Violent Crime Rate Prediction Models – Wisconsin

Joshua Cantera December 6th, 2019

Abstract

The state of Wisconsin has 72 counties, each with some level of violent crime. In order to predict future violent crime rates an analysis of past crime rates, crime growth rates, populations, population growth rates, and additional socioeconomic facts was completed with the goal of creating a valid model. Initial models only included past crime and growth rates while later models considered socioeconomic factors of each county such as education level, poverty level and the age of the population. These two distinct models were then compared and combined to create the best model for predicting future crime rates. The only socioeconomic factor that made it to the final model was the share of the population between the ages of 15 and 19. While additional important variables included the previous year's violent crime rate and the growth factor of violent crime for that county.

Introduction

Predicting the violent crime for every county in a state is a powerful tool. There are many applications such as redistributing state funds among counties and hiring additional police and medical help in increasingly dangerous areas. This analysis produces a forecast of violent crime in each of Wisconsin's 72 counties. The analysis starts out by only looking at past crime and growth rates and then later branches out and includes different socioeconomic factors such as education, poverty and ages of residents. These two different models are then combined to create the best model which is then used to predict the violent crime rate of each county for the year 2019.

Data Sources

Data for this report came from the FBI's Uniform Crime Reporting database and the Census Bureau's American Fact Finder. The UCR data includes crime rates for violent and property offenses in nearly every county. Due to not effect collection, the crime rates of some counties were not found, but the vast majority were available. The American Fact Finder was used to get data relating to each county's age distribution, education levels, poverty levels and unemployment rate. Again, irregularities between these data sources means it is impossible to predict crime rates for every county in the state of Wisconsin, but the vast majority are unaffected. Summary statistics of the collected data can be found in Appendix D.

Analysis

Initial Models

To start the analysis Poisson regression was used with combinations of population and crime data. The dependent variables of each regression are in the left-most column and the root mean square error is in the first row after the header rows.

Model 1:

poisson violent2018 violent2017 violentGrowth property2017 propertyGrowth Inpop popgrowth, robust

Model 2:

poisson violent2018 Inviolent2017 violentGrowth Inproperty2017 propertyGrowth, robust

Model 3:

poisson violent2018 Inviolent2017 violentGrowth, robust

The next task was to use the results from the three model above to see if a better model could be made. This is done by using a series of joint test to see if a combination of variables has combined little effect on the model.

In Model 1 the three growth variables (*violentGrowth*, *propertyGrowth*, *popgrowth*) had very high p-values, I conducted a joint test on them and got a p-value of 0.44. This is statistically significant and is a good indication that these variables don't affect the model. It can be seen in Models 1 & 2, however, that the p-values for the growth statistics decrease greatly, so I am not willing to throw them out yet.

Model 2 has slightly high p-values for both *violentGrowth* and *propertyGrowth* but when a joint test is conducted the given p-value of 0.015 show there is good evidence these variables are influential in the model.

In the end, the best model I found (Model 4) includes *Inviolent2017*, *violentGrowth* and *popgrowth*. Model 3 had the smallest RMSE of all three initial models, but I felt the population was very important to the model (it seems natural that higher populations leads to higher crime rates). I then included both *Inpop* and *popgrowth* separately into Model 3 and concluded that popgrowth is significant in the model while Inpop is not. Additionally, the RMSE of Model 4 is the lowest of them all, which is a good indication that Model 4 is the best option.

Model 4:

poisson violent2018 Inviolent2017 violentGrowth popgrowth, robust

Initial Models – Table 1								
	Model 1	Model 2	Model 3	Model 4				
RMSE	49.16789	13.087796	12.576183	12.041794				
violent2017	0.0172 (0.006)							
violentGrowth	-0.142 (0.409)	-0.839 (0.489)	-0.990 (0.411)	-1.014 (0.434)				
property2017	0.000813 (0.001)							
propertyGrowth	0.00364 (0.004)	0.00385 (0.003)						
Inpop	0.183 (0.095)							
popgrowth	-0.0000381 (0.000)			0.0000770 (0.000)				
Inviolent2017		0.753 (0.132)	0.915 (0.082)	0.865 (0.082)				
Inproperty2017		0.278 (0.121)						
_cons	0.547 (0.896)	-0.546 (0.360)	0.297 (0.274)	0.431 (0.267)				
N	60	60	60	60				

Table 1 (Shown above) contains the regressions of the first four models from **Initial Models**.

Correlates/Drivers of Crime

The second analysis is aimed to see if the socioeconomic variables of a country affects the reported violent crime.

The baseline model includes *lnpop*, *popgrowth*, *shareyoung*, *shareold*, *unemployment*, *sharepoverty*, *lessthanhs* and *bachelorup*.

Model 5: (Baseline Model)

poisson violent2017 Inpop popgrowth shareyoung shareold unemployment sharepoverty less thanhs bachelorup, robust

The correlation matrix and regression VIF was calculated to provide information on the relationships between the variables before the analysis of individual factors begins.

	lnpop	popgro~h	sharey~g	shareold	unempl~t	sharep~y	lessth~s	bachel~p
lnpop	1.0000							
popgrowth	0.4239	1.0000						
shareyoung	0.4020	0.2197	1.0000					
shareold	-0.6527	-0.3490	-0.6418	1.0000				
unemployment	-0.2004	-0.1511	-0.0337	0.3205	1.0000			
sharepoverty	-0.2849	-0.1029	0.2646	0.0650	0.5825	1.0000		
lessthanhs	-0.2262	-0.3321	-0.1879	0.2406	0.1843	0.3358	1.0000	
bachelorup	0.6154	0.5844	0.3539	-0.4415	-0.2004	-0.2769	-0.7107	1.0000

(Table 2)

The correlation matrix shows several relationships that have a high correlation, many which are logical. It is logical to assume a correlation between *sharepoverty* and *unemployment* since higher unemployment means less people have a job and then more people are likely to live in poverty. The percent of people with a bachelor's degree or higher is highly correlated to *lnpop*. This is expected since larger populations tend to be in more urban areas and people living in urban areas are more likely to have jobs that require a bachelor's degree. It is also interesting to see that *shareold* is negatively correlated with *popgrowth* and *shareyoung*. This is again logical since younger people are more likely to live in urban areas (which have higher populations) and having a higher proportion of older people means you must have a lower proportion of younger people. The last relationship that should be mentioned is the negative correlation between *bachelorup* and *lessthanhs*. This is logical since having a large proportion of people with bachelor's degrees or higher means a lower proportion of its population has less than a high school degree.

Variable	VIF	1/VIF
bachelorup	4.39	0.227805
lnpop	3.21	0.311050
shareold	3.01	0.331872
lessthanhs	2.74	0.364430
sharepoverty	2.53	0.395288
shareyoung	2.15	0.465712
unemployment	1.94	0.516337
popgrowth	1.60	0.626263
Mean VIF	2.70	

(Table 3)

The VIF, calculated after a multiple regression, shows slightly high inflation for *bachelorup*. This is expected since that variable has high correlations with other variables (as seen in the above correlation matrix). The variables *unemployment* and *popgrowth* each have low VIF values which is a good indication they are not influenced much by other variables. The remaining variables have middle of the pack VIF values, not too low to be excited about but not too high to be worried about.

Each of the next models in this part of the analysis will be nearly identical to Model 5 except for one variable being replaced by one or more variables that measure the same thing but in a more specific way. Each model will be explained below, including the test to determine if the change was meaningful or not.

Model 6:

poisson violent2017 Inpop popgrowth share15to19 share20to24 shareold unemployment sharepoverty lessthanhs bachelorup, robust

Model 6 replaced *shareyoung* with *share15to19* and *share20to24*. Testing if these variables are the same return a p-value of 0.15. While not that high it is still not the best evidence that these values are different. A joint test of significance returns a p-value of 0.21, again, evidence saying that they have no influence but not overwhelming evidence. When looking at the regression output you see that *share15to19* has a p-value of 0.099 while *share20to24* has a p-value of 0.623. This leads me to believe that *share15to19* influenced the model while *share20to24* does not.

Model 7:

poisson violent2017 Inpop popgrowth shareyoung share65to84 share85up unemployment sharepoverty lessthanhs bachelorup, robust

Model 7 replaced *shareold* with *share65to84* and *share85up*. The test to see if the coefficients of these variables were the same, and this test returned a p-value of 0.52. This means there is no

good evidence to say that the coefficients of these variables differ. The joint test of significance returns a p-value of 0.79. This is strong evidence that these variables don't influence the model. Combined with the p-value of *shareold*, which is 0.78 in the Model 5, there is good evidence that the proportion of people older than 64 do not influence the model on violent crime.

Model 8:

poisson violent2017 Inpop popgrowth shareyoung shareold unemployment sharepoor shareverypoor lessthanhs bachelorup, robust

Model 8 replace *sharepoverty* with *sharepoor* and *shareverypoor*. The test to see if the coefficients were the same had a p-value of 0.99, overwhelming evidence to say their coefficients are most definitely the same. The joint test of significance has a p-value of 0.06. This test has strong evidence that these variables are important to the model. Since these variables are determined to have the same coefficient and are significant to the test, I would say that it is best to keep *sharepoverty* in the model, but it is not necessary to substitute in *sharepoor* and *shareverypoor*.

Model 9:

poisson violent2017 Inpop popgrowth shareyoung shareold unemployment sharepoverty less thanhs bachelor graduate, robust

Model 9 replaced *bachelorup* with *bachelor* and *graduate*. The test to see if these coefficients are the same has a p-value of 0.79 which is good evidence to say these coefficients are the same. The joint test of significance has a p-value of 0.26, not significant enough to say that these variables influence the model. If these variables were to be kept in the model it would be best to include the combined variable *bachelorup* rather than keep them separate.

Model 10:

poisson violent2017 Inpop popgrowth shareyoung shareold unemployment sharepoverty highschool somecollege associate bachelorup, robust

Model 10 replaced *lessthanhs* with *highschool*, *somecollege* and *associate*. The test to see if these variables' coefficients are the same has a p-value of 0.1, which is slight evidence to say their values are not the same. The joint test of significance ahs a p-value of 0.19, again, not definite but evidence to say these variables don't influence the model. When looking at the individual p-values of each of these variables in the regression of Model 10, *somecollege* has a significant p-value of 0.08 while *highschool* and *associate* are not significant with p-value of 0.24 and 0.56 respectively. I conducted one more regression to explore *lessthanhs* and the other variables.

Model 11:

poisson violent2017 Inpop popgrowth shareyoung shareold unemployment sharepoverty somecollege bachelorup, robust

Model 11 is like Model 10 except I removed *highschool* and *associate*. I did this because the p-values of the tests in Model 10 were not significant, but they were close to being significant and the individual p-value for *somecollege* was significant while *highschool* and *associate* were not. The regression results were not that revolutionary. The p-value of *somecollege* was now 0.26, much higher than in Model 10. I still think this regression could be useful and will include it in the table below.

	Correlates/Drivers of Crime - Table 4								
	Model 5	Model 6	Model 7	Model 8	Model 9	Model	Model		
						10	11		
RMSE	18.15666	15.37993	17.35000	18.37145	18.98650	15.44886	16.47857		
	9	8	7	6	1	3	1		
lnpop	0.518	0.542	0.543	0.518	0.513	0.519	0.500		
	(0.102)	(0.104)	(0.109)	(0.103)	(0.104)	(0.098)	(0.090)		
popgrowth	0.000125	0.000167	0.000119	0.000125	0.000135	0.000104	0.000104		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
shareyoung	3.538		3.773	3.537	3.809	3.922	2.998		
	(3.335)		(3.318)	(3.404)	(3.413)	(3.439)	(3.408)		
shareold	1.118	2.711		1.118	1.501	2.818	0.688		
	(4.050)	(4.028)		(4.039)	(4.382)	(4.420)	(4.004)		
unemployme nt	0.144	0.147	0.124	0.144	0.146	0.208	0.202		
	(0.071)	(0.062)	(0.080)	(0.071)	(0.072)	(0.090)	(0.088)		
sharepoverty	-6.417	-6.371	-6.080		-6.203	-8.266	-7.070		
	(2.734)	(2.585)	(2.711)		(2.850)	(2.809)	(2.427)		
lessthanhs	0.0174	0.0190	0.0145	0.0174	0.0213				
	(0.040)	(0.041)	(0.039)	(0.041)	(0.042)				
bachelorup	-0.0266	-0.0273	-0.0292	-0.0266		-0.0820	-0.0300		
	(0.016)	(0.016)	(0.016)	(0.017)		(0.047)	(0.012)		
share15to19		22.59							
		(13.683)							
share20to24		-2.528							
		(5.139)							
share65to84			3.071						
			(5.199)						

share85up			-12.37 (21.146)				
sharepoor				-6.426 (8.574)			
shareverypo or				-6.406			
				(10.157)			
bachelor					-0.0133 (0.052)		
graduate					-0.0446 (0.069)		
highschool						-0.0722 (0.062)	
somecollege						-0.104 (0.061)	-0.0610 (0.054)
associate						0.0280 (0.048)	
_cons	-2.564 (1.473)	-4.055 (1.879)	-2.684 (1.487)	-2.564 (1.528)	-2.755 (1.653)	2.953 (4.876)	-0.888 (2.049)
N	70	70	70	70	70	70	70

After reviewing the models from Table 4, I tried to find the best model by reviewing the analysis above.

Model 12:

poisson violent2017 Inpop popgrowth share15to19 unemployment sharepoverty less than hs bachelorup, robust

Model 12 does not include *share20to24* and *shareold*. Removed them because of the tests and analysis done on Model 6 and Model 7.

Model 13:

poisson violent2017 Inpop popgrowth share15to19 unemployment sharepoverty bachelorup, robust

Model 13 does not include *share20to24*, *shareold* and *lessthanhs*. Like the reasoning for Model 12, I also took out *lessthanhs*, my thoughts on why can be found in analysis of Model 10.

Model 14:

poisson violent2017 Inpop popgrowth share15to19 unemployment sharepoverty less thanhs bachelor graduate, robust

Model 14 does not include *share20to24* and *shareold*, but it substitutes *bachelor* and *graduate* for *bachelorup*. I wanted to see if having *bachelorup* split up affects the RMSE of Model 12, look to analysis of Model 9 for more thoughts.

Model 15:

poisson violent2017 Inpop popgrowth share15to19 unemployment sharepoverty bachelor graduate, robust

Model 15 does not include *share20to24*, *shareold* and *lessthanhs* but it substitutes *bachelor* and *graduate* for *bachelorup*. Just like Model 14, this separates *bachelorup* to see if it affects the RMSE of Model 13.

After reviewing the table below (Table 5), Model 13 is found to have the lowest RMSE. Since this model does not include *lessthanhs* there is good reason to believe this variable does not have high influence on the model. It is also found that splitting *bachelorup* into *bachelor* and *graduate* is not good for the models, since Models 14 and 15 both have higher RMSE because of it. Model 13 is the best model because of its low RMSE.

	Possible	e Best Models –	Table 5	
	Model 12	Model 13	Model 14	Model 15
RMSE	15.342847	14.952309	16.335665	16.401767
Inpop	0.487 (0.076)	0.508 (0.068)	0.483 (0.085)	0.508 (0.072)
popgrowth	0.000144 (0.000)	0.000145 (0.000)	0.000147 (0.000)	0.000144 (0.000)
share15to19	12.72 (9.676)	11.78 (9.361)	12.73 (9.674)	11.79 (9.394)
unemployment	0.155 (0.059)	0.152 (0.059)	0.156 (0.062)	0.152 (0.062)
sharepoverty	-6.482 (2.672)	-5.824 (2.247)	-6.385 (2.766)	-5.848 (2.510)
lessthanhs	0.0212 (0.041)		0.0225 (0.042)	
bachelorup	-0.0256 (0.017)	-0.0312 (0.013)		
bachelor			-0.0211 (0.049)	-0.0319 (0.044)
graduate			-0.0316 (0.063)	-0.0301 (0.064)
_cons	-2.576 (0.860)	-2.487 (0.822)	-2.589 (0.865)	-2.485 (0.825)
N	70	70	70	70

Prediction using Past Crime and other Correlates

Next, it will be determined if socioeconomic factors are worthwhile to predict violent crime data or if all that is needed to predict violent crime is past crime rates and their growth rates. I will be using the best models from each section (Models 4 and 13).

Model 4:

poisson violent2018 Inviolent2017 violentGrowth popgrowth, robust

Model 13:

poisson violent2017 Inpop popgrowth share15to19 unemployment sharepoverty bachelorup, robust

First, I will create a baseline model including all the variables in Models 4 and 13.

Model 16:

poisson violent2018 Inviolent2017 violentGrowth popgrowth Inpop share15to19 unemployment sharepoverty bachelorup, robust

Model 16 is the baseline model. After looking at the regression I completed a joint test on *sharepoverty* and *bachelorup* because their p-values were very high. The test has a p-value of 0.28, not a significant value. I therefore decided to remove those variables.

Model 17:

poisson violent2018 Inviolent2017 violentGrowth popgrowth Inpop share15to19 unemployment, robust

Model 17 does not include *sharepoverty* and *bachelorup* from Model 16. I again joint tested *lnpop* and *unemployment* to see if they were significant despite their low individual p-values. The joint test had a p-value of 0.49, not significant at all. I then chose to drop both of those variables as well.

Model 18:

poisson violent2018 Inviolent2017 violentGrowth popgrowth Inpop share15to19, robust

Model 18 is the same as Model 17 but without *Inpop* and *unemployment*. All variables were significant at a 10% significance level, so I stopped looking for new models here and proceeded to organize them in a table (Table 6) to compare them.

	Prediction Mo	odels – Table 6	
	Model 16	Model 17	Model 18
RMSE	14.016226	12.235904	11.847905
Inviolent2018	0.836 (0.118)	0.839 (0.113)	0.896 (0.084)
violentGrowth	-0.858 (0.478)	-0.941 (0.458)	-1.082 (0.431)
popgrowth	0.0000690 (0.000)	0.0000485 (0.000)	0.0000726 (0.000)
Inpop	0.115 (0.093)	0.0760 (0.074)	
share15to19	-12.12 (4.929)	-10.31 (4.979)	-8.765 (4.532)
unemployment	-0.0701 (0.059)	-0.0279 (0.042)	
sharepoverty	2.039 (2.179)		
bachelorup	-0.00900 (0.013)		
_cons	0.383 (0.612)	0.513 (0.597)	0.931 (0.350)
N	60	60	60

I would consider Model 18 the best model. It has the lowest RMSE out of all the Models. The Model with the next lowest RMSE is Model 3. The only difference between Models 3 and 18 is the inclusion of *share15to19*. This is an indication that the proportion of the population between ages 15 and 19 has influence over the amount of violent crime in a county.

Predictions for 2019

In order to predict violent crime for 2019 the variable *violentGrowth2018* was created (shown in Do-File, Appendix B). I then ran the regression from Model 18 substituting *violentGrowth2018* for *violentGrowth* and *lnviolent2018* for *lnviolent2017*. The forecasts for 2019 can be found in appendix A.

Discussion and Conclusion

After reviewing all the conducted test and calculated statistics predicting future crime rates is more effective with past crime rates and growth rates rather than using socioeconomic data. In fact, the only independent variable used in the final model that wasn't a past crime or growth rate was *share15to19*, which is the percent of the population between the ages of 15 and 19 years. It is important to note that this analysis did not include all the different factors of each county and it is very possible some unexplored factors are responsible for the violent crime rates. It is also possible that missing data accounts for little effects of the socioeconomic factors. Of the 72 counties in Wisconsin, 7 were not able to be predicted because of missing information from either of the two data sources. While more than 90% of the counties had enough data, it is still a significant amount of information to be missing.

The final model (Model 18) included the independent variables *Inviolent2018*, *violentGrowth*, *popgrowth* and *share15to19*, where *Inviolent2018* is the natural log of the 2018 violent crime rate, *violentGrowth* is the growth of the violent crime rate from 2012 to 2018, *popgrowth* is the population growth rate from 2012 to 2017 and *share15to19* is the percentage of the population with ages between the years of 15 up to and including 19. It is important to note that the data in this model is not all from the same year, the violent crime statistics are form 2018, the population growth rate is calculated from 2012 to 2017 and the share of the population between ages 15 and 19 is from 2017 values as well. Getting consistent, up to date data would make this model more effective.

Conclusion

This analysis was able to find the best model to predict the violent crime rate of Wisconsin's counties using the data mentioned above. While these models can be improved, they give you the best possible predictions using the data that was available.

Appendices

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Appendix A: Predicted Violent Crime Rates for 2019

2019 Predicted Violent Crime Rate for Each County in Wisconsin							
County	Prediction	County	Prediction	County	Prediction		
Adams	27	Iowa	12	Polk	35		
Ashland	5	Iron	6	Portage	35		
Barron	2	Jackson	11	Price	9		
Bayfield	16	Jefferson	34	Racine	21		
Brown	103	Juneau		Richland			
Buffalo	3	Kenosha	42	Rock	34		
Burnett	30	Kewaunee	3	Rusk			
Calumet	9	La Crosse	15	Sauk	26		
Chippewa	30	Lafayette	14	Sawyer	13		
Clark	6	Langlade		Shawano	42		
Columbia	21	Lincoln	21	Sheboygan	42		
Crawford		Manitowoc	23	St. Croix	25		
Dane	82	Marathon		Taylor	14		
Dodge	67	Marinette	6	Trempealeau	18		
Door	16	Marquette	3	Vernon	10		
Douglas	20	Menominee	1	Vilas	8		
Dunn	15	Milwaukee	82	Walworth	9		
Eau Claire	30	Monroe	7	Washburn			
Florence	8	Oconto	15	Washington	6		
Fond du Lac	22	Oneida	44	Waukesha	56		
Forest	21	Outagamie	52	Waupaca	65		
Grant	32	Ozaukee	12	Waushara	18		
Green	7	Pepin	10	Winnebago	21		
Green Lake	5	Pierce	15	Wood	17		

Appendix B: Do-File

```
//Joshua Cantera
//QMB 3200
//Project Analysis Tables
log using "C:\Users\Josh\Desktop\QMBProject\Cantera Log Project.smcl",
replace
use "C:\Users\Josh\Desktop\QMBProject\projectData.dta"
cd "C:\Users\Josh\Desktop\QMBProject\"
gen popgrowth = (pop2017 - pop2012) / 5
gen propertyGrowth = (property2017 - property2012) / 5
gen lnproperty2017 = ln(property2017)
//Summary Statistics
//Populations and Population growth
summarize pop15to19 pop20to24 pop65to84 pop85up
summarize shareyoung shareold, detail
summarize popGrowth, detail
summarize pop, detail
//Violent Crimes and growth
summarize violent2012 violent2017 violent2018
summarize Inviolent2012 Inviolent2017 Inviolent2018
summarize violentGrowth
summarize violentGrowth, detail
//Education
summarize highschool somecollege associate bachelor graduate
```

```
summarize bachelorup lessthanhs
//Poverty
summarize poppov verypoor poor
summarize shareverypoor sharepoor sharepoverty
//Unemployment
summarize unemployment, detail
//Data Types
describe
//Inintial Models
loocv poisson violent2018 violent2017 violentGrowth property2017
propertyGrowth lnpop popgrowth
eststo: poisson violent2018 violent2017 violentGrowth property2017
propertyGrowth lnpop popgrowth, robust
test violentGrowth propertyGrowth popgrowth
loocv poisson violent2018 lnviolent2017 violentGrowth lnproperty2017
propertyGrowth
eststo: poisson violent2018 lnviolent2017 violentGrowth lnproperty2017
propertyGrowth, robust
test violentGrowth propertyGrowth
loocv poisson violent2018 lnviolent2017 violentGrowth
eststo: poisson violent2018 lnviolent2017 violentGrowth, robust
test lnviolent2017 violentGrowth
//Best Model
```

loocv poisson violent2018 lnviolent2017 violentGrowth popgrowth eststo: poisson violent2018 lnviolent2017 violentGrowth popgrowth, robust esttab using "initialModelsLog.rtf", se(3) nostar replace eststo clear //Drivers of crime eststo: poisson violent2017 lnpop popgrowth shareyoung shareold unemployment sharepoverty less thanhs bachelorup, robust regress violent2017 lnpop popgrowth shareyoung shareold unemployment sharepoverty less thanhs bachelorup, robust vif correlate inpop popgrowth shareyoung shareold unemployment sharepoverty lessthanhs bachelorup // a eststo: poisson violent2017 lnpop popgrowth share15to19 share20to24 shareold unemployment sharepoverty less thanhs bachelorup, robust test share15to19 share20to24 test share15to19=share20to24 // b eststo: poisson violent2017 lnpop popgrowth shareyoung share65to84 share85up unemployment sharepoverty lessthanhs bachelorup, robust test share65to84 share85up test share65to84=share85up // c eststo: poisson violent2017 lnpop popgrowth shareyoung shareold unemployment sharepoor shareverypoor lessthanhs bachelorup, robust test sharepoor shareverypoor

test sharepoor=shareverypoor

// d

eststo: poisson violent2017 lnpop popgrowth shareyoung shareold unemployment sharepoverty lessthanhs bachelor graduate, robust

test bachelor graduate

test bachelor=graduate

// e

eststo: poisson violent2017 lnpop popgrowth shareyoung shareold unemployment sharepoverty highschool somecollege associate bachelorup, robust

test highschool somecollege associate

test highschool=somecollege=associate

//Additional

eststo: poisson violent2017 lnpop popgrowth shareyoung shareold unemployment sharepoverty somecollege bachelorup, robust

esttab using "crimeDriversLog.rtf", se(3) nostar replace
eststo clear

loocv poisson violent2017 lnpop popgrowth shareyoung shareold unemployment sharepoverty lessthanhs bachelorup, robust

loocv poisson violent2017 lnpop popgrowth share15to19 share20to24 shareold unemployment sharepoverty lessthanhs bachelorup

loocv poisson violent2017 lnpop popgrowth shareyoung share65to84 share85up unemployment sharepoverty lessthanhs bachelorup

loocv poisson violent2017 lnpop popgrowth shareyoung shareold unemployment sharepoor shareverypoor lessthanhs bachelorup

loocv poisson violent2017 lnpop popgrowth shareyoung shareold unemployment sharepoverty lessthanhs bachelor graduate

loocv poisson violent2017 lnpop popgrowth shareyoung shareold unemployment sharepoverty highschool somecollege associate bachelorup

loocv eststo: poisson violent2017 lnpop popgrowth shareyoung shareold unemployment sharepoverty somecollege bachelorup, robust

// Combining models

loocv poisson violent2017 lnpop popgrowth share15to19 unemployment sharepoverty lessthanhs bachelorup

eststo: poisson violent2017 lnpop popgrowth share15to19 unemployment sharepoverty lessthanhs bachelorup, robust

loocv poisson violent2017 lnpop popgrowth share15to19 unemployment sharepoverty bachelorup

eststo: poisson violent2017 lnpop popgrowth share15to19 unemployment sharepoverty bachelorup, robust

loocv poisson violent2017 lnpop popgrowth share15to19 unemployment sharepoverty lessthanhs bachelor graduate

eststo: poisson violent2017 lnpop popgrowth share15to19 unemployment sharepoverty lessthanhs bachelor graduate, robust

loocv poisson violent2017 lnpop popgrowth share15to19 unemployment sharepoverty bachelor graduate

eststo: poisson violent2017 lnpop popgrowth share15to19 unemployment sharepoverty bachelor graduate, robust

esttab using "combinedModelsLog.rtf", se(3) nostar replace eststo clear

```
//Prediction Models
```

loocv poisson violent2018 lnviolent2017 violentGrowth popgrowth lnpop share15to19 unemployment sharepoverty bachelorup

eststo: poisson violent2018 lnviolent2017 violentGrowth popgrowth lnpop share15to19 unemployment sharepoverty bachelorup, robust

test sharepoverty bachelorup

loocv poisson violent2018 lnviolent2017 violentGrowth popgrowth lnpop share15to19 unemployment

eststo: poisson violent2018 lnviolent2017 violentGrowth popgrowth lnpop share15to19 unemployment, robust

test lnpop unemployment

loocv poisson violent2018 lnviolent2017 violentGrowth popgrowth share15to19

eststo: poisson violent2018 lnviolent2017 violentGrowth popgrowth share15to19, robust

esttab using "predictionModelsLog.rtf", se(3) nostar replace eststo clear

// Predict 2019

gen violentGrowth2018 = (violent2018 - violent2012)/6

poisson violent2018 lnviolent2018 violentGrowth2018 popgrowth share15to19, robust

predict prediction2018

save "PredictionLog.dta", replace

log close

Appendix C: Log-File

log: C:\Users\Josh\Desktop\QMBProject\Cantera_Log_Project.smcl log type: smcl opened on: 6 Dec 2019, 16:18:40 . use "C:\Users\Josh\Desktop\QMBProject\projectData.dta" . cd "C:\Users\Josh\Desktop\QMBProject\" C:\Users\Josh\Desktop\QMBProject . gen popgrowth = (pop2017 - pop2012) / 5. gen propertyGrowth = (property2017 - property2012) / 5 (7 missing values generated) . gen lnproperty2017 = ln(property2017) (1 missing value generated) . //Summary Statistics . //Populations and Population growth . summarize pop15to19 pop20to24 pop65to84 pop85up

Max	Min	Std. Dev.	Mean	Obs	Variable
69912	250	9565.036	5544.569	72	pop15to19
77957	157	10918.82	5368.778	72	pop20to24
90146	457	12708.65	9150.125	72	pop65to84
18987	25	2539.943	1645.903	72	pop85up

. summarize shareyoung shareold, detail

shar	- 170	nina
SHAL	C	Julia

	Percentiles	Smallest					
1%	.0856998	.0856998					
5%	.0909701	.0875183					
10%	.0934574	.0896874	Obs	72			
25%	.107801	.0909701	Sum of Wgt.	72			
50%	.1135534		Mean	.1239414			
		Largest	Std. Dev.	.0313313			
75%	.1316317	.2070991					
90%	.1613894	.208073	Variance	.0009816			
95%	.2070991	.2092145	Skewness	1.681			
99%	.2321864	.2321864	Kurtosis	5.459558			
shareold							
	Percentiles	Smallest					
	.1003972	Smallest .1003972					
5%	.1003972	Smallest .1003972 .1027387					
5%	.1003972 .1122361 .1160814	Smallest .1003972	Obs	72			
5%	.1003972	Smallest .1003972 .1027387		72 72			
5% 10%	.1003972 .1122361 .1160814	Smallest .1003972 .1027387 .104415	Obs				
5% 10%	.1003972 .1122361 .1160814	Smallest .1003972 .1027387 .104415	Obs	72			
5% 10% 25%	.1003972 .1122361 .1160814 .1353499	Smallest .1003972 .1027387 .104415	Obs Sum of Wgt.	72			
5% 10% 25%	.1003972 .1122361 .1160814 .1353499	Smallest .1003972 .1027387 .104415 .1122361	Obs Sum of Wgt. Mean	72			
5% 10% 25%	.1003972 .1122361 .1160814 .1353499	Smallest .1003972 .1027387 .104415 .1122361 Largest	Obs Sum of Wgt. Mean	72			
5% 10% 25% 50%	.1003972 .1122361 .1160814 .1353499 .1586834	Smallest .1003972 .1027387 .104415 .1122361 Largest .2308986	Obs Sum of Wgt. Mean Std. Dev.	72 .1638153 .0370411			

[.] summarize popGrowth, detail

popGrowth

	Percentiles	Smallest		
1%	0074749	0074749		
5%	0052114	0064299		
10%	0041265	0052397	Obs	72
25%	0022431	0052114	Sum of Wgt.	72
50%	000012		Mean	.0003725
		Largest	Std. Dev.	.0039692
75%	.0026976	.0077377		
90%	.0048552	.0082249	Variance	.0000158
95%	.0077377	.0125319	Skewness	.8190459
99%	.0130428	.0130428	Kurtosis	4.16537

. summarize pop, detail

Pop

	Percentiles	Smallest		
1%	4232	4232		
5%	7469	4423		
10%	14755	5916	Obs	72
25%	19514	7469	Sum of Wgt.	72
50%	41384		Mean	78985.92
		Largest	Std. Dev.	132198.8
75%	85370	248007		
90%	166426	389891	Variance	1.75e+10
95%	248007	488073	Skewness	4.639431
99%	947735	947735	Kurtosis	28.46624

.

. //Violent Crimes and growth

. summarize violent2012 violent2017 violent2018

Variable	Obs	Mean	Std. Dev.	Min	Max
violent2012	66	24.63636	29.088	0	184
violent2017	70	24.12857	19.48461	0	89
violent2018	71	22.76056	20.45515	0	103

. summarize lnviolent2012 lnviolent2017 lnviolent2018

Variable	Obs	Mean	Std. Dev.	Min	Max
lnviole~2012	65	2.729422	1.0588	0	5.214936
lnviole~2017	68	2.868541	.937405	0	4.488636
lnviole~2018	70	2.772094	.9211613	0	4.634729

. summarize violentGrowth

Variable		Obs	Mean	Std.	Dev.	Min	Max
	-+						
violentGro~h		61 .	.0221093	.1831	783479	5791 .61	82085

. summarize violentGrowth, detail

violentGrowth

	Percentiles	Smallest		
1%	4795791	4795791		
5%	2143602	4200122		
10%	1911023	3649098	Obs	61
25%	0749387	2143602	Sum of Wgt.	61
50%	.0364643		Mean	.0221093
		Largest	Std. Dev.	.1831783

75%	.0989392	.2598566		
90%	.2387845	.308089	Variance	.0335543
95%	.2598566	.3583519	Skewness	.0031043
99%	.6182085	.6182085	Kurtosis	4.550498

.

. summarize highschool somecollege associate bachelor graduate

Variable		Mean	Std. Dev.	Min	Max
	•				
highschool	72	36.15417	5.708751	17.9	45.4
somecollege	72	21.44861	2.071401	17.6	30.4
associate	72	11.14583	1.558614	7.6	15.6
bachelor	72	15.25833	4.775104	8.1	29.9
graduate	72	7.394444	2.993179	3.1	20.1

. summarize bachelorup lessthanhs

Variable	Obs	Mean	Std. Dev	. Min	Max
bachelorup	72	22.65278		11.4	50
lessthanhs	1 72	8.598611	2.491478	3.900001	17.9

.

. summarize poppov verypoor poor

Variable	Obs	Mean	Std. Dev.	Min	Max
	+				
poppov	72	77952.93	132035.2	4289	934232
verypoor	72	4129.194	10508.54	149	84036
poor	72	5491.903	13129.03	213	107937

^{. //}Education

^{. //}Poverty

. summarize shareverypoor sharepoor sharepoverty

Variable	Obs	Mean	Std. Dev.	. Min	Max
shareveryp~r	+ 72	.0486735	.0195342	.0180882	.1584761
sharepoor	72	.0707906	.0234431	.0274545	.1999549
sharepoverty	72	.1194642	.0416488	.0476047	.358431

•

- . //Unemployment
- . summarize unemployment, detail

Unemployment

	Percentiles	Smallest		
1%	2	2		
5%	2.7	2.6		
10%	3.1	2.7	Obs	72
25%	3.5	2.7	Sum of Wgt.	72
50%	4.1		Mean	4.570833
		Largest	Std. Dev.	1.498303
75%	5.3	7.9		
90%	7.1	8.1	Variance	2.244912
95%	7.9	8.1	Skewness	.9741297
99%	8.3	8.3	Kurtosis	3.200197

•

- . //Data Types
- . describe

 ${\tt Contains \ data \ from \ C:\ Users \setminus Josh \setminus Desktop \setminus QMBProject \setminus project Data.dta}$

obs: 72 vars: 51

12 Nov 2019 18:34

storage display value label variable name type format variable label county strl1 %11s County pop2012 long %12.0g Pop2012 pop2017 long %12.0g Pop2017 pop15to19 long %12.0g Pop15to19 Pop20to24 pop20to24 long %12.0g long %12.0g pop65up Pop65up pop85up int %8.0g Pop85up pop65to69 int %8.0g Pop65to69 pop70to74 int %8.0g Pop70to74 pop75to79 int %8.0g Pop75to79 pop80to84 int %8.0g Pop80to84 violent2012 int %8.0g int property2012 %8.0g violent2017 byte %8.0g property2017 int %8.0g violent2018 int %8.0g property2018 int %8.0g highschool float %9.0g HighSchool somecollege float %9.0g SomeCollege associate float %9.0g Associate float %9.0g bachelor Bachelor graduate float %9.0g Graduate %12.0g poppov long PopPov long %12.0g VeryPoor verypoor long %12.0g Poor poor unemployment float %9.0g Unemployment lnpop2012 float %9.0g lnpop2017 float %9.0g lnviolent2012 float %9.0g

lnviolent2017 float %9.0g

violentGrowth	float	%9.0g				
popGrowth	float	%9.0g				
pop	long	%12.0g		Pop		
_merge	byte	%23.0g	_merge			
share15to19	float	%9.0g				
lnpop	float	%9.0g				
share20to24	float	%9.0g				
pop65to84	float	%9.0g				
share65to84	float	%9.0g				
share85up	float	%9.0g				
shareyoung	float	%9.0g				
shareold	float	%9.0g				
shareverypoor	float	%9.0g				
sharepoor	float	%9.0g				
sharepoverty	float	%9.0g				
bachelorup	float	%9.0g				
lessthanhs	float	%9.0g				
lnviolent2018	float	%9.0g				
popgrowth	float	%9.0g				
propertyGrowth	float	%9.0g				
lnproperty2017	float	%9.0g				

Sorted by: county

Note: Dataset has changed since last saved.

. //Inintial Models

. loocv poisson violent2018 violent2017 violentGrowth property2017 propertyGrow

> th lnpop popgrowth

Leave-One-Out Cross-Validation Results
----Method | Value

----+----Root Mean Squared Errors | 49.16789 Mean Absolute Errors | 16.686745 Pseudo-R2 | .32761972 _____ . eststo: poisson violent2018 violent2017 violentGrowth property2017 propertyGr > owth lnpop popgrowth, robust Iteration 0: log pseudolikelihood = -298.99509 Iteration 1: $\log pseudolikelihood = -285.57039$ Iteration 2: $\log pseudolikelihood = -285.53145$ Iteration 3: log pseudolikelihood = -285.53144 Number of obs = 60 Poisson regression Wald chi2(6) = 214.48 Prob > chi2 = 0.0000 Pseudo R2 Log pseudolikelihood = -285.53144 0.5258 ______ Robust violent2018 | Coef. Std. Err. z P>|z| [95% Conf. Interval >] ______ violent2017 | .0172014 .0059838 2.87 0.004 .0054733 .028929 > 5 property2017 | .0008132 .0006969 1.17 0.243 -.0005528 .002179 propertyGrowth | .0036433 .0042864 0.85 0.395 -.0047579 .012044

> 4

- . test violentGrowth propertyGrowth popgrowth
- (1) [violent2018]violentGrowth = 0
- (2) [violent2018]propertyGrowth = 0
- (3) [violent2018]popgrowth = 0

$$chi2(3) = 2.73$$

 $Prob > chi2 = 0.4360$

•

- . loocv poisson violent2018 lnviolent2017 violentGrowth lnproperty2017 property
- > Growth

Leave-One-Out Cross-Validation Results

Method	I	Value
	-+	
Root Mean Squared Errors	I	13.087796
Mean Absolute Errors	1	8.5439274
Pseudo-R2	1	.65138898

. eststo: poisson violent2018 lnviolent2017 violentGrowth lnproperty2017 proper

> tyGrowth, robust

Iteration 0:	10	g pseudolik	elihood = -2	249.16539	9		
Iteration 1:	10	g pseudolik	elihood = -	-248.7585	5		
Iteration 2:	10	g pseudolik	elihood = -2	248.75842	l		
Iteration 3:	10	g pseudolik	elihood = -2	248.75842	1		
Poisson regres	sio	n			Number of	obs =	60
					Wald chi2	(4) =	312.96
					Prob > ch	i2 =	0.0000
Log pseudolike	lih	ood = -248.	75841		Pseudo R2	=	0.5869
> -							
	I		Robust				
violent2018	-	Coef.	Std. Err.	Z	P> z	[95% Conf.	Interval
>]							
	-+-						
> -							
lnviolent2017	I	.7530633	.1323573	5.69	0.000	.4936478	1.01247
> 9							
violentGrowth	.	8388623	.4892003	-1.71	0.086	-1.797677	.119952
> 7							
lnproperty2017	I	.2780459	.1205639	2.31	0.021	.041745	.514346
> 8							
propertyGrowth	.	.0038512	.0025093	1.53	0.125	0010668	.008769
> 3							
_cons	- 1	5457216	.3601207	-1.52	0.130	-1.251545	.16010
> 2							
> -							
(est5 stored)							

[.] test violentGrowth propertyGrowth

```
( 1) [violent2018]violentGrowth = 0
```

(2) [violent2018]propertyGrowth = 0

```
chi2(2) = 8.46

Prob > chi2 = 0.0146
```

•

.

. loocv poisson violent2018 lnviolent2017 violentGrowth

Leave-One-Out Cross-Validation Results

Method	I	Value
	-+	
Root Mean Squared Errors	I	12.576183
Mean Absolute Errors	1	8.8211161
Pseudo-R2	1	.64701083

. eststo: poisson violent2018 lnviolent2017 violentGrowth, robust

Iteration 0: log pseudolikelihood = -274.32254
Iteration 1: log pseudolikelihood = -274.269
Iteration 2: log pseudolikelihood = -274.269

Poisson regression		Number of obs	=	60
		Wald chi2(2)	=	130.85
		Prob > chi2	=	0.0000
Log pseudolikelihood =	-274.269	Pseudo R2	=	0.5445

| Robust

- (est6 stored)
- . test lnviolent2017 violentGrowth
- (1) [violent2018]lnviolent2017 = 0
- (2) [violent2018]violentGrowth = 0

$$chi2(2) = 130.85$$

 $Prob > chi2 = 0.0000$

.

. //Best Model

•

. loocv poisson violent2018 lnviolent2017 violentGrowth popgrowth

Leave-One-Out Cross-Validation Results

Method	1	Value
	-+	
Root Mean Squared Errors	I	12.041794
Mean Absolute Errors	I	8.6250449
Pseudo-R2	I	.67740948

. eststo: poisson violent2018 lnviolent2017 violentGrowth popgrowth, robust

Iteration 0: $\log pseudolikelihood = -270.8161$

```
Iteration 1: \log pseudolikelihood = -265.144
Iteration 2: log pseudolikelihood = -265.1386
Iteration 3: log pseudolikelihood = -265.1386
Poisson regression
                                      Number of obs = 60
                                      Wald chi2(3)
                                                        295.71
                                      Prob > chi2
                                                   =
                                                        0.0000
Log pseudolikelihood = -265.1386
                                     Pseudo R2
                                                        0.5597
          - 1
                      Robust
 violent2018 |
              Coef. Std. Err. z P>|z| [95% Conf. Interval]
lnviolent2017 | .8649144 .0822558 10.51 0.000 .703696 1.026133
violentGrowth | -1.01415 .4340663 -2.34 0.019 -1.864905 -.1633961
   popgrowth | .000077 .0000236 3.26 0.001 .0000307 .0001232
      cons | .4312538 .2668983 1.62 0.106 -.0918573
                                                        .9543649
______
(est7 stored)
. esttab using "initialModelsLog.rtf", se(3) nostar replace
(note: file initialModelsLog.rtf not found)
(output written to initialModelsLog.rtf)
. eststo clear
```

. //Drivers of crime

. eststo: poisson violent2017 lnpop popgrowth shareyoung shareold unemployment

> sharepoverty less thanhs bachelorup, robust

Iteration 0: log pseudolikelihood = -412.37025
Iteration 1: log pseudolikelihood = -411.05959

Iteration	2:	log	pseudolikelihood	=	-411.05533
Iteration	3:	log	pseudolikelihood	=	-411.05533

Poisson regression	Number of obs	=	70
	Wald chi2(8)	=	137.93
	Prob > chi2	=	0.0000
Log pseudolikelihood = -411.05533	Pseudo R2	=	0.3921

	I		Robust				
violent2017	I	Coef.	Std. Err.	. z	P> z	[95% Conf	. Interval]
	+-						
lnpop	I	.5177841	.1024369	5.05	0.000	.3170113	.7185568
popgrowth	I	.0001251	.0000399	3.13	0.002	.0000468	.0002034
shareyoung	I	3.537947	3.335203	1.06	0.289	-2.998931	10.07482
shareold	I	1.118201	4.04999	0.28	0.782	-6.819634	9.056036
unemployment	I	.1435464	.0707333	2.03	0.042	.0049117	.2821811
sharepoverty	I	-6.417162	2.734456	-2.35	0.019	-11.7766	-1.057727
lessthanhs	I	.0174396	.0404676	0.43	0.667	0618754	.0967545
bachelorup	I	0265705	.0164311	-1.62	0.106	0587749	.0056339
_cons	I	-2.564468	1.473326	-1.74	0.082	-5.452133	.3231971

(est1 stored)

> erty lessthanhs bachelorup, robust

Linear regression	Number of obs	=	70
	F(8, 61)	=	9.73
	Prob > F	=	0.0000
	R-squared	=	0.5304
	Root MSE	=	14.201

[.] regress violent2017 lnpop popgrowth shareyoung shareold unemployment sharepov

1		Robust				
violent2017	Coef.	Std. Err.	t	P> t	[95% Conf.	. Interval]
+						
lnpop	12.27476	2.415176	5.08	0.000	7.445322	17.10421
popgrowth	.0046319	.0015862	2.92	0.005	.0014602	.0078037
shareyoung	-9.417672	74.61063	-0.13	0.900	-158.6108	139.7755
shareold	-32.26748	92.71421	-0.35	0.729	-217.661	153.126
unemployment	3.556483	1.87502	1.90	0.063	1928501	7.305816
sharepoverty	-48.06369	42.62143	-1.13	0.264	-133.2905	37.16313
lessthanhs	.4567819	1.015434	0.45	0.654	-1.573704	2.487268
bachelorup	3969344	.4243546	-0.94	0.353	-1.245484	.451615
_cons	-106.3314	30.49586	-3.49	0.001	-167.3117	-45.35118

. vif

Variable	1	VIF	1/VIF
	-+		
bachelorup	1	4.39	0.227805
lnpop	1	3.21	0.311050
shareold	1	3.01	0.331872
lessthanhs	1	2.74	0.364430
sharepoverty	1	2.53	0.395288
shareyoung	1	2.15	0.465712
unemployment	1	1.94	0.516337
popgrowth	1	1.60	0.626263
	-+		
Mean VIF	1	2.70	

[.] correlate lnpop popgrowth shareyoung shareold unemployment sharepoverty lesst

(obs=72)

> hanhs bachelorup

```
lnpop popgro~h sharey~g shareold unempl~t sharep~y lessth~s b
> achel~p
______
> ----
     lnpop | 1.0000
  popgrowth | 0.4239 1.0000
 shareyoung | 0.4020 0.2197 1.0000
   shareold | -0.6527 -0.3490 -0.6418 1.0000
unemployment | -0.2004 -0.1511 -0.0337 0.3205 1.0000
sharepoverty | -0.2849 -0.1029 0.2646 0.0650 0.5825 1.0000
 lessthanhs | -0.2262 -0.3321 -0.1879 0.2406 0.1843 0.3358 1.0000
 bachelorup | 0.6154 0.5844 0.3539 -0.4415 -0.2004 -0.2769 -0.7107
> 1.0000
. // a
. eststo: poisson violent2017 lnpop popgrowth share15to19 share20to24 shareold
> unemployment sharepoverty lessthanhs bachelorup, robust
Iteration 0: \log pseudolikelihood = -407.06725
Iteration 1: log pseudolikelihood = -406.13358
Iteration 2: log pseudolikelihood = -406.13049
Iteration 3: log pseudolikelihood = -406.13049
                                    Number of obs
Poisson regression
                                                        70
                                    Wald chi2(9)
                                                 =
                                                      169.27
                                    Prob > chi2
                                                      0.0000
Log pseudolikelihood = -406.13049
                                    Pseudo R2
                                                      0.3994
_____
                     Robust
              Coef. Std. Err. z P>|z| [95% Conf. Interval]
violent2017 |
______
```

lnpop	1	.5421668	.1041747	5.20	0.000	.3379881	.7463455
popgrowth	1	.0001668	.0000532	3.13	0.002	.0000625	.0002712
share15to19	I	22.59395	13.68331	1.65	0.099	-4.224836	49.41274
share20to24	I	-2.527932	5.13894	-0.49	0.623	-12.60007	7.544205
shareold		2.711416	4.028433	0.67	0.501	-5.184168	10.607
unemployment		.1469954	.0615525	2.39	0.017	.0263548	.2676361
sharepoverty		-6.370541	2.585038	-2.46	0.014	-11.43712	-1.303961
lessthanhs	1	.0189563	.0408667	0.46	0.643	061141	.0990535
bachelorup		0272509	.0164422	-1.66	0.097	059477	.0049752
_cons	1	-4.055459	1.879286	-2.16	0.031	-7.738793	3721257

(est2 stored)

- . test share15to19 share20to24
- (1) [violent2017]share15to19 = 0
- (2) [violent2017]share20to24 = 0

$$chi2(2) = 3.12$$

 $Prob > chi2 = 0.2105$

- . test share15to19=share20to24
- (1) [violent2017]share15to19 [violent2017]share20to24 = 0

```
chi2(1) = 2.12
Prob > chi2 = 0.1457
```

. // b

- . eststo: poisson violent2017 lnpop popgrowth shareyoung share65to84 share85up
- > unemployment sharepoverty less thanhs bachelorup, robust

Iteration 0: $\log pseudolikelihood = -410.74749$

Iteration 1: log pseudolikelihood = -409.49127
Iteration 2: log pseudolikelihood = -409.48726
Iteration 3: log pseudolikelihood = -409.48726

Poisson regression	Number of obs	=	70
	Wald chi2(9)	=	144.00
	Prob > chi2	=	0.0000
Log pseudolikelihood = -409.48726	Pseudo R2	=	0.3945

	Robust				
Coef.	Std. Err.	Z	P> z	[95% Conf.	Interval]
5426835	.1090459	4.98	0.000	.3289575	.7564094
0001192	.00004	2.98	0.003	.0000407	.0001976
3.773446	3.317864	1.14	0.255	-2.729448	10.27634
3.070618	5.198663	0.59	0.555	-7.118575	13.25981
2.36934	21.14572	-0.58	0.559	-53.8142	29.07552
.124313	.0801364	1.55	0.121	0327515	.2813775
5.080302	2.710668	-2.24	0.025	-11.39311	7674895
0145118	.0389723	0.37	0.710	0618726	.0908962
0292312	.016181	-1.81	0.071	0609454	.002483
2.683715	1.487225	-1.80	0.071	-5.598623	.2311923
	.5426835 .0001192 3.773446 3.070618 12.36934 .124313 5.080302 .0145118	Coef. Std. Err. .5426835 .1090459 .0001192 .00004 3.773446 3.317864 3.070618 5.198663 .12.36934 21.14572 .124313 .0801364 5.080302 2.710668 .0145118 .0389723 .0292312 .016181	Coef. Std. Err. z .5426835 .1090459 4.98 .0001192 .00004 2.98 .3.773446 3.317864 1.14 .3.070618 5.198663 0.59 .12.36934 21.14572 -0.58 .124313 .0801364 1.55 .080302 2.710668 -2.24 .0145118 .0389723 0.37 .0292312 .016181 -1.81	Coef. Std. Err. z P> z .5426835 .1090459 4.98 0.000 .0001192 .00004 2.98 0.003 8.773446 3.317864 1.14 0.255 8.070618 5.198663 0.59 0.555 .12.36934 21.14572 -0.58 0.559 .124313 .0801364 1.55 0.121 .5.080302 2.710668 -2.24 0.025 .0145118 .0389723 0.37 0.710 .0292312 .016181 -1.81 0.071	Coef. Std. Err. z P> z [95% Conf. .5426835 .1090459 4.98 0.000 .3289575 .0001192 .00004 2.98 0.003 .0000407 3.773446 3.317864 1.14 0.255 -2.729448 3.070618 5.198663 0.59 0.555 -7.118575 42.36934 21.14572 -0.58 0.559 -53.8142 .124313 .0801364 1.55 0.121 0327515 5.080302 2.710668 -2.24 0.025 -11.39311 .0145118 .0389723 0.37 0.710 0618726 .0292312 .016181 -1.81 0.071 0609454

(est3 stored)

. test share65to84 share85up

- (1) [violent2017]share65to84 = 0
- (2) [violent2017]share85up = 0

chi2(2) = 0.47

Prob > chi2 = 0.7913

```
. test share65to84=share85up
```

(1) [violent2017] share 65 to 84 - [violent2017] share 85 up = 0

chi2(1) = 0.41Prob > chi2 = 0.5210

•

. // c

- . eststo: poisson violent2017 lnpop popgrowth shareyoung shareold unemployment
- > sharepoor shareverypoor lessthanhs bachelorup, robust

Iteration 0: log pseudolikelihood = -412.37009
Iteration 1: log pseudolikelihood = -411.05959
Iteration 2: log pseudolikelihood = -411.05533

Iteration 3: log pseudolikelihood = -411.05533

Poisson regression Number of obs = 70 Wald chi2(9) = 138.16 Prob > chi2 = 0.0000 Log pseudolikelihood = -411.05533 Pseudo R2 = 0.3921

1		Robust				
violent2017	Coef.	Std. Err.	Z	P> z	[95% Conf.	Interval]
lnpop	.5177832	.1025479	5.05	0.000	.3167929	.7187735
popgrowth	.0001251	.0000416	3.00	0.003	.0000435	.0002067
shareyoung	3.537129	3.404036	1.04	0.299	-3.134659	10.20892
shareold	1.118295	4.039072	0.28	0.782	-6.79814	9.03473
unemployment	.1435424	.0705964	2.03	0.042	.0051761	.2819088
sharepoor	-6.426115	8.573936	-0.75	0.454	-23.23072	10.37849
shareverypoor	-6.406171	10.15725	-0.63	0.528	-26.31401	13.50166
lessthanhs	.0174412	.0406185	0.43	0.668	0621696	.0970519

```
bachelorup | -.0265742 .0167198 -1.59 0.112 -.0593444
                                                        .006196
      -5.55907
                                                         .4307044
_____
(est4 stored)
. test sharepoor shareverypoor
 (1) [violent2017]sharepoor = 0
 ( 2) [violent2017]shareverypoor = 0
       chi2(2) = 5.51
       Prob > chi2 = 0.0635
. test sharepoor=shareverypoor
 (1) [violent2017]sharepoor - [violent2017]shareverypoor = 0
        chi2(1) = 0.00
      Prob > chi2 = 0.9991
. // d
. eststo: poisson violent2017 lnpop popgrowth shareyoung shareold unemployment
> sharepoverty lessthanhs bachelor graduate, robust
Iteration 0: log pseudolikelihood = -411.94838
Iteration 1: log pseudolikelihood = -410.76192
Iteration 2: log pseudolikelihood = -410.75749
Iteration 3: log pseudolikelihood = -410.75749
                                      Number of obs
Poisson regression
                                                         70
                                      Wald chi2(9)
                                                    =
                                                         145.25
                                      Prob > chi2
                                                         0.0000
                                                    =
                                      Pseudo R2 =
Log pseudolikelihood = -410.75749
                                                         0.3926
```

violent2017	Coef.	Robust Std. Err.	Z	P> z	[95% Conf.	Interval]
lnpop	.5131852	.1037117	4.95	0.000	.3099141	.7164564
popgrowth	.0001347	.000054	2.50	0.013	.0000289	.0002404
shareyoung	3.80891	3.413405	1.12	0.264	-2.881241	10.49906
shareold	1.500886	4.382222	0.34	0.732	-7.088111	10.08988
unemployment	.1463868	.0724195	2.02	0.043	.0044471	.2883264
sharepoverty	-6.203397	2.850445	-2.18	0.030	-11.79017	6166287
lessthanhs	.0213221	.0420093	0.51	0.612	0610146	.1036589
bachelor	0132843	.052356	-0.25	0.800	1159002	.0893315
graduate	0446037	.0685988	-0.65	0.516	179055	.0898475
_cons	-2.754839	1.652534	-1.67	0.096	-5.993745	.4840672

(est5 stored)

- . test bachelor graduate
- (1) [violent2017]bachelor = 0
- (2) [violent2017]graduate = 0

$$chi2(2) = 2.70$$
 $Prob > chi2 = 0.2597$

- . test bachelor=graduate
- (1) [violent2017]bachelor [violent2017]graduate = 0

$$chi2(1) = 0.07$$
 $Prob > chi2 = 0.7877$

•

```
. // e
```

. eststo: poisson violent2017 lnpop popgrowth shareyoung shareold unemployment

> sharepoverty highschool somecollege associate bachelorup, robust

Iteration 0: log pseudolikelihood = -399.99515
Iteration 1: log pseudolikelihood = -398.50282
Iteration 2: log pseudolikelihood = -398.49887
Iteration 3: log pseudolikelihood = -398.49887

Poisson regression	Number of obs	=	70
	Wald chi2(10)	=	198.69
	Prob > chi2	=	0.0000
Log pseudolikelihood = -398.49887	Pseudo R2	=	0.4107

I		Robust				
violent2017		Std. Err.			[95% Conf.	. Interval]
+						
lnpop	.5191844	.0976631	5.32	0.000	.3277682	.7106007
popgrowth	.0001043	.0000414	2.52	0.012	.0000232	.0001855
shareyoung	3.922412	3.439434	1.14	0.254	-2.818756	10.66358
shareold	2.818076	4.420462	0.64	0.524	-5.845871	11.48202
unemployment	.2082313	.0900407	2.31	0.021	.0317549	.3847078
sharepoverty	-8.265553	2.809045	-2.94	0.003	-13.77118	-2.759926
highschool	0721661	.061826	-1.17	0.243	1933429	.0490107
somecollege	1042602	.0609609	-1.71	0.087	2237413	.0152209
associate	.0280272	.048201	0.58	0.561	066445	.1224994
bachelorup	0820269	.0468995	-1.75	0.080	1739481	.0098944
_cons	2.953093	4.875793	0.61	0.545	-6.603285	12.50947

(est6 stored)

[.] test highschool some college associate $% \left(1\right) =\left(1\right) \left(1\right$

```
( 1) [violent2017]highschool = 0
 ( 2) [violent2017]somecollege = 0
( 3) [violent2017]associate = 0
        chi2(3) = 4.75
       Prob > chi2 = 0.1914
. test highschool=somecollege=associate
(1) [violent2017]highschool - [violent2017]somecollege = 0
( 2) [violent2017]highschool - [violent2017]associate = 0
        chi2(2) = 4.52
       Prob > chi2 = 0.1041
. //Additional
. eststo: poisson violent2017 lnpop popgrowth shareyoung shareold unemployment
> sharepoverty somecollege bachelorup, robust
Iteration 0: log pseudolikelihood = -408.00018
Iteration 1: log pseudolikelihood = -406.78269
Iteration 2: log pseudolikelihood = -406.77898
Iteration 3: log pseudolikelihood = -406.77898
                                      Number of obs
Poisson regression
                                                         70
                                      Wald chi2(8)
                                                    =
                                                         157.67
                                      Prob > chi2
                                                         0.0000
Log pseudolikelihood = -406.77898
                                                         0.3985
                                     Pseudo R2
_____
                      Robust
violent2017 |
              Coef. Std. Err. z P>|z| [95% Conf. Interval]
_____
```

lnpop	1	.4999271	.0902241	5.54	0.000	.3230912	.676763
popgrowth		.0001043	.0000433	2.41	0.016	.0000194	.0001893
shareyoung		2.998253	3.408266	0.88	0.379	-3.681826	9.678331
shareold		.6880529	4.004426	0.17	0.864	-7.160477	8.536583
unemployment		.2023948	.0882539	2.29	0.022	.0294203	.3753694
sharepoverty		-7.069932	2.427216	-2.91	0.004	-11.82719	-2.312676
somecollege		0610434	.0541876	-1.13	0.260	1672491	.0451624
bachelorup		0300401	.0123064	-2.44	0.015	0541603	00592
_cons		8883561	2.048593	-0.43	0.665	-4.903524	3.126812

(est7 stored)

.

. esttab using "crimeDriversLog.rtf", se(3) nostar replace
(note: file crimeDriversLog.rtf not found)

(output written to crimeDriversLog.rtf)

. eststo clear

•

- . loocv poisson violent2017 lnpop popgrowth shareyoung shareold unemployment sh
- > arepoverty lessthanhs bachelorup, robust

Leave-One-Out Cross-Validation Results

Method	1	Value
	-+	
Root Mean Squared Errors	1	18.156669
Mean Absolute Errors	I	13.222717
Pseudo-R2	I	.35033617

- . loocv poisson violent2017 lnpop popgrowth share15to19 share20to24 shareold un
- > employment sharepoverty lessthanhs bachelorup

Leave-One-Out Cross-Validation Results

Method		Value
Root Mean Squared Errors		
-	· 	12.235847
Pseudo-R2	1	.41879987

.

- . loocv poisson violent2017 lnpop popgrowth shareyoung share65to84 share85up un
- > employment sharepoverty lessthanhs bachelorup

Leave-One-Out Cross-Validation Results

Method		Value
	-+	
Root Mean Squared Errors		17.350007
Mean Absolute Errors	I	13.097056
Pseudo-R2	I	.35819884

.

- . loocv poisson violent2017 lnpop popgrowth shareyoung shareold unemployment sh
- > arepoor shareverypoor lessthanhs bachelorup

Leave-One-Out Cross-Validation Results

Method	1	Value
	-+	
Root Mean Squared Errors	1	18.371456
Mean Absolute Errors	I	13.433351
Pseudo-R2	1	.3409986

•

- . loocv poisson violent 2017 lnpop popgrowth shareyoung shareold unemployment sh
- > arepoverty lessthanhs bachelor graduate

Leave-One-Out Cross-Validation Results

Method	I	Value
	-+	
Root Mean Squared Errors	1	18.986501
Mean Absolute Errors	1	13.576504
Pseudo-R2	1	.32578779

.

- . loocv poisson violent 2017 lnpop popgrowth shareyoung shareold unemployment sh
- > are poverty highschool some college associate bachelorup

Leave-One-Out Cross-Validation Results

Method		Value
	т	
Root Mean Squared Errors	I	15.448863
Mean Absolute Errors	1	12.195429
Pseudo-R2	I	.40548981

.

- . loocv eststo: poisson violent2017 lnpop popgrowth shareyoung shareold unemplo
- > yment sharepoverty somecollege bachelorup, robust

Leave-One-Out Cross-Validation Results

Method	I	Value
	-+	
Root Mean Squared Errors	1	16.478571
Mean Absolute Errors	I	12.818964
Pseudo-R2	1	.38739067

.

- . // Combining models
- . loocv poisson violent2017 lnpop popgrowth share15to19 unemployment sharepover
- > ty lessthanhs bachelorup

Leave-One-Out Cross-Validation Results

Method		Value
	-+	
Root Mean Squared Errors	1	15.342847
Mean Absolute Errors	1	12.051063
Pseudo-R2	1	.43705222

- . eststo: poisson violent2017 lnpop popgrowth share15to19 unemployment sharepov
- > erty lessthanhs bachelorup, robust

Iteration 0: log pseudolikelihood = -409.73544

Iteration 1: log pseudolikelihood = -408.52089
Iteration 2: log pseudolikelihood = -408.51812
Iteration 3: log pseudolikelihood = -408.51812

Poisson regression	Number of obs	=	70
	Wald chi2(7)	=	142.38
	Prob > chi2	=	0.0000
Log pseudolikelihood = -408.51812	Pseudo R2	=	0.3959

I		Robust				
violent2017	Coef.	Std. Err.	Z	P> z	[95% Conf	. Interval]
+						
lnpop	.4872675	.0761501	6.40	0.000	.3380161	.636519
popgrowth	.0001436	.0000459	3.13	0.002	.0000538	.0002335
share15to19	12.71581	9.676295	1.31	0.189	-6.249383	31.681
unemployment	.154851	.0588949	2.63	0.009	.0394192	.2702828
sharepoverty	-6.48178	2.671508	-2.43	0.015	-11.71784	-1.24572
lessthanhs	.0212328	.0405269	0.52	0.600	0581984	.1006641
bachelorup	0256356	.0166846	-1.54	0.124	0583369	.0070657
_cons	-2.575799	.8596609	-3.00	0.003	-4.260703	8908945

(est72 stored)

. loocv poisson violent2017 lnpop popgrowth share15to19 unemployment sharepover

> ty bachelorup

Leave-One-Out Cross-Validation Results

Method | Value

Root Mean Squared Errors | 14.952309

Mean Absolute Errors | 11.74114

Pseudo-R2 | .44958327

. eststo: poisson violent 2017 lnpop popgrowth share 15to19 unemployment sharepov $\,$

> erty bachelorup, robust

Iteration 0: log pseudolikelihood = -410.40814
Iteration 1: log pseudolikelihood = -409.25508
Iteration 2: log pseudolikelihood = -409.2525
Iteration 3: log pseudolikelihood = -409.2525

Poisson regression	Number of obs	=	70
	Wald chi2(6)	=	141.71
	Prob > chi2	=	0.0000
Log pseudolikelihood = -409.2525	Pseudo R2	=	0.3948

.----

	1		Robust				
violent2017		Coef.	Std. Err.	Z	P> z	[95% Conf.	Interval]
	+-						
lnpop	I	.5075216	.0678648	7.48	0.000	.374509	.6405343
popgrowth	I	.0001446	.0000458	3.16	0.002	.0000548	.0002345
share15to19	I	11.78132	9.360907	1.26	0.208	-6.565725	30.12836
unemployment	I	.1524327	.0591999	2.57	0.010	.0364031	.2684623
sharepoverty	I	-5.824287	2.246664	-2.59	0.010	-10.22767	-1.420906
bachelorup	I	0311947	.012942	-2.41	0.016	0565605	0058288
_cons	I	-2.486545	.8222774	-3.02	0.002	-4.098179	874911

(est73 stored)

. loocv poisson violent2017 lnpop popgrowth share15to19 unemployment sharepover

> ty lessthanhs bachelor graduate

Leave-One-Out Cross-Validation Results

 _

Method	1	Value
	-+	
Root Mean Squared Errors	I	16.335665
Mean Absolute Errors	1	12.475284
Pseudo-R2	1	.39947824

- . eststo: poisson violent2017 lnpop popgrowth share15to19 unemployment sharepov
- > erty lessthanhs bachelor graduate, robust

Iteration 0: log pseudolikelihood = -409.45941
Iteration 1: log pseudolikelihood = -408.48335
Iteration 2: log pseudolikelihood = -408.48002
Iteration 3: log pseudolikelihood = -408.48002

Poisson regression	Number of obs	=	70
	Wald chi2(8)	=	149.38
	Prob > chi2	=	0.0000
Log pseudolikelihood = -408.48002	Pseudo R2	=	0.3960

	1		Robust				
violent2017	I	Coef.	Std. Err.	Z	P> z	[95% Conf	. Interval]
	-+-						
lnpop	I	.4833222	.084923	5.69	0.000	.3168761	.6497683
popgrowth	I	.0001466	.0000576	2.54	0.011	.0000337	.0002594
share15to19	I	12.72541	9.673905	1.32	0.188	-6.235096	31.68592
unemployment	I	.1561465	.0621983	2.51	0.012	.03424	.278053
sharepoverty	I	-6.385391	2.765687	-2.31	0.021	-11.80604	9647455
lessthanhs	I	.0225381	.0423804	0.53	0.595	060526	.1056022

bachelor	021083	.0491839	-0.43	0.668	1174817	.0753156
graduate	031553	.0629488	-0.50	0.616	1549304	.0918245
_cons	-2.589168	.8651562	-2.99	0.003	-4.284843	8934925
(est74 stored)						

.

- . loocv poisson violent2017 lnpop popgrowth share15to19 unemployment sharepover
- > ty bachelor graduate

Leave-One-Out Cross-Validation Results

Method		Value
Root Mean Squared Errors	I	16.401767
Mean Absolute Errors		12.288472
Pseudo-R2		.39753808

- . eststo: poisson violent2017 lnpop popgrowth share15to19 unemployment sharepov
- > erty bachelor graduate, robust

Iteration	0:	log	pseudolikelihood	=	-410.23702
Iteration	1:	log	pseudolikelihood	=	-409.25413
Iteration	2:	log	pseudolikelihood	=	-409.25127
Iteration	3:	log	pseudolikelihood	=	-409.25127

Poisson regression	Number of obs	=	70
	Wald chi2(7)	=	146.28
	Prob > chi2	=	0.0000
Log pseudolikelihood = -409.25127	Pseudo R2	=	0.3948

1		Robust				
violent2017	Coef.	Std. Err.	Z	P> z	[95% Conf.	Interval]
					.3663061	
					.0000306	
					-6.621748	
unemployment	.1522361	.061693	2.47	0.014	.0313201	.2731522
sharepoverty	-5.847692	2.510242	-2.33	0.020	-10.76768	927708
bachelor	0319199	.043707	-0.73	0.465	1175841	.0537442
graduate	0301096	.0637237	-0.47	0.637	1550057	.0947865
_cons	-2.485102	.8246943	-3.01	0.003	-4.101473	8687305
(est75 stored)						
. esttab using	g "combinedMo	delsLog.rtf"	, se(3) n	nostar re	place	
(note: file co	ombinedModels	Log.rtf not	found)			
(output writte	en to combine	edModelsLog.r	tf)			
. eststo clear	2					
. //Prediction	n Models					
. loocv poisso	on violent201	.8 lnviolent2	017 viole	entGrowth	popgrowth ln	pop share15
> to19 unemployment sharepoverty bachelorup						
Leave-One-Out	Cross-Valid	lation Result	S			

		Value
Root Mean Squared Errors		
Mean Absolute Errors	1	9.683358

Pseudo-R2 | .60378361

- . eststo: poisson violent2018 lnviolent2017 violentGrowth popgrowth lnpop share
- > 15to19 unemployment sharepoverty bachelorup, robust

Iteration 0: log pseudolikelihood = -261.76555
Iteration 1: log pseudolikelihood = -254.82534
Iteration 2: log pseudolikelihood = -254.80953
Iteration 3: log pseudolikelihood = -254.80953

Poisson regression	Number of obs	=	60
	Wald chi2(8)	=	338.20
	Prob > chi2	=	0.0000
Log pseudolikelihood = -254.80953	Pseudo R2	=	0.5768

1		Robust				
violent2018	Coef.	Std. Err.	Z	P> z	[95% Conf	. Interval]
lnviolent2017	.8364854	.1177387	7.10	0.000	.6057218	1.067249
violentGrowth	8584422	.4781311	-1.80	0.073	-1.795562	.0786776
popgrowth	.000069	.0000433	1.59	0.111	0000159	.0001538
lnpop	.1145994	.0932934	1.23	0.219	0682523	.297451
share15to19	-12.11531	4.929093	-2.46	0.014	-21.77615	-2.454462
unemployment	0701173	.0591769	-1.18	0.236	186102	.0458673
sharepoverty	2.039403	2.179005	0.94	0.349	-2.231368	6.310173
bachelorup	0089961	.0125558	-0.72	0.474	0336051	.0156128
_cons	.3831605	.611736	0.63	0.531	8158201	1.582141

(est1 stored)

•

. test sharepoverty bachelorup $% \left(1\right) =\left(1\right) \left(1\right) \left$

```
( 1) [violent2018]sharepoverty = 0
```

(2) [violent2018]bachelorup = 0

```
chi2(2) = 2.56

Prob > chi2 = 0.2781
```

•

- . loocv poisson violent2018 lnviolent2017 violentGrowth popgrowth lnpop share15
- > to19 unemployment

Leave-One-Out Cross-Validation Results

Method	1	Value
	-+	
Root Mean Squared Errors	1	12.235904
Mean Absolute Errors	1	8.8036559
Pseudo-R2	1	.66603695

- . eststo: poisson violent2018 lnviolent2017 violentGrowth popgrowth lnpop share
- > 15to19 unemployment, robust

```
Iteration 0: log pseudolikelihood = -264.35839
Iteration 1: log pseudolikelihood = -258.61308
Iteration 2: log pseudolikelihood = -258.60561
Iteration 3: log pseudolikelihood = -258.60561
```

Poisson regression	Number of obs	=	60
	Wald chi2(6)	=	319.53
	Prob > chi2	=	0.0000
Log pseudolikelihood = -258.60561	Pseudo R2	=	0.5705

violent2018	Coef.	Robust Std. Err.	Z	P> z	[95% Conf.	Interval]
+						
lnviolent2017	.8386199	.1130639	7.42	0.000	.6170188	1.060221
violentGrowth	9405693	.4583478	-2.05	0.040	-1.838915	042224
popgrowth	.0000485	.0000289	1.68	0.093	-8.14e-06	.000105
lnpop	.0759517	.0735728	1.03	0.302	0682483	.2201517
share15to19	-10.30515	4.97881	-2.07	0.038	-20.06344	54686
unemployment	0278689	.0419425	-0.66	0.506	1100747	.0543368
_cons	.513055	.5974949	0.86	0.391	6580135	1.684123

(est2 stored)

- .
- . test lnpop unemployment
- (1) [violent2018]lnpop = 0
- (2) [violent2018]unemployment = 0

$$chi2(2) = 1.44$$

 $Prob > chi2 = 0.4864$

.

. loocv poisson violent2018 lnviolent2017 violentGrowth popgrowth share15to19 $\,$

Leave-One-Out Cross-Validation Results

Pseudo-R2 | .68778041

. eststo: poisson violent2018 lnviolent2017 violentGrowth popgrowth share15to19
> , robust

Iteration 0: log pseudolikelihood = -267.51299
Iteration 1: log pseudolikelihood = -261.48169
Iteration 2: log pseudolikelihood = -261.47481
Iteration 3: log pseudolikelihood = -261.47481

Poisson regression	Number of obs	=	60
	Wald chi2(4)	=	327.77
	Prob > chi2	=	0.0000
Log pseudolikelihood = -261.47481	Pseudo R2	=	0.5658

	Robust				
Coef.	Std. Err.	Z	P> z	[95% Conf.	Interval]
.8961913	.0837888	10.70	0.000	.7319684	1.060414
-1.081979	.4313989	-2.51	0.012	-1.927506	236453
.0000726	.0000237	3.07	0.002	.0000262	.000119
-8.76482	4.531619	-1.93	0.053	-17.64663	.1169892
.9310544	.3503824	2.66	0.008	.2443174	1.617791
	.8961913 -1.081979 .0000726 -8.76482	Coef. Std. Err. .8961913 .0837888 -1.081979 .4313989 .0000726 .0000237 -8.76482 4.531619	Coef. Std. Err. z .8961913 .0837888 10.70 -1.081979 .4313989 -2.51 .0000726 .0000237 3.07 -8.76482 4.531619 -1.93	Coef. Std. Err. z P> z .8961913 .0837888 10.70 0.000 -1.081979 .4313989 -2.51 0.012 .0000726 .0000237 3.07 0.002 -8.76482 4.531619 -1.93 0.053	Coef. Std. Err. z P> z [95% Conf. .8961913 .0837888 10.70 0.000 .7319684 -1.081979 .4313989 -2.51 0.012 -1.927506 .0000726 .0000237 3.07 0.002 .0000262 -8.76482 4.531619 -1.93 0.053 -17.64663

(est3 stored)

•

. esttab using "predictionModelsLog.rtf", se(3) nostar replace
(note: file predictionModelsLog.rtf not found)
(output written to predictionModelsLog.rtf)

. eststo clear

```
. // Predict 2019
. gen violentGrowth2018 = (violent2018 - violent2012)/6
(7 missing values generated)
. poisson violent2018 lnviolent2018 violentGrowth2018 popgrowth share15to19, ro
> bust
Iteration 0: \log pseudolikelihood = -157.14905
Iteration 1: \log pseudolikelihood = -150.62749
Iteration 2: log pseudolikelihood = -150.6168
Iteration 3: log pseudolikelihood = -150.6168
Poisson regression
                                   Number of obs
                                                        65
                                    Wald chi2(3)
                                   Prob > chi2
                                   Pseudo R2
Log pseudolikelihood = -150.6168
                                                     0.7704
                                                =
______
                        Robust
    violent2018 | Coef. Std. Err. z P>|z| [95% Conf. Inter
> val]
______
  lnviolent2018 | 1 1.49e-08 6.7e+07 0.000
violentGrowth2018 | -8.75e-09 2.16e-09 -4.04 0.000 -1.30e-08 -4.51
> e-09
    popgrowth | 3.41e-11 1.09e-11 3.14 0.002 1.28e-11 5.55
> e-11
```

share15to19 | -8.05e-08 6.80e-07 -0.12 0.906 -1.41e-06 1.25

```
> e-06
        _cons | -9.42e-09 5.15e-08 -0.18 0.855 -1.10e-07 9.16
> e-08
_____
> ----
. predict prediction2018
(option n assumed; predicted number of events)
(7 missing values generated)
. save "PredictionLog.dta", replace
(note: file PredictionLog.dta not found)
file PredictionLog.dta saved
. log close
    name: <unnamed>
    log: C:\Users\Josh\Desktop\QMBProject\Cantera_Log_Project.smcl
 log type: smcl
closed on: 6 Dec 2019, 16:20:09
_____
```

Appendix D: Summary Statistics

summarize pop15to19 pop20to24 pop65to84 pop85up

Variable		Obs	Mean	Std. Dev.	Min	Max
	-+					
pop15to19		72	5544.569	9565.036	250	69912
pop20to24		72	5368.778	10918.82	157	77957
pop65to84	1	72	9150.125	12708.65	457	90146
pop85up	1	72	1645.903	2539.943	25	18987

. summarize violent2012 violent2017 violent2018

Variable	Obs	Mean	Std. Dev.	Min	Max
+					
violent2012	66	24.63636	29.088	0	184
violent2017	70	24.12857	19.48461	0	89
violent2018	71	22.76056	20.45515	0	103

. summarize shareyoung shareold, detail

shareyoung

	Percentiles	Smallest		
1%	.0856998	.0856998		
5%	.0909701	.0875183		
10%	.0934574	.0896874	Obs	72
25%	.107801	.0909701	Sum of Wgt.	72
50%	.1135534		Mean	.1239414
		Largest	Std. Dev.	.0313313
75%	.1316317	.2070991		
90%	.1613894	.208073	Variance	.0009816

95%	.2070991	.2092145	Skewness	1.681
99%	.2321864	.2321864	Kurtosis	5.459558

shareold

	Percentiles	Smallest		
1%	.1003972	.1003972		
5%	.1122361	.1027387		
10%	.1160814	.104415	Obs	72
25%	.1353499	.1122361	Sum of Wgt.	72
50%	.1586834		Mean	.1638153
		Largest	Std. Dev.	.0370411
75%	.1878331	.2308986		
90%	.2107245	.2346826	Variance	.001372
95%	.2308986	.2538878	Skewness	.4639113
99%	.2592627	.2592627	Kurtosis	2.613443

. summarize bachelorup lessthanhs

Variable	Obs	Mean	Std. Dev.	Min	Max
+-					
bachelorup	72	22.65278	7.571499	11.4	50
lessthanhs	72	8.598611	2.491478	3.900001	17.9

. summarize violentGrowth

Variable	1	Obs	Mean	Std.	Dev.	Min	Max
	-+						
violentGro~h	1	61 .	0221093	.1831	.783479	5791 .61	182085

[.] summarize violentGrowth, detail

violentGrowth

	Percentiles	Smallest		
1%	4795791	4795791		
5%	2143602	4200122		
10%	1911023	3649098	Obs	61
25%	0749387	2143602	Sum of Wgt.	61
50%	.0364643		Mean	.0221093
		Largest	Std. Dev.	.1831783
75%	.0989392	.2598566		
90%	.2387845	.308089	Variance	.0335543
95%	.2598566	.3583519	Skewness	.0031043
99%	.6182085	.6182085	Kurtosis	4.550498

. summarize popGrowth, detail

popGrowth

	Percentiles	Smallest		
1%	0074749	0074749		
5%	0052114	0064299		
10%	0041265	0052397	Obs	72
25%	0022431	0052114	Sum of Wgt.	72
50%	000012		Mean	.0003725
		Largest	Std. Dev.	.0039692
75%	.0026976	.0077377		
90%	.0048552	.0082249	Variance	.0000158
95%	.0077377	.0125319	Skewness	.8190459
99%	.0130428	.0130428	Kurtosis	4.16537

- . summarize sharevery poor sharepoor shaver poverty variable shaver poverty not found ${\tt r\,(111)\,;}$
- . summarize shareverypoor sharepoor sharepoverty

Variable	Obs	Mean	Std. Dev.	Min	Max
+					
shareveryp~r	72	.0486735	.0195342	.0180882	.1584761
sharepoor	72	.0707906	.0234431	.0274545	.1999549
sharepoverty	72	.1194642	.0416488	.0476047	.358431

- . summarize lnviolent2012 lnviolent2017 lnviolent2018
 variable lnviolent2018 not found
 r(111);
- . gen lnviolent = ln(violent2018)
- (2 missing values generated)
- . gen lnviolent2018 = lnviolent
- (2 missing values generated)
- . drop lnviolent
- . summarize lnviolent2012 lnviolent2017 lnviolent2018

	Variable	Obs	Mean	Std. Dev.		Max
		+				
11	nviole~2012	65	2.729422	1.0588	0	5.214936
11	nviole~2017	68	2.868541	.937405	0	4.488636
11	nviole~2018	70	2.772094	.9211613	0	4.634729

. summarize highschool some college associate bachelor $\ensuremath{\mathsf{graduate}}$

Variable	1	Obs	Mean	Std. Dev.	Min	Max
	+					
highschool	1	72	36.15417	5.708751	17.9	45.4
somecollege	1	72	21.44861	2.071401	17.6	30.4
associate	1	72	11.14583	1.558614	7.6	15.6
bachelor	1	72	15.25833	4.775104	8.1	29.9
graduate	1	72	7.394444	2.993179	3.1	20.1

. summarize poppov verypoor poor

Variable	Obs	Mean	Std. Dev.	Min	Max
	+				
poppov	72	77952.93	132035.2	4289	934232
verypoor	72	4129.194	10508.54	149	84036
poor	72	5491.903	13129.03	213	107937

. summarize unemployment, detail

Unemployment

	Percentiles	Smallest		
1%	2	2		
5%	2.7	2.6		
10%	3.1	2.7	Obs	72
25%	3.5	2.7	Sum of Wgt.	72
50%	4.1		Mean	4.570833
		Largest	Std. Dev.	1.498303
75%	5.3	7.9		

90%	7.1	8.1	Variance	2.244912
95%	7.9	8.1	Skewness	.9741297
99%	8.3	8.3	Kurtosis	3.200197

. describe

Contains data from projectData.dta

obs: 72

vars: 48 12 Nov 2019 16:36

	storage	display	value	
variable name	type	format	label	variable label
county	str11	%11s		County
pop2012	long	%12.0g		Pop2012
pop2017	long	%12.0g		Pop2017
pop15to19	long	%12.0g		Pop15to19
pop20to24	long	%12.0g		Pop20to24
pop65up	long	%12.0g		Pop65up
pop85up	int	%8.0g		Pop85up
pop65to69	int	%8.0g		Pop65to69
pop70to74	int	%8.0g		Pop70to74
pop75to79	int	%8.0g		Pop75to79
pop80to84	int	%8.0g		Pop80to84
violent2012	int	%8.0g		
property2012	int	%8.0g		
violent2017	byte	%8.0g		
property2017	int	%8.0g		
violent2018	int	%8.0g		
property2018	int	%8.0g		
highschool	float	%9.0g		HighSchool

somecollege	float	%9.0g		SomeCollege
associate	float	%9.0g		Associate
bachelor	float	%9.0g		Bachelor
graduate	float	%9.0g		Graduate
poppov	long	%12.0g		PopPov
verypoor	long	%12.0g		VeryPoor
poor	long	%12.0g		Poor
unemployment	float	%9.0g		Unemployment
lnpop2012	float	%9.0g		
lnpop2017	float	%9.0g		
lnviolent2012	float	%9.0g		
lnviolent2017	float	%9.0g		
violentGrowth	float	%9.0g		
popGrowth	float	%9.0g		
pop	long	%12.0g		Pop
_merge	byte	%23.0g	_merge	
share15to19	float	%9.0g		
lnpop	float	%9.0g		
<pre>lnpop share20to24</pre>	float float	%9.0g %9.0g		
share20to24	float	%9.0g		
share20to24 pop65to84	float	%9.0g %9.0g		
share20to24 pop65to84 share65to84	float float float	%9.0g %9.0g %9.0g		
share20to24 pop65to84 share65to84 share85up	float float float float	%9.0g %9.0g %9.0g %9.0g		
share20to24 pop65to84 share65to84 share85up shareyoung	float float float float float float	%9.0g %9.0g %9.0g %9.0g %9.0g		
share20to24 pop65to84 share65to84 share85up shareyoung shareold	float float float float float float float	%9.0g %9.0g %9.0g %9.0g %9.0g		
share20to24 pop65to84 share65to84 share85up shareyoung shareold shareverypoor	float float float float float float float float	%9.0g %9.0g %9.0g %9.0g %9.0g %9.0g		
share20to24 pop65to84 share65to84 share85up shareyoung shareold shareverypoor sharepoor	float	%9.0g %9.0g %9.0g %9.0g %9.0g %9.0g %9.0g		
share20to24 pop65to84 share65to84 share85up shareyoung shareold shareverypoor sharepoor sharepoor	float	%9.0g %9.0g %9.0g %9.0g %9.0g %9.0g %9.0g		
share20to24 pop65to84 share65to84 share85up shareyoung shareold shareverypoor sharepoor sharepoor sharepoverty bachelorup	float	%9.0g %9.0g %9.0g %9.0g %9.0g %9.0g %9.0g %9.0g		

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Sorted by: county

Note: Dataset has changed since last saved.

. summarize pop, detail

Pop

	Percentiles	Smallest		
1%	4232	4232		
5%	7469	4423		
10%	14755	5916	Obs	72
25%	19514	7469	Sum of Wgt.	72
50%	41384		Mean	78985.92
		Largest	Std. Dev.	132198.8
75%	85370	248007		
90%	166426	389891	Variance	1.75e+10
95%	248007	488073	Skewness	4.639431
99%	947735	947735	Kurtosis	28.46624