

## Lecture Note 9

### Modeling with Multivariate Regression Models

#### 1 Saturated Regression Models and Interaction Terms

- LN5 (Sec.4) introduces the idea of *saturated regression models* – let's expand on this
  - A saturated regression model has as many parameters as the corresponding CEF
  - When counting parameters, we include the intercept
- Consider a single multinomial regressor  $X_i \in \{10, 11, 12, \dots, 19\}$ . The CEF  $E[Y_i|X_i]$  assumes up to 10 distinct values.
  - What's the corresponding saturated regression model look like? An intercept plus 9 dummies, one for each value of  $X_i > 10$
  - Other 10-parameter schemes also work, provided the regression implementation is full-rank (has no linear dependencies)
- What about multiple regressors? Suppose  $X_{1i}$  and  $X_{2i}$  are dummies for college graduation status and sex (not that these ever go together):

$$\begin{aligned} X_{1i} &= 1(\text{colgrad}_i = \text{yes}) \\ X_{2i} &= 1(\text{sex}_i = \text{female}) \end{aligned}$$

- The CEF of  $Y_i$  conditional on  $X_{1i}, X_{2i}$  can be written:

$$E[Y_i | X_{1i}, X_{2i}] = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_{12} X_{1i} X_{2i}$$

How many values can this CEF assume?

- The corresponding saturated regression model is
- $$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_{12} X_{1i} X_{2i} + \epsilon_i \quad (1)$$
- Think of saturated models as maximum flexibility
    - Equation (1) allows the college wage effect to differ for men and women:

$$\begin{aligned} Y_i &= \beta_0 + \beta_1 X_{1i} + \epsilon_i && \text{when } X_{2i} = 0 \\ Y_i &= \beta_0 + \beta_1 X_{1i} + \beta_2 + \beta_{12} X_{1i} + \epsilon_i \\ &= (\beta_0 + \beta_2) + (\beta_1 + \beta_{12}) X_{1i} + \epsilon_i && \text{when } X_{2i} = 1 \end{aligned}$$

while also allowing the female effect to differ between those with and without a college degree::

$$\begin{aligned} Y_i &= \beta_0 + \beta_2 X_{2i} + \epsilon && \text{when } X_{1i} = 0 \\ Y_i &= \beta_0 + \beta_1 + \beta_2 X_{2i} + \beta_{12} X_{2i} + \epsilon_i \\ &= (\beta_0 + \beta_1) + (\beta_2 + \beta_{12}) X_{2i} + \epsilon && \text{when } X_{1i} = 1 \end{aligned}$$

- What more could you ask for? (Nothing in this case)
- Regression talk
  - The coefficients on  $X_{1i}$  and  $X_{2i}$  are said to be *main effects*, while  $\beta_{12}$  is an *interaction term* or *2nd-order term*. Models with 3 or more regressors may have *higher-order terms*
  - Models without interactions are said to be *additive*. The additive version of (1) is:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \epsilon_i \quad (2)$$

Additive models can be viewed as either a restriction on, or an approximation to, the CEF

- When choosing the details of a regression model by including or omitting interaction terms, we are said to be *specifying* or *parameterizing* it.
- Critics of your model may object to your *specification* of it

## 2 Not Just for Dummies: Ordinal and Continuous Interactions

Interesting interactions arise in models mixing ordinal and continuous regressors.

- Let

$$\begin{aligned} S_i &= \text{years of schooling} \\ X_{2i} &= 1(\text{sex}_i = \text{female}) \end{aligned}$$

- Repeat equation (1):

$$Y_i = \beta_0 + \beta_1 S_i + \beta_2 X_{2i} + \beta_{12} S_i X_{2i} + \epsilon_i \quad (3)$$

- This model isn't saturated even though it includes an interaction term (why not?)
- Regression model (3) therefore restricts or approximates the CEF (how?)
- With ordinal  $S_i$  and dummy  $X_{2i}$ , models like (3) are usually interpreted (asymmetrically) as allowing the regression of  $Y_i$  on  $S_i$  to differ by  $X_{2i}$ :

$$\begin{aligned} Y_i &= \beta_0 + \beta_1 S_i + \epsilon_i && \text{when } X_{2i} = 0 \\ Y_i &= \beta_0 + \beta_1 S_i + \beta_2 + \beta_{12} S_i + \epsilon_i \\ &= (\beta_0 + \beta_2) + (\beta_1 + \beta_{12}) S_i + \epsilon_i && \text{when } X_{2i} = 1 \end{aligned}$$

- The (female-male) difference in intercepts is  $\beta_2$
- The (female-male) difference in the economic returns to schooling is  $\beta_{12}$
- This parameterization produces results identical to those generated by separate regressions on  $S_i$  for men and women
  - Why? Both the  $S_i$  slope and the model intercept are free to vary with  $X_{2i}$ , which takes on two values
  - We say that model (3) is *fully interacted with*  $X_{2i}$  (although it's not saturated)
- A test of whether the regression on schooling is the same for men and women is a joint test of:

$$H_0 : \beta_2 = \beta_{12} = 0 \quad (4)$$

- Multiple restrictions of this sort are tested with an  $F$  statistic (how many restrictions in (4)?).
- You might be especially interested in testing  $\beta_{12} = 0$ , since, almost certainly,  $\beta_2 \neq 0$

### 3 Testing Linear Restrictions

- We're often interested in testing sets of linear restrictions. A set of  $q$  linearly independent restrictions applied to a regression model with  $k$  coefficients ( $\beta_1, \dots, \beta_k$ ) and an intercept ( $\beta_0$ ) can be written:

$$c_{11}\beta_1 + c_{12}\beta_2 + c_{13}\beta_3 + \dots + c_{1k}\beta_k = c_{10}$$

.

.

$$c_{q1}\beta_1 + c_{q2}\beta_2 + c_{q3}\beta_3 + \dots + c_{qk}\beta_k = c_{q0},$$

where the  $c$ 's are constants (we rarely restrict the intercept)

- Rewriting (3) to match this notation:

$$Y_i = \beta_0 + \beta_1 S_i + \beta_2 X_{2i} + \beta_3 S_i X_{2i} + \epsilon_i \quad (5)$$

The restrictions in (4) can be written as imposing:  $c_{12} = c_{23} = 1; c_{10} = c_{20} = 0$ .

- Let  $e_{Ri}$  be the residuals from a model that imposes these restrictions and let  $e_{Ui}$  be the residuals from the model that doesn't impose them. Estimated residual variances from these models are  $s_R^2 = \frac{1}{n-k-1} \sum e_{Ri}^2$  and  $s_U^2 = \frac{1}{n-k-1} \sum e_{Ui}^2$ . Given classical regression modeling assumptions (linear CEF, fixed regressors, homoskedastic Normal independent resids), we have that:

$$F = \frac{(\sum e_{Ri}^2 - \sum e_{Ui}^2)/q}{\sum e_{Ui}^2/(n-k-1)} = \left( \frac{n-k-1}{q} \right) \times \frac{(s_R^2 - s_U^2)}{s_U^2} \sim F_{q, n-k-1},$$

under the null hypothesis that the restrictions are satisfied

- This  $F$  statistic is used to do an  $F$  test
- An  $F$  distribution has two parameters: *numerator degrees of freedom (df)* equal to the number of restrictions being tested and *denominator df* equal to the sample size minus the number of parameters in the unrestricted model
- As usual, we test a null by looking for surprising draws from the null distribution, fixing the probability of Type I error
- An  $F$ -stat's  $df$  determine the relevant critical values (numerator  $df$  matter most; denominator  $df$  can often be taken to be infinite)
- We are said to be testing *zero restrictions* where  $c_{10} = \dots = c_{q0} = 0$  and all other  $c$ 's are equal to either 1 or 0.

#### $R^2$ version of the F-test

- Write  $R_R^2 = 1 - (s_R^2/s_Y^2)$  and  $R_U^2 = 1 - (s_U^2/s_Y^2)$  for restricted and unrestricted  $R^2$ , respectively. Provided restrictions don't transform the dependent variable (thereby changing its variance), we can write:

$$\begin{aligned} F &= \left( \frac{n-k-1}{q} \right) \times \frac{(s_R^2 - s_U^2)}{s_U^2} = \left( \frac{n-k-1}{q} \right) \times \frac{\left( \frac{s_R^2}{s_Y^2} - \frac{s_U^2}{s_Y^2} \right)}{\frac{s_U^2}{s_Y^2}} \\ &= \left( \frac{n-k-1}{q} \right) \times \frac{(R_U^2 - R_R^2)}{(1 - R_U^2)} \end{aligned}$$

- An F-test gauges the extent to which restrictions reduce  $R^2$  (as they must) by asking whether the change is small enough to be put down to sampling variance under the null
- The large-sample (asymptotic) version of the F-test is a chi-square test. Under weak assumptions like those used to derive robust standard errors,  $qF \sim_a \chi^2(q)$ . In other words, an F-stat times its numerator df is asymptotically (as  $n \rightarrow \infty$ ) distributed chi-square with  $q$  df.
  - A test based on  $\chi^2(q)$  is the asymptopian version of  $F_{q, n-k-1}$ . The relevant chi-square statistic is easily modified to allow for random regressors and non-normal heteroskedastic residuals. Even so, it's still more common to see an old-fashioned F statistic than a chi-square statistic in empirical publications.

### 3.1 Restriction Examples

- Testing additivity

$$(UR) \quad Y_i = \beta_0 + \beta_1 S_i + \beta_2 X_{2i} + \beta_3 X_{3i} + \underbrace{\beta_{12} S_i X_{2i} + \beta_{13} S_i X_{3i} + \beta_{23} X_{2i} X_{3i}}_{\text{2nd order terms}} + \underbrace{\beta_{123} S_i X_{2i} X_{3i}}_{\text{3rd order term}} + \varepsilon_i$$

$$(R) \quad Y_i = \beta_0 + \beta_1 S_i + \beta_2 X_{2i} + \beta_3 X_{3i} + \varepsilon_i$$

In this case, an additivity null imposes four zero restrictions:

$$H_0 : \beta_{12} = \beta_{13} = \beta_{23} = \beta_{123} = 0$$

- Testing constant returns to scale (CRTS) in Cobb-Douglas production. Start with:

$$Y_i = AX_{1i}^{\beta_1} X_{2i}^{\beta_2} X_{3i}^{\beta_3} \eta_i$$

Logging:

$$(UR) \quad \ln Y_i = \beta_0 + \beta_1 \ln X_{1i} + \beta_2 \ln X_{2i} + \beta_3 \ln X_{3i} + \varepsilon_i, \quad (UR)$$

where  $\varepsilon_i = \ln \eta_i$ . CRTS says:

$$H_0 : \beta_1 + \beta_2 + \beta_3 = 1$$

This is a single restriction on an unrestricted model with 4 parameters, so the relevant null distribution is  $F_{1, N-4}$

- This isn't a zero restriction
- $H_0$  can be imposed by using the null to rewrite:

$$\ln Y_i = \beta_0 + (1 - \beta_2 - \beta_3) \ln X_{1i} + \beta_2 \ln X_{2i} + \beta_3 \ln X_{3i} + \varepsilon_i$$

$$\ln Y_i - \ln X_{1i} = \beta_0 + \beta_2 (\ln X_{2i} - \ln X_{1i}) + \beta_3 (\ln X_{3i} - \ln X_{1i}) + \varepsilon_{ii}$$

$$(R) \quad Y_i^* = \beta_0 + \beta_2 X_{2i}^* + \beta_3 X_{3i}^* + \varepsilon_i$$

- The restricted model has a new dependent variable, so the  $R_R^2$  version of  $F$  doesn't work. But Stata's `test` command applied to the unrestricted model gets this right.

- 4 Testing Gender and Race Interactions in the Returns to Military Service (attached)
- 5 Krueger (1993): Computer Interactions in Action (attached)

```
clear
set more off
```

Data from the 2008 IPUMS-CPS <http://cps.ipums.org/cps/>

```
use cps_00013.dta
```

Generate usual weekly and hourly earnings

```
gen uwe = incwage / WKSWORK1
label var uwe "Usual weekly earnings"
gen loguwe = log(uwe)
label var loguwe "log(usual weekly earnings)"
gen logahe = log(incwage/(WKSWORK1*uhrswork))
label var logahe "Log usual hourly earnings"
gen logearn = log(incwage)
label var logearn "log(annual wage and salary earnings)"
```

```
(99,260 missing values generated)
(105,868 missing values generated)
(105,868 missing values generated)
(56,097 missing values generated)
```

Generate approximate years of education

```
gen yearsEd = .
replace yearsEd=0 if educ==2
// additional labeling and output omitted from logs
label var yearsEd "Years of education (approximate)"
gen colgrad = yearsEd>=16

gen age2 = age*age
gen potex = age-yearsEd-6
label var potex "Potential experience"
gen potex2 = potex*potex
```

Code vet, mil, race, sex

```
gen military = (popstat==2)
gen veteran = (vetstat==2) | (military==1)
```

black or part black

```
gen black = (race==200 | race==801 | race==805 | race==806 | race==807)
gen blackEd = black*yearsEd
gen blackvet = black*veteran

gen female=(sex==2)
gen femEd = female*yearsEd
gen femvet = female*veteran
```

```
gen blackfem=female*black
```

```
(49,771 missing values generated)
```

keep men and women aged 30–49, include active duty, sample=inLF

```
keep if age>=30 & age<50
```

```
(146,432 observations deleted)
```

add LFvars

```
gen working = WKSWORK1>0
```

### Summary Stats

```
sum age yearsEd female black veteran femvet blackvet military ///
    colgrad incwage WKSWORK1 uhrswork logahe loguwe working
```

```
sum age yearsEd female black veteran femvet blackvet military colgrad incwage
WKSWORK1 uhrswork logahe loguwe working
```

Variable	Obs	Mean	Std. Dev.	Min	Max
<hr/>					
age	59,972	39.88245	5.681624	30	49
yearsEd	59,972	13.7431	2.900316	0	21
female	59,972	.5254786	.4993546	0	1
black	59,972	.1104015	.3133922	0	1
veteran	59,972	.0612619	.2398121	0	1
<hr/>					
femvet	59,972	.0090042	.0944631	0	1
blackvet	59,972	.0094711	.0968584	0	1
military	59,972	.0067698	.0820007	0	1
colgrad	59,972	.3235843	.4678474	0	1
incwage	59,972	38108.07	48959.97	0	688117
<hr/>					
WKSWORK1	59,972	41.47669	19.27549	0	52
uhrswork	59,972	34.92955	17.70783	0	99
logahe	48,009	2.879673	.730158	-5.897154	9.069273
loguwe	48,009	6.549787	.8281364	-2.261763	11.15625
working	59,972	.852131	.354973	0	1

### Additive model

```
reg logahe yearsEd veteran black female
```

Source	SS	df	MS	Number of obs	=	48,009
<hr/>						
Model	5154.67766	4	1288.66941	F(4, 48004)	=	3026.50
Residual	20439.8621	48,004	.425794977	Prob > F	=	0.0000
<hr/>						
Total	25594.5397	48,008	.533130723	R-squared	=	0.2014
<hr/>						
logahe	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	

yearsEd	.104886	.0010596	98.98	0.000	.1028091	.1069629
veteran	.0367164	.0121419	3.02	0.002	.012918	.0605147
black	-.0988435	.009582	-10.32	0.000	-.1176244	-.0800627
female	-.2972256	.0060911	-48.80	0.000	-.3091643	-.2852869
_cons	1.570199	.0152843	102.73	0.000	1.540242	1.600157

Regression of wages on education and veteran status, by sex, control for race

`bys female: reg logahe yearsEd veteran black`

-> female = 0

Source	SS	df	MS	Number of obs	=	24,552
				F(3, 24548)	=	1844.86
Model	2348.76452	3	782.921508	Prob > F	=	0.0000
Residual	10417.6685	24,548	.424379524	R-squared	=	0.1840
				Adj R-squared	=	0.1839
Total	12766.4331	24,551	.519996459	Root MSE	=	.65144

logahe	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
yearsEd	.1024476	.0014073	72.80	0.000	.0996893 .1052059
veteran	.0348462	.0131176	2.66	0.008	.0091349 .0605575
black	-.1908072	.0143528	-13.29	0.000	-.2189395 -.1626749
_cons	1.61261	.0199472	80.84	0.000	1.573512 1.651707

-> female = 1

Source	SS	df	MS	Number of obs	=	23,457
				F(3, 23453)	=	1523.13
Model	1945.86697	3	648.622324	Prob > F	=	0.0000
Residual	9987.43719	23,453	.425849025	R-squared	=	0.1631
				Adj R-squared	=	0.1630
Total	11933.3042	23,456	.508752735	Root MSE	=	.65257

logahe	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
yearsEd	.1081747	.0016071	67.31	0.000	.1050246 .1113248
veteran	.0681413	.0318518	2.14	0.032	.0057097 .1305729
black	-.0251327	.0128612	-1.95	0.051	-.0503416 .0000761
_cons	1.216732	.0231711	52.51	0.000	1.171315 1.262149

Regression of wages on education and veteran status interacted with sex

```
reg logahe yearsEd femEd veteran femvet black female blackfem
```

Source	SS	df	MS	Number of obs	=	48,009
Model	5189.43401	7	741.347715	F(7, 48001)	=	1743.95
Residual	20405.1057	48,001	.425097513	Prob > F	=	0.0000
				R-squared	=	0.2028
				Adj R-squared	=	0.2026
Total	25594.5397	48,008	.533130723	Root MSE	=	.652

  

logahe	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
yearsEd	.1024476	.0014084	72.74	0.000	.099687 .1052082
femEd	.0057271	.0021359	2.68	0.007	.0015407 .0099135
veteran	.0348462	.0131287	2.65	0.008	.0091138 .0605786
femvet	.0332951	.0344254	0.97	0.333	-.0341792 .1007694
black	-.1908072	.0143649	-13.28	0.000	-.2189626 -.1626518
female	-.3958777	.0305699	-12.95	0.000	-.4557951 -.3359604
blackfem	.1656745	.0192735	8.60	0.000	.1278981 .2034508
_cons	1.61261	.0199641	80.78	0.000	1.57348 1.65174

Test interactions jointly

```
test femEd femvet
test femEd femvet blackfem
lincom black+blackfem
```

( 1) femEd = 0  
( 2) femvet = 0

F( 2, 48001) = 4.14  
Prob > F = 0.0160

( 1) femEd = 0  
( 2) femvet = 0  
( 3) blackfem = 0

F( 3, 48001) = 27.25  
Prob > F = 0.0000

( 1) black + blackfem = 0

lincom estimates linear combinations

logahe	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
(1)	-.0251327	.0128499	-1.96	0.050	-.0503186 .0000532

Regression of wages on education and veteran status, by race, control for sex

bys black: reg logahe yearsEd veteran female

-> black = 0

Source	SS	df	MS	Number of obs	=	42,771
				F(3, 42767)	=	3644.61
Model	4732.42079	3	1577.4736	Prob > F	=	0.0000
Residual	18510.5762	42,767	.432823818	R-squared	=	0.2036
				Adj R-squared	=	0.2036
Total	23242.997	42,770	.543441595	Root MSE	=	.65789

logahe	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
yearsEd	.1048038	.00111	94.41	0.000	.1026281 .1069795
veteran	.0245867	.0132534	1.86	0.064	-.0013903 .0505637
female	-.3160608	.0064956	-48.66	0.000	-.3287923 -.3033293
_cons	1.581149	.0159949	98.85	0.000	1.549799 1.6125

-> black = 1

Source	SS	df	MS	Number of obs	=	5,238
				F(3, 5234)	=	325.53
Model	353.444082	3	117.814694	Prob > F	=	0.0000
Residual	1894.24545	5,234	.361911627	R-squared	=	0.1572
				Adj R-squared	=	0.1568
Total	2247.68954	5,237	.429194107	Root MSE	=	.60159

logahe	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
yearsEd	.1066224	.0035997	29.62	0.000	.0995655 .1136792
veteran	.1253284	.0292934	4.28	0.000	.0679011 .1827557
female	-.1386085	.0172364	-8.04	0.000	-.1723989 -.104818
_cons	1.349591	.0506443	26.65	0.000	1.250307 1.448875

Regression of wages on education and veteran status interacted with race

```
reg logahe yearsEd blackEd veteran blackvet black female blackfem
```

Source	SS	df	MS	Number of obs	=	48,009
Model	5189.71807	7	741.388295	F(7, 48001)	=	1744.07
Residual	20404.8217	48,001	.425091595	Prob > F	=	0.0000
				R-squared	=	0.2028
				Adj R-squared	=	0.2027
Total	25594.5397	48,008	.533130723	Root MSE	=	.65199

  

logahe	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
yearsEd	.1048038	.0011001	95.27	0.000	.1026476 .10696
blackEd	.0018186	.0040534	0.45	0.654	-.0061261 .0097633
veteran	.0245867	.0131345	1.87	0.061	-.0011571 .0503306
blackvet	.1007417	.0343572	2.93	0.003	.033401 .1680823
black	-.2315583	.0571302	-4.05	0.000	-.3435343 -.1195824
female	-.3160608	.0064373	-49.10	0.000	-.3286781 -.3034436
blackfem	.1774524	.0197584	8.98	0.000	.1387256 .2161792
_cons	1.581149	.0158514	99.75	0.000	1.550081 1.612218

Test interactions jointly

```
test blackEd blackvet
test blackEd blackvet blackfem
lincom black+blackfem
```

```
( 1) blackEd = 0
( 2) blackvet = 0

F( 2, 48001) =     4.47
               Prob > F =    0.0114
```

```
( 1) blackEd = 0
( 2) blackvet = 0
( 3) blackfem = 0

F( 3, 48001) =    27.48
               Prob > F =    0.0000
```

```
( 1) black + blackfem = 0
```

logahe	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
(1)	-.054106	.0574678	-0.94	0.346	-.1667436 .0585316

## Krueger 1993

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

Group	1984	1989
All workers	24.6	37.4
<u>Gender</u>		
Men	21.2	32.3
Women	29.0	43.4
<u>Education</u>		
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
<u>Race</u>		
White	25.3	38.5
Black	19.4	27.7
<u>Age</u>		
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
<u>Occupation</u>		
Blue-collar	7.1	11.6
White-collar	33.0	48.4
<u>Union status</u>		
Union member	20.2	32.5
Nonunion	28.0	41.1
<u>Hours</u>		
Part-time	23.7	36.3
Full-time	28.9	42.7
<u>Region</u>		
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 (0.005)	0.750 (0.023)	0.928 (0.026)	2.086 (0.006)	0.905 (0.024)	1.094 (0.026)
Uses computer at work (1 = yes)	0.276 (0.010)	0.170 (0.008)	0.140 (0.008)	0.325 (0.009)	0.188 (0.008)	0.162 (0.008)
Years of education	—	0.069 (0.001)	0.048 (0.002)	—	0.075 (0.002)	0.055 (0.002)
Experience	—	0.027 (0.001)	0.025 (0.001)	—	0.027 (0.001)	0.025 (0.001)
Experience-squared ÷ 100	—	-0.041 (0.002)	-0.040 (0.002)	—	-0.041 (0.002)	-0.040 (0.002)
Black (1 = yes)	—	-0.098 (0.013)	-0.066 (0.012)	—	-0.121 (0.013)	-0.092 (0.012)
Other race (1 = yes)	—	-0.105 (0.020)	-0.079 (0.019)	—	-0.029 (0.020)	-0.015 (0.020)
Part-time (1 = yes)	—	-0.256 (0.010)	-0.216 (0.010)	—	-0.221 (0.010)	-0.183 (0.010)
Lives in SMSA (1 = yes)	—	0.111 (0.007)	0.105 (0.007)	—	0.138 (0.007)	0.130 (0.007)
Veteran (1 = yes)	—	0.038 (0.011)	0.041 (0.011)	—	0.025 (0.012)	0.031 (0.011)
Female (1 = yes)	—	-0.162 (0.012)	-0.135 (0.012)	—	-0.172 (0.012)	-0.151 (0.012)
Married (1 = yes)	—	0.156 (0.011)	0.129 (0.011)	—	0.159 (0.011)	0.143 (0.011)
Married*Female	—	-0.168 (0.015)	-0.151 (0.015)	—	-0.141 (0.015)	-0.131 (0.015)
Union member (1 = yes)	—	0.181 (0.009)	0.194 (0.009)	—	0.182 (0.010)	0.189 (0.010)
8 Occupation dummies	No	No	Yes	No	No	Yes
R <sup>2</sup>	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.

**TABLE III**  
**THE RETURN TO VARIOUS USES OF COMPUTERS, OCTOBER 1989<sup>a</sup>**  
**(DEPENDENT VARIABLE: ln (HOURLY WAGE))**

Use of computer at work	Proportion	Coefficient (std. error)
Uses computer at work for any task <sup>b</sup>	0.398	0.145 (0.010)
<u>Specific Task<sup>c</sup></u>		
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)
<i>R</i> <sup>2</sup>		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 (0.009)	0.177 (0.009)	39.8
Uses computer at home	0.056 (0.021)	0.070 (0.019)	12.5
Uses computer at home and work	0.006 (0.029)	0.017 (0.023)	8.6
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 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)
<i>R</i> <sup>2</sup>	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.

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 <sup>a</sup>				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*.

resulting approximation should be rather good because of the large number of brackets. Adopting a similar specification, we find that this earnings variable yields the same return to schooling in 1985–1986 as reported by Krueger and Pischke [1995] with a continuous earnings variable for 1988. Years of education are imputed from information on schools attended and degrees obtained following Krueger and Pischke [1995]. When we bracket the earnings variable in the October 1984 CPS to be comparable with our 1979 data, in a regression similar to Krueger's we find a computer coefficient of 0.1697 using the original wage variable, and 0.1701 using the bracketed variable. Standard errors are about 3 percent larger with the bracketed variable.

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 (0.008)	0.188 (0.008)	0.204 (0.008)	0.112 (0.010)	0.157 (0.007)	0.171 (0.006)
Years of schooling	0.068 (0.001)	0.075 (0.002)	0.081 (0.002)	0.073 (0.001)	0.063 (0.001)	0.072 (0.001)
Experience	0.028 (0.001)	0.028 (0.001)	0.026 (0.001)	0.030 (0.001)	0.035 (0.001)	0.030 (0.001)
Experience <sup>2/</sup> 100	-0.043 (0.002)	-0.043 (0.002)	-0.041 (0.003)	-0.052 (0.002)	-0.058 (0.002)	-0.046 (0.002)
R <sup>2</sup>	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*).

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	No	No	No	No	Yes	No	No
Occupation <sup>a</sup>							
Tools entered separately							
Computer	0.112 (0.010)	0.157 (0.007)	0.171 (0.006)	0.025 (0.011)	0.022 (0.011)	0.076 (0.008)	0.083 (0.007)
Calculator	0.087 (0.007)	0.128 (0.006)	0.129 (0.006)	0.027 (0.008)	0.025 (0.008)	0.061 (0.007)	0.054 (0.006)
Telephone	0.131 (0.006)	0.114 (0.006)	0.136 (0.006)	0.060 (0.007)	0.057 (0.007)	0.059 (0.007)	0.072 (0.007)
Pen/pencil	0.123 (0.006)	0.112 (0.006)	0.127 (0.006)	0.055 (0.007)	0.052 (0.007)	0.055 (0.007)	0.050 (0.007)
Work while sitting	0.106 (0.006)	0.101 (0.007)	—	0.042 (0.008)	0.041 (0.008)	0.036 (0.008)	—
Hand tool (e.g., hammer)	-0.117 (0.007)	-0.086 (0.006)	-0.091 (0.006)	-0.048 (0.009)	-0.045 (0.009)	-0.020 (0.008)	-0.020 (0.008)

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