Ambient Density and Urban Crime: Evidence from Smartphone Data*

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Abstract

Ambient density — the number of people in a given area at a given time — is believed to be an important determinant of urban safety. Testing this hypothesis has been hindered by the difficulty of measuring the movements of ordinary citizens, which we overcome by using smartphone data. We find that increasing the ambient density in a neighborhood raises the number of crimes reported there but lowers victimization rates. The beneficial effects of density are strongest in neighborhoods with more social capital, and low- to medium-density levels. Finally, we show how the rise of remote work may affect crime rates across different areas of Chicago.

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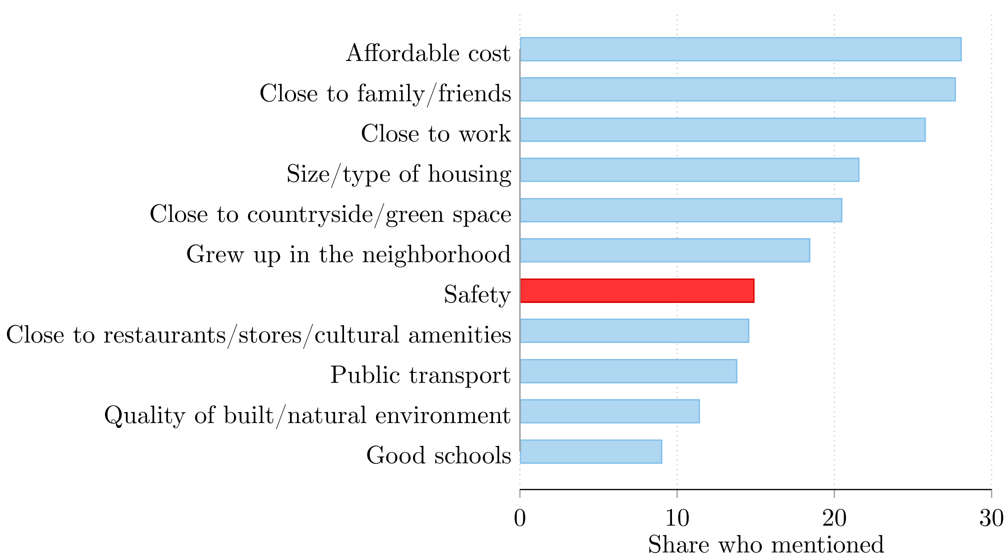
The first thing to understand is that the public peace — the sidewalk and street peace — of cities is not kept primarily by the police, necessary as police are. [It is] enforced by the people themselves.

— Jane Jacobs, *The Death and Life of Great American Cities*, 1961

1 Introduction

Public safety is one of the most valued urban amenities. Survey evidence suggests that it matters more for urban dwellers than other important amenities, such as the proximity to good schools, restaurants, and stores (see Figure 1). As with many other urban amenities, public safety is endogenous and can be affected by policy. In particular, an extensive literature shows how local criminal activity is affected by police presence (see, e.g., Di Tella and Schargrodsky, 2004; Klick and Tabarrok, 2005; Draca et al., 2011). However, as Jane Jacobs suggests in her acclaimed *Death and Life of Great American Cities*, policing in cities is largely undertaken by ordinary citizens who can witness and report crimes. Whether a neighborhood is safe at a given time depends on how busy it is.

Figure 1: Survey — What are the main reasons why you chose your current neighborhood?



Notes: Results of a 2015 YouGov survey of 2080 residents in Great Britain, who were asked for the three main reasons for which they chose to live in their neighborhood.

In this paper, we investigate the effect of ambient density — the number of people in a given area at a given time — on urban crime, using Chicago as a case study. This question is not new; it is, in fact, a key component of most prominent theories of urban crime.[1] All emphasize that

[1] Routine activity theory suggests that crimes happen when a likely offender meets a suitable target in the absence

increasing the activity of a neighborhood may favor crime by making it more likely that a potential criminal finds a target, but it may also deter crime through natural surveillance. Whether ambient density is, on net, associated with positive or negative externalities in terms of public safety is theoretically ambiguous and calls for empirical investigation.

Such investigation has been hindered in the past by two difficulties. The first one is measurement: while administrative data can provide information on the location of police officers, it is much more challenging to track ordinary citizens. Therefore, it has been historically difficult to precisely measure both ambient density and victimization rates — the probability that a person in a given neighborhood will be a victim of a crime at a given time. The second difficulty is causal identification: ambient density is endogenous, and we can expect people to avoid some neighborhoods at times when they are perceived to be unsafe. Therefore, even with precise measures of ambient density and victimization rates, correlational evidence relating these two variables would be of limited interest.

To overcome these empirical challenges, we use smartphone data from a panel corresponding to about 10% of the US population, covering 25 months between January 2018 and January 2020. This data allows us to build a high-frequency measure of ambient density at a high spatial resolution. Unsurprisingly, neighborhoods can witness considerable shifts in ambient density over time. In the Loop, the main section of Chicago's downtown, we find that the ambient density is more than four times higher at noon than at midnight on a regular weekday and more than three times higher during weekdays compared to weekends.

We combine these measures of ambient density with detailed data on crime from the Chicago Police Department (CPD), containing precise information on the timing and location of crimes. For different neighborhoods and times of the day, we compute victimization rates by dividing the number of crimes that took place in a neighborhood during an hour by the ambient population of that neighborhood at that time. The wide variation in crime rates between neighborhoods is well documented. With our data, we can further investigate variation in crime rates within neighborhoods over time. We find that there is as much variation in crime rates within neighborhoods over days of the week and hours of the day as between neighborhoods.

Our data further shows that about a third of those in Chicago during an average day do not live within the city's boundaries — rather, they come from the suburbs or further away. We use data on the origin of visitors to Chicago to build a shift-share instrument for ambient density. For instance, visitors to Chicago from the city's suburbs come at different times of the year and of the

of a capable "guardian" (Cohen and Felson, 1979). Increasing the number of people in a neighborhood makes it more likely that a potential criminal will meet a suitable victim but increases the number of capable guardians around every potential victim. Environmental criminology studies how the built environment and land use affect foot traffic and how it, in turn, affects crime (Jeffery, 1977). Crime pattern theory (Brantingham and Brantingham, 2013; Santos, 2016) considers that locations that attract many people are "crime generators", as they concentrate many potential victims.

day than visitors from Michigan. Furthermore, visitors from the suburbs tend to go to different areas of Chicago than those from Michigan. We build our shift-share instrument by combining data on the number of visitors from different locations (shifts) and the typical areas in Chicago that visitors from different origin locations choose to go to (shares).

Evidence from this instrumental variable strategy confirms the correlational evidence that we document: increasing the number of people in a neighborhood increases the number of recorded crimes but reduces victimization rates. Specifically, increasing the ambient density in a neighborhood by 1% leads the victimization probability to drop by 0.37% for battery and assault, and by 0.25% for robbery and street theft. The number of recorded crimes, however, increases by 0.63% and 0.75%, respectively. For comparison, the estimated elasticities of total crime to police presence in the literature are between -0.3 and -0.5 (O'Flaherty and Sethi, 2015).

These IV estimates correspond to the effect of shifting the population affected by the instrument. Therefore, they might not only reflect our main object of interest — the effect of increasing density on the costs and benefits of committing a crime and, therefore, on the likelihood of a crime — but also a composition effect. In the case of our visitor shift-share IV, the shifted population is composed of visitors to Chicago. If visitors are more likely to be victimized or to engage in criminal activity than locals, or if they exert a lower deterrence, then our IV estimates may not reflect the effect of shifting the local population. We undertake two analyses to assess whether composition effects drive our visitor shift-share IV estimates.

First, we control in our regressions for demographics in each neighborhood at a given time (average income, average age, and the share of whites, all inferred from the home location of smartphones). Controlling for these demographics barely changes our estimates of the effect of ambient density on crime rates.

Second, we estimate the effects of ambient density on crime rates using a different source of variation in ambient density. We retrieve data from the Chicago Transit Authority on temporary closures of the city's 122 "L" (short for "elevated") rail stations for maintenance or upgrading purposes. We find that station closures lead to a drop in density and increased victimization rates in nearby neighborhoods. Using these temporary closures as an instrument for ambient density, we find effects of ambient density on crime similar to those found using the shift-share IV.

Our two empirical strategies complement each other: the visitor shift-share IV provides variation over the entire city, while transit station closures only affect about 15% of Chicago's neighborhoods. However, while the shift-share IV relies on variation in the presence of a specific population (visitors to Chicago), the people shifted by transit closures are likely more representative of the city's general population. Furthermore, these identification strategies leverage variation in ambient density at different time horizons: while the shift-share IV uses medium-run, seasonal shifts in ambient population, our transit closure instrument leverages more short-run changes in density.

We relate our results to two current policy debates. First, many urban planners argue that policies that spread out ambient density (for instance, favoring mixed-use neighborhoods over single-use neighborhoods) are beneficial for public safety. Underlying these arguments is a belief that there are decreasing returns to scale in the effectiveness of density in crime prevention — adding a few people to a deserted street will make it safer, but adding people to a busy street will have little effect. By estimating the effect of shifting ambient density separately for neighborhoods with different average density levels, we find some evidence for decreasing returns to scale: the beneficial effects of density are strongest in low-density and medium-density neighborhoods.

Second, we assess the potential impact of work-from-home on crime rates in different neighborhoods of Chicago. Dingel and Neiman (2020) find that about 39% of jobs in the Chicago metropolitan area could be performed from home. We predict the changes in ambient density that would be observed if work-from-home were to become widespread and estimate corresponding changes in crime rates. We find that work-from-home could increase violent crime rates in the central neighborhoods of Chicago by 8%. Work-from-home is expected to cause large drops in real estate prices in city cores (see, e.g., Gupta et al., 2022; Delventhal et al., 2022). Our results suggest that work-from-home is likely to further strain the central neighborhoods of cities by increasing crime rates there.

This paper makes several contributions to the existing literature. First, we provide new measures of criminal activity in cities. Using data on reported crimes, it is possible to estimate victimization rates with a high temporal resolution (e.g., hour-by-hour) and a low spatial resolution (e.g., at the metropolitan area level), or with a high spatial resolution (e.g., at the neighborhood level), but a low temporal resolution (e.g., year-by-year). Our paper shows how smartphone data can be leveraged to build measures of public safety with a high spatial and temporal resolution over a long time period.[2]

More importantly, instead of using these time-varying measures of crime rates in a prediction exercise to find their best correlates (as in, e.g., De Nadai et al., 2020; Bogomolov et al., 2014; Hanaoka, 2018), we combine it with plausibly exogenous variation to measure the effect of ambient density on crime rates. This relates our paper to the literature on the determinants of criminal

[2]Past research in criminology has well recognized the problem of correctly measuring the denominator of crime rates (see, e.g., Boggs, 1965) and has developed creative ways to measure ambient density: Malleson and Andresen (2015) use data from geolocated Twitter posts, Andresen (2006) uses a prediction of ambient density using the characteristics of each neighborhood, Kadar and Pletikosa (2018) use data from subway and taxi rides, Felson and Boivin (2015) use transportation surveys. Several papers have used smartphone data to measure ambient density and victimization rates but could only leverage data from a short period — from a day to a few weeks (Traunmueller et al., 2014; Bogomolov et al., 2014; Malleson and Andresen, 2016; Song et al., 2019), use a low temporal resolution (Massenkoff and Chalfin, 2022), or use a low spatial resolution (He et al., 2020). Other studies in economics have shown how smartphone data can be used to measure variables that cannot be seen in traditional survey or administrative data, such as informal meetings (Atkin et al., 2022), trip chains (Miyauchi et al., 2022), voting wait times (Chen et al., 2020), social interactions (Chen and Rohla, 2018), and wages in developing countries (Kreindler and Miyauchi, 2019).

activity, such as air pollution (Herrnstadt et al., 2021); high temperatures (Heilmann et al., 2021); population characteristics (Glaeser and Sacerdote, 1999); lead exposure (Reyes, 2007); social cohesion (Sampson et al., 1997); public transportation (Khanna et al., 2022); and land use (Bernasco et al., 2013; Twinam, 2017). In particular, our results relate to the literature evaluating the effect of "guardians" on criminal activity: be that police officers (Chalfin and McCrary, 2018), community monitoring (McMillen et al., 2019; Gonzalez and Komisarow, 2020), or ordinary citizens (Jacobs, 1961).

Our findings also echoes recent literature showing that crime can be reduced at the city level by changing where people work (Khanna et al., 2022; Frankenthal, 2024) or where people live (Aliprantis and Hartley, 2015) within cities. Our evidence suggests that criminal activity can be reduced by spreading where people go during the day.

The literature studying the determinants of crime typically relies on spatial regressions to evaluate the effect of a treatment (e.g., the opening of a new transit station or bar) on crime, measured as the number of crimes observed in a neighborhood (or the number of crimes per resident) over a given period of time. In many cases, the treatment is likely to affect both criminal behavior and ambient density. While researchers are mostly interested in the former effect, our results show that changes in ambient density are likely an important confounder. Opening new stores on a street is likely to increase the number of people passing through it and the number of crimes recorded there, but a researcher should not necessarily conclude that stores make a street less safe. Indeed, our results show that accounting for ambient density in measures of safety would likely flip this result.

We further contribute to the literature studying the endogenous supply of urban amenities (e.g., Ahlfeldt et al., 2015; Diamond, 2016; Couture and Handbury, 2017; Almagro and Domınguez-Iino, 2022; Baum-Snow and Hartley, 2020). Here, instead of inferring overall amenity levels in different neighborhoods from housing prices, we focus on a single amenity that can be directly measured.

Finally, we relate to the literature on the economic effects of density (see Ahlfeldt and Pietrostefani, 2017, 2019, for a review). While past work has underscored the importance of population and employment density in shaping local outcomes, we show evidence that ambient density also affects neighborhood amenities.

The rest of this paper is organized as follows. Section 2 describes our data and stylized facts about crime in Chicago. Section 3 details our empirical strategy and presents our main results. Section 4 explores policy implications of our results, and Section 5 concludes.

2 Data and Stylized Facts

2.1 Smartphone data and ambient density

Measuring ambient density. In this paper, we use the location data continuously sent by smartphones to measure the number of people in a neighborhood at a given point in time, which we refer to as the ambient population of a neighborhood. We use proprietary data from Safegraph (specifically, the "Neighborhood Patterns" dataset), which aggregates pings from millions of smartphones across the United States.

Data from Safegraph has been used and validated in several studies (e.g., Chen and Rohla, 2018; Atkin et al., 2022; Chen et al., 2020; Allcott et al., 2020; Weill et al., 2020). One difference between the dataset we use and those used in many previous studies is that instead of focusing on the number of smartphones detected at specific points of interest (e.g., stores, restaurants), we have access to a measure of the number of people in a given neighborhood at a given time. Specifically, Safegraph clusters smartphone pings to locate individuals at different points in time and provides us with the number of ping clusters that have been detected in each of the 2,194 Census Block Groups (CBGs) of Chicago for each hour between January 2018 and January 2020.[3] Importantly, pings coming from devices traveling at relatively high speeds (e.g., in cars or a train) are filtered out, and we only measure the activity of people moving slowly (e.g., walking) or who are static. Because the Safegraph data is aggregated at the CBG level, CBGs will be our spatial unit of analysis throughout the paper. CBGs in Chicago are, on average, home to 1,200 inhabitants and have a surface area of 0.3 sq. km (or 70 acres). In our analyses, we exclude CBGs with fewer than 200 inhabitants, as ambient density is measured very noisily in these neighborhoods.

There are, on average, approximately 250,000 smartphones residing in Chicago in the Safegraph panel, which corresponds to a sampling rate of around 10%. We estimate the number of people in a neighborhood at a given time by dividing the number of measured ping clusters by the sampling rate.

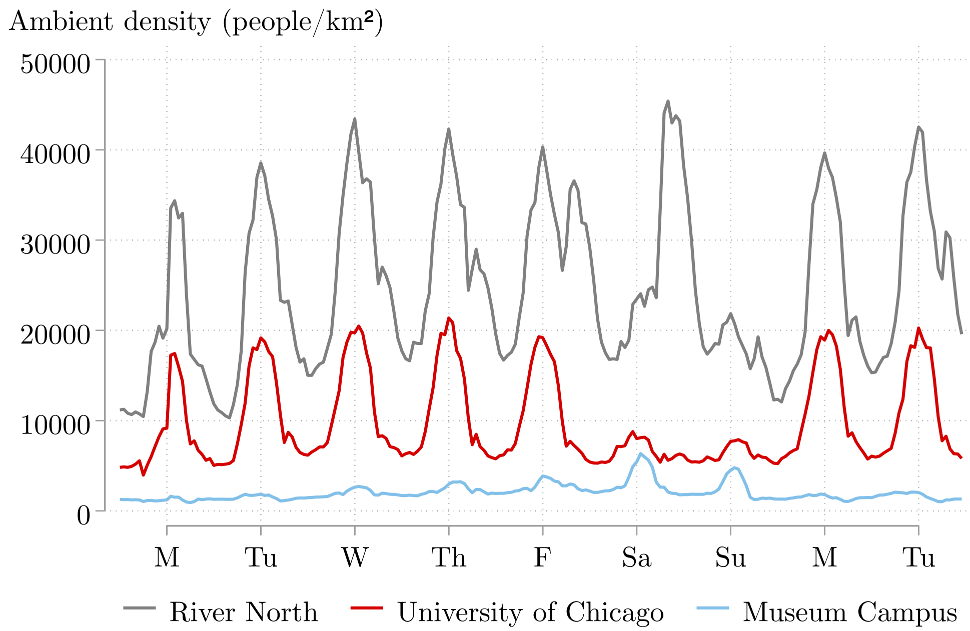
Appendix Figure S.1 shows the average ambient density in different neighborhoods of Chicago separately for weekdays and weekends. As expected, ambient density is highest around the CBD, which is much more active on weekdays than on weekends.

Variation in ambient density. The density of people residing in a neighborhood (i.e., given by the Census) only changes slowly over time, but ambient density can vary widely over short periods of time. Figure 2 shows how ambient density evolved over a short period of time for three CBGs in Chicago. Activity in the commercial neighborhood of River North and on the University of Chicago campus is highest during weekdays, while the Museum Campus is more active during

[3] With 18,240 hours of data and 2,194 neighborhoods, this corresponds to about 40 million observations.

weekends. There are also important changes in ambient density over a single day, with peaks in ambient density during the day for commercial neighborhoods and at night in residential areas.

Figure 2: Hour-by-hour variation in ambient density in three Chicago neighborhoods



Notes: This figure illustrates how ambient density varied in three Chicago CBGs, hour-by-hour between January 6, 2019 and January 16, 2019. River North is a neighborhood in the center of the city, with many shops and restaurants. The Museum Campus is home to the Adler Planetarium, the Shedd Aquarium, and the Field Museum of Natural History. Maps of these three example neighborhoods can be found in Appendix Figure S.2.

Data limitations and representativeness. Unfortunately, we cannot distinguish in our data individuals located outdoors (e.g., in streets or parks) from others in buildings. The latter may be more sheltered from crime, although it is worthwhile to note that about a third of non-domestic crimes against people (primarily assaults and robberies) happen in buildings.

Another potential concern is the representativeness of the Safegraph panel. According to the Pew Research Center, 89% of the urban American population owns a smartphone. However, lower ownership rates among some groups (such as the old and the less-educated) or differences in smartphone usage between groups may make the panel we use unrepresentative of the broader population. In Appendix Figure S.3, we check that the Safegraph panel closely tracks the full population for five neighborhood characteristics: the mean household income, the share of college-educated, the unemployment rate, the percentage of white people, and the share of the population below 30 years old. Sampling rates appear to be higher in poorer neighborhoods, but overall the Safegraph panel seems fairly representative of Chicago's population.

2.2 Crime data

The CPD makes publicly available data on each reported crime in Chicago. For each incident, we observe the time at which it happened, its location[4], whether it was a domestic crime or not, and a description of the crime.

Broadly, crimes can be classified as crimes against persons (e.g., assault, robbery) or crimes against property (e.g., burglaries, retail theft). For the purposes of our study, we restrict our analysis to non-domestic crimes and do not consider crimes against society (e.g., human trafficking, child sexual abuse, narcotics violations, weapons violations, gambling, liquor law violations, white-collar crime) as they usually take place over extended periods of time or are not precisely located. We further exclude instances of theft in which it is unclear from the description of the crime whether items are being stolen from people or buildings (and, therefore, whether the crime should be classified as a crime against persons or a crime against property). Finally, we exclude crimes involving vehicles because we do not have data on the ambient density of vehicles, which makes it difficult to define a victimization probability.[5]

There are 3,444,175 crimes satisfying these restrictions documented in the CPD database between its first publication (in January 2001) and January 2020, just before the start of the COVID-19 pandemic. About 59% of the reported crimes are against persons, and the remaining 41% are crimes against property. Crimes against persons are primarily assaults and battery (about 54%) and robberies/street theft (about 44%). Homicides and other crimes against persons (e.g., kidnapping, stalking) each account for less than 1% of all crimes against persons. Crimes against property are mostly acts of arson and other criminal damage (about 28%), burglaries (about 28%), retail theft/theft from buildings (about 30%), and criminal trespass (13%). A residual fraction of crimes against property is simply labeled in the CPD data as "other crimes against property."

In the main tables of this paper, we report effects of ambient density on battery and assault ("Assault", in our regression tables, for short); robbery and street theft ("Theft"); and all crimes against persons.

In the Appendix, we further report results for homicide, for which estimates tend to be noisy due to the low number of crimes in this category. We further show results for the following crimes against property: burglary; criminal damage and arson ("Damage"); criminal trespass ("Trespass"); and retail theft and theft from buildings ("Retail"). Our focus on crimes against persons stems from the fact that many crimes against property are not witnessed. For these observations, the time of the crime reported in the CPD data is approximative and sometimes corresponds to the time at which the crime was discovered.[6] This measurement problem makes it harder to

[4]Crime locations are precise at the block level. In Appendix A.1, we detail the method we use to allocate crimes to CBGs. Appendix Figure S.4 illustrates the granularity of our dataset.

[5]In Appendix A.2, we provide further details about crimes excluded from the analysis.

[6]For example, reports of burglaries peak at 8 a.m., which likely reflects the moment at which the crime was

interpret our results for these outcomes, although they tend to be consistent across specifications.

Outcome variables. Our crime dataset allows us to estimate standard crime rates as the average number of crimes per hour in each neighborhood $\times$ time cell (for instance, in each neighborhood $\times$ hour of the day $\times$ day of the week cell) divided by the number of residents in that neighborhood. For crimes against property, we use these measures as outcome variables. For crimes against persons, we can estimate the victimization probability (i.e., the probability that a person in a neighborhood at a given time will be a victim of a crime) by dividing the average number of crimes in a neighborhood $\times$ time cell by the average ambient population in that cell. For legibility, we multiply victimization probabilities by one million and the number of crimes per hour by one thousand.

In Appendix Figure S.5, we map average crime rates in different neighborhoods of Chicago. Crime rates are highest in poorer areas of the city (at the South and West) both for crimes against persons and crimes against property — several studies have leveraged this spatial heterogeneity to analyze the socioeconomic determinants of crime (e.g., Cahill and Mulligan, 2003). On top of this spatial variation, there is important temporal variation in urban crime. Appendix Figure S.6 shows that the intensity of criminal activity is higher in the afternoon, peaking at 3 p.m. for assault and retail theft; and at 6 p.m. for robbery and street theft.

Knowing which neighborhoods are associated with higher criminal activity or when criminal activity is most likely to happen in a city does not require using smartphone data. What our measure of ambient density allows is a mapping of victimization rates with both a high spatial and temporal resolution, as we can track the number of potential victims in each neighborhood over time. In Appendix Figure S.7, we map victimization rates in Chicago for different hours of the day.

There is as much within-neighborhood variation as between-neighborhood variation in crime rates. Armed with these high-frequency measures of crime rates, a first question we can answer is the following: is there more variation in crime rates between neighborhoods or within neighborhoods over time? To answer this question, we compute the average crime rate for each neighborhood $\times$ day of the week $\times$ hour of the day cell, and in Table 1, we decompose the variation of these crime rates in within-neighborhood and between-neighborhood variation. We find that there is as much variation in crime rates within neighborhoods over time as across neighborhoods. This is not driven by the fact that criminal activity is more likely at some times than others: we find similar results after residualizing our outcomes on day of the week $\times$ hour of the day fixed effects (see Appendix Table S.1). We find similar results for crimes against property (see Appendix Table S.2).

discovered, as opposed to the moment at which it took place.

Table 1: Within-neighborhood and between-neighborhood variation in victimization rates

	Victimization rates			Crimes per resident		
	(1) Assault	(2) Theft	(3) **All**	(4) Assault	(5) Theft	(6) **All**
Within CBG variance	48.7%	60.2%	44.3%	43.2%	40.3%	34.1%
Between CBG variance	50%	38.9%	54.3%	55.8%	58.4%	64.6%

Notes: This table decomposes variation in crime rates in between-CBG variation and within-CBG variation (over time). The dependent variables are victimization rates and the number of crimes per resident. We use one observation per CBG × day of the week × hour of the day. "Assault" corresponds to assault and battery, "Theft" to battery and street theft, and "All" corresponds to all crimes against persons – see Section 2.2 for details.

Standard crime rates differ substantially from ambient density-adjusted ones. Typically, crime rates in a neighborhood are measured by dividing the number of recorded crimes by the number of residents according to the Census. In contrast, our victimization rate measures use the ambient population as the denominator rather than the resident population. These two measures differ significantly, as shown in Figure 3. In residential neighborhoods, where the ambient population is usually lower than the resident population, traditional measures of crime are lower than ambient population-adjusted victimization rates. Conversely, victimization rates are lower than per-resident crime rates in more central commercial neighborhoods. In the Loop, for instance, the per-resident crime rate is more than twice the victimization rate. On average, the two measures of crime rates differ by 0.35 log points (in either direction), a meaningful difference.

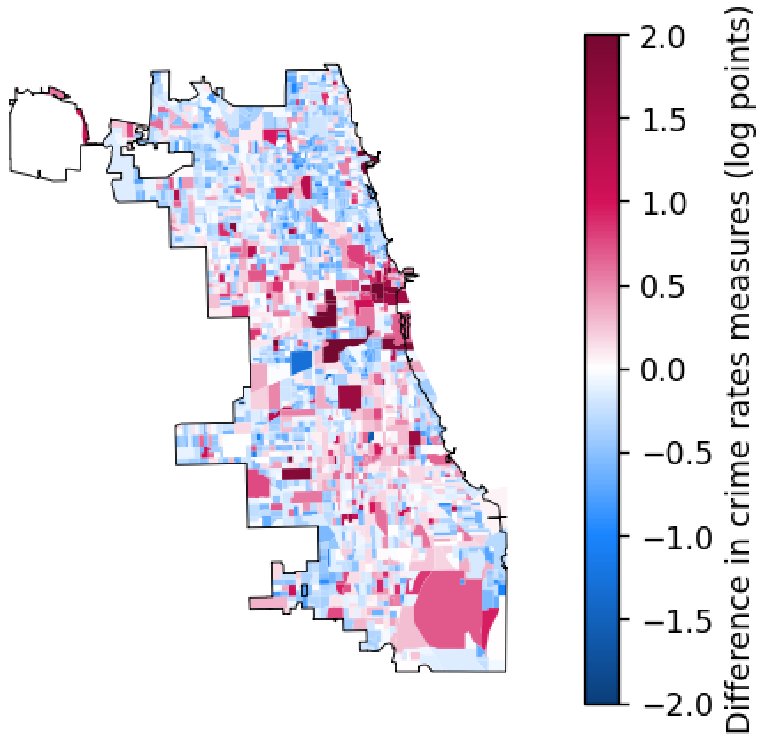
2.3 Crime and ambient density

When ambient density in a neighborhood increases, criminal activity changes due to three effects. First, the number of potential criminals increases, increasing the number of crimes. Second, as ambient density increases, the number of potential victims increases as well and criminals may find it easier to identify suitable targets. Finally, these effects may be counterbalanced by a deterrence effect, corresponding to a higher probability of punishment in busier places.

Jacobs (1961) emphasizes the idea that this third effect (which she calls "eyes on the street") may be particularly strong, making density an asset for safety. In this paper, we distinguish between two "eyes on the street" effects: a "strong" effect, where the deterrence effect is so large that when the number of people in a neighborhood increases, the total number of crimes in that neighborhood drops; and a "weak" eyes on the street effect, where the deterrence effect makes victimization rates decrease with density, but not fast enough to make the total number of crimes decrease.[7] In short, the deterrence effect may be dominated by the number of potential victims

[7] We formalize this distinction in a stylized model of the effect of ambient density on crime in Appendix D.

Figure 3: Difference between standard and ambient population-adjusted measures of crime



Notes: This map shows the difference (in log points) between a standard measure of crime (the number of reported crimes divided by the number of residents) and our victimization rate measure (computed as the number of reported crimes divided by the average ambient population). Areas in red correspond to a per-resident crime rate that is higher than the victimization rate (i.e., the ambient population-adjusted crime rate). For this figure, we compute crime measures for all crimes against persons.

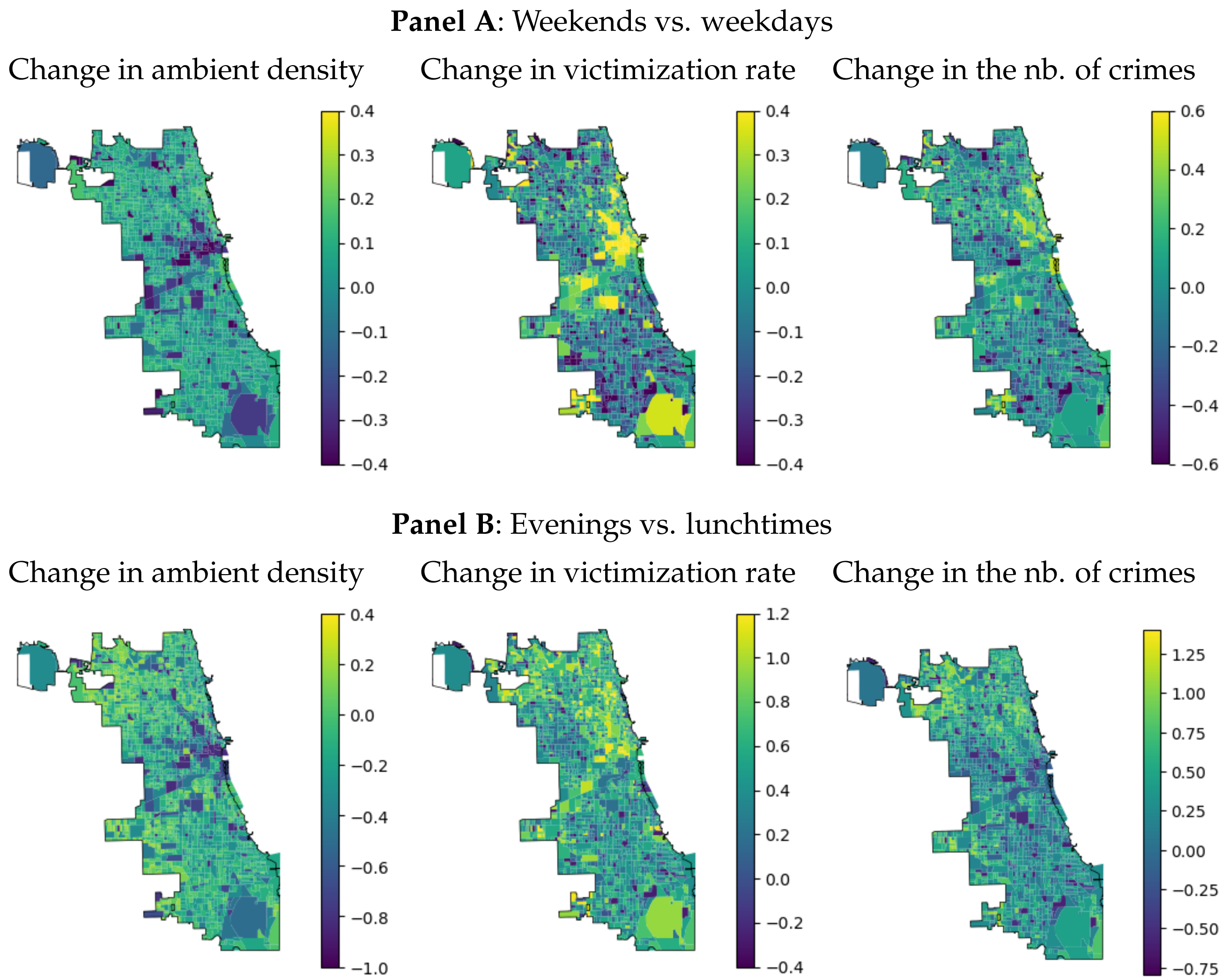
and potential criminals increasing with density, making both the sign and the magnitude of the effect of ambient density on crime ambiguous.

Shifts in crime rates are correlated with shifts in ambient density. In Chicago, denser neighborhoods tend to be safer, as shown in Appendix Figure S.8. However, as people are attracted to safe neighborhoods, this cross-sectional relationship is of limited interest.

In this paper, we leverage the panel variation of our data and always control for neighborhood fixed effects. Therefore, we investigate the within-neighborhood variation in crime rates and analyze what we believe could be an important determinant of this variation: ambient density. In Chicago, victimization rates drop when a neighborhood becomes busier. During the weekends or in the evenings, ambient density drops in the center of the city, which is associated with an increase of victimization rates and a drop in the number of recorded crimes there (see Figure 4). Conversely, ambient density increases in the outer parts of the city concurrently with a drop in victimization rates and an increase in the number of detected crimes.

We can more systematically assess this relationship by regressing crime rates on ambient density at the calendar hour level. We estimate the following equation:

Figure 4: Correlation between changes in density and changes in crime rates



Notes: This figure maps changes in ambient density, victimization rates, and the number of crimes, for all crimes against persons. All changes are measures in log points. Panel A shows how density and crime rates change on weekends relative to weekdays. Panel B shows how density and crime rates change in the evenings (between 6 p.m. and 10 p.m.) relative to lunchtimes (between 11 a.m. and 2 p.m.).

$$\text{crime}_{ih} = \beta \log(\text{density}_{ih}) + \gamma_i + \delta_h + \varepsilon_{ih}, \tag{1}$$

Where crime_{ih} corresponds to a measure of crime (victimization rates for crimes against persons and the number of crimes per hour for crimes against property) in neighborhood i during calendar hour h, density_{ih} is a measure of ambient density, γ_i is a CBG fixed effect, and δ_h is a calendar hour fixed effect.[8] Here and in the following exercises, we use crime rates as an outcome variable rather than the log of crime rates — this means that estimates of β should be interpreted as semi-elasticities rather than elasticities. We make this choice because there are no detected crimes in

[8]The main regressor in our analyses is ambient density rather than ambient population, but using the latter would provide identical estimates because of the inclusion of CBG fixed effects.

most neighborhood × time cells. In Section 3.5, we estimate Poisson models to provide elasticity estimates despite the high prevalence of zeros in the outcome variables.

One issue in estimating this equation for victimization rates is that ambient population appears both as a regressor and in the denominator of the outcome variable (which is the number of crimes divided by the number of potential victims). This leads to a (downward) “division” bias if ambient population is measured with error. This issue can be solved by instrumenting for $\log(\text{density}_{ih})$ (Borjas, 1980). As a first pass, we can instrument for ambient density in a CBG × calendar hour cell with the average ambient density in other observations in the same CBG × month × day of the week × hour of the day cell.

In Table 2, we present correlational evidence on the link between ambient density and crime. In this table as well as the following, we normalize outcome variables so that they have an average of one to facilitate interpretation, and we cluster standard errors at the CBG level. We find that increasing the ambient density of a neighborhood is associated with a drop in victimization rates for all crimes against persons. These results are consistent with previous studies suggesting that natural surveillance is an important determinant of crime rates. For instance, Twinam (2017) uses the first zoning code of Chicago as an instrument for modern land use, and finds that denser areas tend to have lower crime rates; and Ellen et al. (2013) finds that vacancies increase crime in their immediate vicinity using microdata on foreclosures in New York. We also find that increasing the ambient density of a neighborhood is associated with an increase in the number of crimes per resident for all crimes against persons, as well as for most crimes against property (see Appendix Table S.3).

The results of Table 2 do not allow us to conclude that increasing ambient density in a neighborhood makes it safer. Indeed, the estimates we find could be driven by reverse causality. If people avoid some neighborhoods at times when these neighborhoods are unsafe, then we would find a negative correlation between victimization rates and ambient density, even in the absence of a causal effect of ambient density on crime. Omitted variables can also lead to bias in any direction. For instance, large outdoor events increase density in the neighborhoods in which they take place and can separately directly affect crime rates through the deployment of additional police or easier access to victims by criminals as people go outdoors. More generally, composition effects may play a role in explaining our results: people have different probabilities of being involved in criminal activity (either as a perpetrator or a victim). Therefore, the effect of “shifting density” depends on the characteristics of those being shifted. In the next section, we use different sources of variation to alleviate both concerns.

Table 2: Calendar hour-level regressions of crime rates on ambient density

	Victimization rates			Crimes per resident		
	(1) Assault	(2) Theft	(3) **All**	(4) Assault	(5) Theft	(6) **All**
(log) Ambient dens.	-0.258***	-0.276***	-0.268***	0.546***	0.507***	0.532***
	(0.043)	(0.053)	(0.034)	(0.058)	(0.108)	(0.069)
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,547,586	39,547,586	39,547,586	39,547,586	39,547,586	39,547,586
F-statistic	6397.4	6397.4	6397.4	.	.	.
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	2.197	1.667	3.933	2.105	1.545	3.717

Notes: This table reports correlational evidence on the effect of ambient density on crime against persons. The dependent variables are victimization rates and the number of crimes per resident – see Section 2.2 for details. To facilitate interpretation, we normalize outcome variables so that their mean is one – pre-normalization means are reported at the bottom of the table. We include one observation per CBG $\times$ calendar hour between January 2018 and January 2020. In columns (1) to (3), ambient density in one CBG $\times$ calendar hour is instrumented by the average ambient density in other observations in the same CBG $\times$ month $\times$ day of the week $\times$ hour cell. We include CBG and calendar hour fixed effects in each regression. Standard errors are clustered at the CBG level. In Appendix Table S.3, we report estimates for additional types of crime. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3 Do shifts in ambient density affect crime rates?

3.1 A shift-share strategy

Framework. Safegraph can infer where the owner of each smartphone lives by analyzing pings emitted during the night. We were provided with an aggregation of the data at the CBG $\times$ month $\times$ moment of the day level with information on the home location of the smartphones detected in each cell. "Moments of the day" correspond to divisions of the day by Safegraph in time slots of two to five hours (e.g., between 3 p.m. and 4:59 p.m.). For instance, the data may report that among the smartphones that visited CBG D in March 2019 during lunchtime (between 11 a.m. and 2:59 p.m.), 14 reside in CBG O_1, 5 reside in CBG O_2, etc. (details about this dataset can be found in Appendix B.1).[9] Interestingly, we find that during the day, about a third of the people in Chicago do not live in Chicago but rather in the suburbs or further away.

We use this data on origin locations to construct a shift-share instrument (Bartik, 1991), leveraging the fact that people living in different locations (e.g., in the suburbs of Chicago vs. in Michigan) tend to visit Chicago at different times and tend to visit different locations in Chicago when they come.[10]

[9] The moments of the day that Safegraph provide only cover 6 a.m. to midnight, so, unfortunately, most nighttime hours are excluded from the dataset.

[10] Allen et al. (2020) use a similar empirical strategy to instrument variation in expenditure across different neighborhoods of Barcelona.

Specifically, we compute for different home locations j the number of people residing in j who visit Chicago at time t and denote it by X_t^j (here, t corresponds to a month $\times$ moment of the day). The origin locations we consider are Chicago itself, the rest of Illinois, the 49 other states, Washington DC, the overseas territories of the United States, and Canada. We can also compute the probability with which a visitor from j will visit different neighborhoods. Using the flows X_t^j as shifts and the probabilities as shares, we can build a shift-share instrument,

$$Z_{it} = \sum_j X_t^j \pi_{it}^j, \tag{2}$$

Where π_{it}^j represents the probability that a visitor from j at time t will visit neighborhood i. To avoid a mechanical correlation between the instrument and the endogenous variable (in this case, density), we build leave-out shares — the probability π_{it}^j is computed using data from other months of the years (e.g., for observations in January, we only use data from February to December). For this reason, shares are indexed by time. We instrument for (log) ambient density with $\log(Z_{it})$. Details on the instrument's construction can be found in Appendix B.2.

The left panel of Figure 5 shows the variation in flows of visitors from four different origin locations j. While Chicago tends to be more visited in the summer, there is variation in visit patterns across states. For instance, there is a peak in the number of visitors from Minnesota in December, while we do not observe such a pattern for visitors from California. The right panel of Figure 5 maps the ratio between $\pi_{it}^{\text{Chicago}}$ and $\pi_{it}^{\text{Rest of Illinois}}$ (averaged across times t). It illustrates the heterogeneous exposure of different neighborhoods to flows of visitors originating from different locations.

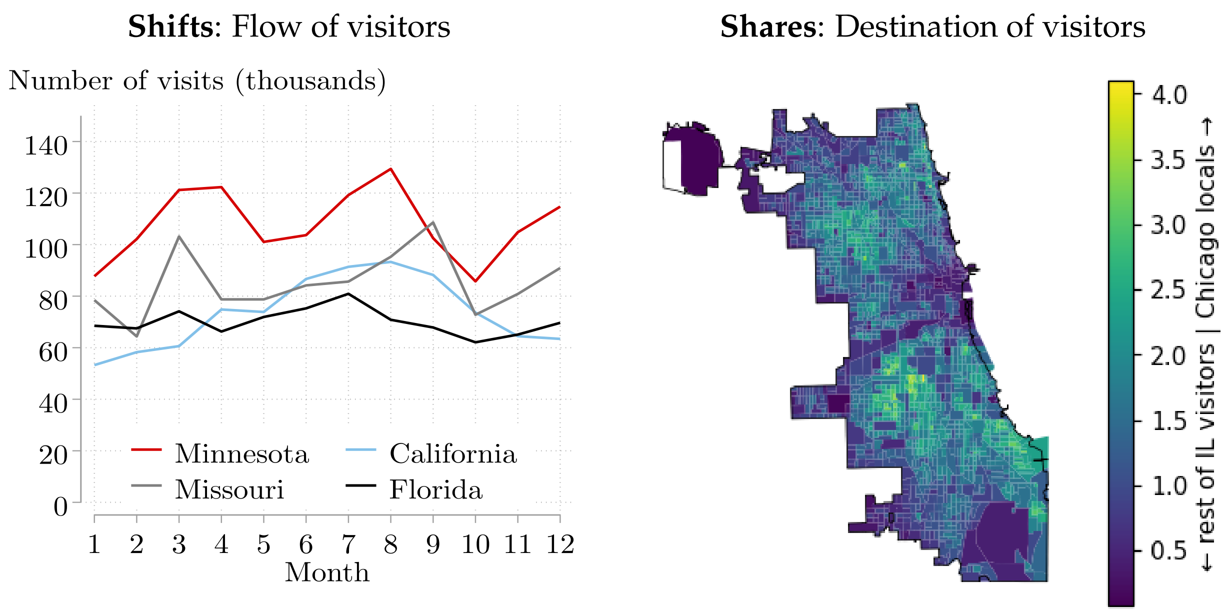
Empirical exercises. Because our shift-share instrument is only available at the CBG $\times$ month $\times$ moment of the day level, we aggregate our data on density and crime rates at that level for our regressions. We then estimate an equation similar to equation (1):

$$\text{crime}_{it} = \beta \log(\text{density}_{it}) + \gamma_i + \delta_t + \varepsilon_{it}, \tag{3}$$

Where crime_{it} corresponds to a measure of crime rates and density_{it} is a measure of ambient density, instrumented with (the log of) our shift-share IV. CBG fixed effects γ_i allow us to control for local time-invariant determinants of crime (such as the presence of a nearby police station), while time (moment of the day $\times$ month) fixed effects δ_t allow us to account for seasonal and daily fluctuations in crime patterns.

To increase precision and limit the number of zeros in the dependent variables, we use our full crime dataset (covering January 2001 to January 2020) to compute the average number of crimes per hour in a CBG $\times$ moment of day $\times$ month cell. Such an aggregation over different time

Figure 5: Illustration of the shift-share instrument



Notes: The left panel shows the number of visits from four states for all months of the year. We use this variation to construct shifts in our shift-share instrument, described in Section 3.1. The right panel illustrates that smartphones originating from different locations visit different parts of Chicago. We map for each neighborhood i the ratio of the probability that a smartphone visits i conditionally on having a home location in Chicago over the probability that a smartphone visits i conditionally on having a home location in the rest of Illinois. We use this variation to build the shares in our shift-share instrument.

periods would be problematic if crime patterns had changed significantly over time in Chicago. In Appendix Figure S.9, we compare the number of crimes per capita in each neighborhood over the period for which we have smartphone data (January 2018 to January 2020) with the number of crimes per capita in each neighborhood over the period for which we do not have smartphone data (January 2001 to December 2017). We find that the geographical distribution of crime remains very stable over time, which is consistent with previous findings of the literature (Clarke et al., 1996; Jean, 2008; Braga et al., 2010; Weisburd et al., 2004). Nonetheless, we will show that our results are robust to using only data from 2018 to 2020 to measure crime rates.

Identification. The exclusion restriction under which our identification strategy is valid is that conditional on fixed effects, our instrument is orthogonal to unobserved determinants of crime, captured in ε_{it}. A sufficient condition under which this assumption holds is that the shifts are exogenous (Borusyak et al., 2022) — in other words, that the timing of the visits to Chicago is uncorrelated with unobservable determinants of crime.

To better illustrate this assumption, we can consider a situation that would violate the exclusion restriction. Suppose that visitors from California disproportionately spend time in the CBD of Chicago and that the CBD of Chicago is less safe in February. If Californians do not visit any part of Chicago in February because they know that the CBD is especially unsafe then, this may lead to a correlation between the instrument and the error term.

3.2 Results and robustness

We present linear IV estimates of equation (3) in Table 3, Panel B. The results we find are aligned with the correlational evidence described earlier. Increasing density by one log point in a neighborhood decreases the probability that someone in that neighborhood will be a victim of an assault (the effect corresponding to 30% of the average assault probability) and of robbery and street theft (corresponding to 42% of the average rate). We also find that the number of reported crimes against persons increases with ambient density. This suggests that the elasticity of victimization rates to ambient density is between -1 and 0. We defer the estimation and discussion of these elasticities to Section 3.5. OLS estimates (Panel A) suggest stronger beneficial effects of density on crime, consistent with reverse causality driving part of the negative relationship between ambient density and crime rates.

Appendix Figure S.10 presents estimation results for more specific crime categories. We find that ambient density has a particularly strong negative effect on the prevalence of sexual assault: higher ambient density in a neighborhood is associated with lower victimization rates and fewer crimes per resident. In contrast, higher ambient density increases victimization rates for pick-pocketing, consistent with the idea that this type of crime is easier to commit in crowded environments.

In Appendix Table S.5, we present IV estimates for homicides and crimes against property. Increasing density decreases both the probability of being victim of a homicide and the number of homicides. We find that increasing ambient density has no statistically significant effect on the probability of burglary and criminal damage. Increasing ambient density is, however, associated with an increase in trespass and in retail theft.[11]

Robustness checks. The data collected by the CPD covers both index crime and additional crimes not tracked by the FBI, such as non-aggravated assaults. In Appendix Table S.6, we check that we obtain similar results when restricting the dataset to index crimes.

In our analyses, we excluded from the data CBGs with fewer than 200 inhabitants, as density measures are very noisy for these neighborhoods. In Appendix Table S.7 and Table S.8, we show that our results are qualitatively unchanged if we decrease or increase this threshold.

In Appendix Table S.9, we show estimation results when using only data on crimes committed

[11] This last effect is particularly large in magnitude. It is driven by large estimated effects in neighborhoods in the center of Chicago with high baseline levels of retail theft. Appendix Figure S.5 shows that this type of crime is concentrated in a handful of neighborhoods, while other types of crime are more evenly distributed throughout the city. The fact that our results may be driven by a few outlier neighborhoods (crime “hotspots”) is potentially worrisome. In Section 3.5, we estimate Poisson models that alleviate this concern.

Table 3: Effects of ambient density on crime against persons

	Victimization rates			Crimes per resident		
	(1) Assault	(2) Theft	(3) **All**	(4) Assault	(5) Theft	(6) **All**
Panel A: OLS						
(log) Ambient density	-0.351***	-0.536***	-0.431***	0.561***	0.508***	0.537***
	(0.028)	(0.028)	(0.022)	(0.062)	(0.079)	(0.057)
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Moment-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130,620	130,620	130,620	130,620	130,620	130,620
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	3.637	2.689	6.410	3.517	2.554	6.150
Panel B: Shift-share IV						
(log) Ambient density	-0.299***	-0.420***	-0.353***	0.824***	0.982***	0.887***
	(0.048)	(0.054)	(0.038)	(0.123)	(0.157)	(0.112)
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Moment-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130,620	130,620	130,620	130,620	130,620	130,620
First stage F-stat	5543.000	5543.000	5543.000	5543.000	5543.000	5543.000
Average	1.0	1.0	1.0	1.0	1.0	1.0
Normalization	3.637	2.689	6.410	3.517	2.554	6.150

Notes: This table reports OLS and shift-share IV estimates of the effect of ambient density on crime against persons. The dependent variables are victimization rates and the number of crimes per resident – see Section 2.2 for details. To facilitate interpretation, we normalize outcome variables so that their mean is one – pre-normalization means are reported at the bottom of the table. We include one observation per CBG $\times$ month $\times$ moment of the day. In Appendix Table S.5, we report estimates for additional types of crime. We show estimates for the first stage regression in Appendix Table S.4. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

between January 2018 and January 2020 instead of between January 2001 and January 2020 to construct the outcome variables in equation (3). The results we obtain are similar to those shown in Table 3.

In Appendix Table S.10, we show results when data is aggregated at higher levels than the CBG. Specifically, we show results when aggregating data at the Census tract, City neighborhood, and community area levels (City neighborhoods and community areas are partitions of Chicago into units larger than Census tracts). At different geographic levels, we find qualitatively similar results.

In Appendix Table S.11, we show that our results are robust to excluding Chicago from the set of origin locations when constructing the shift-share instrument. Finally, in Appendix Table S.12, we show that our results do not change significantly when we expand the number of origin locations by including each ZIP code in Chicago's metropolitan area as a potential origin for visitors.

3.3 Composition effects

The IV estimates of Table 3 correspond to the effect of changing the ambient density of a neighborhood through shifts in the number of visitors in that neighborhood. Because visitors are different than locals, our estimates do not only capture the effect of changing the ambient density of a neighborhood: they also capture the effect of shifting the composition of the ambient population of that neighborhood.

Although we do not know the age, income, or race of the owners of smartphones detected in Chicago, we have data on their CBG of residence. We use this data to approximate the characteristics of those in a given neighborhood at a given time and help us gauge the importance of composition effects. Specifically, we proxy the income of a visitor by the median household income in their CBG of origin, their age by the median age in their CBG of origin, and their probability of being white by the share of whites in their CBG of origin (characteristics of CBGs are taken from the 2015-2019 ACS). This allows us to infer the demographics of people in a neighborhood at a given time

In Table 4, we show estimation results for equation (3) augmented with controls for the composition of the ambient population. Adding these controls barely changes the estimates of density on crime, suggesting that demographic composition only plays a small role in explaining our results.

3.4 Evidence from temporary transit station closures

Controlling for some characteristics of the ambient population partially rules out composition effects but cannot fully account for the differences between locals and visitors living outside the city boundaries. A visitor may be more or less likely to be victimized, to be a criminal, to report a crime, or to act as a witness than a local with the same age, race, and income. To address this concern, we exploit a different source of variation that shifts the density of locals rather than visitors: temporary closures of transit stations for maintenance or upgrading. Phillips and Sandler (2015) shows that crime decreases around transit stations when stations on the same line close for maintenance. However, it is unclear whether this decrease comes from a decrease in victimization rates or a decrease in the number of potential victims. Our data allows us to separate these two channels.

L stations closures. We collect data on L station closures in Chicago between January 2018 and January 2020 from the "Monthly Ridership Reports" published by the Chicago Transit Authority (CTA). These documents report temporary service suspensions due to maintenance and modernization operations. Our sample has 498 distinct closure events, lasting 3.2 days on average. Among the 122 L stations in Chicago, 56 experienced at least one closure in our sample period.

Table 4: Shift-share IV: Composition effects

	Victimization rates			Crimes per resident		
	(1) Assault	(2) Theft	(3) **All**	(4) Assault	(5) Theft	(6) **All**
(log) Ambient density	-0.270***	-0.426***	-0.338***	0.851***	0.981***	0.902***
	(0.046)	(0.055)	(0.038)	(0.123)	(0.157)	(0.112)
(log) Average income	-0.399***	0.306***	-0.102**	-0.259***	0.190***	-0.072
	(0.070)	(0.047)	(0.046)	(0.081)	(0.056)	(0.055)
Average age	-0.010**	-0.005*	-0.008***	-0.011**	0.001	-0.006*
	(0.004)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)
Share white	-0.949***	-0.120	-0.599***	-1.063***	-0.275*	-0.732***
	(0.147)	(0.104)	(0.105)	(0.198)	(0.151)	(0.145)
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Moment-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130,620	130,620	130,620	130,620	130,620	130,620
First stage F-stat	5240.7	5240.7	5240.7	5240.7	5240.7	5240.7
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	3.637	2.689	6.410	3.517	2.554	6.150

Notes: This table reports shift-share IV estimates of the effect of ambient density on crime. We study the same outcomes as in Table 3, adding demographic variables as regressors (see Section 3.3 for details). We include one observation per CBG $\times$ month $\times$ moment of the day. Standard errors are clustered at the CBG level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Empirical strategy. We use these closures as ambient population shifters, considering that when a station closes, it affects all CBGs within a 200-meter radius. 323 CBGs (out of a total of 2,194) are close to a station using this definition. We build a panel of the 323 potentially affected CBGs, with for each of them one observation per day between January 2018 and January 2020. We use the full panel of smartphone data rather than the aggregated version used in the shift-share strategy. Using this panel, we estimate the following equation:

$$\text{crime}_{id} = \beta \log(\text{density}_{id}) + \gamma_{im(d)} + \delta_d + \varepsilon_{id} \tag{4}$$

Where crime_{id} is the crime rate in CBG i during calendar day d, measured using the average daytime density and the number of daytime crimes (where daytime is between 7 a.m. and 11 p.m.); $\gamma_{im(d)}$ is a neighborhood $\times$ month fixed effect; and δ_d is a calendar day fixed effect. We instrument ambient density $\log(\text{density}_{id})$ with Closure_{id}, which is neighborhood i's exposure to transit closures during day d.

When a station closes, we increase exposure in the neighborhoods close to that station by one divided by the number of neighborhoods close to that station. Suppose for instance that there are four neighborhoods within 200 meters of a given L station. Then, if only this station is closed in the network, Closure_{id} will be equal to zero everywhere except for the four neighborhoods close to the closed station, where exposure will be equal to 0.25. On average, there are 3.2 neighborhoods within 200 meters of a station.

This empirical strategy will yield unbiased estimates of the effects of ambient density on criminal activity if transit station closures are orthogonal to the unobserved determinants of crime, captured in ε_{id}. One potential threat to identification is the strategic timing of closures. Maintenance operations are likely conducted when they cause the least disruption. For instance, we find that closures are more likely to take place on weekends. Stations in the CBD may also be more likely to close during the summer when fewer people commute to offices. The calendar day and CBG $\times$ month fixed effects that we include in our regressions allow us to control for these motives to strategically time closures.

Results. Station closures lead to decreases in ambient density in their immediate vicinity: we find that an exposure to transit closures of one is associated with a drop in ambient density of about 0.17 log points — see Appendix Table S.13, Panel A, which corresponds to the first stage of equation (4). Given our definition of exposure, this means that a transit closure decreases ambient density by 5.4% in close neighborhoods, on average. This regression's F-statistic is 19.3, which is smaller than the F-statistic associated with our shift-share regressions but nonetheless sufficient for inference.

To further support the assumption that conditionally on fixed effects, days with a station closure are random, we can check that closures do not affect ambient density at hours during which the L stations are typically closed anyway. In Appendix Table S.13, Panel B, we show that the effect of a closure on the ambient density of nearby neighborhoods during nighttime hours is nonsignificant and much smaller than the effect found for daytime hours (we find an estimate of +0.2%).

Table 5 shows second-stage results. We find again that increasing density is associated with lower victimization rates and an increase in the number of reported crimes.

As transit station closures remain relatively rare, we implement the randomization inference test of Young (2019) as an alternative inference procedure. We randomly reassign 2,000 times transit station closures over the CBG $\times$ calendar days of our panel and compare the regression results associated with these placebo closures with those associated with real closures. Appendix Figure S.11 provides a graphical representation of this test, which gives us results consistent with those of Table 5.

Overall, the estimated effects of ambient density using L station closures as a source of exogenous variation are consistent with those obtained from our shift-share instrument strategy. This, along with the results of Section 3.3, suggests that the correlational evidence presented in Table 2

Table 5: Effects of ambient density on crime against persons

	Victimization rates			Crimes per resident		
	(1) Assault	(2) Theft	(3) **All**	(4) Assault	(5) Theft	(6) **All**
Panel A: OLS						
(log) Ambient density	-0.555***	-0.585***	-0.570***	0.389***	0.337***	0.362***
	(0.049)	(0.048)	(0.041)	(0.081)	(0.065)	(0.066)
CBG-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar day FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	244,281	244,281	244,281	244,281	244,281	244,281
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	3.135	3.076	6.294	3.799	3.784	7.688
Panel B: Transit disruption IV						
(log) Ambient density	-0.640**	-1.067**	-0.861***	0.807**	1.763*	1.192**
	(0.284)	(0.467)	(0.266)	(0.378)	(1.053)	(0.539)
CBG-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar day FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	244,281	244,281	244,281	244,281	244,281	244,281
First stage F-stat	19.3	19.3	19.3	19.3	19.3	19.3
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	3.135	3.076	6.294	3.799	3.784	7.688

Notes: This table reports OLS and IV estimates of the effect of ambient density on crime against persons, using L-station disruption as an instrumental variable. We study the same outcomes as in Table 3, and include one observation per CBG $\times$ calendar day. Standard errors are clustered at the CBG level. In Appendix Table S.14, we report estimates for additional types of crime. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

is not due to reverse causality, omitted variable bias or composition effects. These results further suggest that the effects of ambient density on crime are similar at different time scales. While the shift-share instrument yields estimates of the effect of seasonal, medium-run changes in density, the variation from L station corresponds to short-run and more unexpected changes in ambient density.

3.5 Elasticities

Up to this point, we have focused on estimating semi-elasticities rather than elasticities. This is justified by the very large number of zeros in our outcome variables but complicates the interpretation of the magnitude of our effects.

To obtain elasticity estimates despite the pervasiveness of zeros in our outcome variables, we estimate the Poisson Pseudo-Maximum Likelihood (PPML) counterparts of equations (1), (3), and (4) using the procedure of Correia et al. (2020). Specifically, we estimate

$$\text{crime}_{it} = \exp\left(\beta \log(\text{density}_{it}) + \text{FE}_{it}\right) + \varepsilon_{it}, \tag{5}$$

Where FE_{it} corresponds to fixed effects (CBG and calendar hour fixed effects for equation (1), CBG and moment $\times$ month fixed effects for equation (3), and CBG $\times$ month and calendar day fixed effects for equation (4)).[12] For the PPML counterparts of equations (3) and (4), we again use our shift-share and transit closure instruments for identification. We compute estimates using the control function method of Wooldridge (2015) and estimate standard errors via bootstrap.

These estimates are presented in Table 6. They are consistent with the results described earlier — for victimization rates, we find elasticity estimates that are between 0 and -1, implying that increasing the ambient density of a neighborhood increases the number of crimes but decreases victimization rates.[13] Our preferred estimates are those of Panel B, which leverage the shift-share instrument. They suggest that increasing ambient density by 1% decreases assault rates by 0.37%, theft rates by 0.25%, and crime rates for all crimes against persons by 0.36%.

Elasticities for homicide rates and crimes against properties are presented in Appendix Table S.15. Estimates using the shift-share instrument suggest that increasing ambient density by 1% decreases homicide rates by 1.01%.[14] For crimes against property, our preferred results imply that increasing density by 1% in a neighborhood decreases the number of burglaries by 0.08%, and increases the number of criminal damages by 0.24%, the number of criminal trespass by 0.38% and of retail thefts by 0.93%.

3.6 Mechanisms

The most natural explanation for the beneficial effects of density we measure is what Jane Jacobs called “eyes on the street”: increasing the number of people in a neighborhood leads to more natural surveillance, which deters potential criminals. As described in Section 2.3, the “eyes on the street” effect could be “weak” or “strong”. For most crimes, we find support for the weak effect, but not for the strong one: increasing density lowers victimization rates, but increases the number of crimes. While it is difficult to ascertain that natural surveillance is driving our results, we provide two additional results that support this interpretation, before excluding some alternative explanations.

[12] Because we are estimating a count model here, our outcomes of interest are the number of crimes in each neighborhood. To make results easier to interpret, we report for crimes against people $\beta - 1$ instead of β, and interpret the corresponding estimate as the elasticity of the victimization rate to density. Indeed, because the victimization rate is the number of crimes divided by the ambient population, the elasticity of the number of crimes to density equals one plus the elasticity of the victimization rate to density.

[13] There is one exception: the elasticity of theft rates to density we estimate using transit closures as an instrument falls outside of the [-1, 0] range, although our estimate is statistically indistinguishable from -1.

[14] We estimate a large and positive but extremely noisy elasticity for homicide when using transit closures as an instrument. This is due to the very small number of homicides observed around transit stations during our study period.

Table 6: Effects of ambient density on crime against persons: PPML estimates

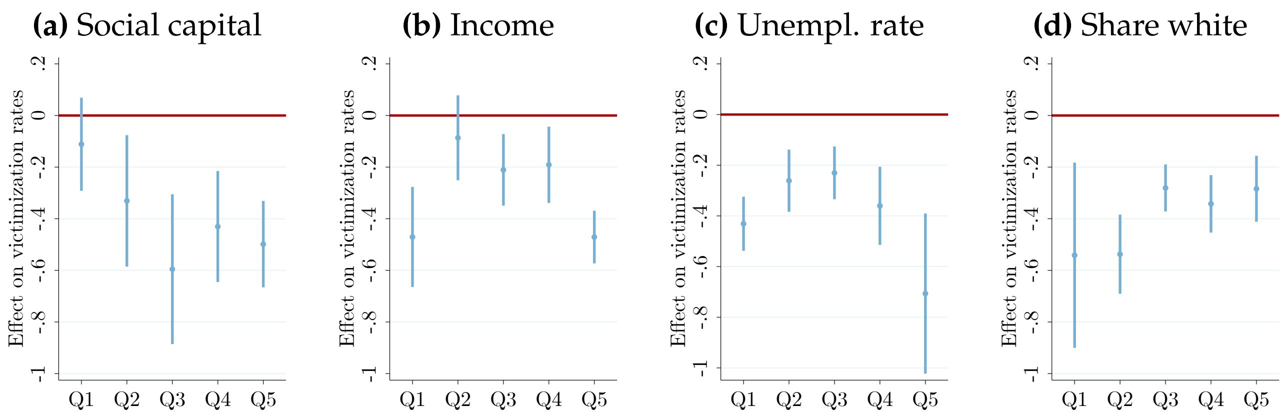
	Victimization rates			Crimes per resident		
	(1) Assault	(2) Theft	(3) **All**	(4) Assault	(5) Theft	(6) **All**
Panel A: Correlational evidence						
(log) Ambient dens.	-0.711***	-0.652***	-0.691***	0.289***	0.348***	0.309***
	(0.023)	(0.033)	(0.021)	(0.023)	(0.033)	(0.021)
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,852,048	39,852,048	39,852,048	39,852,048	39,852,048	39,852,048
Panel B: Shift-share IV						
(log) Ambient dens.	-0.369***	-0.252***	-0.361***	0.631***	0.748***	0.639***
	(0.064)	(0.040)	(0.033)	(0.064)	(0.040)	(0.033)
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Moment-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130,620	130,620	130,620	130,620	130,620	130,620
Panel C: Transit closure IV						
(log) Ambient dens.	-0.756***	-1.086***	-0.973***	0.244	-0.086	0.027
	(0.155)	(0.135)	(0.094)	(0.155)	(0.135)	(0.094)
CBG $\times$ Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar day FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	244,281	244,281	244,281	244,281	244,281	244,281

Notes: This table reports PPML estimates of the effect of ambient density on crime against persons. Estimates for victimization rates correspond to the estimates on crimes per resident, minus one. In Panel A, we use a calendar hour-level panel and do not instrument ambient density. In Panel B, we use the same dataset and instrument as in Table 3. In Panel C, we use the same dataset and instrument as in Table 5. For estimation, we use the control function method, as described in Wooldridge (2015). Standard errors in all panels are clustered at the CBG level. In Appendix Table S.15, we report estimates for additional types of crime. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Social cohesion. According to Jacobs, the beneficial effects of having "eyes on the street" are strongest when social ties are strong. To test whether this hypothesis is supported in the data, we extend equation (3) by interacting ambient density with quintiles of the social capital index developed by Kyne and Aldrich (2020). This metric reflects socioeconomic homogeneity, civic engagement, and community participation.

Results for all crimes against persons, summarized in Figure 6(a), reveal that the beneficial effects of ambient density are stronger in neighborhoods with higher levels of social capital. Moreover, social capital appears to be a stronger predictor of these benefits than traditional sociodemographic characteristics. Neither income levels nor unemployment rates exhibit a clear relationship with the effect of density on crime rates (panels b and c). While panel (d) suggests stronger effects in neighborhoods with lower white population shares, estimates lack precision. Overall, we take these results as supportive evidence for the role of natural surveillance in the beneficial effects of ambient density we uncover.

Figure 6: Heterogeneous effects by neighborhood sociodemographic characteristics



Notes: This figure shows shift-share IV estimates and 90% confidence bands of the effects of ambient density on crime rates (for all crime against persons) for different quintiles of four sociodemographic variables. In panel (a), Q1 corresponds to the 20% of neighborhoods with the lowest social capital index from Kyne and Aldrich (2020), and Q5 corresponds to the 20% of neighborhoods with the highest social capital index. Income, unemployment rates, and the share of white residents are taken from the 2015-2019 ACS.

Daytime vs. nighttime. If natural surveillance contributes to the beneficial effects of density, its influence should be stronger during the day than during the night. Leveraging daylight saving time as an exogenous source of variation in daylight exposure, recent studies demonstrate reduced crime rates during daylight hours (Doleac and Sanders, 2015; Domínguez and Asahi, 2023), consistent with a lower visibility at night reducing the potency of having eyes on the street. In Appendix Table S.16, we show that the beneficial effects of density are strongest during daytime, by estimating equation (3) excluding time intervals predominantly occurring after sunset. This lends further support to natural surveillance playing a role in the beneficial effects of density we find.

Reporting rates. One concern that taints any study of crime is the fact that we can only measure crimes that have been reported to the police. Any variation in observed crime rates is a compound of the variation in the true crime rate and variation in the reporting rate.[15] In our case, increasing ambient density is likely to increase the rate at which crimes are reported, as it makes more likely that bystanders witness a crime. Therefore, varying reporting rates are unlikely to explain our results and instead make our estimates conservative.

[15]This concern is more important for some types of crime than others. Homicides and burglaries have high reporting rates, while retail theft is likely to be very underreported.

Police presence. One channel through which ambient density could affect crime rates is the location of police officers. If police forces follow people, then increasing the ambient density in a neighborhood will increase the density of police officers in that neighborhood. This, in turn, is likely to make crime rates drop (see, e.g., Di Tella and Schargrodsky, 2004; Klick and Tabarrok, 2005; Draca et al., 2011). Through FOIA requests to the CPD, we gathered data on the number of police officers patrolling each police beat during each hour between January 2013 and January 2020. Details about police presence data can be found in Appendix C. We find that police presence decreases when ambient density increases, possibly due to police officers targeting less dense (and hence less safe) neighborhoods – see Table S.17. Therefore, changes in police presence induced by changes in ambient density is unlikely to explain our results and again make our estimates conservative. Moreover, in Appendix Table S.18, we show estimation results for equation (3) augmented with the (log) number of police officers. Adding this control has little effect on the estimates of density on crime, suggesting that police presence is not explaining our results.

4 Policy relevance

In this last section, we relate our results to two recent policy debates. First, we assess whether policies that tend to spread ambient density more evenly can help limit urban crime. Second, we evaluate the potential consequences of a development of work-from-home on ambient density and crime rates in Chicago.

4.1 Should we spread ambient density more?

Urban planners have discussed the effect of ambient density on crime because the distribution of people in cities is shaped by planning decisions. Zoning codes, for instance, largely determine the density of construction in cities and the type of buildings one can find in each neighborhood. A high-density commercial neighborhood will witness high ambient density during weekdays between 9 a.m. and 5 p.m. and more limited density during the nights and on weekends. A single-family zoned neighborhood will have low ambient density levels throughout the week. More generally, a city with a dense core and sprawling outer neighborhoods will have a more concentrated distribution of people than a city with a more uniform building pattern. A city with separated uses (e.g., residential vs. commercial) will have a more concentrated population at any given moment than a city with mixed-use neighborhoods.

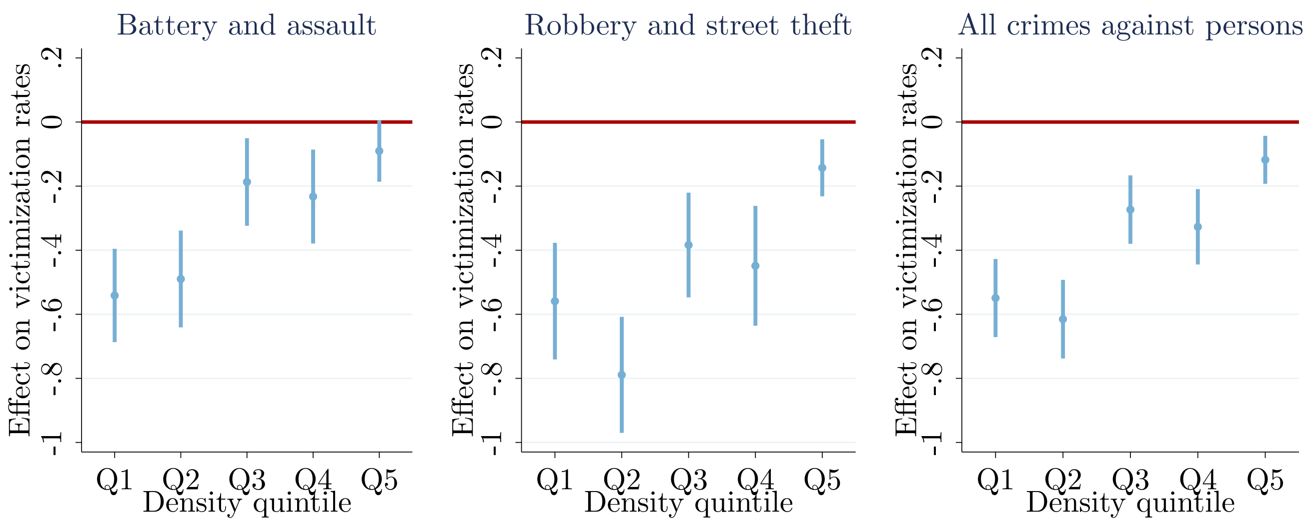
Many urban planners insist that city designs that spread ambient density are beneficial to public safety.[16] Underlying their arguments is the idea that there are decreasing returns to scale

[16]Jane Jacobs, in her 1961 *Death and Life of Great American Cities*, advocated for the development of mixed-use neighborhoods (which have users throughout the day) instead of single-use neighborhoods which are deserted during the

in the efficiency of density to deter crime — adding a small number of people in a deserted street will make it noticeably safer, but adding more people to a busy neighborhood will have little effect.

To assess whether this intuition is confirmed in our data, we augment equation (3) with interactions of ambient density with quintiles of average ambient density. We summarize our results for our baseline categories in Figure 7 — we find that the beneficial effects of density are the largest in low-density and medium-density neighborhoods, and smaller for the densest neighborhoods. These results are consistent with the intuition of urban planners. They suggest that on the margin, gains in public safety can be obtained by moving people away from the busiest neighborhoods to neighborhoods with a lower density.

Figure 7: Heterogeneous effects by average ambient density



Notes: This figure shows shift-share IV estimates and 90% confidence bands of the effects of ambient density on crime rates for different quintiles of average ambient density. Q1 corresponds to the 20% of neighborhoods with the lowest average ambient density, and Q5 corresponds to the 20% of neighborhoods with the highest average ambient density.

4.2 The consequences of work-from-home on crime patterns

Although zoning policy can influence the distribution of ambient density, the most significant change in people flows that cities will witness in the coming decade will likely be due to technological change — specifically through the development of work-from-home. Dingel and Neiman (2020) find that 39% of the workers in the Chicago metropolitan area could work from home. In this section, we evaluate how this change could affect crime rates in Chicago.

day (for exclusively residential neighborhoods) or the evenings (for fully commercial neighborhoods). More recently, the New Urbanism movement has advocated for average-density, mixed-use neighborhoods with similar arguments. According to their charter, the first quality of a safe space is human presence: "The sense that we are not alone and are being observed helps us behave properly and feel safe. [...] Mixed-use buildings help promote 24-hour presence" (Congress for the New Urbanism, 2000).

The effect of work-from-home on ambient population. First, we assess the potential effect of work-from-home on the ambient population distribution in Chicago. To do so, we estimate the following linear model:

$$\log(\text{ambient population}_{idh}) = \beta_{dh} X_i + \varepsilon_{idh} \tag{6}$$

Where i is a CBG, d is a day of the week, and h is an hour of the day, and X is a matrix of CBG characteristics. Intuitively, for each day of the week $\times$ hour of the day, we predict (log) ambient population using a set of time-invariant CBG characteristics.

We use as CBG characteristics the (log) number of people living in the CBG, the (log) number of people working in the CBG, the (log) number of people living and working in CBGs nearby (within a 5-minute drive, or a 5-10 minute drive), and the number of points of interests (POIs) of eight different types (e.g., restaurants, stores).[17]

The model accurately predicts ambient population in different parts of the city, with an adjusted R-squared of 0.89. While we include 14 CBG characteristics in the matrix X, the most important are the number of people working in the CBG and the number of people living in the CBG. Including only these two variables in X yields an adjusted R-squared of 0.86 (see Appendix Table S.19). We report the estimated coefficients for equation (6) in Appendix Figures S.12 and S.13.

We then construct a counterfactual distribution of work locations. In the counterfactual, the number of people working in CBG i is:

$$n_i^{W,\text{cf}} = \sum_j \left[(\text{WFH share}_j) n_i^H s_{ij}^H + (1 - \text{WFH share}_j) n_i^W s_{ij}^W \right] \tag{7}$$

Where n_i^W (resp. n_i^H) is the number of workers (resp. residents) in CBG i, s_{ij}^W (resp. s_{ij}^H) is the share of workers (resp. residents) of CBG i working in industry j, and WFH share$_j$ is the share of workers in industry j that can work from home, which we take from Dingel and Neiman (2020). Industries are 2-digit NAICS sectors, and the shares s_{ij}^W, s_{ij}^H are taken from the LODES dataset.

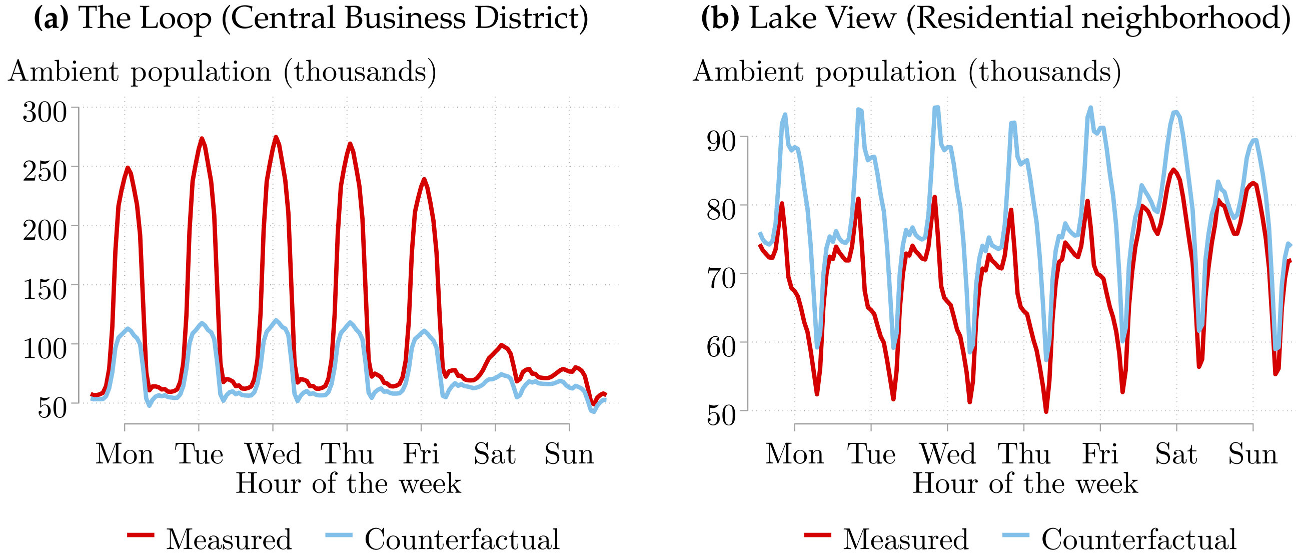
This allows us to build a counterfactual matrix of neighborhood characteristics $\tilde{X}$ and to predict the counterfactual ambient population that we would observe in each CBG, day of the week, and hour of the day (by replacing X by $\tilde{X}$ in equation 6).

Figure 8 shows the result of this procedure for two neighborhoods of Chicago: in the Loop, we unsurprisingly find that ambient density drops sharply during weekdays when work-from-

[17] We obtain the number of people living and working in each neighborhood from the Safegraph data: the home location of each smartphone is obtained as its primary location between 6 p.m. and 7 a.m., and its work location is obtained as its primary location between 9 a.m. and 5 p.m. We estimate travel times between CBGs in the Chicago Metropolitan Area using a Multi-Level Dijkstra algorithm implemented by Luxen and Vetter (2011) in combination with transportation network data retrieved from OpenStreetMap. Data on the number of POIs of each type is retrieved from Safegraph.

home becomes widespread. In the more residential neighborhood of Lake View, ambient density slightly increases throughout the week. Panel (a) of Figure 9 shows how daytime density changes in all CBGs of Chicago in our counterfactual scenario.

Figure 8: The effect of work-from-home: Examples of counterfactual ambient densities



Notes: This figure compares the observed ambient population of two large neighborhoods of Chicago (delineated by the Office of Tourism) with their counterfactual ambient population levels after changing the work location of 39% of the workers in Chicago to be the same as their home location. In each panel, we show ambient density levels for each hour of the week, with vertical dotted lines corresponding to noon.

The effect of work-from-home on crime rates. Armed with these counterfactual ambient density distributions, we estimate how crime rates in different neighborhoods would change if work-from-home became widespread. To this end, we calibrate γ_i and δ_{dh} in the following equation, using as β's those estimated in Section 3.5:

$$\text{crime}_{idh} = \exp(\beta \log(\text{density}_{idh}) + \gamma_i + \delta_{dh}) + \varepsilon_{idh}. \tag{8}$$

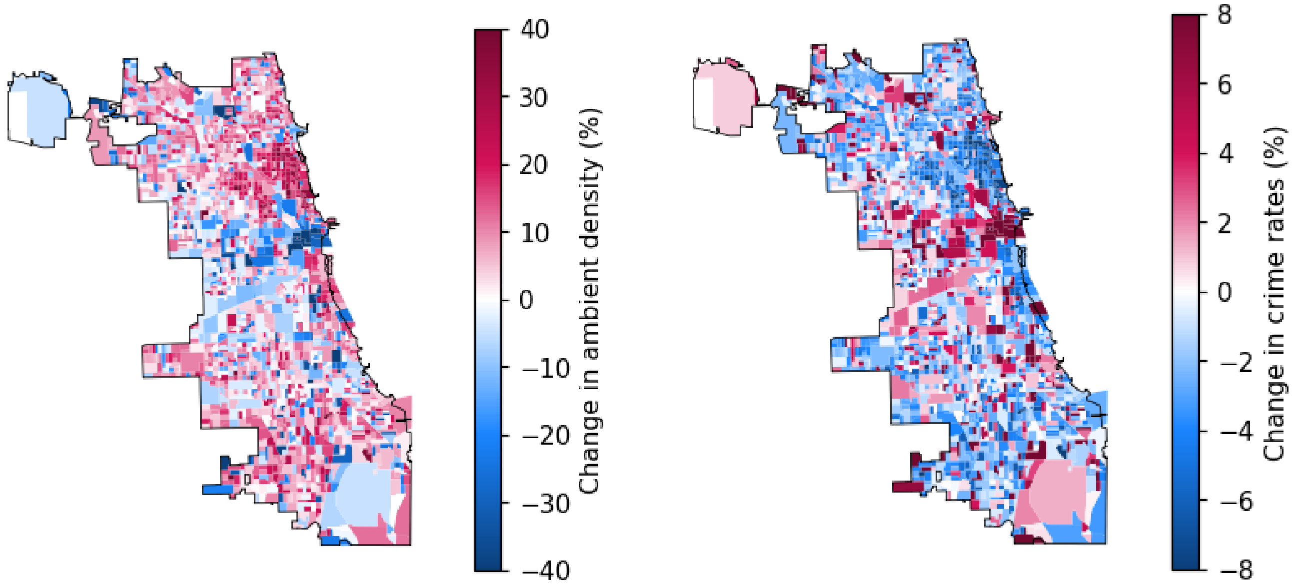
This is the PPML equation that we estimated in Section 3.5, with observations at the CBG $\times$ day of the week $\times$ hour of the day level, instead of the CBG $\times$ month $\times$ moment of the day level. We make this change because variation over days of the week is more relevant than variation over months of the year when studying the consequences of work-from-home.

Counterfactual crime rates are found by replacing in equation (8) density_{idh} by our estimated counterfactual density. We show the results of this procedure in Figure 9(b). As expected, the most important changes in crime rates are in the central neighborhoods of Chicago. In the Loop, the victimization rate for all crimes against persons is predicted to increase by 7.7% (assault rates increase by 8.1%, and theft rates increase by 5.2%). In contrast, crime rates decline in residential neighborhoods on the outskirts of Chicago, echoing the findings of Matheson et al. (2024), who show that the rise of remote work has led to a reduction in burglaries.

Figure 9: The effect of work-from-home: Counterfactual changes in densities and crime rates

(a) Change in daytime density

(b) Change in victimization rates (all crimes against persons)



Notes: This figure maps the predicted change in the average ambient density between 7 a.m. and 10 p.m. (Panel A) and the average victimization rates for all crimes against persons (Panel B) if 39% of workers in Chicago worked from home.

Discussion. Work-from-home is expected to cause large drops in real estate prices in city cores (see, e.g., Gupta et al., 2022; Delventhal et al., 2022). Our results suggest that work-from-home is likely to further strain central neighborhoods of cities by increasing crime rates there. In our exercise, we build a counterfactual ambient density distribution without considering its endogenous response to crime rates. Previous work has shown that higher crime levels in a neighborhood lead to fewer people visiting businesses in that neighborhood (Fe and Sanfelice, 2022). Combined with our work, this evidence shows that neighborhoods can be caught in vicious (or virtuous) cycles: an increase in the crime level in a neighborhood can lead to a decrease in the activity of that neighborhood, which in turn tends to further increases in crime rates. General equilibrium effects, including the relocation of residents and businesses away from the city core, are likely to further magnify the effects that we describe. Overall, our results support the hypothesis that the core neighborhoods of cities are facing the risk of a downward spiral in the coming decades.

5 Conclusion

There is usually considerable variation in public safety within a city. Environmental factors (such as air quality or street lighting) and police presence can explain part of this variation, but the extent to which a neighborhood will be safe depends largely on intricate social interactions (Glaeser et al., 1996; Sampson et al., 1997). In particular, ambient density is believed to be an important determinant of crime rates by continuously changing the potential rewards and costs of crime in each neighborhood. Whether busier areas will be safer is a priori unclear as higher densities of people increase the likelihood that a potential criminal meets a suitable victim but also increase the probability that a crime will be witnessed. While the relationship between ambient density and crime is a key component of most theories of urban crime, the empirical exploration of this link has been complicated by measurement difficulties.

High-frequency measures of ambient density allow us to better study this question for two reasons. First, it allows us to measure crime rates with a high spatial and temporal resolution. This can help us go beyond cross-sectional studies, which is valuable as there is considerable variation in public safety within neighborhoods across time. Second, it provides us sufficient statistical power to measure causal, rather than correlational, relationships. We find that increasing ambient density in a neighborhood increases the number of crimes recorded there but lowers victimization rates.

Our study also illustrates the fact that the effects of density depend on the spatial scale one considers. In the United States, denser cities have higher crime rates, likely because of sorting effects (Glaeser and Sacerdote, 1999). At this macro spatial scale, crime is a congestion force that may limit cities' growth. Conversely, at a more micro scale, the concentration of people appears to be an asset.

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Appendix

A Crime data

A.1 Assignment of crimes to CBGs

The data provided by the Chicago Police Department (CPD) provides for each crime a location coded as a latitude and longitude. For privacy purposes, these coordinates are randomly shifted but fall on the same block as the true coordinates. In several instances, crimes happen on the border between CBGs. To properly allocate crimes to CBGs, we draw a 10-meter radius disk around each set of crime coordinates. For a given crime, if the disk intersects a single CBG, we assign the crime to that CBG. If the disk intersects n CBGs, we assign the crime to these n CBGs, weighing it by $1/n$. For instance, if a crime is on a boundary between two CBGs, we increase the number of crimes in both CBGs by $1/2$.

A.2 Crimes excluded from the analysis

Between January 2001 and January 2020, the CPD has recorded 7,070,606 crimes (about 3.2 crimes per CBG per week). We only keep about half of all recorded crimes in our analysis. Indeed, we drop 939,003 domestic crimes; 1,662,080 crimes against society (mostly narcotics violations and deceptive practices); 335,158 thefts and attempted thefts which cannot be classified as crimes against persons or crimes against property; and 690,190 crimes involving vehicles. This leaves us with 3,444,175 crimes in the analysis dataset.

B Using data on the origin locations of smartphones

B.1 Data provided by Safegraph

On top of data on the number of ping clusters detected in a CBG during a given hour, Safegraph provides us with data on the origin locations of smartphones. For every month in our study period and CBG, Safegraph provides a list of the home locations of the smartphones that visited that CBG during that month. The home location of a smartphone is determined by Safegraph as the CBG that is the primary nighttime location of that smartphone. Safegraph further details the home locations of visitors of each CBG for each month for five "moments of the day":

- Breakfast (between 6 a.m. and 10:59 a.m.);
- Lunchtime (between 11 a.m. and 2:59 p.m.);
- Afternoon (between 3 p.m. and 4:59 p.m.);
- Dinner (between 5 p.m. and 8:59 p.m.);
- Nightlife (between 9 p.m. and midnight).

For instance, Safegraph may report that among the smartphones that visited CBG D during March 2019 between 11 a.m. and 2:59 p.m., 14 reside in CBG O_1, 5 reside in CBG O_2, etc. Because of privacy concerns, Safegraph adds some noise to the number of visitors from each home location.

Specifically, Safegraph adds Laplacian noise to the number of visitors for all origin-destination pairs which are observed in their data. After adding noise, only origin-destination pairs with at least two devices are included in the data. If there are between 2 and 4 visitors in an origin-destination pair, it will be reported in the data as 4 visitors.

B.2 Constructing shifts and shares

Using this data from Safegraph, we can construct a variable $V_{j,i,h,m,y}$ corresponding to the number of visitors from origin j who visited CBG i at time of day h during month m of year y. j can be the city of Chicago itself, the rest of Illinois, one of the the 49 other states, Washington DC, an overseas territory of the United States, or Canada (although our measure of density includes visitors from all countries, Safegraph does not provide a decomposition of the number of visitors by country of origin, with the exception of Canada). i can be any of the 2194 CBGs of Chicago.

Shifts. To construct shifts, we first estimate the number of visitors to Chicago originating from j for all values of h, m, and y: $X^j_{hmy} = \sum_i V_{j,i,h,m,y}$. Then, we average X^j_{hmy} over years.

Shares. To construct shares, we first find for each moment of day h and month m the typical flows of visitors by averaging $V_{j,i,h,m,y}$ over different years in our data ($\bar{V}_{j,i,h,m} = \mathbb{E}_y[V_{j,i,h,m,y}]$). We then find for each (h, m) pair the probability that a visitor for j will go to location i:

$$\tilde{\pi}^j_{ihm} = \frac{\bar{V}_{j,i,h,m}}{\sum_{i'} \bar{V}_{j,i',h,m}}.$$

Finally, we compute shares for a month m as the average value of $\tilde{\pi}^j_{ihm}$ for other months.

C Police presence data

We obtained administrative records on sworn officers using a Freedom of Information Act (FOIA) request to the CPD. The CPD provided us rosters of all active officers between January 2013 and January 2020, with their daily shift and beat assignment. We first map the boundaries of police beats to CBGs. To do so, we intersect the boundaries of CBGs with boundaries of police beats. Because one geography is not strictly contained in the other, we compute the share of each police beat falling in each CBG and allocate officers to CBGs proportionally to these shares. We then count the number of police officers on duty in each CBG and at each moment of the day, and average over years. This provides us with a panel of the number of police officers at the CBG $\times$ month $\times$ moment of day level. In regressions, we use the logarithm of the number of officers and discard the 199 cells with no recorded officers.

D Stylized model of the effect of ambient density on crime

In this section, we build a stylized model of criminal activity to formally describe the mechanisms underlying our reduced-form estimates of the effect of ambient density on crime.

Setting. We consider a single location whose surface area we normalize to one. Ambient density a is the number of agents in that location at a given time. Each agent is a potential criminal, a potential victim, and also a potential witness that can help report crimes. Committing a crime yields a gross reward R, but is associated with a probability of being caught p and a cost of being arrested f (corresponding to a fine or prison time). Agents also have idiosyncratic costs of engaging in criminal activity, denoted by η, which corresponds to an opportunity cost of time (and increases with the agent's wage and value of leisure), as well as the psychological cost associated with breaking the law. Agents decide to engage in a criminal activity if the expected return to crime exceeds its cost, i.e., if $R - pf > \eta$.

Victimization rates and ambient density. We consider that η is drawn from an exogenous distribution with cumulative distribution F. The probability of committing a crime is then $F(R - pf)$, and the average (expected) number of crimes is $c = aF(R - pf)$. The victimization rate, i.e., the number of crimes per person, is equal to $v = F(R - pf)$.

As density increases, the number of potential victims increases and criminals may find it easier to identify suitable targets. We thus assume that the gross reward R increases with ambient density. However, increasing ambient density might increase deterrence through a higher probability of punishment in busier places, so that p increases with ambient density as well.

The effect of ambient density on crime. The elasticity of the victimization rate to density ϵ_a^v is then:

$$\epsilon_a^v = \frac{d\log(v)}{d\log(a)} = \frac{a}{v}F'(R - pf)[R'(a) - p'(a)f] \tag{S.1}$$

$F(.)$ is a cumulative distribution function, so $F'(.) > 0$ and the sign of ϵ_a^v is determined by the term in brackets, the marginal net return to criminal activity. As both R and p are increasing with density, the effect of ambient density on victimization rates is ambiguous.

The number of crimes is $c = va$. Hence, the elasticity of the number of crimes to ambient density:

$$\epsilon_a^c = 1 + \epsilon_a^v$$

"Weak" and "strong" effects. If the marginal increase in deterrence is sufficiently large to outpace the marginal increase in the gross reward to criminal activity, increasing density decreases the victimization rate ($\epsilon_a^v < 0$). When the deterrence effect is so large that $\epsilon_a^v < -1$, the number of crimes decreases with ambient density ($\epsilon_a^c < 0$). We can refer to this scenario as a "strong" effect of ambient density on crime, while when $\epsilon_a^v \in]-1, 0[$, we only have a "weak" effect.

Composition effects. The effect of ambient density on crime may depend on the types of agents that are in the location. Adding to a location people who are easier to rob or more likely to commit a crime will likely have a different effect to adding people who are well shielded from crime or are perfectly law-abiding.

Suppose for instance that the gross return to crime R does not only depend on the level ambient density a but also on the *composition* of ambient density. If there are two types of individuals, 1 and 2, and we denote by s_1 the share of type 1 individuals in the location, then, when $R = R(a, s_1)$, we have:

$$d\log(v) = \underbrace{\epsilon_a^v d\log(a)}_{\text{Baseline}} + \underbrace{\frac{F'(R-pf)}{F(R-pf)} R_{s_1} ds_1}_{\text{Composition}}$$

where ϵ_a^v is now the partial elasticity of the victimization rate to density and R_{s_1} is the partial derivative of R with respect to s_1. The composition effect reflects the different marginal changes in gross return from different types of potential victims.

Alternatively, the gross reward R can vary across individuals as a function of their type (becoming R_1 or R_2). In this case, we have:

$$d\log(v) = \underbrace{\epsilon_a^v d\log(a)}_{\text{Baseline}} + \underbrace{[F(R_1-pf) - F(R_2-pf)]ds_1}_{\text{Composition}}$$

Here, the composition effect reflects the different marginal changes in gross returns to ambient density for different potential criminals.

Non-linear effects of ambient density on crime. Our empirical evidence in Section 4.1 suggests that the elasticity ϵ_a^v decreases in magnitude as ambient density increases. In our model, the derivative of ϵ_a^v with respect to $\log(a)$ is

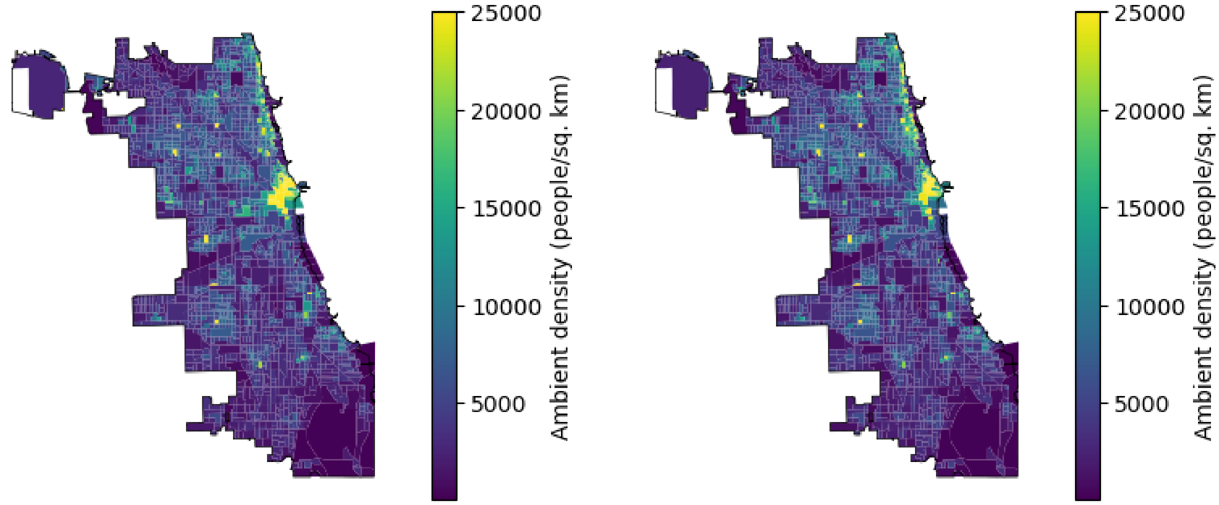
$$\frac{d\epsilon_a^v}{d\log(a)} = \epsilon_a^v + a(R' - p'f)\epsilon_a^v \left[\frac{F''(.)}{F'(.)} - \frac{F'(.)}{F(.)}\right] + a^2(R'' - p''f)\frac{F'(.)}{F(.)}. \tag{S.2}$$

The sign of this expression is ambiguous and depends on the sign of $(R'' - p''f)$ and $\left[\frac{F''(.)}{F'(.)} - \frac{F'(.)}{F(.)}\right]$. When η is drawn from a Fréchet distribution with parameter α, $F(x) = e^{-x^{-\alpha}}$, and $\left(\frac{F''(x)}{F'(x)} - \frac{F'(x)}{F(x)}\right) = -\frac{\alpha+1}{x} < 0$: the first two terms of Equation (S.2) are unambiguously negative, as ϵ_a^v (and $(R' - p'f)$) is negative. Then, whether ϵ_a^v increases with a ultimately depends on whether marginal returns to criminal activity increase with density, i.e., whether $(R'' - p''f) > 0$. Increasing marginal returns to density may emerge through at least two channels. First, the effect of density on the probability of punishment may be lower in already dense neighborhoods. Second, the gross reward to criminal activity may exhibit increasing returns to scale, as it may be easier for potential criminals to find a suitable victim as density increases.

E Additional Figures

Figure S.1: Average ambient density in Chicago

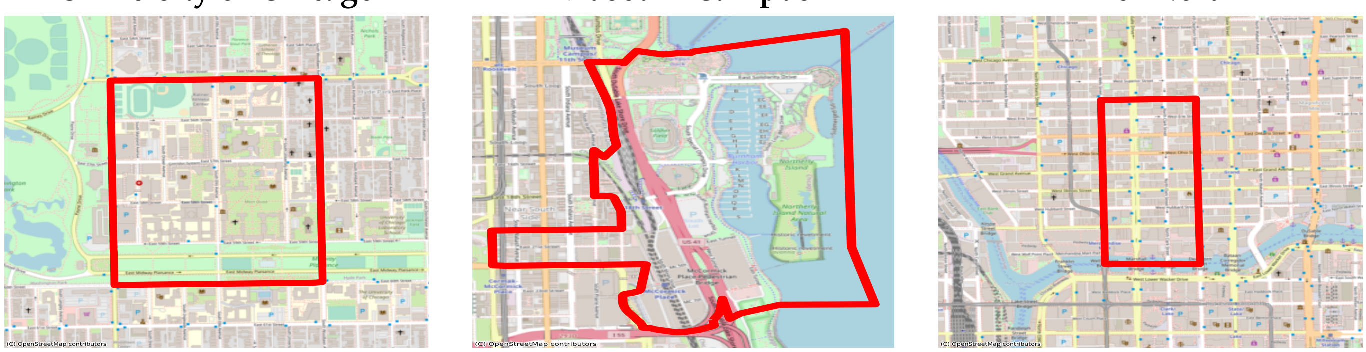
Weekdays | Weekends



Notes: This figure shows the average ambient density in Chicago measured using smartphone pings, separately for weekdays and weekends. During the weekends, there is a considerable drop in ambient density in the city center (the brightest region in both panels).

Figure S.2: Maps of example CBGs

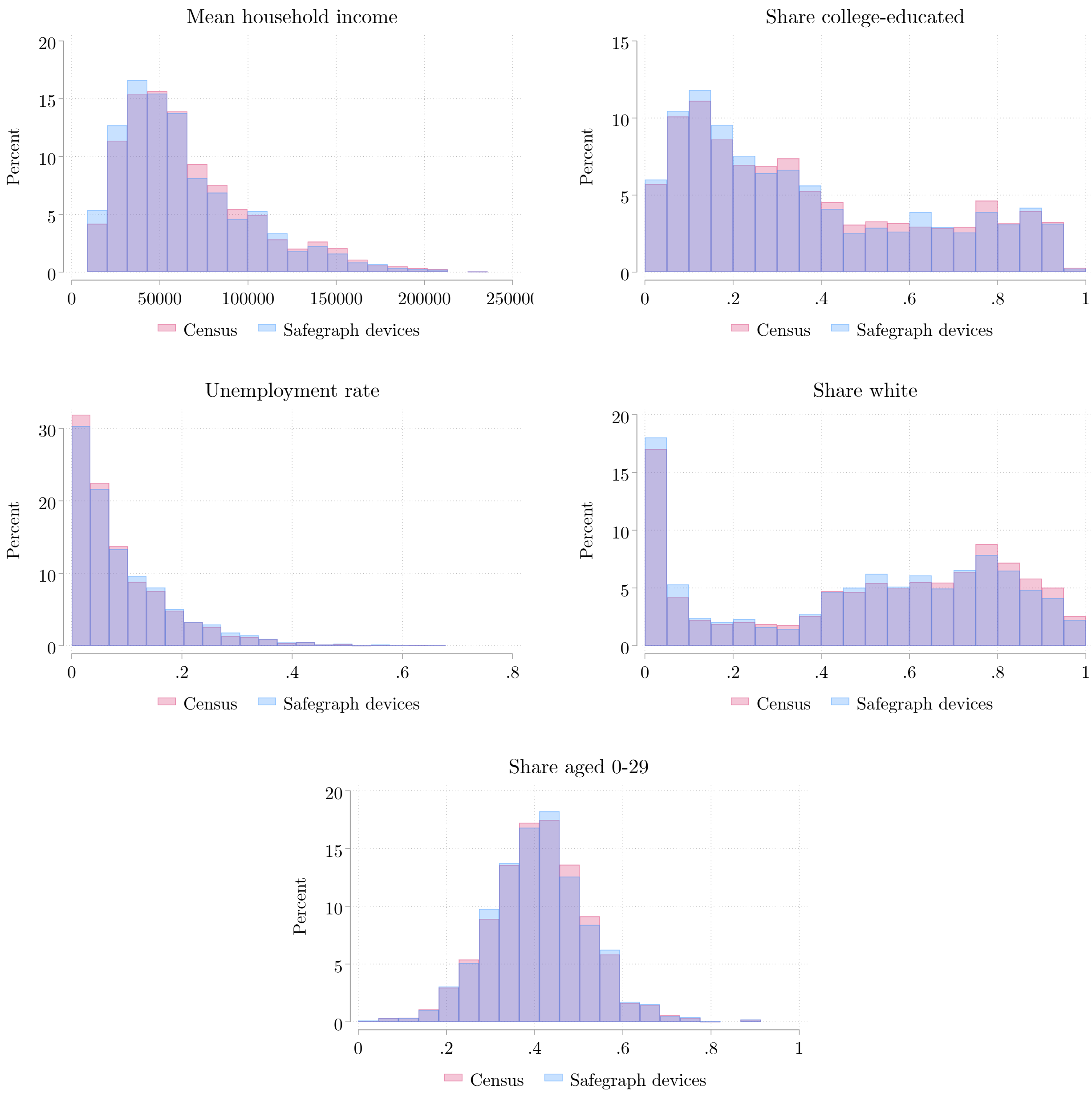
University of Chicago | **Museum Campus** | **River North**



Gothic campus | Planetarium, aquarium | Shops, restaurants

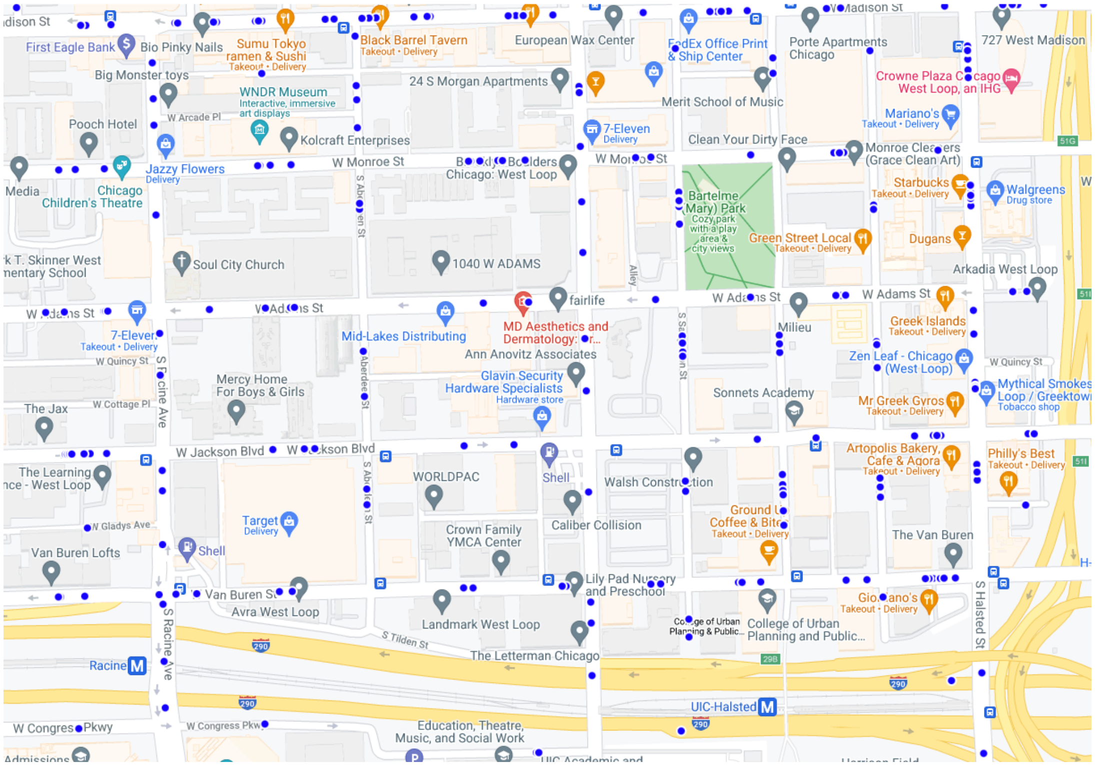
Notes: This figure shows maps of the three CBGs used as examples in Figure 2.

Figure S.3: Representativeness of the Safegraph panel



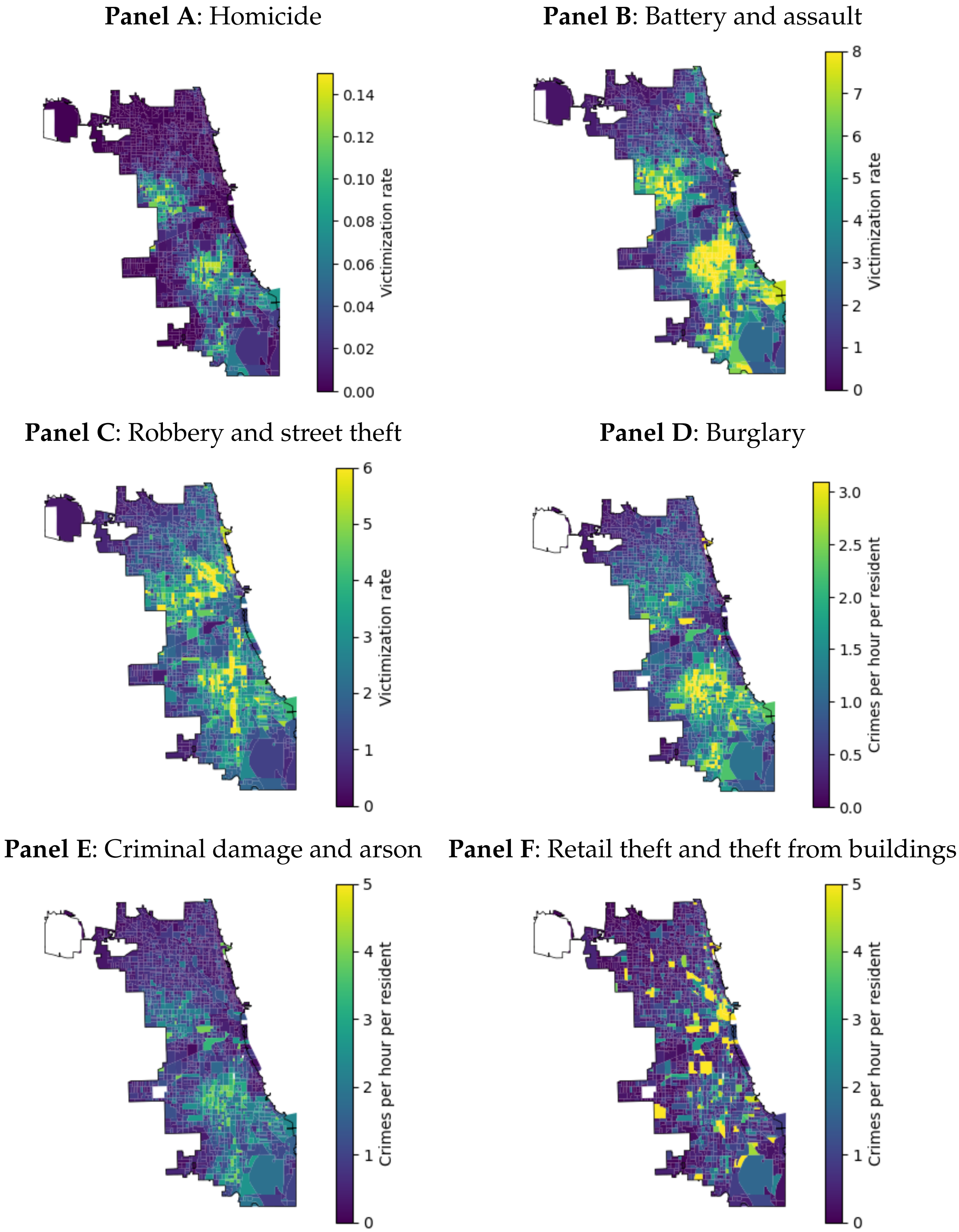
Notes: This figure plots distributions of CBG characteristics (mean household income, share of college-educated in the population above 25, unemployment rate in the civilian labor force above 16, share of whites, and share of the population aged 29 and below) for the full population (according to the 2015-2019 5-year ACS) and for the Safegraph panel.

Figure S.4: Geolocated crime data



Notes: This figure shows all crimes that took place in a neighborhood of Chicago over one year. Each dot corresponds to a crime.

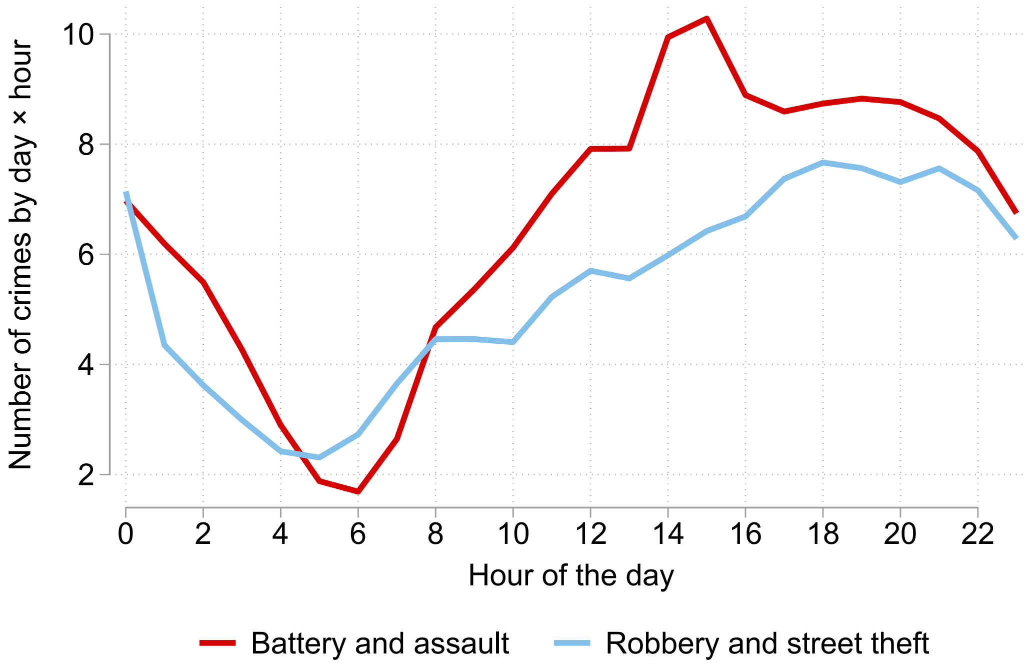
Figure S.5: Crime rates in Chicago: Spatial variation



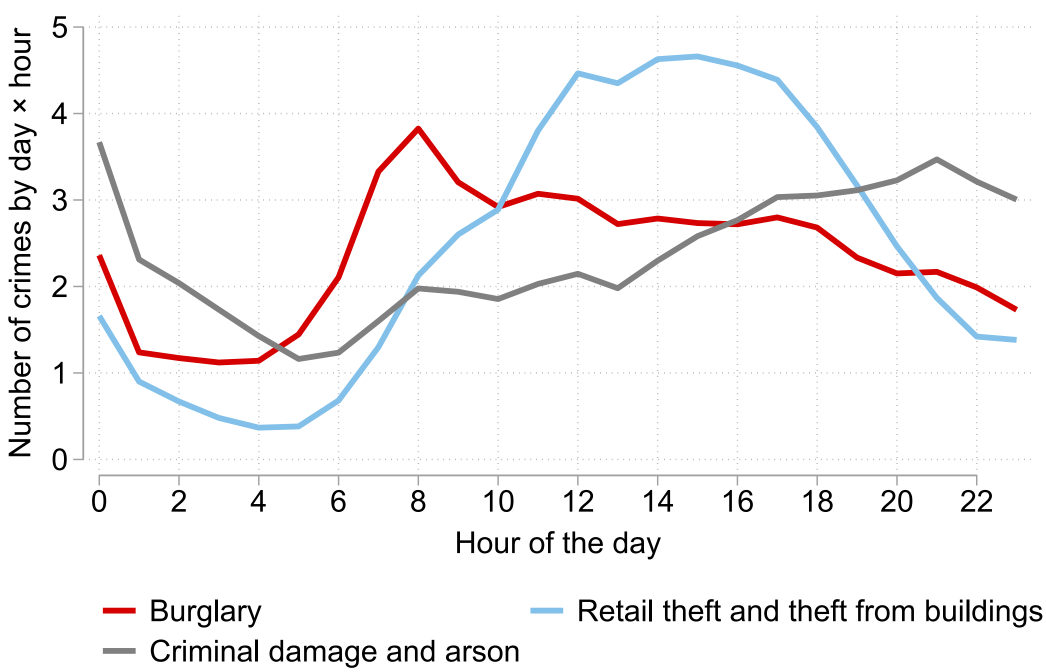
Notes: This figure maps average crime rates in the CBGs of Chicago. For crimes against persons, we report the average victimization rate, i.e., the probability that a visitor in the neighborhood will be a victim of a crime during a given hour. Victimization rates are computed by dividing the number of crimes by the ambient population. For crimes against property, we report the number of crimes per hour per resident. For clarity, both victimization rates and the number of crimes per resident are multiplied by 1,000,000, and variables are winsorized.

Figure S.6: Number of crimes per hour

Panel A: Crimes against persons



Panel B: Crimes against property

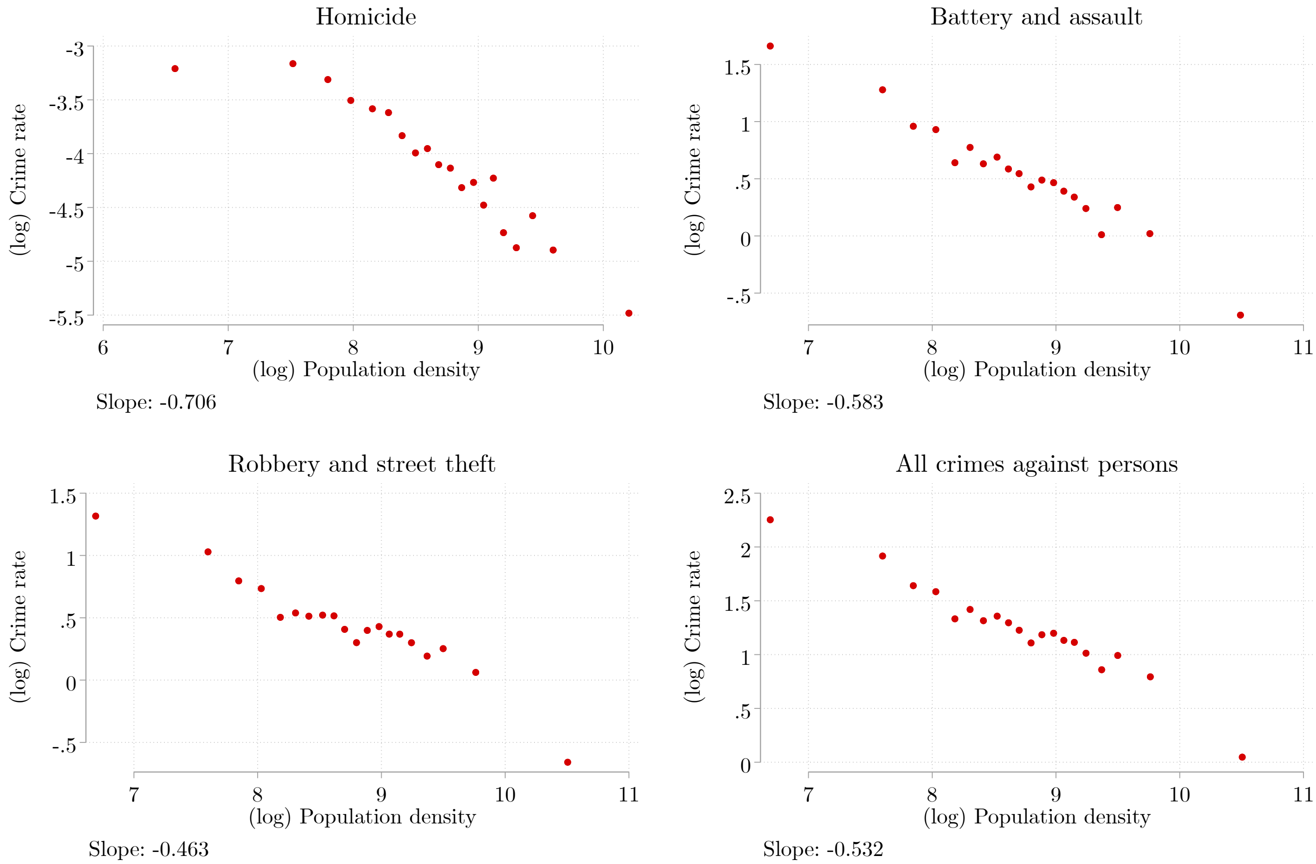


Notes: This figure shows the average number of crimes per hour for different hours of the day.

Figure S.7: Battery and assault victimization rates: Daily evolution

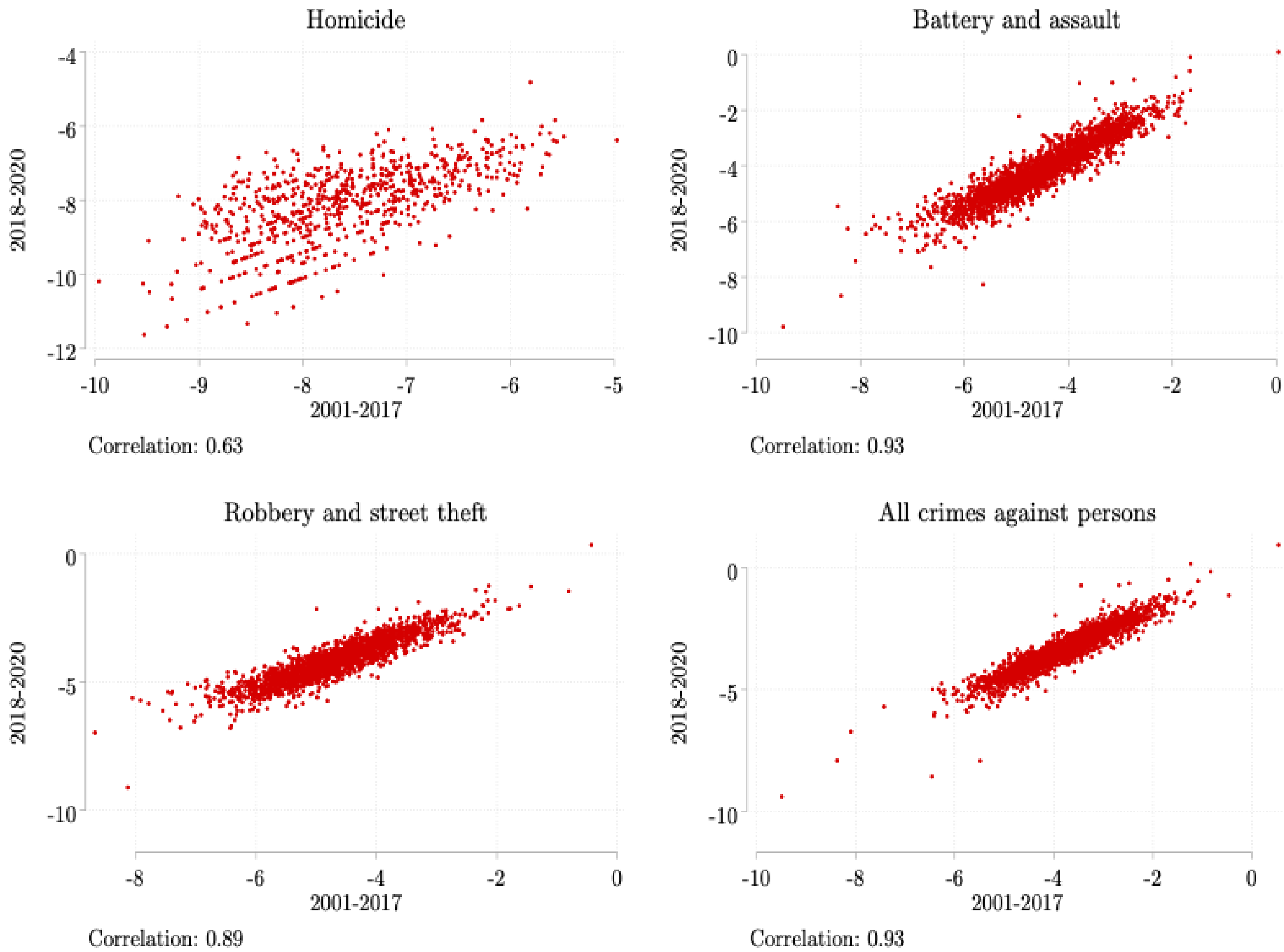
Notes: This figure maps the average battery and assault victimization rate for CBGs in Chicago for several hours of the days.

Figure S.8: Cross-sectional relationship between crime and density



Notes: This figure shows binscatters illustrating the cross-sectional relationship between crime rates and population density at the CBG level. Crime rates are measured as the average number of crimes per resident per hour, times 100,000. The number of residents in a CBG is taken from the ACS.

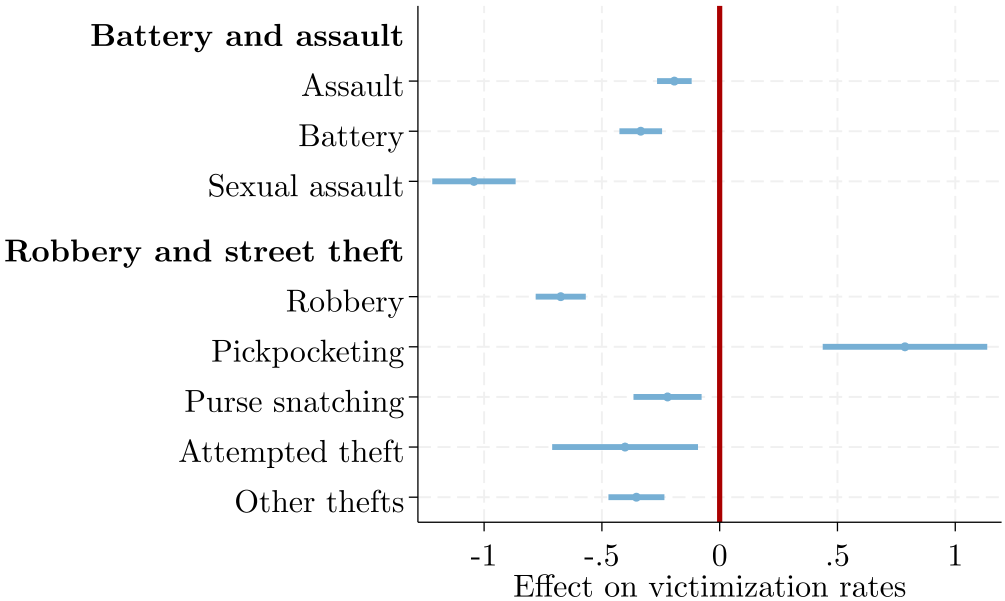
Figure S.9: Persistence of crime rates



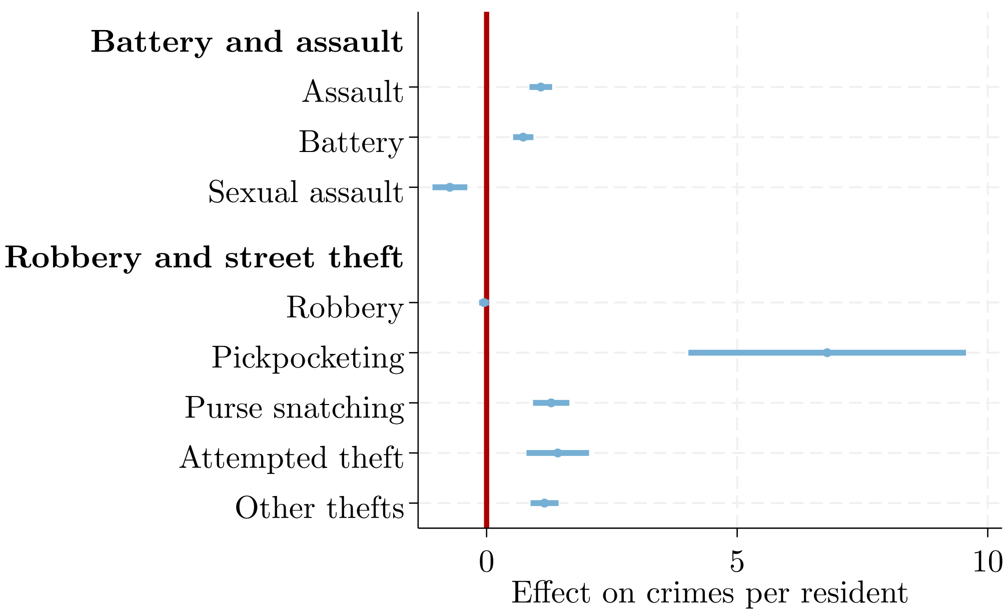
Notes: This figure compares the spatial distribution of crime rates in the time period for which we have smartphone data (January 2018 to January 2020) with the distribution of crime rates in the period for which we do not have smartphone data (January 2001 to December 2017). For different types of crime, we compare the (log) number of crimes per capita and per year in both periods. In all panels, each dot corresponds to a CBG. For both periods, we measure the population of each CBG using the 2015-2019 5-year ACS.

Figure S.10: Effects of ambient density on subcategories of crimes against persons

(a) Victimization rates



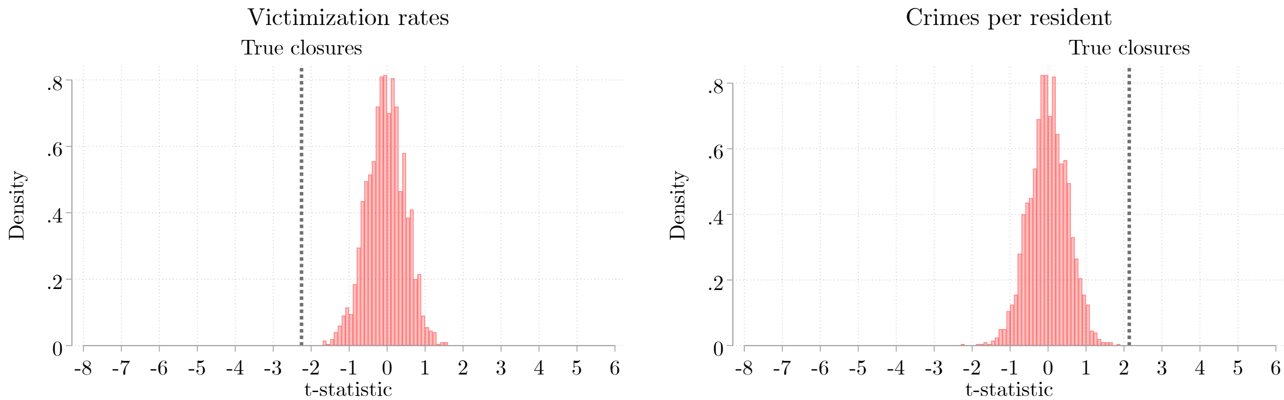
(b) Crimes per resident



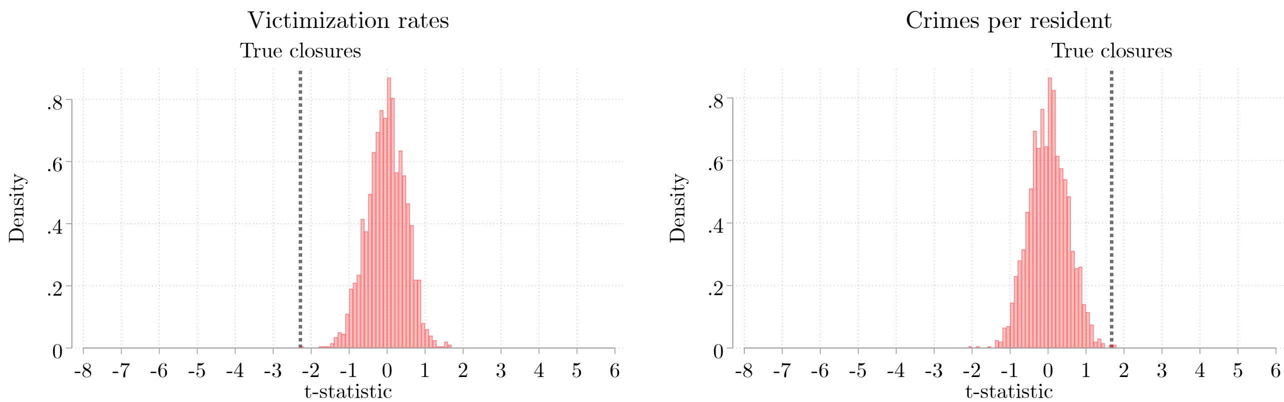
Notes: This figure reports shift-share IV estimates of the effect of ambient density on crime, for finer categorizations of crime than in Table 3. Panel (a) reports results for victimization rates and panel (b) reports results for the number of crimes per resident. All outcome variables are normalized so that their mean is one. As in Table 3, we include one observation per CBG × month × moment of the day, and include both CBG and moment-month fixed effects.

Figure S.11: Transit closure IV: Randomization inference

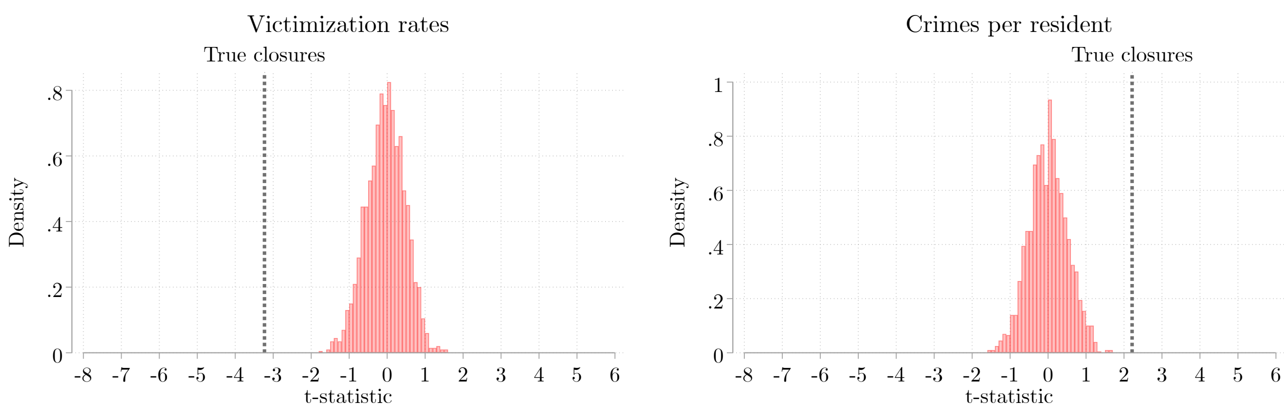
(a) Battery and assault



(b) Robbery and street theft

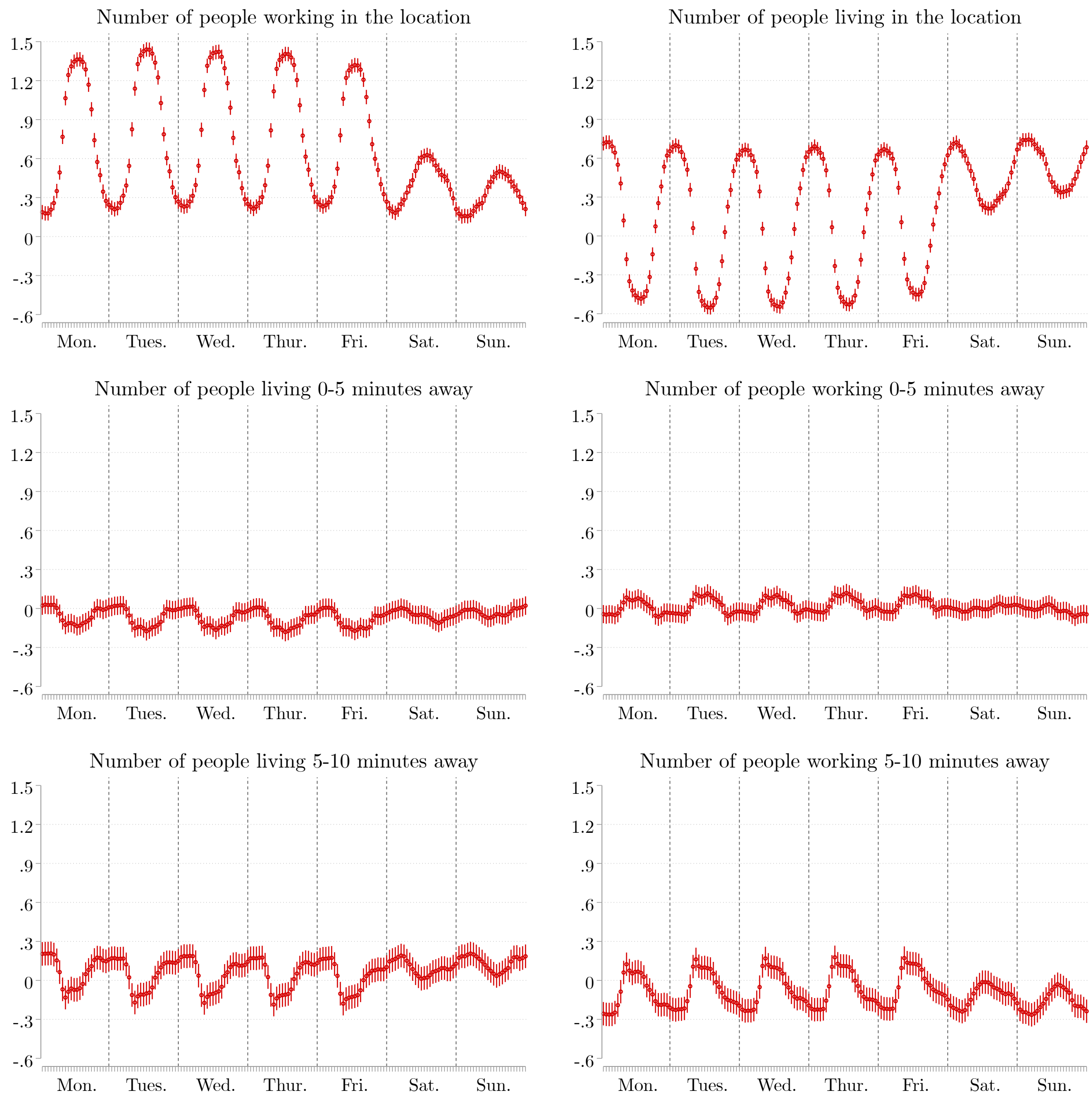


(c) All crimes against persons



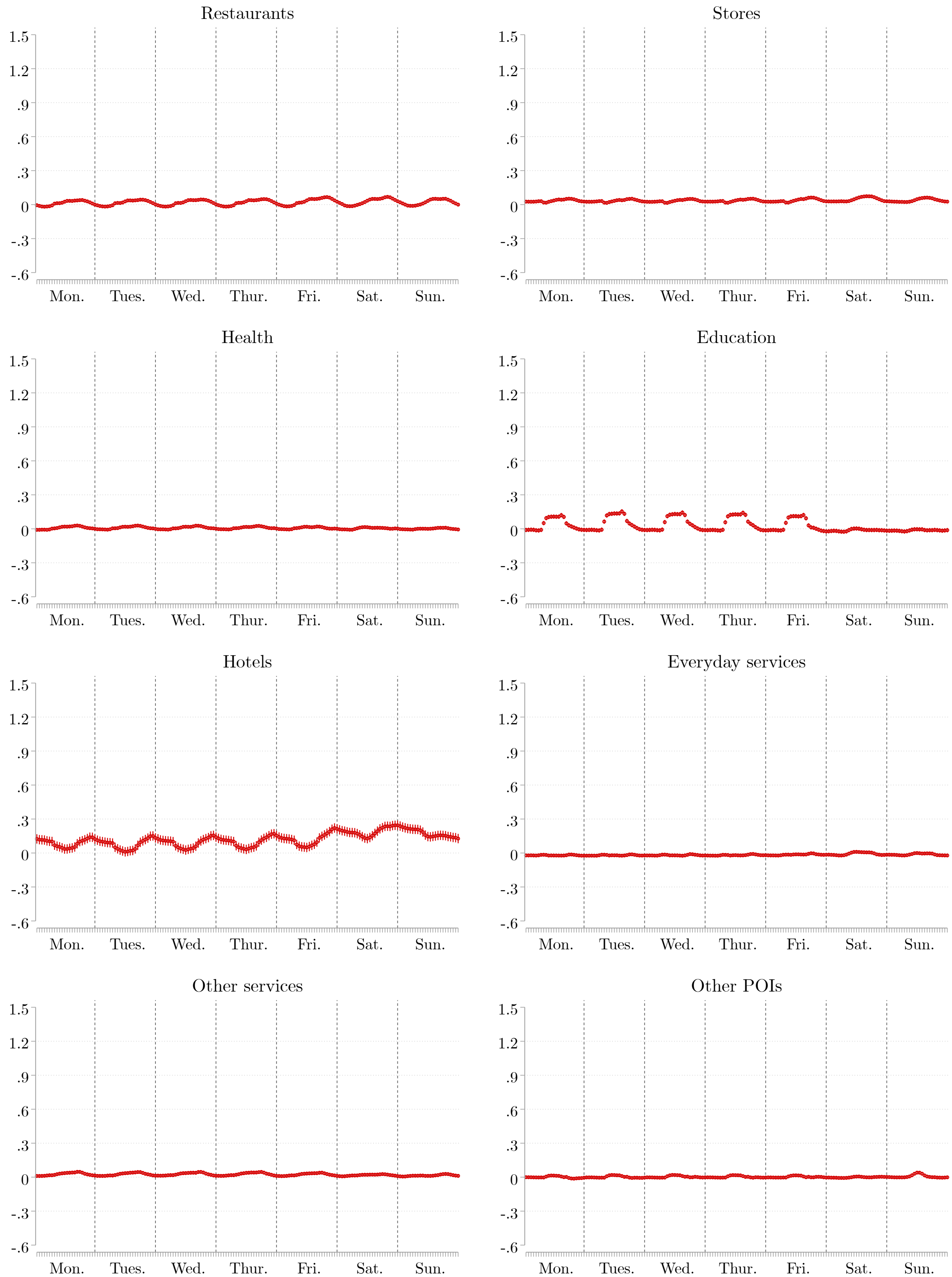
Notes: This figure shows the distribution of the 2000 t-statistics from the randomization inference procedure described in Section 3.4. t-statistics from the true closures are represented by the vertical dashed gray lines. We used the Stata package `parallel` (Vega Yon and Quistorff, 2019) to accelerate the computation of these statistics.

Figure S.12: Predicting ambient density: Estimation results (1)



Notes: In this figure, we show the coefficients of equation (6), estimated by OLS. Each plot corresponds to a neighborhood characteristic, and in each plot, we show coefficients for different hours of the day and different days in the week. This figure only shows coefficient estimates for the number of people living/working in the focal CBG and nearby CBGs. It is continued on Appendix Figure S.13.

Figure S.13: Predicting ambient density: Estimation results (2)



Notes: This figure continues Appendix Figure S.12 with the estimated coefficients for equation (6) corresponding to different POIs.

F Additional Tables

Table S.1: Within-neighborhood and between-neighborhood variation in crime rates: After residualizing time fixed-effects

	Victimization rates			Crimes per resident		
	(1) Assault	(2) Theft	(3) **All**	(4) Assault	(5) Theft	(6) **All**
Within CBG variance	48.4%	59.3%	43.7%	40.6%	38.8%	31.3%
Between CBG variance	50.3%	39.8%	54.9%	58.5%	60%	67.5%

Notes: This table shows the same decomposition as that of Table 1, after crime rates have been residualized on day of the week $\times$ hour of the day fixed effects.

Table S.2: Within-neighborhood and between-neighborhood variation of additional types of crime

	V. rate	Crimes per resident				
	(1) Homicide	(2) Homicide	(3) Burglary	(4) Damage	(5) Trespass	(6) Retail
Within CBG variance	97.3%	95.7%	67.5%	63.3%	42%	53.9%
Between CBG variance	2.6%	4.3%	32.3%	36.2%	56.7%	45%

Notes: This table decomposes variation in homicides rates and crime against property in between-CBG variation and within-CBG variation (over time). The dependent variables are victimization rates in column (1) and the number of crimes per resident in columns (2) to (6). We use one observation per CBG $\times$ day of the week $\times$ hour of the day.

Table S.3: Calendar hour-level regressions of crime rates on ambient density

	V. rate	Crimes per resident				
	(1)	(2)	(3)	(4)	(5)	(6)
	Homicide	Homicide	Burglary	Damage	Trespassing	Retail
(log) Ambient dens.	-0.394**	0.186*	-0.017	0.061***	0.384***	1.579***
	(0.189)	(0.100)	(0.030)	(0.021)	(0.060)	(0.375)
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,547,586	39,547,586	39,547,586	39,547,586	39,547,586	39,547,586
F-statistic	6397.4	.	.	.	.	.
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	1.000	0.028	0.517	0.655	0.272	0.868

Notes: This table reports correlational evidence on the effect of ambient density on homicide rates and crime against property. The dependent variables are victimization rates in column (1) and the number of crimes per resident in columns (2) to (6). To facilitate interpretation, we normalize outcome variables so that their mean is one – pre-normalization means are reported at the bottom of the table. We include one observation per CBG × calendar hour between January 2018 and January 2020. In column (1), ambient density in one CBG × calendar hour is instrumented by the average ambient density in other observations in the same CBG × month × day of the week × hour cell. We include CBG and calendar hour fixed effects in each regression. Standard errors are clustered at the CBG level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.4: Shift-share IV: First stage

	(1)
	(log) Ambient density
SSIV	0.862***
	(0.012)
CBG FE	Yes
Moment-month FE	Yes
Observations	130,620
Within R^2	.338

Notes: This table reports the effect of the shift-share IV on ambient density – this regression corresponds to the first stage of equation (3). We include one observation per CBG × month × moment of the day. Standard errors are clustered at the CBG level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.5: Effects of ambient density on additional types of crime: Shift-share IV

	V. rate	Crimes per resident				
	(1) Homicide	(2) Homicide	(3) Burglary	(4) Damage	(5) Trespass	(6) Retail
(log) Ambient density	-0.761***	-0.576***	0.031	-0.016	0.805***	5.479***
	(0.134)	(0.169)	(0.042)	(0.036)	(0.211)	(1.258)
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Moment-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130,620	130,620	130,620	130,620	130,620	130,620
First stage F-stat	5543.0	5543.0	5543.0	5543.0	5543.0	5543.0
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	0.026	0.026	1.170	1.154	0.555	1.229

Notes: This table reports shift-share IV estimates of the effect of ambient density on homicide rates and crime against property. The dependent variables are victimization rates in column (1) and the number of crimes per resident in columns (2) to (6). To facilitate interpretation, we normalize outcome variables so that their mean is one – pre-normalization means are reported at the bottom of the table. We include one observation per CBG $\times$ month $\times$ moment of the day. We show estimates for the first stage regression in Appendix Table S.4. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.6: Shift-share IV: Restriction to index crimes

	Victimization rates			Crimes per resident		
	(1) Assault	(2) Theft	(3) **All**	(4) Assault	(5) Theft	(6) **All**
(log) Ambient density	-0.651***	-0.420***	-0.477***	-0.082	0.982***	0.718***
	(0.068)	(0.054)	(0.048)	(0.054)	(0.157)	(0.121)
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Moment-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130,620	130,620	130,620	130,620	130,620	130,620
First stage F-stat	5543.0	5543.0	5543.0	5543.0	5543.0	5543.0
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	0.833	2.689	3.549	0.800	2.554	3.379

Notes: This table reports shift-share IV estimates of the effect of ambient density on crime. We study the same outcomes as in Table 3, restricted to index crimes. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.7: Shift-share IV, excluding fewer low-population CBGs

	Victimization rates			Crimes per resident		
	(1) Assault	(2) Theft	(3) **All**	(4) Assault	(5) Theft	(6) **All**
(log) Ambient density	-0.358***	-0.467***	-0.407***	0.931***	0.951***	0.935***
	(0.102)	(0.067)	(0.078)	(0.176)	(0.157)	(0.128)
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Moment-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130,920	130,920	130,920	130,920	130,920	130,920
First stage F-stat	5589.1	5589.1	5589.1	5589.1	5589.1	5589.1
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	3.747	2.724	6.556	3.572	2.578	6.231

Notes: This table reports shift-share IV estimates of the effect of ambient density on crime using the same procedure as in Table 3, excluding in the dataset CBGs with fewer than 100 inhabitants, instead of the exclusion of CBGs with fewer than 200 inhabitants of our baseline specification. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.8: Shift-share IV, excluding more low-population CBGs

	Victimization rates			Crimes per resident		
	(1) Assault	(2) Theft	(3) **All**	(4) Assault	(5) Theft	(6) **All**
(log) Ambient density	-0.286***	-0.423***	-0.347***	0.773***	0.895***	0.821***
	(0.049)	(0.056)	(0.039)	(0.104)	(0.147)	(0.094)
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Moment-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,420	129,420	129,420	129,420	129,420	129,420
First stage F-stat	5330.4	5330.4	5330.4	5330.4	5330.4	5330.4
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	3.571	2.660	6.313	3.370	2.463	5.909

Notes: This table reports shift-share IV estimates of the effect of ambient density on crime using the same procedure as in Table 3, excluding in the dataset CBGs with fewer than 300 inhabitants, instead of the exclusion of CBGs with fewer than 200 inhabitants of our baseline specification. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.9: Shift-share IV, using crime data from January 2018 to January 2020 only

	Victimization rates			Crimes per resident		
	(1)	(2)	(3)	(4)	(5)	(6)
	Assault	Theft	**All**	Assault	Theft	**All**
(log) Ambient density	-0.266***	-0.381***	-0.318***	0.987***	1.244***	1.099***
	(0.056)	(0.096)	(0.053)	(0.144)	(0.286)	(0.178)
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
CBG-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130,620	130,620	130,620	130,620	130,620	130,620
First stage F-stat	5543.0	5543.0	5543.0	5543.0	5543.0	5543.0
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	2.494	1.830	4.403	2.468	1.769	4.315

Notes: This table reports shift-share IV estimates of the effect of ambient density on crime using the same procedure as in Table 3, but with outcomes built using crime data from 2018-2020 only. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.10: Shift-share IV: Different geographical levels

	Victimization rates			Crimes per resident		
	(1) Assault	(2) Theft	(3) **All**	(4) Assault	(5) Theft	(6) **All**
Panel A: CBG						
(log) Ambient density	-0.299***	-0.420***	-0.353***	0.824***	0.982***	0.887***
	(0.048)	(0.054)	(0.038)	(0.123)	(0.157)	(0.112)
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Moment-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130,620	130,620	130,620	130,620	130,620	130,620
First stage F-stat	5543.0	5543.0	5543.0	5543.0	5543.0	5543.0
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	3.637	2.689	6.410	3.517	2.554	6.150
Panel B: Census tract						
(log) Ambient density	-0.421***	-0.392***	-0.411***	0.395***	0.746***	0.540***
	(0.0694)	(0.0850)	(0.0588)	(0.0806)	(0.164)	(0.0948)
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Moment-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,480	48,480	48,480	48,480	48,480	48,480
First stage F-stat	2401.1	2401.1	2401.1	2401.1	2401.1	2401.1
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	3.739	2.779	6.601	3.534	2.585	6.197
Panel C: City neighborhood						
(log) Ambient density	-0.726***	-0.432***	-0.599***	0.559	2.749*	1.576
	(0.137)	(0.138)	(0.105)	(0.493)	(1.609)	(1.007)
Neighborhood FE	Yes	Yes	Yes	Yes	Yes	Yes
Moment-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,760	5,760	5,760	5,760	5,760	5,760
First stage F-stat	624.2	624.2	624.2	624.2	624.2	624.2
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	3.064	2.519	5.653	3.092	2.787	5.951
Panel D: Community area						
(log) Ambient density	-0.936***	-0.500**	-0.760***	-0.207	0.729*	0.172
	(0.273)	(0.198)	(0.228)	(0.202)	(0.399)	(0.256)
CA FE	Yes	Yes	Yes	Yes	Yes	Yes
Moment-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,620	4,620	4,620	4,620	4,620	4,620
First stage F-stat	2156.0	2156.0	2156.0	2156.0	2156.0	2156.0
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	3.515	2.423	6.020	3.371	2.333	5.783

Notes: This table reports shift-share IV estimates of the effect of ambient density on crime, with data aggregated at different geographical levels. There are 2,194 CBGs in Chicago, 811 Census tracts, 96 City neighborhoods, and 77 community areas. As in Table 3, we include one observation per geographical area $\times$ month $\times$ moment of the day. Standard errors are clustered at the geographical area (CBG, Census tract, City neighborhood, or community area) level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.11: Shift-share IV, excluding shifts from Chicago

	Victimization rates			Crimes per resident		
	(1) Assault	(2) Theft	(3) **All**	(4) Assault	(5) Theft	(6) **All**
(log) Ambient density	-0.542***	-0.160**	-0.381***	0.661***	1.277***	0.917***
	(0.072)	(0.067)	(0.053)	(0.141)	(0.180)	(0.131)
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Moment-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130,620	130,620	130,620	130,620	130,620	130,620
First stage F-stat	421.4	421.4	421.4	421.4	421.4	421.4
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	3.637	2.689	6.410	3.517	2.554	6.150

Notes: This table reports shift-share IV estimates of the effect of ambient density on crime. We study the same outcomes as in Table 3, and use a variation of the baseline shift-share instrument, where we exclude data on people originating from Chicago when constructing the instrumental variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.12: Shift-share IV, disaggregating shifters for the Chicago metro area

	Victimization rates			Crimes per resident		
	(1) Assault	(2) Theft	(3) **All**	(4) Assault	(5) Theft	(6) **All**
(log) Ambient density	-0.255***	-0.431***	-0.332***	0.858***	0.937***	0.888***
	(0.043)	(0.050)	(0.035)	(0.111)	(0.142)	(0.102)
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Moment-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130,620	130,620	130,620	130,620	130,620	130,620
First stage F-stat	7948.0	7948.0	7948.0	7948.0	7948.0	7948.0
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	3.637	2.689	6.410	3.517	2.554	6.150

Notes: This table reports shift-share IV estimates of the effect of ambient density on crime. We study the same outcomes as in Table 3, and use a variation of the baseline shift-share instrument where we expand the set of orgin locations corresponding to the Chicago metropolitan area. We replace the origin locations corresponding to Illinois (outside Chicago), Indiana, and Wisconsin with origin locations for each ZIP code in the Chicago metropolitan area (excluding those in Chicago), as well as for the areas of Illinois, Indiana, and Wisconsin that are not in the Chicago metropolitan area. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.13: Transit station closure IV: First-stage and falsification test

	(log) Ambient density
Panel A: First stage (daytime)	
Transit station closure	-0.170***
	(0.0388)
CBG $\times$ Month FE	Yes
Calendar day FE	Yes
Observations	244,281
F-stat	19.3
Panel B: Falsification test (nighttime)	
Transit station closure	0.0242
	(0.0277)
CBG $\times$ Month FE	Yes
Calendar day FE	Yes
Observations	244,281
F-stat	0.8

Notes: This table reports estimated effects of L-stations closures on ambient density. In Panel A, we show results measuring density during daytime hours (7 a.m. to 11 p.m.) – this regression corresponds to the first stage of equation (4). In Panel B, we measure density during the nighttime, and the regression acts as a falsification test. We include one observation per CBG $\times$ calendar day, and standard errors are clustered at the CBG level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.14: Effects of ambient density on additional types of crime: Transit disruption IV

	V. rate	Crimes per resident				
	(1)	(2)	(3)	(4)	(5)	(6)
	Homicide	Homicide	Burglary	Damage	Trespass	Retail
(log) Ambient density	1.273	2.563	-0.911	0.258	0.588	2.175**
	(1.686)	(1.909)	(1.051)	(1.057)	(1.106)	(0.913)
CBG-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar day FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	244,281	244,281	244,281	244,281	244,281	244,281
First stage F-stat	19.3	19.3	19.3	19.3	19.3	19.3
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	0.030	0.034	0.637	0.844	0.593	2.636

Notes: This table reports transit closures IV estimates of the effect of ambient density on homicide rates and crime against property. The dependent variables are victimization rates in column (1) and the number of crimes per resident in columns (2) to (6). To facilitate interpretation, we normalize outcome variables so that their mean is one – pre-normalization means are reported at the bottom of the table. We include one observation per CBG $\times$ calendar day. Standard errors are clustered at the CBG level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.15: Effects of ambient density on on additional types of crime: PPML estimates

	V. rate	Crimes per resident				
	(1) Homicide	(2) Homicide	(3) Burglary	(4) Damage	(5) Trespass	(6) Retail
Panel A: Correlational evidence						
(log) Ambient density	-0.705***	0.295***	-0.115***	0.047**	0.122***	0.353***
	(0.096)	(0.096)	(0.026)	(0.018)	(0.032)	(0.027)
CBG-day-hour FE	Yes	Yes	Yes	Yes	Yes	Yes
CBG-month	Yes	Yes	Yes	Yes	Yes	Yes
Calendar hour FE	39,852,048	39,852,048	39,852,048	39,852,048	39,852,048	39,852,048
Panel B: Shift-share IV						
(log) Ambient density	-1.012***	-0.012	-0.082**	0.238***	0.375***	0.927***
	(0.156)	(0.156)	(0.034)	(0.026)	(0.077)	(0.104)
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Moment-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130,620	130,620	130,620	130,620	130,620	130,620
Panel C: Transit closure IV						
(log) Ambient density	9.471	10.471	-0.274	-0.138	-0.226	0.194**
	(13.158)	(13.158)	(0.375)	(0.757)	(0.304)	(0.090)
CBG $\times$ Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar day FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	244,281	244,281	244,281	244,281	244,281	244,281

Notes: This table reports PPML estimates of the effect of ambient density on homicide rates and crime against property. Estimates for victimization rates correspond to the estimates on crimes per resident, minus one. In Panel A, we use a calendar hour-level panel and do not instrument ambient density. In Panel B, we use the same dataset and instrument as in Table 3. In Panel C, we use the same dataset and instrument as in Table 5. For estimation, we use the control function method, as described in Wooldridge (2015). Standard errors in all panels are clustered at the CBG level. In Appendix Table S.15, we report estimates for additional types of crime. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.16: Effects of ambient density on crime against persons: Shift-share IV during daylight time

	Victimization rates			Crimes per resident		
	(1) Assault	(2) Theft	(3) **All**	(4) Assault	(5) Theft	(6) **All**
(log) Ambient density	-0.497***	-0.507***	-0.500***	0.912***	1.039***	0.958***
	(0.079)	(0.064)	(0.058)	(0.151)	(0.177)	(0.123)
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Moment-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	93,611	93,611	93,611	93,611	93,611	93,611
First stage F-stat	1647.1	1647.1	1647.1	1647.1	1647.1	1647.1
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	3.671	2.456	6.214	3.556	2.386	6.024

Notes: This table reports shift-share IV estimates of the effect of ambient density on crime against persons. The dependent variables are victimization rates and the number of crimes per resident – see Section 2.2 for details. To facilitate interpretation, we normalize outcome variables so that their mean is one – pre-normalization means are reported at the bottom of the table. We include one observation per CBG $\times$ month $\times$ moment of the day. We exclude moments of the day for which more than half of the duration is after sunset. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.17: Effects of ambient density on police presence

	(log) Nb. officers
(log) Ambient density	-0.164**
	(0.0738)
CBG FE	Yes
Moment × Month FE	Yes
Observations	130,421
First stage F-stat	5484.3

Notes: This table reports a shift-share IV estimate of the effect of ambient density on police presence. Police presence is measured by the (log) number of officers on duty, see Appendix C for details. We include one observation per CBG × month × moment of the day. Standard errors are clustered at the CBG level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.18: Shift-share IV, controlling for police presence

	Victimization rates			Crimes per resident		
	(1)	(2)	(3)	(4)	(5)	(6)
	Assault	Theft	**All**	Assault	Theft	**All**
(log) Ambient density	-0.301***	-0.424***	-0.355***	0.831***	0.988***	0.893***
	(0.048)	(0.054)	(0.038)	(0.124)	(0.158)	(0.113)
(log) Nb. officers	-0.005	-0.005	-0.005	-0.001	-0.003	-0.002
	(0.007)	(0.006)	(0.005)	(0.006)	(0.004)	(0.004)
CBG FE	Yes	Yes	Yes	Yes	Yes	Yes
Moment × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130,421	130,421	130,421	130,421	130,421	130,421
First stage F-stat	5476.9	5476.9	5476.9	5476.9	5476.9	5476.9
Average	1.000	1.000	1.000	1.000	1.000	1.000
Normalization	3.637	2.689	6.410	3.517	2.554	6.150

Notes: This table reports shift-share IV estimates of the effect of ambient density on crime. This table reports shift-share IV estimates of the effect of ambient density on crime against persons. The dependant variables are victimization rates and the number of crimes per resident – see Section 2.2 for details. We control for police presence – see Appendix C for details. To facilitate interpretation, we normalize outcome variables so that their mean is one – pre-normalization means are reported at the bottom of the table. We include one observation per CBG × month × moment of the day. Standard errors are clustered at the CBG level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S.19: Comparison of models predicting people flows

	(log) Ambient population		
	(1)	(2)	(3)
(log) living and working pop.	Yes	Yes	Yes
(log) living and working pop. (rings)	No	Yes	Yes
Points of interest	No	No	Yes
Observations	368592	368592	368592
R^2	0.864	0.871	0.887
Adjusted R^2	0.864	0.870	0.886

Notes: This table reports goodness-of-fit measures for our estimation of equation (6) using three different sets of variables to predict people flows. In model (1), we predict people flows using only two variables: the number of people living in the CBG and the number of people working in the CBG. In model (2), we further include the number of people living/working in CBGs that are within 5 minutes of travel, and within 5-10 minutes of travel. In model (3), we further add variables about points of interest in the neighborhood (e.g., schools, stores).