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Job Mobility and Wage Trajectories for Men and Women in the United States

Sylvia Fuller
University of British Columbia

Section A. Model Estimation

Multilevel regression models applied to longitudinal data typically have a two-level structure: individuals are the level-2 units, and the repeated observations are level-1 units. This contrasts with many applications of multilevel modeling in the social sciences where individuals are the level-1 unit nested within larger level-2 units such as schools, geographic regions, or occupations. Variables that can take on different values in different years (such as the number of times an individual has separated from an employer) are level-1 variables. These variables predict individual change trajectories. Variables that are constant across persons over time (such as ethnicity) are level-2 variables. These help predict how the changes modeled at level 1 vary across individuals in accordance with time-invariant individual characteristics.

The models express wage trajectories as a function of time and its square (time is measured as years since entering the labor force, with T = 0 scaled to represent wages during the first year in the labor force), mobility pattern (measured in a variety of ways across models), and an array of controls. A general representation is

$$\ln WAGE_{ti} = \pi_{0i} INTERCEPT_{ti} + \pi_{1i} TIME_{ti} + \pi_2 TIME_{ti}^2 + \pi_{pi} MOB_{ti} + \pi_q X_{ti} + r_{ti}$$
$$\pi_{0i} = \beta_{00} + \beta_{0r} X_{ri} + u_{0i}$$
$$\pi_{1i} = \beta_{10} + u_{1i}$$
$$\pi_{pi} = \beta_{p0} + u_{pi}$$

The first line of the equation captures the wage trajectory (growth curve) for a given individual. On the left-hand side, $\ln(\text{WAGE})_{ti}$ is the natural log of the CPI-deflated average hourly wage earned by individual *i* on occasion *t*. The right-hand side of the first line includes four elements: an intercept term to capture the initial level of the wage, $\pi_{0i} INTERCEPT_{ti}$; a linear trend, $\pi_{1i} TIME_{ti}$, which represents the yearly growth in wages; a quadratic term, $\pi_2 TIME_{ti}^2$, which models the deceleration of the growth curve; and a vector of mobility-related variables ($\pi_{pi} MOB_{ti}$), a vector of control variables ($\pi_q X_{ti}$), and a residual (r_{ti}), which represents the unmeasured year-to-year variability in wages for a given individual (this can also be thought of as a within-person or level-1 random effect).

I allow wage trajectories to vary among individuals both in their starting point (initial wages) and in their slope (wage growth). Since mobility events may have a more positive or negative impact for some workers than for others, I also allow this impact to vary among individuals. The bottom three lines of the equation take inter-individual variation into account in a level-2 (between-person) submodel. This submodel captures the influence of measured and unmeasured person-constant characteristics on the estimates for the intercept, linear growth term, and mobility terms. In the submodel, the coefficients from the first line that are assumed to vary among individuals (those with *i* subscripts to indicate that they are individual-specific) are decomposed into a fixed component that estimates the mean across all individuals and a random component that captures individuals' deviations from the mean.[1] The β terms are the *fixed effects*. Each line includes at least one—a general intercept. The first line in the submodel (predicting the level-1 intercept) also includes a vector of (person-constant) control variables, $\beta_{0r} X_{ri}$. The *u* terms are the level-2 *random effects.* These residuals express the effects of unmeasured, person-constant characteristics that cause systematic deviation from the average for a given individual (they are the same for all time periods for a given individual). Across individuals, I assume these residuals to have a mean of 0 and a variance and covariance that can be estimated. The variance/covariance matrix associated with this model takes the general form

$$\begin{bmatrix} u_{0i} \\ u_{1i} \\ u_{3i} \end{bmatrix} = \begin{bmatrix} \sigma_{u0}^2 \\ \sigma_{u10}\sigma_{u1}^2 \\ \sigma_{u30}\sigma_{u31}^2\sigma_{u3}^2 \end{bmatrix}$$

$$\begin{bmatrix} r_{ti} \end{bmatrix} = \begin{bmatrix} \sigma_{r0}^2 \end{bmatrix}$$

Although, for the most part, I focus on the fixed effects as representations of the average impact of mobility on wages, the variances from this matrix are also interesting. They tell us the degree of residual variation in mobility effects (as well as in wages and wage growth) that remains among men and women in different models. Covariances can be illuminating as well. They reveal the nature and degree of the relationship between residuals for mobility and for wage levels and wage growth (i.e., whether the returns on mobility vary systematically for workers with starting wages or growth that are greater than predicted).

For a given individual, wage observations are likely to exhibit serial correlation because residuals close together in time are more similar than those further apart. I therefore specify a first-order autoregressive component (AR(1)) that allows a correlation structure of measurements within individuals (between time periods) that decreases with increasing lag between measures. Including this term significantly improves the fit of the models. Model parameters are estimated with maximum likelihood using the Newton-Raphson algorithm implemented in SAS proc mixed.

[1] In theory, one could specify a level-2 submodel for every term in the level-1 equation. In practice, including many random effects tends to create convergence problems during model estimation. It is therefore typically best to restrict the specification of random effects to circumstances in which there is a specific need to understand how the context affects the slope (Singer and Willett 2003; Snijders and Bosker 1999).

Section B. Piecewise Regression

To account for differences in the effects of lower and higher levels of tenure and relative mobility, I construct piecewise linear functions.[2] Such functions allow the slope for variables to change at specified nodes. For tenure, I allow the slope to change after an individual has accumulated five years of tenure. For relative mobility, the slope changes at the year-specific mean. Willett, Singer, and Martin (1998) outline the general application of piecewise regression to multilevel models, and I use a coding strategy adapted from this approach by Llabre and colleagues (2001) to create these functions. For tenure, this first entails centering tenure at a common point and then multiplying with two dummy vectors. If 0 is the common point, the vectors are

D1 = 0 if tenure $\geq$ 0
D1 = 1 if tenure < 0
D2 = 0 if tenure $\leq$ 0
D2 = 1 if tenure is > 0

For the sake of illustration, presume tenure ranges from 0 to 10 years, and that it is expressed only in whole years and not fractions. If tenure is centered at 0, this would result in the following interaction vectors:

Lower tenure = D1* tenure: … –5 –4 –3 –2 –1 0 0 0 0 0
Higher tenure = D2* tenure: 0 0 0 0 0 1 2 3 4 5

The final step is to add 5 to the lower tenure vector so the centering value reflects the change in slope at five years of tenure. This means that the intercept captures the wages at the time of job change (when both higher and lower tenure are 0), low tenure captures the slope increment of each additional year of tenure up to the fifth year and is constant (at a value of 5) for values above that point, and high tenure captures the slope increment of each additional year of tenure past this point, while being constant (at 0) when tenure is less than this. As Llabre and colleagues (2001) point out, an alternative way of thinking about the coding is to simply specify two coded vectors—higher tenure and lower tenure—each with varying intervals for the phase it measures and constant values for the phase it does not. Thus, if tenure is less than 5, lower tenure = tenure; higher tenure = 0. If tenure is greater than 5, lower tenure = 5; higher tenure = tenure –5.

The higher and lower mobility functions are created in a similar manner, except that I do not add 5 to the lower mobility term. The "higher relative mobility" term in the tables thus captures the slope increment as mobility exceeds the norm and is constant at 0 when relative mobility is less than average. The "lower relative mobility" term likewise indicates the effect of increasing relative mobility when it is lower than the norm, and it is constant at 0 when relative mobility is higher than average. The intercept captures wages when relative mobility is exactly average.

[2] It is common to model tenure as a quadratic to account for its attenuating value, but the piecewise linear function fit the data better, perhaps because the relatively young age of the sample means that few had long tenure (slightly less than 5 percent had more than 10 years of tenure). A piecewise approach also yields more easily interpretable estimates.

References

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