Unlocking Amenities: Estimating Public Good Complementarity

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Abstract

Public-good complementarities have important implications for economic valuation, but are understudied. We find that public safety and urban parks are powerful complements using detailed crime and housing data in Chicago, New York, and Philadelphia. Ignoring complementarities leads to i) undervaluing public goods; ii) inefficient investments in public capital in high-crime areas; iii) the (wrong) conclusion that public goods are a luxury; iv) overestimation of preference heterogeneity. Our results indicate that reducing crime near parks can turn them from public "bads" to goods. Reductions over the past two decades has "unlocked" $2.8 billion in taxable property value in our sample cities and has the potential to unlock another $8 billion.

Key words: public goods, complements, amenities, crime, environmental amenities, parks, urban development
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1 Introduction

Economic theory leans heavily on the concept that goods may be complements in consumption. While the joint demand of private goods 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 in markets, but only indirectly, such as through the housing market.[1] To the best of our knowledge, no study has estimated the joint demand for for public goods in a well-identified framework. This presents problems for optimal public investment decisions, since as we show below, the value of public goods may depend critically on complementary relationships.

In this paper, we study the complementary relationship between public safety and urban parks in Chicago, New York, and Philadelphia. Our hypothesis is intuitive: parks are less valuable when they are dangerous.[2] As crime rises, the value may fall to zero, or even become negative, to the point that they become "public bads." Our evidence supports this hypothesis. Greater safety is always valued, but urban parks are valuable only with a minimum of safety. Beyond this minimum, greater safety "unlocks" the value of parks. A corollary is that safety is more valuable near parks. Thus, merely displacing crime away from them may have social value. Indeed, reducing crime near parks or other public capital may be a boon to urban revival.[3]

Paying attention to public-good complementarity has important methodological implications. We highlight four. First, ignoring complementarities may bias estimates of the value of public goods. Indeed, we find a negative bias in the value of parks in a naive model that doesn't consider the complementarity between park access and public safety. Second, some public goods are more "primary" than others. Just as steak sauce is best consumed with steak, parks are best consumed with safety. This public-good "hierarchy" has important implications for environmental justice. It can be wasteful to equalize some

[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]The urban planning literature has indeed postulated that parks may be either an amenity or disamenity, depending on other factors (Weiss et al., 2011)

[3]For work on urban revival, see Baum-Snow and Hartley (2017) and Couture and Handbury (2017).

public goods (parks) without equalizing others (safety). Third, acknowledging complementarity can better reveal how demand depends on income. This arises in our setting, as low-income households tend to live in high-crime areas. Thus, modeling income, but not complementarity, will suggest that the poor value parks less: that parks are a luxury. In fact, our results indicate that low-income households in safe areas value parks as much as high-income households. Fourth, variation in willingness-to-pay for public goods may be due to differences in their endowments. Researchers often explain such variation with preferences that vary, sometimes in unobserved dimensions. Few consider interactions with either observed or unobserved endowments. Thus, variation due to public-good complementarity, may mistakenly be assigned to preference heterogeneity.

We apply three different estimation strategies. The first strategy uses cross-sectional variation (purged of time effects) to estimate the park premium and its interaction with local crime. This involves 1,337 neighborhood fixed effects (FE), expanding on similar research designs to control for unobserved neighborhood characteristics (Espey et al., 2001, Anderson and West, 2006). The second strategy takes advantage of the panel, incorporating changes in crime over time. This second strategy finds similar evidence of public good complementarity. Given that unobservables may affect both crime and the park premium, we develop a thrid strategy based on shift-share instrumental variables (IV). It makes use of widespread city-level crime reductions to instrument for local changes, based on the initial distribution of crime. This isolates local changes in crime that are independent of purely local causes.[4] While our preferred estimate makes use of property-level (hyper-local) changes in homicide risk, we also employ an alternate neighborhood-level (semi-local) measure of homicide risk to rule out the possibility that effects are driven by shifts in crime risk within neighborhoods.

This paper addresses two parallel, but mostly disparate, strands of research on hedonic valuation. The first estimates the value of spending on public safety through effects on housing prices. Oates (1969) began this literature, followed by Thaler (1978) and Gibbons

[4]This "shift-share" instrument may even be used for crime rates not interacted with parks. Indeed, IV estimates not only substantiate our hypotheses on amenity complementarities, but also provide plausible estimates on the value of crime reduction.

(2004).[5] A second 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 — although their reliance on cross-sectional data bring raise serious concerns over omitted variables.

In particular, two articles estimate the cross-sectional relationship between parks and crime and find opposite results. Anderson and West (2006) finds crime associated with higher values in Minneapolis, while Troy and Grove (2008) finds crime associated with lower values in Baltimore.[6] Both of these cross-sectional studies are subject to potential bias due to local unobservables, and are conducted in different cities, making it difficult to judge which is more believable. Bowes and Ihlanfeldt (2001) finds crime can affect property values near rail stations, another urban public good. To our knowledge, however, ours is the first analysis to formalize the study of public goods complementarity and, using that framework, the first to focus explicitly on the joint provision of public safety and environmental amenities.[7]

Our empirical analysis uses crime and housing data in Chicago, New York and Philadelphia from 2001 to 2016. In particular, we use 656,164 housing market transactions within a tight radius (3/8 (0.375) miles) around 1,337 parks, which we organize into park neighborhoods. From individual police reports, we match all reported crime incidents to these 1,337 neighborhoods, focusing on homicides. We calculate levels and changes in detailed crime density for park neighborhoods overall, as well as measures at the property level.

Our IV estimates indicate that improving safety near parks could potentially unlock up to $ 8 billion in value per year. Since the beginning of our sample period, crime reductions

[5] Recent studies address measurement error and omitted variables concerns to value 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).

[6] Anderson and West (2006) estimates this relationship with a sample of 24,000 housing transactions and the number of "serious crimes," which includes thefts and assaults. Troy and Grove (2008) utilizes 16,000 transactions. They use a measure of the incidence of robbery and rape. The paper states: "Murder was not chosen because the numbers of these crimes are small," which is true for a single year. They dismiss the use of assaults asserting that these are often indoors and related to domestic violence.

[7] This is not, by any means, the first study to posit the importance of public safety for parks. Anderson and West (2006) and Troy and Grove (2008) are good examples of empirical research that examines crime and open space. Indeed, Troy and Grove (2008) discusses some elements of the complementarity such as a threshold of public safety that is necessary for positive valuation of urban parks.

have already unlocked \$2.8 billion. Targeted investments in public safety through park design, "Hot Spot Policing," or other methods could unlock this value simply by displacing this crime to less public areas.[8]

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, panel, 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.

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. The important difference is that local public goods are bought indirectly through location choices. This intuition is developed in the model below.

Preferences are represented by a Cobb-Douglas function: the utility of person i in location j is $U_{ij} = Q_{ij} h^{\alpha} x^{1-\alpha}$, where h is the quantity of the housing good consumed, with price P_j, x is a numeraire good, and $\alpha \in (0, 1)$ is a fixed parameter. Q_{ij} gives the value of location j to person i, which is log-linear in interacted amenities:

$$\ln Q_{ij} = \left(\theta^E + \theta^{ES} S_j\right) E_j + \theta^S S_j + \ln \xi_j + \epsilon_{ij} \tag{1}$$

where E_j denotes the environmental amenity, S_j denotes public safety, and ξ_j other

[8] A discussion of hot spot policing can be found here: https://www.nij.gov/topics/law-enforcement/strategies/hot-spot-policing/Pages/welcome.aspx. This displacement potentially be achieved in a distributionally neutral fashion, i.e. without helping the rich at the expense of the poor. There is an active discussion among urban designers and planners regarding the best approaches for reducing crime in and around parks. While our data on parks are not sufficiently detailed to evaluate the value of design choices, our results suggest that the benefits from effective strategies could be considerable – perhaps larger than is currently understood in analyses that do not consider or properly evaluate the complementarity that we identify in this paper.

commonly-valued amenities. The parameter ϵ_{ij} is an idiosyncratic taste shock for the neighborhood.

The parameters $\theta^E > 0$ and $\theta^S > 0$ describe the base elasticities of willingness-to-pay for the environmental amenity and safety, respectively. The parameter $\theta^{ES} \geq 0$ describes the interaction: how the elasticity for the environmental elasticity changes with safety. Alternatively, these terms may be arranged as $\left(\theta^S + \theta^{ES} E_j\right) S_j + \theta^E E_j$ to describe how the value of safety rises when the environmental amenity is higher. This implies that safety is worth more in some areas than in others. Mathematically, it is clearer to separate out the interaction $\left(\theta^{ES} E_j \times S_j\right)$.[9]

Our methodology involves creating a safety index based on an inverse measure of crime H_j. Normalizing units, we write $S_j = \bar{S} - H_j + a_j$, where $H_j \geq 0$, $\bar{S}$ is the top level of safety, and a_j is a measurement error term. The coefficient on crime then has the opposite sign, as does the interaction, i.e., $\tilde{\theta}^H = -\theta^S$, and $\tilde{\theta}^{EH} = -\theta^{ES}$, while the base elasticity for the environmental amenity now corresponds to the safest area: $\tilde{\theta}^{EH} = \theta^{ES}\bar{S} + \theta^E$. Measurement error is pushed into the unobserved amenity term $\tilde{\xi}_j = \xi_j + \left(\theta^S + \theta^{ES} E_j\right) a_j$.

Taking these shifts into account, the indirect utility function is given by:

$$\ln V_{ij} = -\alpha \ln P_j + \left(\tilde{\theta}_j^E + \tilde{\theta}^{EH} H_j\right) E_j + \tilde{\theta}^H H_j + \tilde{\xi}_j + \epsilon_{ij}$$

Solving for the price, it is natural to separate out the interation.

$$\begin{aligned} \ln P_j &= \frac{\theta_j^E}{\alpha} E_j + \frac{\theta^H}{\alpha} H_j + \frac{\theta^{EH}}{\alpha}\left(E_j \times S_j\right) + \frac{\xi_j + \epsilon_{ij} - \ln V_{ij}}{\alpha} \\ &\equiv \pi^E E_j + \pi^H H_j + \pi^{EH}\left(E_j \times S_j\right) + \xi_j^* + e_{ij} \end{aligned} \tag{2}$$

where $\pi^k = \tilde{\theta}^k/\alpha, k \in \{E, H, EH\}$, $\xi_j^* = \tilde{\xi}_j/\alpha$, and $e_{ij} = \left(\epsilon_{ij} - \ln V_{ij}\right)/\alpha$. This specification predicts that $\pi^E > 0$, $\pi^H < 0$, and if environment and safety are complementary, $\pi^{EH} < 0$.

[9] Note that, strictly speaking, in a Cobb-Douglas formulation, the marginal value of one amenity increases with respect to the other even without the interaction. But this is not due to any kind of complementarity. Focusing on the elasticity of the value makes the complementary relationship more plain. Complementary amenities are also implied by the canonical Tinbergen model, described in Bartik and Smith (1987) and Ekeland et al. (2004), even though they have only rarely been estimated.

This linear model also predicts that at a certain level of crime, the environmental amenity is "locked" when crime is

$$H_j = -\frac{\pi^E}{\pi^{EH}} = \frac{\theta^E}{\theta^{ES}} \tag{3}$$

At higher levels of crime, the environmental amenity lowers welfare, making it a public bad. Households will pay to live away from it.

3 Data and Descriptive Statistics

We combine data on housing market transactions, crime reports, and neighborhood characteristics for Chicago, New York, and Philadelphia. Our choice of cities is set mainly by the availability of incident-level crime data. For Chicago, our data cover 2001-2016; for New York and Philadelphia, 2006-2016. Housing transaction prices and structural characteristics come from Zillow. We match each house with data on the socio-economic composition of residents living in the Census Block and Block Group from the 2000 and 2010 Censuses, complemented with the 2011-15 American Community Survey. In addition, we use these block and block group level data for benefit calculations and socio-economic changes below.

Parks are defined in 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."[10] The data contain the timing and location of all housing transactions recorded within 3/8 (0.375) miles of 1,337 geo-coded urban parks in all three cities.[11] For concreteness and consistency with empirical evidence presented below, we refer to the 3/8 miles radius around a park as a park's "neighborhood." Our final data comprises 656,164 housing transactions surrounding parks. Table 1 presents basic descriptive statis-

[10]See https://wiki.openstreetmap.org/wiki/Key:leisure
[11]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.

tics and Figure 1 illustrates the number and categorization of housing transactions near Marquette Park in Chicago as an example, and Figures A.1, A.2 and A.3 illustrates our housing transaction data set.

Our safety measure is based on crime reports. These data come from police departments in each city, provided by the Open Data Portal.[12] We use these geo-located reports to calculate crime density maps for every city and year in the study period.

For clarity and comparability, we focus our primary analysis on homicide risk. Prior research suggests that property and other types of crime act as proxies for neighborhoods amenities and wealth, in addition to measuring crime risk. Thus, we put less stock on exercises based on the full set of crime risk, though they are reported in the appendix.[13] We use "crime" and "homicides" interchangeably to refer to safety risk throughout.

Figure 2 illustrates the estimated homicide density for Chicago. Darker-shaded areas indicate higher likelihood of a homicide. To estimate the density we use information on homicides for the previous three years and a bivariate Gaussian kernel with a bandwidth of 2/8 of a mile on a 1/8 mile city grid. A three-year rolling window smooths out short-term fluctuations in homicides at a particular location. The narrow bandwidth and grid allows for rather fine distinctions in crime rates even within neighborhoods. Taking into account the total number of homicides in the city (H_t), we obtain the following measure of homicide risk:

$$Homicide\,Risk = E(H_{lt}) = p_{lt}H_t \tag{4}$$

[12]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. Philadelphia crime incidents come from the Philadelphia Police Department and are available through Open Data Philly at https://goo.gl/gYR96r

[13]Prior research illustrates substantial heterogeneity in the perception and valuation of different types of crime and ambiguous effects of property crimes on housing prices, for example Thaler (1978) finds that property crimes reduce housing prices but Gibbons (2004) finds no effect of burglaries. Ihlanfeldt and Mayock (2010) point to the drawback of using total crimes as a crime risk measure. Using total crime gives implicitly the same weight to all crimes, putting too much weight on low-value crimes. We use willingness-to-pay estimates from Chalfin and McCrary (2017) to construct a unitary measure of homicide-equivalents. Homicide risk appears to provide a better signal of what areas are truly dangerous. Still, the results reported in Tables A.1 and A.2 are robust to this measure.

where p_{lt} is the estimated probability of homicide at location l in year t. Homicide risk is defined as the expected number of homicides per square mile in year t at location l, $E(H_{lt}) = H^e_{lt}$.[14]

To estimate how prices vary with crime risk, we match each dwelling to the homicide risk for that precise address. Figure A.4 shows the ratio of the homicide risk near a park (within 1/8 of a mile) with respect to the rest of the neighborhood (beyond 1/8 but within 3/8 of a mile). Most neighborhoods have a fairly low density of homicide risk: less than 2 per year per square mile. In these neighborhoods, the ratio is close to one, with most neighborhoods having a fairly low density. On average, the crime near parks versus away from parks is roughly the same, if not slightly lower. In more dangerous more dangerous neighborhoods, crime becomes slightly worse near parks.

Figure 3 plots homicide rates trends for each of the cities during the study period. All of the three cities have experienced substantial (>30%) declines in homicide rates during the study period (with the exception of Chicago in 2016). However, declines within cities were not uniform, as some locations experienced increases in risk. We classify park neighborhoods into three groups, according to whether they experienced a i) decrease, ii) increase, iii) (virtually) no change in homicide risk.[15]

4 Identifying Public Good Complements

We consider a sequence of three estimators to obtain the value of the park-safety complementarity. Each exploits a different source of variation. The first uses cross-sectional differences in homicide risk. The second brings in the time variation of homicide risk in our panel. The third uses an instruments those changes over time using city-level changes in crime rates, abstracting away from dynamics of crime reductions across neighborhoods. We then provide additional evidence on the park-safety complementarity by comparing

[14]We also try different weighting schemes to construct our Homicide Risk measure. Results are robust to alternative ways of constructing our Homicide Risk measure.

[15]If the park neighborhood experienced an average yearly reduction of 1% in expected homicides per mi^2 during the study period, we classify them as having experienced a decrease in homicide risk, on the other hand if the park neighborhood experienced an increase above 1% we clasify them as having experienced an increase in homicide risk

effects for large versus small parks.

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

We first consider how the "park premium" varies from low to high-crime neighborhoods using the linear model from 2. This resembles the prior literature (Espey et al., 2001, Anderson and West, 2006), by controlling for time-invariant unobservables, except that our sample is much larger, using 1,337 neighborhood fixed effects. We estimate the park premium using price variation from 1/16 (0.0625) mile-wide indicators for the distance from a house to its neighborhood park. As depicted in Figure 1, each 1/16 mile interval often corresponds to a city block, $I_k \equiv I\left[(1/16) \times k \leq d^j_{il} < (1/16) \times (k+1)\right]$ where d^j_{il} is the distance between each house i in location l to the closest neighborhood park j.[16] A house within a block may have a view. Within two blocks, the park is still rather close, and within earshot of loud sounds, such as gunfire.

To estimate public-good complementarity using The distance bins are interacted with homicide risk in the neighborhood. The regression equation for P^{jc}_{it}, the sales price of house i in neighborhood j, city c, year t, is given by:

$$\ln P^{jc}_{it} = \pi^{H^e}_i + \sum_{k=0}^{6} \pi^E_k I_k + \sum_{k=0}^{6} \pi^{EH}_k I_k \times H^e_i + \beta D_i + \theta N_{it} + \gamma_j + \delta^c_t + u_{it} \tag{5}$$

H^e_i is homicide risk measured by the expected number of homicides per year per square mile over the *entire* sample period immediately around property i. Alternatively we may instead use H^e_j, which is in the average crime rate for the entire neighborhood j.[17] D_i is a vector of (potentially time-varying) dwelling characteristics and N_{it} are time varying block level socio-economic controls.[18] γ^j is the park-neighborhood fixed effect

[16] In Chicago, most blocks are 1/16 of a mile in length, although many East-West blocks are 1/8 of a mile. In New York, many blocks are approximately 1/2 of a mile north-to-south, and often up to 1/7 of a mile, east-to-west. Central Philadelphia blocks are about 1/13 of a mile.

[17] We estimate homicide risk as described in eq. (4) but considering the entire sample period. That is densities are estimated using all years and combined with the total number of homicides experienced in the city on those years. Since we have different sample lengths for the three cities we normalize everything as an yearly average.

[18] Dwelling characteristics include: log distance to the CBD, age of the dwelling, square footage, number of bedrooms and bathrooms, and dwelling type (i.e. Single Family Residence, Condo). Socio-economic

that controls for the fixed unobservables shared within a neighborhood. δ_t^c a fixed effect for city by transaction year to control for city-specific trends. u_{it} is an error term.

Table 2 reports estimates from equation (5), documenting changes in the park premium for the distance intervals. The reference category in this specification is the most distant interval, which is between 5 and 6 16ths of a mile away. All of the regressions include 1,337 neighborhood fixed effects. Column 1 reports estimates from a specification that ignores the interaction between park access and homicide risk, which the others include. Columns 1, 3, and 5 contain socio-economic controls that vary at the block level, and vary over time. Column 2 alternatively omits these controls. Column 4 instead uses census tract fixed effects, on top of the less geographically detailed neighborhood fixed effects.

The estimates presented in all models suggest a large premium within the first interval of distance from a park. This premium disappears rather rapidly with distance from the park, particularly when the block-level time-varying controls are added.[19] These negative interaction terms in columns 2 through 4 for the closest bin all support the hypothesis that the value of park proximity falls in more dangerous areas. This evidence suggests a substantial park premium in safe neighborhoods that shifts to negative in dangerous areas. A comparison of the estimates between Column (1) and Column (3) also indicates that failure to account for the complementarity between crime and park access results in substantial downward bias (nearly 30%) in the estimated park premium – the estimated park premium within 1/16 of a mile is 4.5% in a model that captures the complementarity versus 3.2% in the same model that omits it.[20] This cross-sectional evidence is of course limited, however, since unobserved dwelling and neighborhood characteristics (including

controls include census block and block group socio-economic variables linearly interpolated yearly from the 2000 and 2010 Censuses, and the 2011-2015 ACS: population density, proportion of whites, proportion of blacks, proportion of hispanics, and proportion of other races, proportion of vacant housing units and of rented units at the block level; and median age and median income at the block group level.

[19] Point estimates in this specification decline rapidly and are not statistically significant after the first interval, which offer a close approximation to properties within the first block of a park. However, we note the overall pattern of declining price effects and that the relatively small bandwidth used in this specification (which offer a close approximation to neighborhood blocks) likely affects the precision in the estimates at each interval of distance in this model. For comparison, Bayer et al. (2007) uses bins of 0.1 and 0.2 miles

[20] Note that bias arising from the omission of the complementarity is distinct from omitted variable bias – both models control for the effect of homicide risk in isolation.

homicide risk) may be strongly correlated with park proximity. Nevertheless, the results provide an important point of departure for considering how park premia change with neighborhood-wide levels in safety.

Given the assumption that crime risk is exogenous, the estimates suggest that a homicide risk of 2 per year per square mile would eliminate the park premium for the closest bin altogether. This "locking" effect appears to occur for the second bin as well, possibly more quickly. Figure 4 presents the results in graphical form, using fitted estimates of the park premium based on estimates from Model 5 and fitted values for 0 and 4 expected homicides per year per square mile.[21] The graph illustrates a 4.5% premium for locations within 1/16 miles of a park in low homicide risk neighborhoods (with zero homicides). However, in high-homicide locations neighborhoods (with an expected homicides per year of 4 or more per square mile), there is instead a park discount of 7.8%.

4.2 How Park Premia Vary by Safety Level with Time Variation

In this section, we go beyond the existing empirical literature and consider how prices change over time with changes in crime levels. The main difference to our specification is that we allow homicide risk to change with the year t, either at the property level, H^e_{it}, or at the neighborhood level, H^e_{jt}. To simplify the exposition, we also use a single proximity indicator, for 1/8 of a mile or less. This yields the following estimating equation:

$$\ln P^{jc}_{it} = \pi^E \text{Park}^i + \pi^H H^e_{it} + \pi^{EH} \text{Park}^i \times H^e_{it} + \beta D_i + \theta N_{it} + \gamma_j + \delta^c_t + u_{it} \qquad (6)$$

This equation differs from 5 in that it relies on time variation in homicide risk, given by H^e_{it}.

Columns (1) and (2) of Table 3 report estimates from model 6. Consistent with the results presented in Table 2, these estimates indicate that without accounting of the interaction between parks and safety one may estimate a weaker park premium. However, once the interaction is accounted for, homes in close proximity to an urban park sell at

[21] Among the most dangerous areas in our sample are those surrounding Garfield Park in Chicago's west side, Jackie Robinson Park in the Bronx (NY) and McPherson Square in Philadelphia.

a premium ($\pi^E > 0$) of 2.5 to 2.9 percentage points relative to homes further away from the the same park.[22]

More importantly, the results in Table 3 imply that the value of park proximity declines with crime risk, $\pi^{EH} < 0$. An increase in homicide risk reduces the value of homes within 1/8 miles of a park by .5 - 1.3 percentage points relative to a home within 3/8 miles of the same park. With high enough homicide risk, $H_{it}^j > -\pi^E/\pi^{EH} \approx 3.25(1.26)$, the park premium becomes negative. Column 5 allows for a quadratic in homicide risk. It does provide some evidence that the marginal cost of additional homicide risk is diminishing. Nevertheless, the interaction term is similar to column 3. This implies that it does not result from non-linearities in values lost from homicide risk.

4.3 Property-Level versus Neighborhood-Level Homicide Risk

The property-level measure of crime risk used above, H_{it}^e, utilizes variation both within-neighborhood and time variation to identify the interaction term. We next evaluate these results using a single, neighborhood-level measure of homicide risk H_{jt}^e. With this specification, estimates are based solely from variation within neighborhoods across time. By purging the model of variation within neighborhoods, this model tests the possibility that difference presented above are driven exclusively by variation within-neighborhoods as entire neighborhoods become safer or more dangerous. Table 4 reports these estimates. The interaction effects in these models indicate similar estimates when effects are evaluated at the neighborhood-level, though the estimates are smaller than our preferred estimates with H_{it}^e. This is not surprising given that neighborhood homicide risk may not capture homicide risk between a property and the park particularly well, and thus is measured with error. Nevertheless, the fact that the effect persists despite using this much coarser geography of crime risk implies that evidence of public good complementarity appears even when sub-neighborhood crime effects are completely smoothed away. This means that the effects of parks on crime should not invalidate our estimate; rather the estimates

[22]These estimates for the park proximity premium are smaller than the 4.5% estimate reported in 2, though the treated group in this model includes the transactions within 1/8 miles of a park rather than 1/16 miles.

are influenced by the effect of crime on parks, as we want them to.

4.4 Instrumenting Crime Changes with City-Level Shifts

The estimates provided in Table 3 are identified using variation in reductions (or increases) in crime risk over time, suggesting that reductions in crime risk within a neighborhood are associated with changes in the park premium. The interpretation of these estimates as the causal effect of reductions in crime risk on the amenity value of parks still involves a somewhat restrictive set of assumptions. A threat to our 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.[23]

Another strategy for estimating the complementarity between safety an open space is to use an instrumental variable for local crime in Equation 6. 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 changes in crime at any given location can be decomposed into overall changes in crime at the city level and in the geographic distribution of crime. The evidence that motivates the shift-share instrument in this empirical setting comes directly from Figure 3 – much of the variation in crime risk for any given transaction in our sample can be attributed to substantial declines in aggregate homicide rates in these cities during our study period.

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

[23]These estimates also rely upon the functional form that we have defined for the amenity value of parks as a function of distance. We also check for non-linearities using a quadratic term, to make sure that par park premia are not driven by non-linearities. Fortunately, that is supported by evidence from estimates from Model 5 shown in Column (5) of Table 3 and in Figure A.5.

to the estimated density using the first two years of the sample as a base period.[24] Denoting the total annual homicides in a city in year t as H_t, the probability of a homicide in location l in year t is p_{lt}. Using a base time period, normalized to $t = 0$, the predicted expected number of homicides at each location i is

$$H_{lt}^{iv} = p_{l0} H_t \tag{7}$$

Locations with a higher risk of homicides at the beginning of the period will have similar 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 associated with city level changes are unrelated to local neighborhood dynamics that determine crime and housing prices.[25] Furthermore, since urban parks are pre-determined geographically, the interaction of H_{lt}^{iv} with the park proximity indicator, $I\left[d_i^j \leq \frac{1}{8}\right]$ should also be valid. The instruments' validity is likely made stronger by the conditioning variables, including the neighborhood socio-economic characteristics.

Consistent with the trends illustrated in Figure 3, the first stage results of the IV regression in Table 5 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 increase in homicide risk.

Table 6 reports estimates from our preferred IV specification alongside comparable DD estimates.[26][27] The IV estimates suggest a stronger negative direct effect of homicides on property values, $\pi^H < 0$. Our results show that an increase in homicide risk by 1 reduces housing values by 1.2 percent in the uninteracted model that omits the complementarity, and 1.9 percent in the interacted model that identifies it. Consistent with results from

[24]We use homicide data for 2001-2002 for Chicago, and 2006-2007 for NY and Philadelphia as our base period.

[25]For example, nearby housing demolitions may have had an impact on crime (Aliprantis and Hartley, 2015) as well as on housing prices (Diamond and McQuade, 2016). The change in housing prices may not only be assoicated with crime.

[26]DD estimates in this model are constrained to the period and sample that we use for the IV. Since we use the first two years of the sample to estimate our instrument we discard those from our estimation, constraining our data for the years 2003-2016 for Chicago, 2008-2016 for New York and Philadelphia. This results in our sample being reduced from 656,164 to 521,945 observation

[27]As a robustness check, we drop 2016 to isolate the spike in homicides in Chicago in that year. Results reported in Table A.3 remain unchanged

all prior models, there is no evidence of a premium for park access in specifications that omit the complementarity. Moreover, the estimate of the interaction between park and homicide risk becomes more negative in the IV specification, with $\pi^{EH} \approx 1\%$. 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 $\pi^{E} \approx 2.6\%$. As a result, the homicide level at which park value is unlocked is slightly lower at $-\pi^{E}/\pi^{EH} \approx 2.6$ (1.06).

4.5 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 0.39 square miles ($\sim$ 250 acres). Table 7, which presents results for the both the uninteracted and interacted model, indicates that there is 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 find a negative, if commensurately smaller, estimate for small parks. This finding lends greater confidence in our interpretation that the park premia associated with 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 in the prior section 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 2.5-2.9 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.[28] Using the number of units, the median property value, and our estimates from Table 6 column (5), we estimate the value of parks for each city.

Table 8 shows the estimated park values, which total \$11.3 billion. Parks in Chicago are valued at around \$3.8 billion; in New York, \$6.9 billion; Philadelphia, \$0.5 billion. While the value of urban parks is large overall, our estimates also indicate that the local amenity benefits from parks are dominated by disamenity from crime risk. As defined above, our estimates indicate an average park premium of 2.6% that falls by 1.0 percentage point per increase in annual homicide risk. An actual reduction in homicide risk should result in a 1.6 percentage point increase in the price of a house away from a park, and 2.6 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 1% of value of housing within 1/8 of a mile near parks. Spillover effects for those further from the parks might make this number even higher.

Estimates from Table 8 illustrate that the majority of the value of neighborhood parks in our sample of cities is concentrated in neighborhoods with at low homicide risk (less than one expected homicide by year). However, our estimates in Panel (b) indicate that the most of the amenity value in neighborhoods at medium homicide rates (between one and 3 expected homicides per year) is locked in by crime risk: this value sums to \$3.5 billion: \$1.1 billion in Chicago, \$2.3 billion in New York, and \$179 million

[28] We calculate the area of the block group that is within 1/8 miles of a park to compute the proportion of housing units in each census block group affected by the premium.

in Philadelphia. Again, this could be achieved ostensibly by displacing crime from zones immediately surrounding parks, rather than eliminating it altogether.

The estimates in Panel (c) reveal that accounting for the complementarity between public safety and park amenities can dramatically affect how we assess the value of parks. Both IV and DD estimates that ignore the interaction of crime and parks (Table 6, columns 1 and 3) imply a much lower park premium of 1.3%. This mis-specified model produces an estimate of $4.8 billion for the parks in our sample, underestimating the total value in our sample by approximately 60%.

Table 9 reports estimates of changes in neighborhood park value that have already resulted from reductions or increases in annual homicide risk during the study period. Estimates in Panel A show that substantial value is concentrated in neighborhoods that experienced reductions in homicide risk and estimates in Panel B show that these reductions in homicide rates have unlocked considerable amenity value: $2.5 billion in Chicago, by $5.9 billion in New York, and $101 million in Philadelphia. Increases in homicide rates in other neighborhoods have resulted in simultaneous reductions in the amenity value of parks, totaling $5.7 billion during the study period: $2.1 billion in Chicago, $3 billion in New York, and $575 million in Philadelphia. These results indicate that attention to public goods complementaries can be important for understanding the distributional implications of programs that are designed to affect one, perhaps with little regard for the other.

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 in this analysis, 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.

Our estimates imply that fully accounting for complementarity effects parks are valued at \$3.8 billion; \$6.9 billion, and \$0.5 billion, in Chicago, New York, and Philadelphia, respectively. At the same time, park maintenance and programs, the City of Chicago annually spends \$323 million on parks; New York spends \$342 million, and Philadelphia, \$54 million. 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, the value of park proximity alone would be enough to fund cash expenditures on parks, possibly through a land tax on properties within 1/8 miles. 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 1/8 miles 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. It must be noted that this could be the value of simply *displacing* crime to zones where crime risk does not interact with the parks (ie. outside a 1/8 mile from a park), though this strategy would be problematic if it failed to account for interactions between crime risk and other public goods.

We further note that careful attention must be paid to the overall needs and concerns of neighborhoods that may be adversely affected by crime displacement. If the IV estimates on crime reduction from the main effect are taken seriously, eliminating crime would likely produce much larger increases in value. 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 10 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 demonstrate that accounting for this interaction boosts the premium for low income neighborhoods.

The conflation bias illustrated by the comparison in Table 10 has important implications for considering the distributional effects of expenditures that are justified on the basis of hedonic estimates or any mental model of a policy maker who 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 their assumed or estimated, failure to understand this complementary relationship result in a tendency invest disproportionately in environmental public goods in higher income neighborhoods/populations.

Since prices in this model are 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.

5.4 Socio-Economic Changes

We note that one of the channels through which improvements in neighborhood safety can become capitalized in house prices is by inducing socio-economic changes in a neighborhood. As safety improves, more affluent households may reallocate near urban parks, which in turn may bid up housing prices. Understanding this channel is important for understanding the distributional implications of the unlocking effect as well as interpreting the relationship between the observed capitalization effect and willingness to pay for these complementary public goods. We assess how socio-economic characteristics change with open spaces and homicide risk, estimating the following equation:

$$y_{it}^{j} = \pi^{E}\text{Park}^{i} + \pi^{H}H_{lt}^{e} + \pi^{EH}\text{Park}^{i} \times H_{lt}^{e} + \gamma_{j} + \delta_{t}^{c} + u_{it} \tag{8}$$

y_{it}^{j} measures a demographic characteristics in block (or block group) i in year t, the RHS terms are those described in eq. (6).[29]

Table 11 reports the results of model 8. Estimates in *Panel A* columns (1) and (2) suggest no statistical effect of park safety on the density of the population, but columns (3)-(10) suggest a small effect on the racial composition of households living in census blocks near parks. In particular, these results suggest that increases in park safety result in small (.3%) increases in the share of white households and small (-.2%) reductions in the share of black households living near parks. While small in magnitude, these changes do suggest that increases in parks safety are contemporaneous with shifts in neighborhood composition.

In Table A.4 we utilize the base model in equation 6 to assess the robustness of our results to these compositional changes. In particular, results reported in Table A.4 test

[29] Our measures of demographic characteristics are annualized by interpolating the matched census blocks and block groups from the 2000, 2010 census, and the 2011-15 ACS. Population and population-by-race are obtained at the block level whereas median income and median age at the block group level, which is the finest geography at which they are available.

for heterogeneity in our main effect in blocks that have experienced any between-census increase in the proportion of white households, which represents approximately half of the sample. For comparison, column (3) reports our primary IV results and (4) adds the interaction representing census blocks where we observe an increase in the share of white households. The estimates suggest that main results are not driven by changes in demographics. Table A.5 replicates the test using socio-economic status, using census block groups where households experienced increases in median income. This test suggests that our main estimates are robust to differences in neighborhood-level income growth. Overall, these results indicate that changes in park safety have been accompanied by modest shifts in the composition of neighborhoods that do not appear to play a strong role in determining the value of unlocked safety.

6 Conclusion

This study demonstrates the importance of complementarity in public goods, beginning with the basic insight that accounting for such these interactions can have important implications for how we understand preferences and allocate public expenditures. We provide concrete evidence by focusing on the empirical relationship between public safety and city parks, which is a particularly compelling setting where the level of provision for one public good (public safety) can determine not only the magnitude but even the valence of its complement. Indeed, we find that parks in insecure neighborhoods can be a public bad for local residents. This finding is 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 by our results is that in these communities, a deficit in public safety has locked-in the value of leisure-producing environmental amenities. In particular, we find that homes in neighborhoods with safe public parks sell at a premium of 2.5 - 2.7 percent, but that the amenity value of parks declines and then becomes negative at high enough homicide rates. In our sample, the value of parks is becomes fully locked-in at 2.7 predicted homicides per year.

We show that a naive model of value for city parks that might be identified using exogenous variation but fail to account for the public safety complementarity will assign a zero value to the full sample of parks in our sample. Such a model would also suggest that parks are valued far less in low income neighborhoods. In a more complete model, we show that safe open spaces appear to be valued equally in both low and high-income communities in the same sample. Policy-makers, economists, and urban planners who ignore complementarities might falsely conclude that environmental amenities low-income residents get very little value from their neighborhood parks. Economists who are modeling preference heterogeneity might assume that residents' preferences for environmental amenities are lower in less secure areas, possibly rationalizing it through an under-explained sorting behavior.

Finally, our quantitative estimates imply that the overall public value of open space may be underestimated through naive estimators. Furthermore, the potential value of existing open spaces may be much greater when they are unlocked. Our estimates indicate that (1) public safety improvements (including displacement efforts) in zones near existing parks in these three cities alone has the potential to unlock $7.8 billion of amenity value and (2) this represents a large share of the total amenity value ($10.5 billion) conferred by the parks. Equally important is the observation that this relationship cuts both ways: spikes in violent crime or its redistribution to zones near parks, as observed in Chicago in 2016, can *lock amenity value in.* Public safety is therefore a first-order concern in considering the value of leisure-producing environmental amenities such as open space. 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 on Parks and their Neighborhoods

	Chicago	New York	Philadelphia	Sample
Panel A: Park characteristics and Homicide Risk				
Number of parks examined	571	646	120	1,337
Average park size (square miles)	0.03	0.05	0.10	0.04
Average park-neighborhood size (square miles)	0.64	0.74	0.92	0.71
Average Neigh. Homicide risk (per square mile per year)	1.65	1.47	1.39	1.26
Panel B: Property Transactions				
Properties sold within 1/8 mile	143,146	154,981	11,462	309,589
Properties sold from 1/8 to 3/8 mile	170,474	159,825	18,276	348,575
Average log price within 1/8 mile	12.43	13.37	12.42	12.91
Average log price between 1/8 and 3/8 mile	12.39	13.24	12.22	12.76
Log distance to Central Business District	1.8	1.6	1.4	1.7
Age of Structure	64.6	62.6	72.9	64.1
Square footage	1,456.6	1,678.8	1,437.6	1,579.3
Number of Bedrooms	3.0	1.7	2.8	2.6
Number of Bathrooms	1.4	1.3	1.3	1.4
Single Family Residence fraction	0.20	0.10	0.02	0.32
Condo fraction	0.28	0.38	0.02	0.68
Panel C: Socio-Economic Characteristics				
Population Density	40.8	92.1	34.7	65.1
White fraction	0.52	0.60	0.62	0.56
Black fraction	0.19	0.08	0.18	0.14
Hispanic fraction	0.19	0.13	0.06	0.15
Median Income	34.8	39.5	35.9	37.1
Median Age	68.5	91.5	55.1	78.9
Vacant fraction	0.09	0.11	0.09	0.10
Renter fraction	0.35	0.42	0.34	0.38

Notes: Sample includes transactions within 3/8 of a mile of a park in Chicago (2001-2016), New York (2006-2016), and Philadelphia (2006-2016) from Zillow. Park-neighborhood refers to the 3/8 miles radius around a park.

Table 2. Park Premium and Homicide Risk: Cross-Sectional Estimator across 1,337 Neighborhoods with Flexible Park Proximity Indicators

	Dependent variable: ln *Housing Transaction Price*			
Homicide Risk Level	Property			
Amenity Interaction	No	Yes		
Controls	Time-Varying Controls	Neigh. Fixed Effects	Time-Varying Controls	Tract Fixed Effects
	(1)	(2)	(3)	(4)
Within 1/16 mile of a Park	0.032**	0.058***	0.045***	0.052***
	(0.014)	(0.017)	(0.017)	(0.016)
Within 2/16 mile of a Park	0.002	0.019	0.006	0.019
	(0.012)	(0.015)	(0.015)	(0.013)
Within 3/16 mile of a Park	0.005	0.016	0.003	0.010
	(0.012)	(0.015)	(0.014)	(0.013)
Within 4/16 mile of a Park	−0.012	−0.009	−0.017	0.0003
	(0.012)	(0.015)	(0.014)	(0.013)
Within 5/16 mile of a Park	−0.001	−0.001	−0.006	−0.006
	(0.012)	(0.015)	(0.014)	(0.011)
Within 1/16 mile × Homicide Risk		−0.054***	−0.031***	−0.043***
		(0.006)	(0.006)	(0.007)
Within 2/16 mile × Homicide Risk		−0.046***	−0.023***	−0.037***
		(0.006)	(0.005)	(0.007)
Within 3/16 mile × Homicide Risk		−0.040***	−0.017***	−0.032***
		(0.005)	(0.005)	(0.006)
Within 4/16 mile × Homicide Risk		−0.037***	−0.016***	−0.031***
		(0.005)	(0.005)	(0.007)
Within 5/16 mile × Homicide Risk		−0.036***	−0.015***	−0.030***
		(0.005)	(0.004)	(0.006)
Within 6/16 mile × Homicide Risk		−0.036***	−0.019***	−0.032***
		(0.004)	(0.004)	(0.006)
Park-Neighborhood Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Dwelling Characteristics	Yes	Yes	Yes	Yes
Time-Var Socio-Economic Controls	Yes		Yes	
Census Tract Fixed Effects				Yes
Observations	656,841	656,841	656,841	656,841

Notes: Sample includes transactions within 3/8 mile of a park for Chicago (2001-2016), New York (2006-2016), and Philadelphia (2006-2016) from Zillow. Dependent variable is ln *Housing Transaction Price*. Distance indicators are exclusive, e.g., "Within 2/16 miles of Park" is one if the property is between 1/16 miles and 2/16 miles of a park The reference category in this specification is the most distant interval, which is between 5 and 6 16ths of a mile away. *Homicide Risk* denotes the expected number of homicides per year per square mile measured at the *Property level*. Dwelling characteristics include: log distance to the CBD, age of the dwelling and its square, square footage, number of bedrooms and bathrooms, and dwelling type (i.e. Single Family Residence, Condo). Specifications also include dummies for dwelling with missing characteristics. Results are robust to restricting the sample to dwellings with complete data. Socio-economic controls include census block and block group socio-economic variables linearly interpolated yearly from the 2000 and 2010 Censuses, and the 2011-2015 ACS: population density, proportion of whites, proportion of blacks, proportion of hispanics, and proportion of other races, proportion of vacant housing units and of rented units at the block level; and median age and median income at the block group level. Park-neighborhood refers to the 3/8 miles radius around a park. Standard errors clustered at the census tract level are in parentheses.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 3. Park Premium and Homicide Risk:
Pooled Panel Estimator across 1,337 Neighborhoods over Time

	Dependent variable: ln *Housing Transaction Price*				
	No Inter-action - like (3)	Neigh. Fixed Effects	+ Time-Varying Controls	+ Tract Fixed Effects	Quadratic Homicide Risk
	(1)	(2)	(3)	(4)	(5)
Park Proximity (within 1/8 mi.)	0.015*	0.028***	0.025***	0.025***	0.029***
	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)
Homicide Risk	−0.010***	−0.015***	−0.007***	−0.011***	−0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Homicide Risk Squared					0.0001
					(0.0002)
Park Proximity × Homicide Risk		−0.008***	−0.007***	−0.005**	−0.013***
		(0.002)	(0.002)	(0.002)	(0.004)
Park Prox. × Homicide Risk Squared					0.001*
					(0.0003)
Park-Neighborhood Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Dwelling Characteristics	Yes	Yes	Yes	Yes	Yes
Time-Var Socio-Economic Controls	Yes		Yes		Yes
Census Tract Fixed Effects				Yes	
Observations	656,164	656,164	656,841	656,164	656,164

Notes: Sample includes transactions within 3/8 of a mile of a park for Chicago (2001-2016), New York (2006-2016), and Philadelphia (2006-2016) from Zillow. Dependent variable is ln *Housing Transaction Price*, *Park Proximity* is an indicator for sales within 1/8 mi. of a park, *Homicides Risk* denotes the yearly number of expected homicides per squared mile. The reference category in this specification are properties between 3 and 6 16ths of a mile away. Dwelling characteristics include: log distance to the CBD, age of the dwelling and its square, square footage, number of bedrooms and bathrooms, and dwelling type (i.e. Single Family Residence, Condo). Specifications also include dummies for dwelling with missing characteristics. Results are robust to restricting the sample to dwellings with complete data. Socio-economic controls include census block and block group socio-economic variables linearly interpolated yearly from the 2000 and 2010 Censuses, and the 2011-2015 ACS: population density, proportion of whites, proportion of blacks, proportion of hispanics, and proportion of other races, proportion of vacant housing units and of rented units at the block level; and median age and median income at the block group level. Park-neighborhood refers to the 3/8 miles radius around a park. Standard errors clustered at the census tract level are in parenthesis.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 4. Park Premium and Homicide Risk: Property and Neighborhood Homicide Risk Estimator across 1,337 Neighborhoods over Time

	Dependent variable: ln *Housing Transaction Price*			
Homicide Risk Level	Property	Neighborhood	Property	Neighborhood
Estimator	Pooled Panel Interact (1)	Pooled Panel Interact (2)	Pooled Panel Interact (3)	Pooled Panel Interact (4)
Park Proximity			0.025^{***}	0.021^{**}
			(0.008)	(0.009)
Within 1/16 mile of a Park	0.045^{***}	0.045^{**}		
	(0.017)	(0.018)		
Homicide Risk	-0.019^{***}	-	-0.007^{***}	-0.005^{**}
	(0.004)	-	(0.002)	(0.002)
Park Prox. × Homicide Risk			-0.007^{***}	-0.003^{*}
			(0.002)	(0.002)
Within 1/16 mi. × Homicide Risk	-0.031^{***}	-0.010^{**}		
	(0.006)	(0.005)		
Park-Neighborhood Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Dwelling Characteristics	Yes	Yes	Yes	Yes
Time-Var Socio-Economic Controls	Yes	Yes	Yes	Yes
Observations	656,841	656,841	656,841	656,841

Notes: Sample and controls are those described in Table 3 column (3). Dependent variable is ln *Housing Transaction Price*. *Park Proximity* is an indicator for sales within 1/8 mi. of a park. Columns (1) and (3) report results with *Property level Homicide Risk*, whereas columns (2) and (4) at the *Neighborhood level.* Standard errors clustered at the census tract level reported in parentheses.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 5. First Stage Estimate: Relationship between Neighborhood and City-Level Homicide Risk

	Dependent variable:
	Actual Homicide Risk
	(1)
Local Homicide Risk	0.515***
	(0.012)
1^{st} Stage F-statistic	1,819
Park-Neighborhood Fixed Effects	Yes
Year Fixed Effects	Yes
Dwelling Characteristics	Yes
Time-Var Socio-Economic Controls	Yes
Observations	521,945

Notes: Sample is same as described in Table 3. Homicide Risk per squared mile is instrumented using predicted Homicide Risk per squared mile based on the initial densities (first two years) and the total annual homicides at city level. All specifications include the controls described in column 3 of Table 3. 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. Park Premium and Homicide Risk:
Pooled Panel Estimator using Shift-Share Instrument based on City-Level Crime
(Omits the First Two Years of Sample)

	Dependent variable: ln *Housing Transaction Price*			
Estimator	Pooled Panel No Int. (1)	Pooled Panel Interact (2)	IV Panel No Int. (3)	IV Panel Interact (4)
Park Proximity	0.013*	0.023***	0.013*	0.026***
	(0.007)	(0.008)	(0.007)	(0.009)
Homicide Risk	−0.012***	−0.010***	−0.019***	−0.016***
	(0.002)	(0.002)	(0.005)	(0.005)
Park Prox. × Homicide Risk		−0.007***		−0.010***
		(0.002)		(0.003)
Park-Neighborhood Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Dwelling Characteristics	Yes	Yes	Yes	Yes
Time-Var Socio-Economic Controls	Yes	Yes	Yes	Yes
Observations	521,945	521,945	521,945	521,945

Notes: Sample is same as described in Table 3, 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 construct the instrument. Columns (1) and (2) report pooled panel results, columns (3) and (4) our instrumental variable (IV) specification. Dependent variable is ln *Housing Transaction Price*. *Park Proximity* is an indicator for sales within 1/8 mi. of a park, *Homicides Risk* denotes the yearly number of expected homicides per squared mile measured at the *Property level*. Homicide Risk at every location is instrumented using predicted expected homicides in that location based on the initial homicide density and the total annual homicides at city level. The reference category in this specification are properties between 3 and 6 16ths of a mile away. All specifications include the same controls described in column 3 of Table 3. Standard errors clustered at the census tract level are in parentheses.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 7. Park Premium and Homicide Risk
Effect Heterogeneity by Park Size

	Dependent variable: ln *Housing Transaction Price*			
Estimator	Pooled Panel No Int.	Pooled Panel Interact	IV Panel No Int.	IV Panel Interact
	(1)	(2)	(3)	(4)
Proximity to Large Park	0.090***	0.111***	0.087***	0.128***
(Large > 90th perc. size)	(0.028)	(0.031)	(0.028)	(0.034)
Proximity to Small Park	0.005	0.011	0.004	0.013
(Small < 90th perc. size)	(0.007)	(0.008)	(0.007)	(0.009)
Large Park $\times$Homicide Risk		−0.029***		−0.057***
		(0.010)		(0.015)
Small Park$\times$Homicide Risk		−0.004**		−0.006*
		(0.002)		(0.003)
Homicide Risk	−0.012***	−0.010***	−0.018***	−0.015***
	(0.002)	(0.002)	(0.005)	(0.005)
Park-Neighborhood Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Dwelling Characteristics	Yes	Yes	Yes	Yes
Time-Var Socio-Economic Controls	Yes	Yes	Yes	Yes
Observations	521,945	521,945	521,945	521,945

Notes: Sample and controls are those described in Table 3. Columns (1) and (2) show pooled panel results, columns (3) and (4) our instrumental variable specification. 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 parentheses.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 8. Amenity Value of Park Proximity Plus Value "Locked in" by Homicide Risk, 2016 Values in Millions of Dollars

Homicide Risk	Typical Homicide Risk of Park Neighborhood: Low $H < 1$	Medium $1 < H < 3$	High $H > 3$	ALL
Panel A: Park Proximity Value with Interaction				
Chicago	1,887	1,453	532	3,871
NY	3,132	3,133	727	6,992
Philly	155	203	45	402
Total	5,173	4,789	1,303	11,265
Panel B: Park Proximity Value Locked In by Homicide Risk				
Chicago	300	997	1,035	2,331
NY	659	2,111	1,728	4,499
Philly	30	119	90	240
Total	989	3,227	2,853	7,069
Panel C: No Interaction (Naive) Value				
Chicago	737	568	208	1,512
NY	1,224	1,224	284	2,732
Philly	61	79	17	157
Total	2,021	1,871	509	4,401

Note: Estimates of value of parks for each city are based on the number of units within 1/8 miles of a park and the median value and our estimates from table 6 column (4). We calculate the expected number of homicides in a neighborhood by year and classify them into Low Homicide Risk: less than one expected homicide by year; Medium Homicide Risk: more than one and less than three expected homicides per year; High Homicide Risk: more than three expected homicides per year.

Table 9. Effect of Crime Reductions on
Amenity Value of the Value of Park Proximity,
2016 Millions of Dollars

	Neighborhood's Change in Homicide Risk			
	Decrease	No Change	Increase	Net
	$\Delta H < -0.01$	$-0.01 < \Delta H < 0.01$	$\Delta H > 0.01$	Net
Chicago	2,586	-	-2,007	579
NY	5,488	-	-3,013	2,475
Philly	90	-	-433	-344
Total	8,164	-	-5,454	2,710

Note: Estimates of value of parks for each city are based on the number of units within 1/8 miles of a park and the median value and our estimates, as described in table 8. Based on the expected number of neighborhood homicides we calculate yearly trend using median regression. Park neighborhoods that experienced an average yearly reduction of 1% in expected homicides per mi^2 during the study period are classified as having experienced a decrease in homicide risk. Park neighborhoods that experienced an increase above 1% are clasified as having experienced an increase in homicide risk. All others are classified as No Change.

Table 10. Park Premium and Homicide Risk:
Valuations for High versus Low Income Neighborhoods

	Dependent variable: ln *Housing Transaction Price*			
	Pooled DD No Int.	Pooled DD Interact	IV DD No Int.	IV DD Interact
	(1)	(2)	(3)	(4)
Park Proximity ×High Income	0.021*	0.026**	0.020*	0.028**
	(0.011)	(0.011)	(0.011)	(0.011)
Park Proximity ×Low Income	0.006	0.018*	0.005	0.023**
	(0.007)	(0.009)	(0.007)	(0.011)
Homicide Risk	−0.012***	−0.010***	−0.019***	−0.016***
	(0.002)	(0.002)	(0.005)	(0.005)
Park × Homicide Risk		−0.006***		−0.009***
		(0.002)		(0.004)
Low Income	−0.005	−0.008	−0.004	−0.009
	(0.010)	(0.010)	(0.010)	(0.010)
Park-Neighborhood Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Dwelling Characteristics	Yes	Yes	Yes	Yes
Time-Var Socio-Economic Controls	Yes	Yes	Yes	Yes
Observations	521,945	521,945	521,945	521,945

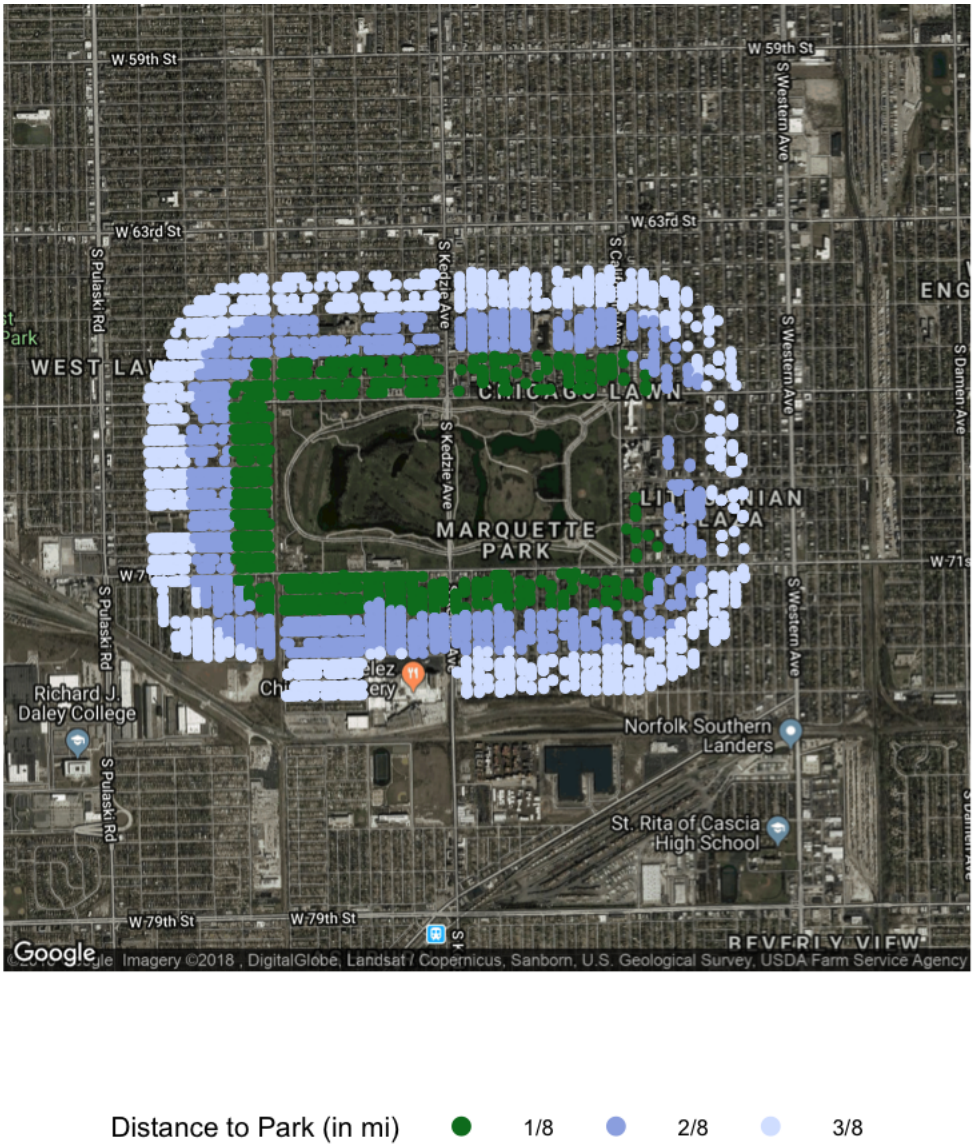
Notes: Sample is the same as in Table 6, and includes the same controls described in Table 6. Columns (1) and (2) show pooled panel results, columns (3) and (4) our instrumental variable specification. High and Low Income are indicator for whether the census track is above/below the 50th percentile of the sample census block median income.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 11. Park Proximity, Homicide Risk, and Socio-Economic Changes

Panel A	*Dependent variable:*									
	ln(Population Density)		White (%)		Black (%)		Hispanic (%)		Other (%)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	DD	IV	DD	IV	DD	IV	DD	IV	DD	IV
Park Proximity	0.012	0.017	0.003	0.004	0.007**	0.004	−0.009**	−0.007	−0.001	−0.002
	(0.011)	(0.013)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
	[0.452]	[0.358]	[0.512]	[0.413]	[0.071]	[0.358]	[0.022]	[0.167]	[0.722]	[0.472]
Homicide Risk	0.018***	0.031***	−0.013***	−0.022***	0.012***	0.018***	0.002	0.004**	−0.0001	−0.0005
	(0.002)	0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.002)	(0.0004)	(0.001)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.202]	[0.029]	[0.847]	[0.551]
Park×Homicide Risk	0.001	0.001	−0.002	−0.003***	0.001	0.002**	0.001	0.0002	0.0002	0.0004
	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.0004)
	[0.655]	[0.842]	[0.115]	[0.004]	[0.441]	[0.039]	[0.441]	[0.842]	[0.596]	[0.577]
Observations	483,493	483,493	483,493	483,493	483,493	483,493	483,493	483,493	483,493	483,493
Panel B	*Dependent variable:*									
		ln(Median Income)		Median Age		Renter (%)		Vacant (%)		
		DD	IV	DD	IV	DD	IV	DD	IV	
Park Proximity		−0.003	−0.005	0.468**	0.520**	−0.005	−0.006	0.003*	0.002	
		(0.008)	(0.008)	(0.145)	(0.159)	(0.005)	(0.005)	(0.001)	(0.001)	
		[0.738]	[0.53]	[0.011]	[0.010]	[0.452]	[0.413]	[0.071]	[0.358]	
Homicide Risk		−0.023***	−0.038***	−0.174***	−0.350***	0.006***	0.011***	0.003***	0.005***	
		(0.002)	(0.004)	(0.023)	(0.043)	(0.001)	(0.002)	(0.0004)	(0.001)	
		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	
Park×Homicide Risk		−0.001	−0.002	−0.039	−0.081*	0.002*	0.002**	−0.001	0.0001	
		(0.002)	(0.002)	(0.029)	(0.036)	(0.001)	(0.001)	(0.0003)	(0.0004)	
		[0.655]	[0.615]	[0.382]	[0.056]	[0.142]	[0.045]	[0.382]	[0.842]	
Observations	483,493	483,493	483,493	483,493	483,493	483,493	483,493	483,493		

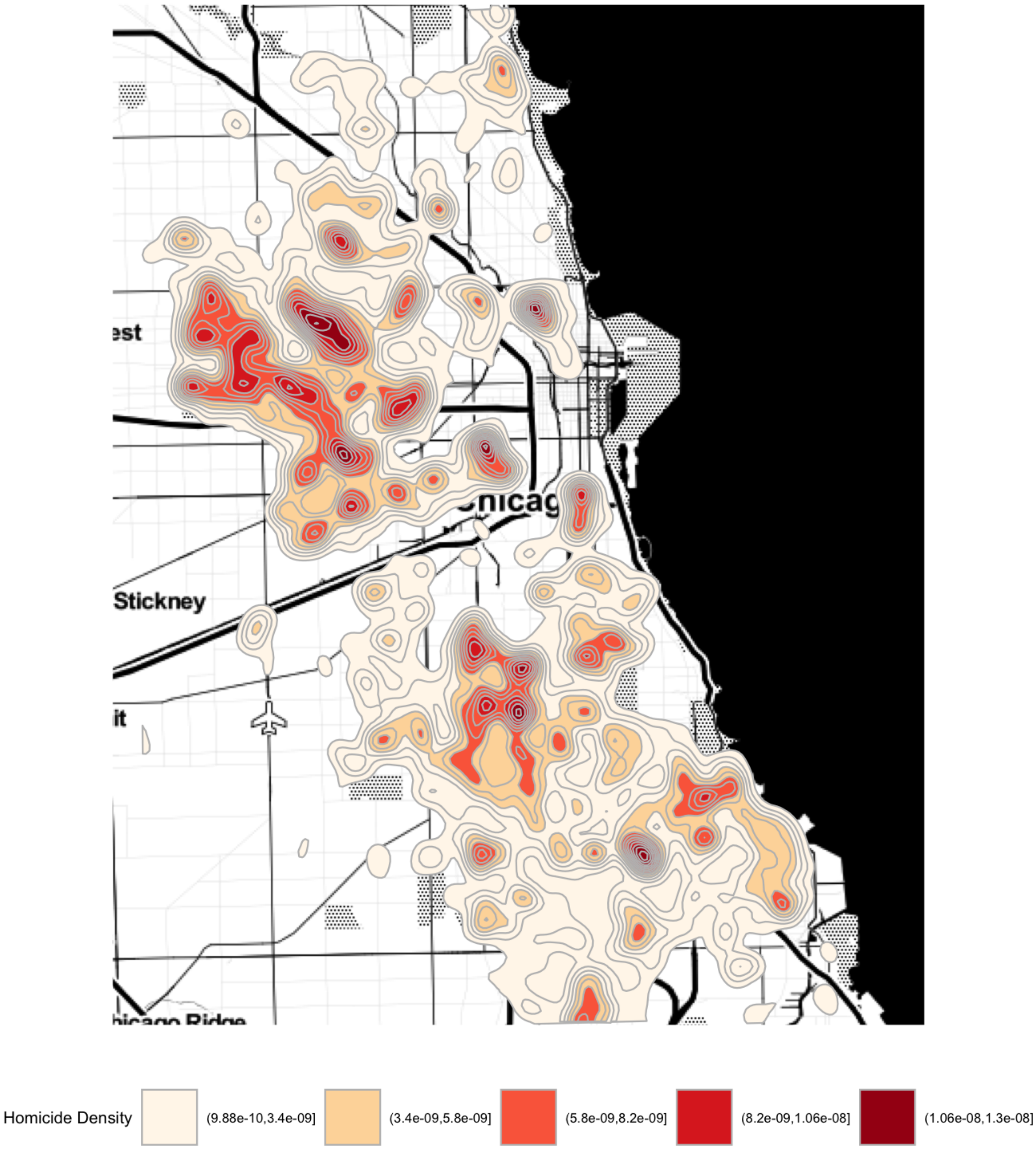
Notes: Sample includes a yearly series of socio-economic characteristics from the 2000, 2010 Censuses and the 2011-15 ACS for the areas within 1/8 miles of a park and between 1/8 and 3/8 miles of a parks. *Homicide Risk* is the expected number of homicides per year in each neighborhood. All specifications include Park-Neighborhood Fixed Effects and Year Fixed Effects. Park-neighborhood refers to the 3/8 miles radius around a park. Standard errors clustered at the city level are in parenthesis.
Benjamini and Hochberg (1995) adjusted p-values in brackets
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level according to Benjamini and Hochberg (1995) adjusted p-values.

Figure 1. Housing Transactions around Parks



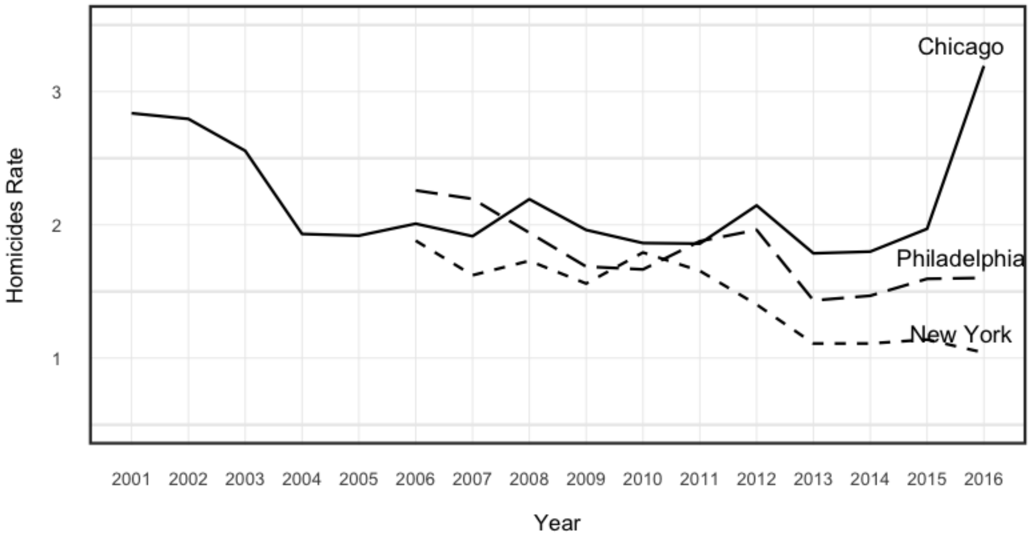
Note: Points represent transactions within 3/8 miles of Chicago's Marquette park in our sample. Different shades denote proximity to the park in intervals of 1/8 mi.

Figure 2. Density of Expected Homicides in Chicago.
Year 2001-2003



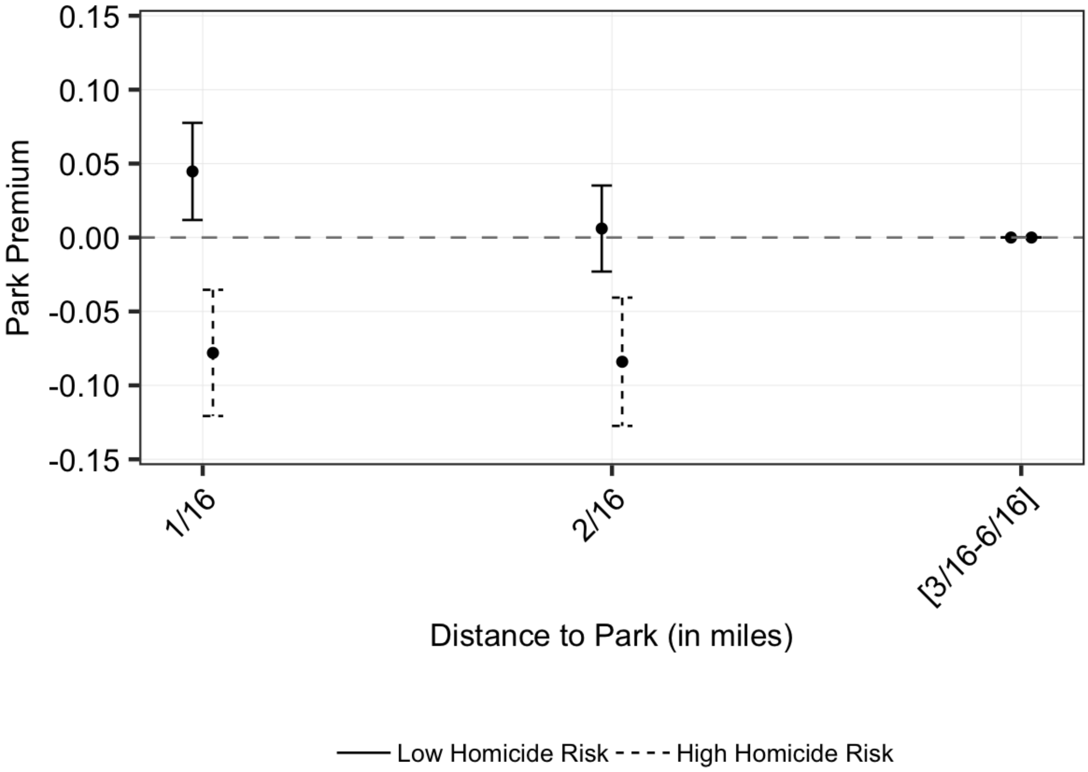
Note: Shades represent a density estimation of being a homicide victim per square mile. Estimates are based geolocated crime data for years 2001-2003 using a bivariate Gaussian kernel with a bandwidth of 2/8 of a mile on a 1/8 mile city grid.

Figure 3. Homicide Rate Trends by City for Sample



Note: Homicide rate is the number of homicides per square mile for Chicago (2001-2016), New York (2006-2016), and Philadelphia (2006-2016)

Figure 4. Conditional Park Premium Alternative



Note: Park premium conditional on Homicide Risk based on Table 2. *Low Homicide Risk* denotes locations with no homicides risk in the sample period, *High Homicide Risk* locations with an expected average of 4 yearly homicides per square mile in the sample period.

A Appendix

Table A.1. First Stage: Homicide Equivalent

	Dependent variable:
	Homicide Equiv. Risk
	(1)
Pred. Homicide Equiv. Risk	0.646***
	(0.013)
1^{st} Stage F-statistic	2351.842
Park-Neighborhood Fixed Effects	Yes
Year Fixed Effects	Yes
Dwelling Characteristics	Yes
Time-Var Socio-Economic Controls	Yes
Observations	521,945

Notes: The specifications are the same as in Table 6. *Homicide Risk* is replaced by *Homicide Equiv. Risk*. *Homicide Equiv. Risk* is constructed using willingness-to-pay estimates from Chalfin and McCrary (2017) to construct a unitary measure of homicide-equivalent crimes. 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.2. Park Premium and Homicide Equivalent Risk

	Dependent variable: ln *Housing Transaction Price*			
	DD	DD	IV	IV
	(1)	(2)	(3)	(4)
Park Proximity	0.012*	0.025***	0.011	0.027***
	(0.007)	(0.008)	(0.007)	(0.009)
Homicide Eq. Risk	−0.014***	−0.012***	−0.017***	−0.015***
	(0.002)	(0.002)	(0.004)	(0.004)
Park×Homicide Eq. Risk		−0.005**		−0.006**
		(0.002)		(0.003)
Park-Neighborhood Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Dwelling Characteristics	Yes	Yes	Yes	Yes
Time-Var Socio-Economic Controls	Yes	Yes	Yes	Yes
Observations	521,945	521,945	521,945	521,945

Notes: Specifications are those described in Table 6. *Homicide Risk* is replaced by *Homicide Equiv. Risk*. *Homicide Equiv. Risk* is constructed using willingness-to-pay estimates from Chalfin and McCrary (2017) to construct a unitary measure of homicide-equivalent crimes. 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: Excluding 2016

	Dependent variable: ln *Housing Transaction Price*			
	DD	DD	IV	IV
	(1)	(2)	(3)	(4)
Park Proximity	0.013*	0.023***	0.012*	0.026***
	(0.007)	(0.008)	(0.007)	(0.009)
Homicide Risk	−0.012***	−0.010***	−0.017***	−0.014***
	(0.002)	(0.002)	(0.005)	(0.005)
Park×Homicide Risk		−0.007***		−0.010***
		(0.002)		(0.003)
Park-Neighborhood Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Dwelling Characteristics	Yes	Yes	Yes	Yes
Time-Var Socio-Economic Controls	Yes	Yes	Yes	Yes
Observations	491,710	491,710	491,710	491,710

Notes: Sample is described in Table 6 without the first two years of the sample for each city, i.e. Chicago (2003-2015), New York (2008-2015), and Philadelphia (2008-2015). The first two years are used 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. 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. 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.4. Park Premium and Homicide Risk:
Neighborhood Increase in White Households

	Dependent variable: ln *Housing Transaction Price*			
	DD	DD	IV	IV
	(1)	(2)	(3)	(4)
Park Proximity	0.023**	0.022**	0.027***	0.027***
	(0.009)	(0.009)	(0.010)	(0.010)
Homicide Risk	−0.012***	−0.012***	−0.018***	−0.018***
	(0.002)	(0.002)	(0.005)	(0.005)
Park×Homicide Risk	−0.007***	−0.005**	−0.010***	−0.008**
	(0.002)	(0.002)	(0.003)	(0.004)
Park×Homicide Risk×White Change		−0.003		−0.004
		(0.003)		(0.004)
Park-Neighborhood Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Dwelling Characteristics	Yes	Yes	Yes	Yes
Time-Var Socio-Economic Controls	Yes	Yes	Yes	Yes
Observations	521,945	521,945	521,945	521,945

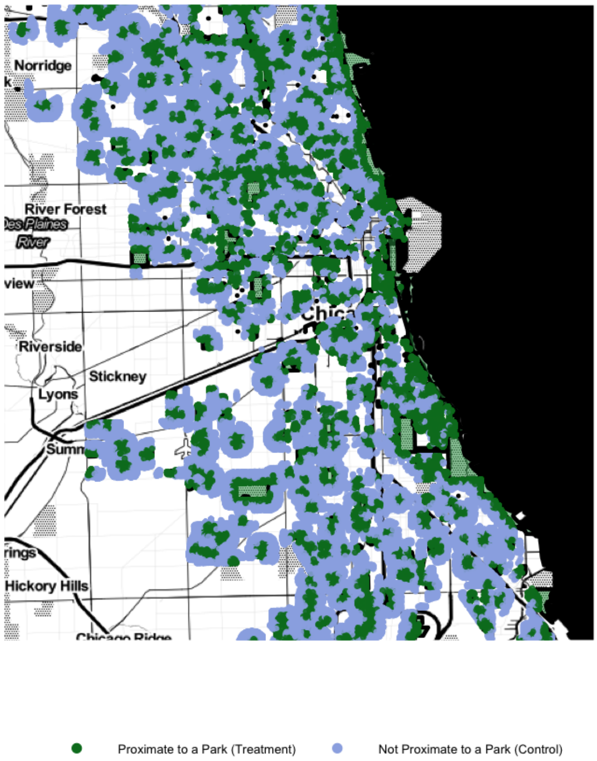
Notes: Sample and controls are those reported in Table 6. Columns (1) and (2) show pooled panel results, columns (3) and (4) our instrumental variable specification. White Change is an indicator that takes one if the Census Block had an intercensal increase in the proportion of white households. Standard errors clustered at the census tract level are in parenthesis.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table A.5. Park Premium and Homicide Risk:
Neighborhood Income Changes.

	Dependent variable: ln *Housing Transaction Price*			
	DD	DD	IV	IV
	(1)	(2)	(3)	(4)
Park Proximity	0.023**	0.022**	0.027***	0.027***
	(0.009)	(0.009)	(0.010)	(0.010)
Homicide Risk	−0.012***	−0.012***	−0.018***	−0.018***
	(0.002)	(0.002)	(0.005)	(0.005)
Park×Homicide Risk	−0.007***	−0.008***	−0.010***	−0.011***
	(0.002)	(0.003)	(0.003)	(0.004)
Park×Homicide Risk×Income Change		0.003		0.001
		(0.003)		(0.004)
Park-Neighborhood Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Dwelling Characteristics	Yes	Yes	Yes	Yes
Time-Var Socio-Economic Controls	Yes	Yes	Yes	Yes
Observations	521,945	521,945	521,945	521,945

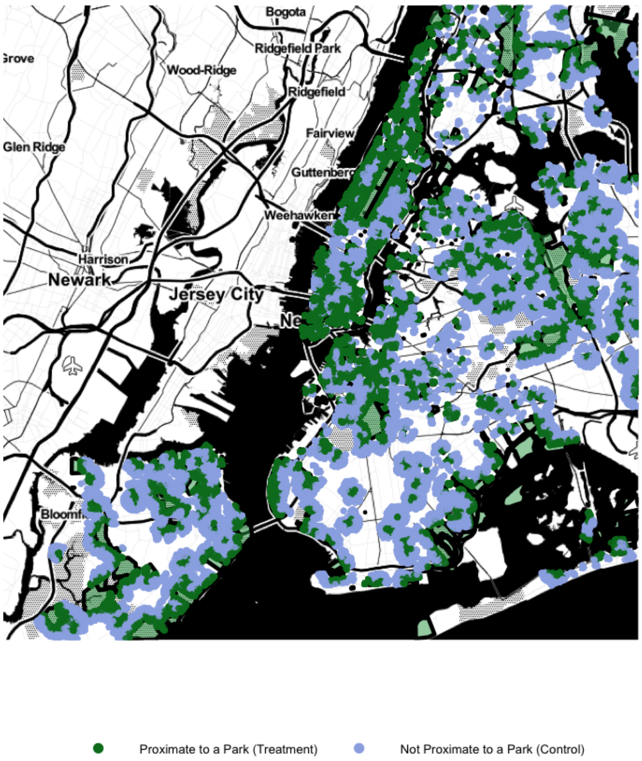
Notes: Sample and controls are those reported in Table 6. Columns (1) and (2) show pooled panel results, columns (3) and (4) our instrumental variable specification. White Change is an indicator that takes one if the Census Block Group had an intercensal increase in the median income of households. Standard errors clustered at the census tract level are in parenthesis.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Figure A.1. Housing Transaction Near Parks, Chicago



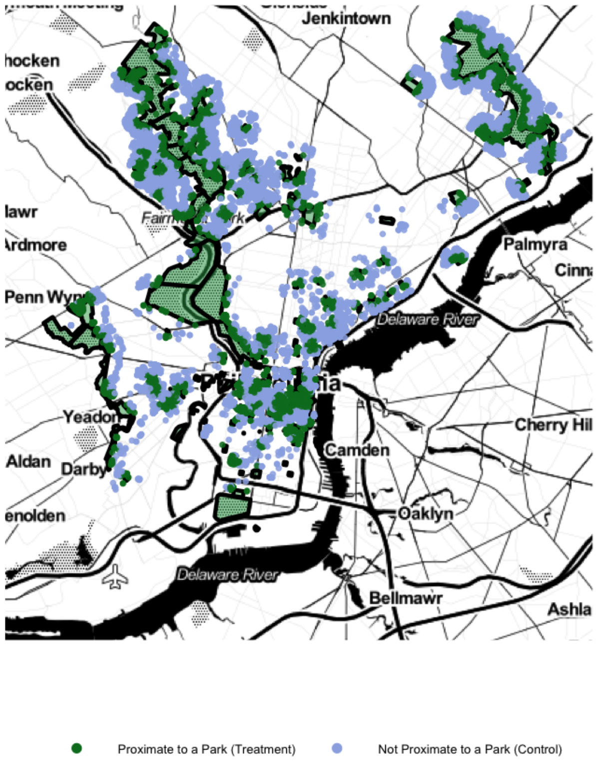
Points represent transactions within 3/8 miles of the nearest Park. Different shades denote proximity to the park. "Proximate to a Park (Treatment)" denotes transactions within 1/8 miles of a Park, "Not Proximate to a Park (Control)" transactions between 1/8 miles and 3/8 miles.

Figure A.2. Housing Transaction Near Parks, New York



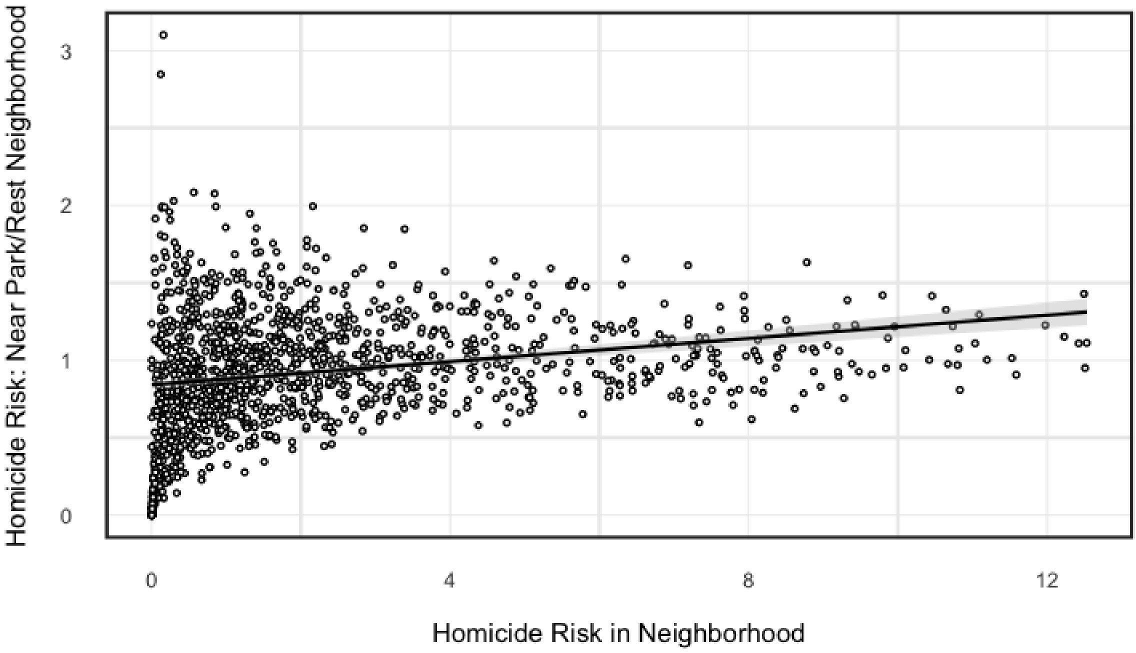
Points represent transactions within 3/8 miles of the nearest Park. Different shades denote proximity to the park. "Proximate to a Park (Treatment)" denotes transactions within 1/8 miles of a Park, "Not Proximate to a Park (Control)" transactions between 1/8 miles and 3/8 miles.

Figure A.3. Housing Transaction Near Parks, Philadelphia



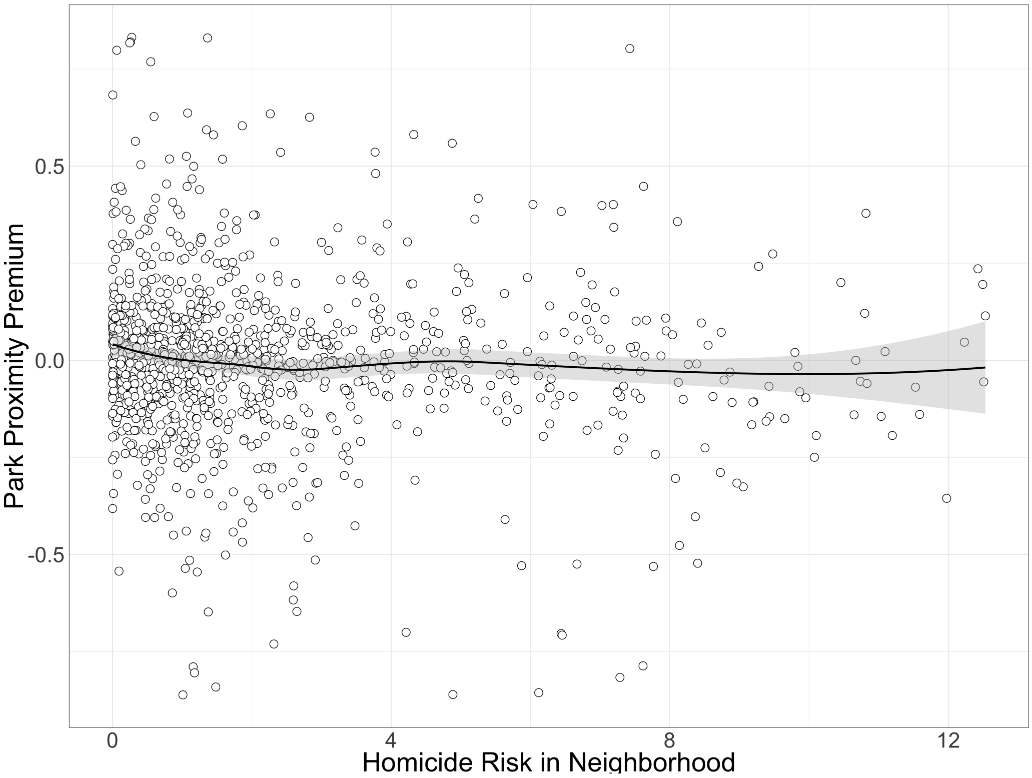
Points represent transactions within 3/8 miles of the nearest Park. Different shades denote proximity to the park. "Proximate to a Park (Treatment)" denotes transactions within 1/8 miles of a Park, "Not Proximate to a Park (Control)" transactions between 1/8 miles and 3/8 miles.

Figure A.4. Homicide Risk near Parks



Note: The vertical axis denotes the ratio of average homicide risk per square mile in the sample period of the areas near a park (within 1/8mi), over those in the the rest of the neighborhood (2-3/8 of a mile). The horizontal axis measures the average yearly homicide risk in the neighborhood (within 3/8 of a mile)

Figure A.5. Homicide Risk and Park Proximity



Note: Figure shows estimated park proximity premiums for each neighborhood and homicide risk measured as the average yearly homicide risk in the neighborhood (within 3/8 of a mile)