean	3.95	1.98	12.16	7.04	41.8	13.6	0.46
sd	0.33	0.73	0.94	0.09	0.6	0.2	0.02
Total							
mean	3.99	1.75	10.35	6.86	39.8	12.6	0.39
sd	0.44	0.94	1.50	0.21	1.5	1.0	0.07
N	304						
Czone Panel							
1980							
mean	3.73	1.34	9.49	6.47	37.9	12.4	0.38
sd	0.69	0.91	1.15	0.13	1.0	0.4	0.03
1990							
mean	3.85	1.27	10.86	6.75	38.2	13.0	0.42
sd	0.65	0.84	1.36	0.12	0.7	0.4	0.03
2000							
mean	3.87	0.82	10.66	6.97	39.8	13.2	0.43
sd	0.61	0.78	1.17	0.12	0.7	0.4	0.02
2010							
mean	3.92	1.95	12.20	7.05	41.9	13.5	0.46
sd	0.54	1.01	1.39	0.13	0.9	0.4	0.02
Total							
mean	3.85	1.37	10.94	6.84	39.7	13.1	0.43
sd	0.62	0.99	1.60	0.25	1.8	0.5	0.04
N	2888						

For each year, the table shows local labor market means and standard deviations of the variables named in the top row. The first to third columns are the full-time and labor force participation gradients $\widehat{\tilde{g}_{lt}}$ and the return to experience skill $\widehat{\tilde{p}_{lt}}$ from regressions (11) and (12), respectively. Column 4 shows the relative supply of experience skill $\widehat{\frac{E_{lt}}{I_{lt}}}$, 5 average age, 6 years of education and 7 the share of females among full-time workers. The top half of the table shows the descriptive statistics for the state panel, the bottom for the commuting zone panel.

information for the czone panel starting in 1980. The means are very similar, but the standard deviations (especially within year) are unsurprisingly larger. Overall there are 304 observations in the state panel and 2,888 observations in the czone panel.

The differences in the age and thus in the experience skill structure across local labor markets and over time originate from a variety of sources. As documented by Jones and Tertilt (2008), rural and urban areas not only had historically different fertility rates, but also underwent the fertility transition at different times and speeds, which to some degree was accompanied by migration from rural to urban areas. The differential changes in family sizes went to a certain extent in hand with variation in birth control and abortion legislation as well as in anti-obscenity laws, which persisted in some areas until the mid-1960s (see Bailey, 2010). These differences in birth and migration rates, and additionally in mortality rates, have very persistent effects on the age structure, potentially even across multiple generations, which is also stressed by Bronson and Mazzocco (2016). The regional variation in the population's age composition feeds on to variation in the experience supply, which is what we exploit in our empirical analysis as described above.

4 The Effect of Demographic Change on Relative Employment Rates and Wages

In this section we estimate the effect of demographic change on the gradient of experience for full-time employment and labor force participation, and on the return to experience in full-time workers' wages. Our baseline results are for states as the local labor market level, since there the data spans a longer timer period, but we also report results at the commuting zones (czones) level as a comparison and robustness check. We then show important alternative specifications and subsamples in further robustness checks as well as results for additional employment-related outcomes.

4.1 Estimation Results

As described in Section 3.2, after constructing the LLM-year panel we estimate (13) for the outcomes of interest, the full-time employment gradient or labor force participation gradient ($\tilde{g}_{lt}$), and the return to experience in full-time workers' wages ($\tilde{p}_{lt}$).

Table 2 reports the relationship of the relative experience skill with the relative full-time employment rate (top segment), relative labor force participation rate (middle), and relative wages of experience-skilled workers (bottom) when the LLM-year panel regression (13) is estimated by OLS. The first column of the table's top segment shows that log relative experience skill and the full-time gradient in experience skill covary positively across the panel of states. This relationship does not change when we control in column (2) for average years of education, which might differ with workforce age. The level-level specification of column (3) indicates a (qualitatively) similar relationship. Columns (4) to (6) conduct the corresponding analysis for czones as LLMs. In the OLS estimates, there is a strong positive relationship between relative experience skill and the full-time employment gradient detectable also on this level.

In contrast to these results, Table 2's middle segment shows that log relative experience skill is not conclusively correlated with the relative labor force participation (LFP) rate of experience-skilled workers. At the state level, the point estimate is negative and slightly weaker than for relative full-time employment while at the czone level it is positive but quantitatively even smaller. All of the estimates are far from statistically significant, however.

The bottom segment of Table 2 reports the return to experience skill according to full-time workers' wages. As was the full-time employment gradient, the return to experience skill is positively and significantly correlated with relative experience skill across LLM-years throughout columns (1)–(3) for states and (4)–(6) for czones. The top and bottom segments of Table 2 therefore suggest a positive relationship between the relative supply of experience and labor market opportunities of experience-skilled workers. On the other hand, the relationship with labor force participation in the middle segment is essentially zero and, more importantly, it is unclear whether one should interpret variation of relative experience across markets in the OLS as due to demand or supply forces, or due to other factors (which might for example also have influenced the null result for labor force participation). We therefore use in the following the instrumental variables strategy we proposed in Section 3.2, in order to isolate variation in relative experience skill that is solely due to supply.

The top segment of Table 3 reports the first stage of this IV regression. In line with

Table 2: Full-Time Employment Gradient, Labor Force Participation Gradient, and Wage Return to Experience (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)
Full-time emp	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100
Ln(Rel.Exper)	6.40**	5.95**		13.15***	12.36***	
	(2.84)	(2.69)		(2.26)	(2.14)	
Yrs Education		-0.36**			-0.89***	
		(0.17)			(0.15)	
Rel.Experience			0.91**			1.93***
			(0.43)			(0.34)
LF participtn	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100
Ln(Rel.Exper)	-3.19	-4.74		3.85	2.23	
	(3.52)	(3.51)		(2.87)	(2.51)	
Yrs Education		-1.23***			-1.82***	
		(0.31)			(0.46)	
Rel.Experience			-0.54			0.50
			(0.53)			(0.44)
Wages	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100
Ln(Rel.Exper)	1.04**	1.04**		1.54***	1.60***	
	(0.50)	(0.50)		(0.27)	(0.26)	
Yrs Education		-0.00			0.07***	
		(0.03)			(0.02)	
Rel.Experience			1.50*			2.33***
			(0.88)			(0.39)
Observations	304	304	304	2888	2888	2888
Fixed Effects	state+year	state+year	state+year	czone+year	czone+year	czone+year
Sample	>=1960	>=1960	>=1960	>=1980	>=1980	>=1980

The table reports results from the estimation (13) using OLS. Dependent and independent variables are constructed from regressions (11) and (12) in each LLM-year using an individual's full-time employment dummy (top segment), labor-force participation dummy (middle) and wage (bottom) as the dependent variable. Columns (1) to (3) show estimates for the panel of states over 1960–2010, columns (4) to (6) for commuting zones over 1980–2010. Robust standard errors in parentheses are clustered on state: * p<0.1, ** p<0.05, *** p<0.01.

Empirical Prediction 1, the coefficients of actual on predicted relative experience skill from the census ten years earlier are positive but clearly smaller than one. For example, in column (1), a one log point predicted increase in relative experience skill according to the previous census and the aggregate change in education (see Equation (14)) leads to a 0.32 log point increase in actual relative experience skill. This is consistent with experience supply having a negative effect on experienced workers' relative employment rates as shown in the supply and demand framework of Section 2. However, it is also consistent with our identification strategy being successful in removing changes in relative experience skill across LLMs that are due to other reasons than supply (such as changes in demand).[27] For this reason, we directly examine the effect of relative supply of experience skill on the employment decision by studying below the effect on the full-time and LFP gradients with respect to experience skill.

The regression coefficients in the top segment of Table 3 are also highly statistically significant, even conditional on LLM and year fixed effects. The corresponding first-stage F-statistics for the excluded instrument are at least 15 in the different czones specifications and even considerably higher at the state level. This underlines the relevancy of our instrument. Following the papers by Autor, Dorn and coauthors that study outcomes at the commuting zone level, we cluster standard errors at the state level throughout the analysis. This allows for correlation within LLMs over time as well as for spatial correlation across commuting zones (Autor, Dorn, and Hanson, 2013).[28] In Section 4.2.1 below, we conduct a series of robustness checks, including one where we directly control for state interacted with year fixed effects in the commuting zone regressions. Overall, the regression results in the top segment of Table 3 therefore show that higher predicted relative experience supply leads to an increase in actual experience skill, but by less than one-to-one. This is consistent with Empirical Prediction 1 but not an explicit test of it as several other factors could lead to the less than one-to-one relationship (see e.g. Footnote 27). We therefore focus in the following on directly testing our main Empirical Prediction 2.

The upper middle segment of Table 3 reports the IV second stage result of the effect of relative supply of experience skill in the LLM on the relative full-time employment rates of experience-skilled workers, as described by the gradient of full-time work with respect to experience. Recall that this gradient measures by how many percentage points one extra unit of experience skill increases the probability that an individual works full-time. As one would expect when the variation that is due to demand

[27] The identification strategy also corrects for measurement error due to sampling variation. Since our census data are subsamples of the population, the supply of experience variables that we compute on the detailed LLM level may be measured with error. As 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 IV estimates. Nonetheless the first-stage may be attenuation-biased as it is itself an OLS regression onto a variable measured with error. Finally, an additional reason why we expect the first-stage coefficients to be below one, are endogenous migration decisions. In fact, we find evidence below that there is a negative effect of rising relative experience in an LLM on the in-migration of experienced compared to inexperienced workers.

[28] If they cross state boundaries, commuting zones are assigned to the state with the highest share of employment for the clustering.

changes is removed by the instrument, the relationships that are very positive in the OLS are smaller in the IV and in fact even turn around to become negative. The relationship between actual relative experience skill and the full-time employment gradient is strongly negative and statistically significant almost throughout.

For example, column (1) implies that an increase in Ln(Rel.Exper) by 0.01, or one log point, reduces 100 times the full-time gradient by 0.2243. Note, the outcome variable is measured in percent (as this gradient captures how full-time employment status varies across individuals with experience skill), so when a local labor market's relative experience skill rises by one log point, it reduces that LLM's full-time gradient by 0.22 percentage points. Given the descriptives for the state panel given in Table 1, this is on the mean a reduction by 5.6 percent (computed as (3.99-0.2243)/3.99). The effects at the czone level are only slightly smaller (compare columns (4)–(6) to (1)–(3)) and overall these relationships are significant, economically as well as statistically.

This result is corroborated and reinforced by the effect of relative experience supply on the relative labor force participation rates of experienced workers, which is displayed in the lower middle segment of Table 3. In particular, a 1 log point higher relative experience supply in the LLM leads to a 0.87 percentage points lower LFP gradient in column (1), which relative to the sample mean is a fall by 49 percent (see again Table 1). The effects on relative labor force participation rates are negative throughout and also statistically significant at least at the five percent levels across specifications and states or czones as local labor markets. Therefore, combined with the effects on the full-time gradient, the two middle segments of Table 3 confirm Empirical Prediction 2 in our data; an increase in the experience supply reduces the relative employment rate of more experience-skilled workers, and it does so substantially.[29]

Finally, the bottom segment of Table 3 provides the instrumental variables regressions with the return to experience skill according to full-time wages as the outcome variable. Again, the relationship becomes more negative with the IV compared to the OLS throughout, which suggests that the former is in fact able to remove variation in actual experience that is due changing demand for experience (and goes in hand with

[29]In the level-level specifications of column (3), a one standard deviation higher experience supply (0.21 in Table 1) leads to a 1.6 standard deviations (i.e. $0.21 \times 3.33 = 0.70$, which is 1.59 of a stdev of 0.44) lower full-time gradient and an almost three standard deviations ($0.21 \times 12.84 = 2.70$, which is 2.87 of a stdev of 0.94) lower LFP gradient of experience.

Table 3: Full-Time Employment Gradient, Labor Force Participation Gradient and Wage Return to Experience (Main IV Results)

	(1)	(2)	(3)	(4)	(5)	(6)
First stage	Ln(Rel.Exp)	Ln(Rel.Exp)	Rel.Exper	Ln(Rel.Exp)	Ln(Rel.Exp)	Rel.Exper
Ln(Pred Rel.Exp)	0.32***	0.42***		0.28***	0.33***	
	(0.07)	(0.06)		(0.07)	(0.07)	
Yrs Education		-0.01***			-0.01***	
		(0.00)			(0.00)	
Pred Rel.Exper			0.33***			0.27***
			(0.07)			(0.07)
Full-time emp	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100
Ln(Rel.Exper)	-22.43***	-12.29**		-17.36**	-3.89	
	(6.40)	(5.40)		(8.29)	(3.49)	
Yrs Education		-0.41**			-1.00***	
		(0.17)			(0.14)	
Rel.Experience			-3.33***			-2.84**
			(0.97)			(1.30)
LF participtn	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100
Ln(Rel.Exper)	-86.58***	-52.98***		-65.43**	-37.38***	
	(29.79)	(11.18)		(30.39)	(13.02)	
Yrs Education		-1.36***			-2.09***	
		(0.24)			(0.33)	
Rel.Experience			-12.84***			-10.07**
			(4.35)			(4.69)
Wages	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100
Ln(Rel.Exper)	-4.12***	-3.73***		0.65	-0.10	
	(1.52)	(1.12)		(1.05)	(1.03)	
Yrs Education		-0.02			0.06***	
		(0.02)			(0.02)	
Rel.Experience			-6.75***			0.68
			(2.44)			(1.74)
Observations	304	304	304	2888	2888	2888
F-Stat First Stage	20.21	56.14	20.91	14.66	20.43	15.72
R^2 First Stage	0.95	0.95	0.95	0.91	0.91	0.91
Fixed Effects	state+year	state+year	state+year	czone+year	czone+year	czone+year
Sample	>=1960	>=1960	>=1960	>=1980	>=1980	>=1980

The top segment of the table reports the regression of full-time workers' relative experience skill onto its own prediction from the census 10 years prior (first-stage of the IV). The two middle segments display the second-stage estimates of eq. (13) for the full-time employment and the labor force participation gradient, respectively. The bottom segment reports the effect on the wage return to experience skill. Columns (1) to (3) show estimates for the panel of states over 1960–2010, columns (4) to (6) for commuting zones over 1980–2010. Observations (i.e. LLM-years) are weighted by their size (i.e. underlying number of working age individuals in the previous period). Robust standard errors in parentheses are clustered on state: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

rising returns to experience skill). The effect is also highly statistically significant and quantitatively strong at the state level. For example, in the first column of the bottom segment, a one log point higher relative experience skill in the LLM leads to a 4.12 log point lower return to experience.[30] At the czone level, the estimated effect is about zero and not statistically significant. However, overall the results in the bottom segment of Table 3 confirm Empirical Prediction 3 in our data; an increase in the experience supply reduces the return to experience skill.

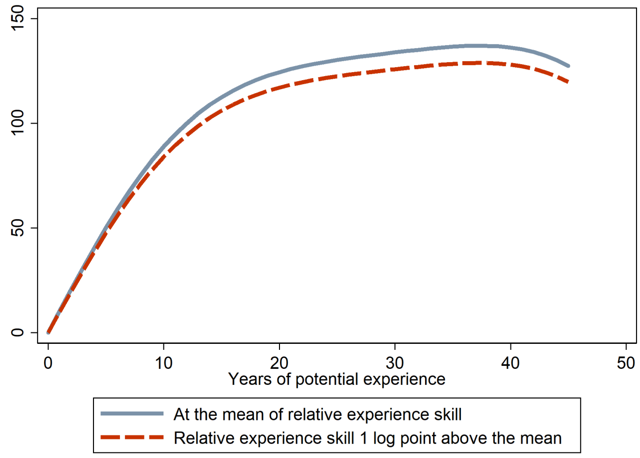
These effects on the price of experience imply that workers' cross-sectional wage–potential experience profiles in equilibrium are affected by the relative supply of experience skill. In particular, as we explained in Section 3.2, changes in the experience price, which are affected by the relative market supply of experience, stretch out or compress the wage profile proportionally to experience skill. Figure 4 illustrates this effect by plotting the percent variation in wages that is due to differences in potential experience (via the mapping into experience skill). First, the solid blue line represents this wage profile under the mean price of experience skill across all LLM-years. When relative experience skill supply in the market is one log point higher, the profile rotates inward (i.e., compresses), which is depicted in the dashed red line. Quantitatively, at the mean, the wage difference due to experience skill between workers of twenty-five versus zero years of potential experience is about 130%. With a one log point higher relative experience skill, this difference declines to 122%. Therefore, changing market supply of relative experience skill has a quite substantial effect on cross-sectional wage differences between workers with varying years of potential experience.

To note is that in the results of Table 3 we have weighted the observations in the panel regression by the LLM-year's underlying number of individuals in the previous census. This raises statistical precision but, by and large, the unweighted estimates are very similar to the weighted results, as we detail in Appendix C.

To sum up, the findings from this section show that rising experience supply has a negative effect on the relative labor market outcomes of experience-skilled workers. It reduces their relative full-time employment rates, labor force participation rates, and wage rates –as predicted by our economic framework. The more negative estimates in the IV compared to the OLS indicate that local shocks in the relative demand for experience skill have occurred and that our identification strategy is important for

[30] In the level-level specification of column (3), a one standard deviation (0.21) higher experience supply leads to an almost one standard deviation (i.e. $0.21 \times 6.75 = 1.42$, which is 0.95 of a stdev of 1.50) lower wage return to experience.

Figure 4: Cross-sectional profiles of potential experience against wages (in %)



Notes: The solid blue line depicts the average wage difference (in %) between workers with different years of potential experience (horizontal axis) and workers with zero experience. This is computed by multiplying the estimated experience skill as a function of potential experience, (10), with the mean price of experience skill of 0.1035 (see summary Table 1). The dashed red line shows how these wage differences change when the market's relative experience skill increases by one log point. Then, the price of experience skill falls by 4.12 log points, according to the estimates of column (1) in Table 3. Both of the series are converted from log point to percent differences.

isolating the supply effect. The effects are also quantitatively very substantial as we have illustrated using the specifications with logs and with levels of experience supply.

4.2 Robustness Checks

We show in this section that our results are robust to various alternative empirical specifications and sample definitions. Just as in our baseline analysis, we first construct for each specification and sample a LLM-year panel in which we then study the outcomes of interest using our instrumental variable strategy.

4.2.1 Alternative Specifications

Non-parametric experience skill profile

The main approach of this paper is to use the concave experience skill constructed from the 4th order polynomial estimation (9) that we developed in Section 3.2.1. As we found in that section, this provides a very good fit to the non-parametric skill profile in which different dummies for each year of potential experience are used in completely flexible manner. As our first robustness check, we now show that also the empirical results for these alternative non-parametric experience skills are rather similar. In particular, we estimate the non-parametric skills as described in detail in Footnote 15 and then assign every worker in the dataset the $\tilde{e_j}$ corresponding to their potential experience and that estimate. We then continue as before, running regressions (11) and (12) in the micro-data, and then relating the resulting LLM-year employment gradients and wage returns to local experience supply (again according to the non-parametric profile) using our instrumental variables strategy.

Table E.2 in the Appendix reports the results, which are qualitatively similar to our main estimates. The F-statistics for the first stage and for states the effects on the full-time employment gradient are comparable, even slightly stronger and highly statistically significant, than in main Table 3 while for czones the full-time effects are somewhat weaker but still positive. The effect of experience supply on the labor force participation gradient of experience skill is negative and significant (and highly for states) albeit again somewhat weaker for czones. Finally, the effects on the wage return to experience are also rather comparable to that of Table 3. We therefore conclude from this robustness check that our key empirical results are unchanged when using the non-parametric skill profile instead of the 4th order polynomial-based experience skills in the main specification.

Splitting workers into 5-year potential experience bins

In our baseline analysis we assumed that all outcomes are linear in experience skill. While the experience skill accumulation profile is inferred in such a way that we capture the average shape of the life-cycle earning profile (against potential experience) and that log wages are indeed linear in $\tilde{e_j}$, the specifications for the employment gradients is more ad hoc. For this reason we analyse as a robustness check the effect of changes in relative experience supply on the outcomes in a more flexible way by studying the changes in outcomes by 5-year potential experience bins. Just as in our baseline estimations we first remove the effects of potentially confounding other determinants by running for each LLM-year a regression similar to (11) and (12) but by replacing $\tilde{e_j}$ with a set of dummies that indicate in which of 9 experience bins (from 0-4 to 40-45 years of potential experience) each individual is. We then relate each bin's full-time employment, labor force participation, and log wages to the local relative experience supply measure that we used in the main results of the paper (i.e. the relative supply of experience skill stemming from all workers aged 16–65) under our IV strategy. Appendix Tables E.3 and E.4 show the IV estimates relative to the omitted bin for the panel of states and of czones respectively, where the omitted bin is the one for individuals with 0 to 4 years of experience.

For the outcomes full-time employment and labor force participation we find in the panel of states (and quite similar in the commuting zone panel, albeit with much less statistical power) for each experience bin relative to the omitted group with 0-4 years of potential experience a negative effect of relative experience supply; the signs of all estimated coefficients is negative and for states all but one of the coefficients are statistically significantly different from zero at conventional levels. These results suggest that an increase in relative experience supply lowers employment and participation for all individuals who have some labor market experience. By itself this indicates that individuals' experience-employment/participation profile is rotated downwards, highlighting that there are indeed effects even within narrow experience bins and that the entire profile changes in response to variations in experience supply. In terms of the effect on log wages, again relative to the omitted group of those with 0 to 4 years of potential experience, in the state panel the effects are negative through all bins with higher experience, and all but one coefficient are significantly different from zero at conventional levels, whereas in the commuting zone panel there is hardly any discernible effect. Overall, these results echo our baseline results of Table 3.

That the outcomes of all individuals change in response to local experience supply movements is in line with the Jeong, Kim, and Manovskii (2015) framework on which we build, where all workers supply some amount of experience skill (with the exception of those who have exactly zero potential experience). Furthermore, as one would expect, the general pattern in the full-time employment and labor force participation outcomes is such that individuals with more experience skills react more strongly to changes in the market's relative experience supply (compare columns 8 and 1 in Table E.3). Yet that the effect in very high experience bins is not stronger than in middle bins is consistent with the experience skill accumulation we estimated, see Figure 3, as beyond 25 years of potential experience any extra year has virtually no impact on this skill. That the results by these 5-year bins are rather similar across bins above 25 years of potential experience is thus in line with our main specification of individual choices and log wages in equations (11) and (12), suggesting that this functional form is well suited to capture the effects not only on wages but also for the employment decisions.

Controlling for state and year interactions at the commuting zone level:
One concern about our empirical strategy could be that there might be policies at the state level, or other time-varying factors, that are correlated with experience supply and at the same time affect the employment gradients or the return to experience skill. For example, there are a whole range of state employment policies, for instance minimum wages and eligibility criteria for unemployment insurance or workers' compensation (see U.S. Chamber of Commerce (2011) for a summary), and if these were correlated with demographic change, our results might be biased.

We thus explore a version of the regressions at the czone level in which we flexibly control for state-year changes using dummies for states, years and their interactions. Appendix Table E.5 shows the results. This is a demanding specification as it allows identification based only on differential variation across czone over time *within* state-year cells. This is reflected by the F-statistics of the first stage, which indicate only borderline relevancy of the excluded instrument. Nonetheless, the effects in Table E.5 of relative experience supply on the full-time gradient and on the labor force participation gradient are qualitatively and quantitatively the same as in our main Table 3. The effects on the return to experience skill are now similarly negative as for states in these baseline results, and they come close to statistical significance at the ten percent level. Therefore, our baseline specifications are robust to changes in time-varying confounding factors at the state level; both employment gradients and wage returns of experience skill react negatively to rising relative experience supply.

Controlling for demographic and employment characteristics:
As a further robustness check, we include in the panel estimation additional controls to address the potential concern that our results might be driven by a third factor that is correlated with our identifying variation but that we have not controlled for. In Table 3 we already added years of education, whereas now we control for key demographic characteristics and the structure of employment in terms of industries and occupations.[31] Appendix Table E.6 shows the results when controlling for the contem-

[31]Note though that changes in these variables (by LLM and year), especially in the occupation and industry structure, very well might be outcomes of the economic mechanism that we are interested in.

poraneous share of full-time employment in goods-producing (i.e. not in services) sectors and in routine occupations,[32] or the employment shares of blacks and of females among full-time workers, or both simultaneously.

In the first segment we see that the first stage of the IV is again strong, also conditional on these variables capturing the LLMs' contemporaneous occupation and industry structure and workforce demographics. The next two segments report the main results on the full-time employment and the labor force participation gradient of experience skill. With these additional controls, the coefficients in the state panel slightly increase (in absolute terms) and slightly decline at the czone level, but overall the results are very similar to our main results in Table 3. The bottom segment of Table E.6 reports the effect on the wage return to experience. Again, including these controls for the demographic and employment structure hardly matters for the results. The estimates on the wage return to experience skill are barely changed.

The results in Appendix Table E.6 suggests that our main results are not driven by changes in the industrial or occupational employment structure nor in the (non-experience skill) demographics of the full-time workforce.

Instrumental variable based on 20 years earlier:

The motivation for our instrumental variables strategy is to extract variation of local relative experience skill that is solely due to changes in supply. That this succeeds is supported by the differences between the estimation results in Tables 2 and 3. The effect of experience supply is negative in the IV in contrast to the OLS because the IV arguably removes experience variation due to changes in demand that work toward a positive relationship of relative experience with employment gradients and with wage returns in the OLS. Nonetheless, one could be concerned that there exists remaining endogeneity of experience supply in our instrument if, for example, workers with (prospectively) more experience skill were to migrate to a labor market with (prospectively) higher experience returns already more than 10 years in advance.

In the last robustness check of this section, we therefore employ the population structure in $t-20$ to predict the relative supply of experience skill in year t. We use the

[32]We focus in the industry dimension on goods production and in the occupation dimension on routine, as both have declined considerably over the past six decades, at least at the U.S. federal level (Bárány and Siegel, 2018).

years 1940 to 1990 for constructing our 20 years removed instrument in 1960 to 2010, respectively, at the state level. We also use 1970–1990 for instrumenting 1990–2010 at the czone level, and we have added the year 1970 instrumented by 1950 to that czone panel.[33] One difficulty in the $t-20$ instrumentation is that the 16–19 year olds among the 16–65 year old working age population are not yet born twenty years earlier. To approximate the corresponding number of "minus 4 to minus 1" year olds in $t-20$, we extrapolate from the number of 0 year olds by duplicating these observations for every age of "minus 4 to minus 1" in a given LLM in year $t-20$. We then write those ages forward by 20 years to obtain the predicted number of 16–19 year olds for constructing the instrument.[34] The justification of this approach is that birth rates in LLMs are very persistent over short periods of time and therefore the number of 0 year olds provides a good prediction of births over the next four years.[35]

The results from the $t-20$ instrumentation are displayed in Table E.7. Overall, they are quite similar to our main estimates using the 10-year IV. The first stage is again strong. The effects on the full-time employment and the labor force participation gradients are similar for states, and they now turn statistically significant throughout for czones. The estimates on the wage return to experience skill are slightly less negative than for the 10 year instrument, but they remain five percent statistically significant for states and indistinguishable from zero for czones.

Our key results are thus robust to using the 20 years removed instrument instead of the 10-year IV, which suggests that remaining endogeneity in our baseline specification is not a first-order issue. In particular, the 20 year prediction seems not to remove

[33]Recall the county group information to construct czones is not available in 1960 but it is available in 1950. For states, we lose two additional observations in 1970 compared ot the 10-year IV, since Alaska and Hawaii were not identified in the 1940 and 1950 censuses and thus cannot be instrumented.

[34]Formally, equation (14) for the 20 year instrument becomes:

$$\left(\frac{E_{lt}}{I_{lt}}\right)^{20yr-IV} = \frac{1}{\sum_j \omega_{jlt-20}} \sum_j \omega_{jlt-20} \cdot \left(\sum_{k=1}^{4} \frac{\widehat{\lambda_k}}{\lambda_1} \left[(\text{age}_{jlt-20} + 20) - \widehat{\text{educ}_{jt}} - 6 \right]^k \right)$$

based on all individuals j observed in location l in year $t-20$ with $-4 \leq \text{age}_{jlt-20} \leq 45$, ages $-4 \leq \text{age}_{jlt-20} \leq -1$ imputed from $\text{age}_{jlt-20} = 0$ observations, ω_{jlt} individual level sampling weights, and $\widehat{\text{educ}_{jt}}$ the educational attainment predicted from national rates in t given j's gender and age.

[35]We have verified within $t-20$ that using 4 year olds in a corresponding prediction of 0–3 year olds is highly accurate (regression coefficient of 0.997, R^2 of 0.988 for both states and czones). What we arguably need for the IV is only a reasonably good approximation of the number of 16–19 year olds, which is what the high short-run persistence of birth rates provides. When we compute the IV, we average over all the predicted experience skills as a function of ages 16–65.

more of the endogenous responses than the 10 year prediction does, whereas the differences between the OLS and the estimates using either the 10 or the 20 year IV are large. This in turn suggests that most of the endogenous changes in local relative experience skill occur over less than 10 years. If despite of this our instruments were not fully successful in removing endogenous changes of experience skill, the strength of the effects that we find would likely be understated as explained in Section 3.2.3.

4.2.2 Alternative Samples

Subsample of only males:
Next we restrict our sample to men only. We do this robustness check because arguably over the time horizon we study there have been many changes to female participation, and perhaps wages too, that may confound our analysis.

Table E.8 in the Appendix reports the results for the men-only sample. These are comparable to the main results for the whole sample at the state level and in fact stronger at the czone level. To note is that in this analysis we only took the variation in male experience supply when studying the effect on (men's) full-time employment and return to experience skill. We did this to remove effects that may be due to changing female labor force participation and to solely study the effects of aging among male workers. As it is conceivable that the rise in female participation, in particular at higher levels of experience, also impacted men, we have further studied labor market outcomes for men when the overall variation in relative experience supply stems from both male and female workers. The results were again rather similar.

Subsample of only 16–55 year olds
Another concern may be related to issues of changing early retirement or part-time employment behavior of elderly workers. In Table E.9 we have therefore restricted the sample to ages 16–55 for estimating full-time employment and LFP gradients as well as wage returns to experience skill in micro-data regressions (11) and (12). We keep computing relative experience skill and its instrument using the full-time workers aged 16–65, however, as these constitute the market supplies that the 16–55 year old workers face and that determine their wage and employment gradients.[36]

[36] Early retired or partially retired workers do not enter these supplies by definition.

The results in Table E.9 show that the effects of changing relative experience skill supplies are very similar for 16–55 year olds as they are for the full working age sample. This may not be too surprising, since all workers above 20 years of potential experience are similarly experience-skilled (see Figure 3) and thus similarly affected by its rising supplies compared to inexperienced (young) workers. That is, the individual's exposure does not differ whether someone is in their early fifties or even late forties compared to someone aged 56–65. These results, like the ones from 5-year experience bins, indicate that the experience skill accumulation profile is well suited to capture the effects not only on relative wages but also on relative employment outcomes. At the same time, the results in Table E.9 imply that location and time specific variation in early retirement (any time-invariant variation will be captured by the fixed effects) seems not to confound our main estimates.

Including part-time workers in the relative experience skill supply:
Another check is to use a wider notion and to include all employment types that might contribute to the relative experience (skill) supply in a market. We have already included females in our baseline measure. Now we add part-time workers, which also captures potentially increased female part-time employment over time.

In order to avoid issues related to the wage measurement for part-time workers, we continue to estimate the wage returns to experience from the Mincer regression in the sample of full-time workers. Likewise, and as throughout the paper because this is a law of nature, we construct the experience skill accumulation profile from Mincer regression (8) using data on full-time workers only. But we then relate this estimated experience price, as well as the gradients of full-time employment and labor force participation, to a measure of experience supply which includes both full-time and part-time workers. In line with common practice, we also assign each part-time observation a weight of 0.5 times the weight of a corresponding full-time observation in our calculation. The results for this broad measure of relative experience skill supply, displayed in Table E.10, are again rather similar.

Separate analysis for college and high-school workers:
Finally, we analyze how changes in a market's (overall) relative experience skill supply affect outcomes for college and high-school workers separately. This is to see whether

there are differences across education groups.

Again, we use relative experience skill supply of all full-time workers (including high-school and college) but we restrict the sample for the outcomes in the micro-data regressions to alternatively high-school or college workers only. The results are reported in Appendix Table E.11. For both education groups, the effects of relative experience skill supply on the full-time and LFP gradients, and on the returns to experience, are qualitatively similar to each other and to the main results in Table 3. The point estimates on the labor force participation gradient are larger (more negative) for high-school than college workers across specifications, whereas the coefficient sizes for the full-time employment gradient are rather similar. The point estimates on the wage returns are stronger for high-school than college workers at the state level while this reverts at the czone level and coefficient are negative only for college workers.

4.3 Effects on Employment Status, Migration, and Program Claims

Finally, we study the employment response to demographic change in further detail. We start by investigating the effect of experience supply on employment status and migration across states. For the former we define an employment indicator which captures whether an individual is currently working, regardless whether it is full-time, part-time, or temporary work. We refer to this as 'overall employment'. For migration we utilize information on previous residence to tag individuals who moved across states.[37] Just as before we are studying how workers with different experience skill are affected differentially. We therefore first estimate (11) for each outcome to obtain for each of them a gradient in experience skill. In the resulting LLM-year panels we then estimate (13) for these outcome gradients using our instrumental variable strategy.

Table 4 shows the results. In column (1) the effect on the overall employment gradient of experience is qualitatively the same, but slightly weaker than for labor force

[37]Information on whether someone moved across states, and from which state, in the Census generally refers to the past five years while it refers to the past year only in the ACS. We therefore pool somewhat differing information for the periods 1960(1970)–2000 versus 2010 in our migration analysis. This is fine under the assumption that, once year fixed effects take out the level difference, gradients of one-year as well as five-year migration rates are similarly affected by local experience supply.

participation (LFP) in Table 3.[38] The difference between the effect on overall employment and full-time employment in Table 3 constitutes an approximate measure of the effect on part-time and temporary workers, which is -53.97 for states and -40.73 for czones but not explicitly reported due to space.[39] That the effect is much stronger for overall employment than for full-time employment in Table 3 (more than three times the coefficient size; almost twice in terms of effects on a standard deviation) is therefore consistent with a weaker attachment to the labor market of part-time and temporary workers. That is, part-time or temporary workers are closer to the margin of participating in the labor market at all than full-time workers are to the margin of choosing part-time or temporary work, or to not participate.

Table 4: Effect on Overall Employment and Migration

	(1) Emplmnt	(2) In-Migrtn	(3) Out-Migrtn	(4) Net-Migrtn	(5) Emplmnt	(6) In-Migrtn
Ln(Rel.Exper)	-76.40***	-26.14*	3.50	-28.84	-58.09*	-40.89***
	(27.23)	(15.49)	(5.41)	(24.39)	(29.39)	(13.70)
Observations	304	304	255	255	2888	2888
Fixed Effects	state+year	state+year	state+year	state+year	czone+year	czone+year
Sample	>=1960	>=1960	>=1970	>=1970	>=1980	>=1980

The table reports results from the second-stage estimation (13) with employment and migration related outcomes: the employment gradient of experience (including part- and full-time), the in-migration gradient, and for states the out-migration and net-migration gradients. The first stage of the IV is the same as in the top segment of Table 3. Robust standard errors in parentheses are clustered on state: * p<0.1, ** p<0.05, *** p<0.01.

In columns (2) and (6) of Table 4 we report the effect of experience supply on the in-migration gradient into the respective local labor market from another state. The impact on this variable is statistically significant and in the direction that we expect, that is, there is a lower relative inflow of experienced workers into LLMs that become more experience skill abundant. The point estimate is also quantitatively substantial and, for example, larger than the one on full-time employment from our main results.

While in-migration rates are more precisely measurable in the Census/ACS data, inflows and outflows generally co-exist (Coen-Pirani, 2010) and relative out-migration

[38] In terms of standard deviations, the effects are the same. A one log point higher relative experience skill leads to a 92% of a standard deviation (effect of 0.76 divided by stdev of 0.83 from Table E.12) lower gradient of overall employment as well as a 92% of a standard deviation (effect of 0.87 from Table 3 divided by stdev of 0.94 from Table 1) lower gradient of labor force participation.

[39] Recall from Section 3.1 that full-time status refers to the previous year whereas (overall) employment status refers to the current year. Therefore, these differences are only an approximation of the effect on part-time and temporary workers.

may also be affected by local relative supply of experience skill.[40] Column (3) in Table 4 reports this effect of experience supply on the out-migration gradient of experience for states. Albeit small and statistically insignificant, the point estimate is positive as theory would predict. This constitutes very tentative evidence that out-migration of more experience skilled workers rises compared to less experience skilled workers when experience supply increases.

One way to summarize the overall effect of experience supply on local demographics is using net migration rates. We estimate a net-migration gradient of experience into each state and then study the effect of experience supply on this variable.[41] The results are reported in column (4) of Table 4. Again as theory predicts, the point estimate on the net-migration gradient is negative, implying that relatively more experienced workers on net move out of a state that becomes more experience skill abundant. The effect is also larger than either the effects on in-migration or out-migration separately, but again not statistically significant at conventional levels. These results on migration are also consistent with the first-stage coefficients in Table 3 being smaller than one (see, e.g., Footnote 27), including the fact that they are smaller in czones as the effects on in-migration gradients are also stronger at czone level.

In Appendix D we use skill measures based on education and earnings to examine whether the effects of demographic change on full-time employment, labor force participation, and migration are heterogeneous across skills. We find some mild evidence that relative experience supply changes affect lower-skilled workers more strongly. Our results suggest that lower-educated experienced workers and those who had no earnings already in the previous year become particularly less likely to participate in the labor market when experience skills become more abundant. However, in the full-

[40] Data from which state someone moved into their current location is available after 1970. We employ this to collect the full set of individuals who are associated with each state l in t, i.e. who currently live in l or who moved to another state from l during the past five years in the census (past year in the ACS), and construct a dummy variable for out-migration which takes value 0 for the former and 1 for the latter group. With this, we run our regressions (11) as before to identify the out-migration gradient of experience for each state and then estimate the effect of relative experience skill supply on that gradient. Notice that above we used moves from a different state also for the in-migration into czones but, as we do not know the origin czone, we cannot construct out-migration (or net-migration) at the czone level.

[41] We construct a "directed migration" variable in our full set of individuals who are associated with each state l in t. This variable takes the value of 1 if the person in-migrated, -1 if the person out-migrated, and 0 if the person did not migrate and stayed in the state running up to t. The resulting gradient from regression (11), with the directed migration variable as the outcome, summarizes the net migration of more compared to less experience-skilled workers into state l at t.

Table 5: Effect on Program Claims

	(1) Soc-Secrty	(2) Disability	(3) Welfare	(4) Soc-Secrty	(5) Disability	(6) Welfare
Ln(Rel.Exper)	20.48**	22.88**	1.55	20.85***	28.35***	4.19*
	(8.47)	(10.24)	(2.39)	(7.76)	(10.22)	(2.46)
Observations	255	255	255	2888	2888	2888
Fixed Effects	state+year	state+year	state+year	czone+year	czone+year	czone+year
Sample	>=1960	>=1960	>=1960	>=1980	>=1980	>=1980

The table reports results from the second-stage estimation (13) with the following outcomes: social security income (including pension and disability) gradient, self-identified disability gradient, and the welfare income (including GA and SSI) gradient of experience. The first stage of the IV is the same as in the top segment of Table 3. Robust standard errors in parentheses are clustered on state: * p<0.1, ** p<0.05, *** p<0.01.

time employment response, as well as in the migration response, we find no strong evidence for differences across skill groups.

Finally, Table 5 investigates some of the constituting components of the employment responses.[42] In the interpretation of these results it is important to bear in mind that our sample includes individuals of age 16 to 65, such that all gradients with respect to experience skill capture the differential responses within the *working-age* population. Columns (1) and (4) show that the social security gradient rises quantitatively and statistically significantly with experience supply at the local level. This means that higher relative experience supply in the LLM leads to a higher relative rate at which more experienced workers draw disability or pension income, thereby reducing experienced workers' relative labor market participation rates. In particular, this effect by itself explains about a quarter of the total impact on labor force participation in Table 3.

Since the social security income variable in the Census does not distinguish between pensions and disability insurance, we examine whether a worker identifies themselves as having any lasting physical or mental condition that causes difficulty working. The effect on this disability outcome (columns (2) and (5)) is also positive and equally strong. This suggests that much of the additional program claims go in hand with a self-assessment of being unable to work, which may reflect the objectively more

[42]Information on welfare and social security income as well as self-identified disability are not available in 1960, which reduces the number of observations at the state level. As in the case of migration, we also harmonized a somewhat different definition of disability for ACS in 2010 with the Census in earlier years. As one would expect given the U.S. retirement rules, which stipulate that workers can draw retirement benefits from age 62, the share of people who report receiving social security income in the data trebles to 32 percent from age 61 to 62 and then increases rapidly to 67 percent at age 65. However it is worth to note that there are a substantial number of claimants of all ages in our sample, consistent with the inclusion of disability insurance income in this variable.

difficult conditions faced in the labor market but also constitute a (self-)justification of one's choice to draw benefits. On the other hand, the effect on the welfare variable, which includes General Assistance (GA) and Supplemental Security Income (SSI), is positive but substantially weaker (columns (3) and (6)). This is consistent with our economic framework of Section 2 where higher relative experience supply lowers the equilibrium price of experience skill, which induces relatively more experienced individuals to decide not to work, drawing relatively generous disability (e.g. Autor and Duggan, 2003) or pension (at age 62+) income, and to a lesser extent GA or SSI benefits.

Overall, the results in this section show that increased relative experience skill supply via demographic change also induces migration responses between local labor markets, and that the very substantial employment changes we identified are in parts mediated via disability and other program claims.

5 Conclusion

In this paper we consider the impact of demographic change on the labor market, explicitly taking the employment margin into account. We show that population aging not only reduces experienced workers' relative wages, as established in existing literature, but also affects negatively and strongly their relative employment rates. We further investigate this novel effect in more detail and find that it is fully driven by experienced workers' relative labor force participation rates. We also demonstrate that our main results are robust to alternative estimation specifications and samples, and that a substantial part of the effect of relative supply of experience skill on relative employment rates is through claiming social security income.

We establish these results by exploiting the differential aging of local labor markets in the U.S. over the past 50 years and drawing on our instrumental variable strategy to estimate a quasi-causal effect of local relative experience skill. That OLS estimates appear upward biased compared to our IV results, and even show the opposite sign, indicates that local demand shocks for experience have occurred which induced a positive correlation between relative experience supply and experienced workers' relative labor market outcomes. Therefore, our identification strategy is indeed important for isolating the experience supply effects due to demographic change. Foremost these effects entail the declines in experienced workers' relative full-time employment rates, labor force participation rates, and wages. We then also investigate migration responses and establish that the relative in-migration rates of experienced workers decline substantially when local relative experience supply rises, which is another novel finding. Our analysis at the local local labor market level supports for the wage return to experience the findings of Jeong, Kim, and Manovskii (2015) based on the aggregate U.S. economy. We complement their paper in terms of the identification method and in reconciling aggregate and local results, once the endogeneity in the local experience skill supply, e.g. due to migration and participation responses, is taken care of.

Our findings suggest that policymakers should take note of the previously unrecognized effect on relative employment rates. Prior research has found that improvements in health and education, societal changes, as well as policies with respect to retirement or age discrimination have been important in determining the evolution of older workers' participation rates over the last decades (e.g. Blau and Goodstein, 2010; Maestas and Zissimopoulos, 2010; Neumark and Song, 2013; Lee, 2016; Coile, 2018). We show that there are also important market forces stemming from the supply of relative experience due to demographic change.

Throughout the paper we worked with a notion of life experience skills and assumed that individuals' accumulation of this skill is invariant across markets and over time. It is, however, conceivable that demographic change may impact how individuals can gain relevant experience. Liang, Wang, and Lazear (2018) for instance argue that the age composition of the workforce affects how individuals accumulate managerial skills. An analysis of how demographic change impacts the actual experience accumulation in tasks would be very interesting but we leave this for future work.

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Online Appendix

A Labor Supply at the Individual Level

According to equation (12), a worker's log wage is the sum of a constant, experience skill e_j times its price p, a vector x_j of observable other productive characteristics with corresponding returns β^1, and unobserved individual characteristics u_j^1:

$$\ln(w_j) = \alpha^1 + p\, e_j + \beta^1 x_j + u_j^1, \tag{A.1}$$

where we have stripped the notation from the main text to its essence, only indexing individual-specific variables with a subscript j to distinguish them from market-level varying variables.

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

$$\ln(\underline{w}_j) = \gamma e_j + \alpha^2 + \beta^2 x_j + u_j^2, \tag{A.2}$$

which allows for the reservation wage to depend on workers' experience skill e_j and other characteristics x_j as well as an idiosyncratic component u_j^2. The coefficient γ could take any sign. A worker j participates in the labor market if $\ln(w_j) > \ln(\underline{w}_j)$ which is equivalent to the following inequality:

$$\underbrace{\alpha^1 - \alpha^2 + (\beta^1 - \beta^2)x_j + (u_j^1 - u_j^2)}_{=z_j} > \underbrace{-(p-\gamma)e_j}_{\underline{z}(e_j,p)}. \tag{A.3}$$

This condition implies that workers participate only if z_j (the left hand side), which is the part of the payoff from working that is not due to the worker's experience skill, exceeds a cutoff that is given by the right hand side. This cutoff rule directly motivates a binary choice regression of participating in the labor market onto e_j and x_j. We implement this as a linear probability model in equation (11) of the main text.

In general, the employment cutoff $\underline{z}(e_j, p) = -(p-\gamma)e_j$ depends on a worker's experience skill 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 skill, implying that more experienced individuals, conditional on other characteristics x_j, have a higher employment rate. Note that $\frac{\partial \underline{z}(e,p)}{\partial e} = -(p-\gamma) < 0$ if $p > \gamma$, and $\frac{\partial^2 \underline{z}(e,p)}{\partial e \partial p} = -1 < 0$, implying that more experienced workers are impacted more strongly by changes in p. This leads to

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

The employment rate for workers with e experience and other skills x is given by the fraction of workers whose payoff from working exceeds the employment cutoff and is given by

$$R(e,p,x) = 1 - G^{z|x}(\underline{z}(e,p)), \tag{A.4}$$

where $G^{z|x}$ is the cumulative distribution function of z conditional on x and we assume that the idiosyncratic component $u^1 - u^2$ in the payoff from working is identically distributed across all levels of experience skill e.

Since $\frac{\partial \underline{z}(e,p)}{\partial p} = -e$, which implies that for $e > 0$ the employment cutoff declines in p, it follows:

Remark 2. *Conditional on non-experience skills x, the employment rate for workers with some experience skill increases in the price of experience.*

To establish how the employment rates change differentially across workers with different experience skill, we investigate the cross-derivative of (A.4) with respect to p and e. Using Remark 1 and denoting the density function of $z|x$ by $g^{z|x} = \frac{\partial G^{z|x}}{\partial z}$, the properties of the model-implied employment rate are $\frac{\partial R(e,p,x)}{\partial p} = -g^{z|x}(\underline{z}(e,p))\frac{\partial \underline{z}(e,p)}{\partial p} > 0$, $\frac{\partial R(e,p,x)}{\partial e} = -g^{z|x}(\underline{z}(e,p))\frac{\partial \underline{z}(e,p)}{\partial e} > 0$ if $p > \gamma$, and the cross-derivative is given by

$$\frac{\partial^2 R(e,p,x)}{\partial e \partial p} = -g^{z|x}(\underline{z}(e,p))\frac{\partial^2 \underline{z}(e,p)}{\partial e \partial p} - \frac{\partial g^{z|x}(\underline{z}(e,p))}{\partial z}\frac{\partial \underline{z}(e,p)}{\partial e}\frac{\partial \underline{z}(e,p)}{\partial p} \tag{A.5}$$

Given Remark 1, the first term is positive and is due to the fact that more experienced workers' employment cutoff responds more strongly to changes in the experience price. By itself, this implies that a rise in the price of experience skill increases the employment rate of experienced by more than of less experienced individuals.

The sign of the second term is in general ambiguous as it depends on the shape of the non-experience skill distribution around this employment cutoff ($\frac{\partial g^{z|x}(\underline{z}(e,p))}{\partial z}$). How it alters the relative employment rates depends on the masses of individuals that are just marginally not-participating. For sufficiently smooth distributions, this term is very close to zero. In fact, if one assumed a constant density, which is implicitly often done in linear probability models, $\frac{\partial g^{z|x}(\underline{z}(e,p))}{\partial z} = 0$ and the second term is zero. More generally, if the density of workers who are just indifferent about participating is relatively constant across different experience skill levels, this term is very small,[43] such that a higher experience price increase the relative employment of more experienced compared to less experienced workers ($\frac{\partial^2 R(e,p,x)}{\partial e \partial p} > 0$). We summarize these considerations as:

Remark 3. *If the share of individuals at the margin of participating in the labor market is sufficiently similar across levels of experience skills, the employment rate of more experienced workers will react stronger to changes in the experience price than the one of less experienced workers.*

It is ultimately an empirical question whether the relative employment rate of experienced compared to inexperienced workers declines when the market-level supply of experience skill rises. For our main analysis, we therefore directly estimate this relationship in the data.

B Structural Wage Equation

As explained in the main text and in the previous section, our modeling framework is based on Jeong, Kim, and Manovskii (2015) and assumes that each worker supplies

[43] While for some classes of distributions, e.g. the Uniform distribution, it is always true that $\frac{\partial^2 R(e,p,x)}{\partial e \partial p} > 0$, for many other distributions it is also highly likely to hold in the empirically relevant range of employment cutoffs. Using the definition $\underline{z}(e,p) = -(p-\gamma)e$ and expressions for its derivatives, (A.5) can be written as $\frac{\partial^2 R(e,p,x)}{\partial e \partial p} = g^{z|x}(\underline{z}(e,p))\left(1 + \frac{\partial g^{z|x}(\underline{z}(e,p))}{\partial \underline{z}(e,p)} \frac{\underline{z}(e,p)}{g^{z|x}(\underline{z}(e,p))}\right)$. A sufficient condition for $\frac{\partial^2 R(e,p,x)}{\partial e \partial p} > 0$ is therefore $\frac{\partial g^{z|x}(\underline{z})}{\partial \underline{z}} \frac{\underline{z}}{g^{z|x}(\underline{z})} > -1$, i.e. that the elasticity of the density function is larger than minus one. For the Normal distribution, at most points in the distribution this is the case. For instance, for $z|x \sim N[0,1]$, $\frac{\partial g^{z|x}(\underline{z})}{\partial z} \frac{\underline{z}}{g^{z|x}(\underline{z})} = -\underline{z}^2$, implying that $\frac{\partial^2 R(e,p,x)}{\partial e \partial p} > 0$ when $-1 < \underline{z} < 1$ which would be associated with employment rates between 16 and 84 percent (and with a larger variance of $z|x$ this range increases further).

both raw labor and experienced labor inputs. In our main analysis, we worked with a linear approximation of the implied specification for log wages. Here, we derive the underlying non-linear equation for log wages and re-estimate our main results based on this structural wage equation.

The framework of Jeong, Kim, and Manovskii (2015) allows for wage differences across workers within a market, apart from experience skills differences, to stem from other productive characteristics under the assumption that these augment both raw labor and experienced labor inputs. This is the reason why the market's relative experience skill supply (4) is a productivity-weighted average. For an individual worker j this implies for their wages

$$w_j = (w^I + w^E e_j)z_j = w^I(1 + pe_j)z_j$$

where w^I and w^E are the market's wage rate per efficiency unit of raw labor and of experienced labor respectively, $p = \frac{w^E}{w^I}$ is the price of experience, and z_j are worker's efficiency units due to other productive characteristics. This implies the following wage regression in logs

$$\ln(w_j) = \ln(1 + p\, e_j) + \ln(w^I) + \beta_1 x_j + u_j \tag{B.1}$$

where the vector x_j includes observable productive characteristics and $z_j = \exp\{\beta_1 x_j\}$, and $\ln(w^I)$ corresponds to the (market-specific) constant. As explained in footnote 18 of the main text, when approximating $\ln(1 + p\, e_j) \approx p\, e_j$ the linear regression specification (12) of the main analysis follows. However, here, we implement our empirical approach on the non-linear 'structural' wage equation (B.1), rather than a linear approximation. As such, following the same multi-step approach as in our main analysis (see page 14), we first estimate using NLLS in each state and year the following log wage regression for full-time workers:

$$\ln w_{jlt} = \ln\left(1 + \sum_{k=1}^{4} \beta_{klt} \text{potexp}_j^k\right) + x_j\gamma_{lt} + \text{error}_{jlt} \tag{B.2}$$

where j is the worker in local labor market l in year t, $\sum_{k=1}^{4} \beta_{klt} \text{potexp}_j^k$ is a 4th order polynomial in potential experience (e) and x is a set of further controls, same as used in the main specification.

As in the main analysis, the estimated coefficients $\beta_{1lt}, \beta_{2lt}, \beta_{3lt}, \beta_{4lt}$ of regressions (B.2) describe the product of the market-level price per unit of experience skill and the coefficients of the underlying experience skill accumulation. Again, we normalize the linear coefficient of experience skill accumulation to be one and back out the higher order skill accumulation coefficients terms from the ratios of estimated coefficients relative to the linear coefficient, averaging over all markets to estimate $\frac{\lambda_k}{\lambda_1}$. These estimates allow us to construct the normalized experience skill as $\widetilde{e_j} = \text{potexp}_j + \frac{\lambda_2}{\lambda_1}\text{potexp}_j^2 + \frac{\lambda_3}{\lambda_1}\text{potexp}_j^3 + \frac{\lambda_4}{\lambda_1}\text{potexp}_j^4$.

Given the experience skill $\widetilde{e_j}$ constructed this way, we then estimate by LLM-year (B.1) to obtain experience prices and (11) as in the main text to obtain experience-employment gradients gradients. The difference to the main analysis is the non-linear specification of (B.2). Therefore, here the estimates of $\frac{\lambda_k}{\lambda_1}$ capture the experience skill accumulation model-consistent (rather than a linear approximation) with the structural wage equation (B.1), and the pricing (p) of these skills is consistent with this model relationship as well.

In the resulting local labor market panel, we then conduct our analysis of how experience prices and gradients are impacted by changing relative experience skill supply using our IV strategy (where the coefficients estimated here are applied in the construction of the supply and of its instrument as well). Table B.1 reports the results.

These results are very similar to those of Table 3 in the main text. The top segment shows that the constructed instrument has a strong first stage. In the two segments below, we see a strong negative effect of relative experience supply on the experience skill gradient of fulltime employment and of labor force participation. In the bottom segment, there is a negative effect of relative experience skill supply on the the wage return to experience in the state panel and no statistically meaningful effect in the panel of commuting zones. Qualitatively, this replicates exactly the findings of Table 3 that are based on the linear approximation.

Moreover, the results are also quantitatively very similar. For example, column (1) of Table B.1 implies that an increase of relative experience skill by one log point (or by approximately one percent) causes 100 times the experience gradient of fulltime employment to drop by -0.2236. Since in this state panel based on the structural wage equation, the experience gradient of fulltime employment times 100 has a mean of 3.87,

Table B.1: Estimates based on non-linear estimation of structural wage equation

	(1)	(2)	(3)	(4)	(5)	(6)
First stage	Ln(Rel.Exp)	Ln(Rel.Exp)	Rel.Exper	Ln(Rel.Exp)	Ln(Rel.Exp)	Rel.Exper
Ln(Pred Rel.Exp)	0.36***	0.46***		0.33***	0.38***	
	(0.08)	(0.06)		(0.09)	(0.09)	
Yrs Education		-0.01***			-0.01***	
		(0.00)			(0.00)	
Pred Rel.Exper			0.37***			0.33***
			(0.08)			(0.08)
Full-time emp	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100
Ln(Rel.Exper)	-22.36***	-12.23**		-16.04*	-3.14	
	(6.23)	(5.50)		(8.21)	(3.28)	
Yrs Education		-0.50**			-1.14***	
		(0.20)			(0.16)	
Rel.Experience			-2.82***			-2.21**
			(0.81)			(1.09)
LF participtn	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100
Ln(Rel.Exper)	-42.60***	-26.32***		-31.77**	-16.75***	
	(14.41)	(5.55)		(15.74)	(6.23)	
Yrs Education		-0.80***			-1.33***	
		(0.16)			(0.23)	
Rel.Experience			-5.36***			-4.09*
			(1.78)			(2.05)
Wages	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100
Ln(Rel.Exper)	-6.54***	-6.11***		0.66	-0.39	
	(2.17)	(1.68)		(1.51)	(1.54)	
Yrs Education		-0.02			0.09**	
		(0.04)			(0.04)	
Rel.Experience			-13.28***			0.63
			(4.80)			(3.56)
Observations	304	304	304	2888	2888	2888
F-Stat First Stage	22.84	62.64	24.14	13.49	19.10	14.75
R^2 First Stage	0.95	0.95	0.95	0.92	0.92	0.92
Fixed Effects	state+year	state+year	state+year	czone+year	czone+year	czone+year
Sample	>=1960	>=1960	>=1960	>=1980	>=1980	>=1980

All results in this table are based on experience skill accumulation derived from the structural wage equation (B.2). The top segment is the IV first stage, the regression of full-time workers' relative experience skill estimated onto its own prediction from the census 10 years prior (first-stage of the IV). The two middle segments display the second-stage estimates of eq. (13) for the full-time employment and the labor force participation gradient, respectively. The bottom segment reports the effect on the wage return to experience skill. Columns (1) to (3) show estimates for the panel of states over 1960–2010, columns (4) to (6) for commuting zones over 1980–2010. Observations (i.e. LLM-years) are weighted by their size (i.e. underlying number of working age males in the previous period). Robust standard errors in parentheses are clustered on state: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

this is on the mean a reduction by 5.8 percent (computed as (3.87-0.2236)/3.87). This is virtually the same as in the estimations based on the linear approximation, where according to column (1) of Table 3, given the mean of the state panel given in Table

1, an increase in relative experience skill by one percent reduces the full-time gradient by 5.6 percent.

For the reduction in the labor force participation gradient induced by a percent higher relative experience skill supply, column (1) of Table B.1 implies a fall by 38 percent (on a mean of 1.14) and Table 3 by 49 percent. While these are not as close as the implied changes in the fulltime gradient, they are also in the same ballpark and so are the changes in the wage returns, which due to the log-log specifications can be directly compared across Tables B.1 and Table 3.

C Unweighted Panel Estimation

In the results of the main text such as Table 3, we have weighted the observations by the LLM-year's underlying number of individuals in the previous census. This raises statistical precision if some labor markets are rather small. An alternative is not to weight and to treat every observation in the LLM-year panel as an equally informative data point. Table C.1 shows the results from this.

Consistent with the statistical precision argument, especially at the czone level the IV first-stage tends to be weaker. The F-statistic for the excluded instrument reported in the bottom of Table C.1 is well below 10 (which is a rule of thumb for instrument relevancy) in two out of the three czone specifications. This is because small czones, where sampling variation in the data might be substantial, receive the same weight as large czones. In fact, for the results of Table 3 we already have removed the 10% smallest LLM-years in order to alleviate the problem of noise due to small LLMs. Had we not removed these smallest markets, the results would have been even more imprecise though qualitatively very similar. This is an issue in all years, therefore affecting both the constructed local relative supply of experience skill and its prediction that we construct based on the previous census. Assigning no weights to LLM-year observations (whose precision inversely varies with their sizes) therefore results in a rather small point estimate in the IV first stage, i.e. a –on average– rather imprecise prediction of relative experience skill. When defining LLMs as states, this is less of an issue and the first stages in columns (1)–(3) of the unweighted results in Table C.1 and of the weighted results in Table 3 are rather similar.

Table C.1: Full-Time Employment Gradient, Labor Force Participation Gradient and Wage Return to Experience (Unweighted)

First Stage	(1) Ln(Rel.Exp)	(2) Ln(Rel.Exp)	(3) Rel.Exper	(4) Ln(Rel.Exp)	(5) Ln(Rel.Exp)	(6) Rel.Exper
Ln(Pred Rel.Exp)	0.33***	0.39***		0.13**	0.18***	
	(0.07)	(0.06)		(0.06)	(0.05)	
Yrs Education		-0.01**			-0.02***	
		(0.00)			(0.00)	
Pred Rel.Exper			0.33***			0.12*
			(0.07)			(0.06)
Full-time emp	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100
Ln(Rel.Exper)	-11.94	-3.58		-44.98	-20.76	
	(8.54)	(6.05)		(27.77)	(13.70)	
Yrs Education		-0.45***			-1.32***	
		(0.15)			(0.30)	
Rel.Experience			-1.80			-7.86
			(1.31)			(5.07)
LF participtn	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100
Ln(Rel.Exper)	-63.76***	-44.85***		-66.35*	-31.23*	
	(17.41)	(9.46)		(38.70)	(17.70)	
Yrs Education		-1.03***			-1.91***	
		(0.29)			(0.43)	
Rel.Experience			-9.55***			-11.28
			(2.68)			(6.83)
Wages	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100
Ln(Rel.Exper)	-5.91***	-5.23***		-3.66	-3.05	
	(1.87)	(1.44)		(3.90)	(2.66)	
Yrs Education		-0.04			-0.03	
		(0.04)			(0.07)	
Rel.Experience			-9.65***			-3.45
			(3.00)			(5.35)
Observations	274	274	274	2573	2573	2573
F-Stat First Stage	21.23	41.19	19.56	5.08	11.22	3.98
R^2 First Stage	0.95	0.95	0.94	0.90	0.90	0.90
Fixed Effects	state+year	state+year	state+year	czone+year	czone+year	czone+year
Sample	>=1960	>=1960	>=1960	>=1980	>=1980	>=1980

The top segment of the table reports the regression of full-time workers' relative experience skill onto its own prediction from the census 10 years prior (first-stage of the IV). The two middle segments display the second-stage estimates of eq. (13) for the full-time employment and the labor force participation gradient, respectively. The bottom segment reports the effect on the wage return to experience skill. Columns (1) to (3) show estimates for the panel of states over 1960–2010, columns (4) to (6) for commuting zones over 1980–2010. Observations (i.e. LLM-years) are nonweighted, but the 10% smallest are excluded. Robust standard errors in parentheses are clustered on state: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The discussion of statistical precision notwithstanding, the unweighted estimates in Table C.1 are very similar to the weighted results in Table 3. The effect of experience supply on the full-time employment gradient is quantitatively somewhat weaker for states and somewhat stronger for czones, and the effect on the labor force participation gradient is very similar as well as statistically highly significant for states. On the wage returns to experience the estimated effects are somewhat stronger than in the weighted case and they are consistently negative even for czones now (albeit not significant). Overall, this confirms our results from Table 3. It also indicates that weighting matters mainly for statistical power and that the impacts of relative experience skill supply are rather homogeneous across locations.

D Effects of Demographic Change by Skill Group

In our analysis we investigate, besides others, individuals' choices to work full-time or to be in the labor force. Rational choices should be such that the response in workers' employment decisions due to demographic change is systematic, in the sense that workers with the lowest rents from employment should be the first to leave when their experience group becomes more abundant. These rents are determined by workers' skills (via potential wages) and by their preferences for working (via reservation wages), see Section A. Since observable skill proxies might also be related to the preferences for working, it is an empirical question how the employment response depends on (observed) skills, which we explore in this section.

In particular, we study how a change in the experience supply impacts the full-time employment gradient, the labor-force-participation gradient, and the in-migration gradient by skill groups. We define skill groups based on workers' education and for the labor force and in-migration outcomes alternatively based on earnings, which we can do as in our data earnings refer to the previous year (see Section 3.1), whereas the labor force status and the migration flag correspond to the current year. Notice that we cannot do this with the full-time employment indicator, since it relies on information on hours and weeks worked in the previous year as do the wages. We therefore mainly focus in this section on labor force participation instead, but also report the effects on the full-time employment gradient by education.

Table D.1 reports how an increase in relative experience skill in a local market affects the various gradients differentially across skill groups. The very top of the table shows the effect of experience supply on the full-time employment gradient by edu-

Table D.1: Effects on LF-Participation and In-Migration by Skill Group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FT Empl by Educ	DrpOut	HS-Grd	So-Col	Collge	DrpOut	HS-Grd	So-Col	Collge
Ln(Rel.Exper)	-8.30	-41.67*	-19.66**	-38.48***	-32.29**	1.10	-10.28	-13.40
	(10.48)	(21.68)	(9.01)	(14.21)	(14.51)	(13.39)	(9.81)	(8.27)
LFP by Educ	DrpOut	HS-Grd	So-Col	Collge	DrpOut	HS-Grd	So-Col	Collge
Ln(Rel.Exper)	-85.95*	-78.88***	-77.42***	-34.15***	-87.41*	-49.57***	-61.64**	-9.45
	(44.59)	(16.13)	(29.57)	(7.41)	(47.56)	(14.34)	(25.96)	(5.75)
LFP by LyEarn	None	Terc 1	Terc 2	Terc 3	None	Terc 1	Terc 2	Terc 3
Ln(Rel.Exper)	-66.22***	-10.00	-28.16***	-20.72***	-35.38**	-16.64**	-16.23**	1.19
	(22.59)	(7.30)	(6.53)	(5.17)	(16.08)	(7.69)	(7.48)	(3.62)
In-Migr by Educ	DrpOut	HS-Grd	So-Col	Collge	DrpOut	HS-Grd	So-Col	Collge
Ln(Rel.Exper)	-29.67***	-20.77	-3.35	5.32	-21.77*	-38.12**	-37.53***	-53.91**
	(7.76)	(24.19)	(12.61)	(18.75)	(10.94)	(14.83)	(12.20)	(20.62)
In-Migr by LyEarn	None	Terc 1	Terc 2	Terc 3	None	Terc 1	Terc 2	Terc 3
Ln(Rel.Exper)	-33.95***	-22.46***	0.18	-12.59	-38.39***	-20.66**	-36.76***	-51.14***
	(12.87)	(8.66)	(19.86)	(18.07)	(13.65)	(8.31)	(12.77)	(16.17)
Observations	304	304	304	304	2888	2888	2888	2888
Fixed Effects	state+yr	state+yr	state+yr	state+yr	cz+yr	cz+yr	cz+yr	cz+yr
Sample	>=1960	>=1960	>=1960	>=1960	>=1980	>=1980	>=1980	>=1980

The table reports results from the second-stage estimation (13) for full-time employment (FT), labor force participation (LFP) and in-migration (In-Migr) by skill group. The first two segments show the effect on the full-time employment and LFP gradients of experience respectively for dropouts, high-school graduates, some college, and college graduates separately. The middle segment shows the effect for individuals with no wages in the previous year and individuals in previous year wage terciles 1–3 separately. The bottom segments show the corresponding effects on the in-migration gradient. The first stage of the IV is the same as in the top segment of Table 3. Robust standard errors in parentheses are clustered on state: * p<0.1, ** p<0.05, *** p<0.01.

cation groups:[44] columns (1) and (5) are highschool dropouts (for states and czones respectively), (2) and (6) highschool graduates, (3) and (7) attended some college, whereas (4) and (8) attained at least a four-year college degree. There is a negative effect on all of these groups, but there is no monotonicity in educational attainment discernible. This indicates that the response of full-time employment is not that systematic in terms of observable (non-experience) skills. As we obtain the experience skill accumulation profile and experience prices from regressions based on full-time workers, this suggests that selection effects are not important for the measurement of these objects.

The next segment of Table D.1 shows the effect on the labor force participation

[44] As the regressor and the instrument are the same, the first stage of the IV throughout Table D.1 is the same as the respective specifications (columns (1) and (4)) in the top segment of Table 3.

gradient of experience for drop-outs, high-school graduates, some college, and college graduates separately, in columns (1) to (4) for states and (5) to (8) for commuting zones. It appears that the effect of relative experience skill supply changes is stronger for individuals the less education they have, which seems plausible if for low-skilled workers the relevant employment margin is whether to participate in the labor market at all. This is corroborated below where we find that the effect on the labor force participation gradient is strongest for those individuals with no earnings at all in the previous year.

While education is one measure of skill, it does not capture all forms of human capital. An alternative is to proxy workers' skills by their earnings (in the previous year). We therefore do an alternative skill grouping in which we assign in each LLM-year individuals into bins based on their position in the earnings distribution amongst people with the same years of experience.[45] We create a bin for no earnings at all and one for each tercile of positive earnings.

We see in the middle segment of Table D.1 that a substantial share of the negative effect on participation are driven by individuals who did not have any labor earnings in the previous year (columns (1) and (5)), while the effect on the terciles of actual wages is much lower. If not having earned wages last year is a proxy for possessing less of the relevant skills, this suggests that a change in the relative experience skill supply affects low-skilled workers more in their labor force participation than higher-skilled workers. More generally, within working-age individuals, those with no earnings in the previous year (for skill or preference reasons) seem on average closest to the margin of participating in the labor market.[46] Together with stronger effects for less educated workers, this suggests that labor force participation effects might be systematic by skill, while full-time employment and migration (in the next paragraph) seem as much a margin of response to changing relative supply of experience skill for the higher-skilled as they are for lower-skilled individuals.

Finally, in the two bottom segments of Table D.1 we study the effects on the in-migration gradient by skill group. In the state panel, the in-migration gradient of less

[45] This corresponds to the definition of skills other than experience as $\beta^p_{lt} x_{jlt} + u^p_{jlt}$ in Equation (12).

[46] Accordingly, Dustmann, Schönberg, and Stuhler (2017) 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.

educated experienced workers declines the most when the LLM sees an increase in its relative experience skill. In terms of last year's earnings, the effect seems to be largest on individuals without any earnings or for those in the lower tercile. On the other hand, in the commuting zone panel, the effects on high-educated and high-earning workers appear stronger and there is no monotonic pattern across czone and state panels overall.

In sum, we find some mild evidence that a rise in experience supply affects labor market participation of lower-skilled more strongly than of higher-skilled individuals. That we do not find a more discernible pattern in the ranking of the full-time and migration effects by skills, supports our approach of estimating the price of experience and the experience skill accumulation profile using data on full-time workers only also in terms of minimizing any potential selection effects. More generally, theory only implies that individuals who are close to indifference of participating are the first to drop out or to enter the labor force when prices change. Whether these are more likely to be low-, middle-, or high-skilled individuals is the purely empirical question that we explored in this section.

E Additional Tables and Figures

Table E.1: Descriptive Statistics for Population and Full-time Workers Aged 16–65

Population	Full-time	LFP	Ln(Wage)	Pot Exper	Age	Yrs Educ	Female
1960							
mean	0.33	0.63	0.50	21.8	38.4	10.3	0.51
sd	0.47	0.48	1.21	14.3	13.8	3.1	0.50
1970							
mean	0.36	0.65	0.93	20.2	37.6	11.2	0.52
sd	0.48	0.48	1.22	14.9	14.5	2.9	0.50
1980							
mean	0.43	0.70	1.61	18.4	36.6	12.0	0.51
sd	0.49	0.46	1.22	14.6	14.4	2.7	0.50
1990							
mean	0.47	0.75	2.20	18.6	37.3	12.6	0.51
sd	0.50	0.43	1.22	13.4	13.4	2.4	0.50
2000							
mean	0.49	0.73	2.62	19.6	38.5	12.7	0.50
sd	0.50	0.44	1.17	13.1	13.3	2.3	0.50
2010							
mean	0.44	0.74	2.79	20.8	39.8	13.0	0.50
sd	0.50	0.44	1.26	14.0	14.2	2.3	0.50
Total							
mean	0.43	0.71	2.00	19.8	38.1	12.2	0.51
sd	0.49	0.45	1.45	14.0	14.0	2.7	0.50
N	10,316,637						
Full-time							
1960							
mean	1.00	1.00	1.13	23.1	40.1	10.8	0.27
sd	0.00	0.00	0.59	12.6	11.8	3.1	0.44
1970							
mean	1.00	1.00	1.54	22.4	40.1	11.5	0.31
sd	0.00	0.00	0.66	13.1	12.5	2.9	0.46
1980							
mean	1.00	0.98	2.20	19.2	37.8	12.5	0.38
sd	0.00	0.15	0.68	13.0	12.4	2.6	0.48
1990							
mean	1.00	0.98	2.77	19.0	38.2	13.1	0.42
sd	0.00	0.15	0.63	11.5	11.2	2.2	0.49
2000							
mean	1.00	0.94	3.11	20.4	39.8	13.2	0.43
sd	0.00	0.24	0.66	11.1	11.1	2.1	0.50
2010							
mean	1.00	0.99	3.37	22.2	41.8	13.6	0.46
sd	0.00	0.10	0.70	11.9	11.7	2.2	0.50
Total							
mean	1.00	0.98	2.62	20.8	39.7	12.7	0.40
sd	0.00	0.15	0.99	12.1	11.8	2.6	0.49
N	4,314,650						

For each year, the table reports individual-level means and standard deviations of the variables named in the top row. The top segment shows everyone aged 16–65 and the bottom segment only full-time workers. Note, as full-time is defined based on work in the previous year, but labor force status refers to the current situation, the former does not imply the latter.

Table E.2: Estimates using the Non-Parametric Experience Skill Profile (IV)

	(1)	(2)	(3)	(4)	(5)	(6)
First Stage	Ln(Rel.Exp)	Ln(Rel.Exp)	Rel.Exper	Ln(Rel.Exp)	Ln(Rel.Exp)	Rel.Exper
Ln(Pred Rel.Exp)	0.37***	0.46***		0.37***	0.41***	
	(0.07)	(0.05)		(0.09)	(0.09)	
Yrs Education		-0.01***			-0.01***	
		(0.00)			(0.00)	
Pred Rel.Exper			0.38***			0.35***
			(0.07)			(0.09)
Full-time emp	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100
Ln(Rel.Exper)	-24.95***	-18.98***		-9.27*	-2.45	
	(6.76)	(6.26)		(5.37)	(3.25)	
Yrs Education		-0.32*			-0.72***	
		(0.19)			(0.12)	
Rel.Experience			-3.92***			-1.56*
			(1.09)			(0.88)
LF participtn	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100
Ln(Rel.Exper)	-73.56***	-52.68***		-38.24*	-20.33**	
	(18.92)	(7.78)		(19.11)	(7.89)	
Yrs Education		-1.12***			-1.90***	
		(0.20)			(0.28)	
Rel.Experience			-11.46***			-5.89*
			(2.91)			(3.09)
Wages	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100
Ln(Rel.Exper)	-3.61**	-3.10***		0.96	0.40	
	(1.42)	(1.01)		(0.85)	(0.88)	
Yrs Education		-0.03			0.06***	
		(0.03)			(0.02)	
Rel.Experience			-5.45**			1.23
			(2.15)			(1.45)
Observations	304	304	304	2888	2888	2888
F-Stat First Stage	28.41	86.04	28.15	15.69	20.54	16.49
R^2 First Stage	0.95	0.95	0.95	0.92	0.92	0.91
Fixed Effects	state+year	state+year	state+year	czone+year	czone+year	czone+year
Sample	>=1960	>=1960	>=1960	>=1980	>=1980	>=1980

The top segment of the table reports the regression of full-time workers' relative nonparametric experience skill onto its own prediction from the census 10 years prior (first-stage of the IV). The nonparametric experience skill is constructed as described in Section 3.2.1 and depicted in Figure 3. The two middle segments display the second-stage estimates of eq. (13) for the full-time employment and the labor force participation gradient, respectively. The bottom segment reports the effect on the wage return to experience skill. Columns (1) to (3) show estimates for the panel of states over 1960–2010, columns (4) to (6) for commuting zones over 1980–2010. Observations (i.e. LLM-years) are nonweighted, but the 10% smallest are excluded. Robust standard errors in parentheses are clustered on state: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.3: Outcomes by Bins in the State Panel

	(1) Exp 5-9 FT 2/1	(2) Exp 10-14 FT 3/1	(3) Exp 15-19 FT 4/1	(4) Exp 20-24 FT 5/1	(5) Exp 25-29 FT 6/1	(6) Exp 30-34 FT 7/1	(7) Exp 35-39 FT 8/1	(8) Exp 40-45 FT 9/1
Ln(Rel.Exper)	-0.92**	-1.25**	-1.56***	-1.15***	-0.63	-1.04**	-1.06**	-1.38**
	(0.43)	(0.49)	(0.53)	(0.44)	(0.55)	(0.47)	(0.49)	(0.65)
	LFP 2/1	LFP 3/1	LFP 4/1	LFP 5/1	LFP 6/1	LFP 7/1	LFP 8/1	LFP 9/1
Ln(Rel.Exper)	-4.21***	-5.04***	-5.17***	-5.45***	-5.37***	-5.56***	-5.37***	-5.47**
	(1.59)	(1.63)	(1.63)	(1.74)	(1.78)	(1.92)	(1.93)	(2.28)
	ln(w) 2/1	ln(w) 3/1	ln(w) 4/1	ln(w) 5/1	ln(w) 6/1	ln(w) 7/1	ln(w) 8/1	ln(w) 9/1
Ln(Rel.Exper)	-1.90***	-1.85***	-2.44***	-2.98***	-3.28***	-2.60**	-1.85*	-1.44
	(0.66)	(0.70)	(0.84)	(0.99)	(1.05)	(1.07)	(1.04)	(0.91)
Observations	304	304	304	304	304	304	304	304
Fixed Effects	state+year	state+year	state+year	state+year	state+year	state+year	state+year	state+year
Sample	>=1960	>=1960	>=1960	>=1960	>=1960	>=1960	>=1960	>=1960

The table reports the IV second-stage estimates in the state panel of the effect of relative experience skill supply on the full-time employment rate, labor force participation rate, and log wages of the respective 5-year experience bins relative to workers with 0–4 years of experience. The rates and wages by bin are constructed by replacing $\widetilde{e_{jlt}}$ in specifications (11) and (12) with a set of dummies corresponding to 9 experience bins (from 0-4 to 40-45 years of potential experience) in the individual-level regressions. The first stage of the IV is the same as in Table 3, column (1) with F-statistic for the excluded instrument of 20.21. Observations (i.e. LLM-years) are weighted by their size (i.e. underlying number of working age individuals in the previous period). Robust standard errors in parentheses are clustered on state: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.4: Outcomes by Bins in the Czone Panel

	(1) Exp 5-9 FT 2/1	(2) Exp 10-14 FT 3/1	(3) Exp 15-19 FT 4/1	(4) Exp 20-24 FT 5/1	(5) Exp 25-29 FT 6/1	(6) Exp 30-34 FT 7/1	(7) Exp 35-39 FT 8/1	(8) Exp 40-45 FT 9/1
Ln(Rel.Exper)	-1.23**	-1.18*	-0.65	-0.97	-0.03	-0.31	-0.41	-1.59*
	(0.58)	(0.63)	(0.52)	(0.62)	(0.45)	(0.46)	(0.59)	(0.92)
	LFP 2/1	LFP 3/1	LFP 4/1	LFP 5/1	LFP 6/1	LFP 7/1	LFP 8/1	LFP 9/1
Ln(Rel.Exper)	-3.28*	-3.46**	-3.69**	-3.67**	-3.61**	-3.68*	-3.70*	-4.38*
	(1.67)	(1.56)	(1.64)	(1.77)	(1.78)	(1.87)	(2.02)	(2.33)
	ln(w) 2/1	ln(w) 3/1	ln(w) 4/1	ln(w) 5/1	ln(w) 6/1	ln(w) 7/1	ln(w) 8/1	ln(w) 9/1
Ln(Rel.Exper)	0.18	1.01	1.51*	0.50	-0.38	0.17	0.00	0.05
	(0.56)	(0.70)	(0.77)	(0.70)	(0.86)	(0.78)	(0.97)	(0.95)
Observations	2888	2888	2888	2888	2888	2888	2888	2888
Fixed Effects	cz+year	cz+year	cz+year	cz+year	cz+year	cz+year	cz+year	cz+year
Sample	>=1980	>=1980	>=1980	>=1980	>=1980	>=1980	>=1980	>=1980

The table reports the IV second-stage estimates in the czone panel of the effect of relative experience skill supply on the full-time employment rate, labor force participation rate, and log wages of the respective 5-year experience bins relative to workers with 0-4 years of experience. The rates and wages by bin are constructed by replacing $\widetilde{e_{jlt}}$ in specifications (11) and (12) with a set of dummies corresponding to 9 experience bins (from 0-4 to 40-45 years of potential experience) in the individual-level regressions. The first stage of the IV is the same as in Table 3, column (4) with F-statistic for the excluded instrument of 14.66. Observations (i.e. LLM-years) are weighted by their size (i.e. underlying number of working age individuals in the previous period). Robust standard errors in parentheses are clustered on state: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.5: Estimates using State Interacted with Year Fixed Effects for Czones (IV)

	(1)	(2)	(3)	(4)	(5)	(6)
First stage & FT	Ln(Rel.Exp)	Ln(Rel.Exp)	Rel.Exper	FTgrad x100	FTgrad x100	FTgrad x100
Ln([Pred]Rel.Exp)	0.14***	0.15***		-15.34	-10.51	
	(0.05)	(0.05)		(11.24)	(9.07)	
Yrs Education		-0.02***			-0.85***	
		(0.00)			(0.18)	
[Pred]Rel.Exper			0.13***			-2.58
			(0.05)			(1.90)
LFP & Wages	LFgrad x100	LFgrad x100	LFgrad x100	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100
Ln(Rel.Exper)	-50.46***	-42.92**		-4.11	-3.76	
	(18.61)	(15.99)		(2.78)	(2.50)	
Yrs Education		-1.33***			-0.06	
		(0.38)			(0.05)	
Rel.Experience			-7.65**			-7.22
			(2.91)			(4.59)
Observations	2888	2888	2888	2888	2888	2888
F-Stat First Stage	7.69	9.11	7.21	7.69	9.11	7.21
R^2 First Stage	0.95	0.95	0.95	0.95	0.95	0.95
Fixed Effects	cz;stateXyr	cz;stateXyr	cz;stateXyr	cz;stateXyr	cz;stateXyr	cz;stateXyr
Sample	>=1980	>=1980	>=1980	>=1980	>=1980	>=1980

The table reports results when we control for state×year fixed effects in regressions on the commuting zone level, whereby overlapping commuting zones are assigned to the state with the highest share of employment. Columns (1)-(3) in the top segment show the regression of full-time workers' relative experience skill onto its own prediction from the census 10 years prior (first-stage of the IV). Columns (4)-(6) of the top segment and columns (1)-(3) of the bottom segment display the second-stage estimates of eq. (13) for the full-time employment and the labor force participation gradient, respectively. Columns (4)-(6) of the bottom segment report the effect on the wage return to experience skill. Observations (i.e. LLM-years) are weighted by their size (i.e. underlying number of working age individuals in the previous period). Robust standard errors in parentheses are clustered on state: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.6: Full-Time Empl. Gradient and Wage Return to Experience (IV, Add. Controls)

	(1)	(2)	(3)	(4)	(5)	(6)
First stage	Ln(Rel.Exp)	Ln(Rel.Exp)	Ln(Rel.Exp)	Ln(Rel.Exp)	Ln(Rel.Exp)	Ln(Rel.Exp)
Ln(Pred Rel.Exp)	0.30***	0.31***	0.28***	0.30***	0.26***	0.28***
	(0.05)	(0.08)	(0.07)	(0.08)	(0.07)	(0.07)
Sh. Goods Ind	-0.04		-0.01	-0.05		-0.03
	(0.05)		(0.03)	(0.04)		(0.04)
Sh. Routine Occ	0.15**		0.13**	0.08		0.08
	(0.07)		(0.06)	(0.06)		(0.06)
Share Black		0.01	0.05		-0.01	-0.00
		(0.06)	(0.06)		(0.04)	(0.04)
Share Female		0.20**	0.19***		0.08	0.07
		(0.08)	(0.06)		(0.06)	(0.05)
Full-time emp	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100
Ln(Rel.Exper)	-27.66***	-24.06***	-32.31***	-12.02*	-17.48*	-12.67*
	(6.81)	(7.27)	(6.68)	(6.22)	(8.75)	(6.58)
Sh. Goods Ind	1.36		2.85*	1.35		1.60*
	(2.00)		(1.51)	(0.83)		(0.92)
Sh. Routine Occ	4.71		4.23	3.45***		3.37***
	(3.19)		(2.75)	(1.17)		(1.22)
Share Black		-0.53	2.78		-0.78	-0.66
		(1.96)	(2.19)		(1.79)	(1.63)
Share Female		7.46**	10.16***		0.75	1.56
		(3.79)	(2.82)		(1.76)	(1.58)
LF participtn	LF-part x100	LF-part x100	LF-part x100	LF-part x100	LF-part x100	LF-part x100
Ln(Rel.Exper)	-94.52***	-87.97***	-99.92***	-62.04**	-60.86**	-58.44**
	(28.45)	(31.12)	(33.39)	(27.80)	(27.48)	(25.18)
Sh. Goods Ind	0.62		2.20	1.39		0.98
	(4.80)		(3.97)	(2.32)		(2.13)
Sh. Routine Occ	9.63		9.62	1.79		1.62
	(9.00)		(9.69)	(3.96)		(3.73)
Share Black		-0.16	4.80		-2.67	-2.62
		(5.96)	(6.25)		(4.50)	(4.34)
Share Female		6.03	9.22		-4.09	-3.60
		(8.15)	(6.65)		(3.16)	(2.84)
Wages	Ln(Rtrn)	Ln(Rtrn)	Ln(Rtrn)	Ln(Rtrn)	Ln(Rtrn)	Ln(Rtrn)
Ln(Rel.Exper)	-3.46*	-4.50***	-3.66*	-0.07	0.86	0.25
	(1.82)	(1.65)	(1.94)	(1.10)	(1.19)	(1.22)
Sh. Goods Ind	-0.85***		-0.74***	-0.40***		-0.46***
	(0.29)		(0.28)	(0.11)		(0.10)
Sh. Routine Occ	0.56		0.38	-0.31**		-0.31**
	(0.52)		(0.51)	(0.14)		(0.14)
Share Black		-0.03	-0.33		-0.13	-0.12
		(0.35)	(0.34)		(0.29)	(0.32)
Share Female		1.63***	1.19**		-0.19	-0.42*
		(0.58)	(0.60)		(0.26)	(0.23)
Observations	304	304	304	2888	2888	2888
R^2 First Stage	0.95	0.95	0.95	0.91	0.91	0.91
F-Stat First Stage	32.09	13.34	17.35	15.06	14.76	14.95
Fixed Effects	state+year	state+year	state+year	czone+year	czone+year	czone+year
Sample	>=1960	>=1960	>=1960	>=1980	>=1980	>=1980

This table includes additional control variables into our main estimations of Table 3. In columns (1) and (4) these are the share of full-time employment in goods-producing sectors and in routine occupations; in columns (2) and (5) the shares of blacks and of females among full-time employment; and both of these together in columns (3) and (6). For any other details, see the notes to main Table 3. Robust standard errors in parentheses are clustered on state: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.7: Employment Gradients and Wage Return to Experience using 20-year IV

	(1)	(2)	(3)	(4)	(5)	(6)
First Stage	Ln(Rel.Exp)	Ln(Rel.Exp)	Rel.Exper	Ln(Rel.Exp)	Ln(Rel.Exp)	Rel.Exper
Ln(Pred Rel.Exp)	0.34***	0.39***		0.23***	0.23***	
	(0.06)	(0.05)		(0.04)	(0.04)	
Yrs Education		-0.01***			-0.00	
		(0.00)			(0.00)	
Pred Rel.Exper			0.35***			0.24***
			(0.06)			(0.04)
Full-time emp	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100
Ln(Rel.Exper)	-19.66***	-12.38**		-16.43***	-14.23***	
	(6.33)	(5.46)		(5.75)	(4.71)	
Yrs Education		-0.41**			-0.46***	
		(0.17)			(0.11)	
Rel.Experience			-2.97***			-2.44***
			(0.98)			(0.86)
LF participtn	LFgrd x100	LFgrd x100	LFgrd x100	LFgrd x100	LFgrd x100	LFgrd x100
Ln(Rel.Exper)	-64.18***	-40.74***		-44.80***	-39.53***	
	(20.62)	(9.68)		(12.16)	(9.44)	
Yrs Education		-1.32***			-1.11***	
		(0.24)			(0.26)	
Rel.Experience			-9.69***			-6.46***
			(3.03)			(1.78)
Wages	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100
Ln(Rel.Exper)	-3.10**	-2.85**		0.97	0.61	
	(1.58)	(1.32)		(1.06)	(1.03)	
Yrs Education		-0.01			0.08***	
		(0.02)			(0.02)	
Rel.Experience			-4.92**			1.32
			(2.49)			(1.62)
Observations	302	302	302	2888	2888	2888
F-Stat First Stage	32.03	57.02	32.57	33.96	36.78	33.37
R^2 (First Stage)	0.95	0.95	0.95	0.85	0.85	0.85
Fixed Effects	state+year	state+year	state+year	czone+year	czone+year	czone+year
Sample	≥1960	≥1960	≥1960	1970;≥1990	1970;≥1990	1970;≥1990

The top segment of the table reports the regression of full-time workers' relative experience skill onto its own prediction from the census 20 years prior (first-stage of the IV). The two middle segments display the second-stage estimates for the full-time employment and the labor force participation gradient, respectively. The bottom segment reports the effect on the wage return to experience skill. Columns (1) to (3) show estimates for the panel of states over 1960–2010, columns (4) to (6) for commuting zones over 1970 and 1990–2010. Observations (i.e. LLM-years) are weighted by their size (i.e. underlying number of working age individuals in the previous period). Robust standard errors in parentheses are clustered on state: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.8: Estimates using Sample of Males only (IV)

First stage	(1) Ln(Rel.Exp)	(2) Ln(Rel.Exp)	(3) Rel.Exper	(4) Ln(Rel.Exp)	(5) Ln(Rel.Exp)	(6) Rel.Exper
Ln(Pred Rel.Exp)	0.27***	0.34***		0.16***	0.17***	
	(0.07)	(0.07)		(0.04)	(0.04)	
Yrs Education		-0.01**			-0.00	
		(0.00)			(0.00)	
Pred Rel.Exper			0.28***			0.16***
			(0.07)			(0.04)
Full-time emp	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100
Ln(Rel.Exper)	-29.22***	-5.42		-43.20**	-18.97**	
	(10.99)	(8.39)		(19.06)	(8.48)	
Yrs Education		-0.69***			-1.24***	
		(0.15)			(0.14)	
Rel.Experience			-4.29***			-7.02**
			(1.60)			(2.97)
LF participtn	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100
Ln(Rel.Exper)	-94.50**	-43.26**		-109.48**	-72.20***	
	(47.34)	(18.15)		(49.42)	(25.72)	
Yrs Education		-1.49***			-1.91***	
		(0.37)			(0.37)	
Rel.Experience			-13.88**			-17.06**
			(6.97)			(7.67)
Wages	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100
Ln(Rel.Exper)	-3.26*	-2.76*		-0.79	-2.01	
	(1.91)	(1.62)		(1.74)	(1.68)	
Yrs Education		-0.01			0.06**	
		(0.02)			(0.02)	
Rel.Experience			-6.72*			-1.44
			(3.53)			(3.27)
Observations	304	304	304	2888	2888	2888
F-Stat First Stage	16.53	25.13	16.48	15.31	22.75	16.4
R^2 First Stage	0.94	0.94	0.94	0.88	0.89	0.89
Fixed Effects	state+year	state+year	state+year	czone+year	czone+year	czone+year
Sample	>=1960	>=1960	>=1960	>=1980	>=1980	>=1980

The table reports results when the whole analysis is restricted to males. The top segment of the table reports the regression of full-time workers' relative experience skill onto its own prediction from the census 10 years prior (first-stage of the IV). The two middle segments display the second-stage estimates of eq. (13) for the full-time employment and the labor force participation gradient, respectively. The bottom segment reports the effect on the wage return to experience skill. Columns (1) to (3) show estimates for the panel of states over 1960–2010, columns (4) to (6) for commuting zones over 1980–2010. Observations (i.e. LLM-years) are weighted by their size (i.e. underlying number of working age males in the previous period). Robust standard errors in parentheses are clustered on state: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.9: Estimates of Outcomes for Ages 16–55 only (IV)

	(1)	(2)	(3)	(4)	(5)	(6)
First stage	Ln(Rel.Exp)	Ln(Rel.Exp)	Rel.Exper	Ln(Rel.Exp)	Ln(Rel.Exp)	Rel.Exper
Ln(Pred Rel.Exp)	0.32***	0.41***		0.28***	0.33***	
	(0.07)	(0.06)		(0.07)	(0.07)	
Yrs Education		-0.01***			-0.01***	
		(0.00)			(0.00)	
Pred Rel.Exper			0.33***			0.27***
			(0.07)			(0.07)
Full-time emp	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100
Ln(Rel.Exper)	-17.97***	-9.39*		-11.86*	-0.37	
	(6.48)	(5.34)		(6.79)	(4.02)	
Yrs Education		-0.34*			-0.86***	
		(0.20)			(0.19)	
Rel.Experience			-2.68***			-2.02*
			(0.98)			(1.07)
LF participtn	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100
Ln(Rel.Exper)	-84.03***	-52.06***		-61.72**	-36.94***	
	(28.18)	(10.95)		(28.07)	(12.84)	
Yrs Education		-1.28***			-1.84***	
		(0.20)			(0.29)	
Rel.Experience			-12.49***			-9.55**
			(4.12)			(4.34)
Wages	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100
Ln(Rel.Exper)	-4.62***	-4.14***		0.75	0.10	
	(1.57)	(1.16)		(1.09)	(1.05)	
Yrs Education		-0.02			0.05**	
		(0.02)			(0.02)	
Rel.Experience			-7.64***			0.82
			(2.58)			(1.81)
Observations	304	304	304	2888	2888	2888
F-Stat First Stage	20.27	56.76	20.99	14.64	20.50	15.68
R^2 First Stage	0.95	0.95	0.95	0.91	0.92	0.91
Fixed Effects	state+year	state+year	state+year	czone+year	czone+year	czone+year
Sample	>=1960	>=1960	>=1960	>=1980	>=1980	>=1980

The IV first stage in this Table is the regression of full-time workers' relative experience skill onto its own prediction from the census 10 years prior (first-stage of the IV). The two middle segments display the second-stage estimates of eq. (13) for the full-time employment and the labor force participation gradient, respectively. The bottom segment reports the effect on the wage return to experience skill. These three outcome variables (i.e. gradients and wage return) are estimated at the micro-level for ages 16–55 only in order to abstract from potential issues related to early retirement. Columns (1) to (3) show estimates for the panel of states over 1960–2010, columns (4) to (6) for commuting zones over 1980–2010. Observations (i.e. LLM-years) are weighted by their size (i.e. underlying number of working age males in the previous period). Robust standard errors in parentheses are clustered on state: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.10: Estimates Including Part-Time Workers in Experience Supply (IV)

	(1)	(2)	(3)	(4)	(5)	(6)
First stage	Ln(Rel.Exp)	Ln(Rel.Exp)	Rel.Exper	Ln(Rel.Exp)	Ln(Rel.Exp)	Rel.Exper
Ln(Pred Rel.Exp)	0.32***	0.42***		0.26***	0.31***	
	(0.07)	(0.05)		(0.07)	(0.07)	
Yrs Education		-0.01***			-0.01***	
		(0.00)			(0.00)	
Pred Rel.Exper			0.34***			0.25***
			(0.07)			(0.07)
Full-time emp	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100
Ln(Rel.Exper)	-22.39***	-12.05**		-18.67**	-3.48	
	(6.38)	(5.34)		(9.16)	(3.74)	
Yrs Education		-0.42**			-0.99***	
		(0.17)			(0.13)	
Rel.Experience			-3.31***			-3.06**
			(0.96)			(1.44)
LF participtn	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100	LFgrad x100
Ln(Rel.Exper)	-86.42***	-52.39***		-70.35**	-38.22***	
	(29.80)	(10.78)		(33.51)	(13.45)	
Yrs Education		-1.38***			-2.09***	
		(0.24)			(0.34)	
Rel.Experience			-12.77***			-10.84**
			(4.34)			(5.20)
Wages	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100
Ln(Rel.Exper)	-4.04***	-3.61***		1.04	0.13	
	(1.54)	(1.12)		(1.05)	(1.04)	
Yrs Education		-0.02			0.06***	
		(0.02)			(0.02)	
Rel.Experience			-6.54***			1.31
			(2.45)			(1.71)
Observations	304	304	304	2888	2888	2888
F-Stat First Stage	19.95	60.19	20.7	12.88	18.11	13.5
R^2 First Stage	0.94	0.95	0.94	0.91	0.91	0.91
Fixed Effects	state+year	state+year	state+year	czone+year	czone+year	czone+year
Sample	>=1960	>=1960	>=1960	>=1980	>=1980	>=1980

The IV first stage in this Table is the regression of full-time plus part-time (with adjusted weight of 0.5) workers' relative experience skill onto its own prediction from the census 10 years prior (first-stage of the IV). The two middle segments display the second-stage estimates of eq. (13) for the full-time employment and the labor force participation gradient, respectively. The bottom segment reports the effect on the wage return to experience skill. Columns (1) to (3) show estimates for the panel of states over 1960–2010, columns (4) to (6) for commuting zones over 1980–2010. Observations (i.e. LLM-years) are weighted by their size (i.e. underlying number of working age males in the previous period). Robust standard errors in parentheses are clustered on state: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.11: Estimates Separately for High-School and College Sample (IV)

	(1)	(2)	(3)	(4)	(5)	(6)
Fullt, HS	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100
Ln(Rel.Exper)	-27.13***	-16.36**		-12.40*	-0.55	
	(7.55)	(6.49)		(6.95)	(5.69)	
Yrs Education		-0.53**			-1.02***	
		(0.21)			(0.19)	
Rel.Experience			-4.03***			-1.73
			(1.16)			(1.04)
LFP, HS	LF-part x100	LF-part x100	LF-part x100	LF-part x100	LF-part x100	LF-part x100
Ln(Rel.Exper)	-95.49***	-60.43***		-68.93**	-39.30***	
	(33.84)	(13.66)		(29.90)	(11.99)	
Yrs Education		-1.71***			-2.54***	
		(0.29)			(0.37)	
Rel.Experience			-14.33***			-10.00**
			(5.02)			(4.34)
Wages, HS	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100
Ln(Rel.Exper)	-3.26	-3.83**		1.29	0.38	
	(2.13)	(1.59)		(2.22)	(1.54)	
Yrs Education		0.03			0.08*	
		(0.03)			(0.04)	
Rel.Experience			-5.58*			3.08
			(3.29)			(3.59)
Fullt, Col	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100	FTgrad x100
Ln(Rel.Exper)	-24.85**	-16.57**		-21.43*	-11.43	
	(10.57)	(7.34)		(12.38)	(9.06)	
Yrs Education		-0.41***			-0.75***	
		(0.15)			(0.15)	
Rel.Experience			-3.95**			-3.52*
			(1.62)			(1.86)
LFP, Col	LF-part x100	LF-part x100	LF-part x100	LF-part x100	LF-part x100	LF-part x100
Ln(Rel.Exper)	-58.35**	-37.23***		-48.57**	-32.25**	
	(28.68)	(13.48)		(21.25)	(12.17)	
Yrs Education		-1.04***			-1.23***	
		(0.26)			(0.26)	
Rel.Experience			-8.77**			-7.04**
			(4.29)			(3.10)
Wages, Col	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100	Ln(Rtrn)	Ln(Rtrn)	Rtrn x100
Ln(Rel.Exper)	-0.14	-0.89		-0.49	-1.04	
	(1.41)	(1.57)		(1.67)	(1.75)	
Yrs Education		0.04			0.04	
		(0.02)			(0.02)	
Rel.Experience			-1.38			-1.70
			(2.75)			(2.94)
Fixed Effects	state+year	state+year	state+year	czone+year	czone+year	czone+year
Sample	≥1960	≥1960	≥1960	≥1980	≥1980	≥1980
F-Stat First Stage	20.21	56.14	20.91	14.66	20.43	15.72
Obs (Fullt & LFP)	304	304	304	2888	2888	2888
Obs (Wages, HS)	304	304	304	2887	2887	2888
Obs (Wages, Col)	304	304	304	2880	2880	2888

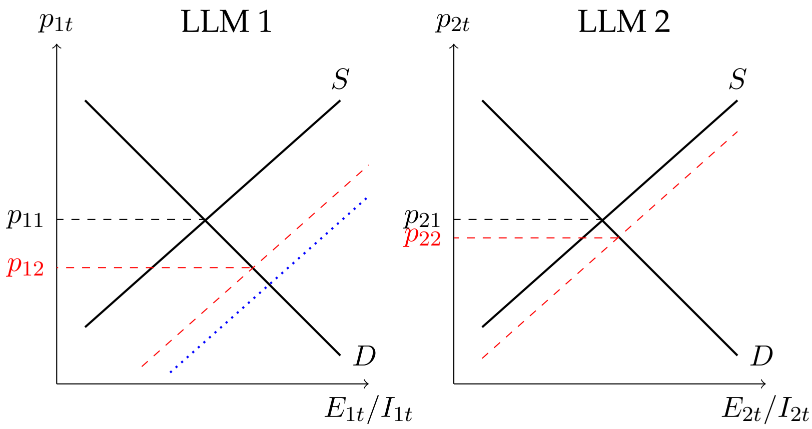
The table reports results when the analysis of outcomes is split by workers' education. The first three segments display for the subsample of high-school workers the second-stage estimates (13) for the full-time employment gradient, the labor force participation gradient, and the wage return to experience skill, respectively. The last three segments show these estimates for the subsample of college workers. Only the F-statistics for the excluded instruments from the IV first stage are reported to save space. Columns (1) to (3) show estimates for the panel of states over 1960–2010, columns (4) to (6) for commuting zones over 1980–2010. Robust standard errors in parentheses are clustered on state: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E.12: Descriptive Statistics for the State and Czone Panels (Additional Variables)

	Emplnt	In-Migrtn	Out-Migrtn	Net-Migrtn	Soc-Secrty	Disability	Welfare
State Panel							
1960							
mean	3.07	-1.40	.	.	.	.	.
sd	0.58	0.60	.	.	.	.	.
1970							
mean	3.04	-2.09	-0.51	-0.98	0.37	1.11	0.09
sd	0.56	0.54	0.17	0.71	0.09	0.21	0.04
1980							
mean	1.83	-1.21	-0.46	-0.16	0.73	1.46	0.18
sd	0.68	0.50	0.17	0.58	0.16	0.24	0.10
1990							
mean	1.81	-1.45	-0.92	-0.25	1.00	1.44	0.28
sd	0.56	0.55	0.36	0.69	0.14	0.21	0.11
2000							
mean	1.53	-1.62	-0.90	-0.43	1.01	1.14	0.45
sd	0.50	0.56	0.37	0.58	0.18	0.19	0.12
2010							
mean	2.48	-0.67	-0.51	-0.11	1.23	1.57	0.50
sd	0.67	0.30	0.19	0.23	0.28	0.39	0.12
Total							
mean	2.22	-1.35	-0.67	-0.47	0.92	1.36	0.33
sd	0.83	0.67	0.34	0.71	0.34	0.32	0.19
N	304						
Czone Panel							
1980							
mean	1.81	-0.58	.	.	0.73	1.47	0.18
sd	0.88	0.36	.	.	0.24	0.32	0.14
1990				.			
mean	1.79	-1.40	.	.	1.00	1.45	0.27
sd	0.86	0.78	.	.	0.26	0.32	0.16
2000							
mean	1.49	-1.60	.	.	1.01	1.13	0.45
sd	0.78	0.83	.	.	0.28	0.31	0.17
2010							
mean	2.46	-0.65	.	.	1.23	1.56	0.50
sd	0.93	0.46	.	.	0.39	0.54	0.19
Total							
mean	1.92	-1.07	.	.	1.02	1.40	0.37
sd	0.94	0.78	.	.	0.35	0.43	0.21
N	2888						

For each year, the table shows local labor market (LLM) level means and standard deviations of the variables named in the top row. The variables are all gradients in experience skill from regression (11), i.e. with regard to employment (full-time or parttime), in-migration into the LLM in question, out-migration from the LLM, net-migration, social security income (including pensions and disability), disability (self-identified), and welfare income (including GA and SSI). Out and net migration cannot be constructed in the 1960 Census. Information on disability as well as welfare and social security claims are not available in 1960. We also harmonized somewhat different definitions of disability and migration for 2010 with the previous years.

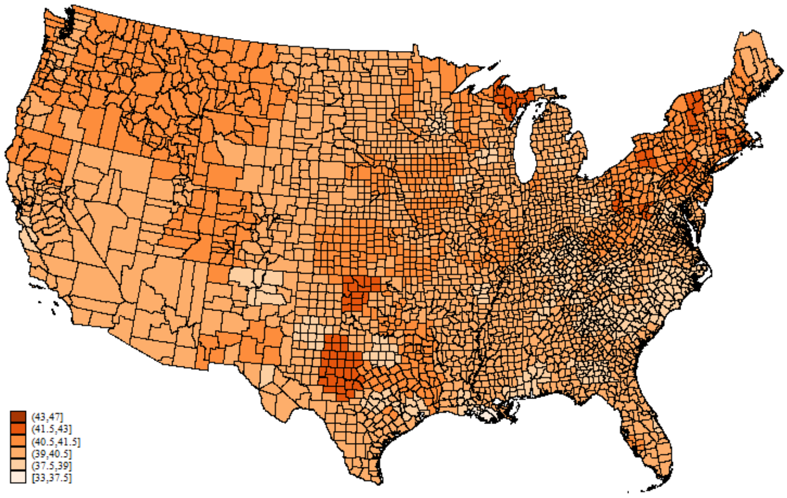
Figure E.1: Relative experience supply shock in LLM 1 with migration response



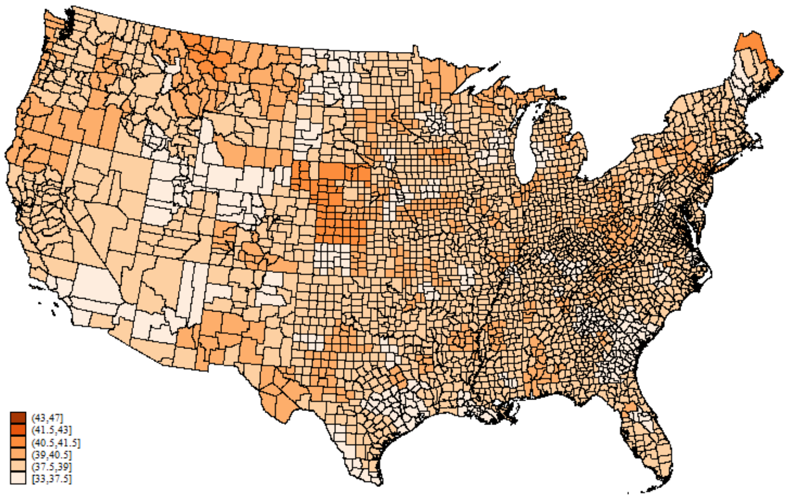
Notes: The Figure illustrates an endogenous migration response of rising relative migration of experienced workers from LLM 1, which was hit by an aging shock, to LLM 2. The original shock in LLM 1 moves the relative supply of experience skill down to the dotted line, which goes in hand with a substantial 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 skill there and reducing it in LLM 1.

Figure E.2: The Distribution of Average Working Age across U.S. Locations and Time

(a) Average Age of Full-time Workers 1970



(b) Average Age of Full-time Workers 1990



(c) Average Age of Full-time Workers 2010