Exploring Links Between Economic Status and Crime

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Introduction:

In an era where crime and gun violence appear in the American media on an uncomfortably frequent basis, crime statistics seem to be more widely discussed and debated than ever. Especially as the 2020 presidential election approaches and opinions on the criminal justice system come into the forefront on a national scale, the debate between reform and retaining the status quo is one of the most pressing issues facing our nation at the moment. While we knew it would be interesting to dive into understanding crime in the United States, we grew to understand it would be incredibly important to be well-informed on a problem that has seemingly always plagued our country. We wanted to examine the general economic status of those who commit crimes and where those people live in order to form a more holistic picture of our prison population. We also wanted to explore how shifts in the police force affect the amount of crime. In our research, we found several positive relationships of varying strengths between economic status, location, and crime rates. Crime rates were higher for the unemployed and higher in metro areas, yet income is not a helpful indicator for predicting crime. Statistics for violent crimes and property crimes are very different, and grouping all forms of crime under one label can be incredibly misleading. While it may be tempting to point to the causality of economics or employment to explain crime rates, poverty and crime are incredibly complex institutions which have been perennially ingrained in American society; correlation of our data is much more likely due to how deeply intertwined economics and crime are.

Literature review:

Plenty of research has examined changes in crime rates and the prison population in the United States. “Income Inequality and Crime in the United States”, a 2008 paper by Jongmook Choe, focuses almost exclusively on how income inequality affects crime rates. Choe simplifies the complexities of economic disparity by using the Gini Index, a measure of wealth dispersion between upper and lower classes, and finds an incredibly strong correlation between income inequality and crimes. “Understanding Prison Policy and Population Trends”, a 1999 paper by Theodore Caplow and Jonathan Simon that examines several factors which influence the American prison population, finds a similar relationship between economic status and crime. Caplow and Simon document that the median pre-incarceration incomes for prisoners was significantly lower than that of the national median income. Caplow and Simon also interestingly found that only 34 percent of prisoners report completing high school. Although not specifically related to economic status, this relationship between education and crime is incredibly interesting and provides another potential explanatory factor which is completely absent from our dataset. Police funding is also a contentious issue, and the 2018 New York Times article “The U.S. Has Fewer Crimes. Does That Mean It Needs Fewer Police?” from Journalist Jose Del Real examines how the relationship between policing and crime is not as clear-cut as some may think. While many may believe increases in the police force must correspond to decreases in crime, Del Real explains how decreases in the police force are often a response to decreases in the crime rate. There is currently a sharp contrast between factions who believe increasing policing is guaranteed to decrease crime and those who believe increasing policing will only sow distrust into a community and lead to more crime. Understanding how changes in the police force and changes in crime are related is necessary to stake a stance on such a complex issue.

Data description:

Our research will be analyzing United States crime statistics and the prison population and the different variables that may influence these values. Our dataset “prison” is from the Boston College database and contains several hundred observations of data on crime and prison populations. For our research, we focused on explaining two variables: violent crimes per 100,000 people and property crimes per 100,000 people. In order to understand the fluctuations we viewed in the aforementioned variables, we took into account many explanatory variables pertaining to the economic status of the prison population, including nominal per capita income, the proportion of the population unemployed, and proportion living in metro areas. To further investigate crime rates, we also analyzed the variable police per 100,000 residents to see if more police officers truly led to less crime.

The variable violent crimes per 100,000 people (criv) represents the amount of times a crime with the intent or use of violence occurs for every 100,000 people. The variable property crimes per 100,000 people (crip) represents the amount of times a crime with the intent of obtaining money, property, or another benefit occurs for every 100,000 people. These are the two variables we sought to explain.

Table 1: Violent Crimes Summary Statistics

viol. crimes per 100,000

	Percentiles	Smallest		
1%	.6188341	.4756278		
5%	1.3156	.5201794		
10%	1.676939	.5390505	Obs	714
25%	2.824324	.5391433	Sum of Wgt.	714
50%	4.515549		Mean	5.078585
		Largest	Std. Dev.	3.440078
75%	6.502207	24.69865		
90%	8.712421	24.70033	Variance	11.83414
95%	10.26512	28.52137	Skewness	2.565897
99%	20.73237	29.21799	Kurtosis	14.77481

Table 2: Basic Prison, Violent Crimes, Property Crimes, and Unemployment Rate Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
pris	714	199.9803	132.7135	20.82695	1286.838
criv	714	5.078585	3.440078	.4756278	29.21799
crip	714	46.43514	12.11724	20.96502	88.39273
unem	714	.0684871	.0221513	.02142	.18033

Table 3: Property Crimes Summary Statistics

prop. crimes per 100,000

	Percentiles	Smallest		
1%	23.24176	20.96502		
5%	27.4979	21.18563		
10%	31.03763	21.69563	Obs	714
25%	38.66514	21.94527	Sum of Wgt.	714
50%	45.18515		Mean	46.43514
		Largest	Std. Dev.	12.11724
75%	54.39778	83.70707		
90%	62.06776	85.54945	Variance	146.8276
95%	67.98484	86.32821	Skewness	.5154289
99%	79.445	88.39273	Kurtosis	3.342707

Figure 1: Scatter plot of Violent Crimes and Proportion in Metro Areas

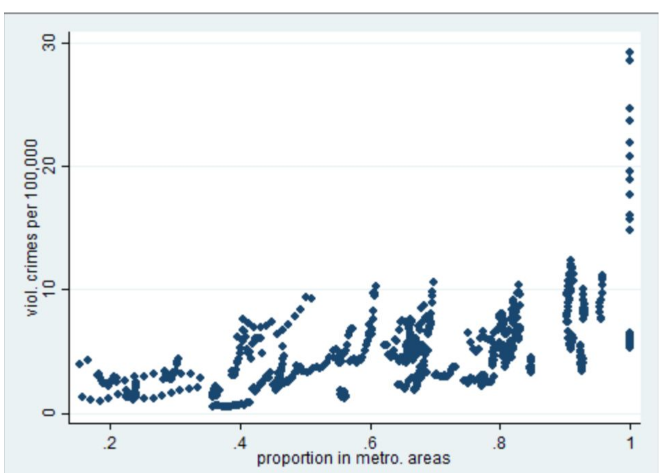
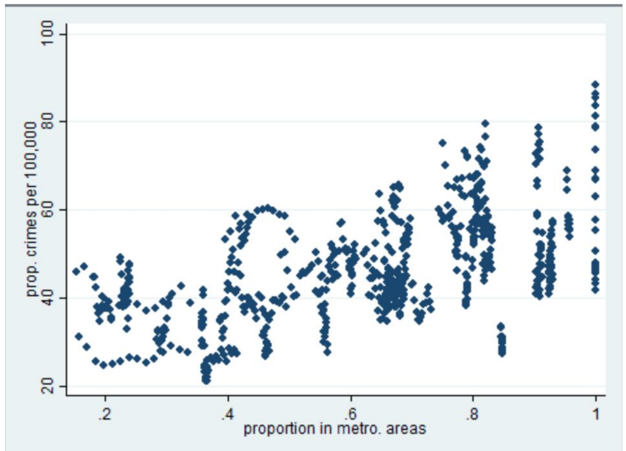


Figure 2: Scatter Plot of Property Crimes and Proportion in Metro Areas



Empirical Strategy:

Our most basic hypothesis is that economic status has an inverse effect on crime rates, meaning as the economic status of an individual or population decreases, their likelihood to commit crimes would increase. We used the phrase “economic status” to lump together our views on several more specific explanatory variables. In order to examine “economic status”, we focused mainly on per capita income and unemployment status. We believed if these variables truly affected crime rates, we would see a strong positive correlation between unemployment and crimes and a strong negative correlation between income and crimes.

Although not explicitly tied to economic status, we also wanted to explore if changes in the police force would affect crime. While there is an argument that areas with a higher economic status may be able to afford more police or better policing initiatives, that data is not readily available in our dataset. For the sake of our data and for fewer crimes in our country, we hoped to see a strong negative relationship between police per 100,000 and crime rates.

We believe the results we find will contain a mix of correlational and causal relationships. Initially, we believed crime rates would be caused by economic status. We had a general idea that the lack of a sense of financial security would make individuals more inclined to commit crimes. However, we understood the complexity of economics in the United States and realized a one-way causal relationship between economic status and crime is far too simple. While we still anticipated to see a decently strong relationship between these variables, we acknowledged how certain areas have been historically underfunded or underdeveloped, and how economics may affect crime rates just as much as crime rates affect economics. Poorer areas may experience high crime, but with the data at hand, it is not reasonable to definitively state whether high crime is a result of sub-standard living conditions or if crime is the factor which continues to perpetuate this cycle of underdevelopment.

Results and Analysis:

One of the first things our data showed us is how our original use of the word “crime” as an umbrella term may be somewhat misleading. Figure 3 shows that property crime happens more frequently than violent crime and is also much more normally distributed. Other instances of our data showed us further disparities between property crime, violent crime, and our explanatory variables. Table 4 examines the correlations between both forms of crime and unemployment. While there was a correlation value of .1220 between violent crimes and unemployment, there was only a correlation of .0273 between property crimes and unemployment. While the correlation between violent crimes and unemployment is weak, it was a step in the original direction we expected. However, the correlation between property crimes and unemployment is almost negligibly small and forced us to reconsider our use of the word “crime” and reinforced a need to consider both forms of crime separate entities. This is further supported by the correlation between violent crimes and property crimes. While the correlation value of .6824 is very strong, it is still a fair distance away from 1, which shows us the presence of either form of crime does not mean the other form is guaranteed to occur.

Figure 3 : Property Crimes and Violent Crimes per 100,000

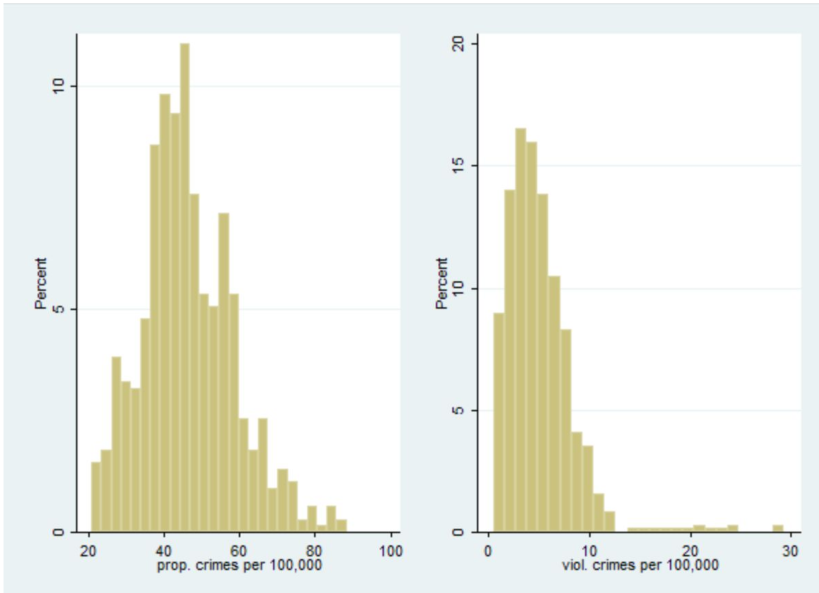


Table 4: Correlation between Unemployment, Property Crimes and Violent Crimes

	unem	crip	criv
unem	1.0000		
crip	0.0273	1.0000	
criv	0.1220	0.6824	1.0000

In order to further view how economic status and location affect crime, we decided to examine how income and living in metro areas is related. In order to do so, we created two binary variables called urban and inc. Urban has a value of 1 if the data is from an area which has an overwhelming majority of its people living in metro areas (above the 75th percentile), and has a value of 0 otherwise. Inc has a value of 0 if the data is from those who have a very low income (below the 25th percentile), and has a value of 1 otherwise. Our purpose with these binary variables is to see how our explanatory variables of income and urban areas are related. Table 5 compares these heavily urban areas and exceedingly poor individuals. This table showed us our original assumptions on economic status and urban areas were misguided. We originally assumed lower economic status would lead to crime and living in an urban area would lead to crime, so cities would be exceedingly poor. However, Table 5 shows that if an individual lives in a metro area, there is actually a 92.66% chance they are above the 25th percentile of wages. While Table 5 does not necessarily disprove our other findings on crime, it helped correct our misconception that metro areas and poverty were closely intertwined. As cities and low income are not as strongly related as we thought, it helped us to separate our findings between urban areas and crime and between income and crimes.

Table 5: Comparison of High Urban and Low Income Populations

	inc		
urban	0	1	Total
0	165 30.73	372 69.27	537 100.00
1	13 7.34	164 92.66	177 100.00
Total	178 24.93	536 75.07	714 100.00

Tables 6 and 7 give us further insight on urban areas and the occurrence of crime. Table 6 focuses on violent crime conditioned on people who live in urban areas, while Table 7 focuses on property crime conditioned on urban areas. Table 6 shows us the mean number of violent crimes jumps from 4.57 to 9.70 when comparing non-urban and urban areas. Table 7 shows the mean of property crimes goes from 45.34 to 56.34 when comparing non-urban and urban areas. These tables again show the dangers of grouping both violent and property crimes under the one label of “crime”. Although the numbers are still very small, the amount of violent crimes more than doubled when looking at urban areas while the amount of property crimes only showed an approximately 25% increase. Due to the amount of data in our dataset which corresponds to non-urban areas, we can see that the 90% confidence interval for these areas is quite tight around the sample mean. While the 90% confidence interval is less tight when looking at urban areas, we still felt we gained a generally accurate perspective on the increase in crime. While both forms of crime seem more likely in urban areas, violent crimes are much more common in urban areas than in non-urban areas.

Table 6: Comparing Means of Violent Crimes in Urban and non-Urban Areas

-> urban = 0

Variable	Obs	Mean	Std. Err.	[90% Conf.	Interval]
criv	643	4.569318	.0969594	4.409603	4.729032

-> urban = 1

Variable	Obs	Mean	Std. Err.	[90% Conf.	Interval]
criv	71	9.690679	.7612163	8.421797	10.95956

Table 7: Comparing Means of Property Crimes in Urban and non-Urban Areas

-> urban = 0

Variable	Obs	Mean	Std. Err.	[90% Conf.	Interval]
crip	643	45.34195	.4560837	44.59067	46.09322

-> urban = 1

Variable	Obs	Mean	Std. Err.	[90% Conf.	Interval]
crip	71	56.33549	1.493897	53.84529	58.82569

Table 8 displays a t-test for violent crimes in urban and non-urban areas. Our null hypothesis is that the mean of violent crimes per 100,000 people (criv) in urban areas will be the same as the mean of criv in non-urban areas. The alternative hypothesis is that the mean of criv in urban areas is not the same as the mean of criv in non-urban areas. We anticipated crime rates being higher in urban areas, but wanted to use a two-tail hypothesis test to remove any preconceptions we had about the data. The critical values we tested the null against are t at the 10% significance level, t at the 5% significance level and t at the 1% significance level. Because there are functionally infinite degrees of freedom, the critical values for t would be 1.282, 1.645 and 1.96 at the 10, 5, and 1 percent significance levels respectively. With the t-statistic being -13.2897, we can confidently reject the null at all levels of significance because it is well outside of our range of critical values. The rejection of the null means we can very confidently state that the mean of violent crimes in urban areas is significantly different than the mean of violent crimes outside of urban areas.

Table 8: T-Test of Violent Crimes in Urban and non-Urban Areas

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	643	4.569318	.0969594	2.458641	4.378922	4.759713
1	71	9.690679	.7612163	6.414122	8.172481	11.20888
combined	714	5.078585	.1287417	3.440078	4.825827	5.331343
diff		-5.121362	.3853634		-5.877946	-4.364777

diff = mean(0) - mean(1)   t = -13.2897
Ho: diff = 0   degrees of freedom = 712

Table 9 gives us the t-test for property crimes in urban and non-urban areas. Again, our null hypothesis would be property crimes in both areas being equal to each other, and the alternate hypothesis we hope for is that the two values are not equal. We found a t-statistic of -7.5330, which again allows us to very confidently reject the null. Therefore, we know that there is a strong relationship between both forms of crime and whether or not the area is urban.

Table 9: T-Test of Property Crimes in Urban and non-Urban Areas

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	643	45.34195	.4560837	11.56512	44.44635	46.23754
1	71	56.33549	1.493897	12.5878	53.35601	59.31498
combined	714	46.43514	.4534765	12.11724	45.54483	47.32545
diff		-10.99355	1.459391		-13.85877	-8.128322

diff = mean(0) - mean(1)   t = -7.5330
Ho: diff = 0   degrees of freedom = 712

Table 10 compares violent crimes for those below the 25th percentile of income and for those above it. For those below the 25th percentile, the amount of violent crimes per 100,000 people is lower than for those above the 25th percentile of income. These results diverged from our original ideas that lower income would lead to more crime. However, as these values are incredibly close and the standard deviations for both lower and higher income are relatively large compared to the means themselves, it is hard to draw any strong conclusions from this data.

Table 10: Comparing Means of Violent Crimes Conditioned on Low Income

-> inc = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
criv	178	3.790392	1.944133	.5390505	10.26512

-> inc = 1

Variable	Obs	Mean	Std. Dev.	Min	Max
criv	536	5.50638	3.712889	.4756278	29.21799

Table 11 compares the occurrence of property crimes for those below the 25th percentile of income and for those above it. Similar to Table 10, we found that the amount of property crimes was lower for those with low income. This was another trend in a direction we were not expecting, but again the values may be too close for us to draw any concrete conclusions.

Table 11: Comparing Means of Property Crimes Conditioned on Low Income

-> inc = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
crip	178	43.28667	11.71459	20.96502	75.1262

-> inc = 1

Variable	Obs	Mean	Std. Dev.	Min	Max
crip	536	47.48072	12.07822	21.69563	88.39273

Although not directly related to economic status, we also wanted to observe how the ratio of police officers affects crime rates. Table 12 shows the correlation between policing rates, violent crimes, and property crimes. The correlation between police per 100,000 and violent crimes per 100,000 is very strong in a positive direction and was at first surprising. The positive correlation led us to believe an increase in police officers increases crime, which seemed very counterintuitive. However, the most likely explanation is that areas with higher crime rates must have larger amounts of police officers. This gives us a causal relationship between the two variables, although it was in the opposite direction that we anticipated. Yet again we viewed a disparity between the correlation of violent crimes to police officers and property crimes to police officers. The higher correlation value of violent crimes gives us insight that governments are more sensitive to hiring police officers in areas where more violent crimes are common. However, as the correlation values for both violent crimes and property crimes are relatively high, they both help to paint a picture on how policing rates respond to crime rates. Although we anticipated finding a negative relationship showing an increase in policing leading to a decrease in crime, Table 12 helped debunk our assumptions and helped paint a more accurate picture that describes the causes of shifts in the police force rather than the effects.

Table 12: Correlation Between Police Officers per 100,000 Population, Violent and Property Crimes

	polpc	criv	crip
polpc	1.0000		
criv	0.8118	1.0000	
crip	0.5602	0.6824	1.0000

In the two regressions we ran for violent crimes, we found slightly different results, but the same general trends. In Table 13, we observed that for urban areas, violent crime increases by 3.85 (occurrences per 100,00) on average, all else equal. For this coefficient the t statistic was 11.04, so it is extremely unlikely that there is no relationship urban areas and violent crimes. We also found a significant relationship between unemployment and violent crimes. For every 1% increase in the unemployment rate, violent crimes increase by 36.1 on average, all else equal. For this coefficient the t statistic was 5.95, so there is a very small chance that there is no relationship between unemployment and violent crimes. We were surprised to see a coefficient of only 1.41 for incpc and criv, a value much smaller than what we expected. In Table 15, the same general trends that we observed in Table 14 exist. While both tables examine economic status and urban populations, Table 14 uses our binary variables while Table 15 uses the dataset’s non-binary variables. We still observed similar coefficients for both tables and reached similar conclusions. We found that violent crime tends to increase when the percent of people living in urban areas increase and when unemployment increases. For income and violent crime, we found coefficients that actually suggested almost no relationship between the two.

Table 13: Multivariate Regression of urban, unemployment, income and violent crimes

Linear regression

Number of obs	=	714
F(3, 710)	=	50.76
Prob > F	=	0.0000
R-squared	=	0.3132
Root MSE	=	2.857

criv	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
urban	3.848704	.3486676	11.04	0.000	3.164161	4.533247
unem	31.88059	5.357507	5.95	0.000	21.36214	42.39904
inc	1.410477	.2117004	6.66	0.000	.9948434	1.826111
_cons	.8822391	.4592741	1.92	0.055	-.0194586	1.783937

Table 14: Multivariate Regression of Metro, Unemployment, Income and Violent Crimes

Linear regression

Number of obs	=	714
F(3, 710)	=	86.75
Prob > F	=	0.0000
R-squared	=	0.4026
Root MSE	=	2.6646

criv	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
metro	7.191686	.4908085	14.65	0.000	6.228076	8.155295
unem	36.08602	6.085297	5.93	0.000	24.13869	48.03335
incpc	.0002317	.0000504	4.59	0.000	.0001327	.0003308
_cons	-5.433112	1.044047	-5.20	0.000	-7.482901	-3.383324

We again utilized two regression tests to analyze property crimes, but our data was more inconclusive than that of violent crimes. Similar to before, the regression in Table 15 uses our binary variables while the regression in Table 16 uses the dataset's non-binary variables. While both regressions give us trends in the same directions, the changes in values are far more significant than our regressions for violent crimes. We decided to focus on the regression using the non-binary variables as it has a substantially higher R-squared value, making it considerably more reliable. This regression shows us as the percentage of people in metro areas rises by one percent, the amount of property crimes per rises by 31. As the unemployment rate rises by one percent, the amount of property crimes rises by nearly 14. However, the robust standard error on unemployment is high and causes us to question our data. We found a similarly strong coefficient in the regression in Table 15, which makes us confident that the relationship between unemployment and property crimes is strong, although the true magnitude of this relationship lies in a much greater range than we hoped for. The coefficients for income are the most interesting. The income coefficient in Table 16 is incredibly small and in the negative direction, meaning as income increases crime decreases. While this supports our original theory, the positive income coefficient in Table 15 does not offer any clarity. This mixture of conflicting results is characteristic of our data as we remained unable to confidently state any ways in which income per capita truly affects crime.

Table 15: Multivariate Regression of Urban, Unemployment, Income and Property Crimes

Linear regression

Number of obs	=	714
F(3, 710)	=	23.43
Prob > F	=	0.0000
R-squared	=	0.1051
Root MSE	=	11.487

crip	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
urban	7.906518	1.096339	7.21	0.000	5.754064	10.05897
unem	43.35401	23.60547	1.84	0.067	-2.990866	89.69889
inc	3.156019	1.105888	2.85	0.004	.9848164	5.327222
_cons	39.13671	2.047847	19.11	0.000	35.11615	43.15727

Table 16: Multivariate Regression of Metro, Unemployment, per capita Income and Property Crimes

Linear regression

Number of obs	=	714
F(3, 710)	=	106.27
Prob > F	=	0.0000
R-squared	=	0.3215
Root MSE	=	10.002

crip	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
metro	31.07181	1.847032	16.82	0.000	27.44551	34.69811
unem	13.8567	20.73652	0.67	0.504	-26.85554	54.56894
incpc	-.0001007	.0001261	-0.80	0.425	-.0003482	.0001469
_cons	27.03431	2.634873	10.26	0.000	21.86124	32.20739

Conclusion:

In our tests, the two strongest relationships we found were between population in metro areas and crime and between unemployment rates and crime. We think these relationships are causal in part, but because there are countless variables that affect crime and due to the complexities of crime and economic institutions, we believe stating the relationships are strictly causal is overly simplistic. Our results had some similarities to those found in existing literature on the subject, yet also contained some profound differences. The main point of divergence was that we did not find a strong correlation, or frankly any correlation at all, between income and either rate of crime. The correlations we found between income and crime rates were incredibly small and in certain instances in the positive direction, as opposed to the strong negative ones obtained in the other studies. Unsurprisingly, our research shows the importance of police and safety initiatives in urban areas. Our data yielded significant differences when conditioning on urban areas, so certain state governments could potentially consider how they allocate their budget when the likelihood of crime is higher in urban areas. However, as an increase in police does not directly correspond to a decrease in crime, governments may want to focus on fighting the underlying causes of crime rather than dumping money into police initiatives which only serve to fight the symptoms. Properly funding initiatives to increase employment or improve the quality of life in urban areas may serve the general population more than overly funding police and worrying the public. In order to make conclusions drawn from our data more concrete, gathering newer data on prison statistics would be incredibly beneficial. Although our results do paint a helpful picture on what factors affect crime the most, our data does not include new economic, political, and social trends. Additionally, similar studies may want to examine specific areas over time to view how changes in economic or political initiatives change the rate of violent and property crime.

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