The Effect of Minneapolis 2040 on Auto-Related Property Crime

Nya Gasowski[*] Rian Russell[†] Will Palmer[‡]

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Abstract

We examine the relationship between upzoning and the occurrence of auto theft and theft from auto in Minneapolis and St. Paul, Minnesota. In 2020, Minneapolis implemented the Minneapolis 2040 Plan, becoming the first U.S. city to eliminate single-family zoning, a reform expected to increase residential density. We consider this policy change as an experimental opportunity to study whether upzoning is in fact associated with real changes in auto-related property crime. Using neighborhood-level monthly crime data from 2017 to 2022, we construct a dataset combining police incident reports from Minneapolis and St. Paul. While only Minneapolis experienced the change in zoning, we consider St. Paul to be a control variable in this context due to its close proximity and similar characteristics to Minneapolis. We estimate Difference-in-Differences models, including linear and Poisson generalized linear models, to compare trends in auto theft and theft from auto before and after the zoning change. (Add results here).

1 Introduction

In recent years, cities across the United States have increasingly turned to upzoning as a tool to address housing shortages, affordability concerns, and urban sprawl. Upzoning allows for higher-density development in previously low-density areas and has the potential to substantially reshape neighborhood composition and activity. While much literature examines the economic and housing-market effects of zoning reform, less is known about its implications for public safety. While many studies predict a positive relationship between density and crime, they often have considerably unique variables and limitations. Other research suggests that upzoning may instead reduce certain types of crime through natural surveillance, especially that which draw on Jane Jacobs' "eyes on the street" theory. This is particularly in contrast to commercial density, which differs in that populations are often transient, creating gaps in surveillance while residential density offers more permanent awareness (Mitre-Becerril & MacDonald, 2024). When putting the Minneapolis 2040 plan into legislation, policy makers did so with the intended goal of improving housing affordability, transportation access, environmental sustainability, economic development, and public safety (City of Minneapolis DCPED, n.d.). The plan highlights pedestrian centered design, lighting, mixed-income housing, and crime prevention through environmental design, suggesting that increased residential density is intended to enhance neighborhood safety rather than exacerbate crime. We

[*]American University
[†]American University
[‡]American University

seek to explore how effective this legislation has really been in affecting crime occurrences, and if it reflects the intentions of the City of Minneapolis.

Our analysis contributes to an ongoing debate about whether upzoning exacerbates crime. Considering theories of social disorganization and the potential of increased population due to the upzoning policy, we hypothesize that upzoning increases auto theft and theft from auto by increasing the number of potential targets and offenders within an area (Braithwaite, 1975). We test this hypothesis using monthly, neighborhood-level crime data from 2017 to 2022.

2 Zoning, Density, and Crime

The influence of zoning density, which is the amount of development permitted in a certain unit of land, on crime rates has become an increasingly researched topic, drawing from a diverse range of fields, from criminology to urban planning. It is important to determine whether new zoning laws have led to an increase in crime so that these laws can be analyzed and amended if necessary.

Many studies focus on psychological and criminological theories in examining the effects of density on crime. Clement et al. (2025) looks at urban density growth in different counties in the U.S. and its effect on crime, referring to the social disorganization and routine activities theories. Ma et al. (2025), which similarly looks at urban density growth in different counties but in China, brings up Maslow's hierarchy of needs and Becker's economic model of crime, which views offenders as individuals who weigh the benefits and costs of their actions.

Recent research includes a variety of results. He & Li (2021) looks specifically at property crime in Dallas and Fort Worth, leading to the conclusion that commercial and mixed-land use development, the number of transit facilities, and alcohol-related establishments like bars are positively associated with property crime rates in the two Texas cities, although the results are not generalizable. Clement et al. (2025) finds that migration, which is the inflow of residents minus the outflow, is positively associated with vehicle theft rate, but many of their hypotheses were rejected. Ma et al. (2025) finds that there is a positive correlation between urban density and urban crime rates, but the results are specific to China. Therefore, it is imperative that more research is done.

In 2020, Minneapolis became the first city in the U.S. to eliminate single-family zoning, which is defined as restricting residential areas to single-family homes, in its 2040 plan. The goal of single-family zoning is to maintain low density neighborhoods, meaning that this plan could lead to higher density neighborhoods (Gu & Murno, 2025). Some research on the effects of the Minneapolis 2040 plan has been done, with Davis et al. (2023) discussing how pro and anti density individuals can be predicted by their house typology and looking at how the disproportionate amount of power Minneapolis grants its local communities affects its residents. Mattila et al. (2025) also focuses on the populist public input in the planning process. However, we want to add to the research done around the Minneapolis 2040 plan by looking at the effects it has had on crime.

3 Data and Methods

We perform this analysis using crime timestamp data from Open Information St. Paul (Saint Paul Minnesota, n.d.) and Open Data Minneapolis (The City of Minneapolis, 2017-2022). The data originally is formatted in crime occurrences. We aggregate this to crime count per month in each city as neighborhood size and county varies by city. This is a common metric for crime analysis like this. We filter the timeframe to 3 years before and after the implementation of Minneapolis' upzoning, ranging from 2017-2022. We choose to specifically filter the data to just auto theft and theft of automobile related crimes. These are often less personal crimes and are more independent of other factors, making them optimal for analysis. These crimes are also generally easier to commit, making them more dynamic, especially with population density, and more likely to appear in data trends (Clement et al., 2025). We also note that both cities define auto-related crime very similarly (McDonough Law). We clean and reformat the data using both R (R Core Team, 2025) and Redivis (Redivis, 2025).

Our analysis follows the DiD model. We create a `treatment` variable, labeled 1 for crimes in Minneapolis (where upzoning occured) and 0 for crimes in St. Paul. We also create a `post` variable, labeled 1 for crimes after January 1st 2020, and 0 for crimes before. We assume that the parallel trends assumption is supported given the proximity and similarity of the cities. They have similar densities, educations, demographics, and population sizes (U.S. Census Bureau). Given this and their proximity, we assume they experience similar shocks from the pandemic, Black Lives Matter protests, and more.

Our DiD model has 2 key components. First we estimate a DiD coefficient using traditional Ordinary Least Squares (OLS) linear model methodology. For this first model the outcome is `crime_rate`, which is defined as crimes per 100,000 residents per month in each city. Crime rate is regressed on the treatment and outcome variable and their interaction. The DiD result is represented by the coefficient on the interaction term (β_3).

$$\text{Crime Rate}_i = \beta_0 + \beta_1(\text{Treatment}_i) + \beta_2(\text{Post}_i) + \beta_3(\text{Treatment}_i * \text{Post}_i) + \epsilon_i.$$

The second model is a Generalized Linear Model (GLM) following the Poisson distribution. Here we look at simply crime count and try to gain more information on non-linear crime trends. This kind of analysis is popular for count based data (Ahmed, 2024). The distribution of our count data also generally follows the patterns and qualification of a Poisson model (Figure 1).

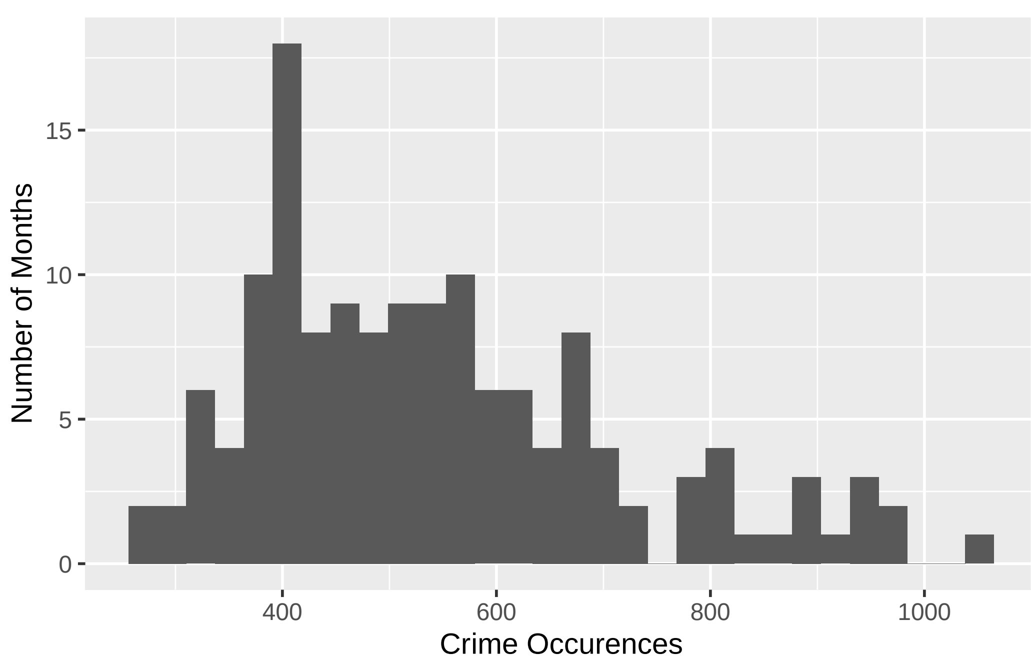

Figure 1: Distribution of Crime Counts (Both Cities)

The predictors are the same for both models. We hope that with both these models we can gain insights into both simple linear and more complex non-linear trends about crime response's to upzoning in cities like Minneapolis. We do however note that without any additional predictors from other datasets, excluding those controlled by St. Paul, there are without doubt numerous confounders which influence our results.

We run a very simple random forest to further explore the model, understanding just how much variation the model represents and the importance of each variable. We use the randomForest (Liaw & Wiener, 2002) package but given our lack of other predictors and smaller dataset size due to aggregation limitations, we don't rely heavily on these results.

Our analysis is performed in R using the tidyverse (Wickham et al., 2019), lubridate (Grolemund & Wickham, 2011), and marginaleffects (Arel-Bundock et al., 2024) packages. These packages primarily help with data wrangling and interpretation of results.

4 Results

We expect the Difference-in-Differences (DiD), Linear Regression, and Poisson models to determine whether the implementation of the Minneapolis 2040 Plan is associated with changes in auto-related property crime. Monthly counts of auto theft and theft from auto from 2017-2022 are compared between Minneapolis (treatment group) and St. Paul (control group), with January 1, 2020 marking the shift to the post-treatment period.

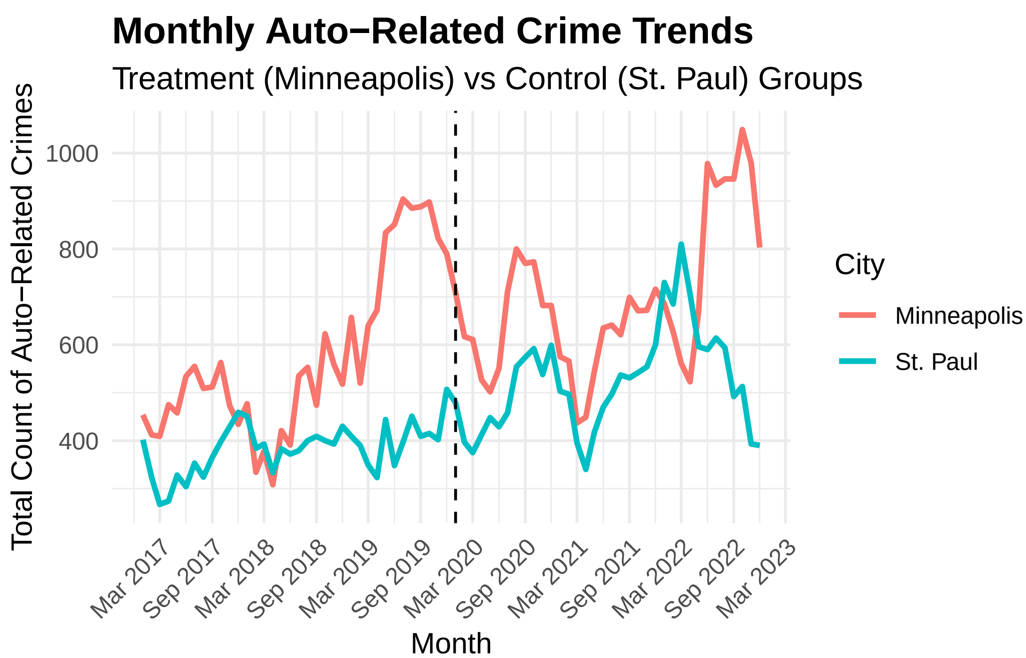

Figure 2

Figure 2 exhibits monthly auto-related crime trends for Minneapolis and St. Paul from 2017 to 2023. Prior to March 2019, the two cities exhibit similar crime levels and largely parallel trends. In March 2019, Minneapolis experiences a substantial increase in auto-related crime, rising from approximately 500 to nearly 900 reported incidents over a six-month period. This represents the largest crime peak observed until 2022. During the same period, St. Paul experiences a smaller and more fluctuating increase in crime.

Following this peak, auto-related crime declines steadily in both cities through May 2020. No sharp or immediate change in crime levels is observed following the implementation of the Minneapolis 2040 upzoning legislation in January 2020. After May 2020, both cities again exhibit roughly parallel trends, with crime increasing during the summer months, and decreasing in the winter months consistent with seasonal patterns.

This pattern continues until March 2022, when St. Paul's auto-related crime exceeds that of Minneapolis for the only time during the study period. At this point, St. Paul records approximately 800 reported incidents, its highest monthly count in the sample, while Minneapolis' crime count falls below 600. Subsequently, crime declines steadily in St. Paul, while Minneapolis experiences a sharp increase before both cities' crime levels fall again during the winter months.

Overall, the evidence presented in Figure 2 reveals that the parallel trends assumption may be violated and our assumptions innaccurate. Here Figure 3 also shows the considerable baseline difference between crime in the two cities, and the considerable decline that occurred around January 2020 as seen in Figure 2.

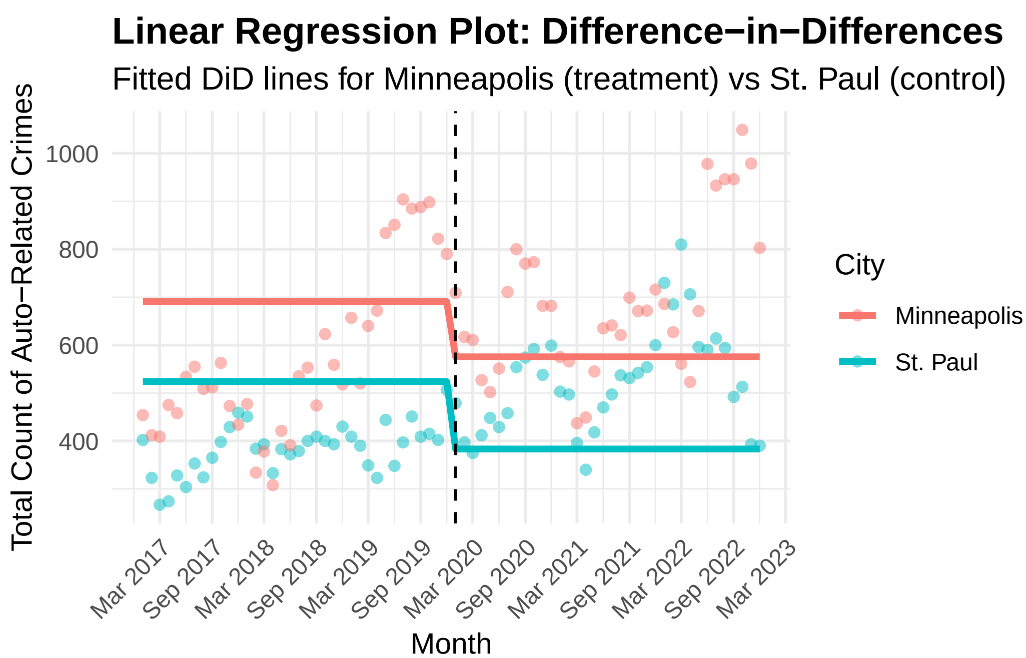

Figure 3

While both Minneapolis and St. Paul experience substantial fluctuations in auto-related crime over time, and a decline is seen immediately around January 2020, post-2020 general trends still indicate a slight relative increase in crime in Minneapolis compared to St. Paul, consistent with the positive DiD estimates reported in the regression analysis (Table 1).

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[1] 16
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Table 2: GLM Results

```
 post Estimate Std. Error    z Pr(>|z|)      S 2.5 % 97.5 %
    0      167       5.81 28.7   <0.001  601.4   156    178
    1      192       5.16 37.3   <0.001 1007.2   182    202

Term: treatment
Type: response
Comparison: 1 - 0
```

Table 1: Linear Regression (DiD) Results: Crime Rate

Term	Estimate	Std.Error	Statistic	P.Value
Intercept	168.93	5.55	30.43	0.00
Treatment	-8.31	7.85	-1.06	0.29
Post	-45.30	7.85	-5.77	0.00
DiD Estimate	18.54	11.10	1.67	0.10

The estimated effects however are not statistically strong enough to conclude that the Minneapolis 2040 planning legislation directly caused or correlates to this outcome. This analysis does not explicitly account for major events occurring during the study period, notably the COVID-19 pandemic or the large-scale Black Lives Matter protests and civil unrest which may have disproportionately affected crime patterns in Minneapolis especially.

Results from the linear DiD regression are displayed in Table 2. The coefficient on the treatment indicator (-8.31) is negative and statistically insignificant, showing no meaningful difference in auto-related crime levels between Minneapolis and St. Paul prior to 2020. The post-period indicator (-45.30) is negative and statistically significant, reflecting a substantial decline in auto-related crime in the control group after 2020. The DiD P-Value ($P = 0.10$) is not significant at the 95% level, implying no real basis for conclusion. This estimate suggests that after considering baseline differences and typical trends over time, Minneapolis experienced approximately 19 additional auto-related crimes per 100,000 people per month compared to St. Paul after the 2040 Plan.

POST - PRE = DID ESTIMATE, SOMEONE NEEDS TO TALK ABOUT THIS I DONT HAVE TIME, INCORPORATE IT INTO THE STUFF BELOW THANK YOU AND SORRY!!!!!!!!!!! (its in terms of count so interpret that way)

To consider the nature of the outcome variable (count), we also estimate a Poisson generalized linear model. Estimates from this model are shown in Table 2. In the linear regression results, the Intercept indicates that in St. Paul before 2020, the average monthly crime count was approximately 523.7, with a standard error of 21.88 ($p < 0.001$). The Treatment coefficient (166.97 (Std.Error $= 30.95$, $p < 0.001$)) shows that Minneapolis had a higher crime rate than St. Paul before 2020, reflecting baseline differences between the cities. The Post coefficient (-140.44 (Std.Error $= 30.95$, $p < 0.001$)) shows that the crime rate in St. Paul decreased by about 140 incidents per month after January 2020.

The DiD Estimate is 25.33 (Std.Error $= 43.76$, $p = 0.56$). This positive estimate suggests that Minneapolis experienced a slight relative increase in crime rate after 2020 compared to St. Paul, but the effect is small and imprecise, as can be seen in the large standard error and insignificant p-value. Ultimately, results from all methods of statistical analysis used do not provide statistically strong evidence that the Minneapolis 2040 zoning reform affected crime rates.

Our random forest model confirms this uncertainty. It reveals that our limited model only accounts for 14.76%, a fraction, of the actual variation in crime rates. It also highlights that the time period predictor seems significantly more important than the treatment city predictor (Figure 4). Potentially this implies future research should focus on including variables which differ between Minneapolis and St. Paul to better capture parallel trends.

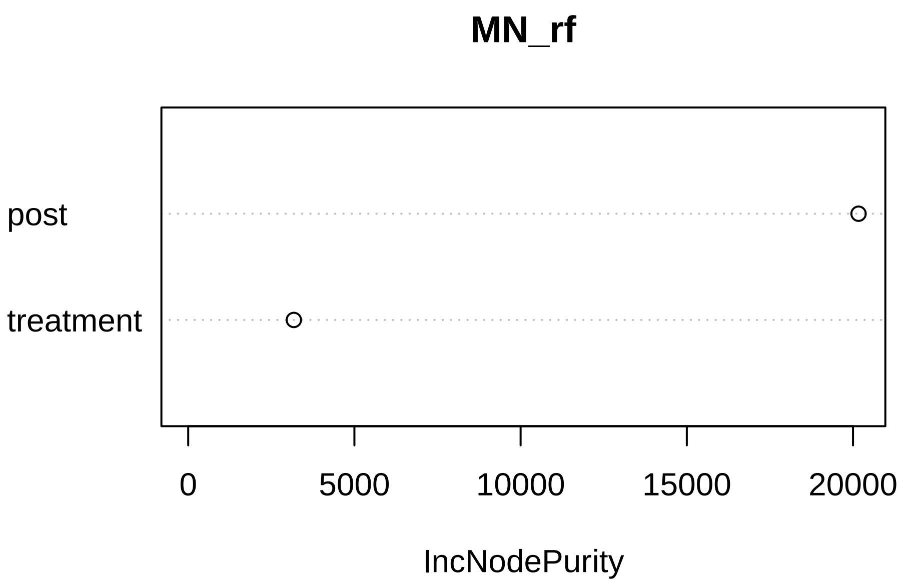

Figure 4: Simple Random Forest (Variable Importance)

5 Discussion

This report tackles a critical modern question, especially in the U.S., about how growing cities and populations can manage safety issues. As housing affordability grows as an issue, zoning and density measures will continue to be experimented with, and reports like this help understand the consequences of those policies.

In this report, we utilize a DiD calculation with both Linear OLS and GLM models to understand how theft crime rates relate to the upzoning measures part of Minneapolis' 2040 plan. Our results are largely incomprehensive and therefore inconclusive. The results we do produce imply there is a positive association between crime rates and the upzoning measure. We believe this implies that many fears about density expansions have some merit and density arguments must continue to be held.

However, we also recommend that more analysis is done, particularly incorporating other controls and predictors into models such as the ones we use to produce more isolated causal results. We especially recommend controlling for zoning differences. Due to time constraints, we estimated aggregate city effects, even though the policy only truly increased density in single family zones.

Potentially looking at only single family districts would provide more exaggerated or different results altogether. We think created a synthetic DiD model could help satisfy the parallel trends assumption by creating a control synthetically much closer to Minneapolis than St. Paul is. We also think looking at upzoning measures in other cities or different kinds of upzoning and density measures could reveal environments or policies which better control crime rates or even manage to reduce them. We recommend methods like random forests to determine which predictors would be valuable to include in future models. Particularly, we recommend understanding lagged and time effects given the slow implementation of increased development and permits.

We believe this report reinforces the importance of debate and continued discussion in the field. All concerns are valid and continued data analysis is perhaps the best way to help determine which direction governments and cities should pursue.

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