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Carjacking and homicide in Minneapolis after the police killing of George Floyd: Evidence from an interrupted time series analysis☆

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ABSTRACT

There is abundant research showing the disproportionate impacts of violence on health in disadvantaged neighborhoods, making an understanding of recent violent crime trends essential for promoting health equity. Carjackings have been of particular interest in the media, although little research has been undertaken on this violent crime. We use interrupted time series models to examine the impact of the police killing of George Floyd on the spatiotemporal patterns of carjacking in Minneapolis in relation to neighborhood disadvantage. To provide grounding, we compare our results to the well-studied patterns of homicides. Results indicate that carjackings both increased and dispersed spatially after the murder of George Floyd and subsequent social unrest, more so than homicides. Socially disadvantaged neighborhoods experienced the greatest absolute increase while more advantaged neighborhoods saw a greater relative increase. The challenge ahead is to identify policy responses that will effectively curb such violence without resorting to harsh and inequitable policing and sentencing practices.

1. Introduction

Much research shows that exposure to community violence and crime negatively impacts health across the life course (Fowler et al., 2009; Hedman et al., 2015; Mayne et al., 2018; Rivara et al., 2019; Wright et al., 2017; Sharkey, 2018). Specifically, direct victimization or witnessing violence is traumatic, significantly increasing the risk of long-term mental health issues, such as posttraumatic stress disorder (PTSD), anxiety, and depression (Fowler et al., 2009; Macmillan, 2001; Sharkey, 2018). Furthermore, indirect exposure to community violence has been linked to a higher incidence of sleep disturbances, asthma, hypertension, and reduced academic performance, even when controlling for confounding variables (Wright et al., 2017; Sampson et al., 2008).

The distribution of crime is not random (Freeman et al., 1996; Ratcliffe, 2010; Weisburd, 2015); violence is more likely to occur in communities of color and in disadvantaged neighborhoods with less "collective efficacy" (Campdelli et al., 2020; Johnson et al., 2019; Kim, 2022; Sampson et al., 1997). This inequitable distribution of violent crime extends to being a direct victim; for example, Black residents made up 14% of the population in the United States, but accounted for 52% of all homicide victims in 2019 (Violence Policy Center, 2022). These differences in exposure to crime and violence appear to be important drivers of health inequities (Armstead et al., 2021; Bailey et al., 2017).

When violent crime rates increase, there are also significant consequences for health and health equity, though the mechanisms can differ depending on where these increases occur. Rising violent crime in disadvantaged neighborhoods can exacerbate health inequities through chronic exposure to traumatic violence among marginalized populations (Dahlberg and Mercy, 2009; Krug et al., 2002). Conversely, when violent crime disperses into less-disadvantaged neighborhoods, residents have greater collective efficacy and, hence, greater capacity to counteract the spread of violence and its health effects (Sampson et al., 1997). This can

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involve increasing supervision and leveraging social capital to prompt swift action from authorities.

Community reactions to real and perceived crime waves can lead to the passage of stricter criminal justice policies (Ly, 2023). These punitive measures, such as mandatory minimum sentences, disproportionately impact disadvantaged neighborhoods, which are often communities of color (Santaularia et al., 2024; Duxbury, 2021, 2023; Kovera, 2019; Kurlychek and Johnson, 2019; Petersilia, 1985; Santaularia et al., 2024; Weitzer, 1996), As a result, they exacerbate health problems and inequities in these neighborhoods (Alang et al., 2017; Clear, 2009; Sugie and Turney, 2017; Wildeman and Wang, 2017).

On May 25, 2020, in Minneapolis, Minnesota, George Floyd, a 46-year-old unarmed Black male, was murdered when a police officer, Derek Chauvin, knelt on his neck for approximately 9 min during the arrest leading to Floyd's death (Hill et al., 2020). This event sparked widespread protests and a global reckoning with police brutality and systemic racism.

Extant research suggests that the period of social unrest following the murder significantly increased violent crime, such as shootings and assaults, though it has continued to cluster in disadvantaged neighborhoods historically affected by such violence, with limited dispersion to more affluent areas (Larson et al., 2023; Drake et al., 2022; Federal Bureau of Investigation, 2022; Wolff et al., 2022). These are predominately communities of color that through historical and current policies continue to be deprived of opportunities for health and safety by those in power and who often have less political and cultural power to influence the narrative (Buggs et al., 2023; Larson et al., 2023; MacDonald et al., 2022; Ratcliffe and Taylor, 2023). Minneapolis also experienced an immediate and notable increase in gun violence, with rates surpassing that of comparable Midwestern cities (Boehme et al., 2022). And, like elsewhere, this increase in gun violence in Minneapolis concentrated in socioeconomically disadvantaged, historically Black neighborhoods (Larson et al., 2023).

This increase in some forms of violent crime likely occurred for several reasons. First, the murder of George Floyd did not happen in isolation; it occurred shortly after the start of the COVID-19 pandemic, a time of high emotional strain and weakened formal and informal social controls. (Agnew, 1985; Cubukcu et al., 2023; Hirschi, 1969). The upheaval following the murder, particularly in the epicenter of Minneapolis, where the 3rd precinct police headquarters was burned and destroyed, may have created widespread perceptions of disorder and further disruption of social controls. Additionally, there was a general perception of lawlessness and normlessness in the immediate aftermath of this upheaval (Forgrave, 2020; Hirschi, 1969; Sampson and Laub, 2005).

In addition to the weakening of social controls, the everyday behavior or "routine activities'' of residents also changed. Routine activities theory posits that crimes occur when there are suitable targets and an absence of capable guardians in the same space as motivated offenders (Cohen and Felson, 1979). Following the murder, we see each of these factors affected in Minneapolis. Similar to other cities across the country, there was a demonstrable decline of capable guardians in the form of police officers (MacFarquhar, 2021). At the start of 2020, the City of Minneapolis had 877 officers. By January 2021, this number had decreased to 817, with only 638 available to work—24 officers took an early retirement at the start of 2021 while 155 were on extended leaves, many related to PTSD. (Navratil, 2021). By May 2023, the number of sworn officers had dropped to 585, cutting the force by over a third, a significantly sharper decline than experienced by comparable cities post-George Floyd (United States Department of Justice, 2023; Stokes, 2024). The evidence is mixed, however, on the impact of police withdrawal on crime rates (Larson et al., 2023; Powell, 2023).

With the decline in social controls and rise in activities as pandemic restrictions were lifted in the months following the murder, there was also an increase in suitable targets. Although routine activities theory is less concerned with the sources of criminal motivation, Cohen and Felson suggest that "circumstances favorable for carrying out violations contribute to criminal inclinations in the long run by rewarding these inclinations" (1979:605). With the actual and perceived loss of formal and informal social controls, as both law enforcement and communities struggled to maintain order, some individuals likely indulged such inclinations under the impression they would not be apprehended (Nagin, 2013). Further, the police murder may have exacerbated already existing collective legal estrangement—the sense among marginalized residents that they exist "within the law's aegis but outside its protection" (Bell, 2017)—which could lead residents to handle grievances using violent "self-help" rather than appeals to police and public authorities (e.g., Desmond et al., 2016) as well as a reduction in engagement in collective efficacy (Kirk and Matsuda, 2011).

Regardless of its etiology, however, this increase in violent crime has potential short- and long-term impacts on health and health equity, making an understanding of recent crime patterns and the ramifications of these trends essential. The media and public discourse have focused particularly on the apparent surge in carjackings (Fies, 2020; Rasa, 2020). Carjacking—taking a vehicle by force or threat of force when the owner is present—typically takes place in a matter of seconds, most likely at or near a victim's home, with the offender(s) usually armed and unknown to the victim (Harrell, 2022; Morewitz, 2019). To succeed, the offender must coerce the victim into surrendering their car during this brief confrontation; this is typically done through instilling fear. As Jacobs (2013) notes, "for the fear to be effective, it must be palpable." Twenty-six percent of carjacking victims are physically injured, and afterwards the majority report high levels of stress and fear of revictimization, often changing their daily routines (Harrell, 2022; James, 2017). The violent and frightening nature of carjacking has led to heightened concern in many communities, prompting some to establish "Carjacking Task Forces'' in response to the perceived surge (Brown, 2022; United States Department of Justice, 2022).

Despite the media and community attention to carjackings, the scientific literature on this violent crime, including the extent and geographic distribution of apparent increases, is lacking. Importantly, it remains unknown whether the rate of carjackings has actually increased since the societal upheavals of 2020—as has been the case for motor vehicle theft—or whether community perception of an increase is influenced by media reports (Garland, 2008; Rosenfeld and Lopez, 2021). It is also unknown whether carjackings, like violent crime more generally, are clustering in socially disadvantaged neighborhoods or whether they are spreading to less disadvantaged neighborhoods, which are less accustomed to such violence and have higher levels of collective efficacy, resources, and political connectedness. In a world in which news media devote "significantly more coverage to carjackings that have more sensational aspects" (Cherbonneau and Copes, 2003), careful empirical studies of the extent and distribution of the phenomenon are sorely needed.

Historically, similar to other violent crimes, carjackings tend to occur in areas high in other types of crime (Jacobs and Cherbonneau, 2023). However, there are a few reasons why carjackings may have behaved differently than other violent crimes after the murder of George Floyd and dispersed to more advantaged areas in Minneapolis that are less accustomed to other forms of violent crime. First, and perhaps most importantly, unlike other forms of violent crime, carjackings are not restricted by space. Offenders and victims are typically strangers and often do not reside in the same neighborhood (Jacobs and Cherbonneau, 2023). In addition, the inherent mobility of vehicles facilitates the spread of carjackings across a city, such that a car taken in one location may be used to commit crime in another location. Second, with Minneapolis police resources stretched thin in 2020–2022, patrols were likely prioritized for more serious crimes, particularly the city's record-setting homicide rate during this period (Mannix and Hargarten, 2021; Powell, 2023; Sawyer and Hargarten, 2023). As a result, there were fewer resources available for both proactive patrol and rapid response to carjacking calls. Third, while there has not been firm evidence that youth were primarily responsible for recent possible increase in carjackings, these crimes have traditionally been carried out by youth with a desire for joyriding and bragging rights (Jacobs and Cherbonneau, 2023). Here too, the pandemic-induced closure of schools and extracurricular activities likely weakened the formal and informal social controls that inhibit youth involvement in high-risk activities like carjacking (Hirschi, 1969). Finally, given the low baseline rates of carjackings, any increase could have been noteworthy, particularly given the violent nature of the crime.

In this study, we seek to examine how the events of 2020 influenced the overall rate and geographic distribution of carjackings. To help contextualize our findings, we do this in comparison to the well-established spatio-temporal patterns for homicides in the epidemiology literature (Goin et al., 2018; Messner et al., 1999; Sparks, 2011; Zeoli et al., 2014). No study to our knowledge has examined the role of the murder of George Floyd on carjacking, nor examined how neighborhood-level (dis)advantage may moderate this effect. We, therefore, aim to fill this research gap by situating our spatio-temporal analysis of carjacking in this broader violent crime literature, comparing and contrasting community rates of carjacking and homicide, and changes in rates over time, in relationship to neighborhood (dis) advantage. For our study, we examine data from the City of Minneapolis, where police killed George Floyd in May of 2020, and the epicenter of the subsequent racial unrest.

1.1. Research questions

Given this prior literature, we hypothesize that carjackings increased since 2020, and that they did so across the city. With the goal of providing a clear descriptive account of the spatial and temporal patterns of carjackings in relationship to neighborhood disadvantage, we develop two overarching research questions:

- Q1 Did carjackings increase in Minneapolis in 2020, particularly after the murder of George Floyd and subsequent unrest, and diffuse spatially throughout the city? Or did the increase remain clustered to neighboring census tracts?
- Q2 *How did this potential increase vary by neighborhood socio-economic (dis)advantage? Did this crime spread to more advantaged neighborhoods in a way not seen with homicides?*

We answer these research questions using two methodological approaches. For Q1, we descriptively examine the spatio-temporal patterns of carjackings over our study period in comparison to homicides, with a focus on assessing dispersion in each outcome over space and time. For Q2, we use interrupted time series models to assess the impact of the police murder of Mr. Floyd on each outcome (carjacking, homicide), modified by neighborhood disadvantage. We then discuss the implications of our findings for population health.

2. Data and methods

2.1. Data

We obtain the outcome variables—carjackings and homicides—from The City of Minneapolis Police Department Open Access Database for 2017–2022 (City of Minneapolis, 2023). The latitude and longitude of each crime occurrence was included in the dataset, and counts were spatially located (via spatial intersection) and aggregated to the census tract level separately for carjackings and homicides. Five (out of 1,752) carjackings did not contain geographical information and were removed. On September 22, 2020, there was a change in the categorization, though not the measurement, of carjacking, when the City began reporting carjacking as a separate crime category. Prior to that date, carjackings were recorded as a subset of robbery. In line with the City of Minneapolis Police Department, our data set applies a consistent definition—"robberies in which a vehicle was listed as stolen"—across both periods, thereby providing a consistent time series for analysis. Both crime outcomes of interest are among the most consistently reported to police—homicides because of their seriousness and evidentiary characteristics—and carjackings because victims must file police reports to receive insurance compensation (Hart and Rennison, 2003).

The 121 census tracts in Minneapolis, Minneapolis are our spatial units of analysis. We apply census tract Cartographic Boundary (CB) shapefiles merged to population estimates from the 5-year American Community Survey (ACS) collected in 2020 using the US Census Application Programming Interface (API) and "tidycensus" R package (Beaghen et al., 2012; Walker and Herman, 2023). Census tracts representing Minneapolis were determined by spatial intersection with the Minneapolis city boundary, with intersections defined by first-order queen contiguity, which defines neighbors as census tracts that share either a common border or common vertex (i.e., a "corner") (Anselin, 1988). To avoid inclusion of census tracts that do not significantly overlap Minneapolis city boundaries (and, therefore, would have artificially low carjacking counts) we remove all intersecting tracts with less than 2% intersection area. By definition, a carjacking can only occur to an individual in or driving a car, therefore, when calculating carjacking rates, the Bureau of Justice Statistics uses a population denominator of age 16 or older (Harrell, 2022). To best align with the Bureau as able with Census data, we use residents age 18 and older as our population denominator.

To capture a census tract's overall (dis)advantage, given the collinearity between variables measuring a neighborhood's socioeconomic position, a concentrated disadvantage index was created using a confirmatory factor analysis (CFA). This index is a continuous variable standardized to a mean of zero for a census tract with "average concentrated disadvantage." Results from the CFA model of concentrated disadvantage can be found in Appendix A. The relationship between concentrated disadvantage and carjacking counts was non-linear. We, therefore, trichotomize the index with the middle 50% of census tracts classified as median, the top 25% as advantaged and the bottom 25% as disadvantaged. Conceptually, it also made more intuitive sense to discuss the impact of shifting between discrete categories of disadvantage on crime rates than quantifying the effect of a 'one-unit' change in disadvantage. Previous studies examining the impact of neighborhood disadvantage on crime and health outcomes use similar index components and cut points (Piza et al., 2023; Sampson et al., 1997, 2008; Wodtke et al., 2011). As a sensitivity check, we estimated models that specified dichotomous high/low categories as well as quintiles for both carjacking and homicide (available by request). The results reported here were robust to these alternative models that used different categorizations of disadvantage.

As age is strongly associated with crime (McCall et al., 2013; Farrington, 1986) and disadvantage (Cagney, 2006), we include the age distribution of the census as a covariate to adjust for across-tract differences in age structure. Specifically, in the case of carjackings, which most commonly (39%) occur at or near the victim's home, the age distribution of the census tract where the crime occurred is most important (Harrell, 2022). Given the wide age distribution of carjacking victims and the change in mobility patterns with the COVID-19 pandemic, we took a conservative approach in our models (Engle et al., 2020; Harrell, 2022). Instead of only controlling for youth, as is common in conventional crime literature, we accounted for the overall age structure of a census tract, using older adults (age 50+) as our reference group. In addition, we consider the neighborhood racial composition separately, in light of the historic racialization of space in Minneapolis and elsewhere (Tuttle, 2022), as well as extant work showing the racialized impact of the Geroge Floyd murder. The census tract's concentrated disadvantage index, age distribution, and percent of residents identifying as Black are treated as time-invariant in our data, meaning we assume stability throughout the five-year study period for each unique census tract.

In a test of robustness, we include the police stop rate (per 1000 residents age 18+), obtained from the Minneapolis Police Department, in our model to assess for mediation. Paralleling our outcome variables, each police stop includes the latitude and longitude of the occurrence. We spatially locate each police stop within census tracts, and then aggregate to the tract level. To prevent potential simultaneity bias where an increase in crime outcomes might influence police stops, we lag police stops by one week before aggregating to the quarter-level.

2.2. Statistical analysis

The data analysis has two main foci to align with our research questions.

First, to answer research question one if carjackings both increased in frequency and became more dispersed throughout the study period, we descriptively assess the temporal and spatial patterns of carjackings in the City of Minneapolis from 2017 to 2022. For the temporal component, we visually inspect the weekly rates of carjackings using time series plots to gain a sense of temporal changes in the city as a whole. Seeing a sharp visual increase in both crimes in our dataset, we empirically identify a structural breakpoint in the time series that minimized the residual sum of squares in the model under the parameter of one breakpoint (Bai and Perron, 2003) and conduct Chow tests to test for statistical significance of the empirically identified breakpoint (Hansen, 2001; King and Massoglia, 2012). We apply the same approach to describe temporal patterns and establish a breakpoint for homicides.

Next, we examine spatial heterogeneity. With increases in crime, it is beneficial to know whether this increase is occurring throughout the city or whether it is more geographically concentrated. To assess the degree of concentration, we compute Ratcliffe's Offense Dispersion Index (ODI) (Ratcliffe, 2010). Separately for carjackings and homicides, we order the census tracts by each crime's increase after the breakpoint and then remove the tracts one by one until there is no overall increase between the two time periods. The ODI is the proportion of census tracts that need to be removed between two periods; it can range from 0 to 1. A value close to 0 indicates that the crime increased in only a few census tracts while a value of 1 indicates that 100% of census tracts contributed to the increase. In other words, a lower ODI provides evidence that the crime is more concentrated while a higher ODI indicates the crime is more dispersed.

Our first research question asks whether the *change* in the crime rates after the structural breakpoint was clustered amongst neighboring census tracts. To answer this, we next explore the data using a Moran's I scatter plot, which graphically depicts how similar a focal census tract's crime rate *change* is to its neighbors (Anselin, 1996). The X axis is the standardized change in the focal tract's crime rate and the Y axis is the standardized spatially lagged variable or average change in the focal tract's neighbors. The slope of the best fit line in this scatter plot is the Global Moran's I, which provides an overall global statistic on the degree of spatial autocorrelation in crime rate *change*. A significant value would reject the null that the change in crime rates occurred at random throughout the city. Global Moran's I ranges from −1.0 to +1.0. Scores closer to +1.0 indicate spatial clustering, with neighboring tracts sharing a similar level of *change* in crime, while scores close to −1.0 show spatial dispersion, with census tracts that experienced similar levels of crime change far apart from each other. A Global Moran's I value close to 0 indicates a random distribution of crime rate changes across the city (Ratcliffe, 2010). Although Moran's I is useful for providing an overall measure of spatial clustering, it does not show local crime clusters. Local Indicators of Spatial Autocorrelation (LISA) help to identify hot (and cold) spots through the decomposition of Moran's I into localized contributing observations (Anselin, 1995).

Our second research question asks how this potential increase in carjackings varies by a census tract's (dis)advantage, compared to homicide. As carjackings and homicides are both relatively rare events, we use quarterly counts of each to provide more stability and interpretability of our outcome estimates. We model the incidence of both carjackings and homicide using negative binomial models, which are suitable for outcome measures distributed as counts. We include the log of the census tract population age 18 or older in our models as an offset to adjust for a tract's population and obtain incidence rates. We estimate our regressions using General Estimating Equations (GEE), which account for our longitudinal count data clustered at the census tract level using an independent working correlation matrix and robust standard errors. We use post-estimation (using the margins command in STATA) to obtain predicted quarterly carjacking counts by census tract disadvantage. The first and last quarters in our dataset were weighted to account for a lower number of weeks in each.

The parameterization of our negative binomial specifications follow an interrupted time series (ITS) design. ITS is useful when, as is our case, one has observations on a population over time and there is a break or interruption in the data (e.g., policy change, event, etc.). The trend in the outcome prior to the breakpoint is assumed to serve as the "counterfactual"—what the outcome would look like in a world where there was no interruption (Bernal et al., 2017). Through an ITS analysis, one can examine both the immediate and sustained impact of the breakpoint. The design exclusively uses *within-unit* over time variation, so time-stable confounders are uncorrelated with the time-varying treatment and the outcome. The base ITS model for our study is as follows:

$$Y_{crime\ \ outcome} = \beta_0 + \beta_1 * Time + \beta_2 * CD + \beta_3 * Immediate + \beta_4 * Sustained\ Effect + \phi X_t$$

with $\boldsymbol{\beta}_1$ the linear crime trend pre-breakpoint, $\boldsymbol{\beta}_2$ the crime rate in each category of concentrated disadvantage (CD) prior to the breakpoint (reference: median), $\boldsymbol{\beta}_3$ the immediate change in the crime rate in the quarter following the structural breakpoint, $\boldsymbol{\beta}_4$ captures the linear crime rate trend starting following the immediate change, and $\phi\ \mathbf{X_t}$ controls for a tract's age distribution. Time trends can be nonlinear in nature; therefore, we assess linearity in both the pre and post time trends. For homicides, both the pre and post time trends were linear. For carjackings, a quadratic time trend after the structural breakpoint was statistically significant and is included in the final model. The immediate, sustained and quadratic post-breakpoint time trends were interacted with concentrated disadvantage to assess how these trends are modified by a tract's (dis)advantage. In other words, we test whether the change in carjackings immediately after the murder of George Floyd, as well as trends in carjackings following the killing, vary between areas with greater or lesser socioeconomic disadvantage. STATA 18 and R v4.1.1 Statistical Software were used for statistical and spatial analyses, respectively (R Core Team, 2021; StataCorp, 2019).

3. Results

3.1. Spatio-temporal patterns

There were 1,747 carjackings in Minneapolis over the course of our study period with complete geographical information. Fig. 1 displays the weekly incidence of carjackings per 1,000 residents age 18 or older in Minneapolis from 1/1/2017 to 12/31/2022. We observe carjackings start to increase in March 2020, potentially coinciding with the COVID-19 pandemic–3/13/2020 was the onset of Minnesota's State of Emergency order and the Governor's Stay-at-Home order ran from 3/28–5/18/2020 (Raifman et al., 2020), though a larger spike appears in late May 2020. A structural breakpoint test indicated the optimal breakpoint in the data was between the weeks of May 18, 2020 and May 25, 2020, which aligns with the murder of George Floyd on May 25th.

This was verified by a statistically significant Chow Test ($F = 51.17$, $p < 2.2 \times 10e\text{-}16$), indicating a significant difference in the rate of carjackings before and after the murder of George Floyd. A breakpoint

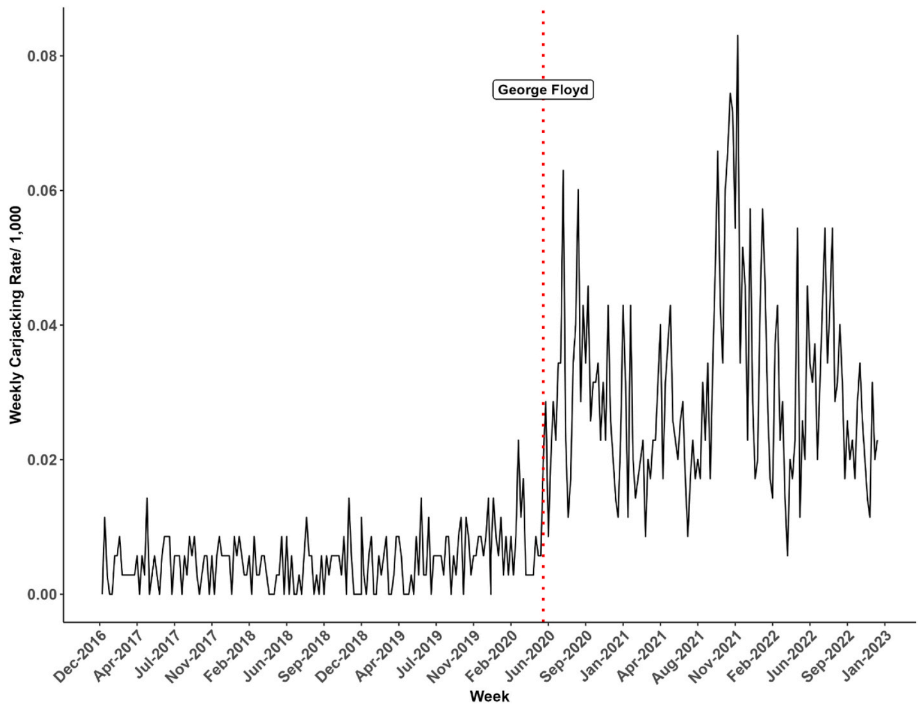


Fig. 1. Temporal trends. Weekly Minneapolis carjacking rates, 2017–2022.

test for homicides also identified the same week in the data and had a statistically significant Chow Test (F = 10.68, p = 1.21e-06). These tests, in combination with our theoretical knowledge of crime patterns at this time, suggest that a breakpoint at the time of the murder of George Floyd was warranted. We, therefore, define a breakpoint of 5/25/20 (the day George Floyd was murdered). Time period one was defined as 1/17/17 to 5/24/20 and time period two as 5/25/20 to 12/31/22.

Prior to the identified breakpoint on May 25, 2020, the average weekly rate of carjackings was 0.0058 carjackings per 1,000 residents aged 18 or older. After the murder of George Floyd, this average weekly rate increased five fold to 0.034, reaching a peak of 0.093 per 1,000 individuals age 18 or older on the week of November 22, 2021 (coinciding with the Thanksgiving holiday). Carjacking thus remained a rare event in Minneapolis throughout the observation period, though a clear increase occurred in the latter half of 2020.

As expected, homicides were much rarer than carjackings. The average weekly homicide rate prior to 5/25/2020 was 0.0021 per 1,000 residents age 18 or older (see Fig. 2). Though not as dramatic or

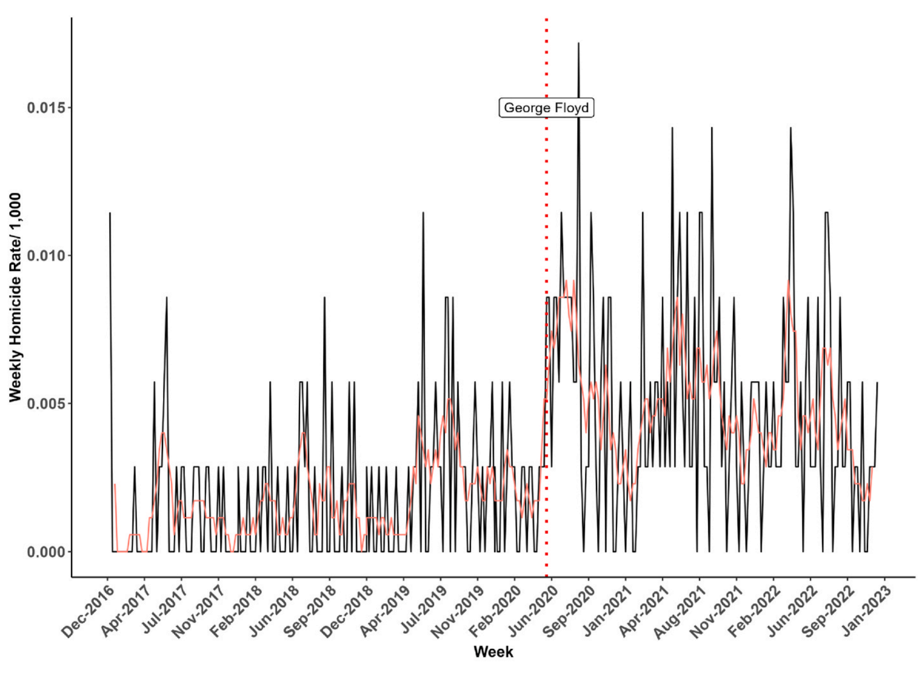


Fig. 2. Temporal trends. Weekly Minneapolis homicide rates, 2017–2022.

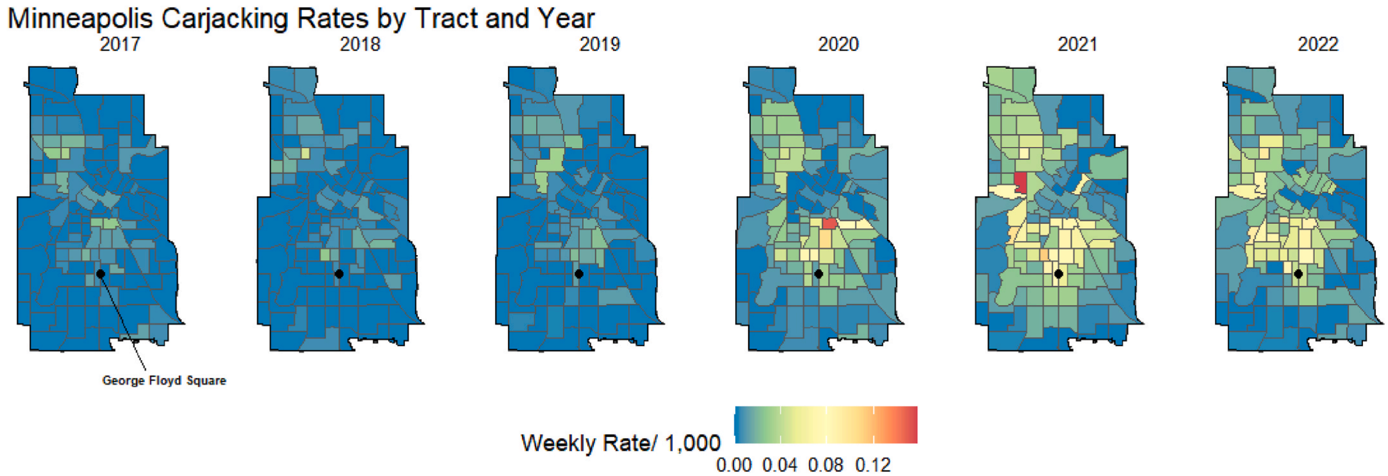


Fig. 3. Spatial trends, carjackings.

sustained as carjackings, homicides also showed a notable increase after the murder of George Floyd, increasing 168% to a mean of 0.0055 homicides a week per 1,000 residents age 18 or older after 5/25/2020.

With the carjacking weekly rates aggregated to the census tract level, Fig. 3 shows the spatial dispersion of carjackings over each of the six years. Carjackings in Minneapolis prior to 2020 were clustered in North Minneapolis—a historically Black and economically disadvantaged community—as well as in the area near what would later be known as George Floyd Square, though at lower rates. In 2020 and 2021, carjackings dispersed throughout much of the city, but the neighborhoods that had a higher rate of carjackings prior to 2020 continued to be hotspots. In 2022, evidence suggests carjackings began contracting but remained at levels higher than prior to 2020. The ODI confirmed these observations with a value of 0.90; that is, 90% (or 109 of 121) of census tracts were responsible for the increase in carjackings throughout the city, suggesting a high level of dispersion.

One way to illustrate the relative pre-post changes in carjacking and homicide is to consider whether residents had any exposure to each crime before and after the George Floyd murder. Prior to the Floyd murder, 71% of census tracts had experienced at least one carjacking over the three and a half years of our study period. After the murder, nearly 97% of census tracts had at least one carjacking. In comparison, 42% of census tracts accounted for all homicides prior to May 25, 2020 while 56% experienced at least one homicide afterwards. There was a steep rise in tract-level exposure to each type of crime, but a more pronounced and widespread rise in exposure to carjacking, such that almost every tract had experienced at least one carjacking in the period following the murder.

Fig. 4 shows the homicide rates aggregated at the census tract level annually from 2017 to 2022. These maps show some increased dispersion throughout the city, though not to the extent that carjackings displayed, with homicides remaining more concentrated in North Minneapolis in the post-2020 period. The ODI for homicides was 0.23, indicating that just 23% (or 28 of 121) of census tracts were responsible for the homicide increase over the study period. A comparison of the two figures and their respective ODIs shows that the rise in carjackings was far more dispersed geographically than the rise in homicides.

Both crimes showed signs of spatial clustering, though neighboring census tracts were more likely to experience similar levels of change for carjackings (Global Moran's I 0.467, $p < 0.001$) than homicides (Global Moran's I 0.186, $p < 0.001$). With the vast majority of census tracts experiencing an increase in carjackings, it was more likely that neighboring tracts also experienced an increase, as seen in the Moran's I scatter plot (Appendix B). Furthermore, LISA plots help to identify areas with high spatial autocorrelation and relatively "hot" and "cold" spots for each crime (Appendix C). After the murder of George Floyd, census tracts neighboring George Floyd square experienced an increase in carjackings while a smaller hotspot near George Floyd square and in north Minneapolis is observed for homicides.

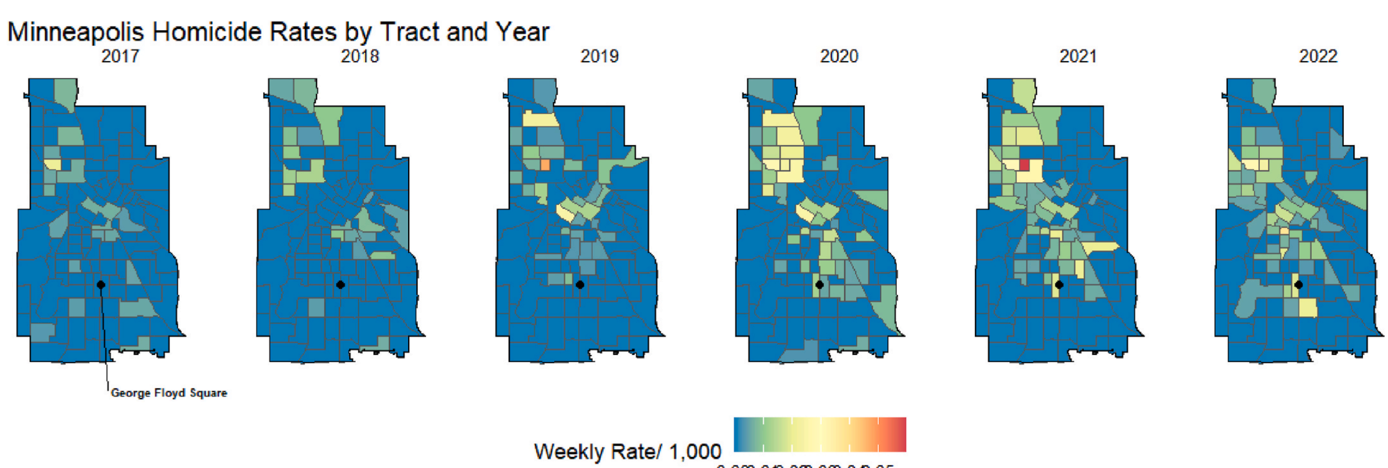


Fig. 4. Spatial trends, homicides.

Table 1
Minneapolis census tract characteristics & average quarterly carjackings by neighborhood disadvantage, 2017–2022.

	Entire Sample		Disadvantaged (Bottom 25%)		Median (25–75%)		Advantaged (Top 25%)	
	(n = 121 Census Tracts)		(n = 30 Census Tracts)		(n = 61 Census Tracts)		(n = 30 Census Tracts)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Census Tract Characteristics								
Population Size	3509	1085	3453	1082	3402	1103	3782	1037
Non-Hispanic White, %	59.0	24.2	28.0	16.2	63.0	15.7	81.9	8.3
Non-Hispanic Black, %	19.1	18.4	39.4	18.5	16.2	13.5	4.8	4.5
Hispanic, %	9.9	8.7	18.3	11.2	8.5	5.9	4.2	2.5
Unemployment Rate	5.8	4.7	10.4	6.8	5.0	2.4	2.7	1.4
Poverty Rate	17.8	14.1	29.8	10.8	16.9	12.8	7.7	10.6
Female Headed Household, %	4.1	2.9	7.5	2.7	3.4	2.0	1.8	1.0
Residents not having a high school diploma, %	6.6	6.0	14.6	4.9	5.4	3.2	1.1	0.9
Age <18 years, %	19.8	10.9	31.0	8.9	16.6	8.7	15.2	9.3
Age 19–29 years, %	24.5	18.0	20.8	6.8	27.0	21.2	23.1	18.3
Age 30–49 years, %	29.9	7.9	27.4	5.5	30.7	9.1	30.6	7.2
Age 50+ years, %	25.8	10.3	20.8	7.2	25.8	10.7	31.1	9.7
Average Number of Quarterly Carjackings								
Before the murder of George Floyd	0.2	0.5	0.4	0.7	0.1	0.4	0.05	0.2
After the murder of George Floyd	1.1	1.7	2.2	2.3	0.8	1.2	0.8	1.5

SD = Standard Deviation.

3.2. *Interrupted time series models*

3.2.1. *Sample demographics*

The analytic panel sample includes 121 census tracts and 25 quarters over the six years, yielding 3025 observations. Table 1 shows the demographics of the census tracts overall and by category of concentrated disadvantage. Overall, 59% of Minneapolis residents were White, 19% Black, and 10% Hispanic. This racial composition varied by census tract with 82% of residents in advantaged neighborhoods identifying as White compared to 28% in disadvantaged neighborhoods. Ten percent of residents in disadvantaged neighborhoods were unemployed, 30% below the poverty line, and 15% were without a high school diploma, all notably higher than advantaged or median census tracts. A map of the census tracts by concentrated disadvantage categorization is found in Appendix D.

3.2.2. *Neighborhood disadvantage and carjackings*

Prior to the murder of George Floyd, carjackings throughout Minneapolis were increasing at a rate of 5% per quarter (95% CI: 0.02 to 0.08). Fig. 5 and Table 2 show that baseline carjacking counts differed by census tract advantage. Controlling for other factors, prior to the murder of George Floyd, disadvantaged census tracts had over two times the incidence rate of carjackings than median census tracts (95% CI: 1.52 to 3.62) while advantaged tracts had a incidence rate less than half that of median tracts (95% CI: 0.22 to 0.80). These baseline associations by disadvantage are similar to what was observed for homicide.

In the quarter following the murder, the immediate post-killing

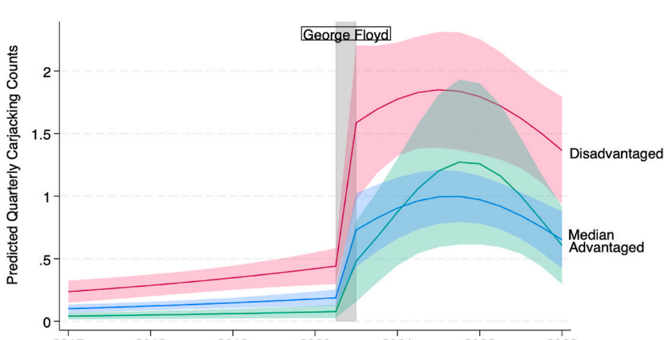


Fig. 5. Predicted quarterly carjacking counts by neighborhood disadvantage Minneapolis, 2017–2022.

Table 2
Negative binomial interrupted time series GEE model (N = 3025).

	IRR [95% CI]	
	Carjackings	Homicides
Time	1.05** [1.02–1.08]	1.06* [1.01–1.12]
Immediate Post-Killing Effect	3.70*** [2.39–5.74]	1.99* [1.13–3.51]
Concentrated Disadvantage (CD) (ref: Median)		
Advantaged	0.42*** [0.22–0.80]	0.37* [0.17–0.79]
Disadvantaged	2.35*** [1.52–3.62]	1.65 [0.87–3.15]
Immediate Effect*CD (ref: Median)		
Advantaged	1.59 [0.72–3.51]	0.48 [0.11–2.02]
Disadvantaged	0.93 [0.55–1.55]	1.84* [1.03–3.30]
Sustained Post-Killing Effect	1.09 [0.96–1.24]	0.87*** [0.80–0.93]
Sustained Effect*CD (ref: Median)		
Advantaged	1.26 [0.95–1.66]	1.22* [1.05–1.41]
Disadvantaged	0.94 [0.78–1.13]	0.93 [0.86–1.00]
Quadratic Post-Killing Effect	0.99* [0.97–0.99]	– –
Quadratic Effect*CD (ref: Median)		
Advantaged	0.98 [0.96–1.01]	– –
Disadvantaged	1.01 [0.99–1.02]	– –
Percent Black	1.01* [1.00–1.03]	1.02** [1.01–1.04]
Age (ref: 50+ years)		
Age <18	1.04** [1.01–1.06]	1.00 [0.97–1.04]
Age 20-29	1.03** [1.01–1.04]	1.00 [0.98–1.02]
Age 30-49	1.04** [1.01–1.07]	1.00 [0.96–1.04]
Constant	0.00*** [0.00–0.00]	0.01*** [0.00–0.08]
Number of Census Tracts	121	121
Number of Observations per Census Tract	25	25

IRR=Incidence Rate Ratio, *p < 0.05; **p < 0.01; ***p < 0.001.

effects varied by census tract socio-economic advantage (Appendix E, Table E1). Disadvantaged tracts experienced the largest immediate increase in predicted quarterly carjacking counts. In the three months leading up to the murder of George Floyd, disadvantaged tracts had on average a predicted 0.44 carjackings per quarter (95% CI: 0.30 to 0.58). In the three months following the murder of George Floyd, the predicted number of carjackings increased to 1.59 (95% CI: 0.97 to 2.20), a nearly threefold increase. Advantaged tracts saw a smaller absolute increase; however, given their low baseline rate the relative immediate increase was larger than in disadvantaged tracks. Specifically, in the quarter prior to the murder of George Floyd, advantaged tracts had an average predicted count of 0.08 carjackings per quarter (95% CI: 0.03 to 0.13). This increased 5-fold to a predicted 0.48 carjackings per quarter in the three months following the murder (95% CI: 0.16 to 0.80 carjackings).

After the murder of George Floyd, there was an initial increase in carjackings which continued through much of 2021 throughout the city before declining. The pattern of these trends varied by census tract disadvantage. In the most disadvantaged tracts, the peak period occurred during the summer of 2021, with a predicted 1.85 carjackings (95% CI: 1.39 to 2.31) quarterly. Conversely, median and advantaged areas witnessed their highest rates slightly later, between August and November 2021. The predicted number of carjackings in these periods was 1.00 (95% CI: 0.80 to 1.20) for median tracts and 1.27 (95% CI: 0.61 to 1.93) for advantaged tracts.

At all time points in the study period, tracts in the top quartile of disadvantage experienced quarterly rates that were higher than median and more advantaged census tracts (Fig. 5). The highest rates of carjackings in advantaged neighborhoods were notably higher than the average rate of carjackings seen in disadvantaged neighborhoods prior to the murder of George Floyd, but still lower than experienced by disadvantaged neighborhoods post-killing.

3.2.3. *Neighborhood disadvantage and homicides*

Homicides display a different time trend than carjackings in relation to the police killing of George Floyd and census tract disadvantage, as seen in Fig. 6 and Table 2 and predicted quarterly homicide counts further detailed in Appendix E. As seen in Table E2 in Appendix E, in the three months prior to the police killing, disadvantaged census tracts could expect an average of 0.14 homicides a quarter (95% CI: 0.07 to 0.22) before increasing threefold to 0.56 quarterly carjackings afterwards (95% CI: 0.34 to 0.79). Median neighborhoods saw homicides double in the quarter after the murder, rising from a predicted 0.08 (95% CI: 0.04 to 0.11) to 0.17 (95% CI: 0.09 to 0.26) quarterly homicides. In contrast, advantaged neighborhoods experienced a very minimal immediate increase, going from 0.03 predicted carjackings both in the quarter prior to the murder (95% CI: 0.01 to 0.06) to 0.04 predicted carjackings in the quarter following (95% CI: 0.00 to 0.07).

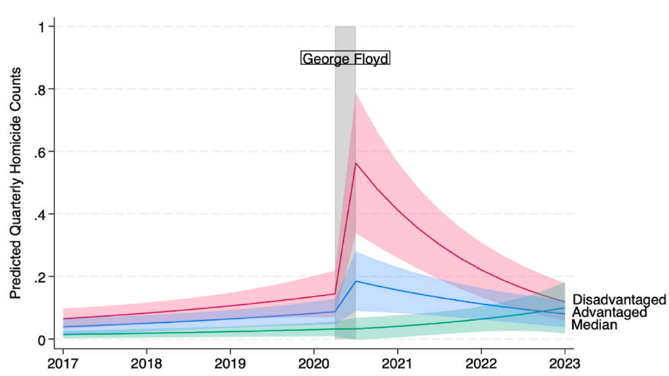


Fig. 6. Predicted quarterly homicide counts by neighborhood disadvantage Minneapolis, 2017–2022.

In terms of sustained effects, homicides peaked in disadvantaged and median neighborhoods in the first quarter after the murder of George Floyd and then decreased to a rate similar to that seen in the months immediately prior to the police killing. In contrast, advantaged neighborhoods experienced a delayed increase in homicides that began in early 2021 and continued throughout the post-killing study period. Given the very low baseline rate in advantaged census tracts, one homicide could have a large impact on these time trends.

3.2.4. *Tests of robustness*

Tests of robustness results are in Appendix F. We predict weekly counts for the quarter preceding the murder of George Floyd (2/24/20–5/24/20) and immediately following (5/25/20–8/24/20) to ensure each crime did not precipitously rise in the weeks prior to the police killing. We find that, as seen in our quarterly data, there is a steady linear increase in the weeks prior, but a notable spike the week of George Floyd's murder. There is less stability of estimates with the weekly counts. A linear model with the quarterly crime rate as the outcome shows similar findings. Finally, the addition of police stops did not substantively change our estimates, suggesting that the effects we observe are not entirely mediated by police behavior.

4. Discussion

Previous literature on the spatial distribution of carjackings focused on the crime's occurrence in proximity to physical features of a neighborhood, such as distance from a bus stop or gas station, and not a community's socio-economic (dis)advantage, which is known to be a strong predictor of other violent crimes (Barton et al., 2021; Felson et al., 2022; Jones-Webb and Wall, 2008; Krivo and Peterson, 1996; Lersch, 2017). This study sought to examine how the rate and geographical distribution of carjackings changed in the wake of the events of 2020 and how it varied by neighborhood socio-economic (dis)advantage. Specifically, we wanted to learn whether the perceived increase in carjackings reflected a true increase or if this perception was influenced by carjackings dispersing in a way that more affluent neighborhoods were also affected. To provide a frame of reference for our spatiotemporal analysis, we benchmarked our novel carjacking findings against homicide, a crime that has been well-researched in criminology and epidemiology.

We observed two key findings. First, the increase in carjackings in Minneapolis from 2017 to 2022 is significant. While carjacking is still a relatively rare event, we saw a fivefold increase in carjackings following the murder of George Floyd and the ensuing social unrest. This uptick was experienced by nearly all census tracts, such that many socially advantaged neighborhoods experienced a carjacking for the first time in the post-killing period during our study period. Second, this change in carjacking rates varied by a census tracts' relative (dis)advantage. In absolute terms, the greatest carjacking increases occurred in disadvantaged neighborhoods. However, more advantaged neighborhoods, where violent crime is extremely rare at baseline, saw a greater *relative* increase. Both of these divergent findings—the overall burden of carjackings being higher in disadvantaged neighborhoods and advantaged neighborhoods having a greater relative increase—have potential implications for health and health equity.

First, exposure to violence is consistently associated with negative mental and physical health outcomes (Rivara et al., 2019). This inequitable exposure to violence in disadvantaged neighborhoods further perpetuates health and social inequities. It reflects systemic racism enacted through policies, such as redlining, that has blocked Black individuals from pathways to homeownership and wealth accumulation leading to racially segregated neighborhoods of concentrated disadvantage with higher levels of violent crime exposure (Poulson et al., 2021; Bailey et al., 2017). Second, the greater relative increase in more advantaged neighborhoods, which tend to have more collective efficacy and higher levels of political connectedness, raises the risk of a disproportionate policy backlash including punitive criminal justice responses, known to have a negative impact on population health, particularly for communities of color (Lane, 2018).

Our first key finding that there was an overall increase in carjackings over our study period aligns with previous research reporting that violent crime has risen in urban areas since the summer of 2020 (Thompson and Tapp, 2022). One could hypothesize that, in line with strain theory (Agnew, 1985), spaces have more elevated criminal activity when under the emotional strain of the COVID-19 pandemic and the high-profile murder of George Floyd by police within the city (Kim and Phillips, 2021)—events that disproportionately affected the mental health of disadvantaged and Black communities (Maffly-Kipp et al., 2021; Santaularia et al., 2024). In tandem, the murder of George Floyd also occurs at a time when social controls and bonds, through the closing of schools, extracurriculars, and community organizations in the first few months of the pandemic, were already weak (Hirschi, 1969).

We see this in our data with a small increase of carjackings in March 2020, coinciding with the beginning of the COVID-19 pandemic, and a much larger spike occurring immediately after the murder of George Floyd. Our observation parallels what Peres and Nivette (2017) observed in Brazil—high social disorganization in a city can lead to an increase in violent crime. Similarly, the police violence and shutdown of these typical community supports may have increased system avoidance and decreased social capital leading to an increase in crime (Brayne, 2014; Szreter and Woolcock, 2004).

However, the spatial dispersion we observed in carjackings diverges from the crime literature. Weisburd (2015) showed that while there is variability in crime across cities, within a city, crimes are typically concentrated in certain areas of the city and remain that way over time. This is true down to the street level, with specific street segments and intersections often responsible for the majority of violent crime in a city (Braga et al., 2010). Existing studies have observed that the spatial clustering of other types of violent crime remains relatively stable even amidst increasing crime (Larson et al., 2023; Chainey and Monteiro, 2019; Drake et al., 2022; Peres and Nivette, 2017). This is counter to what we observed with carjackings in Minneapolis from 2017 to 2022.

Compared to homicide, we saw greater dispersion to areas of the city not typically accustomed to crime. The mobility of motor vehicles likely contributes to this phenomenon, making carjackings less spatially restricted than homicides. During our study period, Minneapolis, like many other US cities, experienced a significant spike in homicides alongside a decrease in police presence (Adams et al., 2023; Cassell, 2020; Mourtgos et al., 2022). With limited police resources focusing on more serious crimes, carjackings were likely able to spread throughout the city (Zhang et al., 2024).

The dispersion of carjackings throughout the city may help account for the greater fear and public concern expressed among persons at relatively low risk of experiencing other forms of victimization, a concern picked up by the media (Sawyer, 2020). Although the relationship between actual crime rates and the fear of crime is complex and often do not align (Farrall et al., 2009; Indermaur and Roberts, 2005; Prieto Curiel and Bishop, 2016; Quillian and Pager, 2001), Prieto Curiel and Bishop (2018) found that, even with a constant crime rate, fear of crime increases with dispersion, as more individuals perceive that they are at risk of being victimized.

We also know that the impact of violence is not limited just to those who are victims of or witnesses to acts of violence; simply living in proximity to an acute violent crime event can have negative effects on an individual (Sharkey, 2010). In our study, after the murder of George Floyd, 90% of census tracts were responsible for the increase in carjackings. Finally, we know that individuals infrequently exposed to adversity can have more exaggerated outcomes when exposed to trauma, as they have not developed the coping mechanisms that those with more chronic exposure have (Liu et al., 2020; Schroeder et al., 2020), which could support our hypothesis of a greater public outcry, as the crime dispersed into advantaged neighborhoods.

This may also explain the increased media attention to carjackings. In well-studied crimes such as homicides, while the prevalence of the crime is higher in Black and Hispanic neighborhoods, the media is more likely to report on those homicides that occur in predominantly non-Hispanic White neighborhoods or when the victim is White (Barton et al., 2021; Bjornstrom et al., 2010; Sorenson et al., 1998; White et al., 2021). The findings of our study suggest that this dynamic may also be true with carjackings. Examining the relationship between where a carjacking occurs and whether it is reported on in the media in future studies would better answer this question.

The fear engendered by dispersion of carjackings into more advantaged neighborhoods may also result in harm to communities of color due to punitive policy reactions. There are racialized perceptions of crime and which victims—often White—matter, triggering more punitive responses (Ghandnoosh, 2014). Advantaged, predominantly White neighborhoods–those with higher levels of home ownership, better housing and more maintained public spaces–are also more likely to have higher levels of collective efficacy (Uchida et al., 2013). It is likely that in response to the rising carjackings, more advantaged neighborhoods would work together through informal social controls to combat the carjackings dispersing into their neighborhood, as well as leverage existing reserves of social and cultural capital to drive media reporting and compel a response from the authorities.

One can envision this happening through a few different mechanisms. First, the increased social ties in advantaged neighborhoods could lead to increased guardianship or supervision in these neighborhoods by residents (Bellair, 2000). This guardianship could come in the form of video doorbell recordings or communications on apps such as NextDoor, notifying neighbors of suspicious activity. Second, it is also likely that neighborhoods with concentrated affluence would use their political capital to keep carjackings out of their neighborhoods, so that they can remain both advantaged and non-victimized (Massey, 1996). Lyons (2007) observed in Chicago that anti-Black hate crimes were more numerous in predominantly White neighborhoods with higher levels of informal social control, illustrative of the advantaged communities' attempts to defend against the perceived threat of Black individuals.

Our second research question asked how the observed increase in carjackings rates varied by neighborhood disadvantage. We found that more advantaged neighborhoods, where violent crime is extremely rare, saw a greater relative increase, due to their low baseline rate. However, the harms of the observed increase in carjackings are borne largely by disadvantaged neighborhoods, which contain a higher proportion of individuals of color and individuals of lower socioeconomic status. This is similar to the carjacking patterns observed both nationally and internationally. In the United States, Black and Hispanic individuals are over three times more likely than non-Hispanic White individuals to be a victim of carjacking, as are households with incomes less than $75,000 (Harrell, 2022) while in South Africa 97% of carjacking victims are Black (Gilbert, 1996).

Exposure to crime is one of the many ways in which neighborhood disadvantage negatively impacts the health of communities and exacerbates health inequities (Ross and Mirowsky, 2001). Crime's impact on health can occur through direct victimization and also through indirect pathways. While being a direct victim of a violent crime is a relatively rare event with an estimated 0.98% of the US population age 12 and older being the victim of a violent crime in 2021, the negative physical and mental health effects of direct victimization is concentrated with the poor and people of color most likely to be victims (Kilpatrick and

Acierno, 2003; Thompson and Tapp, 2022). Indirectly, exposure to neighborhood violence has been linked to a multitude of negative health outcomes across the lifecourse, including preterm birth (Messer et al., 2006), adverse child health and cognitive outcomes (Jackson et al., 2019; Sharkey, 2010; Sharkey et al., 2012), poor mental health (Aneshensel and Sucoff, 1996; Curry et al., 2008; Ellen et al., 2001), decreased quality of life (Hitchens, 2023), and increased overall mortality (Wilkinson et al., 1998) to name a few. Our study contributes new information on carjackings to the large body of literature showing an unequal distribution of other crimes across space—an inequity that has only widened since 2020—with clustering in disadvantaged neighborhoods (Campdelli et al., 2020; Johnson and Roman, 2022; Kim, 2022; Morenoff et al., 2001). Further, our work illustrates how police violence can exacerbate the exposure to violent crime, marking police killings as a distinct health issue.

Our study has several limitations. First, we could only measure those carjackings and homicides for which there was a police report. While crime data can be skewed due a lack of accurate reporting, our study is strengthened by comparing two crimes for which there is relatively accurate reporting (Hart and Rennison, 2003). In addition, data on demographic characteristics (including race) of the victims and offenders are not recorded on police reports or available from other sources. Reporting of race in Minneapolis police reports significantly decreased after the murder of George Floyd (United States Department of Justice, 2023). The race of individuals, as well as the racial characteristics of neighborhoods, may play an important role in carjackings. Although our data can only speak to the latter, our analysis is useful in providing a clear picture of the overall spatial and temporal pattern of carjackings across the city of Minneapolis before and after the George Floyd murder.

Second, our findings may not be generalizable outside of Minneapolis. We know that context matters and crime patterns do not occur across time and place uniformly (Ashby, 2020). Third, there may be misclassification due to change in coding of carjackings by the Minneapolis Police Department in September 2020. While we followed the procedure for coding and decision making that is used within the Police Department, it is possible that the two time periods are not comparable, though the change was a change in classification, and not measurement. Fourth, we did not control for the physical or built environment, which have been associated with carjackings in previous studies. While our ITS design is robust to all time-constant unobserved heterogeneity in Minneapolis, time-varying changes correlated with the timing of the police murder represent a threat to our causal identification. Finally, although carjackings rose after the murder of George Floyd, they remain a relatively rare crime. In light of this rarity and our interest in assessing pre- and post-event change and the influence of tract-level socioeconomic effects characteristics, we chose to aggregate to the Census tract level (following e.g., Baumer et al., 2022). An alternative approach would involve examining hot spot clusters at lower levels of aggregation (e.g., Sadler et al., 2022). Further research at the level of the block or street segment would contribute greatly to understanding of concentration within such tracts (e.g., Felson et al., 2022).

Our analysis suggests that high profile police murders may create social conditions that undermine public safety and increase crimes such as carjackings and homicides. One implication that follows from this analysis is that reducing police brutality should be an important part of a multifaceted strategy to reduce such crimes, and the health consequences that follow from them. As of this writing, the City of Minneapolis is under a court-enforced settlement agreement with the state of Minnesota for civil rights violations by its police department, and a federal consent decree is pending.

To further advance health equity and public safety, a number of interventions to curb carjackings are being proposed and implemented. For instance, in 2023 the Minnesota legislature defined a new crime of carjacking that paralleled existing robbery crimes. After receiving public input, the Minnesota Sentencing Guidelines Commission (2024) ranked carjacking one severity level higher than its robbery counterpart (e.g., whereas robbery at gunpoint is ranked at severity level 8, the Commission ranked carjacking at gunpoint at severity level 9). Recent federal prosecution of more serious or repeat carjacking, such as carjacking groups who have systematically targeted Uber and Lyft drivers, may also increase formal and informal controls (Montemayor, 2024). The city of Minneapolis is also actively recruiting police and non-police public safety personnel. More broadly, however, the certainty of punishment is also enhanced by rising public awareness and greater informal guardianship by community members. Concurrently, it is imperative that policies also address the structural causes of crime and the concentrated disadvantage that helps account for neighborhood differences in carjacking and homicide. Together, such strategies may offer a holistic approach to mitigating carjacking and related crimes, while also promoting equity.

In conclusion, this study adds to the literature by examining the role that the murder of George Floyd had in influencing violent crime rates, specifically carjackings and homicides, in Minneapolis and how that effect was modified by neighborhood disadvantage. We find that carjackings follow the overall trend for other violent crimes and remain at a higher rate in disadvantaged neighborhoods. However, carjackings are unique in their dispersion to areas of the city less accustomed to violent crime. Public policy solutions to reduce crime must be grounded in health equity and avoid harsher sentencing that negatively affects communities of color already suffering most from violent crime.

Ethics approval

Ethics approval was not required for our study using publicly available census tract level data.

CRediT authorship contribution statement

Allison Lind: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Ryan P. Larson:** Writing – review & editing, Visualization, Software, Methodology, Formal analysis. **Susan M. Mason:** Writing – review & editing, Supervision, Methodology. **Christopher Uggen:** Writing – review & editing, Supervision.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

Appendix A. Confirmatory factor analysis (CFA)—concentrated disadvantage

Table A
CFA measurement model of concentrated disadvantage.

	LHS	Specification	RHS	Std (Beta)	SE	P-Value
1	Conc Dis	FL	Unemployment Rate	0.685	0.004	0
2	Conc Dis	FL	Poverty Rate	0.561	0.004	0
3	Conc Dis	FL	Female Headed Household Rate	0.702	0.003	0
4	Conc Dis	FL	No High School Diploma Rate	0.845	0.003	0
5	Conc Dis	Cov.	Poverty Rate	0.198	0.006	0

LR χ^2 vs. saturated (2) = 94.97, RMSEA = 0.035 (PCLOSE = 1.0), CFI = 0.999, SRMR = 0.006.

Appendix Table A represents the creation of the latent neighborhood construct of concentrated disadvantage via a confirmatory factor analysis (CFA) measurement model. Many social science studies using multiple measures as indicators of a latent construct will create a simple summative measure of the indicators, and then use the combined measure in subsequent analysis. This has the limitation of treating the measurement error involved in the creation of the measure as variation in the measure itself, and the use of CFA avoids this limitation by explicitly accounting for measurement error within the measurement model. CFA is a theory-driven technique where proposed relationships between observed indicator variables, and an unobserved latent variable that is purported to account for the dependencies between the observed variables, is specified. The coefficients, or factor loadings, of these ACS items are estimated via maximum likelihood estimation. The model scales the dependent variable, concentrated disadvantage, by assuming that the latent variable's variance is standardized to 1, thereby making the factor loadings represent standardized effects between the latent construct and a particular indicator variable, and can be interpreted as correlation coefficients. Predicted, standardized scores for each ZCTA-week are created from the above measurement model to create measures of concentrated disadvantage used in the subsequent panel modeling.

CFA model fit is captured through four standard measures of model fit: 1) A likelihood-ratio chi-squared test between the fitted model and a saturated model, which is the model that fits the covariances perfectly, 2) the Root Mean Square Error of Approximation, a scaled absolute measure of fit that adjusts the chi-squared for model parsimony (values below 0.05 indicate good model fit; PCLOSE is also reported, the probability under the null hypothesis that RMSEA is below 0.05 that the RMSEA is below 0.05), 3) the Comparative Fit Index (CFI), which compares the fit of the null model and the fitted model adjusting for model complexity (values > 0.9 indicate good model fit) and 4) the Standardized Root Mean Square Residual (SRMR) which quantifies the standardized difference between the observed covariances and the predicted covariances (values < 0.08 indicate good model fit) (Hu and Bentler, 1998). The CFA model for concentrated disadvantage was fit using the 'lavaan' package in R (Rosseel, 2012).

The CFA measurement model, represented in tabular form in Appendix Table A, depicts the CFA of concentrated disadvantage using four different indicators of the latent variable (unemployment rate, poverty rate, no high school degree rate, female headed-household rate) of concentrated disadvantage alongside a specified residual correlation between the unemployment rate and the poverty rate. All estimated factor loadings and specified residual covariances exhibit statistically significant estimates. Overall, all measures of model fit are indicative of excellent model fit. In addition, both the absolute fit measure of RMSEA (0.00, probability <0.05 1.0), and the comparative CFI (1.0), both of which penalize for model complexity, are both indicative of superb model fit. Finally, an SRMR of 0.004, lower than 0.08, is indicative of very little standardized discrepancies between the observed and predicted correlation matrices.

Appendix B. Moran's I scatter plots

Figures B1 and B2 present the Moran's I scatter plots for carjackings and homicides, respectively. The plots allow one to visualize the spatial clustering between a census tract's change in the carjacking or homicide rate after the murder of George Floyd and the change observed in the tract's neighbors. The slope of the best fitted line (seen in blue) is the overall Global Moran's I (Anselin, 1996). The plots are divided into four different quadrants, which represent the four potential relationships between a census tract and its neighbors:

(1) The first quadrant (upper right) displays census tracts in which focal census tract had a high level of change in carjackings after the murder of George Floyd, as did its neighbors ("hot spots")
(2) The second quadrant (top left) shows census tracts that experienced a small change in carjackings surrounded by tracts that also experienced a little change ("cold spots")
(3) The third quadrant (bottom left) indicates census tracts with low levels of change surrounded by high ("outliers")
(4) Finally, the fourth quadrant (bottom right) consists of census tracts that displayed high levels of change in their rate after the murder of George Floyd and are neighbored by low ("outliers")

Both Fig. 3a and b indicate that the slope of the best-fitting line is positive, meaning that the Global Moran's I is greater than the null of 0 and that focal census tracts experienced similar changes in their carjacking and homicide rates to their neighbors after the murder of George Floyd. This slope, and therefore spatial autocorrelation, is higher in carjackings (Global Moran's I 0.467, $p < 0.001$) than homicides (Global Moran's I 0.186, $p < 0.001$), meaning neighboring census tracts were more likely to experience similar levels of change for carjackings than for homicides. This larger Moran's I for carjackings is due to nearly all of the census tracts falling in the upper right quadrant. With the vast majority of census tracts experiencing an increase in carjackings, it was more likely that neighboring tracts also experienced an increase.

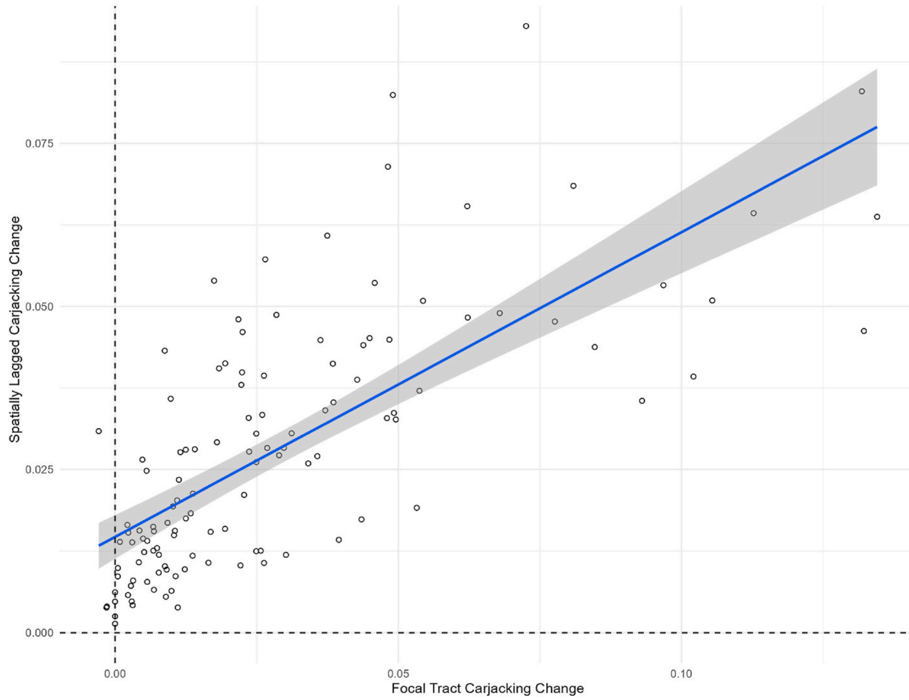


Fig. B1. Moran's I plot carjacking change spatial autocorrelation.

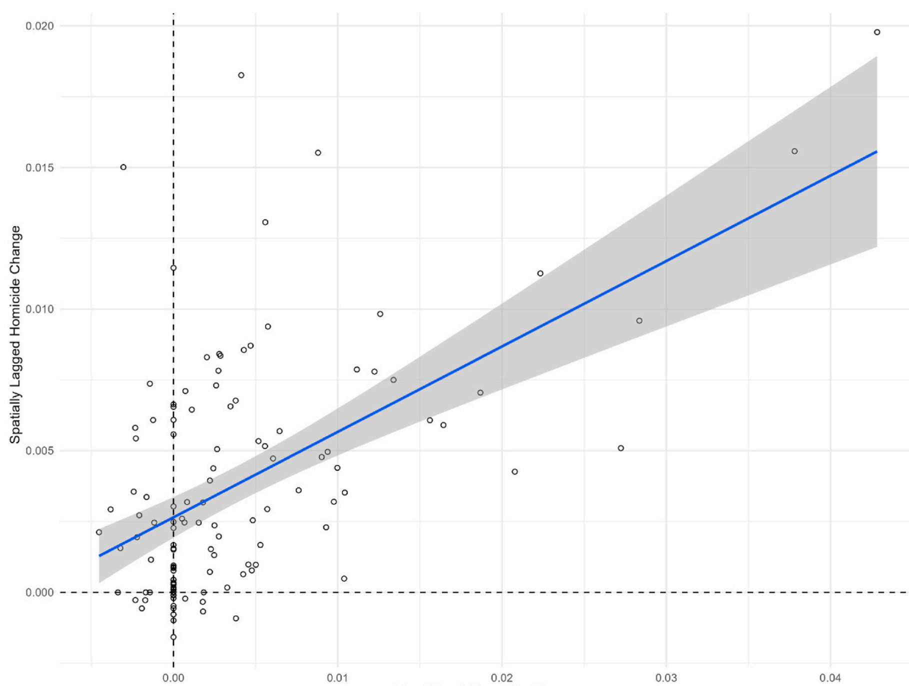


Fig. B2. Moran's I plot homicide change spatial autocorrelation.

Appendix C. LISA plots

To show the location of spatial clusters, a Local Indicator of Spatial Autocorrelation (LISA) was calculated, and clusters with a p-value<0.05 were displayed. LISA is helpful for identifying hot spots– census tracts that saw a large change in crime after the murder of George Floyd surrounded by census tracts that also saw a large change in the crime rate. Cold spots are census tracts that experienced a small change in the crime rate and are surrounded by neighbors that also experienced a similar small change in crime. LISA also identifies outliers–either census tracts with a large crime change surrounded by neighboring tracts with small amounts of change or census tracts with low levels of crime change surrounded by neighboring tracts with a large change in crime (Anselin, 1995).

The LISA maps in Figures C1 (carjackings) and C2 (homicides) show clusters of each crime throughout Minneapolis. In Figure C1 for carjackings, there is a hotspot in the area of south Minneapolis near the area where George Floyd was murdered. Here, tracts that experienced a large amount of change in crime are surrounded by neighbors that also experienced similar levels of change. Those census tracts at the far south of the city and a few near the northern suburbs experienced low levels of change in carjacking rates and were surrounded by neighborhoods that also had low amounts of change in carjacking rates.

With homicides in Figure C2, there are fewer and smaller hot and cold spots, with two clusters of Census tracts with high levels of change in the homicide rate surrounded by neighbors with high homicide change, one in south Minneapolis near the murder of George Floyd and the other in north Minneapolis.

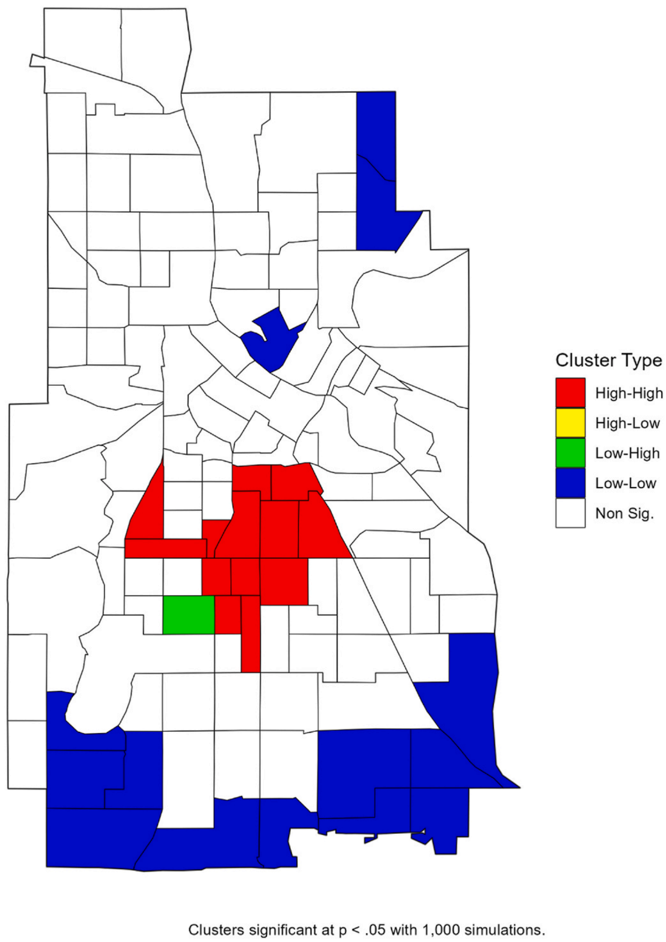
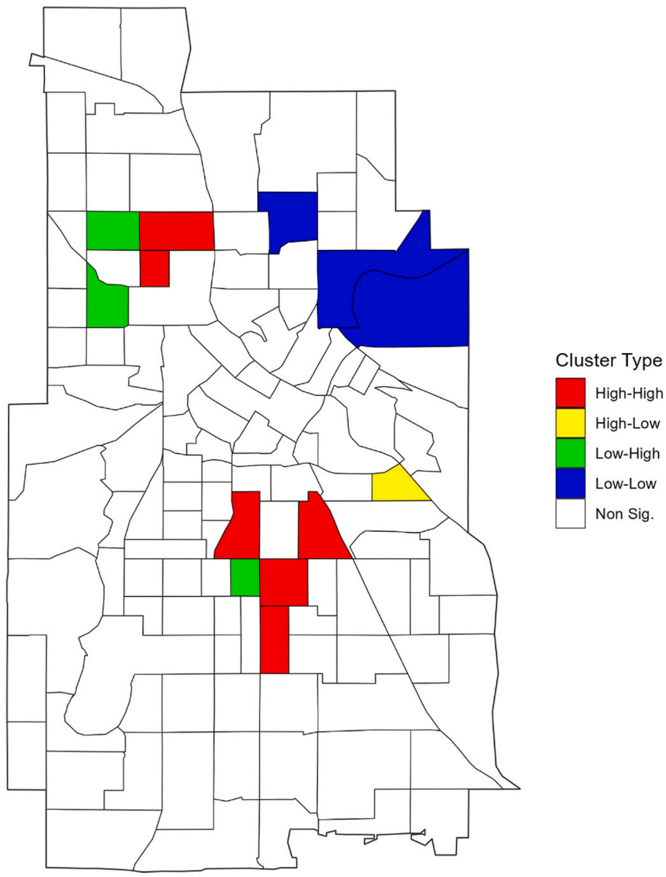


Fig. C1. LISA plot for carjacking change pre/post murder of George Floyd.



Clusters significant at p < .05 with 1,000 simulations.

Fig. C2. LISA plot for homicide change pre/post murder of George Floyd.

Appendix D. Minneapolis census tracts by concentrated disadvantage categorization

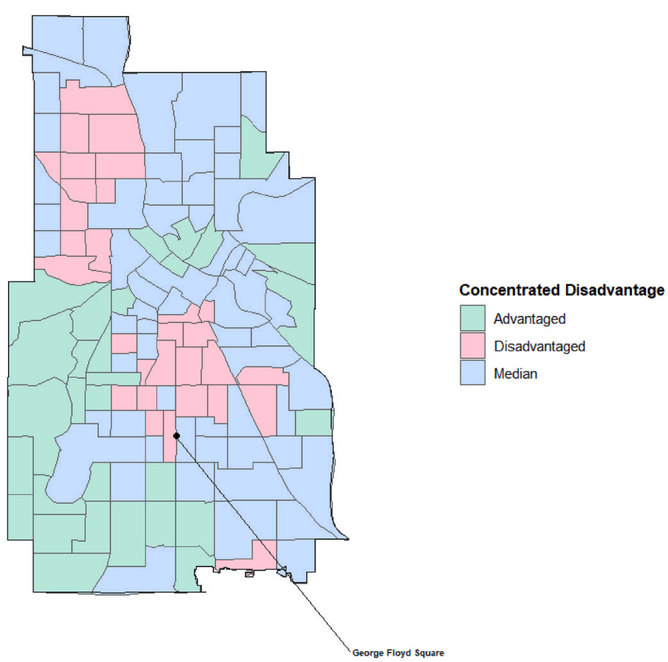


Fig. D. Minneapolis concentrated disadvantage by census tract, 2020 ACS 5-year estimates.

Appendix E. Predicted quarterly crime counts by neighborhood disadvantage

Table E1
Predicted quarterly carjacking counts, by neighborhood disadvantage.

Date Range	Quarters Since Police Killing	Disadvantaged (Bottom 25%)		Median (25–75%)		Advantaged (Top 25%)	
		(n = 30 Census Tracts)		(n = 61 Census Tracts)		(n = 30 Census Tracts)	
		Mean	95% CI	Mean	95% CI	Mean	95% CI
1/1/17–2/26/17	−14	0.24	(0.15, 0.33)	0.10	(0.07, 0.13)	0.04	(0.02, 0.07)
2/27/17–5/28/17	−13	0.25	(0.16, 0.34)	0.11	(0.07, 0.14)	0.04	(0.02, 0.07)
5/29/17–8/27/17	−12	0.26	(0.17, 0.35)	0.11	(0.08, 0.14)	0.05	(0.02, 0.08)
8/28/17–11/26/17	−11	0.27	(0.19, 0.36)	0.12	(0.08, 0.15)	0.05	(0.02, 0.08)
11/27/17–2/25/18	−10	0.29	(0.20, 0.37)	0.12	(0.09, 0.16)	0.05	(0.02, 0.08)
2/26/18–5/27/18	−9	0.30	(0.21, 0.39)	0.13	(0.09, 0.16)	0.05	(0.02, 0.09)
5/28/18–8/26/18	−8	0.32	(0.23, 0.41)	0.13	(0.10, 0.17)	0.06	(0.02, 0.09)
8/27/18–11/25/18	−7	0.33	(0.24, 0.42)	0.14	(0.10, 0.18)	0.06	(0.02, 0.09)
11/26/18–2/24/19	−6	0.35	(0.25, 0.44)	0.15	(0.11, 0.19)	0.06	(0.02, 0.10)
2/25/19–5/26/19	−5	0.36	(0.26, 0.47)	0.16	(0.11, 0.20)	0.06	(0.02, 0.11)
5/27/19–8/25/19	−4	0.38	(0.27, 0.49)	0.16	(0.11, 0.21)	0.07	(0.02, 0.11)
8/26/19–11/24/19	−3	0.40	(0.28, 0.52)	0.17	(0.12, 0.22)	0.07	(0.03, 0.12)
11/25/19–2/23/20	−2	0.42	(0.29, 0.55)	0.18	(0.12, 0.24)	0.07	(0.03, 0.12)
2/24/20–5/20/20	−1	0.44	(0.30, 0.58)	0.19	(0.12, 0.25)	0.08	(0.03, 0.13)
5/25/20–8/23/20	0	1.59	(0.97, 2.20)	0.73	(0.44, 1.02)	0.48	(0.16, 0.80)
8/24/20–11/22/20	1	1.69	(1.18, 2.20)	0.82	(0.56, 1.09)	0.67	(0.31, 1.03)
11/23/20–2/21/21	2	1.78	(1.32, 2.23)	0.90	(0.66, 1.15)	0.87	(0.45, 1.30)
2/22/21–5/23/21	3	1.83	(1.38, 2.28)	0.96	(0.74, 1.19)	1.06	(0.54, 1.58)
5/24/21–8/22/21	4	1.85	(1.39, 2.31)	0.99	(0.78, 1.21)	1.20	(0.59, 1.81)
8/23/21–11/21/21	5	1.84	(1.37, 2.31)	1.00	(0.80, 1.20)	1.27	(0.61, 1.93)
11/22/21–2/20/22	6	1.80	(1.34, 2.25)	0.97	(0.78, 1.16)	1.26	(0.61, 1.90)
2/21/22–5/22/22	7	1.72	(1.29, 2.15)	0.92	(0.74, 1.10)	1.16	(0.59, 1.73)
5/23/22–8/21/22	8	1.62	(1.22, 2.02)	0.84	(0.66, 1.03)	1.00	(0.54, 1.46)
8/22/22–11/20/22	9	1.50	(1.11, 1.89)	0.75	(0.55, 0.96)	0.81	(0.44, 1.17)
11/21/22–12/31/22	10	1.37	(0.94, 1.79)	0.65	(0.43, 0.88)	0.61	(0.30, 0.92)

Table E2
Predicted quarterly homicide counts, by neighborhood disadvantage.

Date Range	Quarters Since Police Killing	Disadvantaged (Bottom 25%)		Median (25–75%)		Advantaged (Top 25%)	
		(n = 30 Census Tracts)		(n = 61 Census Tracts)		(n = 30 Census Tracts)	
		Mean	95% CI	Mean	95% CI	Mean	95% CI
1/1/17–2/26/17	−14	0.06	(0.03, 0.10)	0.04	(0.01, 0.07)	0.01	(0.00, 0.03)
2/27/17–5/28/17	−13	0.07	(0.04, 0.10)	0.04	(0.02, 0.06)	0.02	(0.00, 0.03)
5/29/17–8/27/17	−12	0.07	(0.04, 0.11)	0.04	(0.02, 0.07)	0.02	(0.00, 0.03)
8/28/17–11/26/17	−11	0.08	(0.05, 0.11)	0.05	(0.02, 0.07)	0.02	(0.00, 0.03)
11/27/17–2/25/18	−10	0.08	(0.05, 0.12)	0.05	(0.02, 0.08)	0.02	(0.00, 0.03)
2/26/18–5/27/18	−9	0.09	(0.05, 0.12)	0.05	(0.03, 0.08)	0.02	(0.01, 0.03)
5/28/18–8/26/18	−8	0.09	(0.06, 0.13)	0.06	(0.03, 0.08)	0.02	(0.01, 0.04)
8/27/18–11/25/18	−7	0.10	(0.06, 0.14)	0.06	(0.03, 0.09)	0.02	(0.01, 0.04)
11/26/18–2/24/19	−6	0.11	(0.06, 0.15)	0.06	(0.04, 0.09)	0.03	(0.01, 0.04)
2/25/19–5/26/19	−5	0.11	(0.07, 0.16)	0.07	(0.04, 0.10)	0.03	(0.01, 0.04)
5/27/19–8/25/19	−4	0.12	(0.07, 0.17)	0.07	(0.04, 0.10)	0.03	(0.01, 0.05)
8/26/19–11/24/19	−3	0.13	(0.07, 0.19)	0.08	(0.04, 0.11)	0.03	(0.01, 0.05)
11/25/19–2/23/20	−2	0.14	(0.07, 0.20)	0.08	(0.05, 0.12)	0.03	(0.01, 0.05)
2/24/20–5/20/20	−1	0.14	(0.07, 0.22)	0.09	(0.05, 0.13)	0.03	(0.01, 0.06)
5/25/20–8/23/20	0	0.56	(0.34, 0.79)	0.18	(0.09, 0.28)	0.03	(0.00, 0.07)
8/24/20–11/22/20	1	0.48	(0.30, 0.67)	0.17	(0.09, 0.25)	0.04	(0.00, 0.07)
11/23/20–2/21/21	2	0.41	(0.26, 0.56)	0.16	(0.08, 0.23)	0.04	(0.01, 0.08)
2/22/21–5/23/21	3	0.35	(0.22, 0.48)	0.14	(0.08, 0.21)	0.05	(0.01, 0.08)
5/24/21–8/22/21	4	0.30	(0.19, 0.41)	0.13	(0.07, 0.19)	0.05	(0.01, 0.09)
8/23/21–11/21/21	5	0.26	(0.16, 0.36)	0.11	(0.07, 0.18)	0.06	(0.02, 0.09)
11/22/21–2/20/22	6	0.22	(0.13, 0.31)	0.11	(0.06, 0.16)	0.06	(0.02, 0.10)
2/21/22–5/22/22	7	0.19	(0.11, 0.27)	0.10	(0.06, 0.15)	0.07	(0.03, 0.12)
5/23/22–8/21/22	8	0.16	(0.09, 0.23)	0.10	(0.05, 0.14)	0.08	(0.03, 0.13)
8/22/22–11/20/22	9	0.14	(0.07, 0.20)	0.09	(0.04, 0.13)	0.09	(0.02, 0.16)
11/21/22–12/31/22	10	0.12	(0.06, 0.18)	0.08	(0.04, 0.12)	0.10	(0.02, 0.18)

Appendix F. Tests of robustness

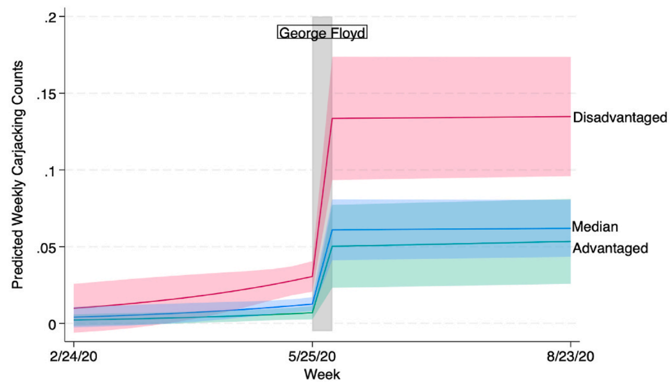


Fig. F1. Predicted weekly carjacking counts by neighborhood disadvantage, quarter prior to and after the murder of George Floyd, 2/24/20–8/23/20.

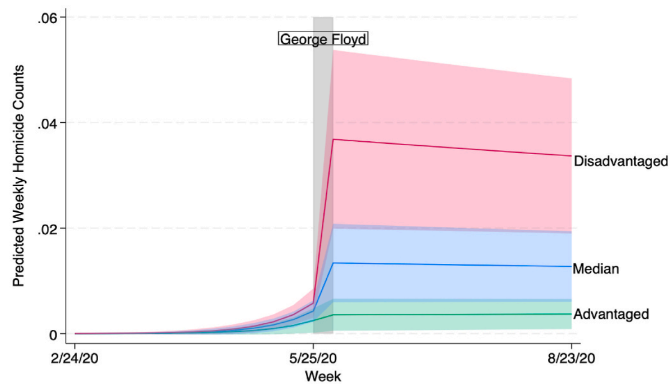


Fig. F2. Predicted weekly homicide counts by neighborhood disadvantage, quarter prior to and after the murder of George Floyd, 2/24/20–8/23/20.

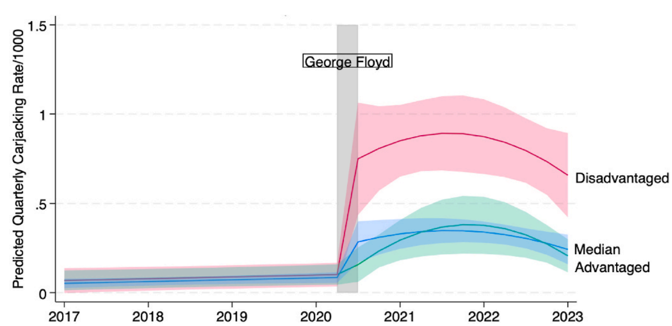


Fig. F3. Predicted quarterly carjacking rate/1000 residents age 18+ by neighborhood disadvantage, Minneapolis 2017–2022.

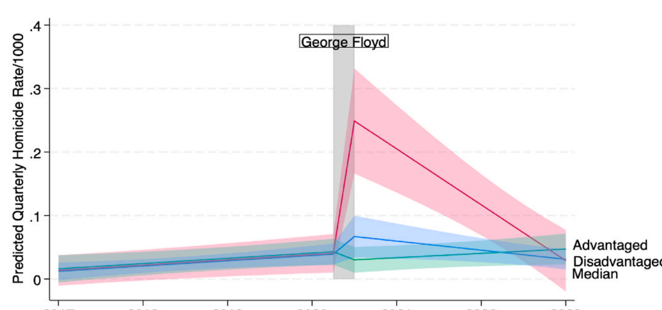


Fig. F4. Predicted quarterly homicide rate/1000 residents age 18+ by neighborhood disadvantage, Minneapolis 2017–2022.

Table F1
Negative binomial interrupted time series GEE model with and without police stops (N = 3025, 121 census tracts with 25 observations per census tract).

	Carjackings (Without Police Stops)		Carjackings (With Police Stops)		Homicides (Without Police Stops)		Homicides (With Police Stops)	
	IRR	95% CI	IRR	95% CI	IRR	95% CI	IRR	95% CI
Time	1.05**	(1.02, 1.08)	1.07**	(1.03, 1.10)	1.06*	(1.01, 1.12)	1.09**	(1.04, 1.14)
Immediate Post-Killing Effect	3.70***	(2.39, 5.74)	3.93***	(2.54, 6.09)	1.99*	(1.13, 3.51)	2.41**	(1.28, 4.53)
Concentrated Disadvantage (CD) (ref: Median)								
Advantaged	0.42**	(0.22, 0.80)	0.46*	(0.25, 0.86)	0.37*	(0.17, 0.79)	0.47	(0.22, 1.01)
Disadvantaged	2.35***	(1.52, 3.62)	2.19***	(1.48, 3.23)	1.65	(0.87, 3.15)	1.59	(0.88, 2.88)
Immediate Effect*CD (ref: Median)								
Advantaged	1.59	(0.72, 3.51)	1.46	(0.68, 3.18)	0.48	(0.11, 2.02)	0.40	(0.09, 1.74)
Disadvantaged	0.93	(0.55, 1.55)	1.00	(0.60, 1.68)	1.84*	(1.03, 3.30)	2.08*	(1.07, 4.03)
Sustained Post-Killing Effect	1.09	(0.96, 1.24)	1.09	(0.97, 1.23)	0.87***	(0.80, 0.93)	0.85***	(0.79, 0.92)
Sustained Effect*CD (ref: Median)								
Advantaged	1.26	(0.95, 1.66)	1.24	(0.94, 1.63)	1.22*	(1.05, 1.41)	1.21*	(1.04, 1.40)
Disadvantaged	0.94	(0.78, 1.13)	0.95	(0.79, 1.14)	0.93	(0.86, 1.00)	0.93	(0.87, 1.00)
Quadratic Post-Killing Effect	0.99*	(0.97, 0.99)	0.98**	(0.97, 0.99)	–	–	–	–
Quadratic Effect*CD (ref: Median)								
Advantaged	0.98	(0.96, 1.01)	0.98	(0.96, 1.01)	–	–	–	–
Disadvantaged	1.01	(0.99, 1.02)	1.00	(0.99, 1.02)	–	–	–	–
Percent Black	1.01*	(1.00, 1.03)	1.01*	(1.00, 1.02)	1.02**	(1.01, 1.04)	1.02**	(1.01, 1.04)
Age (ref: 50+ years)								
Age <18	1.04**	(1.01, 1.06)	1.03**	(1.01, 1.06)	1.00	(0.97, 1.04)	1.00	(0.97, 1.04)
Age 19-29	1.03**	(1.01, 1.04)	1.02**	(1.01, 1.04)	1.00	(0.98, 1.02)	1.00	(0.98, 1.01)
Age 30-49	1.04**	(1.01, 1.07)	1.04**	(1.01, 1.07)	1.00	(0.96, 1.04)	1.00	(0.97, 1.03)
Minneapolis Police Stop Rate (lagged one week)	–	–	1.01***	(1.00, 1.01)	–	–	1.01***	(1.01, 1.01)
Constant	0.00***	(0.00, 0.00)	0.00***	(0.00, 0.02)	0.02***	(0.01, 0.08)	0.01***	(0.00, 0.05)

IRR=Incidence Rate Ratio, *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

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