Econometrics 2 (Part 1)

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Linear Regression and What It Estimates

- The conditional expectation function (CEF)
- CEF and regression
- Regression and causality
- The conditional independence assumption (CIA)
- Omitted variables bias
- Application: effect of computer use on wages

Statistical Model

X_i, Y_i ... random variables
$x_i, y_i \quad i = 1, ...n$ sample of random draws

1. Step Describe the *statistical* relationship between X_i and Y_i
2. Step *Econometric* interpretation of the relationship, causality

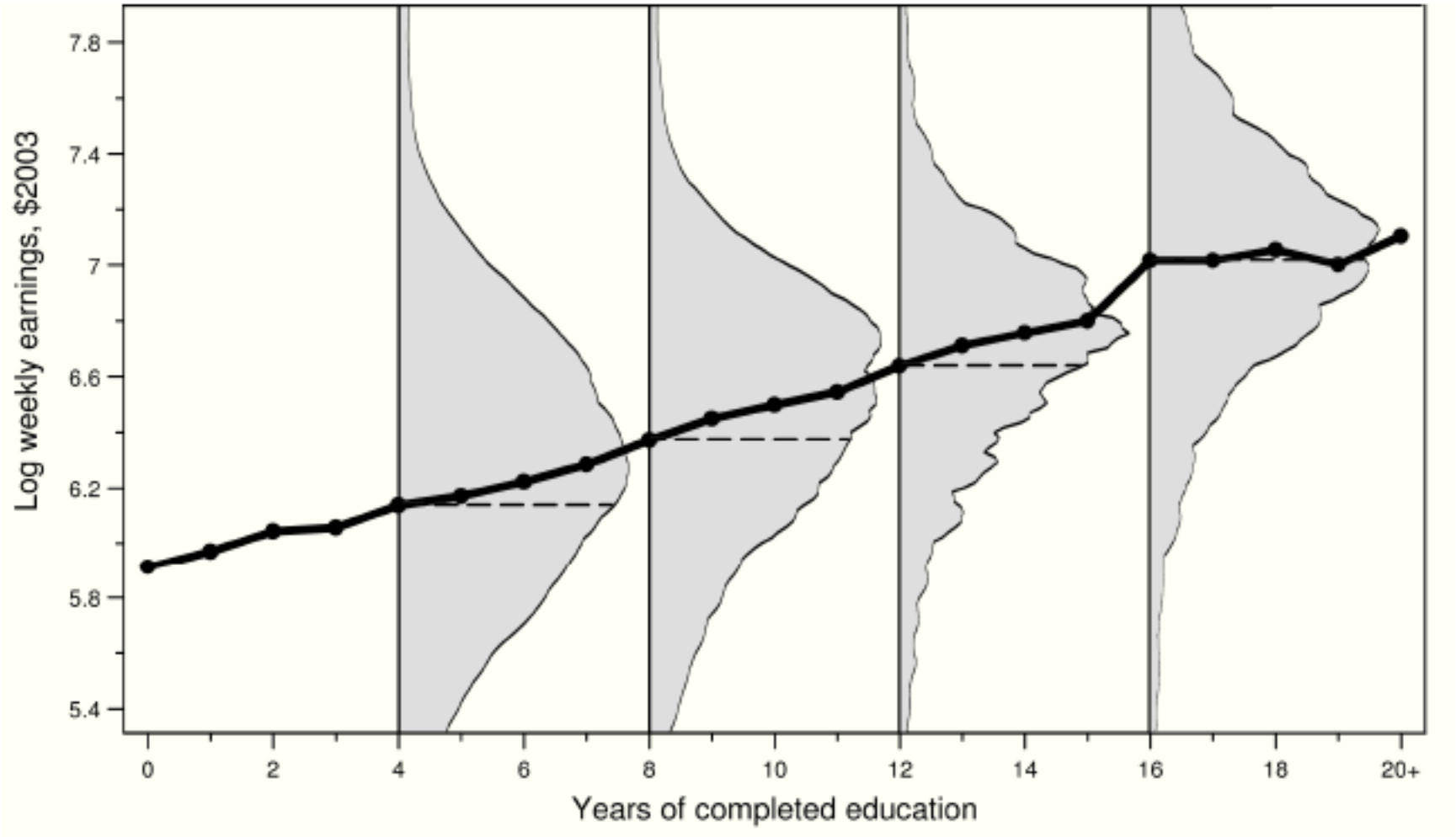
Conditional Expectation Function

Y_i dependent variable
X_i vector of covariates $(K \times 1)$

$E[Y_i|X_i]$ expectation of Y_i holding X_i fixed

X_i random variable
$E[Y_i|X_i]$ random function

Example: conditional expectation of earnings given the level of schooling


Log weekly earnings, $2003
7.8
7.4
7
6.6
6.2
5.8
5.4
0
2
4
6
8
10
12
14
16
18
20+
Years of completed education

CEF decomposition property

Theorem

$$Y_i = E\left[Y_i|X_i\right] + \epsilon_i$$

(i) ϵ_i is mean independent of X_i, $E\left[\epsilon_i|X_i\right] = 0$

(ii) ϵ_i is uncorrelated with any function of X_i

The CEF breaks Y_i into a part that is related to X_i and one that is *orthogonal* to X_i.

Regression Function

Best fitting line generated by minimizing the expected square errors

$$\beta = \underset{b}{argmin}\ E\left[(Y_i - X_i'b)^2\right]$$

where b is a $(K \times 1)$ coefficient vector.

First order condition

$$\begin{aligned} & E\left[X_i(Y_i - X_i'b)\right] = 0 \\ \beta \quad = \quad & E\left[X_iX_i'\right]^{-1} E\left[X_iY_i\right] \end{aligned}$$

By construction the *residual* $e_i = Y_i - X_i'\beta$ is uncorrelated with X_i

Bivariate regression function

Best fitting line generated by minimizing the expected square errors

$$\beta = \underset{b}{argmin}\ E\left[(Y_i - a - bX_i)^2\right]$$

First order condition gives

$$\begin{aligned} \beta &= \frac{Cov(Y_i, X_i)}{Var(X_i)} \\ \alpha &= E\left[Y_i\right] - \beta E\left[X_i\right] \end{aligned}$$

Multivariate regression function

$$Y_i = \beta_1 + \beta_2 x_{2i} + ... + \beta_K x_{Ki} + e_i$$

Regression Anatomy Formula

$$\beta_k = \frac{Cov(Y_i, \tilde{x}_{ik})}{Var(\tilde{x}_{ik})}$$

where $\tilde{x}_{ik}$ is the residual from a regression of x_{ki} on all other X variables.

Proof

$$\begin{aligned} Cov(Y_i, \tilde{x}_{ik}) &= Cov(\beta_1 + ... + \beta_K x_{Ki} + e_i, \tilde{x}_{ik}) \\ &= Cov(\ \beta_k x_{ki}, \tilde{x}_{ik}) = \beta_k Var(\tilde{x}_{ik}) \end{aligned}$$

Regression Function and CEF

Theorem 1 (linear CEF theorem):
Suppose the CEF is linear, then the regression function is the CEF

Theorem 2 (regression CEF theorem):
$X_i'\beta$ provides the MMSE (minimum mean square error) linear approximation to $E[Y_i|X_i]$:

$$\beta = \underset{b}{argmin}\ E\left\{(E[Y_i|X_i] - X_i'b)^2\right\}$$

Even if the CEF is not linear, regression provides the best linear approximation.

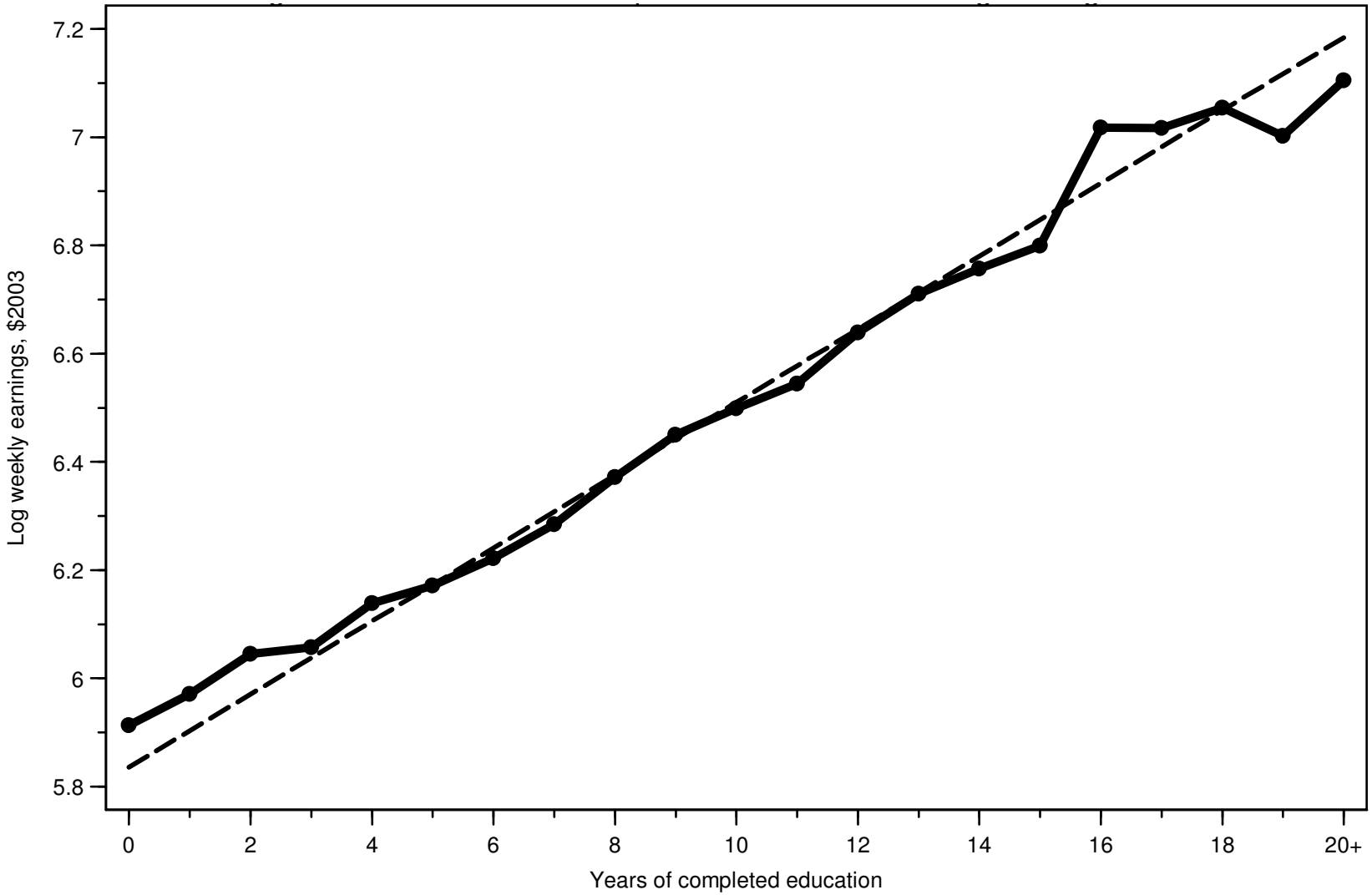


Figure 3.1.2: Regression threads the CEF of average weekly wages given schooling

Estimation

But we only observe a sample $\{x_i, y_i\}_{i=1,\ldots,n}$, not the whole population. Approximate expectations with means $\Rightarrow$ OLS estimator:

$$\beta = E\left[X_i X_i'\right]^{-1} E\left[X_i Y_i\right]$$

turns into

$$\widehat{\beta} = \left[\frac{1}{n}\sum_i x_i x_i'\right]^{-1} \left[\frac{1}{n}\sum_i x_i y_i\right]$$

OLS is well-behaved: it is *consistent* and *asymptotically normal*:

- $\widehat{\beta} \to \beta$ if $n \to \infty$
- $\sqrt{n}(\widehat{\beta} - \beta) \to N[0, V]$ if $n \to \infty$

OLS is consistent, proof

Substitute $y_i = x_i'\beta + e_i$

$$\widehat{\beta} = \left[\frac{1}{n}\sum_i x_i x_i'\right]^{-1}\left[\frac{1}{n}\sum_i x_i y_i\right] = \beta + \left[\frac{1}{n}\sum_i x_i x_i'\right]^{-1}\left[\frac{1}{n}\sum_i x_i e_i\right]$$

Law of large numbers: $\frac{1}{n}\sum_i x_i e_i \xrightarrow{p} E[X_i\epsilon_i]$,
$\frac{1}{n}\sum_i x_i x_i' \xrightarrow{p} E[X_i X_i']$.
Law of iterated expectations + CEF decomposition property:

$$E[X_i\epsilon_i] = E[E[X_i\epsilon_i|X_i]] = E[X_i E[\epsilon_i|X_i]] = E[X_i\cdot 0] = 0.$$

Continuous mapping theorem: if $f(A_n, B_n)$ is continuous in (A_n, B_n), $A_n \xrightarrow{p} a$, $B_n \xrightarrow{p} b$, then $f(A_n, B_n) \xrightarrow{p} f(a, b)$.

Therefore, $\left[\frac{1}{n}\sum_i x_i x_i'\right]^{-1}\left[\frac{1}{n}\sum_i x_i e_i\right] \to 0$.

OLS is asymptotically normal, proof

How does $\widehat{\beta}$ behave around its limit?

$$\sqrt{n}(\widehat{\beta} - \beta) = \left[\frac{1}{n}\sum_i x_i x_i'\right]^{-1}\left[\sqrt{n}\frac{1}{n}\sum_i x_i e_i\right]$$

Central limit theorem: $\sqrt{n}\frac{1}{n}\sum_i x_i e_i \xrightarrow{d} N[0, Var(X_i\epsilon_i)]$.
Slutsky's theorem: Let $A_n \xrightarrow{p} a$ and $B_n \xrightarrow{d} B$. Then,
$A_n + B_n \xrightarrow{d} a + B$ and $A_n B_n \xrightarrow{d} aB$.

This implies

$$\sqrt{n}(\widehat{\beta} - \beta) \xrightarrow{d} N[0, V],$$
$$\text{where } V = E[X_i X_i']^{-1} Var(X_i\epsilon_i) E[X_i X_i']^{-1}$$

We can use this result to test hypotheses about β, find standard errors, etc.

Causality

- Interpretation of CEF, causal vs non-causal:
  - Non-causal: What is the average difference in earnings between people with $s+1$ and s years of schooling?
  - Causal: What would people earn, on average, if we give them 1 year of schooling holding *all* other characteristics fixed?
- Regression causal $\Leftrightarrow$ CEF causal
- Causal Effect: difference in average *potential outcome*
- The CEF is causal if it describes differences in the average potential outcomes for a fixed reference group

Conditional Independence Assumption (CIA)

Idea:

- *selection on observables*
- Causal variable is independent of potential outcome conditional on observable variables X (ability, family, etc.)
- Intuitively, for all individuals with the same X, assignment to treatment is as good as random.

Potential outcome framework

$$
\begin{aligned}
c_i & \quad \text{College} \\
Y_i & = \begin{cases} Y_{1i} & \text{if } c_i = 1 \\ Y_{0i} & \text{otherwise} \end{cases} \\
X_i & \quad \text{observable controls: family income, age, etc.}
\end{aligned}
$$

- Causal Effect $Y_{1i} - Y_{0i}$
- We want to estimate average $Y_{1i} - Y_{0i}$ for some group
- e.g. $E\left[Y_{1i} - Y_{0i} | c_i = 1\right]$ average causal effect for those who went to college.
- Remember:

$$
\begin{aligned}
E\left[Y_i | c_i = 1\right] - E\left[Y_i | c_i = 0\right] &= E\left[Y_{1i} - Y_{0i} | c_i = 1\right] \\
&+ \underbrace{E\left[Y_{0i} | c_i = 1\right] - E\left[Y_{0i} | c_i = 0\right]}_{\text{selection bias}}
\end{aligned}
$$

CIA

The conditional independence assumption asserts that conditional on observable variables X_i selection bias disappears:

$$\{Y_{0i}, Y_{1i}\} \amalg c_i | X_i$$

$$\underbrace{E(Y_i|X_i, c_i = 1) - E(Y_i|X_i, c_i = 0)}_{\text{observed difference |X}} = \underbrace{E(Y_{1i} - Y_{0i}|X_i)}_{\text{difference in pot outcome |X}}$$

Agents can select into treatment, but only based on their X_i.
There is no selection on unobservables associated with (Y_{0i}, Y_{1i}).

Multivalued Case

Multivalued causal variable s_i: level of schooling

Potential earnings for individual i with s years of schooling

$$Y_{s_i} = f_i(s)$$

Conditional independence assumption:

$$Y_{s_i} \amalg s_i | X_i \quad \text{for all} \quad s$$

s_i is *as good as randomly assigned* conditional on X_i
Causal interpretation:

$$E[Y_i|X_i, s_i = s] - E[Y_i|X_i, s_i = s-1] = E[f_i(s) - f_i(s-1)|X_i]$$

Causality

- In the potential outcome framework we get a causal effect for every value of X_i
- Average over X_i using iterated expectations

$$E\left\{E\left[Y_i|X_i, s_i = 12\right] - E\left[Y_i|X_i, s_i = 11\right]\right\}$$
$$= E\left\{E\left[f_i(12) - f_i(11)|X_i\right]\right\} = E\left[f_i\left(12\right) - f_i\left(11\right)\right]$$

- We also get a separate causal effect for each pair of levels of s_i, e.g. $(11, 12), (12, 13), ...$
- Use regression to *summarize* the effects

Regression

- Assumption: $f_i(s)$ is linear in s and the same for all i
- We estimate a weighted average of individual specific $f_i(s) - f_i(s-1)$

- Causal Model:

$$f_i(s) = \alpha + \rho s + \eta_i$$

  linear same relationship for everybody.
- η_i error component: unobserved factors determining potential earnings
- Plug in observed values

$$Y_i = \alpha + \rho s_i + \eta_i$$

- Problem: s_i may be correlated with potential outcomes $f_i(s)$ via η_i.

Conditional Independence

Suppose CIA holds given X_i and the CEF of η_i is linear in X_i. Then,

$$\eta_i = X_i^{'}\gamma + v_i$$

where γ is a vector of population regression coefficients

$$E\left[\eta_i | X_i\right] = X_i^{'}\gamma$$

important: the residual v_i is uncorrelated with X_i.

$$\begin{aligned} E\left[f_i\left(s\right)|X_i, s_i\right] = E\left[f_i\left(s\right)|X_i\right] &= \alpha + \rho s_i + E\left[\eta_i | X_i\right] \\ &= \alpha + \rho s_i + X_i^{'}\gamma \end{aligned}$$

We get the linear causal model:

$$Y_i = \alpha + \rho s_i + X_i^{'}\gamma + v_i$$

Regression

Linear causal model:

$$Y_i = \alpha + \rho s_i + X_i^{'} \gamma + v_i$$

- v_i is not correlated with s_i, or X_i. ρ represents causal effect.
- Key assumption: the observable variables X_i are the only reason that η_i, or s_i are correlated (or $f_i(s)$, and s_i)
- Note: γ is not causal in general!

Omitted Variable Bias

OVB formula describes relationship between regression models with different sets of control variables.

- Short Regression:

$$Y_i = \tilde{\alpha} + \tilde{\rho} s_i + \eta_i$$

- Long Regression:

$$Y_i = \alpha + \rho s_i + A_i \gamma + e_i$$

  where A_i represents ability, family background.
- If CIA applies given A_i then ρ is the coefficient of the linear causal model.

Omitted Variables Bias Formula

$$\widehat{\widetilde{\rho}} = \frac{Cov\left(Y_i, s_i\right)}{Var\left(s_i\right)} = \rho + \gamma^{'}\delta_{As}$$

where δ_{As} vector of coefficients from regressions of A_i on s_i

coef from short regression = coef from long regression *plus* effect of omitted variables $*$ regression coef of omitted on included variables

$$\begin{aligned}
\frac{Cov\left(Y_i, s_i\right)}{Var\left(s_i\right)} &= \frac{Cov\left(\alpha + \rho s_i + A_i^{'}\gamma + e_i, s_i\right)}{Var\left(s_i\right)} \\
&= \frac{\rho Var\left(s_i\right) + \gamma Cov\left(A_i, s_i\right)}{Var\left(s_i\right)} \\
&= \rho + \gamma\frac{Cov\left(A_i, s_i\right)}{Var\left(s_i\right)}
\end{aligned}$$

Interpretation

- $\delta_{As} = 0$, if A_i and s_i are uncorrelated
- Consequences of omitting A_i

Sign of bias

	$Cov(A_i, s_i) > 0$	$Cov(A_i, s_i) < 0$
$\gamma > 0$	positive	negative
$\gamma < 0$	negative	positive

Table 3.2.1: Estimates of the returns to education for men in the NLSY

	(1)	(2)	(3)	(4)	(5)
Controls:	None	Age dummies	Col. (2) and additional controls*	Col. (3) and AFQT score	Col. (4), with occupation dummies
	0.132	0.131	0.114	0.087	0.066
	(0.007)	(0.007)	(0.007)	(0.009)	(0.010)

Notes: Data are from the National Longitudinal Survey of Youth (1979 cohort, 2002 survey). The table reports the coefficient on years of schooling in a regression of log wages on years of schooling and the indicated controls. Standard errors are shown in parentheses. The sample is restricted to men and weighted by NLSY sampling weights. The sample size is 2434.

*Additional controls are mother's and father's years of schooling and dummy variables for race and Census region.

An (almost) hypothetical case for discussion

- The government of Zubrowka suspects that international university rankings (THE, QS, etc) do not reflect true qualities of domestic universities.
- The following study is commissioned:
  - A random sample of college graduates working in Zubrowka are surveyed for their wages and last college attended
  - The data is used to estimate

$$\ln wage_i = \sum_c \alpha_c D_{ci} + \epsilon_i$$

    where $D_{ci} = 1$ if person i graduated from college c.
  - Colleges $c = 1, \ldots, C$ are ranked according to α_c.
- In this ranking, universities based in Zubrowka are quite competitive: the University of Lutz is ranked between MIT and Oxford.

What do you think about this research design? Do you believe the results? Would you approach this task differently?

Bad Controls

- Control for covariates increases likelihood for a causal interpretation of the main relationship. Should we include any controls?
- Caution:
  - Bad controls-variables that might themselves be outcomes in the "thought" experiment.
- Example:
  - Randomly assign college degree (causal effect of mean earnings)
  - Occupation correlated with earnings and education.
- Should we control for occupation? (white collar job)

Bad Controls: more formally

We relate earnings to the college education dummy. Control for occupation: use the white collar workers only ($W_i = 1$).

$$Y_i = \alpha + \rho C_i + \epsilon_i, \quad \text{for all } i \text{ such that } W_i = 1$$

Let's apply the potential outcome framework. What is the DGP?

1. Each agent is born with $(Y_{0i}, Y_{1i}, W_{0i}, W_{1i})$ – wage and occupation for college/no-college state of the world.
2. Treatment is random (just for the sake of argument!)
3. If $C_i = 1$, then $Y_i = Y_{1i}$, $W_i = W_{1i}$ and vice versa.

Key issue: occupation is an outcome. Selecting sample based on W_i — "endogenous sample selection".

Interpret ρ in the potential outcome framework:

$$\begin{aligned}
\rho &= E[Y_i|C_i = 1, W_i = 1] - E[Y_i|C_i = 0, W_i = 1] \\
&= E[Y_{1i}|C_i = 1, W_{1i} = 1] - E[Y_{0i}|C_i = 0, W_{0i} = 1] \\
&= E[Y_{1i} - Y_{0i}|C_i = 1, W_{1i} = 1] \\
&\quad + E[Y_{0i}|C_i = 1, W_{1i} = 1] - E[Y_{0i}|C_i = 0, W_{0i} = 1] \\
&= \underbrace{E[Y_{1i} - Y_{0i}|W_{1i} = 1]}_{\text{effect for the ``white collar after college'' population}} \\
&\quad + \underbrace{E[Y_{0i}|W_{1i} = 1] - E[Y_{0i}|W_{0i} = 1]}_{\text{selection bias}}
\end{aligned}$$

Signing selection bias: need to know more on how agents decide on W_i. Casual intuition – likely negative:

- $W_{0i} = 1$ – Mark Zuckerberg and Bill Gates
- $W_{1i} = 1$ – median college graduate.

Note how the potential outcome model made the discussion tractable.

Application: Returns to Computer Use

- Alan B. Krueger, “How Computers Have Changed the Wage Structure: Evidence from Microdata 1984 - 1989", QJE 1993
- John E. DiNardo and Jorn-Steffen Pischke, “The Returns to Computer Use Revisited: Have Pencils Changed the Wage Structure Too?", QJE 2004

Returns to Computer Use: Motivation

Facts:

- Returns to education rising over time.
- Potential explanation: Skill Biased Technological Change
- Empirical evidence: Returns to computer use

Seminal study Krueger (1993)

- Cross sectional data on wages, computer on the job, CPS 1984, 1989
- Causal effect of computer use on wages plus 15-20% increase

Problem:

- Is there any unobservable characteristic X correlated to computer use? So that all individuals with this characteristic would earn higher wages anyway?

What's behind the data?

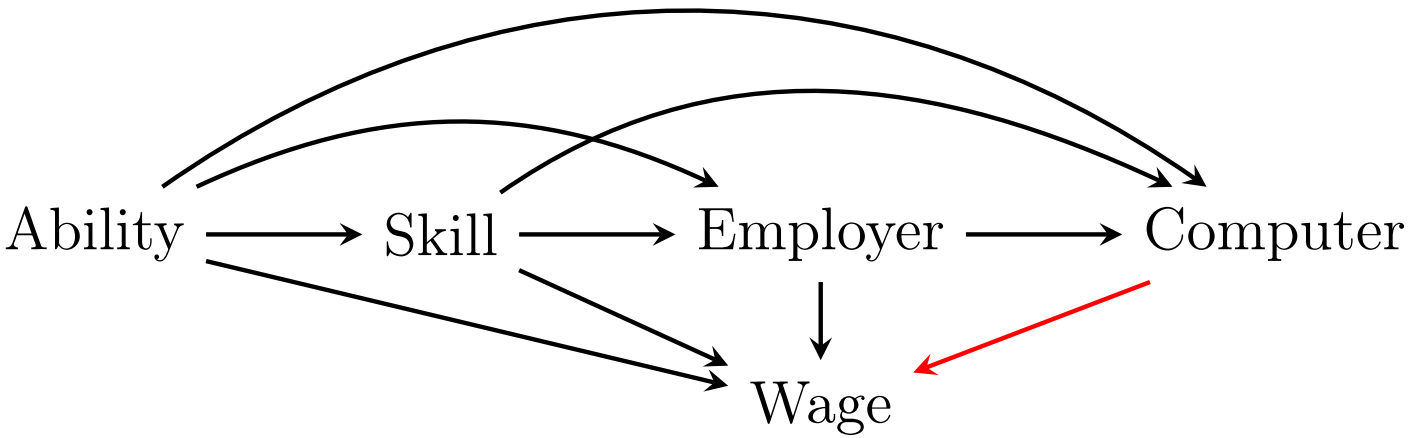


TABLE I

PERCENT OF WORKERS IN VARIOUS CATEGORIES WHO DIRECTLY USE A COMPUTER AT WORK

Group	1984	1989
All workers	24.6	37.4
Gender		
Men	21.2	32.3
Women	29.0	43.4
Education		
Less than high school	5.0	7.8
High school	19.3	29.3
Some college	30.6	45.3
College	41.6	58.2
Postcollege	42.8	59.7
Race		
White	25.3	38.5
Black	19.4	27.7
Age		
Age 18–24	19.7	29.4
Age 25–39	29.2	41.5
Age 40–54	23.6	39.1
Age 55–65	16.9	26.3
Occupation		
Blue-collar	7.1	11.6
White-collar	33.0	48.4
Union status		
Union member	20.2	32.5
Nonunion	28.0	41.1
Hours		
Part-time	23.7	36.3
Full-time	28.9	42.7
Region		
Northeast	25.5	38.0
Midwest	23.4	36.0
South	23.2	36.5
West	27.0	39.9

Source. Author's tabulations of the 1984 and 1989 October Current Population Surveys. The sample size is 61,712 for 1984 and 62,748 for 1989.

TABLE II

OLS Regression Estimates of the Effect of Computer Use on Pay

(dependent variable: ln (hourly wage))

Independent variable	October 1984			October 1989		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	1.937	0.750	0.928	2.086	0.905	1.094
	(0.005)	(0.023)	(0.026)	(0.006)	(0.024)	(0.026)
Uses computer at work (1 = yes)	0.276	0.170	0.140	0.325	0.188	0.162
	(0.010)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)
Years of education	—	0.069	0.048	—	0.075	0.055
		(0.001)	(0.002)		(0.002)	(0.002)
Experience	—	0.027	0.025	—	0.027	0.025
		(0.001)	(0.001)		(0.001)	(0.001)
Experience-squared ÷ 100	—	−0.041	−0.040	—	−0.041	−0.040
		(0.002)	(0.002)		(0.002)	(0.002)
Black (1 = yes)	—	−0.098	−0.066	—	−0.121	−0.092
		(0.013)	(0.012)		(0.013)	(0.012)
Other race (1 = yes)	—	−0.105	−0.079	—	−0.029	−0.015
		(0.020)	(0.019)		(0.020)	(0.020)
Part-time (1 = yes)	—	−0.256	−0.216	—	−0.221	−0.183
		(0.010)	(0.010)		(0.010)	(0.010)
Lives in SMSA (1 = yes)	—	0.111	0.105	—	0.138	0.130
		(0.007)	(0.007)		(0.007)	(0.007)
Veteran (1 = yes)	—	0.038	0.041	—	0.025	0.031
		(0.011)	(0.011)		(0.012)	(0.011)
Female (1 = yes)	—	−0.162	−0.135	—	−0.172	−0.151
		(0.012)	(0.012)		(0.012)	(0.012)
Married (1 = yes)	—	0.156	0.129	—	0.159	0.143
		(0.011)	(0.011)		(0.011)	(0.011)
Married*Female	—	−0.168	−0.151	—	−0.141	−0.131
		(0.015)	(0.015)		(0.015)	(0.015)
Union member (1 = yes)	—	0.181	0.194	—	0.182	0.189
		(0.009)	(0.009)		(0.010)	(0.010)
8 Occupation dummies	No	No	Yes	No	No	Yes
R^2	0.051	0.446	0.491	0.082	0.451	0.486

Notes. Standard errors are shown in parentheses. Sample size is 13,335 for 1984 and 13,379 for 1989. Columns (2), (3), (5), and (6) also include three region dummy variables.

Robustness Checks

- Coefficient gets smaller when other variables added
- Computer use at home and computer use at work.
- Narrow occupations: Secretaries 16% of comp. users in 1984, and 77% in 1989.
- Test Scores, Parental background from High school and beyond survey.

TABLE III

THE RETURN TO VARIOUS USES OF COMPUTERS, OCTOBER 1989[a]

(DEPENDENT VARIABLE: ln (HOURLY WAGE))

Use of computer at work	Proportion	Coefficient (std. error)
Uses computer at work for any task[b]	0.398	0.145
		(0.010)
Specific Task[c]		
Word processing	0.165	0.017
		(0.012)
Bookkeeping	0.100	−0.058
		(0.013)
Computer-assisted design	0.039	0.026
		(0.020)
Electronic mail	0.063	0.149
		(0.016)
Inventory control	0.102	−0.056
		(0.013)
Programming	0.077	0.052
		(0.031)
Desktop publishing or newsletters	0.036	−0.047
		(0.021)
Spread sheets	0.094	0.079
		(0.015)
Sales	0.060	−0.002
		(0.016)
Computer games	0.019	−0.109
		(0.026)
R^2		0.495

a. The sample and other explanatory variables are the same as in column (6) of Table II.

b. The computer use dummy variable equals one if the worker uses computers for any of the ten enumerated tasks or for any other task.

c. The dummy variables for any specific computer task, and the dummy variable for any computer use, are not mutually exclusive.

TABLE IV

THE RETURN TO COMPUTER USE AT WORK, HOME, AND WORK AND HOME

(STANDARD ERRORS ARE SHOWN IN PARENTHESES.)

Type of computer use	October 1984 (1)	October 1989 (2)	Percent of sample, 1989 (3)
Uses computer at work	0.165	0.177	39.8
	(0.009)	(0.009)	
Uses computer at home	0.056	0.070	12.5
	(0.021)	(0.019)	
Uses computer at home and work	0.006	0.017	8.6
	(0.029)	(0.023)	
Sample size	13,335	13,379	

Notes. The table reports coefficients for three dummy variables estimated from log hourly wage regressions. The other explanatory variables in the regressions are education, experience and its square, two race dummies, three region dummies, dummy variables indicating part-time status, residence in an SMSA, veteran status, gender, marital status, union membership, and an interaction between marital status and gender. Covariates are the same as in columns (2) and (5) of Table II.

TABLE V

OLS WAGE REGRESSION ESTIMATES FOR SECRETARIES

(DEPENDENT VARIABLE: ln (HOURLY WAGE))

Independent variable	October 1984 (1)	October 1989 (2)
Intercept	1.387	1.208
	(0.019)	(0.180)
Uses computer at work (1 = yes)	0.059	0.093
	(0.024)	(0.030)
Years of edcuation	0.014	0.035
	(0.008)	(0.008)
Experience	0.009	0.024
	(0.003)	(0.004)
Experience-squared ÷ 100	−0.007	−0.047
	(0.008)	(0.009)
Black (1 = yes)	−0.079	0.065
	(0.012)	(0.053)
Other race (1 = yes)	−0.095	0.065
	(0.080)	(0.074)
Part-time (1 = yes)	−0.321	−0.160
	(0.031)	(0.034)
Lives in SMSA (1 = yes)	0.159	0.152
	(0.024)	(0.025)
Female (1 = yes)	0.090	0.146
	(0.166)	(0.127)
Married (1 = yes)	0.422	−0.027
	(0.219)	(0.027)
Married*Female	−0.387	—
	(0.220)	
Union member (1 = yes)	0.016	0.046
	(0.040)	(0.046)
R^2	0.256	0.222

Notes. Standard errors are shown in parentheses. Sample size is 751 for 1984 and 618 for 1989. Regressions also include three region dummy variables. Mean (standard deviation) of the dependent variable for column (1) is 1.86 (0.36), and for column (2) is 2.08 (0.34).

TABLE VII

OLS Regression Estimates of the Effect of Computer Use on Pay

(dependent variable: ln (hourly wage))

Independent variable	October 1984			October 1989		
	(1)	(2)	(3)	(4)	(5)	(6)
Uses computer at work (1 = yes)	—	0.170 (0.008)	0.073 (0.048)	—	0.188 (0.008)	0.005 (0.043)
Computer use*Education	—	—	0.007 (0.003)	—	—	0.013 (0.003)
Years of education	0.076 (0.001)	0.069 (0.001)	0.067 (0.002)	0.086 (0.001)	0.075 (0.001)	0.071 (0.002)
Experience	0.027 (0.001)	0.027 (0.001)	0.027 (0.001)	0.027 (0.001)	0.027 (0.001)	0.027 (0.001)
Experience-squared ÷ 100	−0.042 (0.002)	−0.041 (0.002)	−0.042 (0.002)	−0.044 (0.002)	−0.041 (0.002)	−0.042 (0.002)
Black (1 = yes)	−0.106 (0.013)	−0.098 (0.013)	−0.099 (0.013)	−0.141 (0.013)	−0.121 (0.013)	−0.122 (0.013)
Other race (1 = yes)	−0.120 (0.020)	−0.105 (0.020)	−0.106 (0.020)	−0.037 (0.021)	−0.029 (0.020)	−0.032 (0.020)
Part-time (1 = yes)	−0.287 (0.010)	−0.256 (0.010)	−0.256 (0.010)	−0.261 (0.010)	−0.221 (0.010)	−0.221 (0.010)
Lives in SMSA (1 = yes)	0.123 (0.007)	0.111 (0.007)	0.111 (0.007)	0.148 (0.007)	0.138 (0.007)	0.138 (0.007)
Veteran (1 = yes)	0.043 (0.011)	0.038 (0.011)	0.039 (0.011)	0.027 (0.012)	0.025 (0.012)	0.029 (0.012)
Female (1 = yes)	−0.140 (0.012)	−0.162 (0.012)	−0.160 (0.012)	−0.142 (0.012)	−0.172 (0.012)	−0.168 (0.012)
Married (1 = yes)	0.162 (0.011)	0.156 (0.011)	0.156 (0.011)	0.169 (0.011)	0.159 (0.011)	0.158 (0.011)
Married*Female	−0.171 (0.015)	−0.168 (0.015)	−0.168 (0.015)	−0.146 (0.015)	−0.141 (0.015)	−0.139 (0.015)
Union member (1 = yes)	0.167 (0.009)	0.181 (0.009)	0.181 (0.009)	0.164 (0.010)	0.182 (0.010)	0.182 (0.010)
R^2	0.429	0.446	0.446	0.428	0.451	0.452
Mean-squared error	0.168	0.163	0.163	0.176	0.169	0.169

Notes. Standard errors are shown in parentheses. Sample size is 13,335 for 1984 and 13,379 for 1989. Regressions also include three region dummy variables and an intercept.

Returns to Computer Use Revisited

DiNardo and Pischke (2004):

- German data, also cross section, but includes multitude of workplace tools i.e: office tools, hand tools etc.
- Qualification and Career Survey: 1985/86, 1991/92
- Check comparability of Germany vs. US
- Are the coefficients similar? External validity.
- What is the impact of other workplace tools on wages?

TABLE I

PERCENT OF WORKERS IN VARIOUS CATEGORIES WHO USE DIFFERENT TOOLS ON THEIR JOB

Group	U. S. 1984	U. S. 1989	U. S. 1993	Germany 1979	Germany 1985–1986	Germany 1991–1992
			Percentage that are computer users			
All workers	25.1	37.4	46.6	8.5	18.5	35.3
Men	21.6	32.2	41.1	7.9	18.5	36.4
Women	29.6	43.8	53.2	9.7	18.5	33.5
Less than high school	5.1	7.7	10.4	3.2	4.3	9.9
High school	19.2	28.4	34.6	8.5	18.3	32.7
Some college	30.6	45.0	53.1	8.5	24.8	48.4
College	42.4	58.8	70.2	13.4	30.5	61.6
Age 18–24	20.5	29.6	34.3	10.1	13.8	27.8
Age 25–39	29.6	41.4	49.8	9.6	21.6	39.9
Age 40–54	23.9	38.9	50.0	6.6	17.2	35.9
Age 55–64	17.7	27.0	37.3	5.9	13.5	23.7
Blue-collar	7.1	11.2	56.6	1.2	3.5	10.7
White-collar	39.7	56.6	67.6	12.8	28.9	50.2
Part-time	14.8	24.4	29.3	6.4	14.7	26.5
Full-time	29.3	42.3	51.0	8.7	19.1	37.0
			Percentage of all workers who use a specific tool			
Computer	25.1	37.4	46.6	8.5	18.5	35.3
Calculator				19.6	35.7	44.2
Telephone				41.8	43.7	58.4
Pen/pencil				54.9	53.4	65.6
Work while sitting[a]				30.8	19.3	—
Hand tool (e.g., hammer)				29.4	32.9	30.5
Number of obs.	61,704	62,748	59,852	19,427	22,353	20,042

a. Variable definition differs in 1979 and 1985–1986. In 1979 it refers to "Never or rarely standing," and in 1985–1986 it refers to "Often or almost always sitting."

Columns 1 to 3 are from Table 3 in Autor, Katz, and Krueger [1996] and come from the October *Current Population Survey.* German data are from the *Qualification and Career Survey.*

TABLE II

OLS REGRESSIONS FOR THE EFFECT OF COMPUTER USE ON PAY

DEPENDENT VARIABLE: LOG HOURLY WAGE

(STANDARD ERRORS IN PARENTHESES)

Independent variable	U. S. 1984	U. S. 1989	U. S. 1993	Germany 1979	Germany 1985–1986	Germany 1991–1992
Computer	0.171	0.188	0.204	0.112	0.157	0.171
	(0.008)	(0.008)	(0.008)	(0.010)	(0.007)	(0.006)
Years of schooling	0.068	0.075	0.081	0.073	0.063	0.072
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Experience	0.028	0.028	0.026	0.030	0.035	0.030
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience^2/100	−0.043	−0.043	−0.041	−0.052	−0.058	−0.046
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
R^2	0.444	0.448	0.424	0.267	0.280	0.336
Number of obs.	13,335	13,379	13,305	19,427	22,353	20,042

Columns 1 to 3 are from Table 4 in Autor, Katz, and Krueger [1996]. Data for columns 1 to 3 are from the October *Current Population Survey;* data for columns 4 to 6 are from the *Qualification and Career Survey.* All models also include an intercept, a dummy for part-time, large city/SMSA status, female, married, female*married. Regressions for the United States in columns 1 to 3 also include dummies for black, other race, veteran status, union membership, and three regions. Regressions for Germany in columns 4 to 6 also include a dummy for civil servants (*Beamter*).

Omitted Variable Bias

- Table III
  - Seperate regressions for each tool

$$y_i = \beta_0 + \beta_1 tool + \beta_2 educ + ... + u$$

- Table III-b
  - Enter tools together to check for correlation in use

$$y_i = \beta_0 + \beta_1 comp + \beta_2 calc + \beta_3 telep + ... + u$$

TABLE III

OLS Regression for the Effect of Different Tools on Pay

Dependent Variable: Log Hourly Wage

(standard errors in parentheses)

Independent variable	Germany 1979	Germany 1985–86	Germany 1991–92	Germany 1979	Germany 1979	Germany 1985–1986	Germany 1991–1992
Occupation indicators	No	No	No	501	501	742	1071
Grades and father's Occupation[a]	No	No	No	No	Yes	No	No
				Tools entered separately			
Computer	0.112	0.157	0.171	0.025	0.022	0.076	0.083
	(0.010)	(0.007)	(0.006)	(0.011)	(0.011)	(0.008)	(0.007)
Calculator	0.087	0.128	0.129	0.027	0.025	0.061	0.054
	(0.007)	(0.006)	(0.006)	(0.008)	(0.008)	(0.007)	(0.006)
Telephone	0.131	0.114	0.136	0.060	0.057	0.059	0.072
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Pen/pencil	0.123	0.112	0.127	0.055	0.052	0.055	0.050
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Work while sitting	0.106	0.101	—	0.042	0.041	0.036	—
	(0.006)	(0.007)		(0.008)	(0.008)	(0.008)	
Hand tool	−0.117	−0.086	−0.091	−0.048	−0.045	−0.020	−0.020
(e.g., hammer)	(0.007)	(0.006)	(0.006)	(0.009)	(0.009)	(0.008)	(0.008)

	Tools entered together						
Computer	0.066	0.105	0.126	0.027	0.024	0.067	0.069
	(0.010)	(0.008)	(0.007)	(0.011)	(0.011)	(0.008)	(0.007)
Calculator	0.017	0.053	0.044	0.015	0.014	0.032	0.022
	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)
Telephone	0.072	0.043	0.045	0.043	0.041	0.035	0.048
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Pen/pencil	0.062	0.031	0.035	0.040	0.038	0.024	0.007
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Work while sitting	0.058	0.050	—	0.036	0.035	0.032	—
	(0.007)	(0.007)		(0.008)	(0.008)	(0.008)	

a. Two variables for self-reported grades in math and German and eleven dummy variables for father's education.

Data are from the *Qualification and Career Survey*. All regressions also include an intercept, years of schooling, experience and experience squared, dummies for part-time, city, female, married, married*female, and for civil servants (*Beamter*).

Selection Problems

- What would be the ideal experiment?
- Randomly assign computers to workers?
- How are *computer skills* awarded in the labor market?
- What about the *skill* of using a pencil or a chair?
- Results point to substantial selection in who uses office tools