Socio-economic determinants of crime in U.S. states

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1 Research question

Our project studies the socio-economic and demographic determinants of crime in the United States at the state level. More precisely, we ask whether economic opportunities and social inequalities are correlated with different types of crime (violent and property crime) across states and over time.

Crime in the United States exhibits substantial variation across states and over time, and understanding the socio-economic factors that contribute to these differences remains a central question in both economics and public policy. Our project aims to investigate how economic conditions, demographic structure, inequality, public spending, and police behaviour correlate with violent and property crime at the state–year level. The objective is not to establish strict causal relationships—an ambitious task given the observational nature of the data—but rather to document robust associations and explore whether crime levels systematically co-evolve with structural socio-economic indicators.

A first motivation for this research question is the long-standing hypothesis that economic opportunity and crime are linked. Periods of slow economic growth and labour market stress may increase incentives for certain types of offences, particularly property crime. To examine this mechanism, we combine the crime data from the CORGIS/FBI series with annual state GDP from the Bureau of Economic Analysis. GDP provides a measure of overall economic activity and allows us to test whether states experiencing strong or weak economic performance also display different crime patterns.

Income inequality is another potential determinant of criminal activity. The World Inequality Database (WID) provides rich information on income shares and fiscal aggregates at the top and bottom of the distribution. High inequality may generate both economic stress and social fragmentation, potentially amplifying incentives for crime or reducing the perceived legitimacy of institutions. By merging the WID data with the crime series, we can evaluate whether states with higher income concentration or lower fiscal income shares among the majority of the population exhibit systematically different violent or property crime rates.

Migration flows constitute a third dimension of interest. Public debate often assumes—sometimes incorrectly—that immigration influences crime rates. The DHS immigration data enable us to incorporate yearly state-level measures of lawful permanent residents, nonimmigrants, asylees, and refugees. Our goal is not to test politically charged claims, but to empirically examine whether changes in migration patterns are associated with changes in state crime trends once we control for other socio-economic conditions.

In addition, we incorporate information on public expenditure and food assistance (from the Census and USDA Food Environment Atlas), which may proxy for the strength of social safety nets and local investment in welfare-related programmes. States with stronger social services may provide better support for vulnerable populations, potentially mitigating some of the socio-economic pressures that contribute to crime. Including these variables allows us to explore such channels empirically.

Finally, we integrate data on police shootings from the Washington Post database. While this dataset does not measure police activity directly, fatal shootings can serve as a proxy for law-enforcement intensity or tension between police and residents. Investigating whether states with higher levels of fatal shootings also differ in crime trends contributes to a broader understanding of institutional and behavioural dimensions of crime.

How do economic conditions, income inequality, immigration flows, public spending, and police activity correlate with violent and property crime across U.S. states?

2 Brief dataset description

We built our panel by usind nine different sources :

- Crime rates distinguishing violent and property offences, and state population (FBI/CORGIS, 1960–2019) ;
- Income inequality providing top income shares by state (WID, 1960–2018);
- GDP and consumption per capita (BEA Regional Accounts, 1998–2023);
- Unemployment rate (BLS, 1976-2025);
- Prison population (The Sentencing Project, 1980–2022), used to produce data on prison population per 100 000 inhabitants ;
- Poverty rates (Census Bureau, 1980–2023);
- Beer consumption per capita for population aged 14 and older (NIAAA, 1970–2022);
- Immigration flows covering legal residents, refugees and asylees (DHS, 2013–2023);
- Police shootings (Washington Post, 2015–2024);
- Public spending on education, welfare, health, corrections and police (Census Bureau, 2017–2023);
- Food assistance participation (USDA Food Environment Atlas, 2012-2023).

Full descriptions are provided in the data cleaning document (Phase 2).

3 Data analysis

Our empirical analysis is divided into two parts, reflecting the heterogeneous temporal coverage of our sources.

The crime, inequality, GDP, consumption, unemployment, prison population, poverty, and alcohol series provide consistent state-year observations between 1998-2018. It allows us to examine the structural relationships between economic conditions and crime using fixed effects panel regressions.

In contrast, immigration flows (2013–2018), police shootings (2015–2018), public spending (2017–2018) and food access (2012-2023) are only available for recent years. Rather than discarding these valuable contemporary indicators, we adopt a two-stage approach: we first exploit the full historical depth of our panel to study structural relationships between economic conditions and crime, then narrow the window to a shorter period to incorporate additional explanatory factors in a richer, shorter-term analysis.

3.1 Long-run analysis (1998–2018)

3.1.1 Descriptive analysis

3.1.1.1 National long-run trends in crime (1998-2018)

To establish a benchmark for the subsequent analysis, we first document the long-run evolution of violent and property crime across U.S. states. Figure 1 displays the average crime rate across states together with the 10th–90th percentile range, providing a synthetic view of both aggregate dynamics and cross-state heterogeneity.

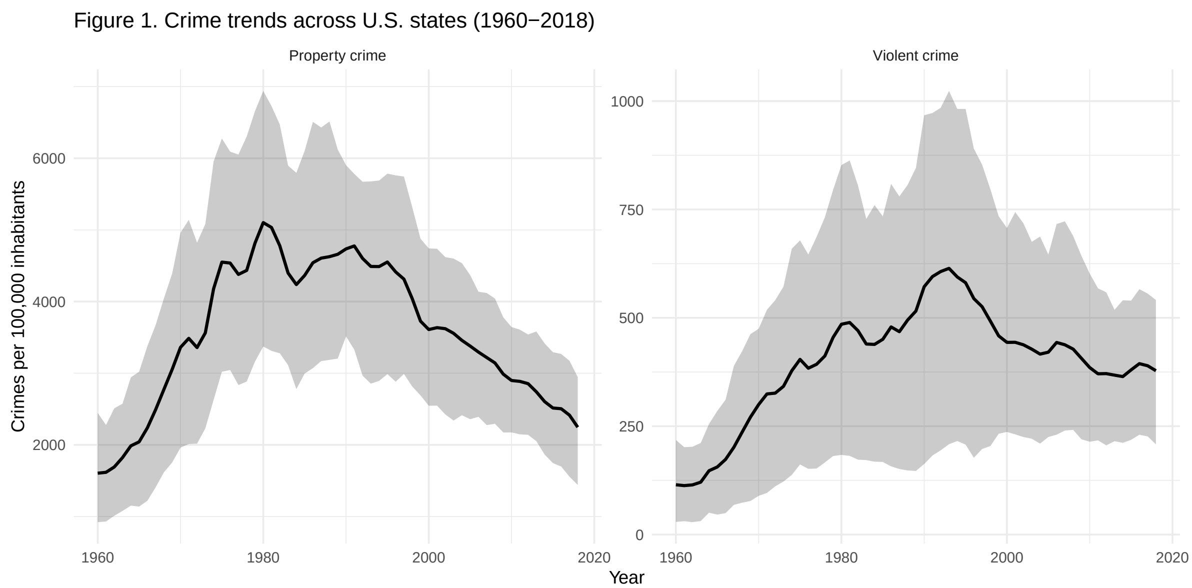


Figure 1: National crime trends and cross-state dispersion (mean and 10th–90th percentiles, 1960–2018)

Both crime categories exhibit a pronounced common time profile, with a strong increase from the 1960s to the late 1980s or early 1990s, followed by a sustained decline. Despite these shared national trends, cross-state heterogeneity remains large throughout the entire period, as illustrated by the wide percentile bands.

Property crime displays a particularly strong rise and fall, whereas violent crime peaks later and declines more gradually, suggesting distinct underlying mechanisms. The persistence of substantial dispersion across states indicates that national trends alone cannot account for observed crime dynamics and highlights the relevance of state-specific factors. These descriptive findings motivate the use of panel models with both state and time fixed effects in the subsequent analysis.

Due to data availability constraints, our focus will be on the period 1998-2018, in the midst of a crime decline in the US states.

3.1.1.2 Evolution of violent crime and property crime among high-crime states

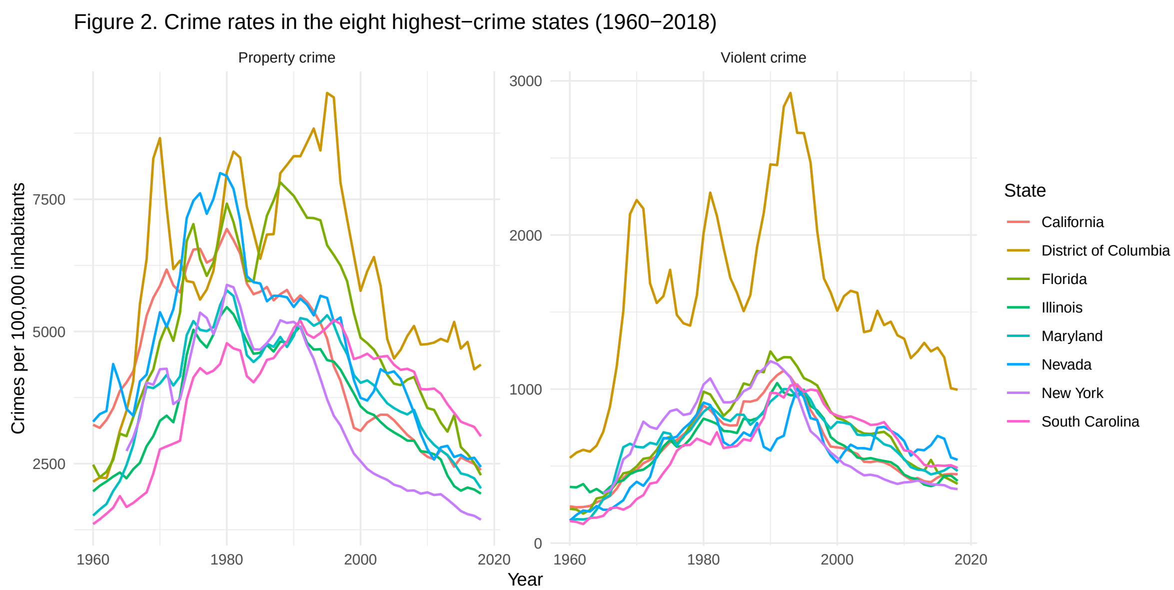


Figure 2: Violent and property crime rates in the eight highest-crime U.S. states (1960–2018)

Figure 2 displays the crime trends for the eight states with the highest crime rate per 100 000 inhabitants between 1960 and 2018. Despite differences in levels, all states exhibit similar trends : a strong increase until the late 1980s or early 1990s, followed by a sustained decline

At the same time, cross-state heterogeneity remains pronounced. The District of Columbia stands out, both for its higher levels and for its volatility, <hich might reflect its unique urban and institutional characteristics. This makes it difficult to compare it with US states. While it is included in this descriptive analysis, it is excluded from the regression sample due to missing values for key variables.

3.1.1.3 Descriptive co-movement with economic structure

Figure 3: Raw co-movement between crime and GDP (pooled state–year observations)

The pooled scatter plot reveals a clear non-linear relationship between property crime and state GDP. At low to intermediate levels of GDP, property crime rates tend to increase, before declining for higher levels of economic activity. The downward-sloping segment at higher GDP levels suggests that economically stronger states tend to experience lower property crime rates, consistent with the hypothesis that improved economic opportunities reduce incentives for financially motivated offences. The dispersion of observations around the fitted curve remains substantial, indicating that GDP alone cannot account for cross-state differences in property crime.

In contrast, the relationship between violent crime and GDP is markedly weaker. While violent crime rates increase sharply at low GDP levels, the association flattens and becomes less systematic as GDP rises. At higher levels of economic activity, violent crime exhibits no clear monotonic decline. This pattern suggests that violent crime is less directly tied to economic performance than property crime and is likely driven by additional social, institutional, and demographic factors.

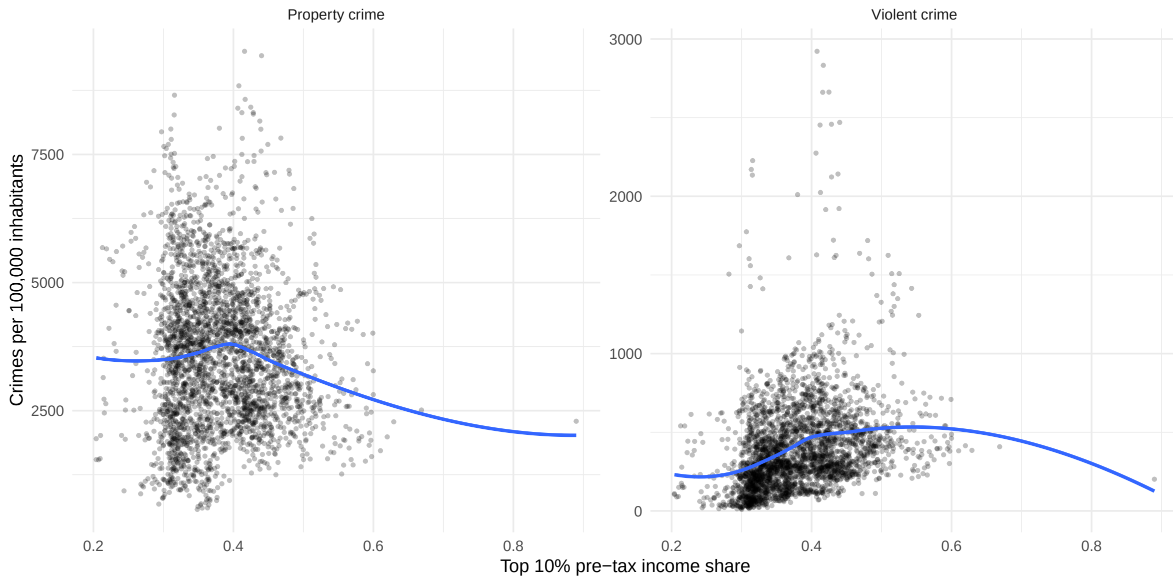


Figure 4: Raw co-movement between crime and income inequality (pooled state–year observations)

The relationship between property crime and income inequality is non-linear and noisy. Property crime rates are highest at intermediate levels of inequality and decline at the upper end of the income share distribution. This inverted-U pattern suggests that inequality may matter for property crime, but its effect is neither simple nor monotonic. The wide dispersion of observations highlights the importance of unobserved state-specific characteristics.

Violent crime displays a more pronounced association with inequality. Crime rates increase strongly as the top income share rises from low to intermediate levels, before declining slightly at very high levels of inequality. This pattern is consistent with theories linking violent crime to social fragmentation, relative deprivation, and institutional stress, rather than purely economic incentives.

Figure 5: Raw co-movement between crime and unemployment rate (pooled state–year observations)

Figure 6: Raw co-movement between crime and percentage of poor (pooled state–year observations)

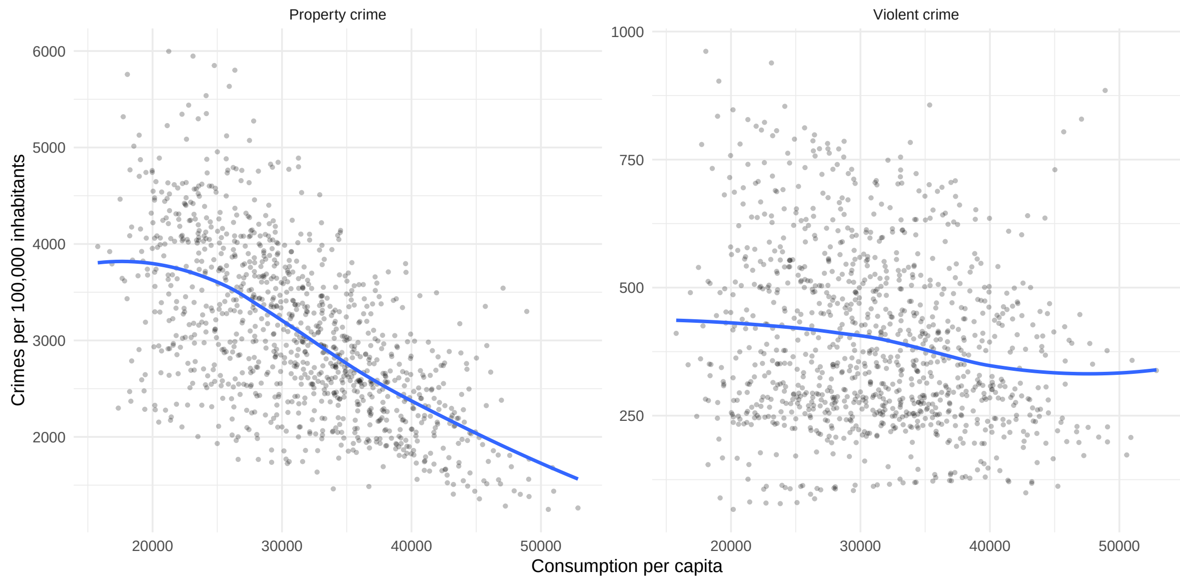


Figure 7: Raw co-movement between crime and consumption per capita (pooled state–year observations)

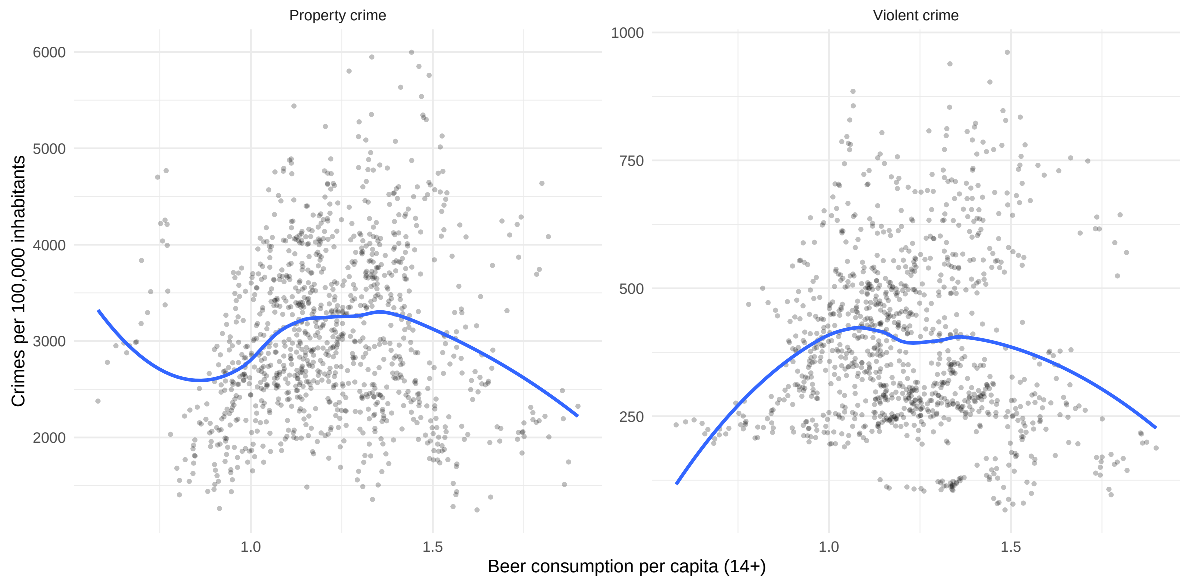


Figure 8: Raw co-movement between crime and beer consumption per capita for people aged 14 and above (pooled state–year observations)

Figure 9: Raw co-movement between crime and prison population per 100 000 inhabitants (pooled state–year observations)

These 5 figures presents pooled scatter plots relating crime rates to key socio-economic variables across state-year observations. **CONTINUE**

3.1.2 Regression analysis

Taken together, the descriptive evidence suggests that crime rates in U.S. states co-evolve with economic conditions and income inequality, but that these relationships are heterogeneous and potentially confounded by persistent state-specific characteristics and common national shocks. To account for these factors and move beyond raw correlations, we now estimate panel regressions with state and year fixed effects, which exploit within-state variation over time while controlling for unobserved heterogeneity.

3.1.2.1 Hypotheses

We test the following hypotheses:

- **H1 (opportunity cost)** : Higher GDP and lower unemployment are associated with lower crime rates, particularly for property crime.
- **H2 (inequality)** : Greater income concentration at the top of the distribution is associated with higher crime rates.

- **H3 (deterrence)** : Larger prison populations are associated with lower crime rates because of incapacitation of criminals.
- **H4 (alcohol as a criminogenic factor)** : Higher alcohol consumption is associated with higher violent crime rates.
- **H5 (crime persistence)** : Crime rates exhibit temporal inertia, i.e. past crime is a strong predictor of current crime (it encourages or discourages entry, it owerwhelms law enforcers…).

We estimate different models for property and violent crime, as property crime is more directly linked to economic incentives (Becker, 1968), while violent crime may be more linked to specific social factors.

3.1.2.2 Tests

Before presenting our results, we conduct a series of tests to validate our approach.

The first question is whether state-level heterogeneity exists. We test this using two complementary approaches.

```
    F test for individual effects

data:  Data.Rates.Property.All ~ log_gdp + share_pretax_income_p90p100 +  ...
F = 148.9, df1 = 49, df2 = 995, p-value < 2.2e-16
alternative hypothesis: significant effects


    Lagrange Multiplier Test - (Breusch-Pagan)

data:  Data.Rates.Property.All ~ log_gdp + share_pretax_income_p90p100 +  ...
chisq = 3047.7, df = 1, p-value < 2.2e-16
alternative hypothesis: significant effects
```

The F-test compares the fixed effects model against pooled OLS. The null hypothesis is that all state fixed effects are jointly equal to zero ($H_0 = \alpha_1 = ... = \alpha_2$). We obtain $F = 148.9$ with $p < 0.001$. Thus, the F-test strongly rejects the null hypothesis that state fixed effects are jointly zero, indicating that pooled OLS is inappropriate.

The Breusch-Pagan Lagrange Multiplier test provides a complementary check. It tests whether the variance of individual effects is zero ($H_0 : \sigma_\alpha^2 = 0$). We obtain $\chi^2 = 3047.7$ with $p < 0.001$, which allows us to reject the null hypothesis.

These tests confirm that individual effects are present and statistically significant. Having established that, we still have to choose between random effects and fixed effects. To do so, we use the Hausman test :

```
	Hausman Test

data:  Data.Rates.Property.All ~ log_gdp + share_pretax_income_p90p100 +  ...
chisq = 595.87, df = 5, p-value < 2.2e-16
alternative hypothesis: one model is inconsistent
```

Under H_0, both fixed effects and random effects are consistent, but random effects is more efficient ; under H_1, only fixed effects is consistent. We obtain $\chi^2 = 595.9$ with $p < 0.001$, so we can reject H_0.

This indicates that state-specific effects are correlated with our explanatory variables (GDP, inequality, etc.), which makes sense since wealthier states likely have different unobserved characteristics than poorer states.

Next, we test for autocorrelation and heteroscedasticity. Because of the nature of crime according to our hypothesis (persistence), and of our explanatory variables (GDP, inequalities, prison population, etc change slowly over time), we may expect serial correlation. Moreover, heteroscedasticity is also plausible given the variation in state size and crime levels. Smaller states might experience more volatility in their crime rates because small absolute changes translate into large percentage changes.

```
	Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data:  Data.Rates.Property.All ~ log_gdp + share_pretax_income_p90p100 +  ...
chisq = 527.44, df = 1, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

```
	studentized Breusch-Pagan test

data:  model_fe
BP = 30.514, df = 5, p-value = 1.168e-05
```

The specification tests reveal two issues, serial correlation and heteroscedasticity. They do not bias our coefficient estimates but invalidate classic standard errors, potentially leading to misleading significance levels. So, we compute robust standard errors, clustered at the state level, and compare them with the correlated and heterodastic standard errors.

Table 1: Comparison of classical vs robust standard errors

Variable	Coefficient	SE_classical	SE_robust	t_classical	t_robust	p_classical	p_robust
log_gdp	-1509.764	47.372	169.348	-31.870	-8.915	0.000	0.000
share_pretax_income_p90p100	-422.110	388.825	710.335	-1.086	-0.594	0.278	0.552
unemployment_rate	-9.029	5.330	6.629	-1.694	-1.362	0.091	0.173
prison_per_100k	0.997	0.248	0.610	4.017	1.633	0.000	0.103
beer_per_capita_14plus	1833.486	132.857	457.610	13.800	4.007	0.000	0.000

Classical standard errors are 1.2 to 3.5 times smaller than robust standard errors, leading to inflated significance levels. For instance, prison population per 100 000 inhabitants appears significant with classical errors ($p < 0.001$) but becomes non-significant with robust errors ($p = 0.103$). Given these findings, all subsequent results use robust standard errors clustered by state.

Finally, we test for multicolinearity, using Variance Inflation Factors (VIF).

```
                   log_gdp                Consumption
                 92.901483                   5.668568
         unemployment_rate               percent_poor
                  1.396563                   1.898890
share_pretax_income_p90p100            prison_per_100k
                  1.563210                   1.688072
     beer_per_capita_14plus                    log_pop
                  1.320346                  86.251748
```

We do not include GDP, consumption and population simultaneously because of the multicollinearity it clearly introduces. Instead, we will estimate alternative specifications to assess which measure is most strongly associated with crime (see following models).

```
                   log_gdp share_pretax_income_p90p100
                  3.528817                    1.423004
         unemployment_rate            prison_population
                  1.366185                    2.737626
              percent_poor       beer_per_capita_14plus
                  1.399074                    1.381321
```

```
              log_pop share_pretax_income_p90p100
             3.325121                    1.331888
    unemployment_rate            prison_population
             1.351089                    2.813038
         percent_poor      beer_per_capita_14plus
             1.353427                    1.335839

          Consumption share_pretax_income_p90p100
             1.290803                    1.474395
    unemployment_rate            prison_population
             1.376565                    1.277906
         percent_poor      beer_per_capita_14plus
             1.484120                    1.124169
```

Without consumption, population, and GDP being included simultaneously, all VIF values are below 5, the conventional threshold for concern, so our explanatory variables are sufficiently independent.

Table 2: Model specification tests

Test	Statistic	P_value	Decision
F-test (Pooled vs FE)	148.89854	< 0.001	FE needed
Breusch-Pagan LM	3047.74448	< 0.001	Individual effects exist
Hausman (FE vs RE)	595.87355	< 0.001	FE preferred
Breusch-Godfrey (autocorr.)	527.44225	< 0.001	Autocorrelation present
Breusch-Pagan (heterosced.)	30.51393	< 0.001	Heteroscedasticity present

3.1.2.3 Models with fixed effects

Our objective is to document robust correlations between socio-economic variables and crime rates, not to establish causal effects. Considering our tests conclusions, we employ fixed effects panel regressions to control for time-invariant state characteristics.

We estimate five panel specifications with state fixed effects to assess the robustness of our findings. All models use robust standard errors clustered by state to account for serial correlation and heteroscedasticity.

Model 1 (Baseline) includes log GDP, income inequality, unemployment rate, prison population per capita, beer consumption, and log population. This specification tests the baseline correlations between economic conditions and crime.

$$\begin{aligned} Crime_{it} = \alpha_i &+ \beta_1 \log(GDP_{it}) + \beta_2 \cdot Inequality_{it} \\ &+ \beta_3 \cdot Unemployment_{it} + \beta_4 \cdot Prison_{it} \\ &+ \gamma_1 \cdot Beer_{it} + \gamma_2 \cdot \log(Pop_{it}) + \epsilon_{it} \end{aligned}$$

where α_i denotes state fixed effects. The coefficients are identified from within-state variation over time.

We measure inequalities by using the share of pre-tax income accruing to the top 10% of the distribution, as provided by the World Inequality Database. A higher share indicates greater income concentration at the top, which could be associated with increased social tension and crime rates (Fajnzylber, Lederman, and Loayza, 2002).

Model 2 (Consumption) replaces $log(GDP)$ by $Consumption$. While GDP measures the size of the state economy, per capita consumption better captures household living standards. Comparing the two allows us to assess which dimension of economic conditions matters most for crime.

$$\begin{aligned} Crime_{it} = \alpha_i &+ \beta_1 \log(Consumption_{it}) + \beta_2 \cdot Inequality_{it} \\ &+ \beta_3 \cdot Unemployment_{it} + \beta_4 \cdot Prison_{it} \\ &+ \gamma_1 \cdot Beer_{it} + \gamma_2 \cdot \log(Pop_{it}) + \varepsilon_{it} \end{aligned}$$

Model 3 (Population) replaces $log(GDP)$ by $log(Pop)$, to test whether the size of the state population is associated with property crime. This allows to compare the influence of the total population per state to the GDP.

$$\begin{aligned} Crime_{it} = \alpha_i &+ \beta_1 \log(Pop_{it}) + \beta_2 \cdot Inequality_{it} \\ &+ \beta_3 \cdot Poverty_{it} + \beta_4 \cdot Prison_{it} \\ &+ \gamma_1 \cdot Beer_{it} + \varepsilon_{it} \end{aligned}$$

Model 4 (Dynamic) adds lagged crime as an explanatory variable to test the persistence hypothesis (H5) (i.e., the tendency of high-crime states to remain high-crime). If crime exhibits inertia, the lagged coefficient should be positive and significant. We acknowledge that including a lagged dependent variable in fixed effects models may introduce Nickell bias, which attenuates the coefficient toward zero when T is small. With T = 20 years, this bias is modest but not negligible.

$$\begin{aligned} Crime_{it} = \alpha_i &+ \theta \cdot Crime_{i,t-1} + \beta_1 \log(GDP_{it}) \\ &+ \beta_2 \cdot Inequality_{it} + \beta_3 \cdot Unemployment_{it} \\ &+ \beta_4 \cdot Prison_{it} + \gamma_1 \cdot Beer_{it} \\ &+ \gamma_2 \cdot \log(Pop_{it}) + \varepsilon_{it} \end{aligned}$$

Model 5 (Two-ways) adds year fixed effects (δ_t) to control for national trends affecting all states simultaneously (e.g., federal policies, economic cycles).

$$\begin{aligned} Crime_{it} = \alpha_i + \delta_t + \theta \cdot Crime_{i,t-1} \\ + \beta_1 \log(GDP_{it}) + \beta_2 \cdot Inequality_{it} \\ + \beta_3 \cdot Unemployment_{it} + \beta_4 \cdot Prison_{it} \\ + \gamma_1 \cdot Beer_{it} + \gamma_2 \cdot \log(Pop_{it}) + \varepsilon_{it} \end{aligned}$$

3.1.2.4 Results

This table condensates all of our regression results for property crime :

	Model 1	Model 2	Model 3	Model 4	Model 5
Log GDP	−1509.732***			−244.226***	−104.716
	(169.415)			(69.330)	(173.391)
Inequality (top 10%)	−421.245	−670.438	−2516.508*	−384.190	−155.350
	(716.024)	(682.399)	(1207.310)	(275.499)	(213.868)
Unemployment rate	−8.948	−9.638	2.247	4.756	1.026
	(7.571)	(8.151)	(9.708)	(2.979)	(8.524)
Prison per 100k	0.997	0.313	0.258	0.069	−0.113
	(0.611)	(0.694)	(0.639)	(0.206)	(0.212)
Beer consumption	1833.025***	1908.015***	1595.683**	454.270**	226.185
	(453.305)	(407.773)	(524.056)	(144.527)	(139.668)
percent_poor	−0.142	0.665	−5.603	−4.088	−2.941
	(7.219)	(7.655)	(8.386)	(3.569)	(3.903)
Consumption		−0.061***			
		(0.006)			
log_pop			−4954.541***		
			(759.530)		
Property crime (t-1)				0.795***	0.811***
				(0.023)	(0.021)
Num.Obs.	1050	1050	1050	1000	1000
R2	0.761	0.752	0.681	0.917	0.716

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Robust standard errors clustered by state are in parenthesis

This table presents the results of our 5 models for property crime, using robust standard errors clustered by state to account for serial correlation and heteroscedasticity.

The variable `log_gdp` shows a strong and consistent negative correlation with property crime. For instance, in the baseline model, a 10% increase in per state GDP is associated to about 151 fewer property crimes per 100 000 inhabitants ($\beta = -1.510$, $p < 0.001$). This effect is attenuated but remains significant when controlling for crime persistence in Model 4 ($\beta = -244$, $p < 0.001$), and becomes non-significant in the two-way fixed effects specification in Model 5, $\beta = -105$, $p > 0.05$). This suggests that the crime-GDP relationship reflects national trends rather than state-specific dynamics.

Personal consumption expenditures, tested as an alternative measure to GDP in Model 2, shows a significant but smaller negative correlation ($\beta = -0.061$, $p < 0.001$). This confirms that household living standards, not just aggregate output, are negatively associated with property crime.

Neither unemployment rate nor poverty rate shows a significant correlation with property crime after controlling for other factors. In a similar fashion, the prison population per 100 000 inhabitants is not significantly correlated to property crime. These null findings contrasts with theoretical expectations. For unemployment, it is not consistent with the literature that shows that, during the 1990s, unemployment dropping caused, in part, an decrease in property crimes (Raphael & Winter-Ebmer, 2001).

Beer consumption per capita is positively and significantly correlated with property crime across all specifications, from $\beta = 1.833$ ($p < 0.001$) in Model 1 to $\beta = 226$ ($p > 0.05$) in Model 5. The attenuation in Model 5 could be linked to the absorption of common trends by year fixed effects.

The lagged crime rate is the strongest predictor in dynamic specifications : in Model 4, a one-unit increase in the previous year's property crime rate is associated with a 0.80-unit increase in the current rate ($\rho = 0.795$, $\theta < 0.001$). This coefficient remains stable in Model 5 ($\theta = 0.811$, $p < 0.001$), confirming substantial crime inertia.

The baseline model explains 76% of within state variation ($R^2 = 0.761$). Adding lagged crime in models 4 and 5 increases R^2 up to 91%, indicating that past crime is a powerful predictor of current crime.

Thus, for property crime, GDP and consumption are negatively correlated with property crime, which partially confirms our first hypothesis. Alcohol consumption is positively correlated with property crime, supporting H_4. Finally, the crime persistence hypothesis (H_5) is strongly supported by our results.

This second table condensates our results for violent crimes :

	Model 1	Model 2	Model 3	Model 4	Model 5
Log GDP	−34.680			8.430	−11.871
	(27.265)			(5.687)	(14.819)
Inequality (top 10%)	−194.683	−187.984	−241.940	15.952	7.167
	(140.576)	(144.638)	(131.145)	(40.477)	(43.797)
Unemployment rate	−9.234***	−9.210***	−8.969***	−2.792***	0.049
	(2.131)	(2.156)	(1.994)	(0.629)	(0.974)
Prison per 100k	0.333*	0.318*	0.316*	0.079	0.043
	(0.135)	(0.134)	(0.135)	(0.043)	(0.041)
Beer consumption	224.109**	221.493***	218.109***	17.271	7.407
	(69.309)	(67.062)	(63.285)	(29.765)	(28.039)
percent_poor	−0.717	−0.683	−0.843	−0.939	−1.302*
	(1.813)	(1.813)	(1.813)	(0.754)	(0.658)
Consumption		−0.002			
		(0.001)			
log_pop			−115.069		
			(112.220)		
Violent crime (t-1)				0.833***	0.877***
				(0.031)	(0.032)
Num.Obs.	1050	1050	1050	1000	1000
R2	0.315	0.317	0.312	0.828	0.812

* p < 0.05, ** p < 0.01, *** p < 0.001

Robust standard errors clustered by state are in parenthesis

The first three models fail to significantly predict violent crime rates as they explain only about 31% of within-state variation ($R^2 = 0.31$), which is substantially less than for property crime ($R^2 \approx 0.76$). This might indicate that violent offences are driven by factors beyond economic conditions alone.

Unlike property crime, `log_gdp` shows no significant correlation with violent crime. Personal consumption is also non-significant. These findings imply that violent crimes are less motivated by economic need than property crimes, and might be more likely to be driven by conflicts or social disorganization.

Interestingly, unemployment rate is significantly and negatively correlated with violent crime in Models 1-4 ($p < 0.001$). This could capture omitted variable bias.

The top 10% income share is not significantly correlated with violent crime ($p > 0.05$ in all models), contrary to theoretical predictions linking inequality to social tension and violence.

Prison population per 100,000 inhabitants shows a small but positive and significant correlation with violent crime ($ 3.2 $, $p < 0.05$ in Models 1-3). This might not imply that incarceration fail to decrease crime, but could reveal reverse causality issues, as states with higher violent crime rates incarcerate more people.

As for beer consumption, it is again strongly and positively correlated with violent crime.

It's interesting to notice that adding lagged crime dramatically improves the models' fit ($R^2 \approx 0.8$ in model 4 and 5). The crime persistence coefficient is large and highly significant ($\theta = 0.833$). It indicates that violent crime exhibits even stronger inertia than property crime. Indeed, holding other factors constant, a state with 100 more violent crimes per 100 000 the past year will have 83 more violent crime the following year. But in these models, almost all variables that previously were significant lose their significance. This might indicate that their effect was linked to crime inertia. In the two-way fixed effect model (Model 5), only poverty remains slightly significant aside from lagged crime, but it has a negative coefficient.

Our estimates capture associations, not causal effects. Indeed, high crime may reduce GDP or increase prison population, which implies reverse causality. Moreover, there are omitted variables in our work, for instance time-varying factors like policing strategies, population structure and demographic shift may confound our estimates.

3.2 Short-run analysis (2015–2018) - Contemporary correlates of crime

3.2.1 Descriptive analysis

3.2.1.1 Descriptive overview of crime and new covariates

We start the short-run analysis by describing crime rates and contemporaneous socio-economic variables over the period 2015–2018, which corresponds to the years for which the richest set of covariates is jointly available. Given the short time dimension, the objective is to document cross-state variation rather than long-run trends.

Table 3: Summary statistics, short-run panel (2015–2018)

variable	N	Mean	SD	P10	Median	
Violent crime rate (per 100k)	204	385.38	179.59	217.87	360.90	
Property crime rate (per 100k)	204	2419.80	672.01	1573.97	2428.65	
Log GDP	204	12.30	1.04	10.92	12.29	
Top 10% pretax income share	204	0.46	0.05	0.41	0.46	
Lawful permanent residents per million	204	2480.04	1553.79	952.88	2043.32	
Police shootings per million	201	3.57	2.23	1.39	3.01	
Public spending: education	102	20243296.58	24730036.07	3067044.90	13495795.00	3936
Public spending: welfare	102	13560265.53	19210452.25	2406766.90	7986219.50	2863
Public spending: health	102	2060307.16	3696803.27	273763.20	871195.50	433
Public spending: corrections	102	1577760.88	2368807.34	226187.10	788440.00	275

Public spending: police	102	2276882.65	3282188.59	334300.60	1304563.50	387
WIC participants (2015)	204	128.33	149.49	14.00	98.00	
School lunch participants (2015)	204	307.67	259.14	1.00	280.00	
School breakfast participants (2015)	204	202.71	177.15	24.00	180.00	
Unemployment rate (%)	204	4.40	1.08	3.00	4.38	
Poverty rate (%)	204	12.25	3.04	8.70	11.75	
Prison population (per 100k)	200	376.72	140.15	203.96	369.07	
Beer consumption per capita	204	1.13	0.22	0.90	1.11	

During this period, violent crime averages 385 incidents per 100,000 inhabitants, while property crime is substantially more prevalent, with an average of 2,420 incidents per 100,000 inhabitants. Both indicators display considerable dispersion across states, especially property crime, highlighting strong heterogeneity in crime exposure even in recent years.

Economic conditions vary moderately across states. Log GDP shows limited dispersion, while income concentration, measured by the top 10% pre-tax income share, averages 46%, with meaningful cross-state variation. Labour market conditions appear relatively favourable on average, with unemployment rates around 4.4%, but poverty remains persistent, affecting roughly 12% of the population.

Migration intensity and police-related variables also differ markedly across states. States host on average 2,480 lawful permanent residents per million inhabitants, while police shootings occur at a rate of about 3.6 per million, with substantial dispersion. These differences motivate their inclusion as potential correlates of crime.

Public spending and social programme indicators (education, welfare, health, corrections, police, and food assistance) exhibit large variability but are available only for a subset of observations, reflecting the short coverage of these datasets. Institutional and behavioural factors further show heterogeneity, with prison populations averaging 377 inmates per 100,000 inhabitants and beer consumption per capita displaying moderate cross-state variation.

3.2.1.2 Contemporary heterogeneity and structural correlates (2015–2018)

To further explore cross-state heterogeneity in the short run, we group state–year observations into quartiles of violent crime intensity and compare average socio-economic and institutional characteristics across these groups. Given the limited time dimension, this exercise is purely descriptive and aims to highlight contemporaneous correlations rather than dynamic effects.

Tab

violent_quartile	Mean_violent_crime	Mean_property_crime	Log_GDP	Inequality_top10	LPR_pe
Low crime	210.95	1867.70	11.73	0.45	
Mid-low	304.23	2334.94	12.43	0.45	

Mid-high	409.25	2387.05	12.89	0.48
High crime	617.10	3089.50	12.14	0.47

Tab

property_quartile	Mean_property_crime	Mean_violent_crime	Log_GDP	Inequality_top10	LPR_p
Low crime	1617.99	256.91	12.21	0.48	
Mid-low	2118.10	324.05	12.27	0.44	
Mid-high	2677.65	429.27	12.56	0.47	
High crime	3265.47	531.31	12.15	0.46	

States in the highest violent crime quartile experience, on average, nearly three times the violent crime rate of those in the lowest quartile, and also display substantially higher property crime rates. These high-crime states are characterised by worse labour market and social conditions, with unemployment rates exceeding 5% and poverty rates above 14%, compared to about 3.9% unemployment and 10.5% poverty in low-crime states.

Institutional and behavioural indicators also differ markedly across quartiles. Prison populations increase monotonically with violent crime intensity, rising from about 293 inmates per 100,000 inhabitants in low-crime states to over 470 per 100,000 in high-crime states. Police shootings per million inhabitants are almost twice as high in the highest violent crime quartile, suggesting higher levels of police–citizen confrontation or enforcement intensity in these states.

A similar pattern emerges when states are grouped by property crime quartiles. High property crime states combine higher violent crime rates, higher poverty, larger prison populations, and substantially more police shootings per capita. In contrast, differences in beer consumption per capita are relatively small across quartiles, suggesting that alcohol consumption varies less systematically with crime intensity in the short run.

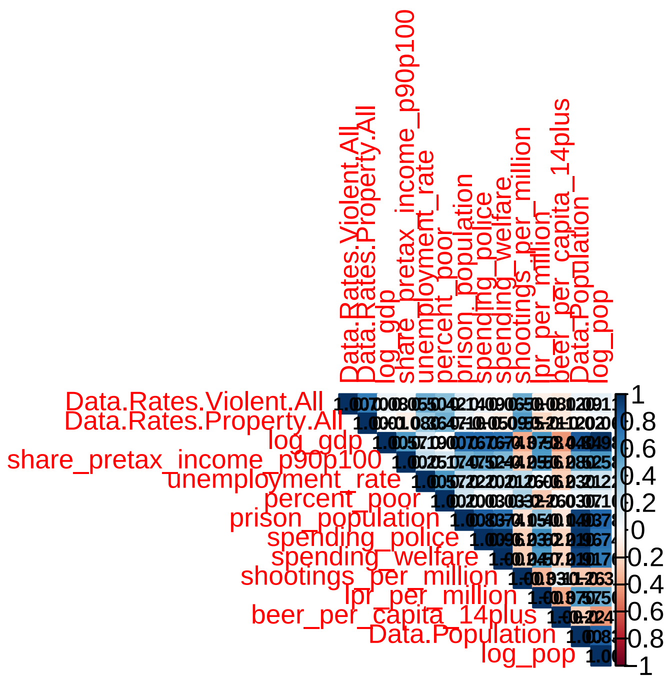
Public spending and food assistance indicators show considerable dispersion but no clear monotonic pattern across quartiles, reflecting both institutional heterogeneity and the limited availability of these variables in the short-run sample.

Overall, this quartile-based comparison indicates that, even over a short horizon, states with higher crime rates tend to be characterised by greater economic stress, higher incarceration rates, and more intense police activity. These patterns motivate the regression analysis that follows, which formalises these associations while controlling for multiple dimensions simultaneously.

3.3 Regression analysis

Because the short-run panel only covers four years (2015–2018), we begin with a purely exploratory correlation analysis. The objective is not statistical inference, but rather to provide a preliminary overview of how violent and property crime co-move with a broad set of socio-economic and institutional variables, and to motivate a parsimonious and structured regression design.

Using the short-run panel, we compute pairwise correlations between crime rates and selected economic, social, and institutional indicators, including GDP, income inequality, unemployment, poverty, prison population, police activity, public spending, immigration, and alcohol consumption. The resulting correlation matrix is summarized using a heatmap.



The correlation matrix highlights several systematic associations. Both violent and property crime rates are positively correlated with poverty, unemployment, and prison population, suggesting that states facing greater economic stress and social vulnerability tend to exhibit higher crime levels. Crime is also positively associated with police shootings per million inhabitants, indicating that high-crime environments coincide with more frequent lethal encounters between police and civilians.

In contrast, log GDP is negatively correlated with crime, consistent with the idea that stronger economic activity is associated with lower crime exposure. Inequality, measured by the top 10% pretax income share, displays a weaker but positive correlation with crime, suggesting that income concentration may matter primarily through broader socio-economic conditions.

Institutional variables exhibit particularly strong correlations among themselves. Prison population, police spending, and welfare spending are highly correlated, reflecting the joint evolution of enforcement intensity and public intervention across states. This pattern cautions against including all institutional variables simultaneously in a short panel setting, as multicollinearity would substantially inflate standard errors.

Overall, the correlation structure points to two related but distinct dimensions: economic stress (income, unemployment, poverty, inequality) and institutional or enforcement intensity (incarceration, policing, public safety spending). This motivates a structured regression strategy.

3.3.1 Hypotheses

We focus on four short-run hypotheses, mapped directly into two model blocks:

- **H1 (economic stress)**: States experiencing worse economic conditions—higher unemployment and poverty—exhibit higher crime rates, especially property crime.
- **H2 (inequality)**: Higher income concentration at the top of the distribution is associated with higher crime rates.
- **H3 (institutional stress)**: Higher incarceration levels and policing activity are associated with different crime patterns, reflecting enforcement intensity rather than deterrence per se.
- **H4 (behavioral factors)**: Higher alcohol consumption is positively associated with violent crime.

(H1–H2 are tested in the economic stress model; H3–H4 in the institutional model.)

3.3.2 Economic stress model (pooled OLS + year FE)

Given the short time dimension, we use a parsimonious pooled OLS specification and include year fixed effects to absorb nationwide shocks common to all states.

$$Crime\_it = \beta_0 + \beta_1 log(GDP_{it}) + \beta_2 Unemployment_{it} + \beta_3 Poverty_{it} + \beta_4 Inequality_{it} + \beta_5 log(Popit) + \delta_t + \varepsilon_{it}$$

where: $Crime_{it}$ denotes either violent or property crime in state i and year t, δ_t are year fixed effects capturing nationwide shocks.

This specification captures short-run associations between economic stress and crime without conditioning on potentially endogenous institutional responses.

```
Call:
lm(formula = Data.Rates.Property.All ~ log_gdp + unemployment_rate +
    percent_poor + share_pretax_income_p90p100 + log_pop + factor(Year),
    data = panel_short_inst)

Residuals:
     Min       1Q   Median       3Q      Max
-1250.88  -434.24    33.47   434.08   963.92

Coefficients:
                            Estimate Std. Error t value Pr(>|t|)
(Intercept)                   865.55    1407.73   0.615  0.54018
log_gdp                       -55.67     384.21  -0.145  0.88511
unemployment_rate             106.62      83.40   1.278  0.20434
percent_poor                   84.04      28.47   2.952  0.00402 **
share_pretax_income_p90p100 -3079.69    1246.70  -2.470  0.01536 *
log_pop                       143.44     397.70   0.361  0.71918
factor(Year)2018              -82.95     112.72  -0.736  0.46369
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 536.4 on 91 degrees of freedom
Multiple R-squared:  0.2911,    Adjusted R-squared:  0.2444
F-statistic: 6.229 on 6 and 91 DF,  p-value: 1.648e-05


Call:
lm(formula = Data.Rates.Violent.All ~ log_gdp + unemployment_rate +
    percent_poor + share_pretax_income_p90p100 + log_pop + factor(Year),
    data = panel_short_inst)

Residuals:
    Min      1Q  Median      3Q     Max
-298.49  -83.32   -1.83   90.42  357.88

Coefficients:
                            Estimate Std. Error t value Pr(>|t|)
(Intercept)                  147.429    351.026   0.420  0.67548
log_gdp                       63.301     95.806   0.661  0.51046
unemployment_rate             69.697     20.796   3.352  0.00117 **
percent_poor                  13.622      7.099   1.919  0.05815 .
```

```
share_pretax_income_p90p100 -378.076    310.872  -1.216  0.22706
log_pop                      -54.328     99.168  -0.548  0.58514
factor(Year)2018              20.165     28.108   0.717  0.47495
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 133.8 on 91 degrees of freedom
Multiple R-squared:  0.2936,    Adjusted R-squared:  0.2471
F-statistic: 6.305 on 6 and 91 DF,  p-value: 1.427e-05
```

3.3.3 Institutions stress model (pooled OLS + year FE)

We estimate a separate specification focusing on contemporaneous institutional intensity and behavioral factors. These covariates are interpreted as descriptive correlates (not exogenous policy instruments), hence we keep them separate from economic stress variables.

$$Crime_{it} = \beta_0 + \beta_1 Prison_{it} + \beta_2 PoliceShootings_{it} + \beta_3 PoliceSpending_{it} + \beta_4 CorrectionsSpending_{it} + \beta_5 Alcohol_{it}$$

This model does not aim to measure deterrence effects, but rather documents how crime co-varies with enforcement intensity and social regulation in the short run.

```
Call:
lm(formula = Data.Rates.Property.All ~ prison_population + nb_police_shootings +
    spending_police + spending_corrections + beer_per_capita_14plus +
    log_pop + factor(Year), data = panel_short_inst)

Residuals:
    Min      1Q  Median      3Q     Max
-937.29 -387.62  -63.45  287.98 1276.63

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)             2.948e+03  1.706e+03   1.728   0.0874 .
prison_population      -1.645e-03  4.379e-03  -0.376   0.7081
nb_police_shootings     2.727e+01  5.158e+00   5.287 8.64e-07 ***
spending_police         1.580e-05  8.723e-05   0.181   0.8566
spending_corrections   -2.415e-04  1.236e-04  -1.953   0.0539 .
beer_per_capita_14plus -4.265e+02  2.943e+02  -1.449   0.1509
log_pop                -1.597e+01  1.036e+02  -0.154   0.8778
```

```
factor(Year)2018       -1.816e+02  1.070e+02  -1.697   0.0932 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 528.7 on 90 degrees of freedom
Multiple R-squared:  0.3189,    Adjusted R-squared:  0.2659
F-statistic: 6.019 on 7 and 90 DF,  p-value: 9.071e-06



Call:
lm(formula = Data.Rates.Violent.All ~ prison_population + nb_police_shootings +
    spending_police + spending_corrections + beer_per_capita_14plus +
    log_pop + factor(Year), data = panel_short_inst)

Residuals:
    Min      1Q  Median      3Q     Max
-238.97 -113.68  -28.77   84.11  519.96

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)             6.670e+02  4.885e+02   1.365   0.1755
prison_population       3.774e-05  1.254e-03   0.030   0.9761
nb_police_shootings     3.664e+00  1.477e+00   2.481   0.0149 *
spending_police         1.975e-05  2.497e-05   0.791   0.4312
spending_corrections   -4.935e-05  3.540e-05  -1.394   0.1667
beer_per_capita_14plus -9.334e+01  8.427e+01  -1.108   0.2710
log_pop                -1.474e+01  2.965e+01  -0.497   0.6203
factor(Year)2018       -1.591e+01  3.064e+01  -0.519   0.6049
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 151.4 on 90 degrees of freedom
Multiple R-squared:  0.1053,    Adjusted R-squared:  0.03566
F-statistic: 1.512 on 7 and 90 DF,  p-value: 0.1731
```

These results should therefore be interpreted as descriptive associations rather than causal effects.

3.3.4 Robustness: Two-way fixed effects (TWFE) for the economic stress model

As a robustness check, we also estimate a two-way fixed effects version of the economic stress model (state FE + year FE). With only four years, this specification is demanding and is used mainly to assess the robustness of the pooled OLS associations to unobserved state-level heterogeneity.

```
Twoways effects Within Model

Call:
plm(formula = Data.Rates.Property.All ~ log_gdp + unemployment_rate +
    percent_poor + share_pretax_income_p90p100 + log_pop, data = panel_short_inst,
    effect = "twoways", model = "within", index = c("State",
        "Year"))

Unbalanced Panel: n = 50, T = 1-2, N = 98

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-127.901  -26.545    0.000   26.545  127.901

Coefficients:
                              Estimate Std. Error t-value Pr(>|t|)
log_gdp                      -425.8314  1197.8196 -0.3555  0.72399
unemployment_rate             129.2804    59.9948  2.1549  0.03695 *
percent_poor                   -3.7092    10.2212 -0.3629  0.71850
share_pretax_income_p90p100   378.5470  1083.8363  0.3493  0.72863
log_pop                     -2612.6020  2363.7286 -1.1053  0.27533
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    271220
Residual Sum of Squares: 235310
R-Squared:      0.13241
Adj. R-Squared: -1.0037
F-statistic: 1.28197 on 5 and 42 DF, p-value: 0.28974
```

4 Conclusion and limitations