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## Estimating Occupation- and Location-Specific Wages over the Life Cycle

Elias Ilin and Ellyn Terry

Working Paper 2021-15  
June 2021

**Abstract:** In this paper we develop a novel method to project location-specific life-cycle wages for all occupations listed in the Occupational Outlook Handbook from the U.S. Bureau of Labor Statistics. Our method consists of two steps. In the first step, we use individual-level data from the Current Population Survey to estimate the average number of years of potential labor market experience that is associated with each percentile of the education-level specific wage distribution. In the second step, we map this estimated average years of experience to the wage-level percentiles reported in the Occupational Employment and Wage Statistics data for each occupation and area. Finally, we develop a model capable of projecting the trajectory of wages across all possible years of experience for each occupation.

JEL classification: J31

Key words: wage growth, wages, experience, education, earnings, Mincer earnings function

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# 1 Introduction

In this paper, we develop a novel method to project life-cycle wages for occupations listed in the Bureau of Labor Statistics Occupational Outlook Handbook (the Handbook). This method is currently utilized by the Career Ladder Identifier and Financial Forecaster tools to project future wages on a career path selected by users.

Our method uses the wage data from the Occupational Employment and Wage Statistics (OEWS). OEWS provides percentiles of the wage distribution for each occupation and for each metropolitan and non-metropolitan area in the United States. OEWS, however, does not have information on worker’s expected years of potential experience associated with each percentile and therefore cannot be used to determine how workers progress along the wage distribution as they gain experience in a job. This last piece of information is required for projecting occupation-specific life-cycle wages.

Our method consists of two steps. In the first step, we group individuals from the Current Population Survey (CPS) by their educational attainment. For each education group, we estimate the distribution of wages. Next, for each percentile of the education-level specific wage distribution we calculate the average number of years of potential experience individuals in that percentile have.<sup>1</sup> In the second step, we map the average years of potential experience to the wage level percentiles reported in the OEWS data for each occupation and area. Finally, we create a model for projecting wages based on education and years of experience and use that model to estimate the trajectory of wages across all possible years of experience for each occupation and location in the OEWS data.

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<sup>1</sup>Years of potential experience is estimated based on age and level of education. The dataset we use, the Federal Reserve Bank of Atlanta Harmonized Variable and Longitudinally Matched CPS, creates this variable using the following assumptions: someone with less than a high school diploma enters the labor force at age 16, someone with a high school diploma enters at age 18, someone with an associate degree at age 20, a bachelors’ degree at age 23, and graduate degree at age 26.

## 2 Data

We use two datasets with different levels of details to estimate the wage growth model. The first dataset is the OEWS dataset, released in May 2020. The OEWS produces annual employment and wage estimates for over 700 occupations in 395 locations.<sup>2</sup> The OEWS reports 10th, 25th, 50th, 75th and 90th percentiles of wages for each occupation at state, metropolitan and non-metropolitan statistical areas levels. Importantly, for each occupation, the OEWS also provides information on the typical education level required for entry, determined at the national level.<sup>3</sup> The OEWS distribution of wages varies across locations and occupations. First, wage levels can differ significantly for the same occupation across different locations. It can be driven by location-specific factors such as living costs, regulations (e.g., minimum wage laws), and supply and demand fundamentals. For example, the median wage for a substitute teacher in Atlanta, GA is \$9.09 per hour compared to \$22.64 per hour in Seattle. Second, the distribution of wages for some occupations is characterized by a relatively low amount of dispersion – possibly reflecting low wage growth over the life cycle.<sup>4</sup> For other occupations, the wage dispersion is relatively high – potentially reflecting large wage growth over the life cycle. For example, the 90th percentile of Property, Real Estate, and Community Association Managers’ hourly wage in Cleveland-Elyria, OH is 9 times that of the 10th percentile. In contrast, there is little variation in pay among Postmasters and Mail Superintendents in the same metropolitan area (the 90th percentile is \$47.60 an hour, comparing to \$35.85 for the 10th percentile). Finally, wage dispersion of a given occupation is not uniform across locations. For example, the 90th percentile of Chefs’ hourly wage in Alexandria, LA is 5 times that of the 10th percentile while in Binghamton, NY 90th percentile is only 50 percent higher than 10th percentile. Thus, the distribution of wages is unique to each occupation and location and needs to be modeled accordingly.

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<sup>2</sup>The OEWS data also contains additional statistics, such as mean and annual wage estimates.

<sup>3</sup>For details on how the BLS determines the typical education needed for entry see <https://www.bls.gov/emp/documentation/education/tech.htm>

<sup>4</sup>Differences in wage dispersion for an occupation across locations and occupations could also be driven by differences in type of employers, age distribution of the population, and other factors.

The second dataset we use is the Federal Reserve Bank of Atlanta Harmonized Variable and Longitudinally Matched CPS (ATL CPS). The ATL CPS is a processed version of the monthly Current Population Survey. The ATL CPS contains individual level data for roughly 60,000 households in each month and has a rich set of demographic indicators. Questions related to income are asked only during two out of eight interviews and therefore ATL CPS has wages information for about one-fourth of the sample in any month. While the ATL CPS also provides occupation and geographic identifiers, it does not contain sufficient observations to conduct an analysis at a detailed occupation or geographic area level. However, the ATL CPS data contains education level of the employed individual that can be matched directly to the OEWS by the typical education level required for entry.

We begin by limiting the ATL CPS data to all monthly surveys between 1994 and 2019 and reduce the dataset to those not in school, working 40 or more hours per week, older than 16 and younger than 62 (the earliest age one can begin to draw social security benefits). This last restriction creates a limitation on years of potential experience; the oldest individuals in our dataset with graduate degrees have maximum of 35 years of potential experience. While those with less education can have more years of potential experience (because it takes less time to graduate and begin working) we impose this age restriction for all education categories to create a consistent range of ages for each level of education. Last, because we are pooling 26 years of data together, we inflation adjust the wage data by 2 percent per year.<sup>5</sup>

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<sup>5</sup>Headline PCE has grown at an annual rate of 1.8 percent and Headline CPI has grown at an annual rate of 2.2 percent over this period.

## 3 Method

### 3.1 Step I: Estimating Life-Cycle Wages by Education Groups

In this paper we use a modified version of Mincer’s earning function as shown in the equation 1.

$$\ln(w_{iE}) = \gamma_{0E} + \gamma_{1E}X_{1E} + \gamma_{2E}X_{iE}^{1/2} + \mu_s + [B_{iE}]^T[C_{iE}] + \epsilon_{iE} \quad (1)$$

For each education level ( $E$ ), we estimate the natural log of wages as a function of years of potential experience ( $X$ ), the square root of years of potential experience, state fixed effects ( $\mu_s$ ), and a set of demographic controls  $C$  (age, race, ethnicity, and gender) to control for changes in the characteristics of the working population over time. The inclusion of the square root of years of potential experience allows for a shape of wage trajectory that monotonically increases in years of experience at a decreasing rate.

This functional form is somewhat different from the version of the Mincer earnings function used commonly in the labor economics literature (Mincer 1958, 1974; Heckman et al. 2003; Lemieux 2006). Standard specification includes a squared term of years of experience instead. We establish that the square root functional form fits the data better because the squared term functional form permits wage growth to turn negative, a phenomenon which we do not observe in the data on average when wage growth rate is measured at the individual level (see Figure A1 in the Appendix).

Estimating equation 1 separately for each education levels also deviates from the standard version of the Mincer’s earning function. In the standard functional form, education is instead included as one of the covariates, which suggests that returns to experience is the same for all education levels. Recent research however has found that the education gap is not a constant function of experience (for example see Lemieux (2006); Lagakos et al. (2018)). For this reason, we estimate equation 1 for each education level separately.

We begin by estimating equation 1 for each education category provided in the OEWS data, the data which we match to in step II. For each occupation, the OEWS data provides

the following typical entry-level educational requirements: no formal education, high school diploma or equivalence, some college no degree, associate degree, bachelor’s degree, master’s degree and doctoral or professional degree. CPS does not have enough data to precisely estimate wages by years of experience for people with doctoral or professional degree. Therefore, we pool people with doctoral or profession degree and those with a master’s degree into one category. Next, we investigate whether more education categories should be pooled together due to commonalities in job market opportunities. Specifically, we examine the correlations between educational attainment and occupation using the Employment Projections Dataset from the Bureau of Labor Statistics (BLS).<sup>6</sup> We find that occupations that tend to have a high share of people employed with a high school diploma also have large shares of workers with less than high school diploma. Additionally, occupations that have high share of workers with high school diploma tend to have large share of people with some college, no degree.<sup>7</sup> Therefore, we pool these three education groups together. Finally, occupations where the largest fraction of employees holds bachelor’s degree also tend to have a large share of workers with master’s degree. Thus, we choose to pool these two education groups together. After consolidating education categories, we re-estimate equation 1 separately only for three education groups – no college degree, associate degree, and bachelor’s degree or higher. For comparison, we provide estimates using six original OEWS education groups in the Figure A3 in the Appendix.

We estimate equation 1 on the ATL CPS using OLS, calculating heteroskedasticity robust standard errors clustered by demographic group (state, race, ethnicity, education, and gender). Figure 1 shows the average predicted wages together with their actual values by years of potential experience and education levels. The logarithm of hourly wages exhibits the pattern like [Rubinstein and Weiss \(2006\)](#) who find that return to experience is the largest

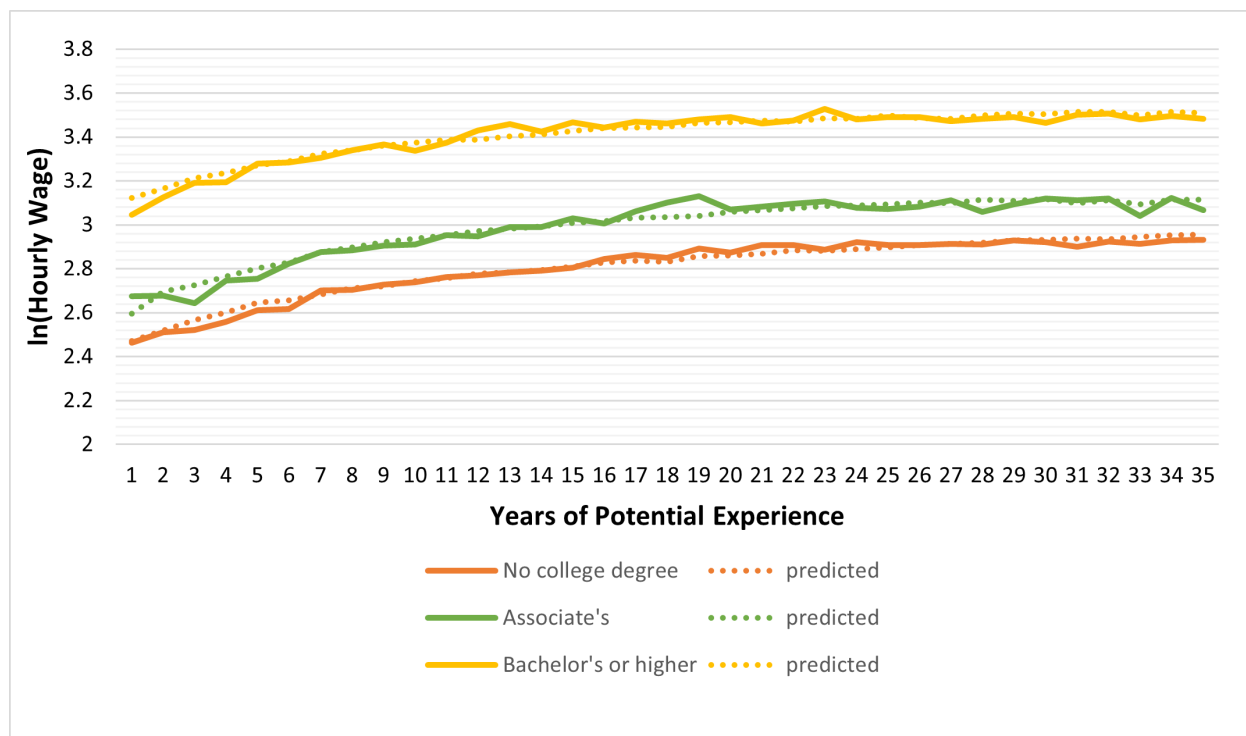
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<sup>6</sup>Specifically, we use the table “Educational attainment for workers 25 years and older by detailed occupation” available at <https://www.bls.gov/emp/>.

<sup>7</sup>The correlation between the share of workers with less than high school diploma and the share of workers with high school diploma is 0.71. The correlation between the share of workers with high school diploma and the share of workers with some college, no degree is 0.56.

for those with relatively few years of experience, then gradually tapers.

Figure 1: Actual and Fitted Values of Wages by Education Level and Years of Potential Experience

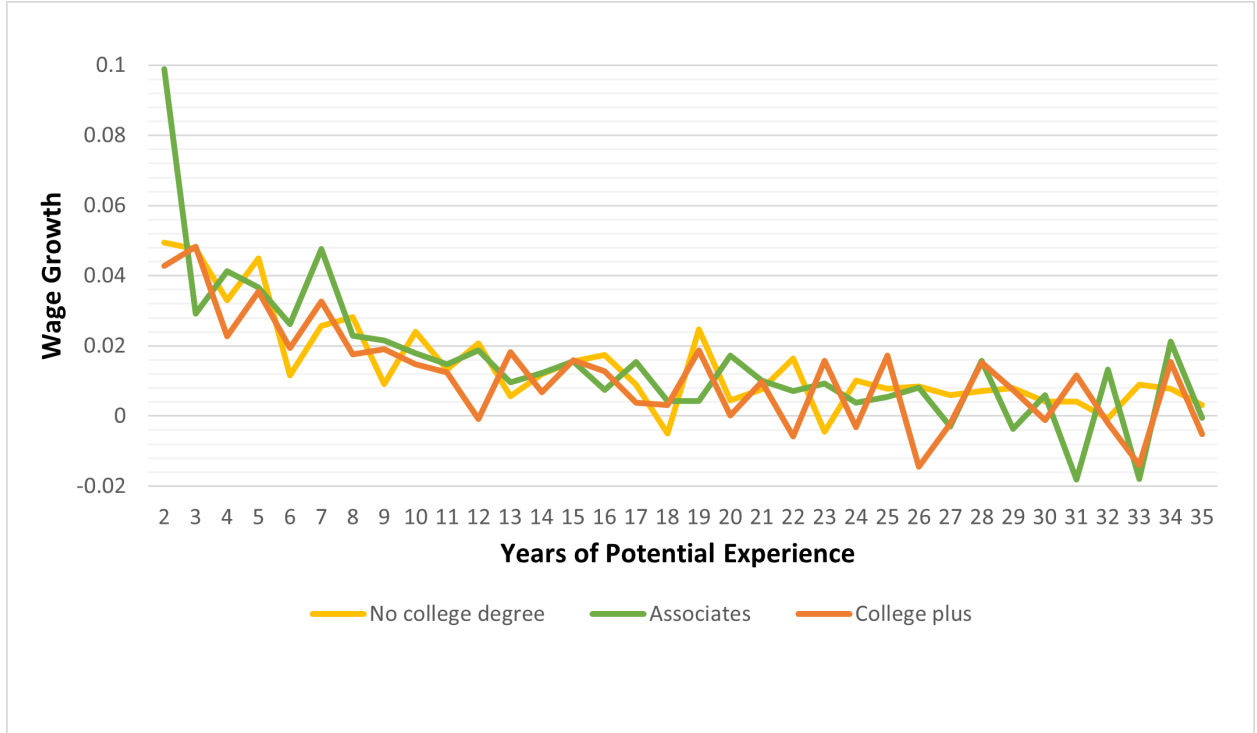


Source: 1994-2019 Current Population Survey, author's calculations

Figure 2 shows the predicted average wage growth at each year of experience by education groups. Average estimated wage growth varies across education groups for low values of potential years of experience and converges to zero once years of experience increase. For example, on average wage growth from gaining the second year of experience is significantly higher for workers with the associates degree. It is important to note that the shape of predicted aggregate wage growth rates by years of experience resembles the shape of average of individual-level wage growth rates (see Figure A1 in the Appendix).



Figure 2: Predicted Wage Growth by Education Level and Years of Potential Experience



Source: 1994-2019 Current Population Survey, author's calculations

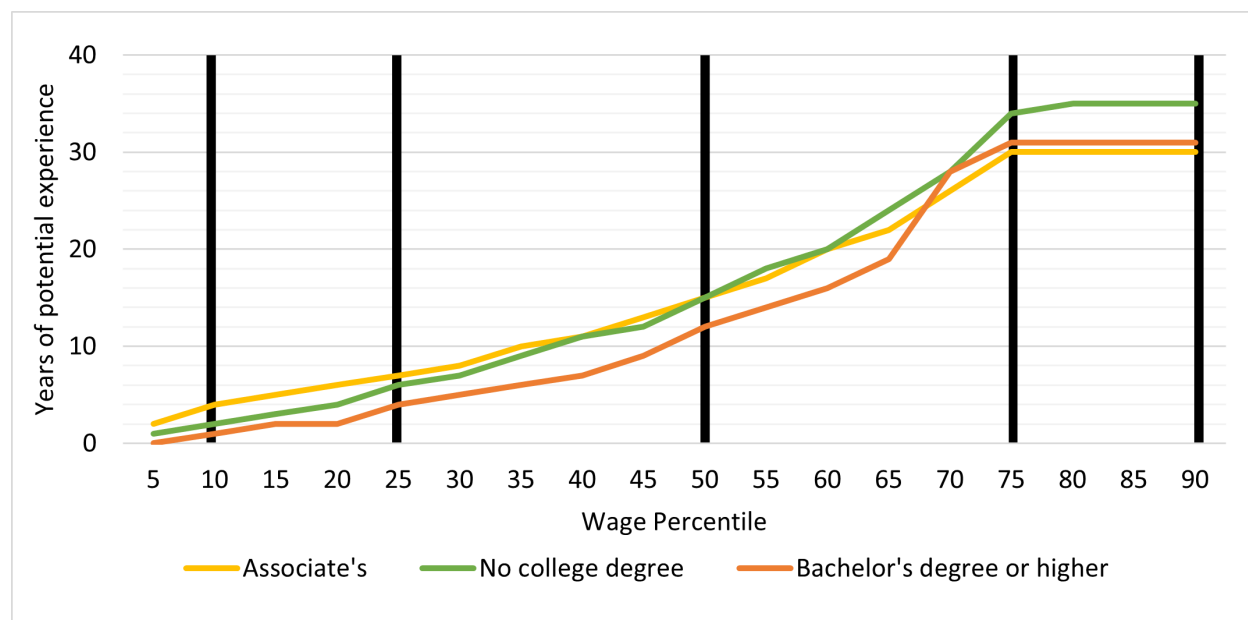
Due to variation in wage levels and wage growth across occupations and locations, the path of aggregate wages estimated with equation 1 cannot be directly used to predict the wage trajectory for a specific occupation in a specific location. To estimate equation 1 at the occupation and location level, we need to match individual-level CPS estimates to the OEWS data.

First, we use predicted aggregate wages to estimate how many years of experience it takes individuals to achieve the 10th, 25th, 50th, 75th and 90th percentile of their education group's wage distribution. To do this, we group the individual level data by education levels and then sort by wages to determine the percentile in the wage distribution that each person falls relative to others in the same education group. Multiple people will be associated with any given wage percentile. For individuals in each wage percentile, we take the average of the number of years of potential experience. Sometimes the average numbers of years of

experience are the same for different wage percentiles. For example, on average, individuals with an associate degree with wages in the 75th – 90th percentiles of the wage distribution all have average thirty years of potential experience. To illustrate this, Figure 3 shows the average number of years of potential experience that coincides with each wage percentile. The black vertical lines show 10th, 25th, 50th and 75th percentiles.

The plotted line for workers with a bachelor's degree or higher is almost always below that for workers in the other two education groups. Thus, workers with a bachelor's degree or higher tend to progress faster in their education group's aggregate wage distribution than those with less education. On average, workers with a bachelor's degree or higher need 4 years of potential experience to achieve the 25th percentile and 12 years of potential experience to achieve 50th percentile. In contrast, workers with an associate degree, on average need 7 years of experience to achieve the 25th percentile and 15 years to achieve the 50th percentile. Table 1 summarizes where each of the black lines intersect with the education-specific wage distributions.

Figure 3: Years of Potential Experience Corresponding to Each Wage Growth Percentile



Source: 1994-2019 Current Population Survey, author's calculations

Table 1: Average Years of Experience at Each Percentile of the Education-Specific Wage Distribution

	Q10	Q25	Q50	Q75	Q90
No college degree	2 years	6 years	15 years	34 years	35 years
Associate's	4 years	7 years	15 years	30 years	30 years
Bachelor's degree or higher	1 year	4 years	12 years	31 years	31 years

Source: 1994-2019 Current Population Survey, author's calculations

### 3.2 Step II: Matching to OEWS

Next, we map estimated years of experience from Table 1 to the wage distribution of each occupation in the OEWS, matching by typical entry-level education. In doing so, we assume that the wage distributions in OEWS and CPS are comparable.

We decide to exclude the 90th percentile of wages, because the 75th and 90th correspond to nearly the same years of experience for every education level and because in some occupations (especially medical professions) the 90th percentile can be significantly larger, causing unexpected shapes in the trajectory of wage levels. One potential explanation is that the high 90th percentile values that occur among some occupations corresponds to certifications or specializations which are not generalizable to the occupation as a whole.

After removing the 90th percentile, for each occupation ( $o$ ), we estimate equation 2.

$$\ln(w_o) = Area + \beta_1(Area \times X_o) + \beta_2(Area \times X_o^{1/2}) + \epsilon_o \quad (2)$$

The specification includes a fixed effect for each geographic area ( $Area$ ) and an interaction of geographic area with years of potential experience ( $X$ ). This allows for a level shift in earnings in different geographic areas to capture differences in the cost of living and supply and demand. The interaction of geographic area with years of potential experience allows for different progressions of wage growth in different geographic areas.

## 4 Estimation Example – Life-Cycle Wages of Licensed Practical Nurses Across the U.S.

Figure 4 shows projected life-cycle wages for the licensed practical nurse (LPN) occupation across all metropolitan and non-metropolitan areas in the U.S., including U.S. territories. Each location is represented by the line of specific color. First, the intercepts are different for each area, reflecting higher starting wages in some areas. Second, initial wage growth varies significantly across areas – depending on the location initial growth rate varies from 1 to 30 percent. Difference in wage growth by years of experience drives differences in shapes of projected paths of wages. Finally, wages progressions follow similar patterns across locations - wage levels increase rapidly with few years of experience, then continue to increase at a decreasing rate of change. Wage growth goes towards zero, but never turns negative.

Figure 4: Projected Life-Cycle Wages for Licensed Practical Nurse (LPN) Across the U.S.



Source: Occupational Employment and Wage Statistics, author's calculations

Note: Each line represents a different location in the United States. The lighter-colored dots are the actual wage levels in the OEWS data associated with the 10th, 25th, 50th, and 75th percentile for each location.

## 5 Adjusting for Expected Increases in Minimum Wages

One challenge with projecting wages into the future is that many states have passed legislations for timed hikes in minimum wages over the next few years. These minimum wage hikes will directly affect those wages that currently pay below the new minimum wage. The economic literature has established that jobs that pay just above the minimum wage will also likely be affected – so called “spillover effects”. For example, [Lee \(1999\)](#) and [Brochu](#)

et al. (2015) find substantial spillover effects of the minimum wage up to about \$2 above the minimum wage while Cengiz et al. (2019) established the existence of so called “excess jobs” (jobs that started to pay at or slightly above the new minimum wage) between the new minimum wage and \$4 above it. One of the mechanical (not employment related) reasons why the spillover effects exist is that employers would want to retain some of the differences in pay that had existed before the minimum wage increase. We follow the methodology used in Congressional Budget Office (2019) to estimate the extent to which minimum wage laws will also affect the wages of jobs paying above the current minimum wage.

We start by specifying all future planned minimum wage hikes and the range of wages that will be affected by the wage spillovers. We assume that jobs that pay between the current minimum wage and the new minimum wage plus 50 percent of the increase will be affected. This range is state-specific as it depends on state-specific laws. For example, on September 30, 2021 Florida’s minimum wage will increase to \$10 per hour, representing a \$1.44 increase from the 2020 minimum wage of \$8.56 per hour. We estimate that when this happens, jobs that, according to the 2020 OEWS data, pay between \$8.56 and \$10.72 (\$10 plus 50 percent of the \$1.44 difference) will be affected.

Next, we model the spillovers for affected jobs. Specifically, we model how starting wages change because of the minimum wage laws. The new starting wage for occupation  $o$  is determined by equation 3.

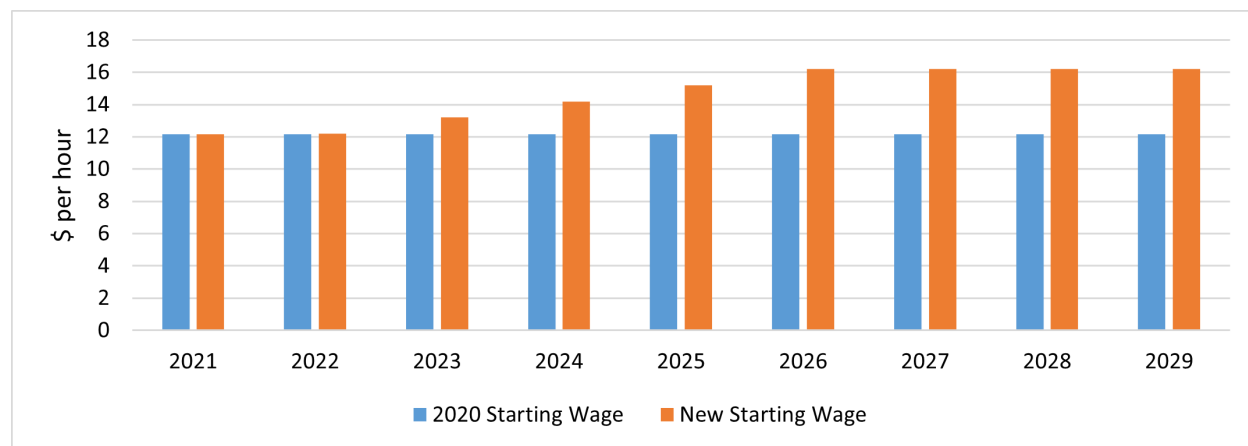
$$NewStartingWage_{ot} = \alpha_o(NewMinWage_t - 2020MinWage) + 2020StartingWage_t \quad (3)$$

Where  $\alpha$  determines the degree of spillover.  $\alpha$  is equal to 1 for jobs that pay the current minimum wage and linearly decays to 0 for jobs that pay the upper bound of affected wages. Continuing with the Florida example,  $\alpha$  for jobs paying \$8.56 per hour is 1,  $\alpha$  for jobs paying \$10.72 is 0, and thus  $\alpha$  for jobs paying halfway between these two numbers (\$9.64) is 0.5. For jobs that paid \$9.64 an hour in 2020, the new 2021 wage after accounting for spillovers

due to minimum wage laws would be \$10.36.

To account for the wage spillovers in our estimations of the life-cycle wage growth, we start by using equation 3 to adjust the intercept in equation 2 (which can be thought of as the fundamental starting wage since it is the wage that coincides with 0 years of experience) to be the new wage, accounting for spillovers. We then calculate how wages change with experience using equation 2. Figure 5 shows how the minimum wage laws are expected to affect the starting wage of an LPN living in Tallahassee, FL. In 2021, the LPN starting wage is \$12.15, above the upper bound of affected wages (\$10.72). Therefore, there is no expected change in the starting wage in 2021. In 2022, the minimum wage increases to \$11/hr. With this increase, the new upper bound of affected wages is \$12.22. As a result, according to the equation 3, the LPN starting wage increases by about \$0.05. By 2026, the minimum wage in Florida is \$15 per hour and the new LPN starting wage is projected to be \$16.20.

Figure 5: The Effect of Planned Minimum Wage Hikes in FL on LPN Starting Wages in Tallahassee, FL



Source: Occupational Employment and Wage Statistics, author's calculations

Figure 6 compares the wage trajectory for an LPN working in Tallahassee, FL before and after accounting for adjustments to the minimum wage law. In 2021, the LPN is assumed to have 1 year of experience. With each year, the LPN gains one additional year of experience,

receiving a corresponding bump in pay according to equation 3. The blue line shows how wages change with years of experience, after accounting for the effect of minimum wage hikes. In 2021, with 1 year of experience, the LPN makes \$14.21/per hour. There is no difference between the blue and the orange lines in this year because the LPN starting wage is above the phaseout threshold. However, as minimum wage hikes continue and the LPN starting wage begins to be affected, there is a divergence between the orange and the blue lines. By 2026, the LPN makes almost \$6 more than if there were no changes to the FL minimum wage law.

Figure 6: The Effect of Planned Minimum Wage Hikes in FL on LPN Starting Wages in Tallahassee, FL



Source: Occupational Employment and Wage Statistics, author's calculations

## 6 Conclusion

Variation in education requirements, supply and demand factors, differences in cost of living across location are some of many factors that contribute the large variance in wages across occupations and locations. In this paper we develop a novel method to project the life-



cycle wages that incorporates these factors by using data on the occupation-location specific distribution of wages.

We combine information from two datasets to create the life-cycle wage growth model for each occupation and location. First, the OEWS data provides the range of wages by occupations and geographical areas. The OEWS data only includes the 10th, 25, 50th, 75th and 90th percentiles of the wage distribution for each occupation and area. It also reports the required entry-level education. However, OEWS does not provide the information necessary to estimate how an individual progresses along the continuum of years of experience. Thus, we use individual-level CPS data to estimate the average years of experience associated with each percentile of the wage distribution among individuals with the same education level. We then merge these values to the OEWS data by the education level required for entry into the occupation. Finally, we use a generalized Mincer equation to project the trajectory of wages across all possible years of experience. Wage growth projection accounts for planned hikes in the state minimum wages and corresponding wage spillovers.

The method developed in this paper is currently utilized by the Career Ladder Identifier and Financial Forecaster tools to project future wages on a career path.

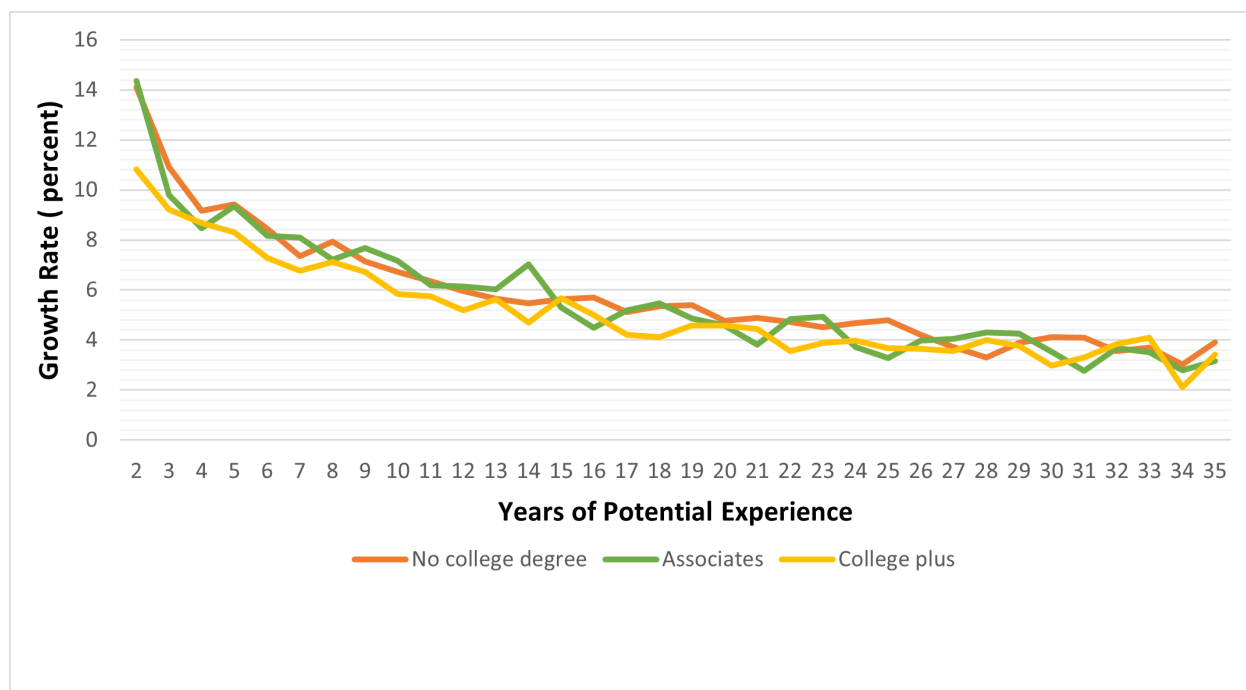
## References

- Brochu, P., Green, D. A., Lemieux, T., and Townsend, J. (2015). The minimum wage, turnover, and the shape of the wage distribution. Technical report, Working paper.
- Bureau of Labor Statistics, U.S. Department of Labor (2021a). Occupational employment and wage statistics. Accessed May 9, 2021 <https://www.bls.gov/oes/>.
- Bureau of Labor Statistics, U.S. Department of Labor (2021b). Occupational outlook handbook. Accessed May 9, 2021 <https://www.bls.gov/ooh/about/ooh-developer-info.htm>.
- Cengiz, D., Dube, A., Lindner, A., and Zipperer, B. (2019). The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics*, 134(3):1405–1454.
- Congressional Budget Office (2019). The effects on employment and family income of increasing the federal minimum wage. Technical report.
- Federal Reserve Bank of Atlanta (2021). Harmonized variable and longitudinally matched current population survey. Accessed May 9, 2021 <https://cps.kansascityfed.org/cps>.
- Heckman, J. J., Lochner, L. J., and Todd, P. E. (2003). Fifty years of mincer earnings regressions. Technical report, National Bureau of Economic Research.
- Lagakos, D., Moll, B., Porzio, T., Qian, N., and Schoellman, T. (2018). Life cycle wage growth across countries. *Journal of Political Economy*, 126(2):797–849.
- Lee, D. S. (1999). Wage inequality in the united states during the 1980s: Rising dispersion or falling minimum wage? *The Quarterly Journal of Economics*, 114(3):977–1023.
- Lemieux, T. (2006). The “mincer equation” thirty years after schooling, experience, and earnings. In *Jacob Mincer a pioneer of modern labor economics*, pages 127–145. Springer.

- Mincer, J. (1958). Investment in human capital and personal income distribution. *Journal of political economy*, 66(4):281–302.
- Mincer, J. (1974). Schooling, experience and earnings (human behavior and social institutions; 2; new york.
- Rubinstein, Y. and Weiss, Y. (2006). Post schooling wage growth: Investment, search and learning. *Handbook of the Economics of Education*, 1:1–67.

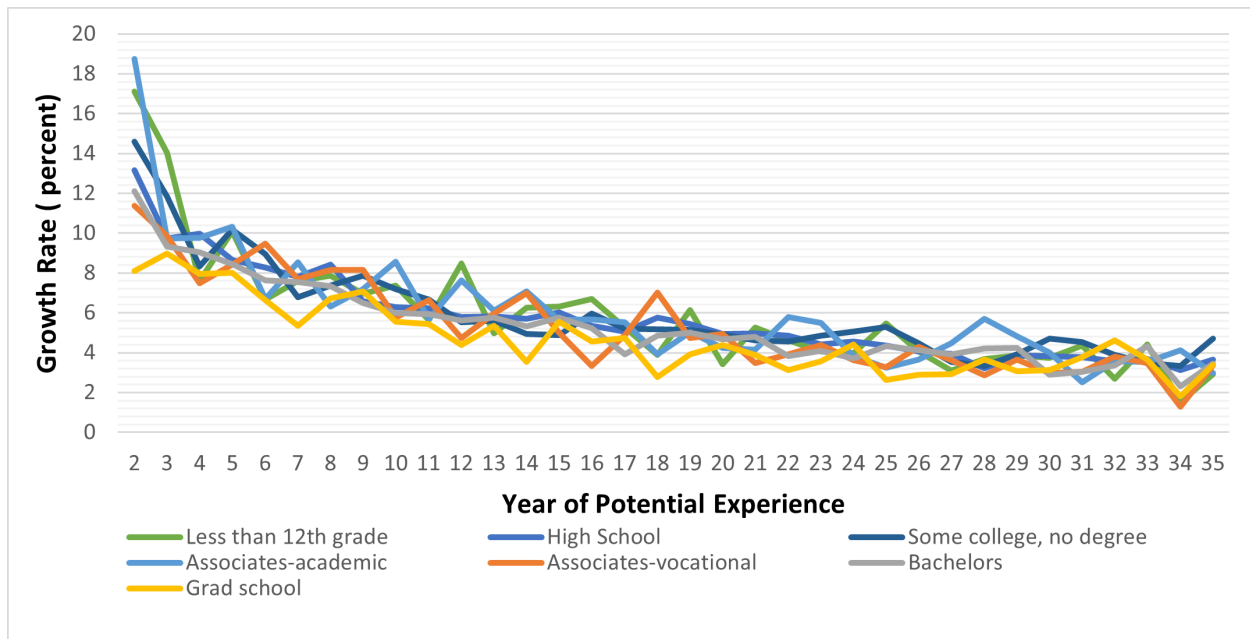
## Appendix

Figure A1: Average of Individual-Level Annual Wage Growth by Education Levels and Years of Potential Experience



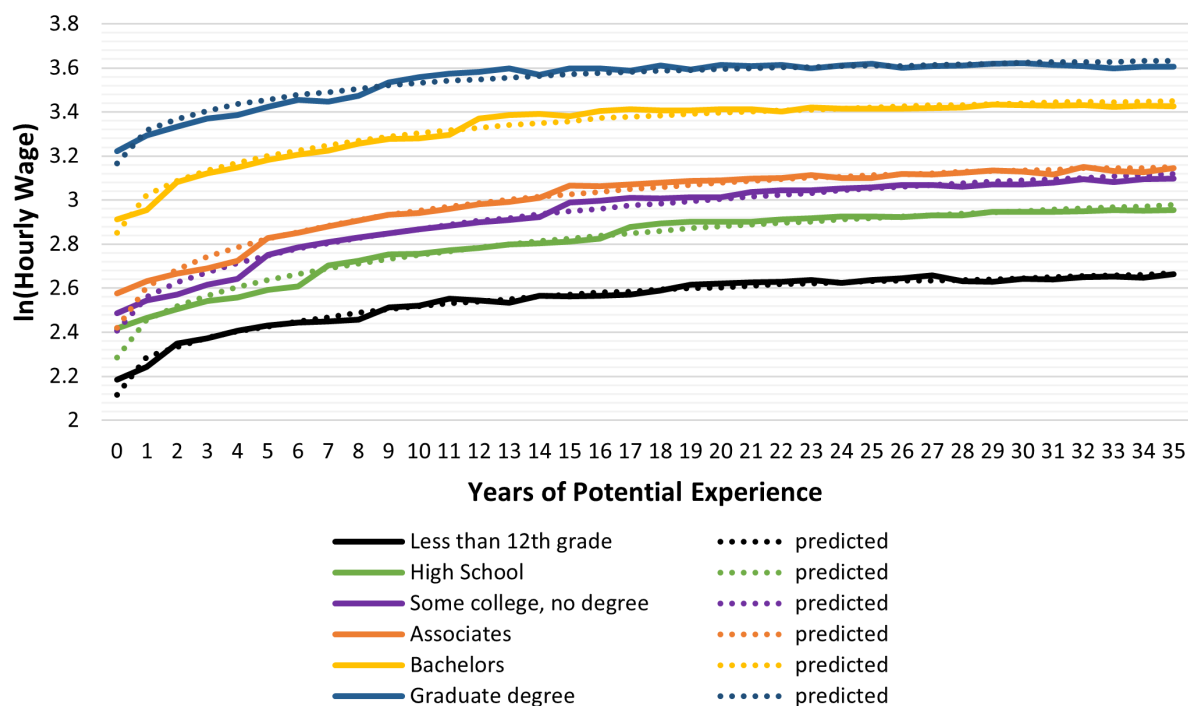
Source: 1994-2019 Current Population Survey, author's calculations

Figure A2: Average Individual-Level Wage Growth by Years of Potential Experience and OEWS Education Groups



Source: 1994-2019 Current Population Survey, author's calculations

Figure A3: Actual and Fitted Values of Wages by Years of Potential Experience and OEWS Education Groups



Source: 1994-2019 Current Population Survey, author's calculations

Table A1: Average Years of Experience at Each Percentile of Aggregate Wage Distribution by OEWS Education Groups

	Q10	Q25	Q50	Q75	Q90
Less than high school	3 years	7 years	18 years	35 years	35 years
High school	3 years	8 years	16 years	33 years	35 years
Some college, no degree	2 years	7 years	15 years	28 years	35 years
Associates	4 years	8 years	16 years	35 years	35 years
Bachelors	1 year	5 years	12 years	35 years	35 years
Grad school	1 year	4 years	13 years	34 years	34 years

Source: 1994-2019 Current Population Survey, author's calculations