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Estimating Occupation and Location Specific Wages over the Life Cycle

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Abstract

In this paper we develop a novel method to project location specific life cycle wages for all occupations listed in the Bureau of Labor Statistics Occupational Outlook Handbook. Our method builds on the commonly used Mincer equation and improves it by providing a more nuanced relationship between years of experience and wages while also incorporating occupation and location specific factors. Our method consists of two steps. In the first step, we use individual level data from the Current Population Survey (CPS) to estimate the average number of years of experience associated with each percentile of the 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 (OEWS) 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 in the OEWS data.

Keywords: Wage growth, Wages, Experience, Education, Earnings, Mincer earnings function

1. Introduction

Labor economists modeling wage levels have long relied on the classical Mincer equation to estimate the relationship between years of experience, education, and wages (Mincer, 1958, 1974; Heckman et al., 2003; Lemieux, 2006). Indeed, Mincer’s finding that earnings rise over the life cycle has been called “one of the robust findings in labor economics” (Neumark, 1995). Individuals who are continuously attached to the labor market typically experience increases to their earnings with years of experience, but at a decreasing rate "until depreciation exceeds human capital accumulation" (Polachek, 2006).

In this paper, we add to the body of literature that has sought to improve the Mincer equation and develop location and occupation specific wage projections that can be used by practitioners. Only a few researchers have improved upon the classical Mincer equation. Lemieux (2006) and Lagakos et al. (2018) argue that the education gap is not a constant function of experience. Murphy and Welch (1990) argue that the quadratic relationship between years of experience and wages provides a poor fit for the data, especially with only a few years of experience. They offer alternatives using cubic, quartic, and nested quadratic forms, examining the prediction errors along a number of dimensions. The authors conclude that "the quartic function provides a reasonably good approximation to the 'true' earnings function". In this paper, we further improve upon this line of research by providing yet another functional form that better fits the data and by incorporating location and job factors. The outcome of the model we develop allows us to project life cycle wages for occupations listed in the Bureau of Labor Statistics Occupational Outlook Handbook (the Handbook). The wage projections that we make are useful for practitioners trying to apply labor market research. Practitioners such as career counselors and financial counselors can use the job and location specific wage projections to help individuals decide between different careers and plan their financial futures. The wage projections from these models are currently being used by the Federal Reserve Bank of Atlanta's Career Ladder Identifier and Financial Forecaster tools. To our knowledge, we are the first to create a model of wages that incorporates information about the trajectory of wages that are specific to location and occupation.

Our method uses the wage data from the Occupational Employment and Wage Statistics (OEWS) dataset. 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 (Note 1). 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.

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 (Note 2). 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 (Note 3). 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 (Note 4). 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.

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 the population whose primary activity is working and that are likely to be working in a job or field where their wage largely is a reflection of their education and years of related experience. Specifically, we remove people that are in school, only work part-time (less than 40 hours per week), or that are retirement age (62 or over; 62 is the earliest age one can draw social security benefits). The removal of people that are retirement age is done in case people that are retired have transitioned into a 'retirement' job but are still working full-time. This retirement job may reflect a job which they enjoy doing instead of reflecting their value in the labor market, based on their number of years of experience.

Further, including individuals that are retirement age may introduce an old-age bias. That is, individuals with the most amount of experience will be retirement age, and older individuals are more likely to be past their peak in terms of cognitive productivity, likely reducing their value in the labor market. If we were to include retirement age individuals then the years of experience variable at old-ages would capture the effect of cognitive abilities and lower-effort job choices that, likely leading to negative wage growth predictions with very high years of experience. Thus, removing retirement age individuals is essential for creating a model intended to isolate the effect of years of experience on wage growth. The age 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 (Note 5).

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 to model individual wages separately for each education group as shown in equation 1.

$$\ln(w_i) = \gamma_0 + \gamma_1 X_i + \gamma_2 X_i^{\frac{1}{2}} + \mu_s + [B_i]^T[C_i] + \epsilon_i \tag{1}$$

Within each education group, individual i's natural log of wages is estimated as a function of years of potential experience (X), the square root of years of potential experience, state fixed effects (μ_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 with years of experience, but 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). The 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 level 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, post-secondary non-degree award, 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 post-secondary non-degree award and doctoral or professional degree. Therefore, we combine people with post-secondary non-degree award and those with associates degree into one education category. Additionally, we pool people with doctoral or profession degree and those with a master's degree into one group. 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) (Note 6). 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 (Note 7). 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.

We estimate equation 1 on the ATL CPS using ordinary least squares (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 a pattern similar to Rubinstein and Weiss (2006), suggesting that the return to experience is the largest for those with relatively few years or experience, then gradually tapers. Table 1 shows the mean squared error of equation 1 by years of experience and education group. The mean squared errors of equation 1 are always below 0.39, indicating that the model provides a good fit to the data. The model fits the best for those with 1-10 years of experience and for those without a college degree.

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. 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).

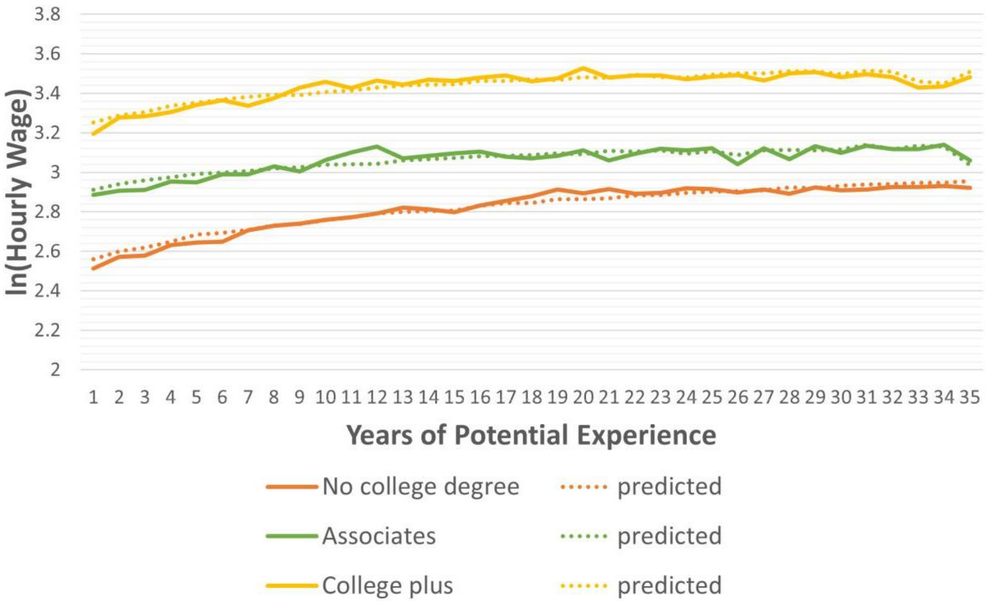

Figure 1. Actual and Fitted Values of Wages by Education Level and Years of Potential Experience

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

Table 1. Mean Squared Error of Equation 1, by Education and Years of Experience

	1-10 years of experience	**11-26 years of experience**	**27-35 years of experience**	**Overall**
No college degree	0.16	0.20	0.21	0.19
Associates	0.21	0.21	0.29	0.23
College plus	0.26	0.31	0.39	0.30

Source: Author's calculations

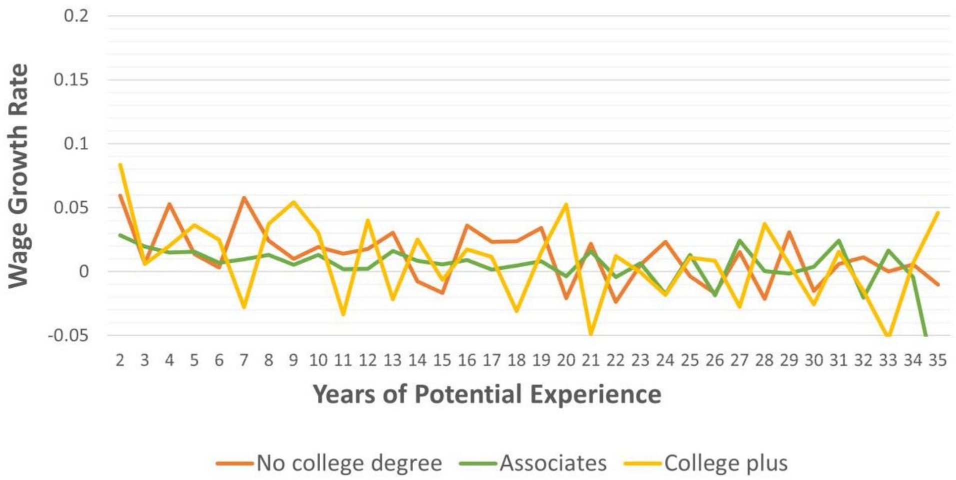

Figure 2. Predicted Wage Growth by Education Level and Years of Potential Experience

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.

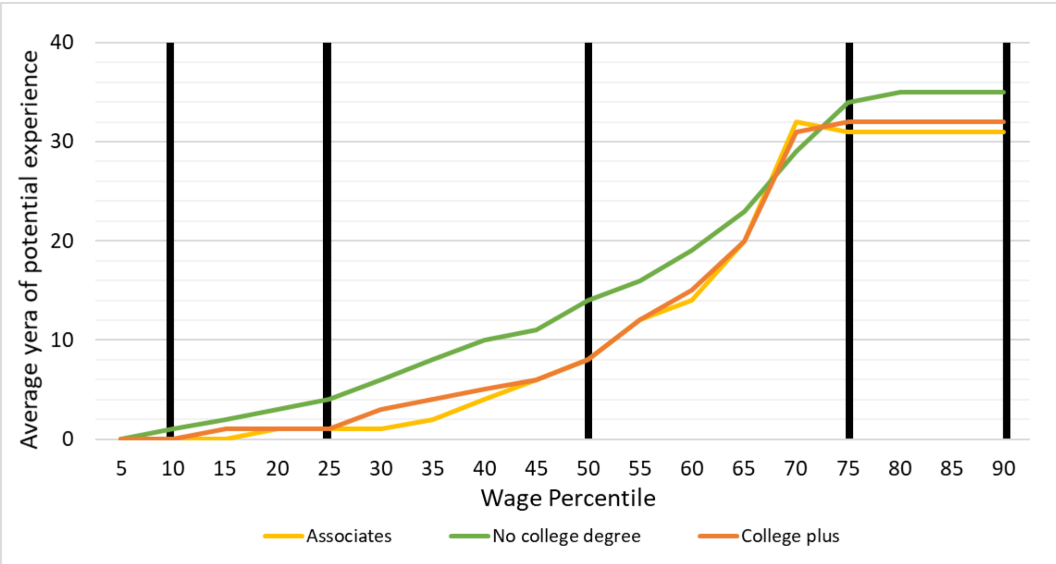

Figure 3. Years of Potential Experience Corresponding to Each Wage Growth Percentile

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

The plotted line for workers with a bachelor's degree or higher closely coincides with that for associate's degree. Both lines are below that for workers with no college degree. Thus, workers with a bachelor's or associate's degrees tend to progress faster in their education group's aggregate wage distribution than those with less education. On average, workers with a college degree or higher need 1 year of potential experience to achieve the 25th percentile and 8 years of potential experience to achieve 50th percentile. In contrast, workers without college degree, on average need 4 years of experience to achieve the 25th percentile and 14 years to achieve the 50th percentile. Table 2 summarizes where each of the black lines intersect with the education-specific wage distributions.

Table 2. Average Years of Experience at Each Percentile of the Education-Specific Wage Distribution

	Q10	**Q25**	**Q50**	**Q75**	**Q90**
No college degree	1 year	4 years	14 years	34 years	35 years
Associates	0 years	1 year	8 years	31 years	31 years
College plus	0 years	1 year	8 years	32 years	32 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 2 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, we estimate equation 2 separately for each occupation from the OEWS data (Note 8).

$$\ln(w_p) = Area + \beta_1(Area \times X_p) + \beta_2\left(Area \times X_p^{\frac{1}{2}}\right) + \epsilon_0 \tag{2}$$

The wage percentiles (p) for each occupation are modeled with 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 turns negative only in a few areas.

Table 3 reports the mean squared error of equation 2 by years of experience averaged across all occupations. All MSEs are below 0.5 indicating that the model fits the data well.

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.

Table 3. Mean Squared Errors of Equation 2, by Years of Experience Averaged Across All Occupations

	1-10 years of experience	**11-26 years of experience**	**27-35 years of experience**	**Overall**
All Occupations	0.42	0.02	0.12	0.16

Source: Author's calculations

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.

$$NewStartingWage_t = \alpha_0(NewMinWage_t - 2020MinWage) + 2020StartingWage_t \tag{3}$$

Where α determines the degree of spillover. α 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, α for jobs paying $8.56 per hour is 1, α for jobs paying $10.72 is 0, and thus α 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, an LPN's starting wage is estimated to be $16.32 per hour, above the upper bound of affected wages ($10.72). Therefore, there is no expected change in the starting wage in 2021. By 2025, however, the minimum wage increases to $14 per hour. With this increase, the new upper bound of affected wages is $16.72 per hour. As a result, according to the equation 3, the LPN starting wage increases by about $0.12. By 2026, the minimum wage in Florida is $15 per hour and the new LPN starting wage is projected to be $17.59 per hour.

Figure 5. The Effect of Planned Minimum Wage Hikes in FL on Licensed Practical Nurse (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 $17.76 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 that starts in 2025. By 2026, an LPN is projected to make almost $1.50 per hour more than if there were no changes to the FL minimum wage law.

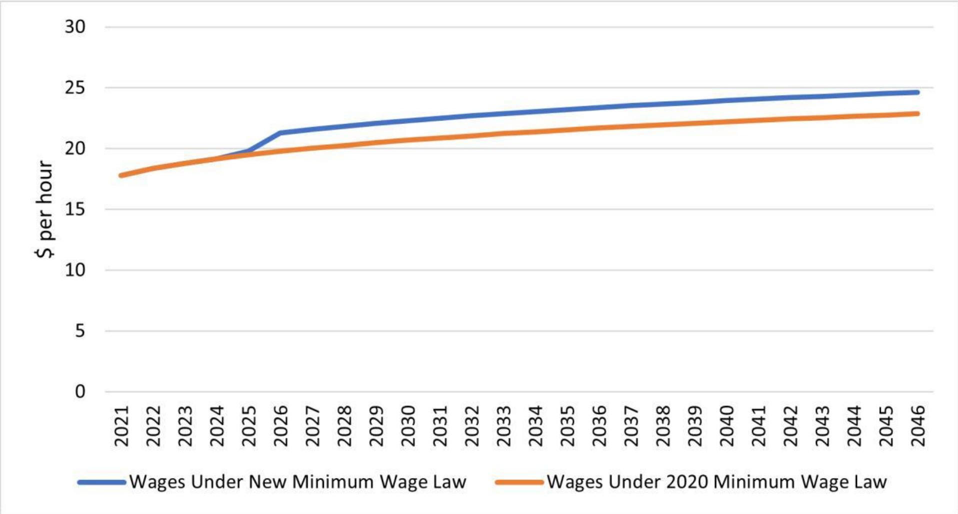

Figure 6. The Effect of Planned Minimum Wage Hikes in FL on Licensed Practical Nurse (LPN) Starting Wages in Tallahassee, FL

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 to 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 occupation-location specific wage distributions. To our knowledge, we are the first to create a model of wages that incorporates information about the trajectory of wages that are specific to location and occupation. In creating this model, we provide an update to the commonly used Mincer equation. The updated Mincer equation features a functional form which provides a more accurate mapping of the relationship between wages and years of experience.

Our method involves combining 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 typical education level required for entry into the job. 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 the updated Mincer equation to project the trajectory of wages across all possible years of experience. Last, we adjust the wage growth projections to account for planned hikes in state minimum wages.

The updated version of the Mincer equation that we develop can be used by researchers hoping to improve model fit, particularly when modeling wages for individuals with many years of experience. Because the model was mostly developed with practitioners in mind, it's use is somewhat limited. For example, it is designed to be used to estimate future wage trajectories in a job where the person is assumed to gain work experience relevant to that job as they age. The model does not take the effect of age separately from years of experience into account; the model is also not calibrated using data that contain individuals older 62. For these reasons, in cases where years of relevant work experience is unknown or the person is retirement age, the model is not expected to perform well.

References

Brochu, P., Green, D. A., Lemieux, T., & Townsend, J. (2015). *The minimum wage, turnover, and the shape of the wage distribution.* Unpublished manuscript.

U.S. Department of Labor. (2021a). *Occupational Employment and Wage Statistics*. [Data set]. BLS. [Online] Available: https://www.bls.gov/oes/

U.S. Department of Labor (2021b). *Occupational Outlook Handbook.* [Codebook]. BLS. [Online] Available: https://www.bls.gov/ooh/about/ooh-developer-info.htm.

Cengiz, D., Dube, A., Lindner, A., & Zipperer, B. (2019). The Effect of Minimum Wages on Low-Wage Jobs. T*he Quarterly Journal of Economics, 134*(3), 1405-1454. https://doi.org/10.1093/qje/qjz014

Congressional Budget Office. (2019). *The effects on employment and family income of in-creasing the federal minimum wage*. Technical report, Congressional Budget Office.

Federal Reserve Bank of Atlanta. (2021). *Harmonized Variable and Longitudinally Matched Current Population Survey.* [Data set]. CADRE. [Online] Available: https://cps.kansascityfed.org/cps.

Heckman, J. J., Lochner, L. J., & Todd, P. E. (2003). *Fifty years of mincer earnings regressions*. Technical report, National Bureau of Economic Research. https://doi.org/10.3386/w9732

Lagakos, D., Moll, B., Porzio, T., Qian, N., & Schoellman, T. (2018). Life cycle wage growth across countries. *Journal of Political Economy*, *126*(2), 797-849. https://doi.org/10.1086/696225

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. https://doi.org/10.1162/003355399556197

Lemieux, T. (2006). The "Mincer Equation" Thirty Years After Schooling, Experience, and Earnings. In S. Grossbard (Ed.), *Jacob Mincer a pioneer of modern labor economics* (pp. 127-145). Kluwer Academic Publishers. https://doi.org/10.1007/0-387-29175-X_11

Neumark, D. (1995). Are rising earnings profiles a forced-saving mechanism? *The Economic Journal*, *105*(428), 95. https://doi.org/10.2307/2235321

Soloman William Polachek. (2003). Mincer's overtaking point and the life cycle earnings distribution. *Review of Economics of the Household*, *1*(4), 273-304. https://doi.org/10.1023/B:REHO.0000004790.49070.13

Notes.

Note 1. Years of potential experience is estimated as a difference between workers' current age and the age at which he or she entered the labor force. The latter depends on worker's education. We assume that workers with less than high school degree and high school degree enter the labor force immediately after graduation – at the age of 16 and 18 respectively. Those with some college, no degree start their education at the age 21 and spend 2 years in school. Thus, they enter the labor force at the age 23. To determine age at which workers with associate and bachelor's degrees enter the labor force, we first use the data from the Beginning Postsecondary Students Longitudinal Study (BPS) conducted by the National Center for Education and Statistics (NCES) to determine the median age at which students start pursuing the associate degree and the bachelor's degree. The median starting age is 22 for an associate degree and 19 for a bachelor's degree. According to the Shapiro et al. (2016) on average, accounting for any gaps in studies, it takes 5 years to complete the associate degree and 6 years to complete the bachelor's degree. Combining these two statistics together, we assume that someone with an associate degree enters the labor force at age 27, a bachelors' degree at age 25, and a graduate degree at age 28 (additional 3 years of schooling after BA is achieved).

Note 2. The OEWS data also contains additional statistics, such as mean and annual wage estimates.

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

Note 4. 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.

Note 5. 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.

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

Note 7. 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.

Note 8. Hourly wages in the OEWS data are top-coded at $100 per hour. Where necessary, we use top-codes to estimate equation 2.

Appendix

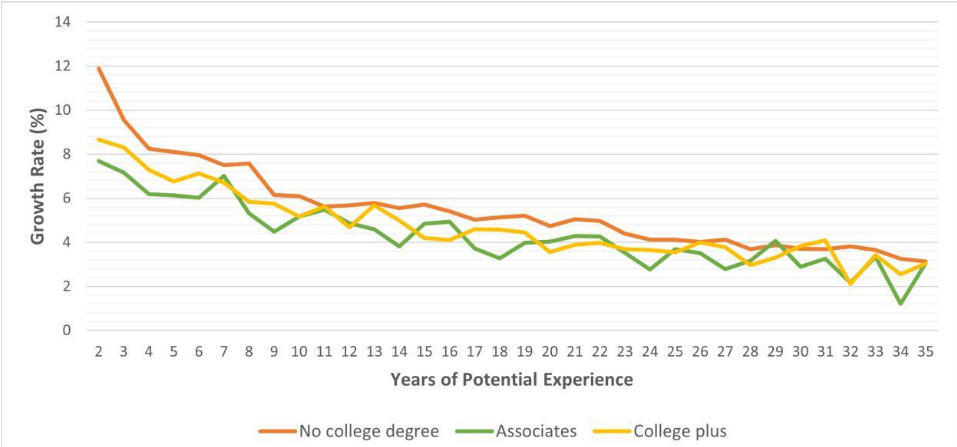

Figure A1. Average of Individual-Level Annual Wage Growth by Education Levels and Years of Potential Experience

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

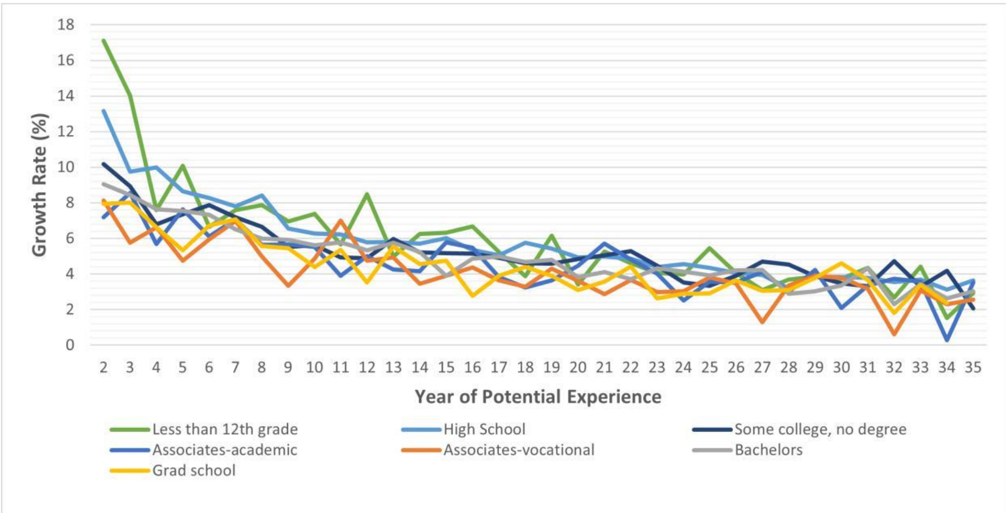

Figure A2. Average Individual-Level Wage Growth by Years of Potential Experience and OEWS Education Groups

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