ECON 613: Applied Econometrics

Methods for Panel Data

March 20, 2019

Linear Models

Applications

Introduction (1)

- Data on cross section that is observed over several unit of time.
- In microeconometrics, panel are usually short.

Introduction (2)

- The error is correlated over time..
- Examples
- Open possibilities..

Introduction (3)

Consider the following Model

$$Y_{it} = \alpha_i + \gamma_{j(t)} + \beta X_{it} + \epsilon_{it} \tag{1}$$

- Estimation of fixed effects
- Correlation between the fixed effects
- Estimation issues

Introduction (4)

Consider the following DGP:

- 1,000 individuals over 10 periods.
- $Y_{it} = \alpha_i + \beta X_{it} + \epsilon_{it}$
- Parametrization
  - $\beta = 1$
  - $\alpha_i \sim \mathit{uniform}(0, 1)$
  - $\epsilon_i \sim \mathbb{N}(0, 1)$

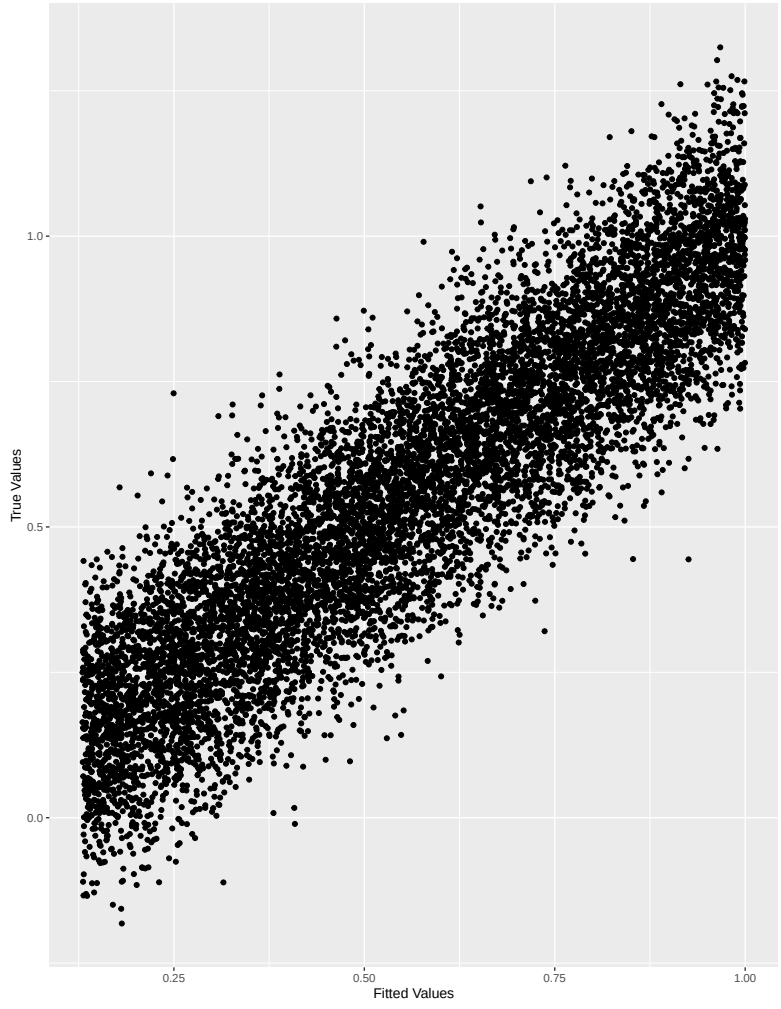
Pooled Estimation

	Model 1
(Intercept)	0.49***
	(0.02)
c(xMat)	0.93***
	(0.00)
R^2	0.87
Adj. R^2	0.87
Num. obs.	10000
RMSE	1.05

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table: Statistical models

Fitted Values (1)



Introduction (5)

Consider the following DGP:

- 1,000 individuals over 10 periods.
- $Y_{it} = \alpha_i + \beta X_{it} + \epsilon_{it}$
- Parametrization
  - $\beta = 1$
  - $\alpha_i \sim \mathit{uniform}(-10, 10)$
  - $\epsilon_i \sim \mathbb{N}(0, 1)$

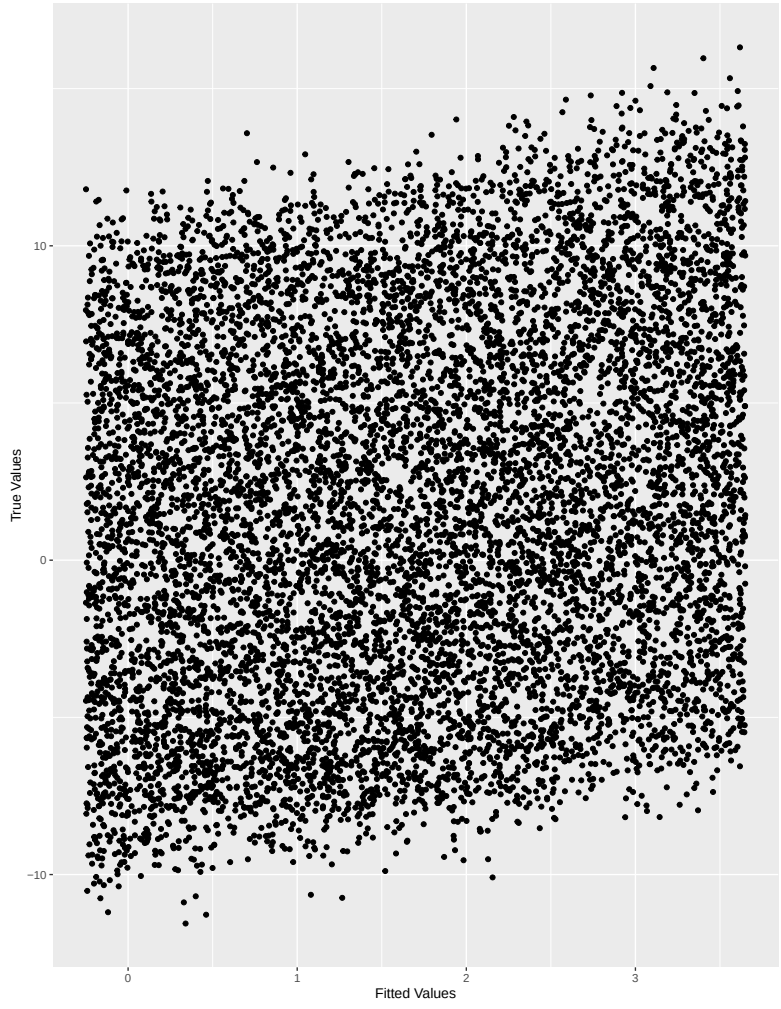
Pooled Estimation

	Model 1
(Intercept)	-0.26^{*}
	(0.11)
c(xMat)	0.40^{***}
	(0.02)
R^2	0.04
Adj. R^2	0.04
Num. obs.	10000
RMSE	5.73

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table: Statistical models

Fitted Values (2)



Effects

- Pooled Estimation is a good starting point.
- Individual VS Time Effect.

Individual Effects

- Fixed Effects
- Random Effects
- Examples: Return to Education

Time Effects

- Long Panel Case
- Example: Seasonality?

Some Models (1)

- Pooled Estimator

$$Y_{it} = \alpha + \beta X_{it} + \epsilon_{it} \tag{2}$$

- Problems

Some Models (2)

- Between Estimator

$$\bar{y}_i = \alpha_i + \beta \bar{x}_i + \bar{\epsilon}_i \tag{3}$$

- Problems

Some Models (3)

- Within Estimator

$$y_{it} - \bar{y}_i = \beta(x_{it} - \bar{x}_i) + (\epsilon_{it} - \bar{\epsilon}_i) \tag{4}$$

- Problems

Some Models (4)

- First Difference Estimator

$$y_{it} - y_{i,t-1} = \beta(x_{it} - x_{i,t-1}) + (\epsilon_{it} - \epsilon_{i,t-1}) \tag{5}$$

- Problems

More Guns, Less Crime

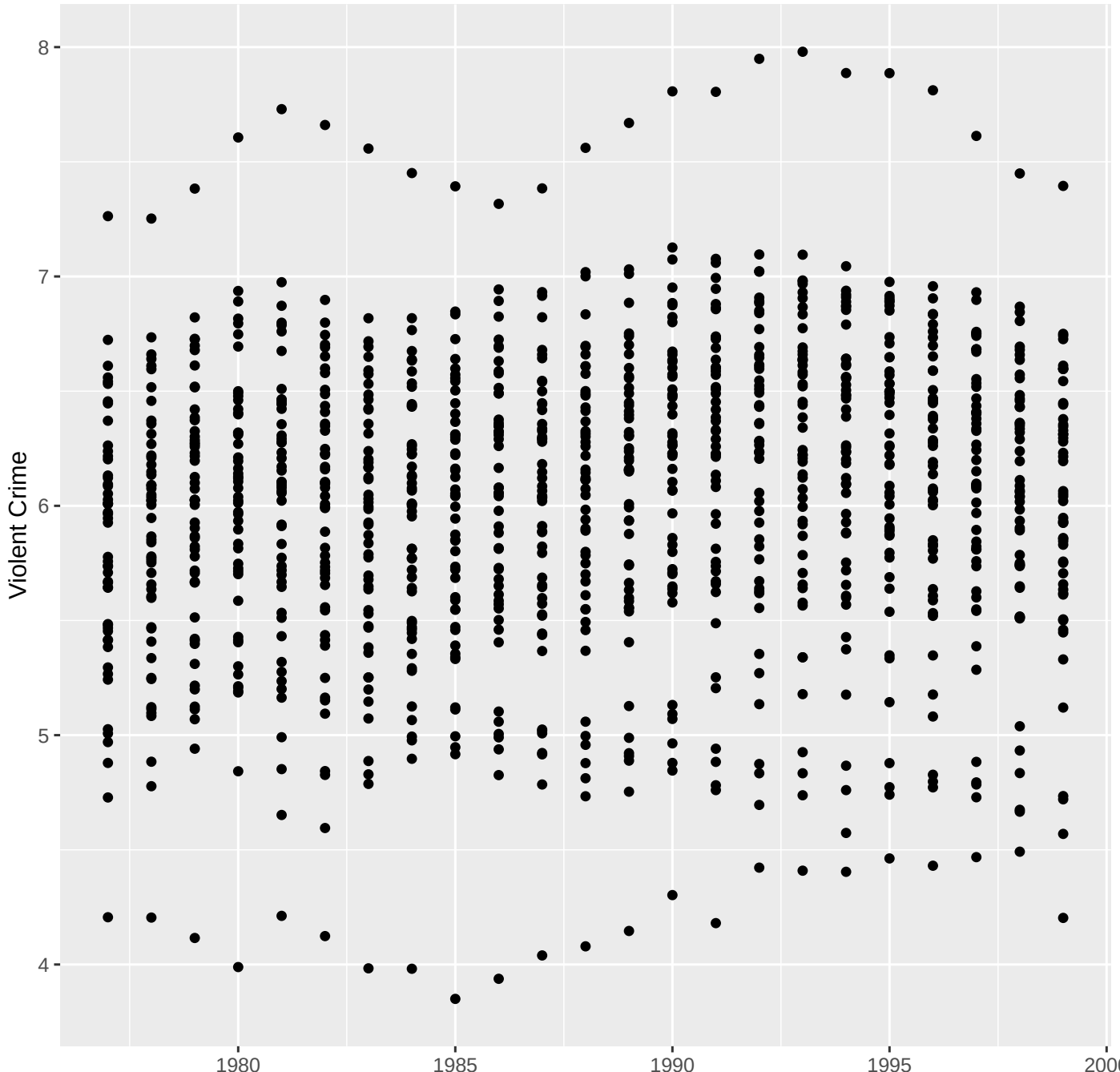
In a remarkable paper published in 1997, John Lott and David Mustard managed to set the agenda for much subsequent work on the impact of guns on crime in America by creating a massive data set of crime across all U.S. counties from 1977 through 1992 and amassing a powerful statistical argument that state laws enabling citizens to carry concealed handguns had reduced crime.1 The initial paper was followed a year later by an even more comprehensive and sustained argument to the same effect in a book solely authored by John Lott entitled More Guns, Less Crime (now in its second edition).

Data: Guns

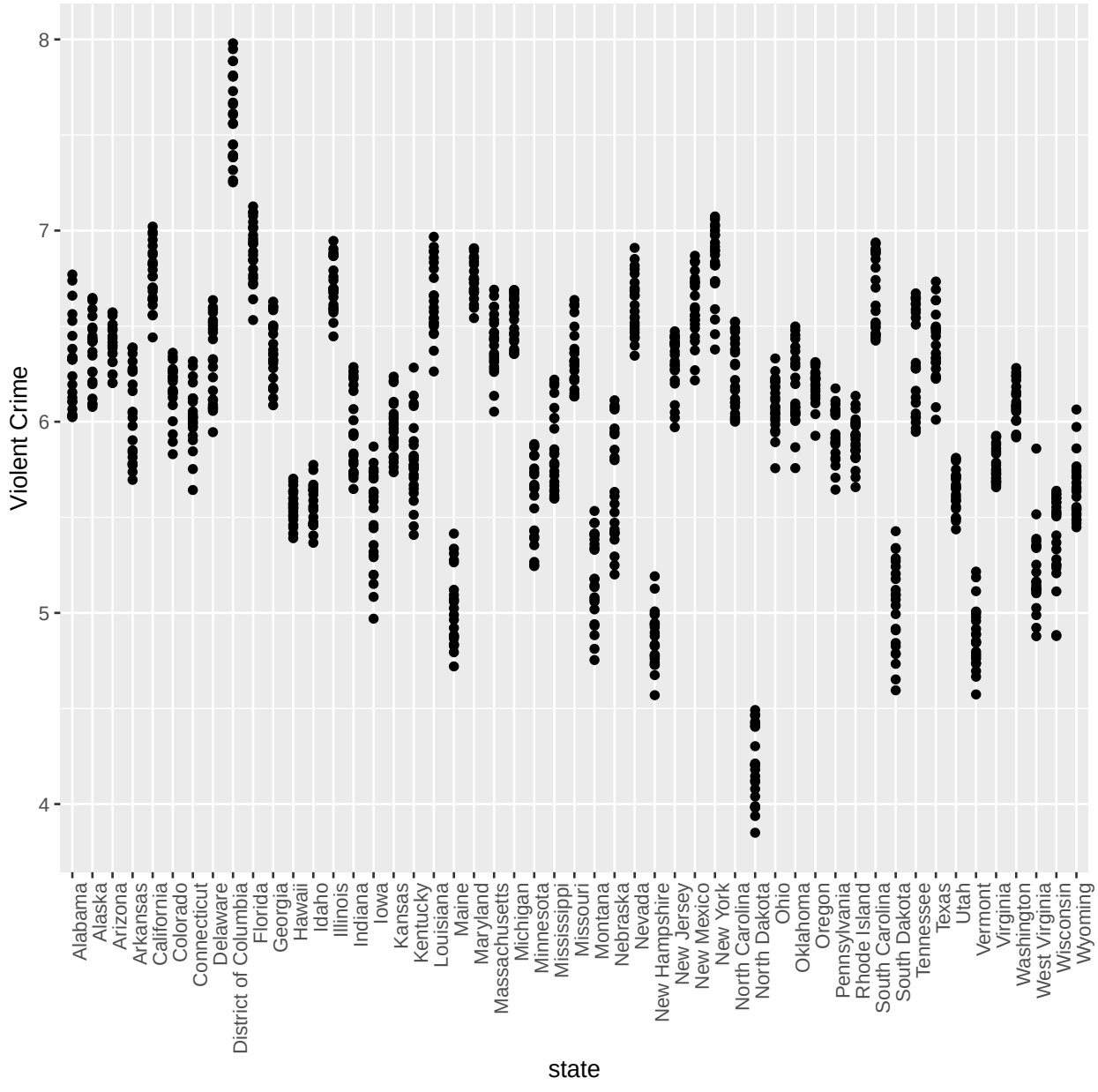
A data frame containing 1,173 observations on 13 variables.

- state: factor indicating state.
- year: factor indicating year.
- violent: violent crime rate (incidents per 100,000 members of the population).
- murder: murder rate (incidents per 100,000).
- robbery: robbery rate (incidents per 100,000).
- prisoners: incarceration rate in the state in the previous year
- afam: percent of state population that is African-American
- cauc: percent of state population that is Caucasian,
- male: percent of state population that is male
- population: state population, in millions of people.
- income: real per capita personal income in the state (US $).
- density population per square mile of land area, divided by 1,000.
- law factor. Does the state have a shall carry law in effect in that year?

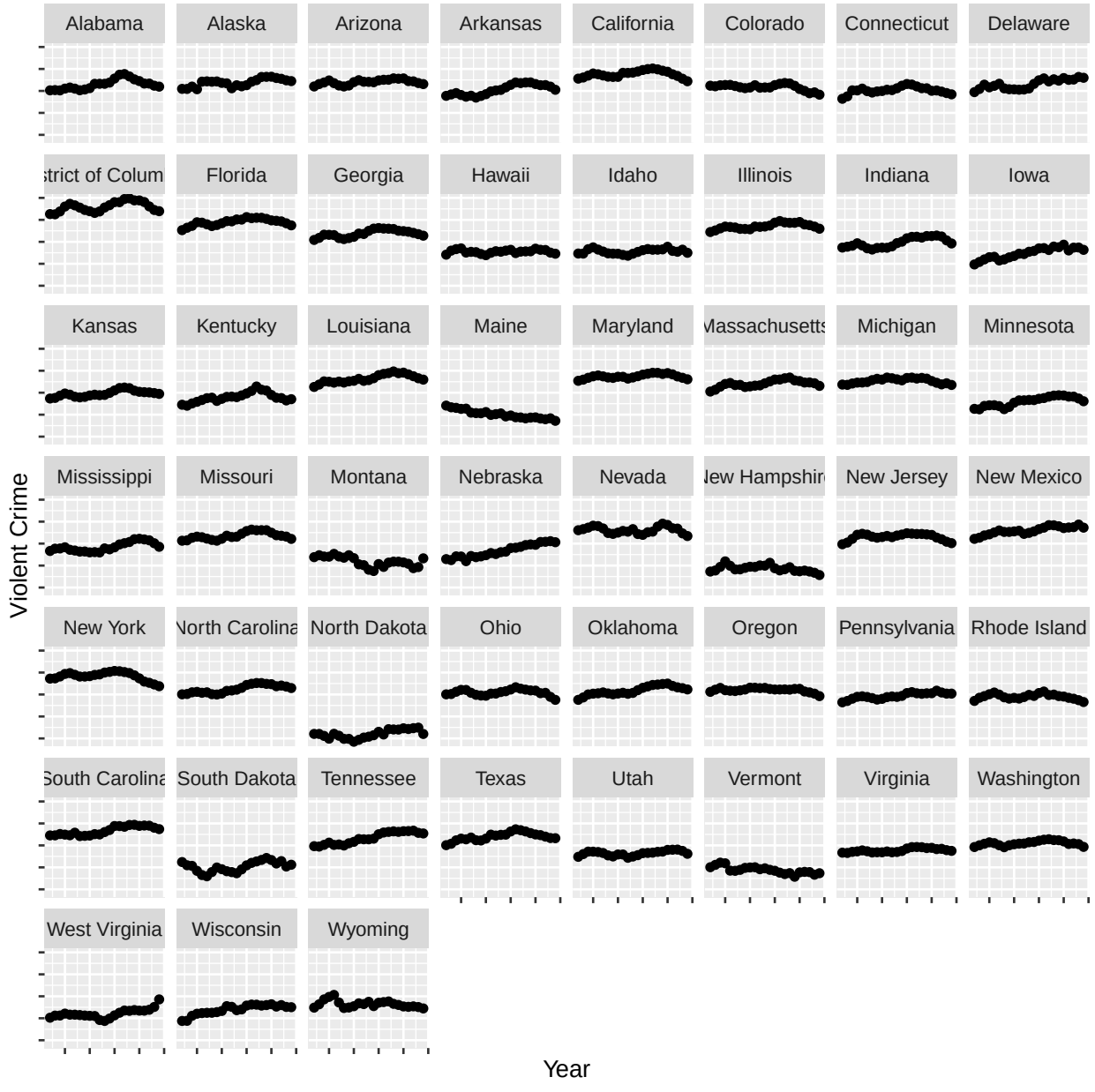
Overtime Variation



Cross-sectional Variation (1)



Cross-sectional Variation (2)



First regressions

	Violent Crime		Robbery	
	Model 1	Model 2	Model 1	Model 2
(Intercept)	6.13^{***}	2.98^{***}	4.87^{***}	0.90
	(0.02)	(0.54)	(0.03)	(0.77)
lawyes	-0.44^{***}	-0.37^{***}	-0.77^{***}	-0.53^{***}
	(0.04)	(0.03)	(0.06)	(0.05)
prisoners		0.00^{***}		0.00^{***}
		(0.00)		(0.00)
density		0.03^{*}		0.09^{***}
		(0.01)		(0.02)
income		0.00		0.00^{***}
		(0.00)		(0.00)
population		0.04^{***}		0.08^{***}
		(0.00)		(0.00)
afam		0.08^{***}		0.10^{***}
		(0.02)		(0.02)
cauc		0.03^{***}		0.03^{*}
		(0.01)		(0.01)
male		0.01		0.03
		(0.01)		(0.02)
R^2	0.09	0.56	0.12	0.60
Adj. R^2	0.09	0.56	0.12	0.59
Num. obs.	1173	1173	1173	1173
RMSE	0.62	0.43	0.90	0.61

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table: Statistical models

Exploiting the Panel Structure

	Model 1	Model 2	Model 3
(Intercept)	4.04^{***}	3.09^{***}	3.97^{***}
	(0.39)	(0.58)	(0.47)
lawyes	-0.05^{*}	-0.29^{***}	-0.03
	(0.02)	(0.03)	(0.02)
prisoners	-0.00	0.00^{***}	0.00
	(0.00)	(0.00)	(0.00)
density	-0.17^{*}	-0.01	-0.09
	(0.09)	(0.01)	(0.08)
income	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
population	0.01	0.04^{***}	-0.00
	(0.01)	(0.00)	(0.01)
afam	0.10^{***}	0.10^{***}	0.03
	(0.02)	(0.02)	(0.02)
cauc	0.04^{***}	0.04^{***}	0.01
	(0.01)	(0.01)	(0.01)
male	-0.05^{***}	-0.04^{*}	0.07^{***}
	(0.01)	(0.02)	(0.02)
State FE	YES	NO	YES
TIME FE	NO	YES	YES
R^2	0.94	0.59	0.96
Adj. R^2	0.94	0.58	0.95
Num. obs.	1173	1173	1173
RMSE	0.16	0.42	0.14

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table: Statistical models