Applied Econometrics

Labor Econometrics

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Econ 753
Outline of Presentation

Three-day plan

1. Wage models
2. Labor demand: the employment effect of the minimum wage
3. Labor supply: the employment effect

Today—Wage models

1. Why study wage determination?
   - Outcome of a labor-market process
   - Distribution of product and surplus
   - Rents (both for themselves and as an indicator of market power)
2. Building an econometric model: Theory and functional form
3. Discrimination
4. Aggregate variables and micro units
Data sources and definitions

1. Census, CPS, NLSY, PSID (US)
2. Luxembourg Income Study (OECD), GSOEP (Germany)

Wage and “wage”

- Annual earnings, weekly earnings, hourly wage, salaries
- Think about the data in rows (observations, records) and columns (variables, fields).
- Read and produce tables of regression output.
Wage-setting models

- Competitive market models
  - Market-clearing wage
  - Human Capital (HK): hedonic wage model
  - Compensating differentials
- Monopsonistic or exploitation models
- Institutional models and discrimination models
  - Segmented labor markets
  - Inter-industry wage differentials
On econometric models of wages

- Does $X$ or $Z$ raise wages?
  - Simultaneity/endogeneity/selection (Does $X$ really raise your wages, or do people with $X$ tend to have high wage?)
    - Signalling critique of Human Capital
    - General equilibrium remark on Human Capital
  - Aggregate explanatory variables
Functional form

- About subscripts and parameters: $y_i$, $y_{it}$, $y_{ijt}$, $\beta$
- Interpreting the semi-log specification
- The Return to Education
- Experience (or tenure)
- Indicator, or dummy, variables
- Indicator interactions
- Differences in the function over time/space/group (e.g., “skill-biased technical change”)
Human Capital Regressions are based on a hedonic model of wage determination: the wage is a function of the valuable characteristics of the worker. What’s the return to attending one [more] year of schooling?

### Career Earnings by Years of School

<table>
<thead>
<tr>
<th>Years attended</th>
<th>0</th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>t</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>$Y_0$</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>$Y_0$</td>
<td>$Y_1$</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>$Y_0$</td>
<td>$Y_1$</td>
<td>$Y_2$</td>
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<tr>
<td>3</td>
<td>$Y_0$</td>
<td>$Y_1$</td>
<td>$Y_2$</td>
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<tr>
<td>...</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T</td>
<td>$Y_0$</td>
<td>$Y_1$</td>
<td>$Y_2$</td>
</tr>
</tbody>
</table>
Return to Education

Note that more years of schooling require foregoing years of earnings. In a very simple model, the return to schooling will equalize the net present value (NPV) of the alternatives (0, 1, 2, or 3 years of schooling).

\[
\text{NPV}(S = 0) = \frac{Y_0}{(1 + r)^0} + \frac{Y_0}{(1 + r)^1} + \frac{Y_0}{(1 + r)^2} + \cdots = \frac{1 + r}{r} \cdot Y_0
\]

\[
\text{NPV}(S = 1) = \frac{0}{(1 + r)^0} + \frac{Y_1}{(1 + r)^1} + \frac{Y_1}{(1 + r)^2} + \cdots = \frac{1}{r} \cdot Y_1
\]

“Equilibrium”: \( \text{NPV}(S = 0) = \frac{1}{r} \cdot Y_1 = \frac{1+r}{r} \cdot Y_0 = \text{NPV}(S = 1) \)

implies

\[ Y_1 = (1 + r_1) \cdot Y_0 \]
Returns to Education

The additional income from one year of school relative to zero years of school represents a return of $r_1$. The same argument implies that

$$Y_2 = (1 + r_2) \cdot Y_1$$

and so on. Substituting recursively, we find

$$Y_s = (1 + r_s)Y_{s-1} = (1 + r_s) \cdots (1 + r_1)Y_0$$

For the moment assume that $r_s = r_{s-1} = \cdots = r_1 = r$, a single percent return to an additional year of education (a testable proposition),

$$Y_s = (1 + r)^s \cdot Y_0$$
Measuring and Estimation

Recall that by a Taylor series approximation, $1 + \delta = e^{\delta}$ and so $(1 + r)^s = (e^r)^s = e^{rs}$ (This might also be familiar from compound-interest formulas.)

$$Y_s = e^{rs}Y_0$$

and taking log of both sides,

$$\ln Y_s = \ln Y_0 + rs$$

which can be interpreted as a semi-log wage equation that we can estimate:

$$\ln Y_s = \alpha + \beta S$$

$Y_s$ and $S$ are measured (earnings and schooling) and $\alpha$ and $\beta$ are estimated parameters. $\beta$ is the return to schooling (expressed in \textit{percent per year}) and $\alpha$ is the intercept (implied log earnings at zero years of education).
Critique of Causality

In observational studies in the U.S. and elsewhere, $\beta$ is rarely estimated below 0.05 (a 5 percent return to schooling) and in L.D.C.’s is sometimes estimated as high as 0.20 (a 20 percent return to schooling). Is $\ln Y_s = \alpha + \beta S$ a causal relationship, i.e., if $\beta$ is positive, does schooling cause higher earnings? Why or why not?

- Omitted variables that cause $\beta$ to be an overestimate (“left” and “right” critiques)
  - Socioeconomic status causes both schooling and earnings
  - Ability causes both schooling and earnings
- Signalling
- General equilibrium and social returns
- Attitudinal modification

We will return to this question in more detail later.
Experience

Next we introduce experience and allow it to have a non-linear effect on earnings. Why?

- Human capital explanations: rational to accumulate HK when young; rapid accumulation of HK in early years on the job (OJT); long time to amortize the cost of training; forgetting and HK deterioration.
- Neo-institutional explanations: solve P/A problem with “bond”; matching and wage gains
- Institutional explanations: customs and norms; seniority in unionized and union-avoiding workplaces; limited evidence on productivity (bus driver safety study)
Tenure and experience

- Would be helpful to resolve some of the competing hypotheses.
- Empirical problem. Few datasets include measures of tenure; then they do, the quality is often poor (for three reasons: recollection bias, definition of job and employer, sampling durations). Potential Experience (Mincerian Experience for Jacob Mincer):

\[
\text{Potential Experience} = \text{Age} - (\text{Years of Schooling} + 6)
\]

Reasonable proxy unless the aim is to make subtle points about tenure versus experience. Note that regressions with Potential Experience and Schooling must omit age to prevent perfect collinearity.
Quadratic specification

\[
\ln Y_i = \alpha + S_i \beta_s + \text{Ex}_i \beta_{\text{Ex}} + \text{Ex}_i^2 \beta_{\text{Ex}^2} + \varepsilon_i
\]

\[
\frac{\partial \ln Y_i}{\partial \text{Ex}_i} = \beta_{\text{Ex}} + 2\text{Ex}_i \beta_{\text{Ex}^2}
\]

This term depends on the level of experience. Typical values are \( \beta_{\text{Ex}} = 0.03 \) and \( \beta_{\text{Ex}^2} = -0.0004 \). The negative quadratic term means that the relationship is concave. The positive linear term and the size of the two terms means that the return begins positive (about 3 percent per year for a new worker at 0 years of experience) and then falls. You can compute the return at any given level of experience by substituting. You can compute the peak of the age-earnings profile by setting the derivative to zero:

\[
\frac{\partial \ln Y_i}{\partial \text{Ex}_i} = \beta_{\text{Ex}} + 2\text{Ex}_i \beta_{\text{Ex}^2} \equiv 0
\]
Experience, continued

which implies that

\[ \text{Ex}_{i}^{\text{peak}} = -\frac{\beta_{\text{Ex}}}{2\beta_{\text{Ex}^2}} \]

For example, with \( \beta_{\text{Ex}} = 0.03 \) and \( \beta_{\text{Ex}^2} = -0.0004 \), the peak of the profile would be at about \( \frac{0.03}{2(-0.0004)} = 38 \) years of experience.
Dummy variables

Allows different intercepts for different categories.
Simplest example: Each observation $i$ is in category $(D_i = 1)$ or not $(D_i = 0)$, e.g., non-white, female, or union member. Categorical nominal variables with a simple level effect.

$$\ln Y_i = \alpha + D_i \delta + X_i \beta_X + \varepsilon_i$$

The estimated coefficient $\hat{\delta}$ is the return (premium or penalty) to being in category $D$, measured in log points (read as percent).
Tip: give $D$ a useful name, e.g., “Female” is a more useful name for an indicator than is “Sex”; “Nonwhite” is a more useful name for an indicator than is “Race”.
Interpreting dummy variables

To interpret the coefficients on dummy variables:
Consider a very simple wage equation:

$$\ln Y_i = \alpha + D_i \delta + \varepsilon_i$$

$Y_i$ is hourly wage for person $i$, $\alpha$ is the intercept, a baseline wage, $D_i$ is an indicator variable for membership in category $D$, e.g., $D_i = 1$ for college degree or more and $D_i = 0$ for less than college degree.
How can we interpret $\delta$, the coefficient on $D_i$?

$$\hat{\ln Y_i} = \hat{\alpha} + D_i \hat{\delta}$$
$$e^{\hat{\ln Y_i}} = e^{\hat{\alpha} + D_i \hat{\delta}}$$
$$Y_i = e^{\alpha} \cdot e^{D_i \delta}$$
Interpreting dummy variables

For a person without a college degree, $D_j = 0$ and expected earnings are:

$$Y_j = e^{\alpha} \cdot e^{0 \cdot \delta} = e^{\alpha} \cdot 1 = e^{\alpha}$$

So the baseline wage (without a college degree is $e^{\alpha}$.

For a person with a college degree, $D_i = 1$, and expected earnings are:

$$Y_i = e^{\alpha} \cdot e^{1 \cdot \delta} = e^{\alpha} e^{\delta}$$

What’s the percent return?
Interpreting dummy variables

\[ \rho \equiv \frac{Y_i - Y_j}{Y_j} = \frac{e^\alpha \cdot e^\delta - e^\alpha}{e^\alpha} = e^\delta - 1 \]

Remark: this formula for percent change always works. If you want to know the percent return when you are given \( \delta \), you can calculate \( \rho = e^\delta - 1 \).

But there is a shortcut when \( \delta \) is small. Consider a first-order Taylor approximation of the percent return \( \rho \) as a function of the coefficient \( \delta \). As we just saw, \( \rho(\delta) = e^\delta - 1 \).

\[
\begin{align*}
\rho(\delta) &\approx \rho(0) + \rho'(0) \cdot (\delta - 0) \quad \text{near } \delta = 0 \\
\rho'(\delta) &= e^\delta \\
\rho(0) &= e^0 - 1 = 1 - 1 = 0 \\
\rho'(0) &= e^0 = 1 \\
\rho(\delta) &\approx 0 + 1 \cdot \delta = \delta
\end{align*}
\]
The Returns to Computer Use


- Enormous increase in inequality in the United States
  - Between categories
  - Within categories (“residual inequality”)
- Skill-biased technical change
  - Alternatives: trade, trade/SBTC, institutions
  - What are the technical changes in question?
  - Alan Krueger offers computers
The Returns to Computer Use

**Table II**

OLS Regressions for the Effect of Computer Use on Pay

**Dependent Variable: Log Hourly Wage**

*(Standard errors in parentheses)*

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Computer</td>
<td>0.171</td>
<td>0.188</td>
<td>0.204</td>
<td>0.112</td>
<td>0.157</td>
<td>0.171</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.010)</td>
<td>(0.007)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Years of schooling</td>
<td>0.068</td>
<td>0.075</td>
<td>0.081</td>
<td>0.073</td>
<td>0.063</td>
<td>0.072</td>
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<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Experience</td>
<td>0.028</td>
<td>0.028</td>
<td>0.026</td>
<td>0.030</td>
<td>0.035</td>
<td>0.030</td>
</tr>
<tr>
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<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Experience²/100</td>
<td>-0.043</td>
<td>-0.043</td>
<td>-0.041</td>
<td>-0.052</td>
<td>-0.058</td>
<td>-0.046</td>
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<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>R²</td>
<td>0.444</td>
<td>0.448</td>
<td>0.424</td>
<td>0.267</td>
<td>0.280</td>
<td>0.336</td>
</tr>
<tr>
<td>Number of obs.</td>
<td>13,335</td>
<td>13,379</td>
<td>13,305</td>
<td>19,427</td>
<td>22,353</td>
<td>20,042</td>
</tr>
</tbody>
</table>
The Returns to Computers—and Pencils!

### TABLE III

**OLS Regression for the Effect of Different Tools on Pay**

*Dependent Variable: Log Hourly Wage*

*(Standard errors in parentheses)*

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Occupation indicators</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>501</td>
<td>501</td>
<td>742</td>
<td>1071</td>
</tr>
<tr>
<td>Grades and father's</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Occupation*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Tools entered separately**

<p>| | | | | | | | |</p>
<table>
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<tr>
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<th></th>
<th></th>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Computer</strong></td>
<td>0.112</td>
<td>0.157</td>
<td>0.171</td>
<td>0.025</td>
<td>0.022</td>
<td>0.076</td>
<td>0.083</td>
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<tr>
<td></td>
<td>(0.010)</td>
<td>(0.007)</td>
<td>(0.006)</td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.008)</td>
<td>(0.007)</td>
</tr>
<tr>
<td><strong>Calculator</strong></td>
<td>0.087</td>
<td>0.128</td>
<td>0.129</td>
<td>0.027</td>
<td>0.025</td>
<td>0.061</td>
<td>0.054</td>
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<td></td>
<td>(0.007)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.007)</td>
<td>(0.006)</td>
</tr>
<tr>
<td><strong>Telephone</strong></td>
<td>0.131</td>
<td>0.114</td>
<td>0.136</td>
<td>0.060</td>
<td>0.057</td>
<td>0.059</td>
<td>0.072</td>
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<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td><strong>Pen/pencil</strong></td>
<td>0.123</td>
<td>0.112</td>
<td>0.127</td>
<td>0.055</td>
<td>0.052</td>
<td>0.055</td>
<td>0.050</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td><strong>Work while sitting</strong></td>
<td>0.106</td>
<td>0.101</td>
<td>—</td>
<td>0.042</td>
<td>0.041</td>
<td>0.036</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.007)</td>
<td></td>
<td>(0.008)</td>
<td>(0.008)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Hand tool</strong> (e.g., hammer)</td>
<td>−0.117</td>
<td>−0.086</td>
<td>−0.091</td>
<td>−0.048</td>
<td>−0.045</td>
<td>−0.020</td>
<td>−0.020</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.008)</td>
<td>(0.008)</td>
</tr>
</tbody>
</table>
Multiple dummy variables

Multiple nominal categories, e.g., race, industry, occupation. Create a 1/0 dummy variable for each category. Must omit one of the classes or the dummies will be collinear with the intercept. (Can alternatively omit the intercept.) The omitted class is associated with the intercept, and all differences (the coefficients on the dummies) are read relative to the omitted class.

\[ \ln Y_i = \alpha + D_{2i}\delta_2 + D_{3i}\delta_3 + X_i\beta_X + \epsilon_i \]
Other uses for dummy variables

Can also create dummies for a small (relative to $N$ number of ordered categories—a less parametric approach, e.g., a return for every year of schooling, $\delta_1, \delta_2 \ldots \delta_{16}$ instead of restricting all years to have a single return, $\beta_s$.

Dummies are equivalent to a **within-group** approach. The response (slope) within every group is constrained to be the same, but the groups can be at different levels.

Many dummy variables (fixed effects), e.g., for every state, for every city, for every person.

Needs more than one observation per fixed effect. Cannot nest fixed effects, e.g., neighborhoods and cities.
## Dummy interactions

- **Dummy-dummy interactions**
  - Interactions among categorical variables.
  - Differences in function over time, place, or group.
  - For example, do black women suffer as much discrimination as do black men? Are union premiums larger for women or for men? Were union premiums larger in 1970 or in 1980?

\[
\ln Y_i = \alpha + \text{Fem}_i \beta_{\text{Fem}} + \text{Nonwhite}_i \beta_{\text{NW}} + \text{Fem}_i \times \text{Nonwhite}_i \beta_{\text{Fem-NW}} + X_i \beta_X + \varepsilon_i
\]

(Show regression output.) For this example, \( \beta_{\text{Fem}} < 0, \beta_{\text{NW}} < 0 \), but \( \beta_{\text{Fem-NW}} > 0 \) enough to “offset” one of the two forms of discrimination, i.e. black women do not receive the **cumulative** effect of sex and race discrimination.
Dummy-dummy interactions

Advantages of pooling: (1) restrict other coefficients to equality; (2) easy to test hypotheses.
Interact dummy variables for each category of first characteristic with dummy variables for each category of second characteristic.
Include dummies (level, or main, effect) and all dummy interactions. To include interactions but not the main effect, you must have a good reason or model.
Multiple interactions are possible.
Preview treatment-control before-after model (identify quasi-experimental effects):

\[ y_{it} = \alpha + \text{Post}_{it} \delta_{\text{Post}} + \text{Treatment} \text{ grp}_{it} \delta_{\text{Treatment grp}} + \text{Post}_{it} \times \text{Treatment}_{it} \times \delta_{\text{Effect}} + \epsilon_{it} \]

\[ \delta_{\text{Effect}} \] is the effect of treatment on the outcome because it expresses the difference between the treatment and control groups after treatment has been received. Note the use of interacted dummy variables.
Dummy interactions

- Dummy-continuous interactions (different slopes for different folks)
Aggregate explanatory variables (Moulton)

Contextual explanations of individual outcomes (neighborhood, city, industry). May want to explain an individual outcome with an aggregate characteristic, e.g., a worker’s wage may depend on the capital-labor ratio of the industry. For worker $i$ in industry $s$:

$$\ln Y_{is} = \alpha + Z_{is} \gamma + (K/L)_s \beta + \epsilon_{is} + \eta_s$$

with

$$\epsilon_{is} \sim N(0, \sigma^2_\epsilon)$$
$$\eta_s \sim N(0, \sigma^2_\eta)$$
$$\text{cov}(\epsilon_{is}, \eta_s) = 0$$
$$\text{cov}(\epsilon_{is}, \epsilon_{js}) = 0$$
$$\text{cov}(\eta_s, \eta_t) = 0$$
Moulton

1. $\hat{\beta}^{OLS}$ is unbiased; but
2. s.e.$(\hat{\beta}^{OLS})$ is underestimated.

Standard OLS estimation will generate an unbiased estimate of $\beta$ (how capital-labor ratio affects wage), but the standard error of $\beta$ is underestimated. Intuition: because $(K/L)_s$ is aggregate, all workers in industry $s$ have the same $K/L$ and the same industry-specific error $\eta_s$. There are effectively $S$ not $I \times S$ observations. Ignoring this understates the estimated standard error of $\beta$. (Good exercise.)
### Table 1.—Definitions of Aggregate State Variables Used in Regression Examples

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Economic Variables:</strong></td>
<td></td>
</tr>
<tr>
<td>$x_1$</td>
<td>Estimated rate of state employment growth.</td>
</tr>
<tr>
<td>$x_2$</td>
<td>Current state relative employment disturbance, $\eta_t^s$.</td>
</tr>
<tr>
<td>$x_3$</td>
<td>Predicted state disturbances, $\hat{\eta}_{t+\tau}^s$. Linear combination of forecasts of state relative disturbances from time-series models.</td>
</tr>
<tr>
<td>$x_4$</td>
<td>Live birth rate per 1,000 population, 1980 ($\times 10^{-2}$).</td>
</tr>
<tr>
<td>$x_5$</td>
<td>Legal abortions per 1,000 live births, 1980 ($\times 10^{-4}$).</td>
</tr>
<tr>
<td>$x_6$</td>
<td>Death rate from heart diseases per 100,000 population, 1980 ($\times 10^{-3}$).</td>
</tr>
<tr>
<td>$x_7$</td>
<td>Death rate from suicide per 100,000 population, 1980 ($\times 10^{-2}$).</td>
</tr>
<tr>
<td>$x_8$</td>
<td>Death rate from perinatal conditions per 100,000 population, 1980 ($\times 10^{-2}$).</td>
</tr>
<tr>
<td>$x_9$</td>
<td>Rate of divorces and annulments per 1,000 population, 1980 ($\times 10^{-2}$).</td>
</tr>
<tr>
<td>$x_{10}$</td>
<td>Percentage of persons 5–17 years old enrolled in public elementary and secondary schools, 1980 ($\times 10^{-2}$).</td>
</tr>
<tr>
<td>$x_{11}$</td>
<td>Total land area in square kilometers ($\times 10^{-7}$).</td>
</tr>
<tr>
<td>$x_{12}$</td>
<td>Total water area in square kilometers ($\times 10^{-5}$).</td>
</tr>
<tr>
<td>$x_{13}$</td>
<td>Elevation of highest point in meters ($\times 10^{-5}$).</td>
</tr>
<tr>
<td>$x_{14}$</td>
<td>Per capita state legislative appropriations for arts agencies, FY1983 ($\times 10^{-4}$).</td>
</tr>
<tr>
<td>$x_{15}$</td>
<td>Total number of black elected officials, July 1982 ($\times 10^{-4}$).</td>
</tr>
<tr>
<td>$x_{16}$</td>
<td>Daily newspaper circulation per capita, 1982 ($\times 10^{-1}$).</td>
</tr>
<tr>
<td>$x_{17}$</td>
<td>Random normal digits from Kmenta (1971, p. 628) ($\times 10^{-2}$).</td>
</tr>
</tbody>
</table>

Note: Variables $x_1$ through $x_3$ are derived from annual state and national data for 1958–81 on total nonagricultural employment. The series were adjusted for employment changes due to population changes.
## Moulton results

**Table 2. Estimated Effects of Aggregate State Variables on the Log of Individual Weekly Wage and Salary Income, 1981**

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th></th>
<th>(2)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient Estimate</td>
<td>Unadjusted t statistic</td>
<td>Adjusted t statistic</td>
<td>Coefficient Estimate</td>
</tr>
<tr>
<td>Economic Variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$x_1$</td>
<td>0.71</td>
<td>2.90</td>
<td>0.64</td>
<td>-0.02</td>
</tr>
<tr>
<td>$x_2$</td>
<td>0.38</td>
<td>1.57</td>
<td>0.43</td>
<td>0.69</td>
</tr>
<tr>
<td>$x_3$</td>
<td>-0.14</td>
<td>-1.21</td>
<td>-0.32</td>
<td>-0.25</td>
</tr>
<tr>
<td>Irrelevant Variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$x_4$</td>
<td></td>
<td></td>
<td></td>
<td>0.62</td>
</tr>
<tr>
<td>$x_5$</td>
<td></td>
<td></td>
<td></td>
<td>1.10</td>
</tr>
<tr>
<td>$x_6$</td>
<td></td>
<td></td>
<td></td>
<td>-0.43</td>
</tr>
<tr>
<td>$x_7$</td>
<td></td>
<td></td>
<td></td>
<td>0.31</td>
</tr>
<tr>
<td>$x_8$</td>
<td></td>
<td></td>
<td></td>
<td>0.67</td>
</tr>
<tr>
<td>$x_9$</td>
<td></td>
<td></td>
<td></td>
<td>0.15</td>
</tr>
<tr>
<td>$x_{10}$</td>
<td></td>
<td></td>
<td></td>
<td>0.14</td>
</tr>
<tr>
<td>$x_{11}$</td>
<td></td>
<td></td>
<td></td>
<td>0.99</td>
</tr>
<tr>
<td>$x_{12}$</td>
<td></td>
<td></td>
<td></td>
<td>-0.49</td>
</tr>
<tr>
<td>$x_{13}$</td>
<td></td>
<td></td>
<td></td>
<td>-1.46</td>
</tr>
<tr>
<td>$x_{14}$</td>
<td></td>
<td></td>
<td></td>
<td>1.39</td>
</tr>
<tr>
<td>$x_{15}$</td>
<td></td>
<td></td>
<td></td>
<td>-0.71</td>
</tr>
<tr>
<td>$x_{16}$</td>
<td></td>
<td></td>
<td></td>
<td>0.01</td>
</tr>
<tr>
<td>$x_{17}$</td>
<td></td>
<td></td>
<td></td>
<td>-1.66</td>
</tr>
</tbody>
</table>
 Aggregate explanatory variables (Moulton)

Alternative solutions

1. Estimate with standard errors adjusted for “clustering”
2. Estimate with dummy variables for the aggregates

\[ y_{is} = z_{is} \gamma + \delta_s + \epsilon_{is} + \]

Then estimate the relationship between the \( s \) premium and characteristics of aggregate \( s \):

\[ \delta_s = x_s \beta + u_s \]
Labor-Market Discrimination

- What are the right questions?
- What’s wrong with “reverse regression”?
- Oaxaca decomposition
  - Decomposition of inter-group average-wage gap into average characteristics and price per characteristic.
  - Compute means for the explanatory variables for the two groups
  - Run separate regressions for the two groups

\[
\ln(Y^w) - \ln(Y^b) = \bar{X}^w \beta^w - \bar{X}^b \beta^b
\]

\[
= \bar{X}^w \beta^w - \bar{X}^w \beta^b + \bar{X}^w \beta^b - \bar{X}^b \beta^b
\]

\[
= \bar{X}^w (\beta^w - \beta^b) + (\bar{X}^w - \bar{X}^b) \beta^b
\]

= discrimination in returns + difference in characteristics
Notes on Oaxaca decomposition

• Note and interpret the alternative decomposition.

\[
\ln(Y^w) - \ln(Y^b) = X^w \beta^w - X^b \beta^b \\
= X^w \beta^w + X^b \beta^w - X^b \beta^w - X^b \beta^b \\
= X^b (\beta^w - \beta^b) + (X^w - X^b) \beta^w
\]

(1)

• Recall that \(X\) includes the constant “1”: \([1_i \ S_i \ X_i \ X_i^2]\)
Labor Demand

- Minimum-wage.
- Immigration
- Factor demand models
Time-Series Minimum Wage Studies

10 percent increase in the minimum wage causes a 1–3 percent reduction in teenage employment.

Critiques

- Kaitz index, $MW_t = \sum_i f_{it} (m_t / w_{it} c_{it})$
  (coverage and relative wage)
- Sensitive to specification
- Publication bias ($t$-ratios do not grow with the square root of sample size).
- Sex oddity
Minimum Wage Natural Experiment

“Employer Responses to the Minimum Wage: Evidence from the Fast-Food Industry”

The Employment Effects of the New Jersey Minimum Wage

- Date of New Jersey minimum-wage increase: 1 April 1992.
- New Jersey minimum wage before 1 April 1992: $4.25 per hour
- New Jersey minimum wage after 1 April 1992: $5.05 per hour
- Federal minimum wage before and after 1 April 1992: $4.25 per hour
- Pennsylvania minimum wage before and after 1 April 1992: $4.25 per hour
Research Design

- Where will the minimum wage have “bite”?  
- Confounding factors  
  - National or regional trends  
  - Policy endogeneity  
- Control or comparison groups
The fast food industry

Approximately one-half of employees are 20 years of age or older.
66 percent of employees are female
77 percent of employees are white
65 percent of employees have at least a high-school diploma
Turnover is very high (one-half of employees have less than one year of job tenure)

Work is gender segregated; female employees and employees with higher seniority are more likely to work in the front of the store.
Survey Method

- Telephone survey of almost 500 Burger King, KFC, Wendy’s, and Roy Rogers restaurants in eastern Pennsylvania and New Jersey.

- First wave of survey February-March 1992 (87 percent response rate)

- Second wave of survey November-December 1992 (100 percent of first-wave respondents)

- Full-time equivalent (FTE) employment $\equiv$ full-time employees + one-half of part-time employees
Analysis

- Establish that the NJ minimum wage had bite in New Jersey and not in Pennsylvania (the treatment group received treatment and the comparison group did not).
- Measure the average change in employment in NJ restaurants
- Appropriate **counterfactual**: average change in employment in PA restaurants
## Results

### Table 2.2
Average Employment per Restaurant Before and After Increase in New Jersey Minimum Wage

<table>
<thead>
<tr>
<th>Description</th>
<th>All (1)</th>
<th>PA (2)</th>
<th>NJ (3)</th>
<th>Difference (4)</th>
<th>NJ - PA</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. FTE Employment Before, All Available Observations</td>
<td>21.00</td>
<td>23.33</td>
<td>20.44</td>
<td>-2.89</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.49)</td>
<td>(1.35)</td>
<td>(0.51)</td>
<td>(1.44)</td>
<td></td>
</tr>
<tr>
<td>2. FTE Employment After, All Available Observations</td>
<td>21.05</td>
<td>21.17</td>
<td>21.03</td>
<td>-0.14</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.46)</td>
<td>(0.94)</td>
<td>(0.52)</td>
<td>(1.07)</td>
<td></td>
</tr>
<tr>
<td>3. Change in Mean FTE Employment</td>
<td>0.05</td>
<td>-2.16</td>
<td>0.59</td>
<td>2.76</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.50)</td>
<td>(1.25)</td>
<td>(0.54)</td>
<td>(1.36)</td>
<td></td>
</tr>
<tr>
<td>4. Change in Mean FTE Employment, Balanced Sample of Restaurants^c</td>
<td>-0.07</td>
<td>-2.28</td>
<td>0.47</td>
<td>2.75</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.46)</td>
<td>(1.25)</td>
<td>(0.48)</td>
<td>(1.34)</td>
<td></td>
</tr>
<tr>
<td>5. Change in Mean FTE Employment, Setting FTE at Temporarily Closed Restaurants to Zero^d</td>
<td>-0.26</td>
<td>-2.28</td>
<td>0.23</td>
<td>2.51</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.47)</td>
<td>(1.25)</td>
<td>(0.49)</td>
<td>(1.35)</td>
<td></td>
</tr>
</tbody>
</table>
Other Outcomes
Labor Supply

- Participation and hours
- Structural models: income and substitution effects
- Natural experiment models
- Criticisms: labor demand
- Structural models
- Reduced form/difference–in–difference