The Geography of Life Cycle Wage Growth in the United States*

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Abstract

This paper uses representative large-sample household surveys to document that life cycle wage growth varies substantially across areas within the United States. Wages grow more over the life cycle in richer Combined Statistical Areas (CSA) with higher income per capita. For example, after 20 years of experience, the average worker's wage is about 90.2% higher in Washington, DC, the richest area in the sample, but only by 66.1% in El Paso, TX, the poorest CSA in the sample. These geographic disparities persist even after conditioning on educational attainment groups. A counterfactual accounting exercise suggests that differences in educational attainment plays only a modest role by accounting for about 13.1% of the differences in experience-wage profiles. The result is consistent with theories in which workers in poor areas accumulate less human capital on the job, or stronger search frictions in poor areas prevent workers from climbing the job ladder.

JEL Codes: E24, J24

Keywords: Age-Earnings Profiles, Human Capital, Growth Accounting

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1 Introduction

This paper documents substantial variation in life cycle wage growth across different areas within the United States. On average, wages growth is steeper over the life cycle in richer Combined Statistical Areas (CSA) with higher income per capita. This pattern persists across all levels of educational attainment. While differences in educational attainment play a minor role in explaining these geographical variations, they do contribute positively. This aligns with theories suggesting that workers in less affluent areas may accrue less human capital on the job (Becker (1964), Ben-Porath (1967), Manuelli and Seshadri (2014), Lagakos et al. (2018a)) or encounter greater labor market frictions (Burdett (1978), Jovanovic (1984), Bagger et al. (2014)).

The idea that wages grow substantially over a worker's life cycle dates back to Mincer (1974). More recent work has documented that there can be large differences in life cycle wage growth across countries (Lagakos et al. (2018b), Engbom (2022)). One hypothesis for the observed differences is that wealthier areas have a higher proportion of highly educated workers. Earlier studies from Mincer (1974) found similar wage profiles across different educational groups. However, more recent research indicates that educated workers tend to experience steeper wage growth (Lemieux (2006)). At the same time, it is also known that there are large geographic differences in intergenerational mobility (Black and Devereux (2011)), either across countries (Björklund and Jäntti (1997)) or across neighborhoods within the same country (Solon (1999), Chetty et al. (2014)).

However, there has been little evidence comparing differences in life cycle wage growth across various regions within a country. Such estimates are important for understanding the importance of human capital and labor market frictions for explaining the large geographic differences in economic development within the U.S. This paper addresses this gap by measuring life cycle wage growth in major CSAs in the U.S. using the same data source and measurement method, offering insights that are challenging to obtain through cross-country comparisons.

2 Data

This paper follows Lagakos et al. (2018b) in constructing a nationally representative household survey sample for the United States. The surveys included in the sample are from the *Census of Population Housing* (decennial from 1940 to 2000, 1% sample until 1970, 5% sample for 1980 to 2000) and the *American Community Survey* (annual from 2001 to 2021, 1% sample). Observations are weighted using the sampling weights provided in each survey. The data has been downloaded through the Integrated Public Use Microdata Series (IPUMS). Finally, data on annual income per capita for each CSA has been downloaded from the Bureau of Economic Analysis (BEA).

The main variables of interest are the worker's wage and potential experience. Wage is defined as the worker's total annual earnings divided by the annual number of hours worked. Earnings is measured before taxes and hours is defined as the usual weekly hours worked. Earnings and hours worked combine both primary and secondary jobs. Earnings and wages are expressed in units of 2015 U.S. dollars by using the Consumer Price Index to deflate nominal values. To minimize the impact of differences in top-coding procedures across surveys, outliers at the top and bottom 1% of wages have been removed.

Potential experience is defined as the years of experience a worker could have accumulated assuming that the worker begins work at age 18 or after finishing schooling, whichever one occurs later. Specifically, it is defined as age − schooling − 6 for workers with 12 or more years of schooling, and otherwise equal to age − 18 for workers with less than 12 years of schooling. A worker's years of schooling is imputed using educational attainment data.

The sample is restricted to male full-time wage-earning workers in the private sector with 0-40 years of experience, positive labor income, and non-missing survey responses on age and schooling. Focusing on male workers abstracts from differences in female labor force participation across CSAs with various levels of development. An individual is considered to be a full-time worker if its hours worked is greater than 30 hours per week. The restriction to wage-earning workers excludes self-employed workers, whose earnings can contain returns from not only labor but also from capital. Focusing on private sector workers abstracts from potential non-wage compensation that public sector workers can receive for their labor. Workers are grouped into CSAs based on the location of their housing unit at the time of each survey. The CSAs considered in this analysis are Combined Statistical Areas (CSA) whose survey data covers at least 15 years and 10,000 workers.

3 Empirical Specification

As a starting point that imposes minimal assumptions on the data, I focus on experience-wage profiles as the main measure of life cycle wage growth. The experience-wage profiles are estimated from Mincer (1974) regressions of the workers' wages on their years of schooling and potential experience. Consider a variant of the regression in Lagakos et al. (2018b), by regressing the logarithm of wages on schooling, a set of dummy variables for 5-year experience groups, and a set of time period dummy variables:

$$\log w_{ict} = \alpha + \theta s_{ict} + \sum_{x \in X} \phi_x D_{ict}^x + \gamma_t + \varepsilon_{ict} \tag{1}$$

where w_{ict} is the wage of worker i from CSA c observed at time t. s_{ict} is the worker's years of schooling. D_{ict}^x is a dummy variable that equals one if a worker is in experience group $x \in X =$

$\{5-9, 10-14, \ldots, 35-39\}$. γ_t is a vector of time period dummy variables which controls for secular trends that apply to all workers, such as the rental price of human capital (Fang and Qiu (2023)). ε_{ict} is a mean zero error term. I estimate equation (1) separately for each CSA, and then study how the estimated coefficients $\{\phi_x\}_{x \in X}$ varies across CSAs.

The coefficients $\{\phi_x\}_{x \in X}$ identify the experience-wage profile evaluated at each point x. Specifying potential experience as a set of 5-year experience bins allows the relationship between wages and experience to be potentially nonlinear. The omitted reference group is for 0-4 years of experience, meaning that the coefficients $\{\phi_x\}_{x \in X}$ estimate the average wage of workers in experience group x relative to the average wage of workers with less than 5 years of experience. I follow the standard Mincer (1974) regression in assuming that schooling and experience are additively separable. The profiles use experience instead of age because years of experience is more comparable across workers with different levels of educational attainment and ages of entry into the labor market.

4 Results

Life cycle wage growth varies substantially across areas within the United States. Figure 1 plots heat maps of the baseline measure of life cycle wage growth by Combined Statistical Areas (CSA). The baseline measure summarizes life cycle wage growth as the height of the experience-wage profile by 20–24 years relative to 0–4 years of potential experience. The profiles were sliced at the 20-24 experience bin because most of the life cycle wage growth in the U.S. occur within the first 20-24 years of potential experience (Lagakos et al. (2018b)).

Wages grow more over the life cycle in richer CSAs with higher income per capita. Figure 2 shows that the height of the experience-wage profile increases with the income level of the CSA. For example, after 20 years of experience, the average worker's wage is about 90.2% higher in Washington, DC, the richest area in the sample, but only by 66.1% in El Paso, TX, the poorest CSA in the sample. The straight line plots the linear fit of the scatter plot. The slope of this regression is 32.47 with a t-statistic of 5.99 and an R^2 of 0.42.

Differences in life cycle wage growth persist even after conditioning on educational attainment, meaning that workers in richer areas experience steeper life cycle wage growth compared to workers in poorer areas with the same level of educational attainment. Figure 3 re-estimates the experience-wage profiles separately for sub-samples split by the worker's educational attainment: college graduates, high school graduates, and less than high school educated workers. The slope of the relationship between the height of the experience-wage profile and log income per capita remains significant and positive for all education groups. The slope of the relationship for college graduates, 34.69, is steeper than the slope for high school graduates, 31.72. Since college and high school graduates make up most of the labor force in the U.S., the result suggests that educational attainment can potentially play some role in explaining geographic disparities in the experience-wage profiles.

A counterfactual accounting exercise suggests that differences in the distribution of educational attainment can explain about 13.1% of life cycle wage growth across CSAs. Figure 4 estimates the contribution of educational attainment to cross-CSA differences in experience-wage profiles. The counterfactual exercise asks: What would a CSA's experience-wage profile look like if that CSA had the same distribution of educational attainment as Washington–Baltimore–Arlington, DC-MD-VA-WV-PA CSA? Washington, DC is the CSA with the highest share of college graduates as of 2015. If all differences in experience-wage profiles were due to differences in educational attainment, then this counterfactual would eliminate all such differences. In this case, the counterfactual heights for all CSAs would lie on a straight horizontal line, marked 100%, at the level of Washington–Baltimore–Arlington, DC-MD-VA-WV-PA CSA. On the other extreme, if educational composition explained none of the differences, all CSAs would lie on the 45 degree line, marked 0%.

The black dashed line of Figure 4 plots the best linear fit of the scatter plot from an OLS regression. The contribution of education to differences in experience-wage profiles is calculated as distance in the slope of this linear fit against the 45 degree line, and this number is reported on the lower left corner above the fitted line. The estimated contribution of educational attainment lies in between the two extremes of 0% and 100%, but is relatively closer to the 45 degree line, implying a modest contribution of about 13.1%.

5 Conclusion

This paper documents that life cycle wage growth is substantially steeper in richer CSAs than poorer ones. The pattern holds for all major groups of educational attainment, meaning that college graduates, high school graduates, and less than high school educated workers in richer areas experience faster life cycle wage growth than workers in poor areas with the same level of educational attainment. A counterfactual accounting exercise suggests that differences in educational attainment account for a small share of the differences in the wage profiles. While educational attainment emerges as a likely factor contributing to differences in life cycle wage growth across CSAs, its relatively modest impact, as revealed by the counterfactual analysis, suggests the presence of other significant factors. For example, differences in educational quality (Schoellman (2011)), interactions with other workers (Lucas and Moll (2014)), discrimination (Hsieh et al. (2019)) or the composition of industries and occupations (Herrendorf and Schoellman (2015)) across areas could potentially explain the gap in life cycle wage growth across areas within the U.S.

Discussion: Puzzling that there are persistent returns to experience across areas. Why doesn't labor move from poor to rich areas? If the return to experience is higher in richer areas, is there a friction that is preventing workers from moving to these richer areas? A potential explanation could be that poorer areas might be slower to recover from recessions. For example, unemployment could recover more slowly in poorer areas. Unemployment could hinder a worker from climbing the job ladder. If a worker's human capital depreciates more quickly during unemployment, their human capital growth over the life cycle could be slower.

In the U.S., fixed rate mortgages could be a friction that prevents workers from migrating to different areas. When rates on new mortgages are currently high, homeowners that have already locked in to a low mortgage rate in the past have less of an incentive to move to a different home, since they likely need to get a new mortgage at a higher rate than they have been paying. When rates on new mortgages are currently low, homeowners have a stronger incentive to move to a different home since they can potentially lock in to a lower fixed mortgage rate. If the hypothesis is true, workers are more likely to migrate when/where mortgage rates are lower. But challenging to identify because mortgage rates likely low during recessions when unemployment is high and financial constraints are binding. Homeowners often wish to move to a different area in order to get a different job. Lower mortgage rates would make it easier for homeowners to buy a new home in order to move to the different job. Brookings article: The long-term fall in domestic migration, Local movement declined, but longer-distance migration ticked up: `https://www.brookings.edu/articles/americans-local-migration-reached-a-historic-low-in-2022-but-long-distance-m`

Internal Migration in the United States Raven Molloy Christopher L. Smith Abigail Wozniak This paper examines the history of internal migration in the United States since the 1980s. By most measures, internal migration in the United States is at a 30-year low. The widespread decline in migration rates across a large number of subpopulations suggests that broad-based economic forces are likely responsible for the decrease. An obvious question is the extent to which the recent housing market contraction and the recession may have caused this downward trend in migration: after all, relocation activity often involves both housing market activity and changes in employment. However, we find relatively small roles for both of these cyclical factors. While we will suggest a few other possible explanations for the recent decrease in migration, the puzzle remains. Finally, we compare U.S. migration to other developed countries. Despite the steady decline in U.S. migration, the commonly held belief that Americans are more mobile than their European counterparts still appears to hold true.

The Determinants of Declining Internal Migration William W. Olney and Owen Thompson Internal migration in the United States has declined substantially over the past several decades, which has important implications for individual welfare, macroeconomic adjustments, and other key outcomes. This paper studies the determinants of internal migration and how they have changed over time. We use administrative data from the IRS covering the universe of bilateral moves between every Commuting Zone (CZ) in the country over a 23 year period. This data is linked to information on local wage levels and home prices, and we estimate bilateral migration determinants in rich regression specifications that contain CZ-pair fixed effects. Consistent with theoretical predictions, results show that migration is decreasing with origin wages and destination home prices, and is increasing with destination wages and origin home prices. We then examine the contributions of earnings and home prices to the noted overall decline in internal migration. These analyses show that wages on their own would have led to an increase in migration rates, primarily because migrants are increasingly responsive to high earnings levels in potential destination CZs. However, these wage effects have been more than offset by housing related factors, which have increasingly impeded internal mobility. In particular, migration has become much less responsive to housing prices in the origin CZ, such that many households that would have left in response to high home prices several decades ago now choose to stay.

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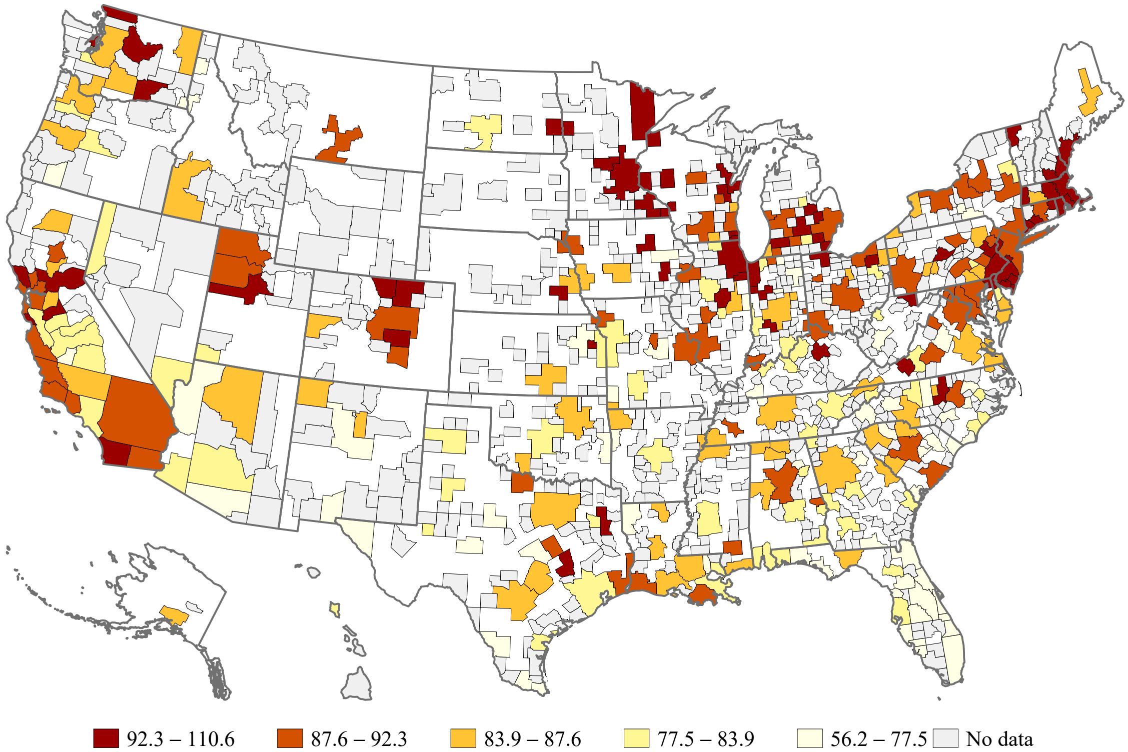
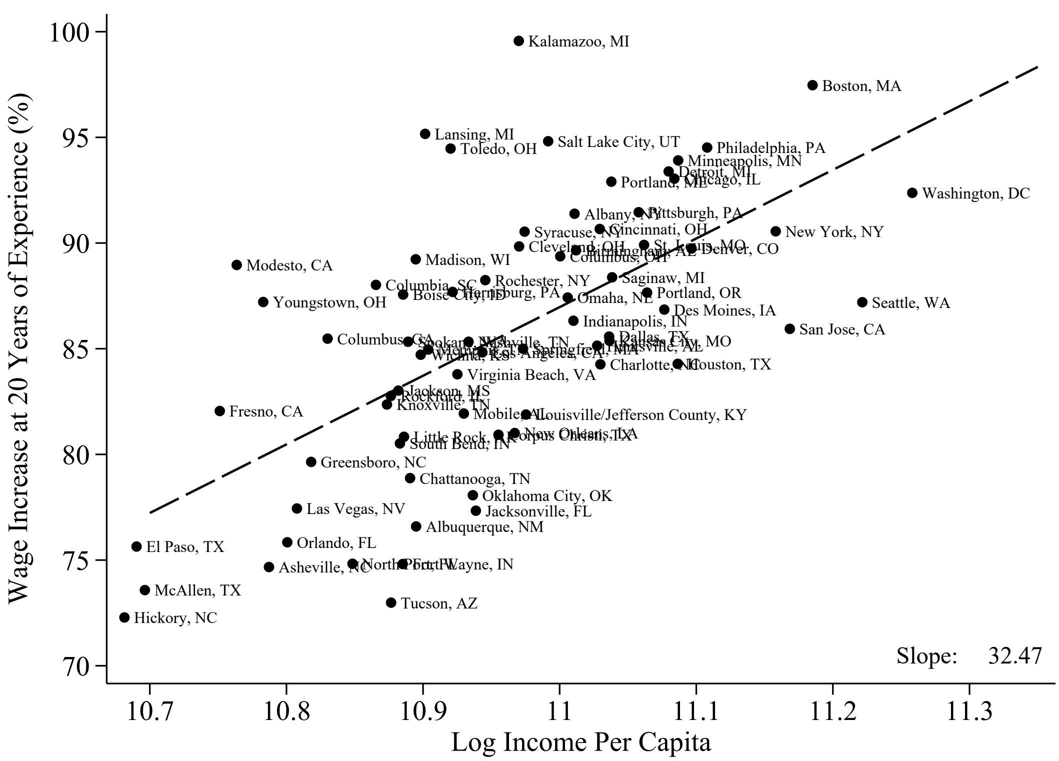
Figure 1: The Geography of Life Cycle Wage Growth



Notes: This figure plots heat maps of the baseline measure of life cycle wage growth by Combined Statistical Areas (CSA). The baseline measure summarizes life cycle wage growth as the height of the experience-wage profile by 20–24 years relative to 0–4 years of potential experience. Experience-wage profiles are estimated from equation (1), which are Mincer (1974) regressions of the workers' log wages on their years of schooling, dummy variables for 5-year potential experience groups, and time fixed effects. The regression is estimated separately for each CSA. Profiles are for full time male private sector wage earners and are grouped into CSAs based on the location of their housing unit at the time of each survey. Workers at all education levels are included in the sample. The sample is from the Census (Decennial from 1940 to 2000) and the American Community Survey (annual from 2001 to 2021). The CSAs included in the analysis are those whose survey data covers at least 15 years and 10,000 workers. Potential experience is defined as the number of years elapsed since a worker finished schooling or turned 18, whichever is smaller. Wage is defined to be earnings divided by hours worked. Earnings is measured before taxes and hours is defined as the usual weekly hours worked. Earnings and hours worked combine both primary and secondary jobs. Earnings and wages are expressed in units of 2015 U.S. dollars by using the Consumer Price Index to deflate nominal values. Outliers are removed based on the top and bottom 1% of wages.

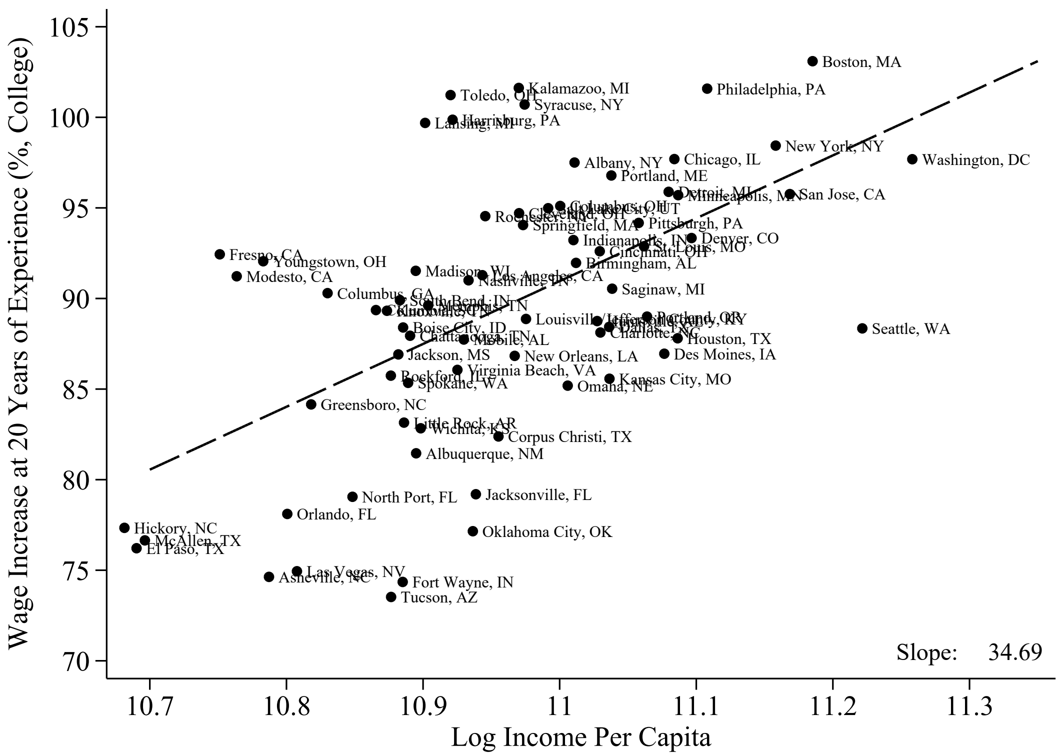
Figure 2: Wage Increase at 20-24 Years Experience by Log Income Per Capita: All Education Levels



Notes: This figure plots the heights of experience-wage profiles by 20–24 years relative to 0–4 years of potential experience, against the CSA's log income per capita in 2015. Experience-wage profiles are estimated from equation (1), which are Mincer (1974) regressions of the workers' log wages on their years of schooling, dummy variables for 5-year potential experience groups, and time fixed effects. The regression is estimated separately for each CSA. Profiles are for full time male private sector wage earners and are grouped into CSAs based on the location of their housing unit at the time of each survey. Workers at all education levels are included in the sample. The sample is from the Census (Decennial from 1940 to 2000) and the American Community Survey (annual from 2001 to 2021). The CSAs included in the analysis are those whose survey data covers at least 15 years and 10,000 workers. Potential experience is defined as the number of years elapsed since a worker finished schooling or turned 18, whichever is smaller. Wage is defined to be earnings divided by hours worked. Earnings is measured before taxes and hours is defined as the usual weekly hours worked. Earnings and hours worked combine both primary and secondary jobs. Earnings and wages are expressed in units of 2015 U.S. dollars by using the Consumer Price Index to deflate nominal values. Outliers are removed based on the top and bottom 1% of wages.

Figure 3: Wage Increase at 20-24 Years Experience by Log Income Per Capita and Education Group

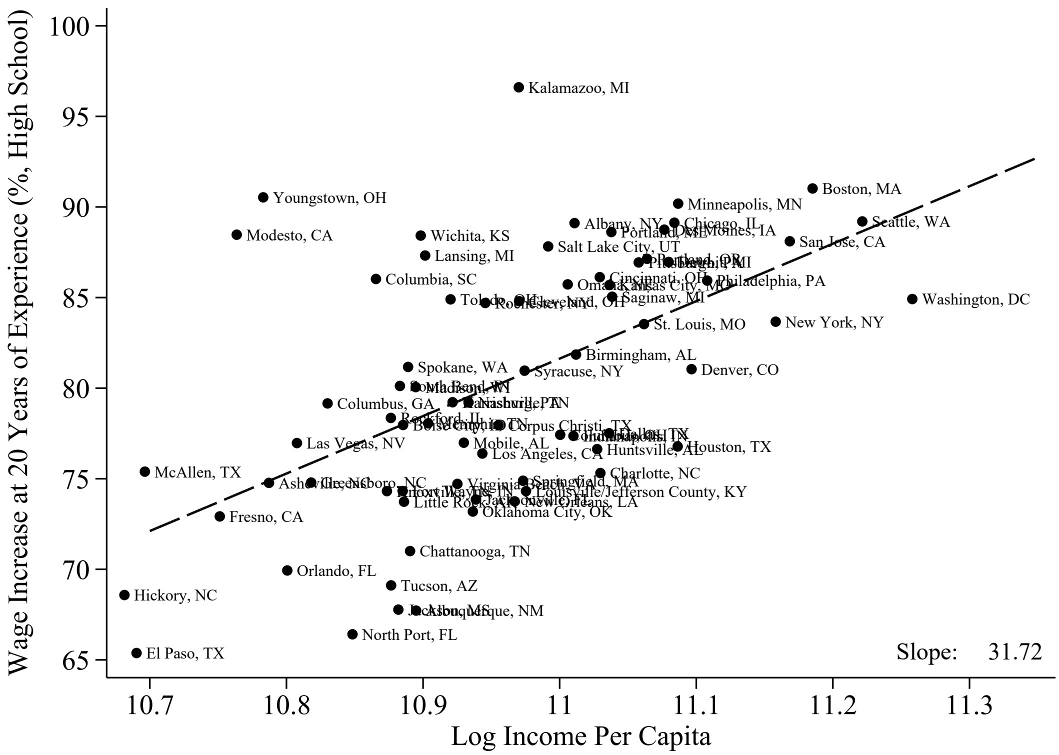
(a) College Graduates



Notes: This figure plots the heights of experience-wage profiles by 20–24 years relative to 0–4 years of potential experience, against the CSA's log income per capita in 2015. Experience-wage profiles are estimated from equation (1), which are Mincer (1974) regressions of the workers' log wages on their years of schooling, dummy variables for 5-year potential experience groups, and time fixed effects. Profiles are for full time male private sector wage earners and are grouped into CSAs based on the location of their housing unit at the time of each survey. The regression is estimated separately for each CSA and education group. The sample is restricted to workers that completed college. See Section 2 for more details about the sample.

Figure 3: Wage Increase at 20-24 Years Experience by Log Income Per Capita and Education Group (Continued)

(b) High School Graduates



Notes: This figure plots the heights of experience-wage profiles by 20–24 years relative to 0–4 years of potential experience, against the CSA's log income per capita in 2015. Experience-wage profiles are estimated from equation (1), which are Mincer (1974) regressions of the workers' log wages on their years of schooling, dummy variables for 5-year potential experience groups, and time fixed effects. Profiles are for full time male private sector wage earners and are grouped into CSAs based on the location of their housing unit at the time of each survey. The regression is estimated separately for each CSA and education group. The sample is restricted to workers that completed high school. See Section 2 for more details about the sample.

Figure 3: Wage Increase at 20-24 Years Experience by Log Income Per Capita and Education Group (Continued)

(c) Less than High School

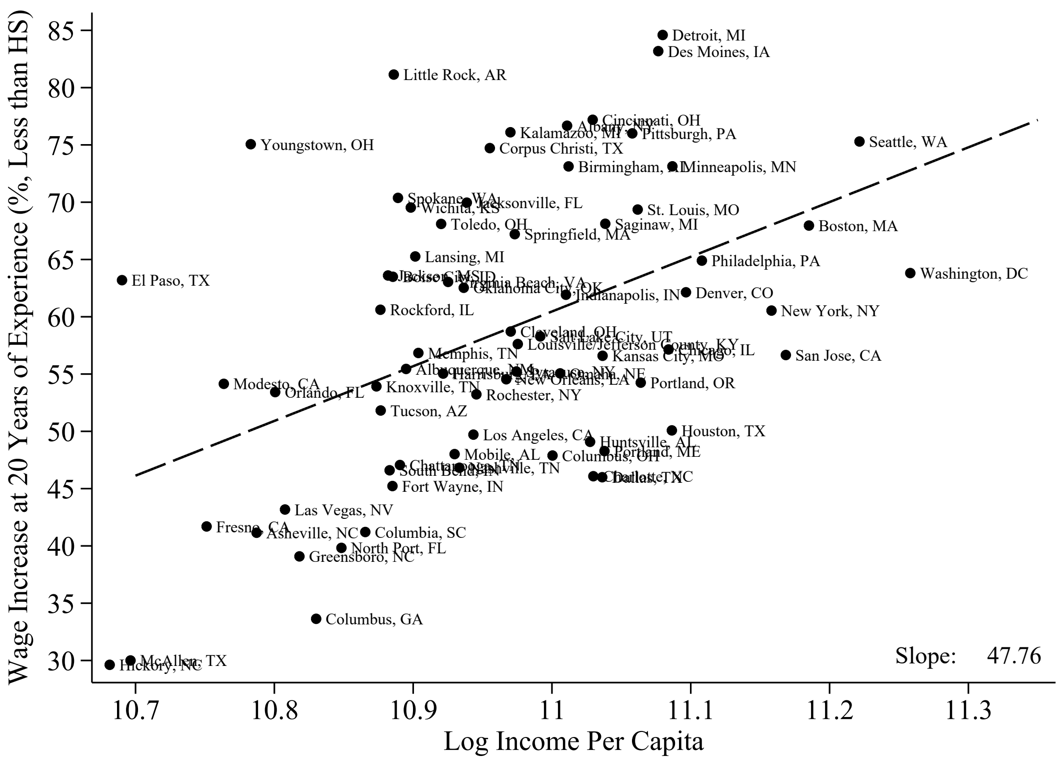


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Figure 4: Contribution of Education to Cross-CSA Differences in Experience-Wage Profiles

Notes: This figure plots the contribution of education to differences in experience-wage profiles across Combined Statistical Areas (CSA). Each point on the graph shows the actual and counterfactual average height of the experience-wage profile for each CSA by 20–24 years relative to 0–4 years of potential experience. The counterfactual average height is the same statistic calculated under the assumption that the fraction of workers in each education bin–college, high school, and less than high school–is the same as in Washington–Baltimore–Arlington, DC-MD-VA-WV-PA CSA, which is the CSA with the highest share of college graduates as of 2015. The black dashed line plots the best linear fit of the scatter plot from an OLS regression. The contribution of education to differences in experience-wage profiles is calculated as distance in the slope of this linear fit against the 45 degree line, and this number is reported on the lower left corner above the fitted line. If the educational composition explained all cross-CSA differences in the returns to experience, the counterfactual heights for all CSAs would lie on the dotted grey horizontal line, marked 100%, at the level of Washington–Baltimore–Arlington, DC-MD-VA-WV-PA CSA. If educational composition explained none of the differences, all CSAs would lie on the dotted grey 45 degree line marked 0%. Experience-wage profiles are estimated from equation (1), which are Mincer (1974) regressions of the workers' log wages on their years of schooling, dummy variables for 5-year potential experience groups, and time fixed effects. The regression is estimated separately for each CSA and education group. See Section 2 for more details about the sample.