Panel Data Analysis

Violent Crime & Shall Law

Pooled OLS

Assumptions of Pooled OLS

1. **No Serial Correlation**
   Errors are uncorrelated across time and entities. In panel data, this is often violated, requiring adjustments (e.g., clustered standard errors).
2. **Homoscedasticity**
   Constant variance of errors across observations.
3. **Exogeneity**
   No correlation between independent variables and the error term.
4. **Linear Relationship**
   Assumes a linear relationship between predictors and the dependent variable.

Because we have panel data, our first model is Pooled OLS. We will compare the standard errors by running regression with and without robust standard errors. If we compare the tables 1 and 2, we see a vast difference in standard errors. This is because Pooled OLS assumes no correlation between errors corresponding to the same individual, however, this is not sensible. Unobservable characteristics that are included in the error term are likely to be correlated for the same across time. Additionally, variance of error terms may also be different in different time periods. Proceeding with least squares estimation without recognizing the existence of serially correlated errors and heteroskedasticity would mean that the formulas for the standard errors usually computed for the least squares estimator are no longer correct. Confidence intervals and hypothesis tests that use these standard errors will be misleading. With cluster robust standard errors, S.E are correct, even though the estimator is still not BEST (not efficient). If we use pooled OLS without robust standard errors, the following two assumptions are most likely violated:

$$\mathrm{cov}(e_{it}, e_{is}) = 0$$
$$\mathrm{var}(e_{it}) = \sigma_t^2$$

Model Without Robust Standard Errors

```
Pooling Model

Call:
plm(formula = lvio ~ shall + lincarc_rate + density + avginc +
    pm1029 + pw1064 + pb1064, data = pdata, model = "pooling")

Balanced Panel: n = 51, T = 23, N = 1173

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-1.51778028 -0.27522483  0.00031108  0.29975034  1.13808497

Coefficients:
               Estimate Std. Error  t-value  Pr(>|t|)
(Intercept)   1.2821571  0.5474702   2.3420   0.01935 *
shall        -0.3508261  0.0316821 -11.0733 < 2.2e-16 ***
lincarc_rate  0.6839661  0.0271037  25.2352 < 2.2e-16 ***
density       0.0340543  0.0115953   2.9369   0.00338 **
avginc        0.0487339  0.0073067   6.6697  3.95e-11 ***
pm1029        0.1045599  0.0113019   9.2516 < 2.2e-16 ***
pw1064       -0.0149590  0.0080790  -1.8516   0.06434 .
pb1064       -0.0278862  0.0162979  -1.7110   0.08734 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    488.63
Residual Sum of Squares: 203.25
R-Squared:      0.58404
Adj. R-Squared: 0.58154
F-statistic: 233.675 on 7 and 1165 DF, p-value: < 2.22e-16
```

Table 1

Model With Robust Standard Errors

```
t test of coefficients:

              Estimate Std. Error t value  Pr(>|t|)
(Intercept)   1.282157   2.364008  0.5424 0.5876702
shall        -0.350826   0.103048 -3.4045 0.0006855 ***
lincarc_rate  0.683966   0.104621  6.5376 9.333e-11 ***
density       0.034054   0.031882  1.0681 0.2856766
avginc        0.048734   0.022926  2.1257 0.0337390 *
pm1029        0.104560   0.030622  3.4145 0.0006610 ***
pw1064       -0.014959   0.034914 -0.4285 0.6683996
pb1064       -0.027886   0.069967 -0.3986 0.6902890
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Table 2

We can see that after using robust standard errors, not only the values of the errors change but also some estimates that were previously significant become insignificant (for instance, population density). Thus, without accounting for serial correlation and heteroskedasticity, inferences can be misleading and so for our upcoming analyses, we will focus only on robust standard errors.

Interpretation of Shall

The violent crime rate in states with shall law is 35.08% less than the crime rate in states without shall law. The estimate is significantly different from 0.

Given that pooled OLS does not take into account the heterogeneity of the states, 35% seems to be downwardly biased. We will now run the Entity and Time Fixed Effects models to assess the impact, if any, of the unobserved differences in states on the crime rate.

Fixed Effects

Entity – Fixed Effects

In the entity fixed effects model, individual intercepts control for observed and unobserved individual heterogeneity. All individual-specific, time-invariant characteristics will be included in the fixed effect. This model allows us to control for unobserved heterogeneity, and obtain unbiased and consistent estimators to variables that are endogenous with OLS.

Model Without Robust Standard Errors

```
Oneway (individual) effect Within Model

Call:
plm(formula = lvio ~ shall + lincarc_rate + density + avginc +
    pm1029 + pw1064 + pb1064, data = pdata, model = "within")

Balanced Panel: n = 51, T = 23, N = 1173

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.5670182 -0.1011816  0.0098321  0.1037902  0.5642055

Coefficients:
               Estimate Std. Error t-value  Pr(>|t|)
shall        -0.0443000  0.0185444 -2.3889   0.01707 *
lincarc_rate -0.0627605  0.0281610 -2.2286   0.02604 *
density      -0.1498418  0.0633561 -2.3651   0.01820 *
avginc       -0.0068767  0.0059072 -1.1641   0.24462
pm1029       -0.0607753  0.0079398 -7.6546 4.186e-14 ***
pw1064        0.0422742  0.0051220  8.2534 4.309e-16 ***
pb1064        0.1158200  0.0178916  6.4734 1.433e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 28.699
R-Squared:      0.21992
Adj. R-Squared: 0.18004
F-statistic: 44.9046 on 7 and 1115 DF, p-value: < 2.22e-16
```

Table 3

Model With Robust Standard Errors

```
t test of coefficients:

               Estimate Std. Error t value Pr(>|t|)
shall        -0.0443000  0.0412002 -1.0752 0.282501
lincarc_rate -0.0627605  0.0658556 -0.9530 0.340796
density      -0.1498418  0.0813290 -1.8424 0.065680 .
avginc       -0.0068767  0.0129625 -0.5305 0.595865
pm1029       -0.0607753  0.0238685 -2.5463 0.011022 *
pw1064        0.0422742  0.0144136  2.9329 0.003426 **
pb1064        0.1158200  0.0314237  3.6857 0.000239 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Table 4

Interpretation of Shall

The violent crime rate in states with shall law is 4.43% less than the crime rate in states without shall law. The estimate is now insignificant.

We see that when we allow for state heterogeneity, the deterrent effect of the shall carry law is much less. Relying on results of the pooled OLS may be misleading. Fixed effects seems to be a more reliable model than the pooled OLS estimate because it accounts for unobserved heterogeneity across the 51 states. This unobserved heterogeneity could capture factors like socioeconomic, policy, governance and cultural differences that remain constant within each state but vary across states, potentially influencing both crime and implementation of laws.

F-Test

We will conduct an F-test to evaluate whether entity-fixed effects are actually significant while gauging the impact of shall law on violent crime rates.

H_0 : $\beta_{1,1} = \beta_{1,2} = \ldots\ldots = \beta_{1,51}$
H_1 : Not all are equal
The F-test output is as follows:

```
        F test for individual effects

data:  lvio ~ shall + lincarc_rate + density + avginc + pm1029 + pw1064 +  ...
F = 135.64, df1 = 50, df2 = 1115, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Figure 1

The calculated value is F = 135.64 and the p-value is zero. Thus, we reject H_0 and conclude that the state level effects are not all zero. This gives statistical backing to prefer fixed effects over pooled OLS.

Time Fixed Effects

Now that the importance of state fixed effects has been established, we want to assess whether time fixed effects have an impact on violent crime rates. The time dummies will control for unobserved factors that are constant across states but vary over time.

```
Call:
plm(formula = lvio ~ shall + lincarc_rate + density + avginc +
    pm1029 + pw1064 + pb1064 + factor(year), data = pdata, model = "within")

Balanced Panel: n = 51, T = 23, N = 1173

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.4456937 -0.0798400  0.0030633  0.0794684  0.7119230
```

Model Without Robust Standard Errors

```
Coefficients:
                 Estimate Std. Error t-value  Pr(>|t|)
shall          -0.0346610  0.0171690 -2.0188  0.043751 *
lincarc_rate   -0.0916219  0.0278055 -3.2951  0.001015 **
density        -0.1455874  0.0563779 -2.5823  0.009942 **
avginc          0.0010696  0.0063591  0.1682  0.866453
pm1029          0.0759659  0.0148345  5.1209 3.592e-07 ***
pw1064          0.0062267  0.0070659  0.8812  0.378388
pb1064          0.0205186  0.0221000  0.9284  0.353381
factor(year)78  0.0625587  0.0279851  2.2354  0.025591 *
factor(year)79  0.1755236  0.0285390  6.1503 1.083e-09 ***
factor(year)80  0.2309185  0.0290893  7.9383 5.056e-15 ***
factor(year)81  0.2352882  0.0301405  7.8064 1.372e-14 ***
factor(year)82  0.2244437  0.0322277  6.9643 5.687e-12 ***
factor(year)83  0.1998784  0.0350197  5.7076 1.475e-08 ***
factor(year)84  0.2401057  0.0385618  6.2265 6.789e-10 ***
factor(year)85  0.2969113  0.0420392  7.0627 2.900e-12 ***
factor(year)86  0.3837056  0.0461465  8.3149 2.702e-16 ***
factor(year)87  0.3906933  0.0502967  7.7678 1.832e-14 ***
factor(year)88  0.4595723  0.0548198  8.3833 < 2.2e-16 ***
factor(year)89  0.5217430  0.0590378  8.8374 < 2.2e-16 ***
factor(year)90  0.6400148  0.0705799  9.0680 < 2.2e-16 ***
factor(year)91  0.7001377  0.0740984  9.4488 < 2.2e-16 ***
factor(year)92  0.7384000  0.0781744  9.4455 < 2.2e-16 ***
factor(year)93  0.7659106  0.0811218  9.4415 < 2.2e-16 ***
factor(year)94  0.7574443  0.0846049  8.9527 < 2.2e-16 ***
factor(year)95  0.7585778  0.0881857  8.6021 < 2.2e-16 ***
factor(year)96  0.7098729  0.0917028  7.7410 2.237e-14 ***
factor(year)97  0.6949709  0.0949741  7.3175 4.883e-13 ***
factor(year)98  0.6454127  0.0986405  6.5431 9.242e-11 ***
factor(year)99  0.5913108  0.1018157  5.8077 8.299e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Total Sum of Squares:    36.789
Residual Sum of Squares: 21.219
R-Squared:      0.42322
Adj. R-Squared: 0.38154
F-statistic: 27.6558 on 29 and 1093 DF, p-value: < 2.22e-16
```

Table 5

Model With Robust Standard Errors

```
t test of coefficients:

                 Estimate Std. Error t value  Pr(>|t|)
shall          -0.0346610  0.0401373 -0.8636 0.3880191
lincarc_rate   -0.0916219  0.0654213 -1.4005 0.1616504
density        -0.1455874  0.0779164 -1.8685 0.0619587 .
avginc          0.0010696  0.0159214  0.0672 0.9464491
pm1029          0.0759659  0.0511415  1.4854 0.1377247
pw1064          0.0062267  0.0229757  0.2710 0.7864333
pb1064          0.0205186  0.0504285  0.4069 0.6841717
factor(year)78  0.0625587  0.0147422  4.2435 2.387e-05 ***
factor(year)79  0.1755236  0.0240739  7.2910 5.890e-13 ***
factor(year)80  0.2309185  0.0347887  6.6377 5.006e-11 ***
factor(year)81  0.2352882  0.0390922  6.0188 2.395e-09 ***
factor(year)82  0.2244437  0.0480455  4.6715 3.362e-06 ***
factor(year)83  0.1998784  0.0597076  3.3476 0.0008428 ***
factor(year)84  0.2401057  0.0749395  3.2040 0.0013945 **
factor(year)85  0.2969113  0.0893123  3.3244 0.0009154 ***
factor(year)86  0.3837056  0.1049987  3.6544 0.0002700 ***
factor(year)87  0.3906933  0.1212184  3.2231 0.0013058 **
factor(year)88  0.4595723  0.1352047  3.3991 0.0007005 ***
factor(year)89  0.5217430  0.1487674  3.5071 0.0004714 ***
factor(year)90  0.6400148  0.1875152  3.4131 0.0006657 ***
factor(year)91  0.7001377  0.1955519  3.5803 0.0003583 ***
factor(year)92  0.7384000  0.2068617  3.5695 0.0003731 ***
factor(year)93  0.7659106  0.2146734  3.5678 0.0003756 ***
factor(year)94  0.7574443  0.2215122  3.4194 0.0006507 ***
factor(year)95  0.7585778  0.2303299  3.2934 0.0010214 **
factor(year)96  0.7098729  0.2408196  2.9477 0.0032691 **
factor(year)97  0.6949709  0.2469838  2.8138 0.0049833 **
factor(year)98  0.6454127  0.2581057  2.5006 0.0125447 *
factor(year)99  0.5913108  0.2686867  2.2007 0.0279627 *
```

Table 6

Interpretation of Shall

The violent crime rate in states with shall law is 3.47% less than the crime rate in states without shall law. The estimate is insignificant.

Once again, we see a reduction in the deterrent effect of the shall law on violent crime rate when we control for unobserved heterogeneity that varies over time but remains the same across states. Perhaps, technological advancements like surveillance or change in other federal policies influences crime rates that was not taken into consideration in the model without time dummies.

Impact of Time Dummies

All time dummies are significant. We see that the the crime rate in 1978 was 6.26% more than that in 1977 (reference). The crime rate appears to be increasing till 1981, slightly drops in the following two years and then again increases till 1993. 1994 and onwards, the crime rate appears to decrease, with a slight increase in 1995.

While statistically significant individually, we will now evaluate whether the time dummies are jointly significant. For that, we will conduct the F-test.

F test for time dummies

H_0 : D78 = D79 = ….. = D99 = 0
H_1 : Not all are 0
The F-test output is as follows:

```
> cat("F-statistic:", F_stat, "\n")
F-statistic: 18.3296
> cat("p-value:", p_value, "\n")
p-value: 1.693126e-60
```

Figure 2

Figure 2 shows the calculated value of F = 18.3296 and the p-value is zero. Thus, we reject H_0, concluding that the time dummies are not all zero and time fixed effects actually do impact violent crime rates over the years.

Random Effects

Random effects model assumes there is no correlation between the unobserved heterogeneity and the explanatory variables. However, our analysis till now indicates potential endogeneity because of the vast difference between coefficient estimates of the pooled OLS and fixed effects model. Running the random effects model will entail high risk of endogeneity, given our results. We will still try running the random effects model and conduct the Hausman Test to formally compare the two models. The random effects model will estimate the effects of variables that are individually time-invariant as individual differences are not assumed to be fixed. Because time dummies were significant, we will include the same in our random effects model as well.

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = lvio ~ shall + lincarc_rate + density + avginc +
    pm1029 + pw1064 + pb1064 + factor(year), data = pdata, model = "random")

Balanced Panel: n = 51, T = 23, N = 1173

Effects:
                  var std.dev share
idiosyncratic 0.01941 0.13933 0.158
individual    0.10328 0.32137 0.842
theta: 0.91

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-0.548386 -0.082836  0.010393  0.094130  0.662402
```

Model Without Robust Standard Errors

Coefficients:

	Estimate	Std. Error	z-value	Pr(>|z|)	
(Intercept)	3.5154057	0.4533719	7.7539	8.910e-15	***
shall	-0.0318512	0.0180294	-1.7666	0.0772908	.
lincarc_rate	-0.0035649	0.0280804	-0.1270	0.8989765	
density	0.0151393	0.0341642	0.4431	0.6576686	
avginc	0.0132436	0.0062641	2.1142	0.0344989	*
pm1029	0.0505852	0.0148684	3.4022	0.0006685	***
pw1064	0.0147877	0.0070577	2.0952	0.0361492	*
pb1064	0.0576816	0.0179020	3.2221	0.0012726	**
factor(year)78	0.0485677	0.0295088	1.6459	0.0997900	.
factor(year)79	0.1514555	0.0299703	5.0535	4.337e-07	***
factor(year)80	0.2056062	0.0303857	6.7665	1.319e-11	***
factor(year)81	0.2007772	0.0313023	6.4141	1.416e-10	***
factor(year)82	0.1743430	0.0331663	5.2566	1.467e-07	***
factor(year)83	0.1309623	0.0357048	3.6679	0.0002445	***
factor(year)84	0.1513724	0.0389036	3.8910	9.985e-05	***
factor(year)85	0.1928360	0.0421116	4.5792	4.668e-06	***
factor(year)86	0.2624189	0.0459393	5.7123	1.115e-08	***
factor(year)87	0.2535426	0.0498173	5.0894	3.591e-07	***
factor(year)88	0.3059708	0.0540359	5.6624	1.493e-08	***
factor(year)89	0.3524635	0.0579655	6.0806	1.198e-09	***
factor(year)90	0.4379954	0.0686762	6.3777	1.798e-10	***
factor(year)91	0.4882117	0.0720576	6.7753	1.242e-11	***
factor(year)92	0.5120512	0.0758428	6.7515	1.463e-11	***
factor(year)93	0.5298758	0.0785987	6.7415	1.567e-11	***
factor(year)94	0.5095093	0.0818515	6.2248	4.822e-10	***
factor(year)95	0.4981880	0.0851973	5.8475	4.991e-09	***
factor(year)96	0.4372777	0.0884518	4.9437	7.666e-07	***
factor(year)97	0.4101063	0.0914302	4.4855	7.276e-06	***
factor(year)98	0.3448833	0.0947225	3.6410	0.0002716	***
factor(year)99	0.2784393	0.0975717	2.8537	0.0043215	**

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 40.452
Residual Sum of Squares: 24.802
R-Squared: 0.38688
Adj. R-Squared: 0.37133
Chisq: 721.24 on 29 DF, p-value: < 2.22e-16

Table 7

Model With Robust Standard Errors

t test of coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	3.5154057	1.1938000	2.9447	0.0032979	**
shall	-0.0318512	0.0398467	-0.7993	0.4242572	
lincarc_rate	-0.0035649	0.0689004	-0.0517	0.9587446	
density	0.0151393	0.0506823	0.2987	0.7652157	
avginc	0.0132436	0.0168244	0.7872	0.4313503	
pm1029	0.0505852	0.0481313	1.0510	0.2934887	
pw1064	0.0147877	0.0237604	0.6224	0.5338245	
pb1064	0.0576816	0.0521325	1.1064	0.2687679	
factor(year)78	0.0485677	0.0161319	3.0107	0.0026640	**
factor(year)79	0.1514555	0.0258213	5.8655	5.856e-09	***
factor(year)80	0.2056062	0.0348117	5.9062	4.611e-09	***
factor(year)81	0.2007772	0.0386738	5.1915	2.467e-07	***
factor(year)82	0.1743430	0.0476615	3.6579	0.0002658	***
factor(year)83	0.1309623	0.0596483	2.1956	0.0283229	*
factor(year)84	0.1513724	0.0748677	2.0219	0.0434230	*
factor(year)85	0.1928360	0.0894126	2.1567	0.0312372	*
factor(year)86	0.2624189	0.1049176	2.5012	0.0125167	*
factor(year)87	0.2535426	0.1187440	2.1352	0.0329565	*
factor(year)88	0.3059708	0.1310405	2.3349	0.0197193	*
factor(year)89	0.3524635	0.1438300	2.4506	0.0144126	*
factor(year)90	0.4379954	0.1815819	2.4121	0.0160173	*
factor(year)91	0.4882117	0.1895653	2.5754	0.0101364	*
factor(year)92	0.5120512	0.1998145	2.5626	0.0105154	*
factor(year)93	0.5298758	0.2071063	2.5585	0.0106413	*
factor(year)94	0.5095093	0.2142841	2.3777	0.0175834	*
factor(year)95	0.4981880	0.2235207	2.2288	0.0260195	*
factor(year)96	0.4372777	0.2353895	1.8577	0.0634719	.
factor(year)97	0.4101063	0.2432692	1.6858	0.0921048	.
factor(year)98	0.3448833	0.2557943	1.3483	0.1778342	
factor(year)99	0.2784393	0.2666135	1.0444	0.2965418	

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table 8

Interpretation of Shall

The violent crime rate in states with shall law is 3.19% less than the crime rate in states without shall law. The estimate is insignificant. This is a slight reduction from the estimate we got from the time fixed effects model.

Hausman Test

The Hausman Test formally compares the Fixed Effects and Random Effects models to determine which is more appropriate for the data.

Hypotheses:

- H0: Random Effects model is appropriate (no correlation between explanatory variables and unobserved heterogeneity).
- H1: Fixed Effects model is appropriate (correlation exists between explanatory variables and unobserved heterogeneity).

The output is as follows:

```
        Hausman Test

data:  lvio ~ shall + lincarc_rate + density + avginc + pm1029 + pw1064 +  ...
chisq = 29.522, df = 29, p-value = 0.4381
alternative hypothesis: one model is inconsistent
```

Figure 3

The result of the Hausman Test shows a high p-value, suggesting there is no sufficient evidence to prove endogeneity. According to the Hausman Test, the Random Effects model appears to be reliable in understanding the impact of shall law on violent crime rates.

Murder & Shall Law

Following the same thought process we had for violent crime rates, we will now run models for gauging the impact of the shall law on murder rate.

Pooled OLS

Model Without Robust Standard Errors

```
Pooling Model

Call:
plm(formula = lmur ~ shall + lincarc_rate + density + avginc +
    pm1029 + pw1064 + pb1064, data = pdata, model = "pooling")

Balanced Panel: n = 51, T = 23, N = 1173

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-2.306108 -0.270704  0.038302  0.323495  1.186606

Coefficients:
               Estimate Std. Error t-value  Pr(>|t|)
(Intercept)  -4.1272196  0.5844974 -7.0611 2.832e-12 ***
shall        -0.2844972  0.0338249 -8.4109 < 2.2e-16 ***
lincarc_rate  0.7306776  0.0289368 25.2508 < 2.2e-16 ***
density       0.0683535  0.0123795  5.5215 4.142e-08 ***
avginc       -0.0284319  0.0078009 -3.6447 0.0002795 ***
pm1029        0.1516565  0.0120662 12.5687 < 2.2e-16 ***
pw1064       -0.0002732  0.0086254 -0.0317 0.9747377
pb1064        0.0228473  0.0174001  1.3131 0.1894235
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    579.9
Residual Sum of Squares: 231.68
R-Squared:      0.60049
Adj. R-Squared: 0.59809
F-statistic: 250.154 on 7 and 1165 DF, p-value: < 2.22e-16
```

Table 9

Model With Robust Standard Errors

```
t test of coefficients:

               Estimate Std. Error t value  Pr(>|t|)
(Intercept)  -4.1272196  1.9892587 -2.0748 0.0382286 *
shall        -0.2844972  0.1033282 -2.7533 0.0059908 **
lincarc_rate  0.7306776  0.1177690  6.2043 7.619e-10 ***
density       0.0683535  0.0347647  1.9662 0.0495153 *
avginc       -0.0284319  0.0233802 -1.2161 0.2242063
pm1029        0.1516565  0.0405885  3.7364 0.0001957 ***
pw1064       -0.0002732  0.0306102 -0.0089 0.9928805
pb1064        0.0228473  0.0660342  0.3460 0.7294114
```

Table 10

Similar to what we observed for violent crime rates, the use of robust standard errors results in vast changes of standard errors values and also the significance of some coefficient estimates.

Interpretation of Shall

The murder crime rate in states with shall law is 28.4% less than the murder crime rate in states without shall law. The estimate is significantly different from 0.

Given that pooled OLS does not take into account the heterogeneity of the states, 28% seems to be downwardly biased. We will now run the Entity and Time Fixed Effects models to assess the impact, if any, of the unobserved differences in states on the murder rate.

Fixed Effects

Entity – Fixed Effects

Model Without Robust Standard Errors

```
Oneway (individual) effect Within Model

Call:
plm(formula = lmur ~ shall + lincarc_rate + density + avginc +
    pm1029 + pw1064 + pb1064, data = pdata, model = "within")

Balanced Panel: n = 51, T = 23, N = 1173

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-1.68635905 -0.11435191  0.00045372  0.12305343  0.89638441

Coefficients:
               Estimate Std. Error t-value  Pr(>|t|)
shall        -0.0767859  0.0252909 -3.0361 0.0024522 **
lincarc_rate -0.1823704  0.0384060 -4.7485 2.316e-06 ***
density      -0.4811398  0.0864053 -5.5684 3.220e-08 ***
avginc        0.0272846  0.0080563  3.3868 0.0007319 ***
pm1029        0.0158787  0.0108283  1.4664 0.1428180
pw1064        0.0203328  0.0069854  2.9107 0.0036775 **
pb1064        0.0384817  0.0244006  1.5771 0.1150613
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    63.314
Residual Sum of Squares: 53.378
R-Squared:      0.15693
Adj. R-Squared: 0.11383
F-statistic: 29.6499 on 7 and 1115 DF, p-value: < 2.22e-16
```

Table 11

Model With Robust Standard Errors

```
t test of coefficients:

              Estimate Std. Error t value Pr(>|t|)
shall        -0.076786   0.040895 -1.8776 0.060693 .
lincarc_rate -0.182370   0.062717 -2.9078 0.003712 **
density      -0.481140   0.156160 -3.0811 0.002113 **
avginc        0.027285   0.016180  1.6863 0.092024 .
pm1029        0.015879   0.019773  0.8030 0.422123
pw1064        0.020333   0.013179  1.5428 0.123164
pb1064        0.038482   0.065782  0.5850 0.558674
---
```

Table 12

Interpretation of Shall

The murder crime rate in states with shall law is 7.68% less than the murder crime rate in states without shall law. The estimate is significantly different from 0.

We see that when we allow for state heterogeneity, the deterrent effect of the shall carry law is much less. Similar to what we observed for violent crime rates, relying on results of the pooled OLS may be misleading. Fixed effects seems to be a more reliable model than the pooled OLS estimate because it accounts for unobserved heterogeneity across the 51 states. Like discussed above, this unobserved heterogeneity could capture factors like socioeconomic, policy, governance and cultural differences that remain constant within each state but vary across states, potentially influencing both murder and implementation of laws.

F-Test

We will conduct an F-test to evaluate whether entity-fixed effects are actually significant while gauging the impact of shall law on murder crime rates.

H_0 : $\beta_{1,1} = \beta_{1,2} = \ldots.. = \beta_{1,51}$
H_1 : Not all are equal
The F-test output is as follows:

```
        F test for individual effects

data:  lmur ~ shall + lincarc_rate + density + avginc + pm1029 + pw1064 +  ...
F = 74.489, df1 = 50, df2 = 1115, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Figure 4

The calculated value is F = 74.489 and the p-value is zero. Thus, we reject H_0 and conclude that the state level effects are not all zero. This gives statistical backing to prefer fixed effects over pooled OLS for murder rate also.

Time Fixed Effects

Now that the importance of state fixed effects has been established, we want to assess whether time fixed effects have an impact on murder crime rates. The time dummies will control for unobserved factors that are constant across states but vary over time.

Model Without Robust Standard Errors

```
Oneway (individual) effect Within Model

Call:
plm(formula = lmur ~ shall + lincarc_rate + density + avginc +
    pm1029 + pw1064 + pb1064 + factor(year), data = pdata, model = "within")

Balanced Panel: n = 51, T = 23, N = 1173

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-1.7296044 -0.1040813 -0.0015471  0.1090835  0.8758715


Coefficients:
                  Estimate Std. Error t-value  Pr(>|t|)
shall           -0.0252769  0.0250332 -1.0097   0.31285
lincarc_rate    -0.0912175  0.0405417 -2.2500   0.02465 *
density         -0.4854030  0.0822016 -5.9050 4.702e-09 ***
avginc           0.0598690  0.0092719  6.4571 1.603e-10 ***
pm1029           0.0511260  0.0216293  2.3637   0.01827 *
pw1064           0.0115576  0.0103024  1.1218   0.26218
pb1064           0.0338826  0.0322228  1.0515   0.29326
factor(year)78  -0.0033701  0.0408036 -0.0826   0.93419
factor(year)79   0.0590643  0.0416112  1.4194   0.15606
factor(year)80   0.0904345  0.0424136  2.1322   0.03321 *
factor(year)81   0.1008362  0.0439462  2.2945   0.02195 *
factor(year)82   0.0263431  0.0469894  0.5606   0.57517
factor(year)83  -0.0237985  0.0510603 -0.4661   0.64125
factor(year)84  -0.1306975  0.0562248 -2.3246   0.02028 *
factor(year)85  -0.0832452  0.0612950 -1.3581   0.17471
factor(year)86  -0.0090902  0.0672837 -0.1351   0.89256
factor(year)87  -0.0268207  0.0733349 -0.3657   0.71464
factor(year)88  -0.0172842  0.0799297 -0.2162   0.82884
factor(year)89  -0.0158093  0.0860798 -0.1837   0.85432
factor(year)90   0.0392622  0.1029087  0.3815   0.70289
factor(year)91   0.0846200  0.1080388  0.7832   0.43366
factor(year)92   0.0458065  0.1139819  0.4019   0.68785
factor(year)93   0.1305601  0.1182792  1.1038   0.26991
factor(year)94   0.0174987  0.1233579  0.1419   0.88722
factor(year)95   0.0287356  0.1285788  0.2235   0.82320
factor(year)96  -0.0421900  0.1337070 -0.3155   0.75241
factor(year)97  -0.1494506  0.1384766 -1.0792   0.28072
factor(year)98  -0.2153017  0.1438224 -1.4970   0.13468
factor(year)99  -0.2870831  0.1484520 -1.9338   0.05339 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    63.314
Residual Sum of Squares: 45.109
R-Squared:      0.28753
Adj. R-Squared: 0.23603
F-statistic: 15.2102 on 29 and 1093 DF, p-value: < 2.22e-16
```

Table 13

Model With Robust Standard Errors

```
t test of coefficients:

                 Estimate Std. Error t value Pr(>|t|)
shall          -0.0252769  0.0424709 -0.5952 0.5518618
lincarc_rate   -0.0912175  0.0611386 -1.4920 0.1359932
density        -0.4854030  0.1447454 -3.3535 0.0008253 ***
avginc          0.0598690  0.0157314  3.8057 0.0001492 ***
pm1029          0.0511260  0.0430637  1.1872 0.2353996
pw1064          0.0115576  0.0215860  0.5354 0.5924692
pb1064          0.0338826  0.0806638  0.4200 0.6745333
factor(year)78 -0.0033701  0.0320570 -0.1051 0.9162922
factor(year)79  0.0590643  0.0289768  2.0383 0.0417570 *
factor(year)80  0.0904345  0.0413078  2.1893 0.0287871 *
factor(year)81  0.1008362  0.0488724  2.0633 0.0393242 *
factor(year)82  0.0263431  0.0574498  0.4585 0.6466547
factor(year)83 -0.0237985  0.0643528 -0.3698 0.7115932
factor(year)84 -0.1306975  0.0713414 -1.8320 0.0672232 .
factor(year)85 -0.0832452  0.0860068 -0.9679 0.3333132
factor(year)86 -0.0090902  0.0910701 -0.0998 0.9205095
factor(year)87 -0.0268207  0.0996495 -0.2692 0.7878647
factor(year)88 -0.0172842  0.1190941 -0.1451 0.8846344
factor(year)89 -0.0158093  0.1367455 -0.1156 0.9079821
factor(year)90  0.0392622  0.1729310  0.2270 0.8204354
factor(year)91  0.0846200  0.1835126  0.4611 0.6448094
factor(year)92  0.0458065  0.1928541  0.2375 0.8122985
factor(year)93  0.1305601  0.1983184  0.6583 0.5104610
factor(year)94  0.0174987  0.2119263  0.0826 0.9342089
factor(year)95  0.0287356  0.2124033  0.1353 0.8924092
factor(year)96 -0.0421900  0.2220145 -0.1900 0.8493187
factor(year)97 -0.1494506  0.2275110 -0.6569 0.5113873
factor(year)98 -0.2153017  0.2389536 -0.9010 0.3677769
factor(year)99 -0.2870831  0.2457005 -1.1684 0.2428893
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Table 14

Interpretation of Shall

The murder crime rate in states with shall law is 2.53% less than the murder crime rate in states without shall law. The estimate is insignificant.

Once again, we see a reduction in the deterrent effect of the shall law on murder crime rate when we control for unobserved heterogeneity that varies over time but remains the same across states.

Impact of Time Dummies

Most time dummies are insignificant, unlike what we observed for violent crime rates. We will now evaluate whether the time dummies are jointly significant. For that, we will conduct the F-test.

F test for time dummies

H_0 : D78 = D79 = ….. = D99 = 0
H_1 : Not all are 0
The F-test output is as follows:

```
F-statistic: 9.531697
> cat("p-value:", p_value, "\n")
p-value: 1.544322e-29
```

Figure 5

Figure 5 shows the calculated value of F = 9.53 and the p-value is zero. Thus, we reject H_0, concluding that the time dummies are not all zero and time fixed effects actually do impact murder crime rates over the years.

Random Effects

Because time dummies were significant, we will include the same in our random effects model as well.

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = lmur ~ shall + lincarc_rate + density + avginc +
    pm1029 + pw1064 + pb1064 + factor(year), data = pdata, model = "random")

Balanced Panel: n = 51, T = 23, N = 1173

Effects:
                  var std.dev share
idiosyncratic 0.04127 0.20315 0.288
individual    0.10208 0.31950 0.712
theta: 0.8686

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-1.878677 -0.110056  0.014366  0.126558  0.732880
```

Model Without Robust Standard Errors

```
Coefficients:
                  Estimate Std. Error z-value  Pr(>|z|)
(Intercept)     -1.1326280  0.6454221 -1.7549 0.0792825 .
shall           -0.0184258  0.0265572 -0.6938 0.4877989
lincarc_rate     0.1031643  0.0402732  2.5616 0.0104188 *
density         -0.0723278  0.0384003 -1.8835 0.0596299 .
avginc           0.0669671  0.0088854  7.5367 4.819e-14 ***
pm1029           0.0240547  0.0212292  1.1331 0.2571754
pw1064           0.0148755  0.0100410  1.4815 0.1384788
pb1064           0.0766937  0.0236055  3.2490 0.0011582 **
factor(year)78  -0.0190435  0.0436899 -0.4359 0.6629244
factor(year)79   0.0250686  0.0442943  0.5660 0.5714244
factor(year)80   0.0513621  0.0448398  1.1455 0.2520195
factor(year)81   0.0483110  0.0460614  1.0488 0.2942526
factor(year)82  -0.0559953  0.0485966 -1.1522 0.2492200
factor(year)83  -0.1378099  0.0520540 -2.6474 0.0081104 **
factor(year)84  -0.2696501  0.0563648 -4.7840 1.718e-06 ***
factor(year)85  -0.2436980  0.0607558 -4.0111 6.043e-05 ***
factor(year)86  -0.1951207  0.0660321 -2.9549 0.0031273 **
factor(year)87  -0.2363338  0.0713902 -3.3105 0.0009315 ***
factor(year)88  -0.2494425  0.0772047 -3.2309 0.0012339 **
factor(year)89  -0.2702411  0.0826249 -3.2707 0.0010728 **
factor(year)90  -0.2513476  0.0971863 -2.5862 0.0097028 **
factor(year)91  -0.2241058  0.1019682 -2.1978 0.0279633 *
factor(year)92  -0.2826693  0.1071755 -2.6374 0.0083534 **
factor(year)93  -0.2129034  0.1110016 -1.9180 0.0551084 .
factor(year)94  -0.3417671  0.1154824 -2.9595 0.0030816 **
factor(year)95  -0.3493596  0.1201140 -2.9086 0.0036309 **
factor(year)96  -0.4377030  0.1245939 -3.5130 0.0004430 ***
factor(year)97  -0.5608977  0.1286431 -4.3601 1.300e-05 ***
factor(year)98  -0.6458535  0.1330580 -4.8539 1.210e-06 ***
factor(year)99  -0.7335286  0.1368940 -5.3584 8.398e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    72.238
Residual Sum of Squares: 54.521
R-Squared:      0.24526
Adj. R-Squared: 0.22611
Chisq: 371.426 on 29 DF, p-value: < 2.22e-16
```

Table 15

Model With Robust Standard Errors

```
t test of coefficients:

                 Estimate Std. Error t value  Pr(>|t|)
(Intercept)     -1.132628   0.993339 -1.1402 0.2544321
shall           -0.018426   0.040503 -0.4549 0.6492466
lincarc_rate     0.103164   0.091901  1.1226 0.2618629
density         -0.072328   0.062284 -1.1613 0.2457758
avginc           0.066967   0.027432  2.4412 0.0147876 *
pm1029           0.024055   0.035893  0.6702 0.5028850
pw1064           0.014876   0.020073  0.7411 0.4588140
pb1064           0.076694   0.056418  1.3594 0.1742954
factor(year)78  -0.019044   0.032430 -0.5872 0.5571724
factor(year)79   0.025069   0.032013  0.7831 0.4337511
factor(year)80   0.051362   0.039973  1.2849 0.1990858
factor(year)81   0.048311   0.040894  1.1814 0.2377032
factor(year)82  -0.055995   0.053348 -1.0496 0.2941114
factor(year)83  -0.137810   0.062728 -2.1969 0.0282246 *
factor(year)84  -0.269650   0.075623 -3.5657 0.0003779 ***
factor(year)85  -0.243698   0.099644 -2.4457 0.0146077 *
factor(year)86  -0.195121   0.108947 -1.7910 0.0735625 .
factor(year)87  -0.236334   0.119317 -1.9807 0.0478623 *
factor(year)88  -0.249442   0.126594 -1.9704 0.0490312 *
factor(year)89  -0.270241   0.153824 -1.7568 0.0792162 .
factor(year)90  -0.251348   0.168980 -1.4874 0.1371745
factor(year)91  -0.224106   0.179134 -1.2511 0.2111710
factor(year)92  -0.282669   0.190144 -1.4866 0.1373944
factor(year)93  -0.212903   0.192977 -1.1033 0.2701475
factor(year)94  -0.341767   0.221962 -1.5398 0.1238963
factor(year)95  -0.349360   0.221041 -1.5805 0.1142644
factor(year)96  -0.437703   0.227162 -1.9268 0.0542487 .
factor(year)97  -0.560898   0.245634 -2.2835 0.0225858 *
factor(year)98  -0.645853   0.261999 -2.4651 0.0138436 *
factor(year)99  -0.733529   0.272600 -2.6909 0.0072307 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Table 16

Interpretation of Shall

The murder crime rate in states with shall law is 1.84% less than the murder rate in states without shall law. The estimate is insignificant. This is a slight reduction from the estimate we got from the time fixed effects model.

Hausman Test

To compare the fixed effects model with the random effects model, we now conduct the Hausman Test. The output is as follows:

```
        Hausman Test

data:  lmur ~ shall + lincarc_rate + density + avginc + pm1029 + pw1064 +  ...
chisq = 69.196, df = 29, p-value = 3.903e-05
alternative hypothesis: one model is inconsistent
```

Figure 6

The result of the Hausman Test shows p-value is almost zero, suggesting there is sufficient evidence to prove endogeneity. We reject the null hypothesis of no endogeneity and select Fixed Effects as our model explaining the impact of shall law on murder rate. According to the Hausman Test, the Fixed Effects model is consistent but random effects estimator is not, that is, it will not converge to the value of the true parameter.

Robbery as Dependent

Pooled OLS

Model Without Robust Standard Errors

```
Pooling Model

Call:
plm(formula = lrob ~ shall + lincarc_rate + density + avginc +
    pm1029 + pw1064 + pb1064, data = pdata, model = "pooling")

Balanced Panel: n = 51, T = 23, N = 1173

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-2.212450 -0.412462  0.050779  0.484588  1.840657

Coefficients:
              Estimate Std. Error  t-value  Pr(>|t|)
(Intercept)   0.600208   0.899960   0.6669   0.50495
shall        -0.562358   0.052081 -10.7978 < 2.2e-16 ***
lincarc_rate  0.573980   0.044554  12.8827 < 2.2e-16 ***
density       0.033008   0.019061   1.7317   0.08359 .
avginc        0.114494   0.012011   9.5323 < 2.2e-16 ***
pm1029        0.131515   0.018579   7.0789 2.506e-12 ***
pw1064       -0.035930   0.013281  -2.7055   0.00692 **
pb1064       -0.037661   0.026791  -1.4057   0.16007
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    1068
Residual Sum of Squares: 549.24
R-Squared:      0.48575
Adj. R-Squared: 0.48266
F-statistic: 157.202 on 7 and 1165 DF, p-value: < 2.22e-16
```

Table 17

Model With Robust Standard Errors

```
t test of coefficients:

              Estimate Std. Error t value  Pr(>|t|)
(Intercept)   0.600208   4.105690  0.1462 0.8837973
shall        -0.562358   0.168756 -3.3324 0.0008881 ***
lincarc_rate  0.573980   0.183150  3.1339 0.0017678 **
density       0.033008   0.053250  0.6199 0.5354642
avginc        0.114494   0.037659  3.0403 0.0024162 **
pm1029        0.131515   0.063756  2.0628 0.0393533 *
pw1064       -0.035930   0.051555 -0.6969 0.4859827
pb1064       -0.037661   0.102275 -0.3682 0.7127632
---
```

Table 18

Similar to what we observed for violent crime rates and murder rate, the use of robust standard errors results in vast changes of standard error values and also the significance of some coefficient estimates.

Interpretation of Shall

The robbery rate in states with shall law is 56.2% less than the robbery rate in states without shall law. The estimate is significantly different from 0.

Given that pooled OLS does not take into account the heterogeneity of the states, 56.2% seems to be extremely downwardly biased. We will now run the Entity and Time Fixed Effects models to assess the impact, if any, of the unobserved differences in states on the robbery rate.

Fixed Effects

Entity-Fixed Effects

Interpretation of Shall

Table 20 shows that the robbery crime rate in states with shall law is 0.275% less than the murder crime rate in states without shall law. The estimate is significantly different from 0.

We see that when we allow for state heterogeneity, the deterrent effect of the shall carry law on robbery rate is almost 0. Similar to what we observed for violent crime rates and murder rates, relying on results of the pooled OLS may be misleading. Fixed effects seems to be a more reliable model than the pooled OLS estimate because it accounts for unobserved heterogeneity across the 51 states. Like discussed above, this unobserved heterogeneity could capture factors like socioeconomic, policy, governance and cultural attitudes towards guns that remain constant within each state but vary across states, potentially influencing both murder and implementation of laws.

Model Without Robust Standard Errors

```
Oneway (individual) effect Within Model

Call:
plm(formula = lrob ~ shall + lincarc_rate + density + avginc +
    pm1029 + pw1064 + pb1064, data = pdata, model = "within")

Balanced Panel: n = 51, T = 23, N = 1173

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.7299942 -0.1352032  0.0015064  0.1383947  0.8259804

Coefficients:
               Estimate Std. Error t-value  Pr(>|t|)
shall        -0.0027524  0.0245574 -0.1121   0.91078
lincarc_rate -0.2026318  0.0372921 -5.4336 6.778e-08 ***
density      -0.1981704  0.0838993 -2.3620   0.01835 *
avginc       -0.0082731  0.0078226 -1.0576   0.29047
pm1029       -0.0266316  0.0105142 -2.5329   0.01145 *
pw1064        0.0342501  0.0067828  5.0495 5.171e-07 ***
pb1064        0.1477044  0.0236929  6.2341 6.434e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    53.526
Residual Sum of Squares: 50.327
R-Squared:      0.059771
Adj. R-Squared: 0.011706
F-statistic: 10.1259 on 7 and 1115 DF, p-value: 2.4955e-12
```

Table 19

Model With Robust Standard Errors

```
t test of coefficients:

               Estimate Std. Error t value  Pr(>|t|)
shall        -0.0027524  0.0557929 -0.0493 0.9606630
lincarc_rate -0.2026318  0.1021743 -1.9832 0.0475903 *
density      -0.1981704  0.1140310 -1.7379 0.0825108 .
avginc       -0.0082731  0.0225236 -0.3673 0.7134579
pm1029       -0.0266316  0.0370635 -0.7185 0.4725750
pw1064        0.0342501  0.0176714  1.9382 0.0528559 .
pb1064        0.1477044  0.0413653  3.5707 0.0003711 ***
```

Table 20

F-Test

We will conduct an F-test to evaluate whether entity-fixed effects are actually significant while gauging the impact of shall law on murder crime rates.

H_0 : $\beta_{1,1} = \beta_{1,2} = \ldots.. = \beta_{1,51}$
H_1 : Not all are equal
The F-test output is as follows:

```
        F test for individual effects

data:  lrob ~ shall + lincarc_rate + density + avginc + pm1029 + pw1064 +  ...
F = 221.07, df1 = 50, df2 = 1115, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Figure 7

The calculated value is F = 221.07 and the p-value is zero. Thus, we reject H_0 and conclude that the state level effects are not all zero. This gives statistical backing to prefer fixed effects over pooled OLS for robbery rate also.

Time Fixed Effects

Now that the importance of state fixed effects has been established, we want to assess whether time fixed effects have an impact on robbery rates. The time dummies will control for unobserved factors that are constant across states but vary over time.

```
Oneway (individual) effect Within Model

Call:
plm(formula = lrob ~ shall + lincarc_rate + density + avginc +
    pm1029 + pw1064 + pb1064 + factor(year), data = pdata, model = "within")

Balanced Panel: n = 51, T = 23, N = 1173

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-0.70380296 -0.11194757  0.00021097  0.11238710  0.66922331
```

Model Without Robust Standard Errors

```
Coefficients:
                  Estimate Std. Error t-value  Pr(>|t|)
shall            0.0106647  0.0234567  0.4547 0.6494467
lincarc_rate    -0.2270405  0.0379885 -5.9766 3.081e-09 ***
density         -0.0908938  0.0770248 -1.1801 0.2382336
avginc           0.0139066  0.0086879  1.6007 0.1097376
pm1029           0.1130149  0.0202672  5.5763 3.096e-08 ***
pw1064          -0.0201910  0.0096536 -2.0915 0.0367095 *
pb1064          -0.0042960  0.0301935 -0.1423 0.8868825
factor(year)78   0.0434312  0.0382339  1.1359 0.2562332
factor(year)79   0.1665173  0.0389906  4.2707 2.118e-05 ***
factor(year)80   0.2785521  0.0397425  7.0089 4.195e-12 ***
factor(year)81   0.3194772  0.0411787  7.7583 1.966e-14 ***
factor(year)82   0.2896452  0.0440302  6.5783 7.362e-11 ***
factor(year)83   0.2212177  0.0478447  4.6237 4.220e-06 ***
factor(year)84   0.1937137  0.0526840  3.6769 0.0002476 ***
factor(year)85   0.2408633  0.0574349  4.1937 2.967e-05 ***
factor(year)86   0.3343945  0.0630464  5.3039 1.371e-07 ***
factor(year)87   0.3178864  0.0687165  4.6261 4.173e-06 ***
factor(year)88   0.3687553  0.0748960  4.9236 9.807e-07 ***
factor(year)89   0.4402469  0.0806588  5.4581 5.952e-08 ***
factor(year)90   0.5828610  0.0964278  6.0445 2.053e-09 ***
factor(year)91   0.7154342  0.1012349  7.0671 2.814e-12 ***
factor(year)92   0.7273527  0.1068037  6.8102 1.606e-11 ***
factor(year)93   0.7558465  0.1108304  6.8198 1.505e-11 ***
factor(year)94   0.7833631  0.1155892  6.7771 2.001e-11 ***
factor(year)95   0.8022920  0.1204813  6.6591 4.355e-11 ***
factor(year)96   0.7598628  0.1252865  6.0650 1.815e-09 ***
factor(year)97   0.7053047  0.1297558  5.4356 6.731e-08 ***
factor(year)98   0.6237213  0.1347649  4.6282 4.130e-06 ***
factor(year)99   0.5588836  0.1391030  4.0178 6.277e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    2.2604
Residual Sum of Squares: 1.8433
R-Squared:      0.18455
Adj. R-Squared: 0.12561
F-statistic: 8.52958 on 29 and 1093 DF, p-value: < 2.22e-16
```

Table 21

Model With Robust Standard Errors

```
t test of coefficients:

                Estimate Std. Error t value  Pr(>|t|)
shall           0.010665   0.051460  0.2072  0.835859
lincarc_rate   -0.227041   0.112468 -2.0187  0.043762 *
density        -0.090894   0.126933 -0.7161  0.474096
avginc          0.013907   0.022772  0.6107  0.541533
pm1029          0.113015   0.069893  1.6170  0.106173
pw1064         -0.020191   0.030613 -0.6595  0.509683
pb1064         -0.004296   0.080910 -0.0531  0.957665
factor(year)78  0.043431   0.020899  2.0781  0.037928 *
factor(year)79  0.166517   0.033527  4.9667 7.896e-07 ***
factor(year)80  0.278552   0.048692  5.7207 1.369e-08 ***
factor(year)81  0.319477   0.053340  5.9894 2.854e-09 ***
factor(year)82  0.289645   0.069686  4.1564 3.485e-05 ***
factor(year)83  0.221218   0.092993  2.3789  0.017537 *
factor(year)84  0.193714   0.107090  1.8089  0.070744 .
factor(year)85  0.240863   0.124958  1.9276  0.054169 .
factor(year)86  0.334394   0.147571  2.2660  0.023647 *
factor(year)87  0.317886   0.164639  1.9308  0.053765 .
factor(year)88  0.368755   0.183292  2.0118  0.044481 *
factor(year)89  0.440247   0.208539  2.1111  0.034991 *
factor(year)90  0.582861   0.260747  2.2354  0.025596 *
factor(year)91  0.715434   0.273211  2.6186  0.008951 **
factor(year)92  0.727353   0.287435  2.5305  0.011530 *
factor(year)93  0.755846   0.301479  2.5071  0.012316 *
factor(year)94  0.783363   0.312577  2.5061  0.012350 *
factor(year)95  0.802292   0.323856  2.4773  0.013388 *
factor(year)96  0.759863   0.339744  2.2366  0.025515 *
factor(year)97  0.705305   0.346678  2.0345  0.042145 *
factor(year)98  0.623721   0.355833  1.7528  0.079908 .
factor(year)99  0.558884   0.370100  1.5101  0.131310
```

Table 22

Interpretation of Shall

We now see a change in sign of the estimated coefficient. The robbery rate in states with shall law is 1.07% more than the robbery rate in states without shall law. The estimate is, however, insignificant.

Unlike the impact we saw for violent crimes and murder, here we see that the shall law actually has no deterrent impact on robbery. Instead, states with shall law have a 1.07% higher robbery rate when we control for unobserved heterogeneity that varies over time but remains the same across states.

Possible Explanation of change in sign

Violent crime and murder are more likely to have severe punishments so criminals are actually deterred by the shall law. This leads to lower crime rates in states with the shall law. However, robbery is not as violent as the other two; criminals may actually plan wisely and reduce the risk of getting caught- robbing when there are no people in a store or at home. Thus, even with the shall law, criminals take the chance to rob. They might also choose robbery as an alternative to violent crime or murder, increasing the robbery rate.

Key Takeaway: *This result suggests that while the shall law has a deterrent impact on violent crimes, it may actually not deter non-violent crimes like robbery.*

Impact of Time Dummies

All time dummies are significant except 1999, similar to what we observed for violent crime rates. We will now evaluate whether the time dummies are jointly significant. For that, we will conduct the F-test.

F test for time dummies

H_0 : D78 = D79 = ….. = D99 = 0
H_1 : Not all are 0
The F-test output is as follows:

```
> cat("F-statistic:", F_stat3, "\n")
F-statistic: 14.07453
> cat("p-value:", p_value, "\n")
p-value: 7.292464e-46
```

Figure 8

Figure 5 shows the calculated value of F = 14.07 and the p-value is zero. Thus, we reject H_0, concluding that the time dummies are not all zero and time fixed effects actually do impact robbery rates over the years.

Random Effects

Interpretation of Shall

Table 24 shows that the robbery rate in states with shall law is 1.4% more than the murder rate in states without shall law. The estimate is insignificant. This is a slight increase from the estimate we got from the time fixed effects model.

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = lrob ~ shall + lincarc_rate + density + avginc +
    pm1029 + pw1064 + pb1064 + factor(year), data = pdata, model = "random")

Balanced Panel: n = 51, T = 23, N = 1173

Effects:
                  var std.dev share
idiosyncratic 0.03624 0.19036 0.116
individual    0.27706 0.52636 0.884
theta: 0.9248

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.8325628 -0.1175766  0.0065188  0.1337952  0.5609109
```

Model Without Robust Standard Errors

Coefficients:

	Estimate	Std. Error	z-value	Pr(>|z|)	
(Intercept)	3.7335679	0.6194635	6.0271	1.669e-09	***
shall	0.0139786	0.0242977	0.5753	0.5650853	
lincarc_rate	-0.1486791	0.0381773	-3.8944	9.843e-05	***
density	0.0371529	0.0514190	0.7226	0.4699552	
avginc	0.0289613	0.0085546	3.3855	0.0007106	***
pm1029	0.0788982	0.0202512	3.8960	9.780e-05	***
pw1064	-0.0074337	0.0096230	-0.7725	0.4398232	
pb1064	0.0455516	0.0253271	1.7985	0.0720925	.
factor(year)78	0.0265765	0.0397155	0.6692	0.5033855	
factor(year)79	0.1387842	0.0403666	3.4381	0.0005858	***
factor(year)80	0.2490182	0.0409588	6.0797	1.204e-09	***
factor(year)81	0.2792686	0.0422418	6.6112	3.812e-11	***
factor(year)82	0.2332078	0.0448343	5.2016	1.976e-07	***
factor(year)83	0.1445863	0.0483576	2.9899	0.0027903	**
factor(year)84	0.0939090	0.0528093	1.7783	0.0753604	.
factor(year)85	0.1232715	0.0572508	2.1532	0.0313042	*
factor(year)86	0.1972942	0.0625375	3.1548	0.0016060	**
factor(year)87	0.1625902	0.0678901	2.3949	0.0166247	*
factor(year)88	0.1942088	0.0737167	2.6345	0.0084254	**
factor(year)89	0.2476024	0.0791441	3.1285	0.0017570	**
factor(year)90	0.3484550	0.0939838	3.7076	0.0002092	***
factor(year)91	0.4698885	0.0986177	4.7647	1.891e-06	***
factor(year)92	0.4650529	0.1038502	4.4781	7.531e-06	***
factor(year)93	0.4824085	0.1076508	4.4812	7.421e-06	***
factor(year)94	0.4959452	0.1121437	4.4224	9.761e-06	***
factor(year)95	0.5008470	0.1167606	4.2895	1.791e-05	***
factor(year)96	0.4445057	0.1212609	3.6657	0.0002467	***
factor(year)97	0.3757909	0.1253959	2.9968	0.0027280	**
factor(year)98	0.2761994	0.1299847	2.1249	0.0335982	*
factor(year)99	0.1970638	0.1339535	1.4711	0.1412545	

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    59.262
Residual Sum of Squares: 44.878
R-Squared:      0.24272
Adj. R-Squared: 0.22351
Chisq: 366.349 on 29 DF, p-value: < 2.22e-16
```

Table 23

Model With Robust Standard Errors

t test of coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	3.7335679	1.7519067	2.1311	0.0332901	*
shall	0.0139786	0.0508133	0.2751	0.7832916	
lincarc_rate	-0.1486791	0.1104476	-1.3462	0.1785207	
density	0.0371529	0.0646575	0.5746	0.5656678	
avginc	0.0289613	0.0235199	1.2314	0.2184448	
pm1029	0.0788982	0.0657439	1.2001	0.2303554	
pw1064	-0.0074337	0.0303532	-0.2449	0.8065720	
pb1064	0.0455516	0.0658496	0.6918	0.4892337	
factor(year)78	0.0265765	0.0219077	1.2131	0.2253374	
factor(year)79	0.1387842	0.0337926	4.1069	4.295e-05	***
factor(year)80	0.2490182	0.0456490	5.4551	5.998e-08	***
factor(year)81	0.2792686	0.0480837	5.8080	8.189e-09	***
factor(year)82	0.2332078	0.0629763	3.7031	0.0002231	***
factor(year)83	0.1445863	0.0851437	1.6981	0.0897527	.
factor(year)84	0.0939090	0.0992623	0.9461	0.3443135	
factor(year)85	0.1232715	0.1168195	1.0552	0.2915429	
factor(year)86	0.1972942	0.1385861	1.4236	0.1548288	
factor(year)87	0.1625902	0.1530001	1.0627	0.2881514	
factor(year)88	0.1942088	0.1679717	1.1562	0.2478411	
factor(year)89	0.2476024	0.1908985	1.2970	0.1948802	
factor(year)90	0.3484550	0.2399456	1.4522	0.1467135	
factor(year)91	0.4698885	0.2507474	1.8740	0.0611920	.
factor(year)92	0.4650529	0.2640207	1.7614	0.0784337	.
factor(year)93	0.4824085	0.2763118	1.7459	0.0810997	.
factor(year)94	0.4959452	0.2868543	1.7289	0.0840953	.
factor(year)95	0.5008470	0.2971617	1.6854	0.0921775	.
factor(year)96	0.4445057	0.3125092	1.4224	0.1551898	
factor(year)97	0.3757909	0.3210737	1.1704	0.2420762	
factor(year)98	0.2761994	0.3288328	0.8399	0.4011185	
factor(year)99	0.1970638	0.3427698	0.5749	0.5654615	

Table 24

Hausman Test

To compare the fixed effects model with the random effects model, we now conduct the Hausman Test. The output as follows:

```
        Hausman Test

data:  lrob ~ shall + lincarc_rate + density + avginc + pm1029 + pw1064 +  ...
chisq = 508.91, df = 29, p-value < 2.2e-16
alternative hypothesis: one model is inconsistent
```

Figure 9

The result of the Hausman Test shows p-value is almost zero, suggesting there is sufficient evidence to prove endogeneity. We reject the null hypothesis of no endogeneity and select Fixed Effects as our model explaining the impact of shall law on robbery rate. According to the Hausman Test, the Fixed Effects model is consistent but random effects estimator is not, that is, it will not converge to the value of the true parameter.

Summary for Panel Data Analysis

Dependent Variable	Final Model	Impact of Shall Law on Crime Rate
Violent Crime Rate	Random Effects	-3.19%
Murder Rate	Entity & Time Fixed Effects	-2.53%
Robbery Rate	Entity & Time Fixed Effects	+1.07%

Policy Implications

Strengthening Concealed Weapon Laws for Violent Crimes and Murder:

- Our analysis found negative impacts on violent crime and murder rates suggesting that the "shall" law may be effective in deterring these types of crimes. The impact may not be large but it does exist. These crimes risky for criminals especially when they know victims could be armed.
    - States without this law can implement the same, ensuring background checks for gun ownership first. Public awareness should be created, detailing the consequences of criminal activities.

Addressing the Increase in Robbery:

- Analysis found a positive impact on robbery rates suggesting that while the "shall" law may deter violent crimes, it could also lead to criminals shifting to less risky crimes, such as robbery.
    - Policymakers should instead focus on increasing policing and surveillance in residential and commercial areas to protect homes and business stores from robbery.