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17 December 2024

California vs. Texas: A Difference-in-Differences Analysis of Policy Change on Auto Thefts

I. Abstract

Auto theft in America is a pervasive problem that can impact citizen's lives significantly. This study seeks to find a causal effect of the October 2011 California policy change AB 109, which made sentencing requirements for motor vehicle theft less severe, on auto theft rates. A difference-in-differences regression analysis was used to compare California's auto rate changes before and after the policy implementation with a control group, Texas. The results found that California did see a slight increase in motor vehicle theft relative to Texas, with a DiD estimator of 0.26 from before to after the policy change. However, in the regression analysis using all of the FBI data, the interaction term (β_3) was not statistically significant, so therefore the null hypothesis that the policy had no causal effect cannot be rejected. Though causality was not found, these results contribute to the existing literature and show that more research is needed on specific policies on crime to find solutions that show significant results.

II. Introduction

Motor vehicle theft is a major issue that significantly affects our communities. It can cause considerable financial losses for victims, disrupt their daily lives, and inflict emotional distress. The negative effects of motor vehicle theft extend beyond the individuals whose vehicles were stolen. Society also pays the price in the form of resources for law enforcement and prosecution, disruptions to traffic, inflated insurance premiums across the market, and increased risks posed by dangerous drivers. Also, stolen vehicles are often used to commit other crimes, which further compounds the societal impact of this crime. To properly address this issue, it is essential to understand the factors influencing motor vehicle theft and the role that public policy can play in exacerbating or alleviating the problem.

This study will deal with the overall theme of how criminal policy, particularly the classification of crimes and severity of associated punishments, affects rates of criminal activity. Specifically, the main research question is: *What was the causal effect of California's 2011 reclassification of motor vehicle theft as a nonviolent property crime on motor vehicle theft rates in the state?*

Past research on the factors affecting crime rates has pointed to economic conditions, policing strategies, and legislative policies, as some of the most important players. When it comes to legislative policy, existing literature has been mixed, without a clear consensus. Some scholars have suggested that harsher penalties lead to reductions in criminal activities. This deterrence effect is attributed to an internal and sometimes subconscious cost-benefit analysis (i.e. higher punishments make crimes seem less "worth it"). The National Bureau of Economic Research (NBER) has published a research paper lending credibility to this view. In their study of California Proposition 8, which required sentencing enhancements in certain cases, the researchers found that "the law requiring longer sentences has been effective in lowering crime. Within three years, crimes covered by the law fell an estimated 8 percent. Seven years after the law changed, these crimes were down 20 percent" (Kessler and Levitt).

However, other experts have argued that criminals don't always know the penalties associated with the crimes they intend to commit and that harsher penalties have little if any effect on crime rates. The United States Department of Justice, through its Office of Justice Programs (OJP) and the National Institute of Justice, has published literature aligned with this stance. According to an OJP report, “increasing the severity of punishment does little to deter crime” due to the fact that “criminals know little about the sanctions for specific crimes” (National Institute of Justice). Another piece of existing literature that supports this view can be found in *Empirical Economics*, an economic journal publishing research papers that apply advanced econometric methods. Maurice Bun, an econometrics professor and economic researcher, published a paper, entitled “Crime, deterrence and punishment revisited”, in 2019 in this journal. In his research, Professor Bun finds that crime rates don’t react much to increasing severity of punishment, but do seem to respond well to increasing probability of arrest (Bun et al.).

This study hopes to contribute to the existing literature by focusing on a specific policy intervention, California’s AB 109 Public Safety Realignment Act of 2011. Given the current lack of agreement on this issue and the sweeping policy implications of this debate, the investigation of this specific law, and the natural experiment that it provides, aims to inject some clarity into the current discourse. The intention is to conduct a difference-in-differences analysis using data from California, the treatment group, and Texas, the control group. The central data will be sourced from the monthly crime reports released by the FBI through their Crime Data Explorer.

III. Data

The data for this project was sourced from the FBI Crime Data Explorer which aggregates reported crime statistics for police departments all over the U.S. The downloaded data specifically looked at motor vehicle theft for California and Texas between 2006 and 2016. This 10-year time period is split up by month as each month is a data point for Motor Vehicle Theft Reported by Population. In terms of the data type, this is repeated cross-sectional as the data collected is a new sample from the same population at different points in time.

In 2011 a public safety measure called AB 109 was passed in California. This measure made sentencing for motor vehicle theft less severe. This is the treatment group as discussed, whereas the control group, Texas, has stronger penalties. Texas was also the most similar state in terms of population, large metropolitan areas, and the necessity of having a car. This data made Texas the clear choice to be the control group.

Below Figure 1 shows the descriptive statistics. The sample size is 132 months for each state as data is taken monthly from January 2006 to October 2016. The mean value is the average rate per 100,000 people of motor vehicle theft reported and the standard deviation is each state's deviation from that reported mean per 100,000 people. For California, the mean is 39.32, and for Texas, the mean is 24.45. The standard deviation is also higher in California, which makes sense given the higher mean value.

	Descriptive Statistics		
State	**Sample Size**	**Mean Value**	**Standard Deviation**
California	132	39.32886	7.536861
Texas	132	24.45220	5.249897

Figure 1: Descriptive Statistics for Motor Vehicle Theft in California and Texas (2006-2016)

IV. Methods

An initial descriptive analysis was conducted to summarize trends in the data, with a particular focus on satisfying the parallel trends assumption needed to conduct difference-in-differences regression analysis. The results of this descriptive analysis are included above. This analyzed both samples' auto thefts per 100,000 people over five years before and after the California policy change, which occurred in October 2011. When conducting this descriptive analysis, there were hopes to see the auto theft trends be as closely parallel as possible in the five-year period before the policy change (Figure 2).

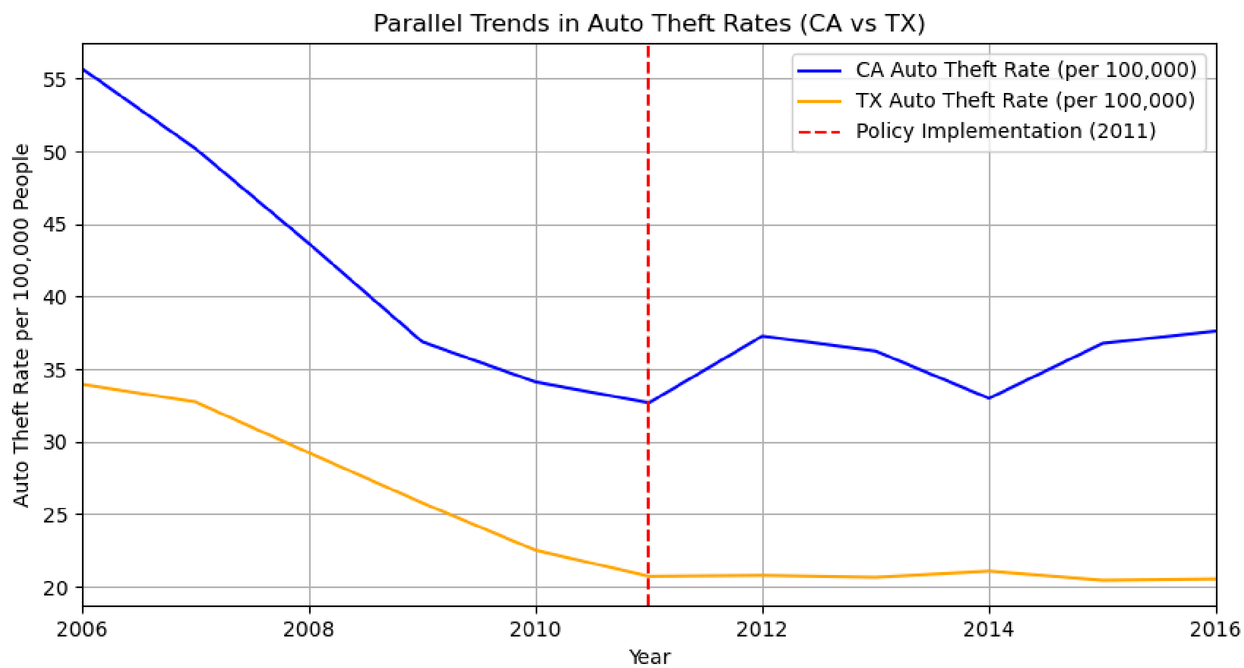

Figure 2: Parallel Trends in Auto Theft Rates in California & Texas

After graphing, it was found that the two samples exhibited relatively parallel trends in the period before the policy change. Both California and Texas were experiencing similar declines in auto theft rates, as well as seasonal dips at the beginning of each year. Finding parallel trends allowed to continue with the proposed methodology: difference-in-differences regression analysis. The difference-in-differences analysis was chosen for this dataset because it had a clear policy change that impacted one area but not the other. California and Texas were selected as the treatment and control groups, respectively, due to their relatively similar size, number of large cities, and the fact that Texas did not have any similar policy changes during the period being investigated.

To perform this difference-in-differences analysis, this regression equation was created:

$$\widehat{Y} = \beta_0 + \beta_1 post + \beta_2 California + \beta_3 postXCalifornia$$

In this regression equation, three terms are included in the standard difference-in-differences format, where the coefficient β_3 will represent the causal effect of the policy change on the treatment group (California) in the time period after the change is implemented. The coefficient β_0 can be interpreted as the average auto theft rate in Texas before October 2011. The coefficient β_1 represents the change in the average auto theft rate in the control group (Texas) after the policy change, relative to its value before the policy change was implemented. Finally, coefficient β_2 can be interpreted as the difference in average rates of auto thefts in California and Texas before the policy change occurred. $\widehat{Y}$ captures the predicted value of auto thefts per 100,000 people according to the model. The coefficient that matters most for finding a causal effect is β_3, and if this is statistically significant, it will have potentially captured the causal impact of the California policy change on rates of auto thefts per 100,000 people using the difference-in-differences regression model.

V. Results

This study began conducting a full difference-in-differences analysis by determining the difference-in-differences estimator to be:

$$(\overline{Y}_{\text{CA, A}} - \overline{Y}_{\text{CA, B}}) - (\overline{Y}_{\text{TX, A}} - \overline{Y}_{\text{TX, B}}) = (35.84 - 42.51) - (20.83 - 27.76) = \mathbf{0.26}$$

A positive DiD value (+0.26) means that California's decrease in theft rates was smaller compared to Texas, implying a relative increase in theft rates in the treatment group (California) after the policy. This suggested that after accounting for trends in the control group, the policy implementation in California led to an approximate increase of 0.26 units in motor vehicle theft rates overall. Therefore, the policy was expected to have a small but positive impact on auto theft rates. After calculating the DiD estimator and satisfying the parallel trends assumption, R was looked to in order to obtain the main regression outputs (Figure 3).

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Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)      27.6803     0.6673  41.478  < 2e-16 ***
post             -6.8727     0.9737  -7.058 1.53e-11 ***
california       14.7064     0.9438  15.583  < 2e-16 ***
postXcalifornia   0.3624     1.3771   0.263    0.793
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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5.583 on 260 degrees of freedom
Multiple R-squared:  0.6841,    Adjusted R-squared:  0.6805
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Figure 3: Output for Difference-in-Differences Regression

From the output, many relevant statistics were given per independent variable, such as coefficient estimates, standard errors, t-values, and significance codes. Given the coefficients in the output, the estimated regression equations was able to be completed:

$$\widehat{Y} = 27.6803 - 6.8727 post + 14.7064 California + 0.36240 postXCalifornia$$

The completed regression equation suggests that the initial estimated auto theft rate in Texas prior to the policy’s enactment would have been about 27.7%. β_1 suggests that the auto theft rate in Texas decreased by about 6.9 percentage points after the policy occurred. β_2 implies that the difference in auto theft rates between California and Texas before the policy occurred was about 14.7 percentage points and β_3 implies that the policy increased rates by about 0.36 percentage points.

According to the output, each independent variable, except β_3, was statistically significant, having a p-value of zero or nearly zero. β_3 was the primary variable of interest and its coefficient shows that the policy had a small but positive effect, which supports the hypothesis that the policy increased car thefts. However, its relatively high p-value indicates that its effects were not statistically significant. Because of these findings, it cannot be said the policy had a causal effect.

VI. Discussion and Conclusion

As aforementioned in the results section, the clear key takeaway from the difference-in-differences regression was the DiD estimator, which yielded a value of approximately +0.26, indicating that there was a smaller decrease in motor vehicle theft rates in California compared to Texas following the implementation of AB 109. Although both states experienced a relative downwards trend in theft rates during the total analyzed period, California's decline actually slowed relative to that of Texas, implicating a relative rise in auto theft rates within the state following the implementation of the policy. Given that this value was positive, it can be potentially articulated that the reclassification of motor vehicle theft as a nonviolent property offense may have indeed weakened the more deterrent effect of instead utilizing stricter enforcement in response to such crimes. Unfortunately, while this conclusion can be seen, it cannot be stated with statistical certainty, as the previously stated coefficient of interest was not statistically significant under any typical significance levels and, regardless, was relatively small. This high p-value (0.793) associated with the interaction term (postXcalifornia) points to insufficient evidence to declare the policy change as having this causal effect upon auto theft rates. With that being said, policymakers should interpret these results with caution, researching other potential factors that were unobserved within this regression model.

Prior to even being able to conduct any analysis, the core establishment within this regression was the fact that it was indeed able to identify parallel trends between the control group (Texas) and the treatment group (California). If these two groups had not exhibited relatively similar trends in auto theft rates prior to the implementation of AB 109, the difference-in-differences model would be immediately invalidated, prohibiting any proper conclusion occurring from analysis. Fortunately, as exhibited within Figure 2, the two states followed consistently downward trends in motor vehicle theft per 100,000 people despite a higher intercept value in California, even exhibiting the same seasonal fluctuations (sharp decline at the start of each year possibly due to weather, economic cycles, or even law enforcement cycles). Given these parallel trends, it became much more apparent that after the implementation of AB 109, Texas continued its downward trajectory while that of California appeared to slow, aligning with the observed difference-in-differences estimator and suggesting that the policy may have weakened the decline of auto theft rates in California.

Although the regression analysis allowed for the extraction of meaningful insights, it conversely highlighted the potential limitations of AB 109's measured effects upon motor vehicle theft rates. Other variables involved within the regression (post and California, in terms of non-interaction) all proved to be statistically significant at the individual level, suggesting that both location and time were, in fact, important factors to consider in identifying trends among auto theft rates. Unfortunate to the hopes of identifying causal effect, the interaction term (representing the effect of AB 109 on motor vehicle theft rates) had a very large p-value of 0.793, indicating that its effect may have likely been a result of random variation, in turn making it very difficult to attribute the policy change towards any causal effect (statistically, the coefficient equates to zero). As a result, while the regression model supports the hypothesis of a slight increase in rates post-policy, the lack of statistical significance prevents any definitive conclusions, particularly in terms of causal effect.

There is much debate regarding the effect of severity of punishment upon likelihood/rate of crime committed, with many scholars arguing that more intense consequences would push potential crime-committers to decide it is in their best interest to not commit the crime, given the increased risk of being caught and punished for doing so (Kessler & Levitt). Contrastingly, other researchers argue that potential crime-committers are either unaware of the severity of punishment or would commit the crime regardless of punishment, meaning that harsher policies have little to no effect when compared to more lenient and forgiving policies (National Institute of Justice; Bun et al.). In the case of this research, regression, and analysis regarding AB 109 in California versus Texas as a control, the lack of statistical significance in the coefficient of the interaction term provides evidence for the first argument. Because reducing the severity of the penalty for auto theft in California led to a statistically insignificant increase in related crime rates, the regression points to the hypothesis that there is little to no effect at all in changing policy severity (therefore must fail to reject the null hypothesis that a reduction to nonviolent property offense for motor vehicle theft has no effect on the rate of motor vehicle theft). All in all, both sides of the debate provide valuable understanding into the complex nature of severity of punishment and rate of associated crime, with factors such as offender awareness of consequences, nature of crime, and legal as well as social contexts all playing significant roles in quantifying or understanding this relationship.

To understand how these results can be used to inform public and private policies, one must first evaluate the intended purpose of AB 109. While it initially was approved with the intent of reducing overcrowding in prison and shifting nonviolent offenders to local jurisdiction, policymakers must understand and try to quantify potential adverse effects, such as an increase in the rates of the crimes that are reduced in terms of punishment. In the case of motor vehicle theft, from a statistical standpoint, the policy was likely successful in its hopes, reducing the amount of criminals in prison while not significantly increasing the rate of the associated crime. Furthermore, if the goal of future policies is to reduce crime rates of a specific crime, this lack of statistical significance should push policymakers to look to alternative methods of decreasing crime rates. In the case of motor vehicle theft, policymakers may want to look towards allocating more resources towards increased surveillance via mediums such as security cameras or emphasizing neighborhood initiatives that inform the public on how they can protect themselves from experiencing vehicle theft. From a private sector perspective, this research and the corresponding findings may be very relevant to the market of insurance, refining risk models to include the awareness of the potential lack of effect that deterrence policies may have. Contrastingly, even though the interaction term in the DiD model proved to be statistically insignificant, insurance companies may find value in the smaller decline in auto theft rates that California experienced post-AB 109. If future implementations of such policies begin to prove significant increases or decreases in crime rate (dependent upon the purpose of the policies), insurance companies may look to increase or decrease insurance premiums related to motor vehicles correspondingly.

VII. References

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