Unlocking Amenities: Estimating Public Good Complementarity

June 9, 2018

Abstract

Research on public goods generally considers the value of individual public goods in isolation, when in fact there may be strong complementarities between them. This study examines the implications of public goods complementarities for economic valuation and efficient public investment, using the setting of public safety and open space in inner cities. Cross-sectional, difference-in-difference, and instrumental-variable estimates from Chicago, New York, and Philadelphia all indicate that local crime lowers the amenity value of public parks to nearby residents. Public safety improvements "unlock" the value of open-space amenities, and could raise the value that properties receive from adjacent parks from $22 billion to $31 billion in those three cities. Ignoring these complementarities risks over-estimating benefits in dangerous areas, under-estimating benefits in poor areas or conflating reduced amenity value with the preferences of local populations, and under-estimating benefits overall. While safety is more fundamental in a hierarchy of amenities, open spaces are not a luxury.

Key words: public goods, complements, amenities, crime, environmental amenities, parks, urban development
JEL Classification: H41, Q51, Q56

1 Introduction

Economic theory leans heavily on the concept that goods may be complements in consumption. While the joint demand of private goods, purchased directly in markets, has been studied extensively, little has been said on the joint demand for public goods. Studying the joint demand for public goods is difficult since they cannot be purchased directly, but only indirectly, such as access through the housing market.[1] To our knowledge, no prior study has priced relationships between public goods in a well-identified causal framework. As we demonstrate below, efficient investment in public goods depends critically on understanding complementary relationships.

In this paper, we study the complementary relationship between public safety and park access in three major U.S. cities. Intuitively, our point of departure is that parks are not valued by nearby homeowners if they are dangerous; in fact, they may even be a public bad. We find strong evidence that, while greater safety is always valued, open space is only valued once a threshold level of safety is reached. The net value of open space can be negative below this threshold, implying that increases in public safety increase or "unlock" the value of open spaces. A corollary is that residents value safety more near open spaces. Indeed, crime reductions in cities particularly near predetermined public goods such as urban parks, may be boons to urban revival.[2]

We examine the implications of valuing the benefits from a public good while ignoring interactions with its complement. In the case of open space, we demonstrate that estimators that ignore such interactions would naively suggest that environmental amenities have high value in low crime neighborhoods but zero value in high crime neighborhoods. In our setting, heterogeneity in crime could even be conflated with heterogeneity in preferences for open space, resulting in a belief that a luxury good that only high-income households value. However, once the fact that poor neighborhoods tend to be unsafe is accounted for, parks have the same percentage impact on housing prices in low income

[1]The closest analyses we know of consider the relationship between amenities and private consumption: Connolly (2008) and Graff Zivin and Neidell (2014) examine the relationship between weather and time use, and thus leisure as a good; Cuffe (2017) examines how rainfall influences museum attendance.
[2]See Baum-Snow and Hartley (2017) and Couture and Handbury (2017).

neighborhoods as in high-income ones. While open spaces are not a luxury, public safety may be considered a more "primary" public good than some environmental amenities. Public investments in environmental amenities which ignore these facts risk being wasted in unsafe areas, or overly targeted towards high-income areas.

This paper combines two parallel, but mostly disparate, strands of research on hedonic valuation. The first involves estimating the value of public spending, starting with (Oates, 1969), and Thaler (1978) and Gibbons (2004), who examine the magnitude of capitalization effects and the channels through which it operates. More recent studies address measurement error and omitted variables concerns to estimate the value of general policing (Chalfin and McCrary, 2017, Di Tella and Schargrodsky, 2004); targeted public safety and crime prevention programs (Donohue et al., 2013, Draca et al., 2011); and the relocation of sex offenders (Linden and Rockoff, 2008). A virtually independent literature estimates the value of increases (Gamper-Rabindran and Timmins, 2013) and reductions (Currie et al., 2015, Davis, 2004, Muehlenbachs et al., 2015) in environmental amenities. Many authors estimate the value of access to open space — see Brander and Koetse (2011) for a meta-analysis — though omitted variables concerns have limited the reliability of estimates of the demand for access to parks.

Our empirical analysis is based on crime and housing data in Chicago, New York and Philadelphia from 2001 to 2016. In particular, we use 365,431 housing market transactions within a tight radius (600 meter) around 1,277 parks, which we organize into park neighborhoods. Using police data, we then tie all reported crime incidents to these 1,277 neighborhoods, focusing on homicides. Using cross-sectional and difference-in-difference (DD) estimates, using variation within each neighborhood, we show how the price premium associated with park proximity falls substantially with crime density. Moreover, while the park premium is substantial in neighborhoods with little crime, it appears to be *negative* in the highest crime areas, suggesting that parks in these areas are a public bad. Reinforcing the idea that our results are truly driven by parks, we find that larger parks command a higher premium, which is more severely reduced by crime.

An advantage of our methodology is that while open space is largely predetermined,

crime changes over time in ways that are rather uncorrelated with the presence of parks. Nevertheless, given potential endogeneity problems with local crime rates, we develop a shift-share instrumental variables (IV) approach that makes use of widespread city-level crime reductions that occurred across these cities in the early 2000's (2001-2016) to test our hypotheses. This approach uses city-level changes in crime, combined with local heterogenity in crime rates in a base period, to predict future crime in every neighborhood. This isolates local changes in crime that are independent of purely local causes. Thus, the shift-share is also a useful instrument for changes in crime rates not interacted with parks. Indeed, IV estimates not only substantiate our hypotheses on amenity complementarities, but also provide credible estimates on the value of crime reduction, as well as higher park premia.

Our key IV estimates indicate that parks contribute $22 billion in total (annualized) value to nearby homeowners in the three cities. This value is comparable to the present value of all resources spent on park activities and maintenance. If completely unlocked through safety improvements this value would rise to $31 billions. Since the beginning of our sample period, reductions in crime have unlocked almost a $ billion in value already.

Our findings also suggest that simply displacing crime from area to another can improve welfare. Concentrating criminal activity away from parks through targeted investments in public safety or crime-inhibiting park design may unlock considerable value, even if would create more value to eliminate it altogether.[3]

This paper proceeds as follows. Section 2 presents a theory of complementary public goods in a hedonic setting and reveals how a sufficiently low level of one amenity can lock in the value of its complement. Section 3 describes the data that are used in our valuation of public safety and open space. In Section 4, we present evidence from cross-sectional, difference-in-difference, and IV estimates of the relationship between public safety and open space amenities. Section 5 discusses the implications of this evidence for the valuation and public provision of complementary public goods. Section 6 concludes.

[3]This displacement potentially be achieved in a distributionally neutral fashion, i.e. without helping the rich at the expense of the poor.

2 Public Good Complements "Unlocked"

In principle, complementary preferences between public goods, e.g., warm weather and a community pool, are no less important than between private goods, swimming trunks and goggles. Public and private goods may also be complementary, swimming trunks and a pool.

Complementary amenities are actually implied by the canonical Tinbergen model, adapted here from Bartik and Smith (1987) and Ekeland et al. (2004), even though they have only rarely been explored. It even allows for "unlocking" effects, as we show below. This model characterizes a hedonic setting with two amenities q_1, q_2, and a numeraire good, x. There are also two corresponding taste parameters, χ_1, χ_2.

$$U\left(q_1, q_2, x; \chi_1, \chi_2\right) \quad \text{subject to } p\left(q_1, q_2\right) + x = m$$

We identify amenity 1 as outdoor open space, and amenity 2 as safety.

2.1 Utility specification and Marginal Willingness to Pay

The specific utility specification follows a quadratic form

$$U = \frac{1}{2}\left(q_1 - \chi_1\right)^2 \theta_{11} + \frac{1}{2}\left(q_2 - \chi_2\right)^2 \theta_{22} + \left(q_1 - \chi_1\right)\left(q_2 - \chi_2\right)\theta_{12}$$

Where $\theta_{11}\theta_{12} > \left(\theta_{12}\right)^2$, and χ_1 and χ_2 are (high-valued) bliss points, so that in all relevant ranges, $\chi_1 > q_1$, and $\chi_2 > q_2$. The marginal willingness to pay of an individual is given by

$$\frac{\partial U}{\partial q_1} = \left(q_1 - \chi_1\right)\theta_{11} + \left(q_2 - \chi_2\right)\theta_{12}$$
$$\frac{\partial U}{\partial q_2} = \left(q_2 - \chi_2\right)\theta_{22} + \left(q_1 - \chi_1\right)\theta_{12}$$

The case we consider is where $\theta_{11}, \theta_{22} < 0$, which ensures that, discounting the interaction effect, both amenities are good. We explore the conditions under which the interaction

"locks in" the value of amenity 1. In particular, we allow for a negative interaction where $\theta_{12} > 0$, which creates the "locking" effect. It is clear to see that the marginal willingness to pay for amenity 1 will be negative when

$$(\chi_1 - q_1)(-\theta_{11}) < (\chi_2 - q_2)\theta_{12}$$

If safety is very low, $q_2 << \chi_2$, and the amenity effect here is negative, especially when θ_{11} is not much larger than θ_{12}. If the direct demand for safety, θ_{22} is sufficiently large, then the condition that safety is a good is easily satisfied

$$(\chi_2 - q_2)(-\theta_{22}) > (\chi_1 - q_1)\theta_{12}$$

even when θ_{12} is non-zero.

3 Data and Descriptive Statistics

We combine data on housing market transactions, homicides and neighborhood characteristics for the cities of Chicago, New York, and Philadelphia. Our choice of cities is determined by the availability and length of incident-level crime data. For the city of Chicago, our data set contains the years 2001-2016; for New York, 2006-2016; for Philadelphia, 2006-2015. Housing transactions prices and structural characteristics come from Zillow. Each house is matched with data on the demographic composition of residents living in the Census Tract coming from the 2011-15 American Community Survey. In addition, we use block and block group level data from the Census and American Community Survey on demographics and housing units for benefit calculations below.

Parks are defined from our source, openstreenmap.org as "open, green area for recreation, usually municipal, and are differentiated from other public/private open spaces such as: golf courses, stadiums, nature reserves (which may not have public access), and marinas".[4] The data contain the precise timing and location of all housing transactions

[4]See https://wiki.openstreetmap.org/wiki/Key:leisure

recorded within 3/8 (0.375) miles of 1,339 geo-coded urban parks in the three cities, 90 percent of which are in Chicago and New York. For concreteness, we refer to the 3/8 miles radius around a park as a park's "neighborhood". Our final data comprises 529,606 housing transactions surrounding parks. Figure 1 presents a sample of the data on housing transactions near Marquette Park in Chicago.

Crime report data comes from police departments in each city, provided by the Open Data Portal, which provides the geolocation of each report.[5]

We use geolocated reports to calculate crime density maps for each city and year. Figure 2 illustrates the estimated crime density for Chicago in 2003. Darker-shaded areas indicate higher likelihood of a homicide. To estimate the density we use information on homicides for the previous three years and use a bivariate Gaussian kernel with a bandwidth of 2/8 of a mile on a 1/8 mile city grid. By using a three year rolling window we smooth out any short term fluctuations in homicides at a particular location, and the narrow bandwidth on the fine grid chosen allows us to better captures the likelihood at a given location. We then combine the estimated likelihood at a given location with the total number of homicides in the city we obtain our homicide risk measure

$$Homicide\,Risk = E(H_{it}) = p_i H_t \tag{1}$$

where p_i is the estimated probability of homicide at location i. Then homicide risk measure is the expected number of homicides per square mile in year t at location i

In order to estimate how prices vary with crime risk, using the geolocation of the transactions dataset we match each dwelling location to the estimated homicide risk per square mile at that location.[6] For clarity and comparability, the main results are restricted to homicides, though results from exercises based on the full set of crime risk

[5]For the City of Chicago the data are extracted from the Chicago Police Department's CLEAR (Citizen Law Enforcement Analysis and Reporting) system and available through the Chicago Data Portal at https://goo.gl/D8Vm82 New York City data from the New York City Police Department (NYPD) and available through NYC Open Data portal at https://goo.gl/zGp8Z2. For Philadelphia crime incidents are from the Philadelphia Police Department, available through Open Data Philly at https://goo.gl/gYR96r

[6]In the appendix we also use annual neighborhood crime rates, which are the number of crimes occurring within each park neighborhood. We show that our results are consistent to using these neighborhood crime rates, which capture the overall safety of an area rather than simply what occurs in a given point.

are reported in the appendix.[7]

Figure 5 shows the ratio of the homicide risk near a park (treated area) with respect to the rest of the neighborhood (control area). On average the crime density on parks in higher in more dangerous neighborhoods relative to the overall neighborhood. Relatively safe neighbourhoods show a lot of variation, however, in more dangerous neighborhoods, parks have a higher homicide risk.

Figure 3 shows that cities have experienced substantial decrease in overall homicides (with the exception of Chicago in 2016). However, within cities the decrease was not uniform, with some locations experiencing decreases, increases or no changes in homicide risk. Figure 4 shows the parks in our sample classified by the changes in homicide risk. We classify parks in three groups, those that have experienced a Decrease, Increase or No Change in their homicide risk. If the park neighborhood experienced a median decrease of .4 expected homicides per year per mi^2 in the study period we classify them as having experienced a decrease in homicide risk, by the same token, we say they Increased their homicide risk if they experienced a median increase of .4 in expected homicides per year per mi^2 in their neighborhood in the study period, and No Change otherwise. About 13% of the neighborhood parks have experienced a decrease in homicide risk, 15% an increase, and 72%

[8]

4 Identifying Public Good Complements

Below we consider a sequence of three estimators for the value of the park-safety complementarity. To identify the complementarity effect we exploit various sources of variation. We begin by solely focusing on cross sectional variation of within-neighborhood hous-

[7]Prior research illustrates substantial heterogeneity in the perception and valuation of different types of crime and ambiguous effects of property crimes on housing prices. We utilize willingness-to-pay estimates from Chalfin and McCrary (2017) to construct a unitary measure of homicide-equivalents. We find that homicide risk dominates the index and that our results reported in Tables **??** and **??** are robust to this measure.

[8]We subdivide some of the largest parks, such as Central Park in New York, Lincoln Park in Chicago and Fairmount Park in Philladelphia, in order to capture the effects of crime in particular neighborhoods that they span.

ing prices, interacted with neighborhood homicide risk. The second and third strategies exploit the spatial variation of crime within neighborhoods and develops a difference-in-difference strategy; the third uses an instrumental variable strategy based on a shift share. We finish, by considering how large parks are valued more than smaller ones.

4.1 How Park Premia Vary by Safety Level in the Cross Section

We begin by considering the cross-sectional "park premium" using a simple linear model to compare low and high-crime neighborhoods. It estimates price variation using 1/16 (0.0625) miles wide indicators for the distance from a house to its neighborhood park. These approach helps us focus on the price gradient generated by proximity to parks. These bins are interacted with homicide risk, measured per square mile of the neighborhood, H_j. The cross-sectional model for P_{it}^{jc}, the sales price of house i in neighborhood j, city c, year t, is given by

$$\begin{aligned} \ln P_{it}^{jc} = & \sum_{k=0}^{6} \pi_k^0 I\left[(1/16) \times k \leq d_i^j < (1/16) \times (k+1)\right] \\ & + \sum_{k=0}^{6} \pi_k^H I\left[(1/16) \times k \leq d_i^j < (1/16) \times (k+1)\right] \times H_i^{e,j} \\ & + \theta D_i + \alpha_j + \delta_t^c + u_{it} \end{aligned} \tag{2}$$

d_i^j is the distance between each house and its neighborhood park. H^j is homicide risk measured by the expected number of homicides per year per square mile over the sample period in neighborhood j. D_i is a vector of (potentially time-varying) dwelling characteristics and census tract demographic controls.[9] α^j is a neighborhood fixed effect so that we identify results based on transactions within neighborhoods. δ_t^c a fixed effect for city by transaction year to control for city-specific time patterns. u_{it} is an error term.

[9]Dwelling characteristics include: age of the dwelling and it's square, number of bedrooms and an indicator for dwelling type (i.e. Single Family Residence, Condo, etc.). Census tract controls include: log Distance centroid of park to the CBD, and census tract demographic variables from the 2011-15 ACS: median income, % males between 15 and 35, % of hispanics, % of blacks, median age, average household size, % of vacant units, and number of housing units

In neighborhoods with zero homicide risk, the estimated park premium for bin k is given by π_k^0; with homicides, the predicted park premium is $\pi_k^0 + \pi_k^H$. The hypothesis that safe open spaces are goods is represented by the prediction that $\pi_k^0 > 0$ and that $\pi_k^0 \geq \pi_{k+1}$ for $k \leq k'$ some threshold k' at which point parks no longer mater. The hypothesis that safety and open space are complements is that $\pi_k^H < 0$ for $k \leq k'$. That the amenity values of open spaces are sometimes locked is that there exists H^j, such that $H^j > -\pi_k^0/\pi_k^H$.

Figure 6 presents fitted estimates of the park premium based on the regression results presented on Table A.2, using fits for 0 and 5 expected homicides per year per square mile. The graphs illustrate a 4.2% premium for locations within 1/16 miles of a park in low homicide risk neighborhoods (with zero homicides). However, in high-homicide risk neighborhoods (with an expected homicides per year of 5 or more per square mile), there is instead a park discount of 2.5%. Both the park premium and discounts dissipate entirely beyond 1/8 (0.125) miles from the neighborhood park.[10]

The above evidence is suggestive of a park premium that shifts to negative in dangerous areas. This cross-sectional evidence is of course limited, however, since unobserved dwelling and neighborhood characteristics may be strongly correlated with park proximity. Since urban parks are only rarely created or eliminated in dense areas, time-variation is not very useful in identifying park premia, especially since park creations or removals are unlikely to be exogenous. Nevertheless, the results do provide an important point of departure for considering how park premia change with neighborhood-wide changes in safety.

4.2 How Park Premia Change with Crime over Time

The next step is to consider whether park premia increased in places that saw reductions in crime over the time period. Using the steep decay function revealed above, we develop a difference-in-difference (DD) estimation procedure, based on a simplified "treatment-control" framework. We divide housing within 1/8 miles of a neighborhood park —

[10] Our relatively small bandwidth makes this design related to border design. In comparison, Bayer et al. (2007) uses bins of 0.1 and 0.2 miles.

subject to a park "treatment" – from housing 1/8 and 3/8 miles away from the park park – the control.

We begin with a standard difference-in-difference identifying assumption. Namely, conditional on our controls, local processes that affect housing prices within a neighborhood that are correlated with safety will affect houses less than and away from 1/8 miles from parks equally. The control homes constitute 284,369 transactions. The key identifying assumption in this model is that both proximate and control homes are affected by the the same localized crime patterns and by interactions between crime and unobserved factors that are changing at the neighborhood level (ex. increased policing). This leads to the following within-neighborhood difference-in-difference equation:

$$\ln P_{it}^{ct} = \pi^0 I\left[d_i^j \leq \frac{1}{8}\right] + \gamma H_t^{ic} + \pi^H I\left[d_i^j \leq \frac{1}{8}\right] \times H_t^{ic} + \theta D_i + \alpha_j + \delta_t^c + u_{it} \qquad (3)$$

This equation differs from (2) in that it relies on time variation in homicide risk, given by H_t^{ic}. As a shorthand, we call the indicator $I\left[d_i^j \leq \frac{1}{8}\right]$, as simply "Park" to reflect park proximity.

Table 2 reports estimates from model 3. Difference-in-differences estimates indicate that without accounting of the interaction between parks and safety one may conclude there's no premium for being near an urban park. However, once the interaction is accounted for, homes in close proximity to an urban park sell at a premium ($\pi^0 > 0$) of between 2.5 and 2.8 percentage points relative to homes further away from the the same park.

More importantly, the results in table 2 imply that the value of park proximity declines with crime risk, $\pi^H < 0$. An increase in homicide risk reduces the value of homes within 1/8 miles of a park by .7 - 1.1 percentage points relative to a home within 3/8 miles of the same park. With high enough homicide risk, $H_{it}^j > -\pi^0/\pi^H \approx 2.66(0.095)$, the park premium goes negative.

One point worth noting, that without accounting for the complementarity the park premium effect is non existent, but when the interaction is accounted it clearly shows a

positive premium for park access at low levels of homicide risk and a clear negative effect at high levels.

The interpretation of the estimates provided in Table 2 as the causal effect of crime on the amenity value of parks still involves a somewhat restrictive set of assumptions. The primary threat to identification is the possibility that the increases in the amenity value of parks are not coming from the effect of reductions in local crime, but rather from time-varying unobservables that are correlated with local crime reductions but differentially affect housing prices immediately surrounding parks. This identification assumption is not directly testable.[11]

4.3 Instrumenting Crime Changes with City-Level Shifts

Another strategy for estimating the complementarity between safety an open space is to use an instrumental variable for local crime in equation (3). In order to estimate this relationship consistently, a valid instrumental variable for local crime is needed. We consider a shift-share instrumental variable strategy, similar to those developed by Bradbury et al. (1982) and Bartik (1991) for other variables, and examined by Goldsmith-Pinkham et al. (2017). The shift-share instrument makes use of the fact that reductions in crime around any given location can be decomposed into overall reductions in crime at the city level and changes in the geographic distribution of crime. We construct a relative crime index that makes use of exogeneous variation in crime incidence at the city level, but can be used to predict changes in crime at any given location.

The shift-share instrument proportionally assigns homicides in a city according to the estimated density using the first two years of the sample. Denoting the total annual homicides in city c in year t as H_t^c, the probability of a homicide in location i in city c is p_0^{ci}. Using a base time period, normalized to $t = 0$, the predicted expected number of homicides at each location i is

$$\hat{H}_t^{ic} = p_0^{ic} H_t^c \tag{4}$$

Locations with a higher risk of homicides at the beginning of the period will have simi-

[11] These estimates also rely upon the functional form that we have defined for the amenity value of parks.

lar levels of predicted crimes in subsequent years, with location-level reductions occurring in proportion to the city as a whole. The idea is that local crime changes induced by city level changes are orthogonal to local neighborhood dynamics that might favor a park area over another. Furthermore, since urban parks are pre-determined geographically, another valid instrument is the interaction of $\hat{H}_t^{iv}$ with the park proximity indicator, $I\left[d_i^j \leq \frac{1}{8}\right]$.

The first stage results of the IV regression in table 3, indicate that city-level reductions in homicide risk are a strong predictor of location-level homicide risk. Our estimates indicate that 1 homicide increase in the shift-share instrument predicts a 0.52 homicide risk increase.

Table 4 reports estimates from our preferred IV specification alongside DD estimates. The IV estimates find a much stronger negative direct effect of homicides on property values, $\gamma < 0$, consistent with intuition. An increase in homicide density by 1, reduces housing 2.8 percent in the uninteracted model, and 2.5 percent in the interacted model.

Moreover, the estimate of the interaction between park and homicide density becomes more negative, with $\pi^H \approx 1.1\%$. In words, reductions in crime in the neighborhood have a larger and more significant effect ($p < 0.01$). The safe park premium also rises in this specification to $\pi^0 \approx 2.4\%$. As a result the homicide level at which parks are unlocked is slightly lower at $-\pi^0/\pi^H \approx 2.11(0.63)$.

4.4 Magnitudes and Park Size

It seems almost obvious that a larger park is a greater amenity than a smaller one. Finding that larger parks increase housing prices more than smaller ones not only supports this idea, but also the auxiliary hypothesis that our proposed methodology indeed identifies the effect of parks. Indeed, if there is more value to lose, larger parks should lose greater value if they are seen as dangerous.

To test these ideas, we define a large park as above the 90th percentile in area, which has a minimum size of $0.39mi^2$ (~ 250 acres). Table 5, which presents results for the both the uninteracted and interacted model, finds a much higher base premium for living by a large park than by a small park. Furthermore, the interacted model shows a greater effect

homicide risk on large parks than on small parks. Nevertheless, we do see a negative, if commensurately smaller, estimate for small parks. This finding helps assure us that the park premia associated cross-sectional variation in park location is indeed due to parks, and that the interacted model produces sensible, well-identified results.

5 Complementarities and Public Goods Provision

The estimates above indicate that the complementarity between publicly provided goods has first-order implications for the valuation of public goods and ultimately for public policy decisions. In this section, we examine the implications of these results for the valuation and provision of environmental amenities and for complementary public goods more broadly.

5.1 Implications of Complementarities for Valuation and Unlocking Value

Our IV estimates suggest that the amenity value of open space in the average neighborhood in our sample of 3 major cities in the United States is large, with a park premium in the average neighborhood in our sample of 4.5 percentage points. To calculate the implied value of parks in our sample, we compute the number of housing units and median property value at the census block group level from the 2000 census.[12] Using the number of units, the median value and our estimates from table 4 column (5), we estimate the value of parks for each city.

Table 6 shows the estimated park values, which total $21 Billion. Parks in Chicago are valued at around $6.6 Billion; in New York, $14.3 B; Philadelphia, $0.7 Billion. While the value of urban parks is large overall, our estimates indicate that the local amenity benefits from parks are dominated by disamenity from crime risk. As estimated above, our estimates indicate an average park premium of 4.5% that falls by 7.9 percentage points per increase in annual homicide density. An actual reduction in homicide density should result in a 5.5 percentage point increase in the price of a house away from a park, and

[12] We calculate the area of the block group that is within 200 meters of a park to compute the proportion of housing units in each census block group affected by the premium.

13.5 percentage points by a park. On the other hand, simply *displacing* crime away from neighborhoods with parks should still in principle increase values city-wide, possibly by 7.9% of value of housing within 200 meters near parks. Spillover effects for those further from the parks might make this number even higher.

Estimates from table 6 illustrate that the majority of the value of neighborhood parks in our sample of cities is concentrated in neighborhoods with at least one annual homicide. Our estimates in Panel (b) indicate that the amenity value that is still locked-in by crime: this value sums up to $8.9 Billion: $2.7 Billion in Chicago, $5.8 Billion in New York, and $387 Million in Philadelphia. Again, this could be achieved ostensibly by displacing crime, rather than eliminating it altogether.

The estimates in Panel (c) reveal that accounting for the complementarity between public safety and park amenities can affect how we assess the value of parks. Both IV and DD estimates that ignore the interaction of crime and parks (Table 4, columns 1 and 4) imply a much lower park premium of 2.4%. This mis-specified model produces an estimate of $11.8 Billion for the parks in our sample, underestimating the total value in our sample by 46%.

Table 7 reports estimates of changes in neighborhood park value that have resulted from reductions or increases in annual homicide rates during the study period. These estimates indicate that reductions in homicide rates have unlocked considerable amenity value in certain neighborhoods: $127 Million in Chicago, by $500 Million in New York, and $28 Million in Philadelphia. Increases in homicide rates in other neighborhoods have resulted in simultaneous reductions in the amenity value of parks, totaling $183 Million during the study period: $67 Million in Chicago, $107 Million in New York, and $10 Million in Philadelphia.

5.2 Implications for Public Goods Provision

A second key implication of this research concerns the cost-effectiveness of investments in public goods that are affected by "lock-in". When leisure-producing environmental amenities are locked in by high levels of crime risk, it is likely that the marginal benefit of

investments made to improve their quality (without addressing crime risk) will be limited. While we do not have adequate data to fully determine the marginal cost of parks at this stage, it is still possible to shed some light on optimal public expenditures. For instance, there may be an argument that Chicago, with its large stock of parks, has potentially much to gain from security improvements.

Using a capitalization rate of 5 percent, our price estimates on the stock of housing imply annual flow values of $332Millions; $717Millions, and $39Millions, in Chicago, New York, and Philadelphia, respectively. At the same time, park maintenance and programs, the City of Chicago annually spends $323Millions on parks; New York spends $342Millions, and Philadelphia, $54Millions. This does not reflect the full cost of parks, since it ignores the opportunity cost of the land for alternative development.

The numbers above imply that in New York, the value of park proximity alone would be enough to fund cash expenditures on parks, possibly through a land tax on properties within 200 meters. In Chicago and Philadelphia, such revenues would cover much of the budget but not completely. With the value of parks unlocked, however, the flow value of parks would rise to $468Millions, very close to the expenditures by the park authority. The same is roughly true for Philadelphia. On the other hand, the naive estimators would provide just over half as much potential revenue for covering park expenses. These valuations should be considered a lower bound as they clearly ignore all of the benefits and spillovers parks provide to residents more than 200 meters away, but which are too diffuse as to produce an identifiable park premium in housing prices.

The numbers also imply that residents near parks would pay a premium to remove or displace crime from their neighborhoods, in proportion to the value added. In Chicago, park-side residents alone should be willing to pay up to $200Millions to rid their neighborhoods of crime. Comparable expenditures in police are $1,040Millions. Depending on how effective the police are at reducing crime, this could justify increasing police expenditures by almost 20 percent. It must be noted that this could be the value of simply *displacing* crime to parts of the city with no parks nearby. If the IV estimates on crime reduction from the main effect are taken seriously, eliminating crime would likely produce

much larger increases in value.

In comparison, comparable New York police expenditures are $3,755Millions; for Philadelphia, $442Millions. Increases in value would be proportionally smaller. relative to these budgets. One possible implication of this study is that Chicago's relatively abundant supply of "unlocked" parks, means that its residents would value increases in safety relatively more than other cities. Whether that could be accomplished through policing, or through other means, more efficiently, remains an open question.

5.3 Disentangling Complementarities from Taste and Income Heterogeneity

A caution that emerges from these findings is that models that examine the value of environmental amenities may confound the effect of complementarities with heterogeneity in preferences or income effects. Indeed, estimates of revealed preference for parks that derive from a model that does not account public safety complementarities will create the appearance that residents in high crime neighborhoods place a lower value on their neighborhood parks.

A more coherent explanation than exogenous taste differences is to try to model differences in income. High and low-income individuals may have similar tastes, but value different goods on the margin because of their purchasing power. Indeed, many authors, e.g. Black (1999), that many amenities are luxuries, implying that consumption goods purchased from markets directly are necessities. The results presented in Table 9 explore the possibility that environmental amenities are a luxury by splitting effects according to the median income of the neighborhood. Neighborhoods whose median income is below the 25th percentile are deemed low income. The results from the uninteracted regression in columns (1) and (3) both suggest no park premium in low-income neighborhoods. Both the DD and IV results show that accounting for the interaction boost the premium for low income neighborhoods; in the IV case, the point estimate is even slightly higher for low-income neighborhoods.

Since the price is expressed in logarithms, and houses tend to be much cheaper in low-income areas, the premium paid in dollars to be near a park will still be lower. However,

with a conventional utility function such as Cobb-Douglas, a similar coefficient in the semi-log form would support that parks are a neutral good, and thus neither a luxury nor a necessity. This finding is rather intuitive, since low-income households should value the largely free benefits that most parks confer to nearby residents.

The conflation bias illustrated by the comparison in Table 9 has important implications for considering the distributional effects of expenditures that are justified on the basis of hedonic estimates or even a mental model that fails to consider the complementary nature of public safety and a leisure-producing environmental amenity. To the extent that public expenditures that are used to create, manage or improve environmental amenities such as urban parks are rationalized on the basis of estimates of their value to the local population, there would be a tendency to investments disproportionately in environmental public goods in higher income neighborhoods/populations.

5.4 Socio-Demographic Changes

Improvements in safety can not only be capitalized in house prices but also induce socio-demographic changes. As safety improves, more affluent households may reallocate near urban parks, which in turn may bid up housing prices. We assess whether we see demographic changes near parks, estimating the following equation

$$y_{it}^{j} = \pi^{0} I\left[d_i^j \leq \frac{1}{8}\right] + \pi^{0} I\left[d_i^j \leq \frac{1}{8}\right] * Post + \gamma H_t^{jc} + \alpha_j + \delta_t^c + u_{it} \tag{5}$$

y_{it}^{j} is a demographic characteristic near a park $i = I\left[d_i^j \leq \frac{1}{8}\right]$ or further away $i = I\left[\frac{1}{8} < d_i^j \leq \frac{3}{8}\right]$ on "neighborhood" j and in year t. *Post* denotes the latest five years of the sample. As before, α^j is a neighborhood fixed effect so that we identify results based on within neighborhood variation. δ_t^c a fixed effect for city by year to control for city-specific time patterns. u_{it} is an error term.

Table 8 shows results for this specification. In *Panel A* the transform the dependent

variables to logs which give us a semi-elasticity. First we see that on average richer and older households live near parks. But we don't observe any significant changes in population, income or age around parks in the later years.

Population may not be changing but it's composition might. In *Panel B* we look at changes in racial composition of the population. Our dependent variable now is the percentage of people on a given race living near parks. First we must note that on average a higher proportion of whites and black live near parks. Furthermore, we do see small changes of less that 1% on the proportion of whites and black moving in near urban parks in later years when overall safety is improving. However, these changes are very small and although statistically significant, may not be economically significant.

6 Conclusion

This study illustrates that accounting for complementarities in public goods can have important implications for how we understand preferences and allocate public expenditures. Open spaces in insecure neighborhoods can actually be a public bad for local residents. This finding is very important for policy makers and environmental justice advocates who might conclude from incomplete evidence that more public investments to disadvantaged communities are always highly desirable for their redistributive effects. The conclusion suggested here is that in these communities, a deficit in public safety has locked-in the value of leisure-producing environmental amenities.

In a more complete model, we show that preferences for safe open spaces appear to be valued rather equally in both low and high-income communities. Economists who ignore complementarities might falsely conclude that environmental amenities are a luxury that residents would get very little value from. Others, modeling preference heterogeneity might just assume that residents' preferences for environmental amenities might just be lower in less secure areas, possibly rationalizing it through an under-explained sorting behavior.

Finally, our quantitative estimates imply that the value of open spaces may be under-

estimated through naive estimators. Furthermore, the potential value of existing open spaces, may be much greater when they are unlocked. This is of particular importance to cities that have a considerable historical endowment of open spaces relative to their population, such as Chicago. Past improvements in safety have improved welfare considerably in unlocking green spaces, and further improvements could have even larger effects.

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7 Tables and Figures

Table 1. Descriptive Statistics

	Chicago	New York	Philadelphia	Sample
Number of Parks	571	647	121	1,339
Average park size (in mi2)	0.024	0.047	0.097	0.042
Average neighborhood size (in mi2)	0.641	0.737	0.915	0.712
Expected homicides within 3/8mi.	1.638	1.456	1.368	1.262
No. Properties sold within 1/8mi.	139,400	93,176	10,545	243,121
No. Properties sold between 1/8 mi. and 3/8mi.	165,994	104,044	16,447	286,485
Av. log price within 1/8mi.	12.44	13.479	12.402	12.836
Av. log price between 1/8 mi. and 3/8mi.	12.372	13.306	12.194	12.701

Notes: Sample includes transactions of Single-Family Residence and Condos within 3/8 mi. of a park. for Chicago (2001-2016), New York (2006-2016), and Philadelphia (2006-2015) from Zillow. We refer to the 3/8 miles radius around a park as a park's "neighborhood"

Table 2. Park Premium and Homicide Risk: Base Results

	Dependent variable:			
	ln Price			
	(1)	(2)	(3)	(4)
Park	0.009	0.027***	0.025***	0.025***
	(0.008)	(0.009)	(0.009)	(0.008)
Homicide Risk	−0.019***	−0.019***	−0.014***	−0.016***
	(0.002)	(0.002)	(0.002)	(0.002)
Park*Homicide Risk		−0.011***	−0.010***	−0.008***
		(0.002)	(0.002)	(0.002)
Property Char.	Yes	Yes	Yes	Yes
Census Tract Controls	Yes	No	Yes	No
Tract FE	No	No	No	Yes
Neighborhood FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	529,606	529,606	529,606	529,606

Notes: Sample includes transactions within 3/8 mi. of a park for Chicago (2001-2016), New York (2006-2016), and Philadelphia (2006-2016) from Zillow. Dependent variable is log of sales price, *Park* is an indicator for sales within 1/8 mi. of a park, *Homicides Risk* denotes number of expected homicides per squared mile. All regression include controls for dwelling characteristics, neighborhood and year fixed effects. Standard errors clustered at the census tract level are in parenthesis

* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 3. First Stage

	Dependent variable:
	Homicide Risk
	(1)
Pred. Homicide Risk	0.518***
	(0.013)
Property Char.	Yes
Census Tract Controls	Yes
Neighborhood FE	Yes
Year FE	Yes
Test of excluded Instruments	
F-statistic	1,703.88
P-value	< 0
Week IV (Sanderson and Windmeijer, 2015)	
F-statistic	89.678
Observations	430,453

Notes: The sample is the same as in Table 4. Homicide Risk per squared mi are instrumented using predicted homicide risk per squared mi based on the initial densities and the total annual homicides at city level.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 4. Park Premium and Homicide Risk: Shift-Share Instrument

	Dependent variable:			
	logprice			
	(1)	(2)	(3)	(4)
Park	0.009	0.020**	0.008	0.024**
	(0.007)	(0.009)	(0.007)	(0.010)
Homicide Risk	−0.019***	−0.016***	−0.028***	−0.025***
	(0.002)	(0.002)	(0.005)	(0.005)
Park*Homicide Risk		−0.007***		−0.011***
		(0.002)		(0.003)
Property Char.	Yes	Yes	Yes	Yes
Census Tract Controls	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	430,453	430,453	430,453	430,453

Notes: Sample is the same as in Table 2 without the first two years of the sample for each city, i.e. Chicago (2003-2016), New York (2008-2016), and Philadelphia (2008-2016). We use the first two years to build the likelihood of homicides at each location. Dependent variable is log of sales price, *Park* is an indicator for sales within 1/8 miles of the park, *Homicide Risk* denotes number of expected homicides per squared mile. Columns (1)-(2) present difference in difference estimates similar to those in 2, and columns (3)-(4) instrumental variable estimates. Homicide Risk at a location is instrumented using predicted expected homicides in that location based on the initial homicide density and the total annual homicides at city level. All regression include controls for dwelling characteristics, census tract demographic controls, neighborhood and year fixed effects. Columns (3) and (6) adds pre/post 2008 specific trends for sales within 200mts of a park and for between 200mts and 600mts. Standard errors clustered at the census tract level are in parenthesis.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 5. Park Premium and Homicide Risk: By Park Size

	Dependent variable:			
	ln Price			
	DD	DD	IV	IV
	(1)	(2)	(3)	(4)
Large Park	0.088***	0.110***	0.085**	0.121***
	(0.034)	(0.039)	(0.034)	(0.040)
Small Park	0.001	0.008	0.001	0.011
	(0.007)	(0.008)	(0.007)	(0.009)
Large Park * Homicide Risk		−0.031**		−0.050***
		(0.013)		(0.019)
Small Park* Homicide Risk		−0.004*		−0.007**
		(0.002)		(0.003)
Homicide Risk	−0.015***	−0.013***	−0.022***	−0.019***
	(0.002)	(0.003)	(0.006)	(0.006)
Property Char.	Yes	Yes	Yes	Yes
Census Tract Controls	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	430,453	430,453	430,453	430,453

Notes: Sample is the same as in Table 4, i.e. Chicago (2003-2016), New York (2008-2016), and Philadelphia (2008-2016). Large/Small Park denotes a dummy that takes one if the area of the park is above/below the 90th percentile. Standard errors clustered at the census tract level are in parenthesis.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 6. Amenity Value of Parks (in mill)

	Homicide Risk			
	Low	Medium	High	
Panel (a): Amenity Value				
Chicago	1,745	1,343	492	3,580
NY	2,896	2,898	672	6,466
Philly	170	256	42	467
Total	4,811	4,497	1,206	10,514
Panel (b): Amenity Value locked in by Homicide Risk				
Chicago	330	1,096	1,138	2,564
NY	725	2,323	1,901	4,948
Philly	39	179	100	317
Total	1,093	3,598	3,139	7,830
Panel (c): Naive Amenity Value				
Chicago	591	455	167	1,212
NY	981	981	228	2,190
Philly	57	87	14	158
Total	1,629	1,523	408	3,560

Note:

Table 7. Amenity Value of Parks (in mill)

	Change in Homicide Risk			
	Decrease	No Change	Increase	
Panel (a): Amenity Value				
Chicago	256	3,124	200	3,580
NY	1,155	4,514	525	6,194
Philly	19	335	113	467
Total	1,430	7,973	838	10,242
Panel (b): Amenity Value locked/unlocked in by Change in Homicide Risk				
Chicago	98	0	−63	34
NY	4,101	0	−1,956	2,145
Philly	79	0	−400	−321
Total	4,279	0	−2,420	1,859

Note:

Table 8. Socio-Demographic Changes

Panel A

		Population per mi^2		Income		Age	
		(1)	(2)	(3)	(4)	(5)	(6)
Park		0.007	0.007	0.009**	0.009**	0.005	0.005
		(0.031)	(0.031)	(0.004)	(0.004)	(0.006)	(0.006)
Park*Post		−0.001	−0.001	−0.006	−0.006	0.002	0.002
		(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Homicide Risk			0.0004		0.005*		0.00003
			(0.001)		(0.002)		(0.0002)
Park Pre Mean		27.830		57.606		32.374	
Observations	34,976	34,962	33,559	33,545	30,876	30,862	

Panel B

	White (%)		Black (%)		Hispanic (%)		Asian (%)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Park	0.748***	0.749***	0.426**	0.426**	−0.833***	−0.833***	−0.408***	−0.406***
	(0.069)	(0.069)	(0.187)	(0.187)	(0.229)	(0.229)	(0.006)	(0.004)
Park*Post	0.624***	0.622***	0.274**	0.274**	0.259	0.259	0.590*	0.582*
	(0.232)	(0.233)	(0.112)	(0.112)	(0.175)	(0.175)	(0.328)	(0.318)
Homicide Risk		−0.181***		0.075***		0.090*		−0.078*
		(0.056)		(0.020)		(0.049)		(0.045)
Park Pre Mean	38.777		30.922		22.709		8.960	
Neighborhood FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,842	34,828	34,582	34,572	34,922	34,908	32,636	32,622

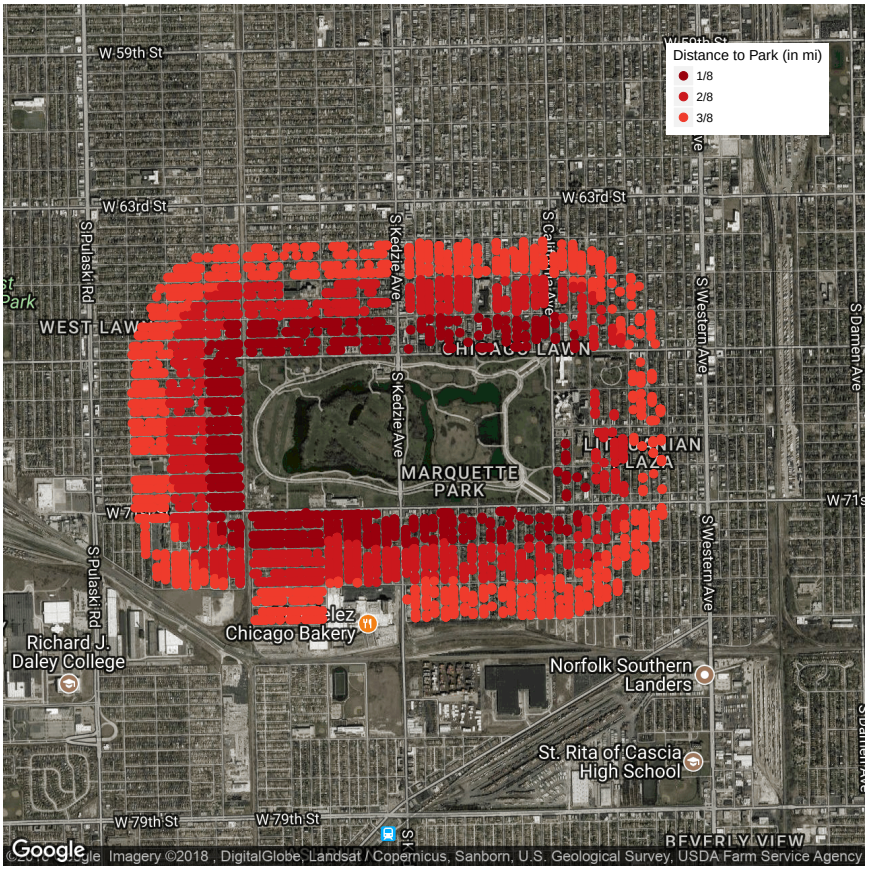
Standard errors clustered at the city level are in parenthesis
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 9. Park Premium and Homicide Risk: High/Low Income Neighborhoods

	Dependent variable:			
	ln Price			
	DD	DD	IV	IV
	(1)	(2)	(3)	(4)
Park*High Income	0.015	0.022**	0.014	0.025**
	(0.010)	(0.010)	(0.009)	(0.010)
Park*Low Income	−0.006	0.014	−0.009	0.025*
	(0.009)	(0.013)	(0.009)	(0.015)
Homicide Risk	−0.019***	−0.017***	−0.030***	−0.026***
	(0.002)	(0.003)	(0.005)	(0.005)
Park*Homicide Risk		−0.007**		−0.012***
		(0.003)		(0.004)
Low Income	−0.020	−0.025*	−0.017	−0.025**
	(0.013)	(0.013)	(0.012)	(0.013)
Property Char.	Yes	Yes	Yes	Yes
Census Tract Controls	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	430,453	430,453	430,453	430,453

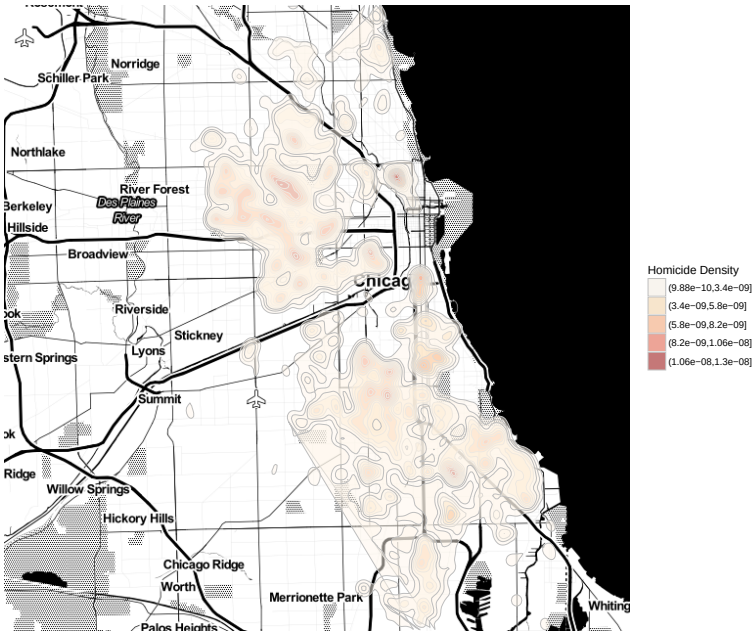
Notes: Sample is the same as in Table 4, i.e. Chicago (2003-2016), New York (2008-2016), and Philadelphia (2008-2016). High and Low Income are indicator for whether the census track is above/below the 25th percentile of the sample census tract median income.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Figure 1. Housing Transactions around Parks



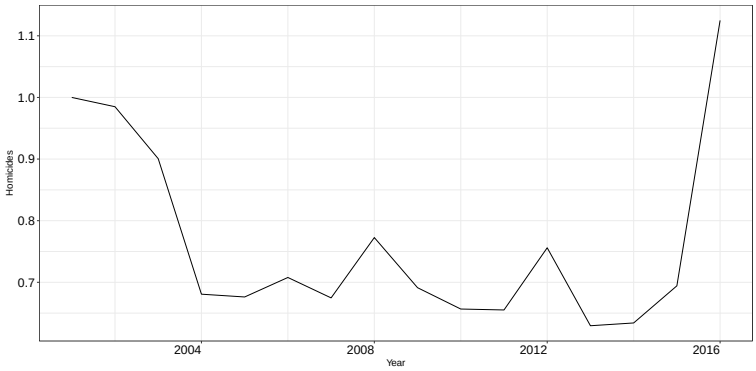
Note: Dots represents transactions within 3/8 miles of Chicago's Marquette park in our sample. Different shades denote proximity to the park.

Figure 2. Density of Expected Homicides in Chicago. Year 2003

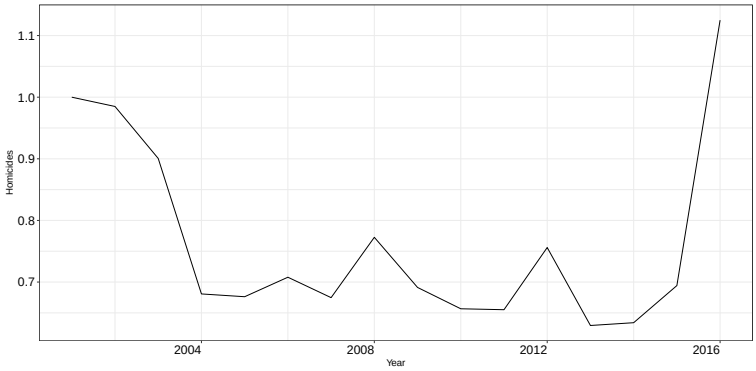


Note: Shades represent a density estimation of being a homicide victim per square mile. Estimates are based geolocated crime data for years 2001-2003 using a bivariate Gaussian kernel with a bandwidth of 2/8 of a mile on a 1/8 mile city grid.

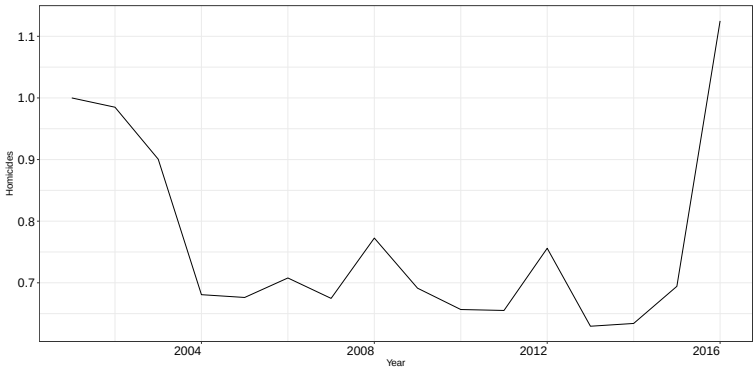
Figure 3. Homicide Trends by City



(a) Chicago. 2001 = 1 (664 homicides)



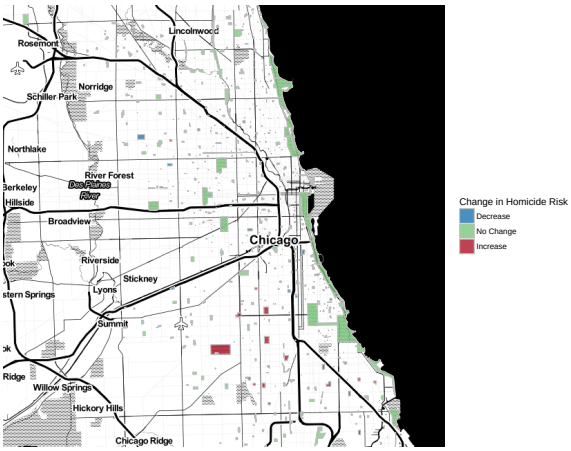
(b) New York. 2006 = 1 (573 homicides)



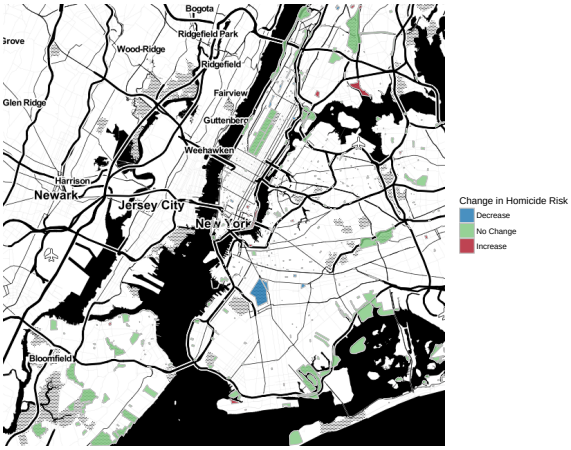
(c) Philadelphia. 2006 = 1 (320 homicides)

Note: Number of homicides per year and cities normalized with respect to the first year of the sample

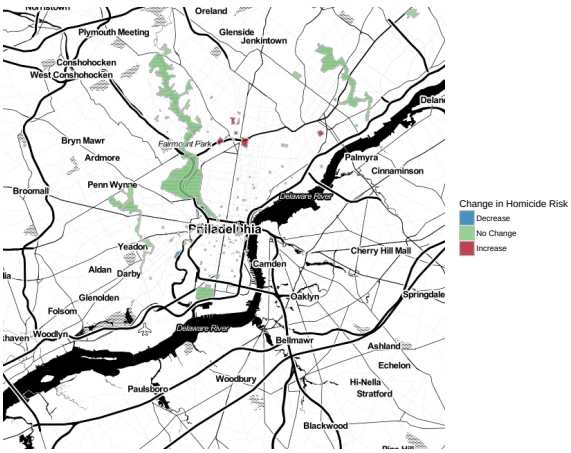
Figure 4. Homicide Risk Change by Park



(a) Chicago



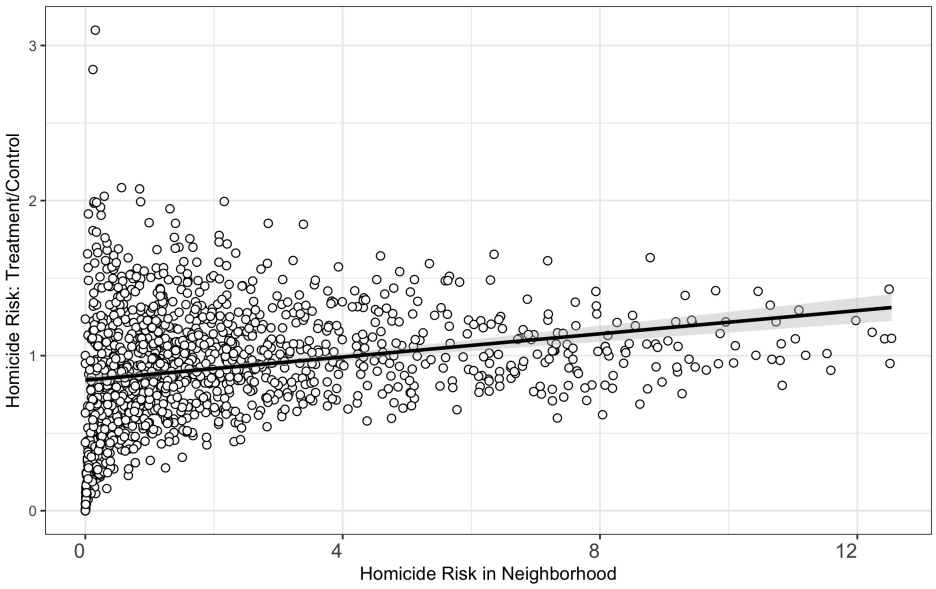
(b) New York



(c) Philadelphia.

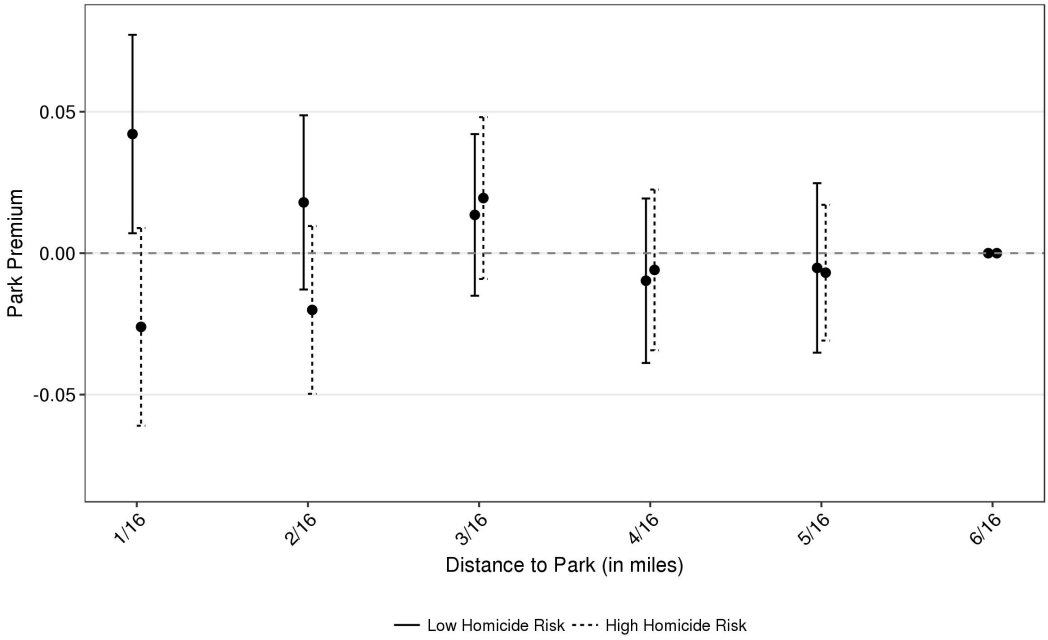
Note: Change in Homicide Risk in Park Neighborhood. We classify parks in three groups, those that have experienced a Decrease, Increase or No Change in their homicide risk. If the park neighborhood experienced a median decrease of .4 expected homicides per year per mi^2 in the study period we classify them as having experienced a decrease in homicide risk, by the same token, we say they Increased their homicide risk if they experienced a median increase of .4 in expected homicides per year per mi^2 in their neighborhood in the study period, and No Change otherwise.

Figure 5. Homicide Risk near Parks



Note: The vertical axis denotes the ratio of the density of homicides per square miles in the sample period of the treated areas within 1/8 of a mile of a park, over those in the control areas (1-3/8 of a mile). The horizontal axis measures the yearly density in the neighbourhood (within 3/8 of a mile)

Figure 6. Conditional Park Premium



Note: Park premium conditional on Homicide Risk based on Table A.2. *Low Homicide Risk* denotes neighborhoods with no homicides risk in the sample period, *High Homicide Risk* neighborhoods with an expected average of 5 yearly homicides per square mile in the sample period.

A Appendix

Table A.1. Transactions per year: Within 1/8mi. and 3/8mi. of a Park

Year	Within 1/8mi. of a Park	Within 3/8mi. of a Park	Total
2,001	11,137	12,681	23,818
2,002	10,507	11,495	22,002
2,003	10,766	12,906	23,672
2,004	15,359	18,281	33,640
2,005	17,421	21,186	38,607
2,006	27,972	33,739	61,711
2,007	22,211	26,200	48,411
2,008	16,338	18,946	35,284
2,009	12,729	15,485	28,214
2,010	15,064	17,952	33,016
2,011	12,405	14,089	26,494
2,012	13,252	14,759	28,011
2,013	16,138	19,089	35,227
2,014	15,767	18,479	34,246
2,015	16,299	19,253	35,552
2,016	9,756	11,945	21,701

Notes: Sample includes transactions within 3/8 mi. of a park for Chicago (2001-2016), New York (2006-2016), and Philadelphia (2006-2016) from Zillow.

Table A.2. Park Premium and Homicide Risk: Distance to Park. 1/16 miles bins

	Dependent variable:		
	ln Price		
	(1)	(2)	(3)
Within 1/16mi. of a Park	0.024*	0.042**	0.042***
	(0.014)	(0.018)	(0.016)
Within 2/16mi. of a Park	0.007	0.018	0.018
	(0.012)	(0.016)	(0.013)
Within 3/16mi. of a Park	0.016	0.014	0.007
	(0.011)	(0.015)	(0.013)
Within 4/16mi. of a Park	−0.008	−0.010	−0.004
	(0.012)	(0.015)	(0.013)
Within 5/16mi. of a Park	−0.006	−0.005	−0.015
	(0.012)	(0.015)	(0.011)
Within 1/16 mi. * Homicide Risk		−0.014***	−0.010**
		(0.005)	(0.005)
Within 2/16mi. * Homicide Risk		−0.008*	−0.005
		(0.004)	(0.004)
Within 3/16mi. * Homicide Risk		0.001	0.001
		(0.004)	(0.004)
Within 4/16mi. * Homicide Risk		0.001	0.0003
		(0.004)	(0.004)
Within 5/16mi. * Homicide Risk		−0.0003	0.004
		(0.004)	(0.003)
Property Char.	Yes	Yes	Yes
Census Tract Controls	Yes	Yes	No
Tract FE	No	No	Yes
Neighborhood FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	529,606	529,606	529,606

Notes: Sample includes transactions within 3/8 mi. of a park for Chicago (2001-2016), New York (2006-2016), and Philadelphia (2006-2016) from Zillow. Dependent variable is log of sales price. Within 1/16 mi. (2/16 mi.) of Park is an indicator that takes one if the property is within 1/16 miles of a park. Within 2/16 miles of Park is an indicator that takes one if the property is between 1/16 miles and 2/16 miles of a park. Similar of the other variables. Our base are properties between 5/16 mi. and 6/16mi. of a park. *Homicide Risk* denotes the expected average number of homicides per squared mile in the neighborhood over the sample period. Standard errors clustered at the census tract level are in parenthesis.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table A.3. Park Premium and Homicide Risk: Base Results

	Dependent variable:			
	ln Price			
	(1)	(2)	(3)	(4)
Park	0.034**	0.049***	0.047***	0.038*
	(0.015)	(0.019)	(0.018)	(0.022)
Homicide Density	−0.012***	−0.002	−0.002	−0.003
	(0.005)	(0.006)	(0.006)	(0.006)
Park*Homicide Density		−0.028***	−0.028***	−0.019**
		(0.008)	(0.008)	(0.009)
Census Tract Controls	Yes	Yes	No	Yes
Tract FE	No	No	Yes	No
Observations	263,724	264,136	263,724	264,136

Notes: Sample includes transactions within 3/8 mi. of a park for Chicago (2001-2016), New York (2006-2016), and Philadelphia (2006-2015) from Zillow. Dependent variable is log of sales price, *Park* is an indicator for sales within 1/8 mi. of the park, *Homicide Density* denotes three year average number of homicides per squared mile in the neighborhood. All regression include controls for dwelling characteristics, neighborhood and year fixed effects. Standard errors clustered at the census tract level are in parenthesis

* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.