Financial Econometrics
Shanghai Jiao Tong University
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Empirical Exercise 10.1
With Solutions

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Reference: Stock, J.H. and Watson, M.W., Introduction to Econometrics (4th Edition, Global Edition)

Data: `Guns.csv`, a balanced panel of the 50 US states plus the District of Columbia for the years 1977–1999.

Empirical Exercise 10.1. Some US states have enacted laws that allow citizens to carry concealed weapons. These laws are known as "shall-issue" laws because they instruct local authorities to issue a concealed-weapons permit to all applicants who are citizens, are mentally competent, and have not been convicted of a felony. (Some states impose additional restrictions.) Proponents argue that if more people carry concealed weapons, crime will decline because criminals will be deterred from attacking other people. Opponents argue that crime will increase because of the accidental or spontaneous use of the weapons. In this exercise, you will analyse the effect of concealed-weapons laws on violent crime.

The data file is `Guns.csv`, a balanced panel of the 50 US states plus the District of Columbia for the years 1977–1999. The variable names follow the S&W `Guns` file: `vio`, `rob` and `mur` are the violent-crime, robbery and murder rates (incidents per 100,000 residents); `shall` equals 1 if a shall-issue law was in effect that year and 0 otherwise; `incarc_rate` is the incarceration rate; `density` is population per square mile; `avginc` is real per-capita personal income; `pop` is the state population; `pb1064`, `pw1064` and `pm1029` are the percentages of the population that are black aged 10–64, white aged 10–64, and male aged 10–29; `stateid` identifies the state; and `year` identifies the year.

(a) Estimate (1) a regression of ln(`vio`) on `shall`, and (2) a regression of ln(`vio`) on `shall`, `incarc_rate`, `density`, `avginc`, `pop`, `pb1064`, `pw1064` and `pm1029`.

(i) Interpret the coefficient on `shall` in regression (2). Is this estimate large or small in a "real-world" sense?

(ii) Does adding the control variables in regression (2) change the estimated effect of a shall-carry law in regression (1), as measured by statistical significance? As measured by the "real-world" significance of the estimated coefficient?

(iii) Suggest a variable that varies across states but plausibly varies little (or not at all) over time and that could cause omitted-variable bias in regression (2).

(b) Do the results change when you add fixed state effects? If so, which set of regression results is more credible, and why?

(c) Do the results change when you add fixed time effects? If so, which set of regression results is more credible, and why?

(d) Repeat the analysis using ln(`rob`) and ln(`mur`) in place of ln(`vio`).

(e) In your view, what are the most important remaining threats to the internal validity of this regression analysis?

(f) Based on your analysis, what conclusions would you draw about the effects of concealed-weapons laws on these crime rates?

Solution:

Data Overview

The data set `Guns.csv` is a balanced panel: every one of the 50 US states plus the District of Columbia ($n = 51$ entities) is observed in each of the 23 years from 1977 to 1999 ($T = 23$), giving $51 \times 23 = 1{,}173$ observations. The dependent variables are the natural logarithms of three crime rates, so a coefficient can be read (after multiplying by 100) as an approximate percentage change in the crime rate.

Variable	Description	Role
vio, rob, mur	Violent-crime, robbery, murder rates (per 100,000)	Outcomes (in logs)
shall	1 if a shall-issue law is in effect, 0 otherwise	Regressor of interest
incarc_rate	Incarceration rate (prisoners per 100,000)	Control
density	Population per square mile	Control
avginc	Real per-capita personal income	Control
pop	State population	Control
pb1064	% black, aged 10–64	Control
pw1064	% white, aged 10–64	Control
pm1029	% male, aged 10–29	Control
stateid, year	Entity and time identifiers	Panel structure

Note: Throughout, the seven control variables are `incarc_rate`, `density`, `avginc`, `pop`, `pb1064`, `pw1064` and `pm1029`. Standard errors are clustered by state, which allows for heteroskedasticity and for serial correlation of the errors within a state. Calculations follow the Stata file `EE_10_1.do`.

Key Notation and Formulas

The panel regression with entity and time fixed effects is

$$\ln(\mathit{Crime}_{it}) = \beta_1\, \texttt{shall}_{it} + \boldsymbol{X}_{it}'\boldsymbol{\beta} + \alpha_i + \lambda_t + u_{it},$$

where α_i is a state fixed effect (it absorbs everything about state i that is constant over time) and λ_t is a time fixed effect (it absorbs anything common to all states in year t). With a logged dependent variable, the coefficient on `shall` is interpreted as an approximate proportional change in the crime rate:

$100 \times \hat{\beta}_1 \approx$ percentage change in the crime rate associated with a shall-issue law.

(a) Violent Crime: Pooled OLS, Without and With Controls

The two pooled regressions of ln(`vio`) are reported in columns (1) and (2) of the summary table below. The full set of specifications, including the fixed-effects regressions used in parts (b) and (c), is collected in the same table so that the columns can be compared directly.

Dependent variable: ln(`vio`)	(1)	(2)	(3)	(4)
`shall`	0.443	0.368	0.0461	0.0280
	(0.157)	(0.114)	(0.042)	(0.041)
95% CI	[−0.76, −0.13]	[−0.60, −0.14]	[−0.13, 0.04]	[−0.11, 0.05]
Controls	No	Yes	Yes	Yes
State effects	No	No	Yes	Yes
Time effects	No	No	No	Yes
F-statistic (p-value) for excluded time effects				
Time effects = 0	—	—	—	21.6 (0.00)

Controls: `incarc_rate`, `density`, `avginc`, `pop`, `pb1064`, `pw1064`, `pm1029`. Clustered (by state) standard errors in parentheses.

(i) Interpreting the coefficient on `shall` in regression (2)

In column (2) the coefficient on `shall` is 0.368. Read literally on the log scale, this suggests that a shall-issue law is associated with roughly a **36% lower violent-crime rate**. That is a very large effect in a real-world sense: a one-third reduction in violent crime would be an enormous public-policy achievement. The size of the estimate is exactly why it deserves a sceptical second look, which the fixed-effects specifications in parts (b) and (c) provide.

(ii) Does adding controls change the estimate?

Adding the seven control variables moves the coefficient on `shall` only modestly, from 0.443 in column (1) to 0.368 in column (2). Both estimates are highly statistically significant (the t-statistics are well above 2, and neither confidence interval contains zero). So:

- **Statistical significance:** essentially unchanged, both estimates are strongly significant.
- **Real-world significance:** a small drop (from about 44% to about 37%), but the implied effect remains very large.

(iii) A source of omitted-variable bias

We need a variable that differs across states but changes little over time, because such a variable is exactly what a state fixed effect will later absorb. Two plausible examples:

- **Attitudes towards guns and crime** (a state's prevailing culture), which differ sharply between states but evolve only slowly.
- **The quality of policing and other crime-prevention programmes**, which is a fairly persistent feature of a state.

If such factors are correlated both with whether a state passes a shall-issue law and with its crime rate, then their omission biases the column (2) estimate.

(b) Adding State Fixed Effects

Column (3) adds state fixed effects (with the same controls). The coefficient on `shall` falls sharply, from 0.368 in column (2) to

$$\boxed{\hat{\beta}_{\texttt{shall}} = 0.0461 \quad (\text{SE} = 0.042), \qquad \ln(\texttt{vio}),\ \text{state effects.}}$$

This is a large reduction in the estimated effect. The estimate is no longer statistically significantly different from zero: the 95% confidence interval $[-0.13, 0.04]$ comfortably contains zero.

Which is more credible? The state-fixed-effects results in column (3) are more credible. The big drop in the coefficient once state effects are included is direct evidence that there was important omitted-variable bias in column (2): persistent, state-level factors (such as the cultural and policing variables suggested in part (a)(iii)) were correlated both with the presence of a shall-issue law and with the crime rate. By holding constant everything about a state that does not change over time, the state fixed effects remove that source of bias.

(c) Adding Time Fixed Effects

Column (4) adds time fixed effects on top of the state effects and controls. The coefficient on `shall` falls a little further, to

$$\boxed{\hat{\beta}_{\texttt{shall}} = 0.0280 \quad (\text{SE} = 0.041), \qquad \ln(\texttt{vio}),\ \text{state and time effects.}}$$

It remains insignificantly different from zero (the 95% interval $[-0.11,\ 0.05]$ again includes zero). The time effects are themselves jointly significant: the F-statistic for excluding them is 21.6 with a p-value of 0.00.

Which is more credible? Because the time effects are jointly significant, they belong in the model, so column (4) is better specified than column (3). Time effects control for nationwide influences that move all states together in a given year (for example, the broad rise and fall of crime over the 1980s and 1990s, or national economic conditions). Column (4) is therefore the preferred specification.

(d) Robbery and Murder

Repeating the four specifications with ln(`rob`) and then ln(`mur`) as the dependent variable (controls included throughout) gives the coefficients on `shall` below.

Dependent variable: ln(`rob`)	(1)	(2)	(3)	(4)
`shall`	0.773	0.529	0.008	0.027
	(0.225)	(0.161)	(0.055)	(0.052)
F-statistic (p-value) for excluded time effects				
Time effects = 0	—	—	—	25.9 (0.00)

Dependent variable: ln(`mur`)	(1)	(2)	(3)	(4)
`shall`	0.473	0.313	0.061	0.015
	(0.149)	(0.099)	(0.037)	(0.038)
F-statistic (p-value) for excluded time effects				
Time effects = 0	—	—	—	19.61 (0.00)

All regressions include the seven controls; clustered (by state) standard errors in parentheses. In columns (1) and (2) the `shall` coefficients are significant at the 1% level.

What the pattern shows. The story is the same as for violent crime. In the pooled specifications, columns (1) and (2), shall-issue laws appear to have a large, highly significant association with lower robbery and murder rates (coefficients of 0.773 and 0.529 for robbery, and 0.473 and 0.313 for murder). Once state fixed effects are added in column (3), and time effects in column (4), the coefficients collapse towards zero (robbery: 0.008 then 0.027; murder: 0.061 then 0.015) and are no longer significant. The large pooled effects are spurious: they reflect omitted-variable bias, exactly as columns (3) and (4) reveal for each crime category.

(e) Remaining Threats to Internal Validity

Even the preferred specification in column (4) faces threats that fixed effects cannot remove. The most important is **simultaneous (two-way) causality**, which can arise in two places:

- **Incarceration and crime.** This year's incarceration rate is included as a control, but it is itself partly determined by the amount of crime (more crime leads to more imprisonment). Because this year's incarceration rate is very similar to last year's, there is a genuine two-way causality problem that biases its coefficient and can contaminate the others.
- **Shall-issue laws and crime.** A similar two-way causality issue links crime and `shall`: states experiencing rising crime may be more (or less) likely to adopt a concealed-weapons law, so the law is not cleanly exogenous.

State and time fixed effects control only for omitted variables that are constant over time within a state, or common to all states in a year. They do nothing about reverse causality or about omitted factors that vary across both state and year.

(f) Overall Conclusion

The most credible results are those in regression (4), with both state and time fixed effects. There, the coefficient on `shall` is small and statistically insignificant. Stated as a proportional effect on the violent-crime rate, the 95% confidence interval runs from about **an 11.0% decrease to a 5.3% increase**, a range that includes zero.

Conclusion: Once persistent state-level differences and common year-to-year shocks are held constant, there is **no statistically significant evidence that shall-issue (concealed-weapons) laws affect violent-crime, robbery or murder rates.** The large effects seen in the pooled regressions are an artefact of omitted-variable bias.

Summary: Coefficient on `shall` Across Specifications

Dependent variable	(1) Pooled	(2) +Controls	(3) +State FE	(4) +Time FE
ln(`vio`)	0.443	0.368	0.046	0.028
ln(`rob`)	0.773	0.529	0.008	0.027
ln(`mur`)	0.473	0.313	0.061	0.015
Significant?	Yes	Yes	No	No

The Big Picture

This exercise illustrates the central lesson of panel-data methods:

1. **Omitted-variable bias can be large.** Persistent state-level factors (gun culture, policing quality) are correlated both with shall-issue laws and with crime. Ignoring them, as the pooled regressions do, produces a large but spurious estimated effect.

2. **State fixed effects do the heavy lifting.** Holding constant everything about a state that does not change over time shrinks the `shall` coefficient from about 0.37 to about 0.05 for violent crime, with similar collapses for robbery and murder. The size of that change is itself the evidence of bias.

3. **Time fixed effects matter too.** They are jointly significant for all three crimes, so common national trends belong in the model; the state-and-time specification is the one to trust.

4. **Fixed effects are not a cure-all.** They cannot address reverse causality (crime affecting both incarceration and the adoption of shall-issue laws) or omitted variables that move across both state and year. The honest conclusion is no significant effect, reported with these caveats.

Calculations performed using Stata. See accompanying `EE_10_1.do` file.