Chapter 10
Regression with Panel Data

■ Solutions to Empirical Exercises

1.

	(1)	(2)	(3)	(4)
shall	–0.443**	–0.368**	–0.0461*	–0.0280
	(0.048)	(0.035)	(0.019)	(0.017)
incar_rate		0.00161**	–0.00007	0.0000760
		(0.00018)	(0.00009)	(0.000090)
density		0.0267	–0.172**	–0.0916
		(0.014)	(0.085)	(0.076)
avginc		0.00121	–0.00920	0.000959
		(0.0073)	(0.0059)	(0.0064)
pop		0.0427**	0.0115	–0.00475
		(0.0031)	(0.0087)	(0.0079)
pb1064		0.0809**	0.104**	0.0292
		(0.020)	(0.018)	(0.023)
pw1064		0.0312**	0.0409**	0.00925
		(0.0097)	(0.0051)	(0.0079)
pm1029		0.00887	–0.0503**	0.0733**
		(0.012)	(0.0064)	(0.016)
Intercept	6.135**	2.982**	3.866**	3.766**
	(0.019)	(0.61)	(0.38)	(0.47)
State Effects	No	No	Yes	Yes
Time Effects	No	No	No	Yes
F-Statistics and *p*-values testing exclusion of groups of variables				
State Effects			210.38	309.29
			(0.00)	(0.00)
Time Effects				13.90
				(0.00)
$\bar{R}^2$	0.09	0.56	0.94	0.95

(a) (i) The coefficient is –0.368, which suggests that shall-issue laws reduce violent crime by 36%. This is a large effect.

(ii) The coefficient in (1) is –0.443; in (2) it is –0.369. Both are highly statistically significant. Adding the control variables results in a small drop in the coefficient.

(iii) Attitudes towards guns and crime. Quality of schools. Quality of police and other crime-prevention programs.

(b) In (3) the coefficient on *shall* falls to –0.046, a large reduction in the coefficient from (2). Evidently there was important omitted variable bias in (2). The 95% confidence interval for β_{Shall} is now –0.086 to –0.007 or –0.7% to •8.6%. The state effects are jointly statistically significant, so this regression seems better specified than (2).

(c) The coefficient falls further to –0.028. The coefficient is insignificantly different from zero. The time effects are jointly statistically significant, so this regression seems better specified than (3).

(d) This table shows the coefficient on *shall* in the regression specifications (1)–(4). To save space, coefficients for variables other than *shall* are not reported.

	Dependent Variable = ln(*rob*)			
	(1)	**(2)**	**(3)**	**(4)**
shall	–0.773** (0.070)	–0.529** (0.051)	–0.008 (0.026)	0.027 (0.025)
F-Statistics and *p*-values testing exclusion of groups of variables				
State Effects			190.47 (0.00)	243.39 (0.00)
Time Effects				12.39 (0.00)
	Dependent Variable = ln(*mur*)			
shall	–0.473** (0.049)	–0.313** (0.036)	–0.061* (0.027)	–0.015 (0.027)
F-Statistics and *p*-values testing exclusion of groups of variables				
State Effects			88.22 (0.00)	106.69 (0.00)
Time Effects				9.73 (0.00)

The quantative results are similar to the results using violent crimes: there is a large estimated effect of concealed weapons laws in specifications (1) and (2). This effect is spurious and is due to omitted variable bias as specification (3) and (4) show.

(e) There is potential two-way causality between this year's incarceration rate and the number of crimes. Because this year's incarceration rate is much like last year's rate, there is a potential two-way causality problem. There are similar two-way causality issues relating crime and *shall*.

(f) The most credible results are given by regression (4). The 95% confidence interval for β_{Shall} is +1% to –6.6%. This includes $\beta_{Shall} = 0$. Thus, there is no statistically significant evidence that concealed weapons laws have any effect on crime rates. The interval is wide, however, and includes values as large as –6.6%. Thus, at a 5% level the hypothesis that $\beta_{Shall} = -0.066$ (so that the laws reduce crime by 6.6%) cannot be rejected.

2.

Regressor	**(1)**	**(2)**	**(3)**
sb_useage	0.00407^{***} (0.0012)	-0.00577^{***} (0.0012)	-0.00372^{***} (0.0011)
speed65	0.000148 (0.00041)	–0.000425 (0.00033)	-0.000783^{*} (0.00042)
speed70	0.00240^{***} (0.00047)	0.00123^{***} (0.00033)	0.000804^{**} (0.00034)
ba08	-0.00192^{***} (0.00036)	-0.00138^{***} (0.00037)	-0.000822^{**} (0.00035)
drinkage21	0.0000799 (0.00099)	0.000745 (0.00051)	-0.00113^{**} (0.00054)
lninc	-0.0181^{***} (0.0011)	-0.0135^{***} (0.0014)	0.00626 (0.0039)
age	–0.00000722 (0.00016)	0.000979^{**} (0.00038)	0.00132^{***} (0.00038)
State Effects	No	Yes	Yes
Year Effects	No	No	Yes
	0.544	0.874	0.897

(a) The estimated coefficient on seat belt useage is *positive* and statistically significant. One the face of it, this suggests that seat belt useage leads to an *increase* in the fatality rate.

(b) The results change. The coefficient on seat belt useage is now negative and the coefficient is statistically significant. The estimated value of $\beta_{SB} = -0.00577$, so that a 10% increase in seat belt useage (so that *sb_useage* increases by 0.10) is estimated to lower the fatality rate by .000577 fatalities per million traffic miles. States with more dangerous drving conditions (and a higher fatality rate) also have more people wearing seat belts. Thus (1) suffers from omitted variable bias.

(c) The results change. The estimated value of $\beta_{SB} = -0.00372$.

(d) The time effects are statistically significant − the F-statistic = 10.91 with a p-value of 0.00. The results in (3) are the most reliable.

(e) A 38% increase in seat belt useage from 0.52 to 0.90 is estimated to lower the fatality rate by $0.00372 \times 0.38 = 0.0014$ fatalities per million traffic miles. The average number of traffic miles per year per state in the sample is 41,447. For a state with the average number of traffic miles, the number of fatalities prevented is $0.0014 \times 41{,}447 = 58$ fatalities.

(f) A regression yields

$$\widehat{sb\_useage} = \underset{(0.021)}{0.206} \times primary + \underset{(0.011)}{0.109} \times secondary +$$

(*speed65, speed70, ba08, drinkage21, logincome, age, time effects, state effects*) where the coefficients on the other regressors are not reported to save space. The coefficients on *primary* and *secondary* are positive and significant. Primary enforcement is estimated to increase seat belt useage by 20.6% and secondary enforcement is estimated to increase seat belt useage by 10.9%.

(g) This results in an estimated increase in seatbelt useage of 0.206–0.109 = 0.094 or 9.4% from (f). This is predicted to reduce the fatality rate by $0.00372 \times 0.094 = 0.00035$ fatalities per million traffic miles. The data set shows that there were 63,000 million traffic miles in 1997 in New Jersey, the last year for which data is available. Assuming the same number of traffic miles in 2000 yields $0.00035 \times 63{,}000 = 22$ lives saved.