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ABSTRACT

Our results indicate that improving safety near parks can turn them from public bads to goods. Ignoring complementarities may lead to i) undervaluing the potential value of public goods; ii) overestimating heterogeneity in preferences; and iii) understating the value of public goods to low income households. Recent reductions in crime have "unlocked" $3 billion in property value in these three cities. Still over half of the potential value of park proximity (approximately $9 billion) remains locked in.

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Data and replication files are available at https://github.com/uiuc-bdeep/Unlocking-Amenities

1 Introduction

Economic theory leans heavily on the idea 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, their 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]

Complementarity may also imply that some public goods are more primary than others. It can be wasteful to equalize some public goods (parks) without equalizing others (safety). This public-good hierarchy has important implications for environmental justice.

Paying attention to public-good complementarity has important methodological implications. We highlight three. First, ignoring complementarities may bias estimates of the value of public goods. Indeed, we cannot extrapolate the value of parks from safe

[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).

neighborhoods to unsafe ones, or vice versa. Public good complements may have first-order implications for benefit-cost analysis. Our empirical results indicate that the effect of reducing crime on the value of parks is similar in magnitude to the amenity benefits of parks themselves. In fact, the majority of park value may be locked-in by high levels of crime.

Second, variation in observed willingness-to-pay for public goods may be due to differences in public good endowments. Researchers often model such variation with individual preferences that vary. Few model interactions with endowments, observed or not. Through lack of proper modeling, one may assign variation to unobserved preferences when they are actually due to potentially observable endowments.

Third, modeling 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. Our results suggest that ignoring complementarity would cause us to infer that low-income residents care less for parks than they actually do.

Our empirical analysis uses crime and housing data in Chicago, New York and Philadelphia from 2001 to 2016. In particular, we use 656,841 housing market transactions within a tight radius (3/8 miles) around 1,336 parks. We organize these transactions into "park neighborhoods." From individual police reports, we match all reported crime incidents to these 1,336 neighborhoods, focusing on homicides. We then create long average and time-varying measures of crime risk at both property and neighborhood levels.

We apply three strategies to estimate the effect of complementarity between parks and public safety. The first strategy uses cross-sectional variation (purged of time effects) to estimate the park premium and its interaction with local crime. This involves including 1,336 park-neighborhood fixed effect (FE) controls, as well as time-varying socio-economic characteristics. This strategy helps us to delineate how the premium of being near a park changes with distance.

The second strategy uses the data panel to examine the effects of changes in crime over time. It finds similar evidence of public good complementarity in a pooled panel, a repeat sales, and a matching variant of the repeat-sales estimator.

Time-varying unobservables may affect the incidence of crime and the park premium across neighborhoods over time. To address the potential influence of these variables, our third strategy makes use of a shift-share instrumental variable (IV). It uses 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. We find that estimates are similar in repeat sales and repeat sales as a matching variants of this estimator.[4]

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 (2004).[5] A second strand 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. A primary challenge in this literature is that open space is never randomly assigned. 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, whereas 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, ours is

[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.

[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.

the first analysis to formalize public-good complementarity and, with that framework, to focus on the joint provision of public safety and environmental amenities.[7]

Our IV estimates indicate that improving safety near parks could unlock up to \$6 billion in value. Since the beginning of our sample period, crime reductions have already unlocked \$3 billion. Targeted investments in public safety through park design, "hot spot policing," or other methods could unlock considerable value simply by displacing this crime to less public areas.[8]

Section 2 below presents a theory of complementary public goods in a hedonic setting. Section 3 describes our data. Section 4 presents the main estimates on the relationship between public safety and open space amenities from the cross-sectional, panel, and IV strategies. Section 5 discusses the implications of complementarity for public good provision and environmental justice. 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

[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.

[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.

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 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 amenity 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:

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

[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.

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

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

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

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

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

At higher levels of crime, the environmental amenity lowers welfare, making it a public bad. Households will pay to live away from it. The error term could include differences in the preference shock relative to utility.[10] As shown in Banzhaf (2018) for the case of individual amenities, hedonic estimates that exploit exogenous changes in the level of one or both public goods complements may shift an entire hedonic price function and identify a lower bound on the Hicksian equivalent surplus rather than the exact willingness to pay.

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

[10]The framework may be used to motivate a logit estimator based on how many people choose to live in an area based on its proximity to a park and local safety. Such an approach would require a nuanced understanding of local housing supply.

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."[11] The data contain the timing and location of all housing transactions recorded within 3/8 (0.375) miles of 1,336 geo-coded urban parks in all three cities.[12] 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. Figure 1 illustrates our park-neighborhood definition. It shows housing transactions within 3/8 miles of Marquette Park in Chicago. Our final data comprises 656,841 housing transactions surrounding parks. Table 1 presents basic descriptive statistics 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 their Open Data Portal.[13] We use these geo-located reports to calculate crime risk 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 focus on exercises based on the broader definition of crime risk, though we analyze the robustness of our estimates to measures that include all crimes and report those estimates in two tables in the appendix.[14] We use "crime" and "homicides" interchangeably to refer to safety

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

[12]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.

[13]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

[14]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

throughout.

Figure 2 illustrates the estimated homicide risk 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:

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

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, $E(H_{lt}) = H^e_{lt}$.[15]

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 neighborhoods, crime becomes slightly worse near parks.

Figure 3 plots trends in homicide rates for each of the cities during the study period. All of the three cities have experienced substantial (>30%) declines in homicide rates

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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.

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

during the study period (with the exception of Chicago in 2016). However, the declines within cities were not uniform. Figure 2 shows that most areas in the city became safer, however, there are areas that saw no change or even experienced an increase in homicide risk.

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 and controls for unobserved differences at the property level with repeat sales. The third instruments for 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 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 Section 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 1,336 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, $I_k \equiv I\left[(1/16) \times k \leq d_{il}^j < (1/16) \times (k+1)\right]$ where d_{il}^j 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.

[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.

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

$$\ln P_{it}^{jc} = \pi_i^{H^e} + \sum_{k=0}^{6} \pi_k^E I_k + \sum_{k=0}^{6} \pi_k^{EH} I_k \times H_i^e + \beta D_i + \theta N_{it} + \gamma_j + \delta_t^c + u_{it} \qquad (5)$$

H_i^e 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_j^e, 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 that controls for the fixed unobservables shared within a neighborhood. δ_t^c is a fixed effect for transaction year to control for trends. u_{it} is an error term.

Table 2 reports estimates from equation (5), documenting changes in the park premium at the different 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 1,336 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, 4, and 5 contain socio-economic controls that vary at the block level, and vary over time. Column 2 alternatively omits these controls. Column 3 instead uses census tract fixed effects, on top of the more geographically coarse neighborhood fixed effects.

Column 5, importantly, uses the neighborhood level of homicide risk H_j^e, instead of

[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 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, proportion of vacant housing units and of rented units at the block level, and median age and median income at the block group level.

the property-level measure, H_i^e. With this specification, estimates are based solely from variation between neighborhoods. This is worth checking in case unobserved variables correlated with property-level measures of crime are driving the results. The similarity of the results with those in the other columns suggests that is unlikely to be the case.

The estimates imply a housing price premium of 3 to 6 percent for being within 1/16 of a mile to 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. The difference between columns 1 and 4 indicate that not accounting for safety-park complementarity results in a lower estimate of the park premium – the park premium within 1/16 of a mile is 4.2% with complementarity versus 2.7% without it.[20] This estimate applies to parks with no homicide risk, while the typical park has a homicide risk of 1.55. Thus, the model predicts that typical park proximity is valued at 2.6%.

If the park and park-risk interaction variables are exogenous, the estimates imply that a homicide risk near 3 or 4 per square mile annually will eliminate the park premium for the closest distance bin. 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 column 5 and fitted values for 0 and 10 expected homicides in the neighborhood per year per square mile.[21] The graph illustrates a 4.3% 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 10 or more expected homicides per year per square mile), there is

[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.

[21]Direct evidence of a park discount in high crime areas can be seen in figure A.5. Among the most dangerous areas in our sample are those surrounding Garfield Park in Chicago's west side, Jackie Robinson Park in the Bronx (NYC) and McPherson Square in Philadelphia.

instead a park discount of 5.4%.

Cross-sectional evidence is limited since unobserved dwelling and neighborhood characteristics (including 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.

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.[22] 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 in Table 2, these estimates indicate that ignoring the park-safety interaction underestimate the full potential value of parks. Once the interaction is accounted for, homes in close proximity to an urban park sell at a premium ($\pi^E > 0$) of 2.4 to 2.7 percentage points relative to homes further away from the the same park.[23]

More importantly, the results in Table 3 imply that the value of park proximity falls with crime, $\pi^{EH} < 0$. An increase in homicide risk reduces the value of homes within 1/8 miles of a park by 0.7 - 1.1 percentage points relative to a home within 3/8 miles of the same park. With high enough homicide risk, $H^j_{it} > -\pi^E/\pi^{EH} \approx 3.19(1.04)$, the park

[22] Table A.4 also reports primary estimates using models that use 1/16th of a mile as the treated zone and exclude the interval between 1/16-2/16 from the analysis.

[23] 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. We view this as a more conservative estimate. Table A.4 also reports primary estimates using models that use 1/16th miles as the treated zone and exclude the interval between 1/16-2/16 from the analysis.

premium becomes negative at just over 2 homicides per square mile annually.

One concern with these estimates is that properties being transacted near park may differ in unobserved ways differ from those used as controls (further away). If so, then the estimates in Column 2 identify heterogeneity in the effect of crime reductions as a function of proximity to a park, but may miss the value of complementarity itself. To control for unobserved fixed differences in housing characteristics, we estimate repeat-sales models in Columns 3 and 4. Column 3 provides estimates from a standard repeat sales model, where estimates are estimated from the changes in transaction prices for a subset of homes with multiple transactions. The coefficient on park proximity is differenced out of the estimating equation in this specification.

Column 4 reports estimates from a repeat sales as a matching (RSM) estimator developed by McMillen (2012). It generates a matched counterfactual by matching home sales in the first year of the sample to properties in each subsequent year. However, the interaction between park proximity and homicide risk is unchanged.[24]

Column 5 allows for a quadratic in homicide risk. The additional terms are insignificant, but suggest the marginal cost of additional homicide risk is diminishing. Nevertheless, the interaction term is similar to column 3. Thus, it does not appear to result from omitted non-linearities in functional form.

4.3 Property-Level versus Neighborhood-Level Homicide Risk

The property-level measure of crime risk used above, H^e_{it}, 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^e_{jt} as in Column 5 of Table 2. With this specification, estimates are based solely from variation across neighborhoods across time and not from the dynamics of safety within a neighborhood. There is reason to prefer property-level measures of crime, which are better measured and control for local dynamics. Overall, it is most reassuring if these measures produce mutually consistent estimates.

[24]Park proximity is an observed characteristic and is used as a control in this model. Because the sample is properly balanced, it is insignificant.

Table 4 reports estimates using the alternative crime measures. The main effect of crime is slightly higher and the interaction effect slightly smaller when crime is measured at the neighborhood level. This may be due to measurement error. Changes in safety may be better measured at the neighborhood level than at the property level. But changes in the neighborhood crime-park interaction may may miss important local crime dynamics. Nevertheless, the fact that the interaction effect remains significant using this coarser crime geography appears to further support the hypothesis regarding complementarity.

Columns 3 and 4 of Table 4 report estimates from these property-level and neighborhood-level models while excluding crimes that occur within close proximity (1/8 miles) of a park or within a park itself. This check is designed to test whether our estimates of the complementarity between park access and public safety are driven solely by changes in the occurrence of homicides within or around parks themselves. They are not.

4.4 Instrumenting Crime Changes with City-Level Shifts

The estimates in Table 3 are identified using changes in crime over time, finding that reductions in crime increase the value of parks to nearby home owners. Claiming these estimates give the causal effect of crime reduction on the amenity value of parks still involves a somewhat restrictive set of assumptions. Our identification is threatened if increases in the amenity value of parks are come not from local crime reductions, but rather from time-varying unobservables. Such an observables that are correlated with local crime reductions but differentially affect housing prices immediately surrounding parks. This identification assumption is not directly testable.[25]

Our third strategy for estimating the complementarity between safety and open space is to use an instrumental variable for local crime in Equation 6. We consider a shift-share instrumental variable, similar to those developed by Bradbury et al. (1982) and Bartik (1991) for non-crime measures, and examined by Goldsmith-Pinkham et al. (2017). The shift-share instrument uses the fact that changes in local crime can be decomposed into

[25] 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 estimates of 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.

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 crime index that uses 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 as a base period.[26] 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 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.[27] 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.

Table 6 reports estimates from our preferred IV specification alongside comparable

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

[27] 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.

pooled estimates.[28] 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 2.2 percent in the uninteracted model that omits the complementarity, and 1.9 percent in the interacted model that identifies it. Consistent with results from 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 $\pi^E \approx 2.4\%$. As a result, the homicide level at which park value is unlocked is slightly lower at $-\pi^E/\pi^{EH} \approx 2.45$ (0.77).

In Columns 5-8, we test the robustness of these results using two repeat sales estimators that provide evidence that these results identify a true complementarity rather than heterogeneity in the effect of crime reduction in different types of properties. Columns 5 and 6 report estimates from a standard repeat sales model, where the first differences in the prices of repeat-transacted properties are regressed on changes in homicide risk. The sample of repeat transacted homes is less that 50% of our total sample, which reduces the power of our tests considerably.[29] Columns 7 and 8 report the results from a repeat sales as a matching estimator (McMillen, 2012), which generates a matched counterfactual by matches home sales to other properties using all observed characteristics.[30]

[28]Pooled 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 656,841 to 521,945 observations. As a robustness check, we drop 2016 to isolate the spike in homicides in Chicago in that year. The results, which are reported in Table A.3, remain unchanged.

[29]Note: In the repeat sales specification, a single observation reflects a pair or triplet of transactions of the same property.

[30]If homeowners expect additional changes in crime, then our estimates may be biased Bishop and Murphy (2015). However, recent crime trends appear to deviated from historical trends in the last few years. This makes it difficult to construct a forecast that would credibly match expectations of home buyers.

4.5 Magnitudes and Park Size

A larger park is likely to be a greater amenity than a smaller one. Moreover, finding that larger parks increase housing prices relatively should support the idea that our methodology indeed identifies the value of park proximity. Furthermore, the interaction between proximity to a larger park and crime should be greater, as there is more value to lose.

To test these ideas, we define a large park as above the 75th percentile in area for each city.[31] Table 7 indicates that there is a higher base premium for living by a large park than by a small park, with both uninteracted and interaced crime effects. In fact, the small park premium is insignificant.

More central to the main hypothesis, the interaction with homicide risk for large parks is also greater. Nevertheless, we do find a negative, if commensurately smaller, estimate for small parks. These findings suggest the level of crime that "locks" up the value of small parks may be lower than for larger parks. Whatever the case, the significant interaction lends greater credence to the idea crime reduces the value of park proximity.

4.6 Socio-Economic Changes

Improvements in neighborhood safety may influence house prices not just by offering greater direct benefits, but also by inducing socio-economic changes in a neighborhood. As safety improves, more affluent households may locate near urban parks. This demographic change may induce others to bid up housing prices even more, according to their preferences for neighbors. 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

[31] In Chicago, a "large" park has a minimum size of 4.83 acres, in New York 4.18 acres, and 10.88 acres in Philadelphia.

risk, estimating the following equation:

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

where N_{it}^{j} measures a socio-economic characteristic for block (or block group) i, in neighborhood j in year t. The right-hand-side terms are those described in equation (6).[32]

As we are testing for eight different characteristics, the significance of individual hypothesis tests must be discounted. We use a p-value adjustment proposed by Benjamini and Hochberg (1995) to control for rates of false discovery. We remain particularly focused on the interaction term.

Table 8 reports the results of model (8). Estimates in *Panel A* columns 1 and 2 suggest no statistical effect of park proximity or park safety on population density. Thus there does not appear be an affect on overall demand beyond what is observed on prices. Population density is significant, but this is likely due to the fact that more populous areas have more crime, other things equal. Thus, it was important to control for population density, as we did in our regressions.

Columns 3-8 examine racial composition to see if there are changes in the relative demand to live near parks. The results imply a small effect of the park-safety interaction on race. In particular, 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, these changes do suggest that increases in parks safety were accompanied with minor shifts in neighborhood composition. On the other hand, column 9 through 16 reveal almost no significant change in household income, age, renter or vacancy status.[33]

[32]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 that they are available.

[33]Table A.6 uses the base model in equation (6) to assess the robustness of our results to these compositional changes. In particular, results reported in Table A.6 test 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.7 replicates the test using socio-economic status, using census block groups where households experi-

5 Complementarities and Public Goods Provision

The complementarity of goods has first-order implications on how to value public goods and invest in safety and public capital. Below, we examine the quantitative implications of these results.

5.1 Implications of Complementarities for Valuation and Unlocking Value

Our IV estimates suggest that the amenity value of park proximity with no crime is 2.4 percentage points of housing values. This premium falls by 1.0 percentage point per increase in local homicide risk. To calculate the implied value of urban parks on our 3 cities, we compute the number of housing units and median property value at the census block group level from the 2000 census.[34] 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. As discussed above in the theory section, these estimates provide an estimate of the lower bound on the overall benefit from the complementary amenities.

The estimates in Panel A of Table 9 reveal that accounting for the complementarity between public safety and park amenities can dramatically affect how we assess the value of parks. Both pooled and IV estimates that ignore the interaction of crime and parks Table 6, columns 1 and 2 imply a much lower park premium of 1.1%. This mis-specified model produces an estimate of $3.9 billion for the parks in our sample.

Panel B reports the total value of park proximity having accounted for the complementarity with safety, illustrating that the majority of the value of neighborhood parks in our sample of cities is concentrated in neighborhoods with low homicide risk (less than 1 predicted homicide per year). The estimated value of parks in these safe neighborhoods is nearly double the estimated value from the naive model ($3.32 billion vs. $1.76 billion). However, as seen in the third column of Panel B, the value of park proximity in high

enced 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.

[34]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.

crime neighborhoods (more than 3 predicted homicides per year) is indeed negative: the cost of having these public bads to local home owners is \$1.47 billion. Taking Columns 2 and 3 together, the local amenity benefits from parks in neighborhoods with greater than 1 homicide per year are dominated by disamenities arising from the complementarity. Thus, home-owners in high crime areas may be unwilling to invest in parks, unless such an investments were to improve safety. Whether that could be accomplished through policing, or other means more efficiently, remains an open question.

According to our IV estimates, an actual reduction in homicide risk should result in a 1.4 percentage point increase in the price of a house away from a park, versus a 2.4 percentage point increase next to 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 in Panel C indicate that the most of the amenity value of parks in the three cities that we study is currently locked in by crime risk: this value sums to \$6.33 billion: \$0.98 billion in Chicago, \$1.52 billion in New York, and \$0.08 billion in Philadelphia. Interestingly, the benefit of removing all crime from parks (\$6.3 billion) is substantially higher than the realized net value of parks themselves (\$2.9 billion).

Panel D constructs a counterfactual value of parks if there were no safety issues (zero predicted homicides). These estimates indicate a total value of \$9.24 billion: \$3.35 billion in Chicago, \$5.45 billion in New York, and \$0.45 billion in Philadelphia. Comparing estimates of the total value of parks from the naive model (Panel A) to the total value at zero crime risk (Panel D), suggests that the naive estimate would underestimating the total value in our sample by approximately 60%. These 3 cities are endowed with public parks that could substantially improve quality of life if they were made safe. Indeed, the gains from park proximity might be achieved simply by displacing crime away from parks, insofar as that as possible.

How much park value has already been unlocked? Table 10 reports estimates of changes in neighborhood park value that have already resulted from reductions or increases in annual homicide risk during the study period. Our results show that reductions in homicide rates have unlocked considerable amenity value: \$1.4 billion in Chicago, \$2.4 billion in New York, and \$111 million in Philadelphia. Increases in homicide rates in other neighborhoods have resulted in simultaneous reductions in the amenity value of parks, totaling \$700 million during the study period: \$279 million in Chicago, \$336 billion in New York, and \$84 million in Philadelphia. These results indicate that attention to public good complementarities 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 currently valued at \$1.16 billion; \$1.58 billion, and \$0.18 billion, in Chicago, New York, and Philadelphia, respectively. In comparison, for park maintenance and programs, Chicago annually spends \$323 million; 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 cash expenditures on parks are worth more than park proximity's effect on housing values using most rates of return. Yet, a significant portion of park expenditures might be raised through a property tax increment on houses near parks. But given that the majority of the value of urban parks is still locked in by crime risk, it appears that any valuation of expenditures made on parks will depend critically on the level (and cost) of public safety.

Park proximity does in principle offer greater potential to generate revenues. Whether general equilibrium effects might cause property values overall to change remains a question. Greater demand for housing near parks might lower demand for houses away from parks. However, overall demand to live in the city to take advantage of urban parks over an 1/8 of a mile could rise substantially. A substantial enough increase could possibly justify even greater property tax increments.

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.

5.3 Disentangling Complementarities from Taste and Income Heterogeneity

The above results imply that insufficient modeling may confuse complementarities for preference heterogeneity or income effects. Indeed, models that ignore 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 goods differently on the margin because of their purchasing power. Indeed, other authors, e.g. Black (1999) have found that many amenities are luxuries, implying that consumption goods purchased from markets directly are necessities. The results presented in Table 11 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 50th 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. However, both the Pooled and IV results demonstrate that accounting for this interaction, columns 2 and 4, boosts the premium for low income neighborhoods.

The conflation bias illustrated in Table 11 has important implications for policy makers interested in allocating public goods. Ignoring complementarity and endowments, policy makers may conclude that low income households do not value public parks. They might assume (falsely) that only higher income households have the type of private consumption that allows them to enjoy public parks.[35] In fact, low-income households may enjoy parks as much as high-income households. Picnics and sports games in safe local parks are rather affordable ways to enjoy leisure time.

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.

6 Conclusion

The evidence above provides considerable evidence of complementarity between public goods. This negative association between crime risk and urban proximity appears both across neighborhoods and over time within neighborhoods. It holds in both hedonic and repeat-sales price indices. It also appears in the variation given by the shift-share instrument. The complementarity holds for different size parks, and in both low and high income neighborhoods. Moreover, it does not appear driven by changes in local socio-economic dynamics. Technically, our estimates apply only to nearby homeowners, but it is likely that making parks safer has much broader appeal.

Estimates of the value of park proximity alone, in safe areas, are consistently positive. These estimates do depend on cross-sectional variation, which we cannot be as confident about. But the results imply that safe parks are public goods, while unsafe ones are public bads. In fact, lack of safety appears to have locked up much of the value of urban parks. This finding is important for policy makers and environmental justice advocates. Based on principles of categorical equity, they may endorse providing greater open space

[35] Table A.5 includes all possible interactions between income, park proximity, and homicide risk. The coefficient on the park-income interaction is reduced by including the park-homicide interaction by roughly the same amount in the fully interacted model as in Table 11.

in safe and unsafe areas alike. Yet, those in unsafe areas could actually be hurt by such investments. Unsafe areas may benefit more from additional "eyes on the street" from residents inside nearby buildings or targeted safety programs (Jacobs, 1961, McMillen et al., 2017). Open spaces reduce such protections, particularly at night.

Whatever the case, the estimates of park proximity and its (more robust) interaction with crime suggest that over half of the value of park proximity remains "locked." Our large IV estimates suggest that these effects are not weaker when crime falls city wide. The value of crime reductions also appear to be much larger near parks. Moreover, the results imply that simply displacing crime away from parks may have great value. This relationship cuts both ways: spikes in violent crime, as observed in Chicago in 2016, can *lock amenity value in.*

Overall, complementarities are essential to determining the value of at least two public goods. Park proximity can become a public bad for nearby residents in the absence of safety. Safety, while always valuable, is more valuable near parks. We suspect that research on the value of public goods in other settings is likely to find complementarity to be important.

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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	645	120	1,336
Average park size (in mi2)	0.02	0.05	0.10	0.04
Average neighborhood size (in mi2)	0.64	0.74	0.92	0.71
Average local homicide risk	1.65	1.47	1.39	1.55
Panel B: Property Transactions				
Properties sold within 1/8 mile	142,085	154,952	11,461	308,498
Properties sold from 1/8 to 3/8 mile	170,463	159,680	18,200	348,343
Average price within 1/8 mile	300,635.6	903,967.0	304,424.2	603,816.9
Average price from 1/8 to 3/8 mile	278,347.2	770,175.7	248,357.0	502,233.9
Log distance to Central Business District	2.2	1.3	1.5	2.0
Age of Structure	75.1	76.2	70.3	75.0
Square footage	1,457.0	1,078.0	1,442.9	1,403.1
Number of Bedrooms	3.0	1.6	2.8	2.8
Number of Bathrooms	1.4	1.4	1.4	1.4
Single Family Residence fraction	0.21	0.10	0.02	0.33
Condo fraction	0.27	0.38	0.02	0.67
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 Age	34.9	39.5	36.0	37.2
Median Income	68.8	91.6	55.3	79.1
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 1,336 Neighborhoods with Flexible Park Proximity Indicators

	Dependent variable: ln *Housing Transaction Price*				
Homicide Risk Level	Property	Property	Property	Property	Neighborhood
	No Interaction - like (4)	Neigh. Fixed Effects	+ Tract Fixed Effects	+ Time-Varying Controls	+ Time-Varying Controls
	(1)	(2)	(3)	(4)	(5)
Within 1/16 mile of a Park	0.027**	0.056***	0.052***	0.042**	0.043**
	(0.014)	(0.017)	(0.018)	(0.021)	(0.018)
Within 2/16 mile of a Park	0.003	0.021	0.018	0.008	0.008
	(0.013)	(0.016)	(0.013)	(0.017)	(0.017)
Within 3/16 mile of a Park	0.007	0.017	0.008	0.005	0.004
	(0.012)	(0.015)	(0.014)	(0.016)	(0.016)
Within 4/16 mile of a Park	−0.010	−0.008	−0.000	−0.015	−0.014
	(0.012)	(0.015)	(0.014)	(0.015)	(0.016)
Within 5/16 mile of a Park	0.003	0.002	−0.005	−0.001	−0.002
	(0.012)	(0.015)	(0.011)	(0.014)	(0.015)
Within 1/16 mile × Homicide Risk		−0.017***	−0.011**	−0.011**	−0.010*
		(0.004)	(0.005)	(0.005)	(0.005)
Within 2/16 mile × Homicide Risk		−0.010**	−0.004	−0.003	−0.003
		(0.004)	(0.003)	(0.004)	(0.005)
Within 3/16 mile × Homicide Risk		−0.003	−0.000	0.002	0.003
		(0.004)	(0.003)	(0.004)	(0.004)
Within 4/16 mile × Homicide Risk		−0.001	0.000	0.003	0.003
		(0.003)	(0.003)	(0.003)	(0.004)
Within 5/16 mile × Homicide Risk		0.000	0.002	0.003	0.003
		(0.003)	(0.002)	(0.003)	(0.004)
Homicide Risk	−0.016***	−0.033***	−0.030***	−0.016***	-
	(0.004)	(0.005)	(0.006)	(0.005)	-
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	656,841	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. The level at which it is measured is indicated in the column heading, i.e. *Property level* or *Neighborhood 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, proportion of vacant housing and of rented units at the block level; median age and median income at the block group level. Park-neighborhood refers to the 3/8 miles radius around a park. Column 5 reports estimates from a model that uses a single estimate of homicide risk per neighborhood and thus drops the coefficient on homicide risk. 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 1,336 Neighborhoods over Time

	Dependent variable: ln *Housing Transaction Price*				
	Pooled Panel		True	Matching	Quadratic
	No Interaction	Interaction	Repeat Sales	Repeat Sales	Homicide Risk
	(1)	(2)	(3)	(4)	(5)
Park Proximity	0.013*	0.024***	-	-	0.027***
	(0.007)	(0.008)	-	-	(0.009)
Homicide Risk	−0.013***	−0.010***	−0.012***	−0.009***	−0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Homicide Risk Sq.					−0.002
					(0.021)
Park Prox. × Homicide Risk		−0.008***	−0.007**	−0.008***	−0.011**
		(0.002)	(0.003)	(0.003)	(0.004)
Park Prox. × Homicide Risk Sq.					0.032
					(0.037)
Park-Neighborhood Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Dwelling Characteristics	Yes	Yes		Yes	Yes
Time-Var Socio-Economic Controls	Yes	Yes	Yes	Yes	Yes
Observations	656,841	656,841	172,399	543,256	656,841

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 at the *Property level.* 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. Column 3 reports estimates from repeat sales model that differences out the coefficient on park proximity. Column 4 reports estimates from repeat sales as a matching estimator where park proximity becomes a control. 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 1,336 Neighborhoods over Time

	Dependent variable: ln *Housing Transaction Price*			
Homicide Risk Level	Property	Neighborhood	Neighborhood Excluding Risk within 1/8 miles of Park	Neighborhood Excluding Risk in Park
Estimator	Pooled Panel Interact	Pooled Panel Interact	Pooled Panel Interact	Pooled Panel Interact
	(1)	(2)	(3)	(4)
Park Proximity	0.024***	0.022**	0.022**	0.022**
	(0.008)	(0.009)	(0.009)	(0.009)
Homicide Risk	−0.010***	−0.013***	−0.017***	−0.014***
	(0.002)	(0.002)	(0.002)	(0.002)
Park Prox. × Homicide Risk	−0.008***	−0.004**	−0.005**	−0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
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 report results with *Property level Homicide Risk*, whereas columns 2-4 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 Local and City-Level Homicide Risk

	Dependent variable:		
	Actual Homicide Risk		
	Panel Pooled Pooled	True Repeat Sales	Matching Repeat Sales
	(1)	(2)	(3)
Local Homicide Risk	0.519***	0.927***	0.533***
	(0.016)	(0.029)	(0.013)
1^{st} Stage F-statistic	1025.02	991.28	1666.28
Park-Neighborhood Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Dwelling Characteristics	Yes	Yes	Yes
Time-Var Socio-Economic Controls	Yes	Yes	Yes
Observations	521,945	113,482	240,690

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				True Repeat Sales		Matching Repeat Sales	
	No Interaction		Interaction		Interaction		Interaction	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Park Proximity	0.011	0.010	0.021**	0.024***	-	-	-	-
	(0.007)	(0.009)	(0.008)	(0.009)	-	-	-	-
Homicide Risk	−0.014***	−0.022***	−0.011***	−0.019***	−0.004*	−0.026***	−0.014***	−0.024***
	(0.002)	(0.006)	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.005)
Park Prox. × Homicide Risk			−0.007***	−0.010***	−0.005**	−0.012**	−0.007**	−0.009**
			(0.002)	(0.003)	(0.003)	(0.006)	(0.003)	(0.004)
Park-Neighborhood Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dwelling Characteristics	Yes	Yes	Yes	Yes			Yes	Yes
Time-Var Socio-Economic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	521,945	521,945	521,945	521,945	113,482	113,482	240,690	240,690

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 1-2 report pooled panel models, columns 3-4 instrumental variable (IV) specification. Columns 5-6 report estimates from repeat sales model that differences out the coefficient on park proximity. Columns 7-8 report estimates from repeat sales as a matching estimator where park proximity becomes a control. 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	0.040***	0.049***	0.037**	0.057***
(Large > 75th perc. size)	(0.015)	(0.017)	(0.015)	(0.019)
Proximity to Small Park	0.001	0.009	0.000	0.009
(Small < 75th perc. size)	(0.008)	(0.009)	(0.008)	(0.010)
Homicide Risk	−0.013***	−0.011***	−0.022***	−0.019***
	(0.002)	(0.002)	(0.005)	(0.005)
Large Park × Homicide Risk		−0.008*		−0.019**
		(0.005)		(0.008)
Small Park × Homicide Risk		−0.005**		−0.006*
		(0.002)		(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 described in Table 3. Columns 1-2 report pooled panel models, columns 3-4 instrumental variable (IV) specification. Large/Small Park denotes a dummy that takes one if the area of the park is above/below the 75th 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. Park Proximity, Homicide Risk, and Socio-Economic Changes

Panel A	*Dependent variable:*							
	ln(Population Density)		White (%)		Black (%)		Hispanic (%)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel	IV	Panel	IV	Panel	IV	Panel	IV
Park Proximity	0.012	0.017	0.003	0.004	0.007*	0.004	−0.009**	−0.007
	(0.011)	(0.013)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
	[0.402]	[0.318]	[0.455]	[0.367]	[0.063]	[0.318]	[0.019]	[0.149]
Homicide Risk	0.018***	0.031***	−0.013***	−0.022***	0.012***	0.018***	0.002	0.004**
	(0.002)	0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.002)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.180]	[0.025]
Park Prox.×Homicide Risk	0.001	0.001	−0.002	−0.003***	0.001	0.002**	0.001	0.0002
	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	[0.655]	[0.842]	[0.102]	[0.004]	[0.392]	[0.035]	[0.392]	[0.842]
Observations	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 (%)	
	Panel	IV	Panel	IV	Panel	IV	Panel	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]	[0.01]	[0.009]	[0.402]	[0.367]	[0.063]	[0.318]
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 Prox.×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]	[0.656]	[0.340]	[0.049]	[0.126]	[0.040]	[0.340]	[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.

Table 9. 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 – No Complementarity				
Chicago	678	535	202	1,415
NY	1,019	1,030	251	2,300
Philly	69	105	16	190
Total	1,766	1,670	469	3,905
Panel B: Realized Park Proximity Value with Complementarity				
Chicago	1,336	326	-506	1,156
NY	1,860	645	-925	1,580
Philly	130	91	-43	178
Total	3,326	1,063	-1,474	2,914
Panel C: Park Proximity Value Locked in by Crime				
Chicago	270	941	984	2,194
NY	553	1,793	1,519	3,865
Philly	33	157	81	271
Total	855	2,891	2,584	6,330
Panel D: Potential Park Proximity Value with No Crime in Parks				
Chicago	1,606	1,267	478	3,350
NY	2,413	2,439	594	5,445
Philly	162	249	38	449
Total	4,181	3,954	1,110	9,244

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 park-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 10. 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	1,414	-	-279	1,134
NY	2,440	-	-336	2,103
Philly	111	-	-84	27
Total	3,964	-	-700	3,264

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 9. Based on the expected number of park-neighborhood homicides we calculate yearly percentage changes using a linear regression by park-neighborhood . We classify park-neighborhoods as having experienced a decrease if the average yearly reduction in homicide risk was below 1%, if the park-neighborhood saw a change above 1% we classify them as having experienced an increase. All others are classified as having no change.

Table 11. Park Premium and Homicide Risk:
Valuations for High versus Low Income Neighborhoods

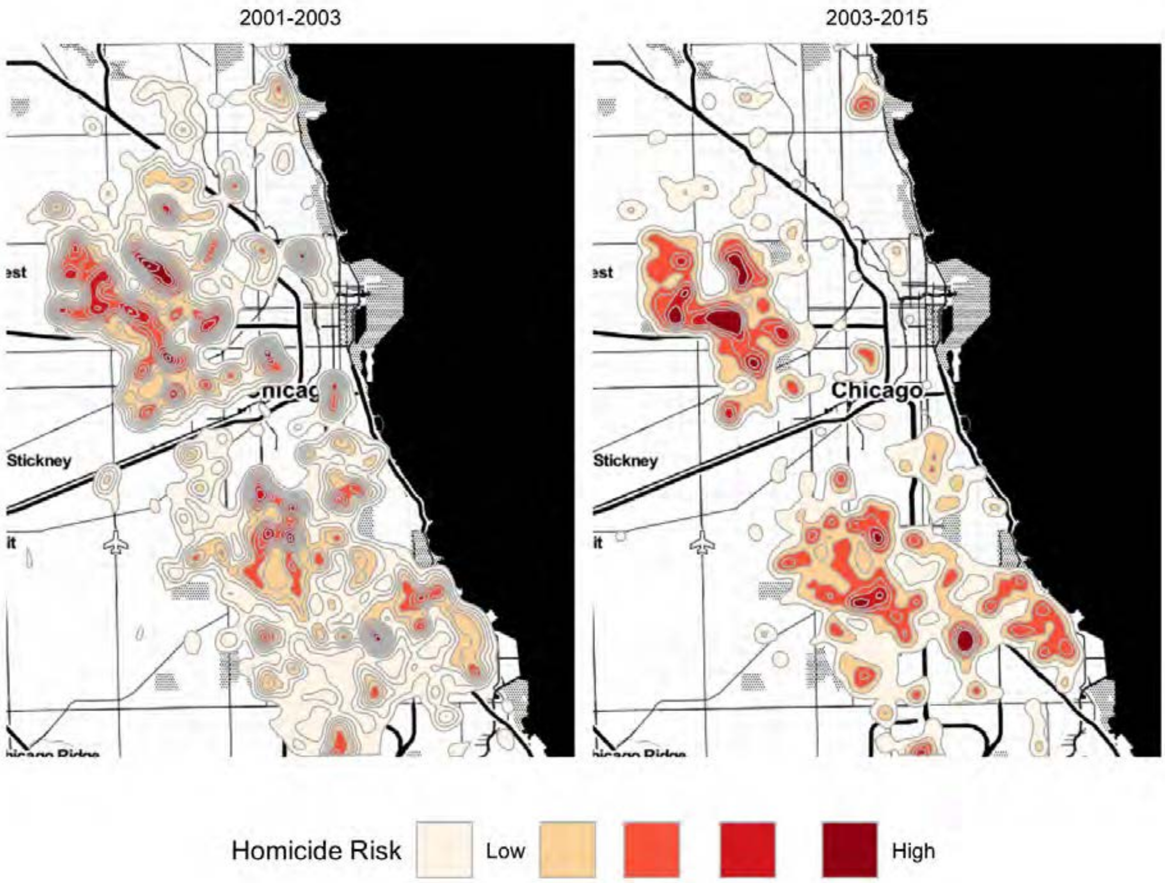
	Dependent variable: ln *Housing Transaction Price*			
	Pooled Panel No Int.	Pooled Panel Interact	IV Panel No Int.	IV Panel Interact
	(1)	(2)	(3)	(4)
Park Proximity × High Income	0.019*	0.024**	0.018	0.026**
	(0.011)	(0.011)	(0.011)	(0.011)
Park Proximity × Low Income	0.002	0.013	0.001	0.018*
	(0.007)	(0.009)	(0.007)	(0.011)
Homicide Risk	−0.015***	−0.013***	−0.024***	−0.021***
	(0.002)	(0.002)	(0.005)	(0.005)
Park Prox. × Homicide Risk		−0.006**		−0.009**
		(0.002)		(0.004)
High Income	0.047***	0.050***	0.046***	0.050***
	(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 and includes the same controls described in Table 6. Columns 1-2 report pooled panel models, columns 3-4 instrumental variable (IV) specification. High and Low Income are indicator for whether the census block 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.

Figure 1. Housing Transactions around Parks

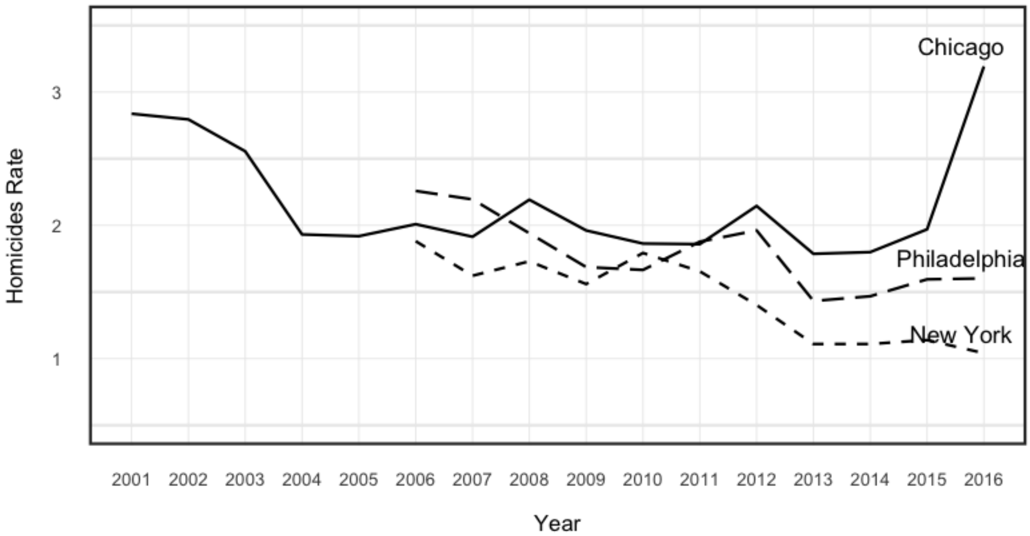
Note: Points represent transactions within 3/8 miles of Chicago's Marquette park in our sample. Different shades denote proximity to the park in intervals of 1/8 mi.

Figure 2. Homicide Risk in Chicago.



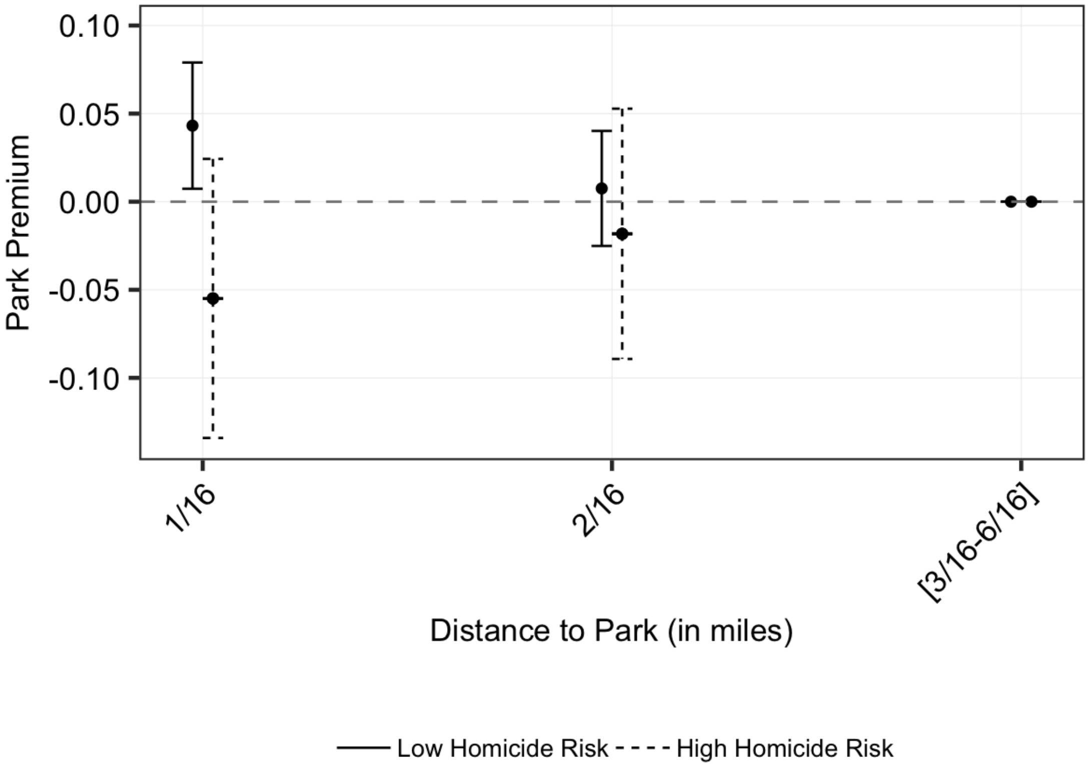
Note: Shades represent a density estimation of being a homicide victim per square mile. Estimates are based geolocated crime data for years 2001-2003 and 2013-2015 using a bivariate Gaussian kernel with a bandwidth of 2/8 of a mile on a 1/8 mile city grid.

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. Neighborhood Crime



Note: Park premium conditional on Homicide Risk based on Table 2. *Low Homicide Risk* denotes neighborhoods with no homicides risk in the sample period, *High Homicide Risk* neighborhoods with an expected average of 10 yearly homicides per square mile in the sample period.

A Appendix

Table A.1. First Stage Estimate: Relationship between Local and City-Level Homicide Equivalent Risk

	Dependent variable:		
	Actual Homicide Equiv. Risk		
	Panel Pooled Pooled	True Repeat Sales	Matching Repeat Sales
	(1)	(2)	(3)
Local Homicide Equiv. Risk	0.649***	0.963***	0.661***
	(0.020)	(0.030)	(0.014)
1^{st} Stage F-statistic	1009.6	1026.5	2365.1
Park-Neighborhood Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Dwelling Characteristics	Yes	Yes	Yes
Time-Var Socio-Economic Controls	Yes	Yes	Yes
Observations	521,945	113,482	240,690

Notes: The specifications are the same as in Table 5. *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:
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				True Repeat Sales		Matching Repeat Sales	
	No Interaction		Interaction		Interaction		Interaction	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Park Proximity	0.010	0.009	0.022***	0.023**	-	-	-	-
	(0.007)	(0.009)	(0.008)	(0.009)	-	-	-	-
Homicide Equiv. Risk	−0.014***	−0.018***	−0.013***	−0.016***	−0.003	−0.005	−0.014***	−0.016***
	(0.002)	(0.005)	(0.002)	(0.004)	(0.002)	(0.005)	(0.002)	(0.004)
Park Prox. × Homicide Equiv. Risk			−0.005**	−0.005**	−0.005**	−0.011**	−0.006**	−0.006*
			(0.002)	(0.003)	(0.002)	(0.005)	(0.003)	(0.003)
Park-Neighborhood Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dwelling Characteristics	Yes	Yes	Yes	Yes			Yes	Yes
Time-Var Socio-Economic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	521,945	521,945	521,945	521,945	113,482	113,482	240,690	240,690

Notes: 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.3. Park Premium and Homicide Risk: Excluding 2016

	Dependent variable: ln *Housing Transaction Price*							
Estimator	Pooled Panel				True Repeat Sales		Matching Repeat Sales	
	No Interaction		Interaction		Interaction		Interaction	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Park Proximity	0.011	0.010	0.020**	0.023***	-	-	-	-
	(0.007)	(0.009)	(0.008)	(0.009)	-	-	-	-
Homicide Risk	−0.013***	−0.019***	−0.011***	−0.016***	−0.003	−0.023***	−0.014***	−0.022***
	(0.002)	(0.006)	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.005)
Park Prox. × Homicide Risk			−0.006***	−0.009***	−0.004	−0.008	−0.007**	−0.009**
			(0.002)	(0.003)	(0.003)	(0.006)	(0.003)	(0.004)
Park-Neighborhood Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dwelling Characteristics	Yes	Yes	Yes	Yes			Yes	Yes
Time-Var Socio-Economic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	491,710	491,710	491,710	491,710	103,692	103,692	223,084	223,084

Notes: The specifications are the same as in Table 6 excluding the 2016 year. 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: Excluding 2/16th miles

	Dependent variable: ln *Housing Transaction Price*							
Estimator	Pooled Panel				True Repeat Sales		Matching Repeat Sales	
	No Interaction		Interaction		Interaction		Interaction	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Park Proximity	0.023^{**}	0.022	0.035^{***}	0.035^{***}	-	-	-	-
	(0.010)	(0.014)	(0.012)	(0.013)	-	-	-	-
Homicide Equiv. Risk	-0.012^{***}	-0.015^{**}	-0.011^{***}	-0.013^{***}	-0.004^{*}	-0.024^{***}	-0.014^{***}	-0.022^{***}
	(0.002)	(0.007)	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.005)
Park Prox. $\times$ Homicide Equiv. Risk			-0.009^{***}	-0.009^{**}	-0.007^{*}	-0.008	-0.005	-0.006
			(0.003)	(0.005)	(0.003)	(0.008)	(0.003)	(0.005)
Park-Neighborhood Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dwelling Characteristics	Yes	Yes	Yes	Yes			Yes	Yes
Time-Var Socio-Economic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	394,820	394,820	394,820	394,820	85,726	85,726	188,382	188,382

Notes: The specifications are the same as in Table 6 excluding properties between 1/16 miles and 2/16 miles of 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 A.5. Park Premium and Homicide Risk:
Valuations for High versus Low Income Neighborhoods

	Dependent variable: ln *Housing Transaction Price*							
	Pooled Panel	Pooled Panel	Pooled Panel	Pooled Panel	IV Panel	IV Pane	IV Panel	IV Panel
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Park Proximity	0.002	0.013	0.002	0.011	0.001	0.018*	0.000	0.016
	(0.007)	(0.009)	(0.007)	(0.009)	(0.007)	(0.011)	(0.007)	(0.011)
Homicide Risk	−0.015***	−0.013***	−0.011***	−0.010***	−0.024***	−0.021***	−0.022***	−0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
High Income	0.047***	0.050***	0.062***	0.064***	0.046***	0.050***	0.056***	0.067***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.012)	(0.013)
Park Proximity × High Income	0.017	0.011	0.017	0.012	0.018	0.008	0.018	0.010
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)	(0.014)
Park Proximity × Homicide Risk		−0.006**		−0.005**		−0.009**		−0.008**
		(0.002)		(0.002)		(0.004)		(0.003)
High Income × Homicide Risk			−0.015***	−0.014***			−0.011	0.006
			(0.005)	(0.005)			(0.007)	(0.008)
Park Proximity × High Income × Homicide Risk				−0.001				−0.022***
				(0.005)				(0.008)
Park-Neighborhood Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dwelling Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-Var Socio-Economic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	521,945	521,945	521,945	521,945	521,945	521,945	521,945	521,945

Notes: Sample is the same as in Table 11, and includes the same controls described in Table 6. Columns 1-4 report pooled panel models, columns 5-8 instrumental variable (IV) 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 A.6. Park Premium and Homicide Risk:
Neighborhood Increase in White Households

	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)
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 Prox.×Homicide Risk	−0.007***	−0.005**	−0.010***	−0.008**
	(0.002)	(0.002)	(0.003)	(0.004)
Park Prox.×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

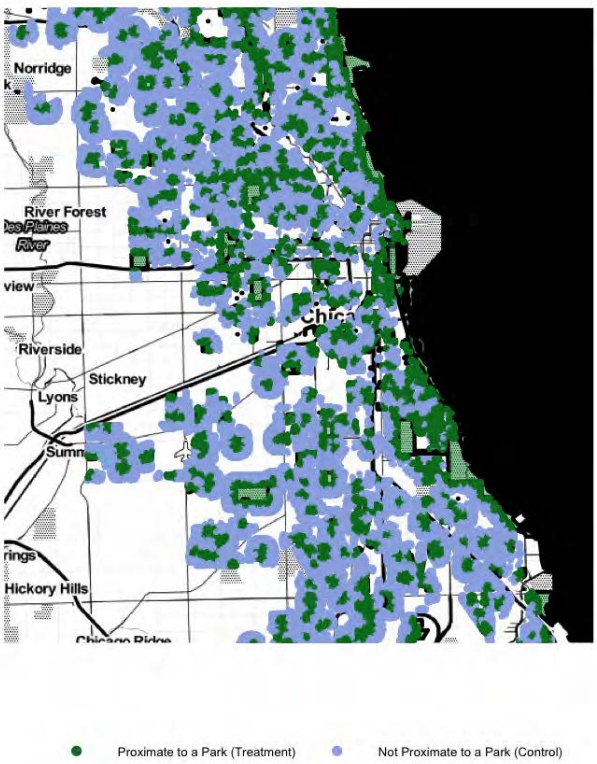
Notes: Sample and controls are those reported in Table 6. Columns 1-2 report pooled panel models, columns 3-4 instrumental variable (IV) specification. White Change is an indicator that takes one if the Census Block had an intercensal increase in the proportion of white households. Standard errors clustered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

Table A.7. Park Premium and Homicide Risk:
Neighborhood Income Changes.

	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)
Park Proximity	0.017**	0.017**	0.020**	0.020**
	(0.008)	(0.008)	(0.009)	(0.009)
Homicide Risk	−0.011***	−0.011***	−0.017***	−0.017***
	(0.002)	(0.002)	(0.005)	(0.005)
Park Prox. × Homicide Risk	−0.006***	−0.007***	−0.009***	−0.009***
	(0.002)	(0.002)	(0.003)	(0.003)
Park Prox. × Homicide Risk × Income Change		0.002		0.0002
		(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

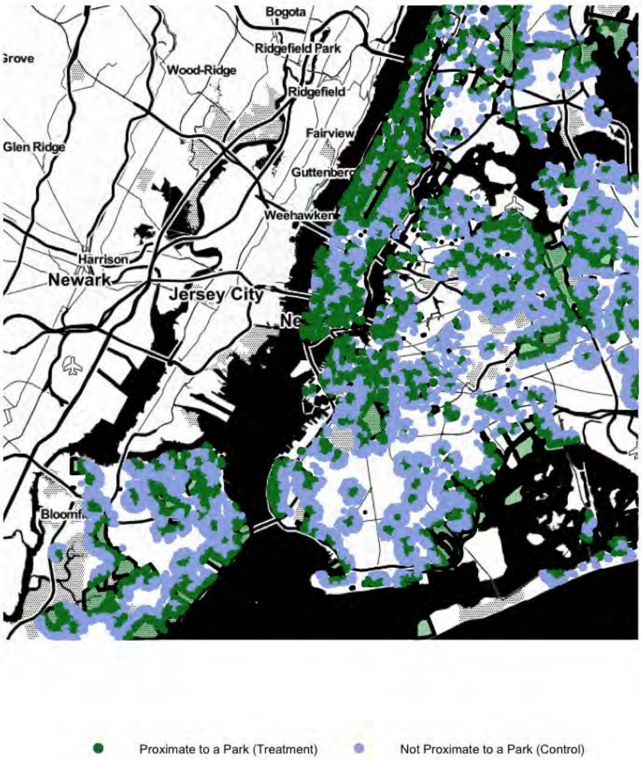
Notes: Sample and controls are those reported in Table 6. Columns 1-2 report pooled panel models, columns 3-4 instrumental variable (IV) specification. White Change is an indicator that takes one if the Census Block Group had an intercensal increase in the median income of households. Standard errors 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



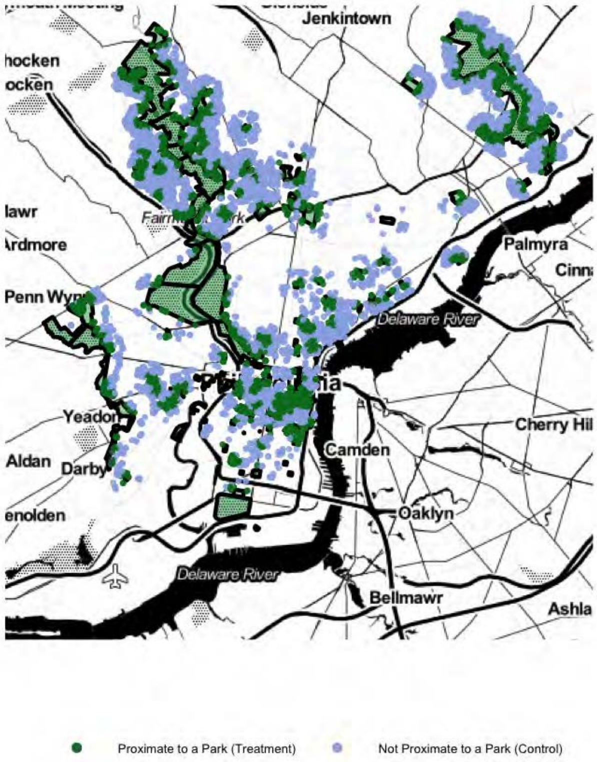
Points represent transactions within 3/8 miles of the nearest Park. Different shades denote proximity to the park. "Proximate to a Park (Treatment)" denotes transactions within 1/8 miles of a Park, "Not Proximate to a Park (Control)" transactions between 1/8 miles and 3/8 miles.

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



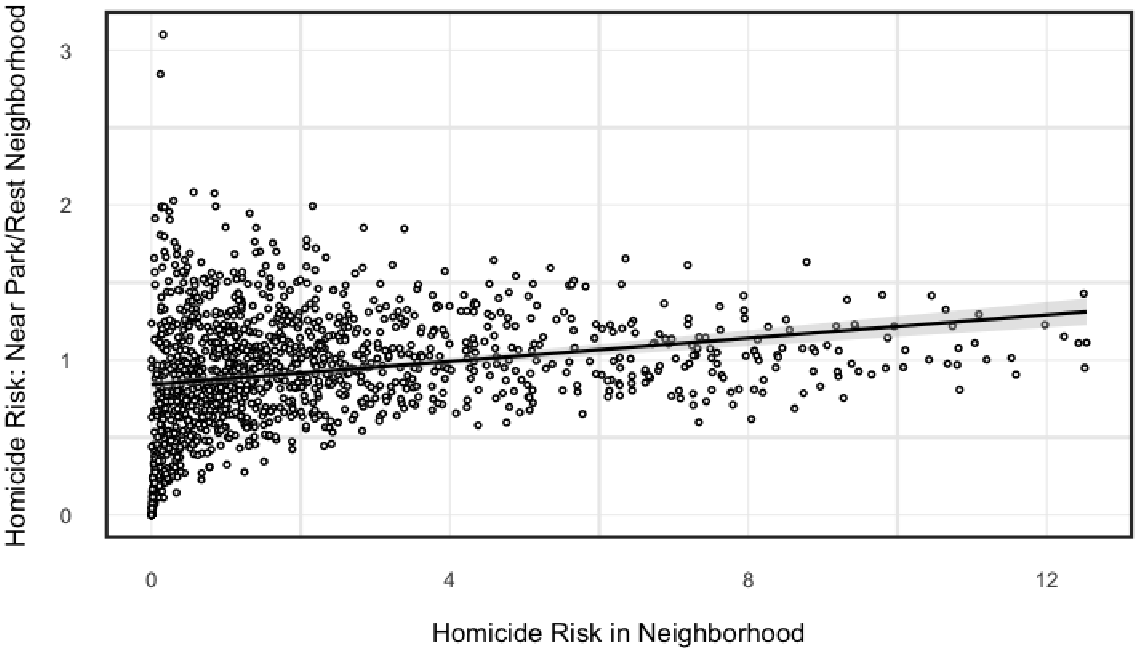
Points represent transactions within 3/8 miles of the nearest Park. Different shades denote proximity to the park. "Proximate to a Park (Treatment)" denotes transactions within 1/8 miles of a Park, "Not Proximate to a Park (Control)" transactions between 1/8 miles and 3/8 miles.

Figure A.3. Housing Transaction Near Parks, Philadelphia



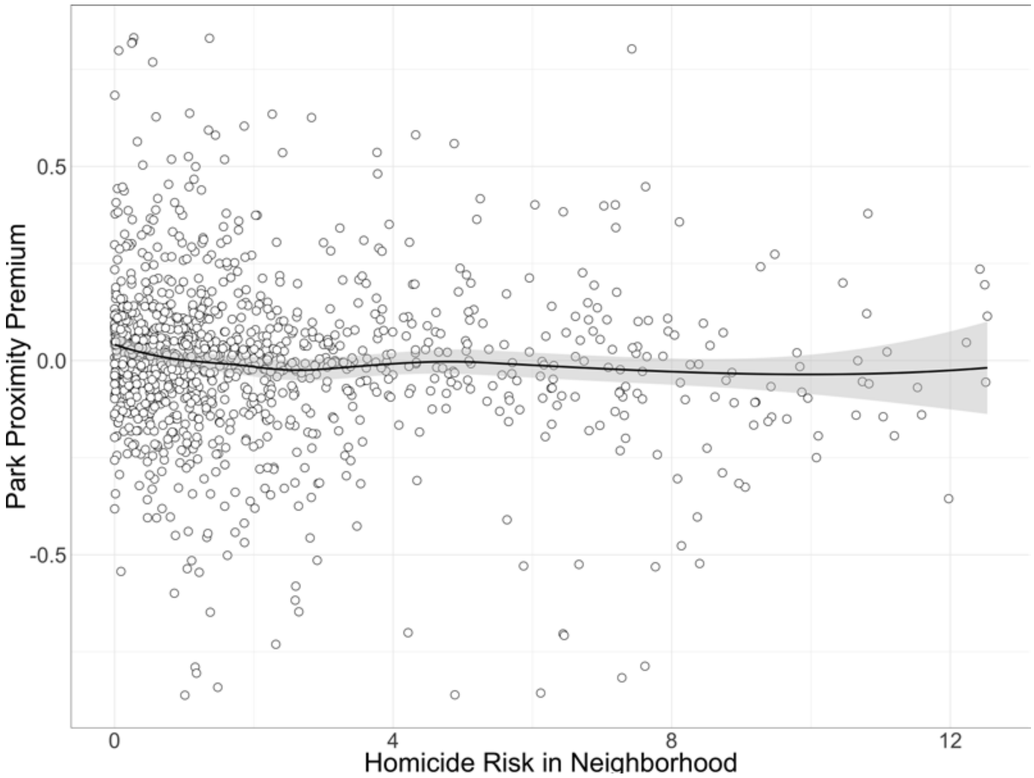
Points represent transactions within 3/8 miles of the nearest Park. Different shades denote proximity to the park. "Proximate to a Park (Treatment)" denotes transactions within 1/8 miles of a Park, "Not Proximate to a Park (Control)" transactions between 1/8 miles and 3/8 miles.

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)