The Scale and Nature of Neighborhood Effects on Children

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Abstract

Recent research documents a causal impact of place on the long-run outcomes of children. However, little is known about which neighborhood characteristics are most important, and at what scale neighborhood effects operate. By using the quasi-random assignment of public housing along with administrative data from Denmark, we get inside the "black box" of neighborhood effects by defining neighborhoods using various characteristics and scales. Results indicate effects on mental health and especially education are large but local, while effects on drug possession operate on a much broader scale. Additionally, unemployment and education are better predictors of outcomes than neighborhood income.

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Introduction

The influence of housing and neighborhoods on the economic and social well-being of humans is an established narrative in modern society. However, only recently have scholars begun to provide causal evidence on how a person's place of residence matters for the long-term accumulation of human capital. Evidence is most prominent in studies of Moving to Opportunity (MTO) and its positive influence on some children's academic, behavioral, health and even adult labor market outcomes (Chetty, Hendren & Katz (2016); Kling, Liebman, and Katz (2007); Ludwig, Jens, et al. (2013); Ludwig, Jens, et al. (2008)). The subsequent benefit of place is also present in public housing reassignment (Chyn (2018)), immigrant neighborhood assignment (Damm & Dustmann (2014)) and disaster displacement (Deryugina and Molitor (2020)). More broadly, Chetty & Hendren (2018), Deutscher (2020) and Chetty et al. (2014) highlight that places matter for the intergenerational mobility of children.

Collectively, this existing literature provides compelling evidence that places and neighborhoods can have profound influences on the long-term outcomes of children. However, little is known about the "black box" of neighborhood effects. In particular, what neighborhood characteristics are most important for human capital development, and at what geographic scale do neighborhood effects operate? These questions are important, because mixed results across a number of MTO studies suggest that neighborhoods likely engender a complicated set of effects on children.[1] As discussed by Chyn & Katz (2021), both the scale and channels through which neighborhoods matter are poorly understood in the literature, yet these dimensions of neighborhood effects are important for crafting policies that can improve places and the outcomes of their residents.

The purpose of this paper is to examine how various measures of neighborhood quality, measured at varying geographic scales, impact children's educational attainment, mental health, and criminal involvement. We do so using rich administrative data from Denmark along with data on the quasi-random assignment of disadvantaged households to social housing in Copenhagen. In particular, we exploit the social housing assignment policy instituted by the Municipality of Copenhagen in 2009-2014 that assigned every third unit that became available in Copenhagen's social housing stock to a household that is housing insecure or homeless.[2] This setting differs from MTO in that compliance is higher (63% versus 48% in MTO), and the newly assigned housing unit can be in a neighborhood of higher or lower

[1] For example, Ludwig, Jens et al. (2013) and Kling, Liebman, and Katz (2007) find no consistent effect of children's educational achievement from MTO, but some benefits to girls in terms of risky behavior and health outcomes. Using the same MTO data and experiment, Chetty, Hendren & Katz (2016) find that moving to a lower-poverty neighborhood when young (before age 13) increases college attendance and earnings and reduces single parenthood rates, but there are no effects on older kids. Additionally, MTO studies (with the exception of Aliprantis & Richter (2020)) often find more limited benefits for adult MTO movers apart from health outcomes.

[2] Roughly 20% of all housing in Copenhagen is designated social housing and is spread across a range of different types of neighborhoods.

quality than one's previous residence. More importantly, while the MTO control group consists of non-movers, nearly all of the families who decline the first housing offer accept a subsequent offer, which means we are able to estimate the effect of neighborhood separate from the impact of moving to a new housing unit.

Consistent with the institutional details underlying the housing assignment policy, we show that the assignment of children to social housing is consistent with a random process by documenting that the attributes of children/families are uncorrelated with the neighborhood quality of the new housing assignment. In particular, we show that the attributes of children/families are uncorrelated with the neighborhood quality of the new housing assignment. We show that this is true both for each individual attribute, as well as for each predicted outcome, where all the child and family characteristics are used to predict each outcome of interest.

The setting and data enable us to make three contributions to the existing literature. To our knowledge, this is the first paper that combines quasi-experimental variation in neighborhood with detailed administrative data that enable us to explore the spatial scale at which we define neighborhoods.[3] Put simply, we are not constrained by decisions made by government to aggregate data into Census tracts, or any other geographic unit, which may or may not measure the neighborhood relevant for a given household.[4] Rather, we use the various underlying individual-level measures available in the administrative data to construct neighborhood characteristics that vary from a radius of a 2-minute walk, up to a 15-minute walk, from one's residence. Combined with the exogenous variation in neighborhood, this allows us to assess the extent to which neighborhood effects are highly localized, or if neighborhood characteristics farther away matter nearly as much. In addition, by measuring neighborhood in a way that most closely corresponds to an individual's actual neighborhood, we minimize measurement error in neighborhood quality and therefore the potential for attenuation bias. Secondly, we can examine various measures of neighborhoods, including unemployment levels, income, education and property values.[5] Thirdly, we are able to examine the effects of neighborhoods amongst movers (and net of disruption effects) for a broad range of administrative outcomes, including matriculating at an

[3] Chetty, Friedman, Hendren, Jones, and Porter (2020) examine spatial decay across Census tracts and block groups Census Block Groups in the relationship between poverty rates and upward mobility for Whites. The advantages of our analysis is that we are able to do this i) across any size neighborhood rather than being constrained to use government-assigned boundaries, and, and more importantly, ii) using a research design that exploits exogenous variation in housing assignment, which contrasts with the cross-sectional and observational approach used in Figure VII of Chetty, Friedman, Hendren, Jones, and Porter (2020).
[4] This is particularly true for those living near a boundary of a defined geographic area, which is especially problematic when using small geographic units.
[5] Aliprantis (2017) highlights the importance of incorporating different measures of neighborhood quality in the context of MTO and Aliprantis & Richter (2020) provides evidence that neighborhood effects for adults are more prominent using measures of neighborhood quality beyond poverty rates as well as focusing on subsets of program participants.

upper secondary education institution, criminal arrest, drug possession, and whether the child received any mental health treatment.[6]

Results yield two broad findings. The first is that neighborhood characteristics matter, but are highly localized in some cases. Intent-to-treat (ITT) estimates indicate that when defining neighborhoods as a two-minute walk—essentially the same or adjacent building—a one standard deviation improvement in neighborhood quality generates a 6% increase in attending an upper secondary education institution, a 23% decrease in adult drug possession (though no effect on overall adult crime), and a 17% reduction in any mental health visits. Given a compliance rate of 63%, treatment on the treated (ToT) estimates indicate a 9.5% increase in attending an upper secondary education institution, a 37% decrease in drug possession, and a 27% decrease in mental health visits. However, results also indicate that the effects on both upper secondary education matriculation and, to a lesser extent, mental health are largely local, as estimates are both substantially smaller and statistically insignificant for neighborhood distances of 10- to 15-minute walks. In addition, effects on education and drug possession are largest for boys and ethnic minorities, while effects on mental health are largest for boys and ethnic majorities. Overall, these results suggest that educational attainment and mental health are perhaps most impacted by factors that operate at a small geographic scale (e.g. peers and social networks), while drug use is more impacted by factors that operate at a larger geographic scale (e.g. schools, policing and infrastructure). They also suggest that it is difficult for families to avoid the negative effects of neighborhood with respect to drug use.

The second main finding is that neighborhood unemployment and education levels seem to be the best predictors of individual outcomes. In contrast, average neighborhood income has smaller and mostly statistically insignificant effects on both drug possession and mental illness, though like unemployment and education it has large local effects on educational attainment.

While these findings are consistent with the evidence cited earlier from MTO and other settings showing the importance of location in generating long-term outcomes, we note that some of the existing literature finds little to no effect. For example, Oreopoulos (2003) shows limited impact of neighborhood quality on later adult outcomes for Toronto based public housing assignment, and Barnhardt, Field, and Pande (2017) find no impacts of a housing lottery that moved families out of Indian slums to better neighborhoods other than increased feelings of social isolation. In

[6] We focus on these outcomes, rather than contemporaneous outcomes such as test scores, because longer-term adult outcomes are often the most consequential for understanding the impacts of neighborhoods. All outcomes are based on the extensive margin and if the outcome occurred by the end of 2020. In Denmark, upper secondary education starts at age 16 or 17 and we can measure criminal arrests and drug possession starting at age 15. In addition, with respect to health outcomes, we chose not to use general doctor's visits since they are often preventative, and more extreme measures of health such as serious illness and mortality are too rare to study for this population of young adults.

addition, results are mixed in other settings. Gibbons, Silva, and Weinhardt (2013) find no effects of changes in neighborhood composition on academic outcomes. Fryer & Katz (2013) show that across several prominent interventions, higher-quality neighborhoods can improve well-being and health but have no detectable effects on labor market outcomes or risky behavior. Our study provides a potential explanation for the mixed findings across this literature. In particular, we show that effects that are present when neighborhoods are defined locally are absent for larger definitions of neighborhood, and that how one measures neighborhood quality can impact one's findings.

Overall, our results highlight that the scale of neighborhood effects may be quite small in practice. Additionally, results are consistent with the existing literature in showing that neighborhood effects are heterogenous across individuals. These results have implications for housing policies more broadly. In particular, they suggest there may be benefits from placing at-risk children with lower-risk peers, and that policies that focus on smaller-scale definitions of neighborhoods could benefit at-risk children. These results are also consistent with a larger peer effect literature that highlights impacts of likely or actual peers on a variety of long-term labor market outcomes in schools, neighborhoods, and correctional settings (Billings, Deming & Rockoff (2014), Billings & Hoekstra (2022), Black, Devereux, and Salvanes (2013), Carrell, Hoekstra, and Kuka (2018), Bayer, Hjalmarsson, and Pozen (2009), Damm & Gorinas (2020)).

Denmark Social Housing Policy

Non-profit housing associations own and manage the social housing stock in Denmark, which in Copenhagen comprises 20% of the total housing stock. In addition, they administer the allocation of apartment units to wait-listed families. Every third social housing unit that becomes vacant is reserved by the municipality for households with "urgent needs", defined as those who cannot afford housing at private market rents or are unable to wait the standard amount of time for social housing. This third of units set aside for urgent need households is determined on a "rolling" basis as vacancies occur. Copenhagen delineates 122 mutually exclusive geographic areas within the city called "housing sections" ("local areas," hereafter), each of which contains an average of four social housing developments. Finally, we note that in an effort to avoid assigning urgent need households to the most disadvantaged sectors in Copenhagen, any apartment located in a local area that exceeded a (very high) 40% rate of resident adult unemployment on January 1st of any given year is ineligible for assignment to urgent needs households for that year. Even with this restriction, however, there exists a wide range of social environments to which disadvantaged families can be assigned.

The process of obtaining municipal social housing starts most often with a citizen contacting the municipality regarding a housing problem. A social counselor screens the household's housing urgency and determines whether it requires counseling or social housing allocation. In the latter case, the social counselor is responsible for filling out the application in terms of affordable rent and household size, both of which are based on administrative data, rather than information reported by the family. As a result, it is unlikely, if not impossible, for applicants to manipulate either measure, both of which are used to assign households to housing. Each time a housing unit reserved by the municipality is ready to be inhabited, the allocation program generates a queue of relevant applicants from the waiting list that matches the characteristics of the apartment in terms of household size and composition, and selects the application with the oldest referral date (e.g. the application that has waited the longest).

It is critical to emphasize that the allocation criteria employed by the social counselor do not consider any characteristics of neighbors, such as income or criminality, when it comes to which unit of social housing is offered to an applicant. Similarly, applicants have no ability to influence the first offer of housing based on neighborhood or preference for particular social housing units. This lack of consideration of neighborhood exists because the presence of locational preferences is deemed to be in direct contradiction to having an urgent need for housing. Given the geographical dispersion of social housing units, most social housing applicants are offered apartments far away from their last residences.[7]

Unlike those on the generic social housing waiting lists who must wait years before being allocated a unit, urgent need households on average receive a first housing offer 139 days after application. It is this first offer that we use in this study as our measure of the assigned housing unit. Though no household can be forced to accept an offer, most of them (63%) accept their first one due to their precarious situations. The first offer can be rejected because of officially acceptable reasons offered by applicants (close to rival gangs, close to violent ex-husband) or officially unacceptable reasons (geographic and apartment preferences). Whereas applicants providing acceptable reasons are eligible to receive at least one additional offer, those providing unacceptable reasons may be deemed ineligible for future offers. Approximately 80% of all applicants end up accepting a social housing assignment. Upon receiving a new housing assignment, households can immediately move into the new housing unit. The children are given the opportunity either to stay in the school from the previous residence, or attend the school assigned to the new housing unit. In our sample of urgent needs households, 86% of kids stay in their former school in the year they move. Few students seem to transition to the new neighborhood schools even after that, as 85% of kids stay in their former school two years after the move. The median distance from a new housing unit to a resident's previous address is approximately 1 hour walking distance, or 5.5 kilometers.

Data and Empirical Model

[7] Across the 10 roughly equally sized post towns in Copenhagen, social housing is located in the following distribution: Copenhagen S (20.75% of apartments), Brønshøj (19.98% of apartments), Copenhagen Ø (14.43% of apartments), Copenhagen NV (13.58% of apartments), Valby (12.72% of apartments), Copenhagen N (6.66% of apartments), Vanløse (5.47% of apartments), Copenhagen SV (4.01% of apartments), Copenhagen V (1.45% of apartments), and Copenhagen K (0.94% of apartments).

Data

We incorporate the richness of the Denmark administrative data that allow us to follow the residential location and family structure of all residents of Copenhagen (Statistics Denmark 2021). These data allow us to define individuals as living with biological parents or in single-parent households as well as overall tenure in a home and neighborhood. Our records also provide information on gender, immigration history, ethnicity and details on the number and ages of all children in the household. We have also merged in detailed information on employment, social assistance, criminal charges made after the age of 16, income and education. These data also provide some health outcomes as they relate to mortality as well as general and mental health doctors' visits.

Our main sample of quasi-randomly assigned children to social housing consists of 1,171 children who were provided housing in the years 2009 to 2014. Table 1 provides the individual attributes of these children as well as the larger population of all neighbors in Copenhagen within a 15-minute walking distance of a social housing unit. The top panel of Table 1 provides individual attributes of each sample used to create our measures of neighborhood quality as well as to document that assigned social housing is unrelated to individual attributes. The bottom panel of Table 1 provides measures of our four individual outcomes. The first outcome is educational attainment, as measured by whether the student enrolled in an upper secondary institution of higher learning. We also examine whether the individual was arrested for any violent or property crime (non-drug & non-technical) after age 16 and whether the individual was arrested for the possession of drugs after age 16. Finally, we measure whether the student received any treatment for mental illness. In all cases, we examine outcomes only after a child's family received their first offer for social housing. Table 1 indicates that the children assigned to social housing are roughly 16 percentage points (20 percent) less likely than neighboring children to enroll in upper secondary education, 130 percent more likely to be arrested, 100 percent more likely to be arrested for drug possession, and 120 percent more likely to be treated for mental illness compared to those living within a 15-minute walk of their newly assigned social housing.

Perhaps unsurprisingly, children who were assigned social housing over this time period are more likely to be non-western immigrants, live in single parent households, have unemployed parents, and come from lower income, less educated, and higher crime families than their neighbors located within a 15-minute walking distance of social housing. The standard deviation in column 4 of Table 1 provides a measure of how much neighborhood attributes vary across our neighborhoods that receive an urgent needs household with a child. These descriptive statistics show that the standard deviation for our largest measure of neighborhood is approximately 20-30% as large as the overall neighborhood mean for later measures of neighborhood quality such as unemployment and income. These standard deviations indicate that children are assigned to a variety of neighborhood types. In addition, we note that this is a lower bound, as there is even more variation when neighborhoods are defined to be smaller than a 15-minute walk.

As a point of reference, the 15-minute walking distance definition of neighborhood used in Table 1 is approximately equal to either a larger U.S. zip code or to around six census tracts. Later models show results for various neighborhood sizes ranging from a 2-minute walking distance (i.e., own building plus very close neighboring building) up to this 15-minute walking radius definition. We define neighborhoods in terms of walking distances given the overall dense development pattern of Copenhagen as well as to define an area in which individuals are most likely to interact with their neighbors and physical environment.[8] In addition, this walking distance definition likely reduces any attenuation bias that could arise if nearby individuals located on opposite sides of administrative boundaries (e.g. census geographies, postal areas, etc.) were not considered to be neighbors.

Measurement of neighborhood quality

In order to provide results that are comparable to the existing literature, we begin by characterizing neighborhoods based on average family income, unemployment, and adult years of education. These three variables all capture something about the labor market success of people living in each neighborhood. All our neighborhood measures are calculated immediately prior to a household's new housing assignment and scaled to be mean zero with a standard deviation of one. In addition, we note that the limited number of urgent needs households and the geographic dispersion of social housing limit any concerns about our kids influencing any measure of neighborhood quality more broadly. In addition to showing results for these three measures of neighborhood quality, we also provide a summary index of neighborhood quality based off of these three measures of neighborhoods, where the sign of the unemployment variable is switched so that larger values represent a positive measure of labor market success. These indices are constructed using the methodology of Anderson (2008) and have mean zero and standard deviation of one.

Identification and Empirical Model

The identifying assumption of our study is that the neighborhood quality of the social housing assignment is unrelated to a child's preexisting individual attributes. While we have every reason to believe this assumption should hold given the housing assignment process described above, we also conduct a series of balance tests for every walking distance definition of neighborhood that we later incorporate into our analysis. To simplify presentation of these results, we assess whether assigned neighborhood quality is correlated with predicted outcome based (only) on individual attributes.[9] To do so, we first use the individual attributes highlighted in the row headings of Table 1 to predict each

[8] For each address of a social housing apartment, we identified all residential addresses within 3 km bird's-eye distance from the social housing apartment. From each of the selected addresses, the route network from OpenStreetMap is used to compute walking time of nearest path (this including streets and other types of paths that can be transited by foot) between each address and the social housing apartment.

[9] In addition, we also perform a more standard balance test in which we regress each individual covariate on assigned neighborhood for four definitions of neighborhood size and quality. Given that Figure 1 provides a joint test of significance using a linear

of our four outcomes for the entire population of children used in column 2 of Table 1. We conduct this test using pre-assignment neighbors and neighbor attributes to eliminate the possibility that the children newly assigned to the neighborhood would influence our measure of predicted outcomes. Specifically, we estimate equation 1 with a logit model, which does not include any measure of neighborhood as a control. Our corresponding estimate of $\hat{p}_i$ represents expected adult outcomes for child *i* based simply on individual attributes x_i as well as controls for the time-period λ_t at which these outcomes are measured.

$$p_i = \alpha + \xi x_i + \lambda_t + \varepsilon_i \quad (1)$$

Figure 1 provides four panels (one for each outcome) to highlight the relationship between $\hat{p}_i$ and an index of neighborhood quality for each newly assigned child. Each point and corresponding confidence interval represent the coefficient from a bivariate model with our index of neighborhood quality as the independent variable and $\hat{p}_i$ as the dependent variable for each walking distance definition of neighborhood. Intuitively, we ask whether neighborhood quality is uncorrelated with the child's and family's pre-determined characteristics, where those characteristics are weighted in such a way as to best predict the outcome of interest. Under random assignment, we would expect a horizontal line at zero for each of the four outcomes. Indeed, results indicate that across all these definitions of neighborhoods and outcomes, an applicant's newly assigned social housing neighborhood quality is unrelated to a child's attributes.

We estimate neighborhood effects on the young adult outcomes of schoolchildren with the following model:

$$y_i = \alpha + \beta w_i + \vartheta a_i + \varepsilon_i \quad (2)$$

where y_i is our binary outcome for child i between the date of assignment and December 2020, w_i is a continuous variable measuring the quality of neighborhood assigned to child i, a_i is a set of housing application characteristics (indicator variables for year of assignment, month of assignment, size of household, application with special needs), and ε_i is an idiosyncratic error. Given the presence of more than one more child in some families, we cluster standard errors at the family. The ITT estimate β measures the effect of a one standard deviation increase in a measure of neighborhood quality w_i on outcome Y_i. Consistent with this literature, we primarily report the ITT effect, but for

combination of all covariates ($\hat{p}_i$), we do not perform a joint test of significance for our results shown in appendix Table A1. Only 1 estimate is significant at either the ten or the five percent level.

our main results we report treatment on the treated (TOT) estimates, which simply scale up our ITT coefficients by our compliance rate, which averages 63%.

Results

We first provide some evidence of results for simple measures of neighborhood quality based on the average income, education and unemployment rates of individuals in the neighborhood of a newly assigned family. These definitions are based on families, couples and individuals and are comparable to the proportion of families in poverty used in the MTO literature. Our main scales for defining neighborhoods are based on four different walking distances – 2, 5, 10, and 15 minutes. The 2-minute definition limits neighborhood to a given housing unit's building and neighboring buildings and averages 527 neighbors. The 5-minute definition averages 2,835 neighbors, which is almost twice the size of a Census block group. The 10-minute definition corresponds to 10,930 neighbors, which is closer to two or three Census tracts. Finally, the 15-minute definition averages 24,198 neighbors, which is equivalent to around six Census tracts or one large U.S. zip code. We provide the full range of results when defining neighborhoods for each minute of walking distance graphically in Figure 2.

Results are shown in Table 2. Each panel represents one of our four outcomes of interest, while each column represents a different measure of neighborhood quality. Estimates in column (4) show results using an index of neighborhood quality using income, unemployment, and education levels. In addition, within each panel, we show results for neighborhoods defined as areas within 2, 5, 10, and 15-minute walks. Table 2 also provides results for a randomization inference exercise upon which we test if our results are statistically different than that of a randomly generated housing assignment. Specifically, we take each child in our sample and randomly assign them to a different urgent need social housing unit that became available in the same 6 month period. We then estimate β using Equation 2. We repeat this exercise 1,000 times to generate a counterfactual distribution for our main results. The results of this exercise are the reported two-sided p-values in square brackets in Table 2 and they highlight that our main estimates still report similar levels of statistical significance.

Results for education, drug possession, and to a lesser extent mental illness indicate that effects of neighborhood quality are large but local. For example, for our neighborhood quality index, results indicate that a one standard deviation increase in overall neighborhood quality, defined using a 2-minute walking distance, results in a 6% increase in attending an upper secondary education institution relative to the pre-assignment mean. This represents a treatment-on-the-treated effect of 9.5% based on the average compliance rate of 63%. However, as shown in the remaining columns of Panel A as well as the top left panel of Figure 2, this effect on educational attainment steadily decreases with distance, and becomes statistically insignificant once the neighborhood definition exceeds a 2-minute walking distance. Indeed, the top left panel of Figure 2 indicates that we are only able to detect a neighborhood effect on educational attainment because our data enable us to define "neighborhoods" that are smaller than any of those in the existing literature.

Results in Panel B of Table 2 and the top right panel of Figure 2 indicate there is no effect of neighborhood on adult property and violent crimes for any of the spatial definitions of neighborhood. However, results in Panel C of Table 2 and the lower left panel of Figure 2 indicate there are large effects on drug possession. For example, results using the 2 and 15 minute definitions of neighborhood indicate that a one standard deviation improvement in the overall index of neighborhood quality results in 23% and 21% reductions in drug possession, respectively.[10]

Results in Panel D show estimates of the effect on neighborhood quality on whether the child ever had a mental health visit. As with educational attainment, results indicate that neighborhood effects are highly localized. Specifically, a one standard deviation improvement in the 2-minute walk neighborhood index generates a 17% reduction in the likelihood of a mental health visit, though the bottom right of Figure 2 indicates that while these effects have a larger scale than education, they start to dissipate for neighborhoods defined by 10-minute walks or larger.

Overall, results are largely similar across the three measures of neighborhood quality in which neighborhood is defined by income, unemployment and education. In particular, results are very similar across neighborhood definitions with respect to the effect on education enrollment and crime. By comparison, there are some differences across neighborhood definitions with respect to the effects on drug possession and mental illness, as effects on both are smaller and statistically insignificant when measuring neighborhood quality using income levels, rather than unemployment or education.

In addition to using income, unemployment, and education levels as measures of neighborhood quality, we also do so using a measure based on residential property sale prices. The advantage of this approach is that both observed and unobserved neighborhood amenities are likely capitalized into housing prices. The disadvantage—aside from the possibility that housing prices may not capture those neighborhood factors most relevant for the disadvantaged students we study—is that we are unable to examine the impact of geographically small neighborhoods due to an insufficient number of sales. Results are shown in Appendix Figure A1, which are derived from a neighborhood

[10] One concern regarding any result involving a crime outcome is the extent to which it measures civilian behavior, rather than police enforcement. On the one hand, since Copenhagen police are known to engage in hot spot policing near public housing, if effects were driven by enforcement we would expect the effects to be local, which contrasts with what we find. On the other hand, we acknowledge that it is likely impossible to rule out the possibility that at least some of any effect on criminal behavior due to neighborhood assignment is due to enforcement, rather than civilian behavior.

quality measure estimated with a hedonic regression model using sales price for all market-based transacted homes in the neighborhood boundary one year before assignment.[11] Specifically, we estimate a standard housing hedonic model with log sales price as the dependent variable and house attributes and time period fixed effects as the right-hand side variables. The resulting residuals from this model are then averaged for each walking distance used to define neighborhood, which then serves as our measure of neighborhood quality. This provides a single-dimensional measure that captures how the market values the various neighborhood characteristics, irrespective of whether they are observed to us.

As alluded to above, however, the main disadvantage is that given the limited number of transactions near each unit of social housing, we are limited to larger definitions of neighborhoods (i.e., 5 to 15-minute walking distances). In practice, this means we have no way of assessing whether we observe the highly localized effects of neighborhood on educational attainment found in Table 2. However, with that caveat, we note that overall results are similar in that we find no effect on educational enrollment using 5 to 15-minute walking distances, no effect on overall crime, and persistent effects of neighborhood quality on drug possession across neighborhoods of different sizes. The one difference is that while we observed some evidence of effects of neighborhood quality on mental health when using human capital-based measures of neighborhood quality in Table 2, we see no such effects when using property values.

Finally, given the neighborhood effects literature consistently finds heterogeneous effects, we also estimate effects by subgroup. Results are shown in Table 3, which show results separately by gender (columns 1 and 2), and for ethnic majorities and minorities (columns 3 and 4). In each column, we report the effect of a one standard deviation increase in the neighborhood quality index. Results indicate that the localized effects on educational attainment are twice as large for boys as for girls, and twice as large for ethnic minorities compared to the ethnic majority. Effects on drug possession are again persistent across spatial neighborhood definitions and are present only for ethnic minorities and boys. The relatively localized impact of neighborhood on mental illness are only present for boys and ethnic majorities.

Conclusions

While there has been much research on the role of neighborhood in shaping the long-run outcomes of children, relatively little is known about which neighborhood characteristics best predict outcomes, and at what scale

[11] House sales price and home attributes are obtained from Copenhagen property listings through a secondary web service, Boliga (https://www.boliga.dk/). Covariates included in the regression model are "size of residential area", "size of basement", "size of garden", "number of rooms", "house age", "squared house age", "house is an apartment", "house is a terraced house", "house is a villa", "indicator for municipality", indicators for "year of sale", indicators for "month of sale", and indicators for "(A, B, C, D, F, or G) -energy label of house". In Denmark energy-labelling of buildings is mandatory and aims to promote energy savings by visualizing the amount of energy that a building consumes.

neighborhood effects operate. In this study, we use administrative data from Denmark along with the quasi-random assignment of housing to families in urgent need to address these questions. Results indicate that a one standard deviation improvement in neighborhood quality, defined using a 2-minute walk radius from one's residence, leads to an 9.5 percent increase in upper secondary education matriculation and a 27 percent reduction in the likelihood of a mental health visit. In both cases, however, the role of neighborhoods is very local: we find no statistically significant effect on education for neighborhoods defined using a 5-minute or greater walking distance, and no effect on mental health using a 15-minute walking distance radius. Results for these two outcomes are consistent with descriptive work in the U.S. on the relationship between Census Block Group poverty measures and upward mobility (Chetty, Friedman, Hendren, Jones, and Porter, 2020). In contrast, while we find no effect on adult violent or property crime, we estimate that a one standard deviation increase in neighborhood quality generates a 34 to 39 percent reduction in drug possession as an adult that is roughly similar across a variety of neighborhood scales. This suggests that it is difficult for families to avoid the effect of neighborhoods on drug possession, especially relative to effects on education. Results also indicate the effects on both educational attainment and adult drug possession are driven entirely by ethnic minorities. This suggests that at-risk populations are most impacted by neighborhood quality.

While it is clear that neighborhood scale matters with respect to impacts on adult outcomes, it is less clear that the measure of neighborhood quality itself matters. In particular, results are similar when measuring neighborhood quality using unemployment, education, and property values. The exception is that measures of poverty (i.e., unemployment) and education are better predictors of both drug possession and mental illness compared to neighborhood income.

Collectively, these results provide useful insights regarding the role of neighborhoods in shaping the adult outcomes of children, and which children in particular are most impacted by neighborhoods. In addition, the results also provide insight into the main mechanisms at play. In particular, results show that while the neighborhood determinants of education and mental health are likely those neighbors in close proximity to oneself, larger neighborhood factors are likely at play when it comes to drug use. These findings can also help make sense of the mixed findings in the literature on neighborhood effects, given that the scale and, to a lesser extent, the measure of neighborhoods, can impact estimates in meaningful ways.

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Tables and Figures

Table 1: Descriptive statistics

	Children assigned to Social Housing		Neighbor children within 15' walk	
	Mean	*SD*	Mean	*SD*
A. Pre-assignment characteristics				
Age (years)	10.18	*2.56*	10.15	*0.53*
Girl (%)	49.96	*50.02*	49.42	*1.25*
Non-western origin (%)	50.64	*50.02*	32.33	*14.73*
Lives with both parents (%)	16.23	*36.88*	58.17	*5.24*
Placed out of home (%)	16.91	*37.50*	3.51	*1.08*
At least 10 doctor visits (%)	25.19	*43.43*	22.28	*2.18*
Family education (years)	10.79	*2.46*	12.72	*0.71*
Family unemployment (%)	62.94	*33.65*	30.29	*8.73*
Family income (0-100 scale)	27.04	*23.23*	40.42	*7.11*
Family arrest for any crime (%)	23.94	*42.69*	8.14	*2.44*
Family arrest for possession of narcotic drugs	4.95	*21.69*	1.45	*0.47*
B. Outcomes				
Education enrollment (%)	63.12	*48.27*	78.87	*8.20*
Arrest for any crime (%)	27.92	*44.88*	12.20	*3.66*
Arrest for possession of narcotic drugs (%)	9.99	*30.00*	4.84	*1.99*
Mental illness (%)	12.55	*33.15*	5.73	*0.96*
N	1,171		24,198	

Notes: The first set of columns presents means and standard deviations of characteristics and outcomes for our sample of school-aged children in grades 0-8, while the second set of columns shows means across children and their families in that child's neighborhood as well as the standard deviation of the neighborhood averages. "Lives with both parents" denotes that the child resides with both biological parents. "Placed out of home" denotes that the child has been placed out of the home at some point prior to the social housing assignment. "At least 10 doctor visits" denotes that the child had at least 10 contacts with doctors in the five years preceding the year of social housing assignment. "Family education" denotes the average years of schooling of family members who were 25 years or older before the social housing assignment. "Family unemployment" denotes the average unemployment rate of all family members who were 18 years or older in the five years before the social housing assignment. "Family income" denotes the average rank in disposable income among families of similar composition in the five years before the social housing assignment. "Family crime" denotes that at least one member of the family was charged for an offense to the penal code in the five years prior to the social housing assignment. "Family possession" of narcotic drugs denotes that at least one member of the family was charged for possession of narcotic drugs in the five years prior to the social housing assignment. "Education enrollment" denotes that the child was enrolled in upper secondary education between the date of the first social housing offer and January 1, 2021. "Crime" denotes that the child was charged for offenses to the Penal Code in Denmark after the first social housing assignment and after age 16. "Possession of narcotic drugs" denotes that the child was charged for possession of narcotic drugs after the first offer of social housing and after age 16. "Mental illness" denotes that the child had contact with psychiatric treatment and care in the four years after the date of the first offered social housing apartment. Sample size for the second set of columns indicates the average number of neighbors within a 15 min walk of each child assigned to social housing.

Table 2: Neighborhood Effects

Neighborhood Boundary (Minutes' walk)	Income	Unemployment	Education	Neighbor quality
A. Effect on education enrollment				
2	0.0366**	−0.0334**	0.0275*	0.0382**
	(0.0150) [0.0150]	(0.0150) [0.0310]	(0.0148) [0.0740]	(0.0160) [0.0160]
5	0.0110	−0.0130	0.0069	0.0116
	(0.0153) [0.4500]	(0.0147) [0.4110]	(0.0148) [0.6760]	(0.0158) [0.4890]
10	−0.0015	0.0006	−0.0043	−0.0036
	(0.0150) [0.9070]	(0.0146) [0.9760]	(0.0146) [0.7520]	(0.0157) [0.8230]
15	−0.0055	0.0053	−0.0060	−0.0071
	(0.0154) [0.7020]	(0.0149) [0.7050]	(0.0150) [0.6600]	(0.0167) [0.6540]
B. Effect on arrest for any crime				
2	0.0051	0.0118	0.0029	−0.0017
	(0.0136) [0.7060]	(0.0138) [0.3840]	(0.0146) [0.8340]	(0.0150) [0.8950]
5	0.0042	0.0070	−0.0027	−0.0012
	(0.0142) [0.7390]	(0.0142) [0.5960]	(0.0146) [0.8290]	(0.0152) [0.9300]
10	0.0034	−0.0005	0.0030	0.0040
	(0.0132) [0.8060]	(0.0132) [0.9600]	(0.0135) [0.8000]	(0.0142) [0.7990]
15	0.0027	0.0072	−0.0007	0.0040
	(0.0135) [0.8190]	(0.0136) [0.5870]	(0.0139) [0.9430]	(0.0150) [0.7930]
C. Effect on arrest for possession of narcotic drugs				
2	−0.0134	0.0259***	−0.0211**	−0.0230**
	(0.0097) [0.1170]	(0.0098) [0.0020]	(0.0092) [0.0170]	(0.0104) [0.0120]
5	−0.0182*	0.0245**	−0.0252***	−0.0247**
	(0.0100) [0.0420]	(0.0103) [0.0060]	(0.0095) [0.0070]	(0.0106) [0.0100]
10	−0.0142	0.0187**	−0.0256***	−0.0230**
	(0.0092) [0.1070]	(0.0091) [0.0370]	(0.0091) [0.0070]	(0.0098) [0.0180]
15	−0.0103	0.0177*	−0.0253***	−0.0213**
	(0.0093) [0.2510]	(0.0094) [0.0560]	(0.0091) [0.0090]	(0.0102) [0.0330]
D. Effect on mental illness				
2	−0.0126	0.0192**	−0.0249***	−0.0210**
	(0.0093) [0.2400]	(0.0093) [0.0880]	(0.0094) [0.0290]	(0.0097) [0.0800]
5	−0.0097	0.0191*	−0.0223**	−0.0180*
	(0.0109) [0.3620]	(0.0097) [0.0800]	(0.0099) [0.0510]	(0.0107) [0.1200]
10	−0.0064	0.0193**	−0.0205**	−0.0147
	(0.0099) [0.5280]	(0.0093) [0.0480]	(0.0095) [0.0470]	(0.0104) [0.1670]
15	0.0006	0.0079	−0.0146	−0.0079
	(0.0100) [0.9500]	(0.0095) [0.4350]	(0.0096) [0.1490]	(0.0110) [0.4810]

Notes: Coefficients are from Equation 2 and estimate the effect of assignment to a neighborhood with one standard deviation higher quality along the dimension indicated in the column heading. Standard errors, clustered by family, are in parentheses, and statistical significance is indicated by: *, **, and ***, which indicate $p<0.10$, $p<0.05$, and $p<0.01$, respectively. Square brackets provide the two-sided p-value of each coefficient as compared to randomly assigning children to other urgent need social housing units during the same six-month period. The details of this random inference exercise are described in the main text. Income, Unemployment and Education are as defined as family attributes in Table 1 and along with the Neighborhood quality index are all mean zero, standard deviation one.

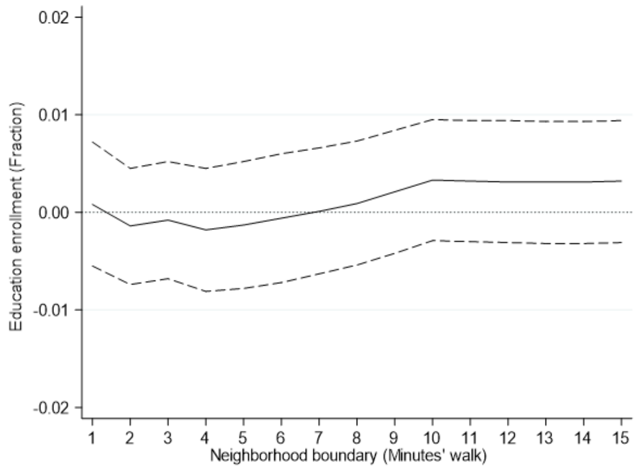
Table 3: Heterogeneity of neighborhood effect on children

Neighborhood Boundary (Minutes' walk)	Boys	Girls	Ethnic Majority	Ethnic Minority	Previous residence at most 50' walk from offered apartment	Previous residence at least 50' walk from offered apartment
A. Effect on education enrollment						
2	0.0592***	0.0251	0.0230	0.0514**	0.0377	0.0455*
	(0.0222)	(0.0227)	(0.0237)	(0.0216)	(0.0233)	(0.0235)
5	0.0278	0.0041	□ 0.0024	0.0187	□ 0.0064	0.0279
	(0.0224)	(0.0220)	(0.0233)	(0.0208)	(0.0229)	(0.0222)
10	0.0019	□ 0.0089	□ 0.0064	□ 0.0087	□ 0.0035	□ 0.0000
	(0.0231)	(0.0220)	(0.0228)	(0.0210)	(0.0241)	(0.0224)
15	0.0001	□ 0.0175	□ 0.0143	□ 0.0136	□ 0.0059	□ 0.0061
	(0.0242)	(0.0234)	(0.0238)	(0.0226)	(0.0252)	(0.0236)
B. Effect on arrest for any crime						
2	0.0156	□ 0.0106	□ 0.0224	0.0151	□ 0.0271	0.0158
	(0.0225)	(0.0185)	(0.0199)	(0.0214)	(0.0238)	(0.0219)
5	0.0226	□ 0.0231	□ 0.0221	0.0226	□ 0.0144	0.0134
	(0.0224)	(0.0183)	(0.0208)	(0.0212)	(0.0240)	(0.0216)
10	0.0285	□ 0.0155	□ 0.0093	0.0195	□ 0.0009	0.0114
	(0.0215)	(0.0191)	(0.0189)	(0.0212)	(0.0219)	(0.0210)
15	0.0296	□ 0.0149	□ 0.0033	0.0130	□ 0.0022	0.0148
	(0.0228)	(0.0197)	(0.0203)	(0.0222)	(0.0231)	(0.0222)
C. Effect on arrest for possession narcotic drugs						
2	□ 0.0378**	□ 0.0029	□ 0.0017	□ 0.0446***	□ 0.0296*	□ 0.0125
	(0.0185)	(0.0080)	(0.0152)	(0.0148)	(0.0165)	(0.0144)
5	□ 0.0515***	0.0054	□ 0.0009	□ 0.0505***	□ 0.0318**	□ 0.0114
	(0.0186)	(0.0074)	(0.0146)	(0.0159)	(0.0158)	(0.0153)
10	□ 0.0442***	0.0056	□ 0.0035	□ 0.0449***	□ 0.0320**	□ 0.0115
	(0.0169)	(0.0066)	(0.0140)	(0.0141)	(0.0149)	(0.0153)
15	□ 0.0401**	0.0052	0.0034	□ 0.0506***	□ 0.0267*	□ 0.0110
	(0.0176)	(0.0073)	(0.0135)	(0.0153)	(0.0139)	(0.0164)
D. Effect on mental illness						
2	□ 0.0422***	□ 0.0028	□ 0.0357**	□ 0.0093	□ 0.0139	□ 0.0236*
	(0.0149)	(0.0124)	(0.0161)	(0.0126)	(0.0142)	(0.0139)
5	□ 0.0297*	□ 0.0086	□ 0.0205	□ 0.0134	□ 0.0108	□ 0.0182
	(0.0157)	(0.0141)	(0.0170)	(0.0128)	(0.0162)	(0.0149)
10	□ 0.0176	□ 0.0091	□ 0.0137	□ 0.0127	□ 0.0042	□ 0.0172
	(0.0160)	(0.0135)	(0.0176)	(0.0124)	(0.0152)	(0.0148)
15	□ 0.0098	□ 0.0012	□ 0.0064	□ 0.0050	0.0002	□ 0.0060
	(0.0171)	(0.0134)	(0.0181)	(0.0132)	(0.0157)	(0.0154)

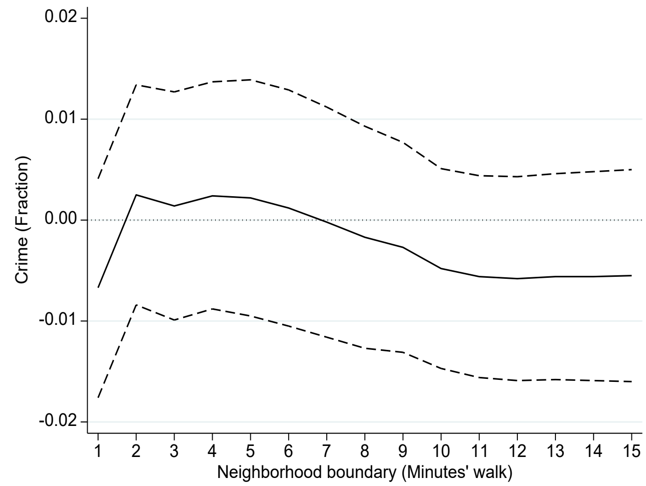
Notes: Ethnic minority includes assigned children with non-western origin; ethnic majority includes all others. Sample size is 586 for females, 585 for males, 578 for ethnic majorities, 593 for ethnic minorities, 543 for less distant reallocations and 543 for most distant reallocations.. All models include a summary index of neighbor quality based on "Education", "Unemployment", and "Income". Each index is normalized to have a mean of zero and standard deviation of one. Standard errors clustered by family are in parentheses. *p<0.10 *, p<0.05 **, p<0.01 ****

Figure 1: Balance test of index of neighborhood quality

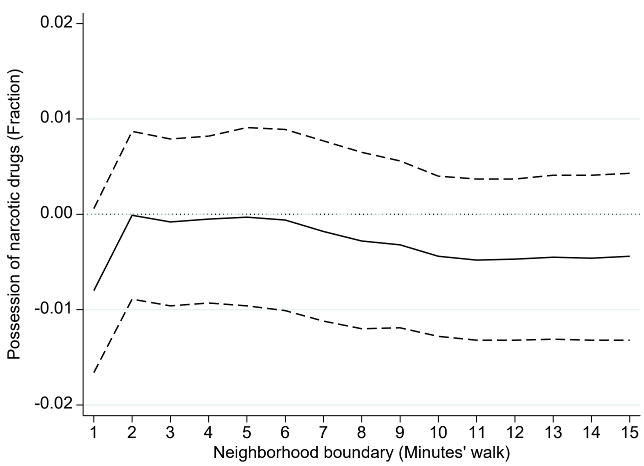
A. Correlation between neighborhood quality and expected education enrollment



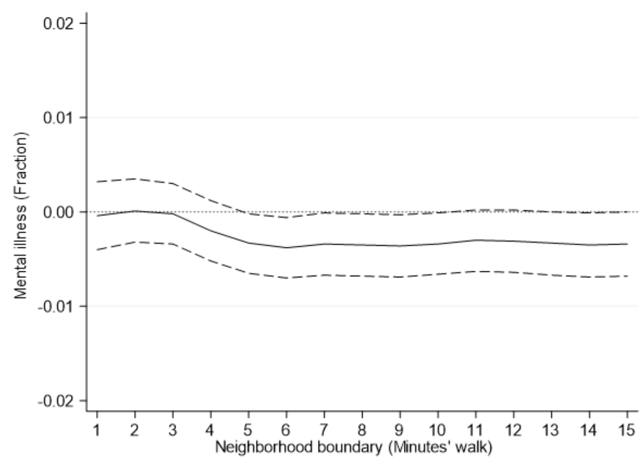
B. Correlation between neighborhood quality and expected crime



C. Correlation between neighborhood quality and expected possession of narcotics



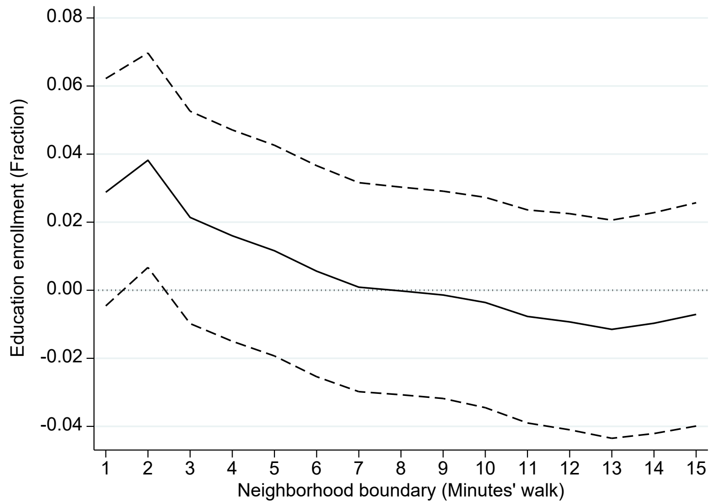
D. Correlation between neighborhood quality and expected mental illness



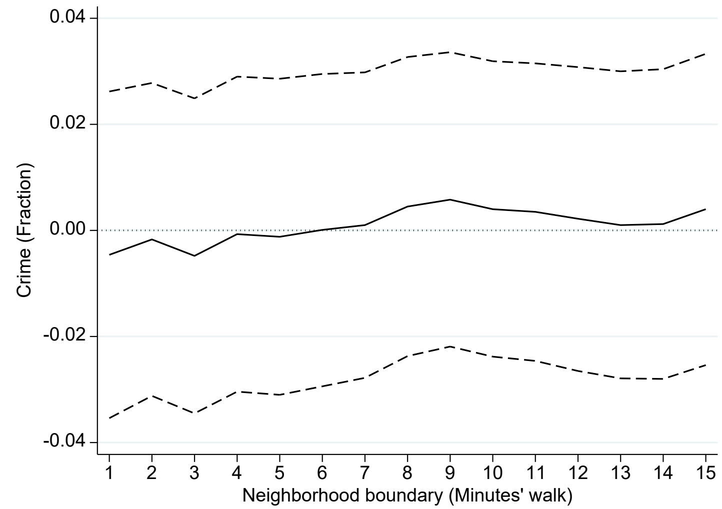
Notes: Each figure shows the relationship between the expected outcome given all predetermined family characteristics and neighborhood quality. The measure of expected outcome shown on the y-axis comes from regressing the outcome on all predetermined family (but not neighborhood) characteristics, as in Equation (1). The resulting predicted values and corresponding confidence intervals are plotted for each geographic definition of neighborhood.

Figure 2: Average neighborhood effect on children by neighborhood boundary

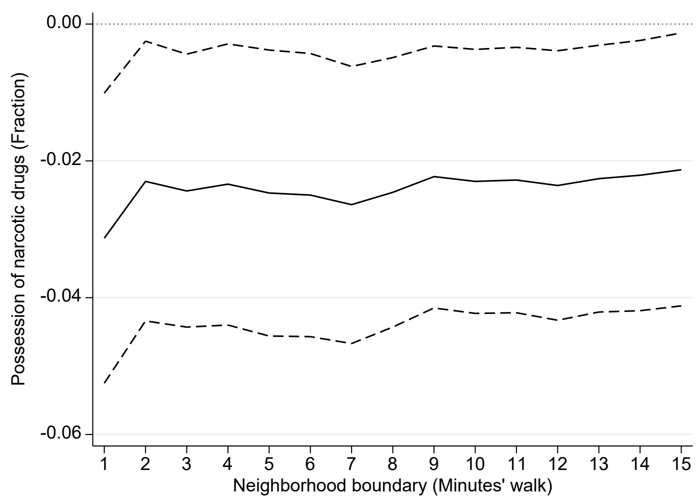
A. Effect on education enrollment



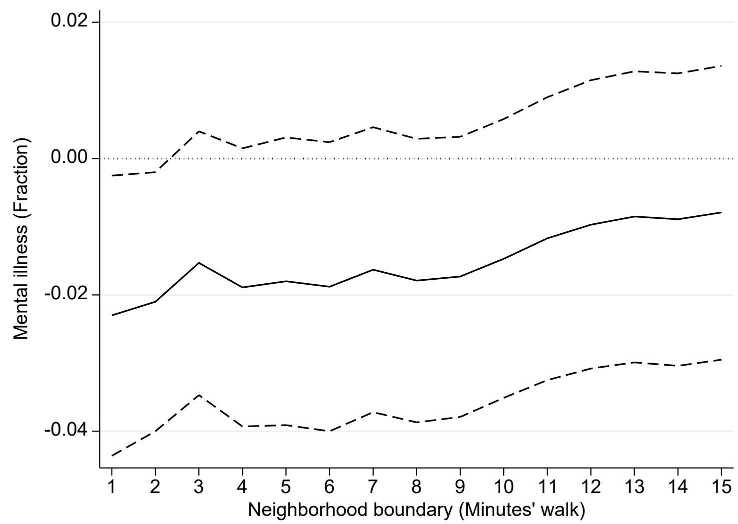
B. Effect on arrest for any crime



C. Effect on arrest for possession of narcotic drugs



D. Effect on mental illness



Notes: These figures are based on estimation of Equation 2 in which each outcome is regressed on our measure of neighborhood quality. The resulting coefficients are plotted for each definition of neighborhood size, defined by minutes of walking distance from one's own residence.

Online Appendix

Table A1: Balance test of characteristics of assigned children and measures of neighborhood quality

Pre-assignment characteristic of children assigned to Social Housing Name	Mean	Neighborhood Boundary	Regression coefficient of on neighborhood quality Income	Unemployment	Education	Quality
Age (years)	10.18	2	0.10	-0.06	0.09	0.10
Age (years)	10.18	5	0.09	-0.03	0.02	0.06
Age (years)	10.18	10	0.12	-0.09	0.06	0.10
Age (years)	10.18	15	0.14	-0.11	0.05	0.11
Girl (%)	49.96	2	0.45	-2.33	2.25	1.84
Girl (%)	49.96	5	0.88	-0.79	1.90	1.29
Girl (%)	49.96	10	1.88	-1.90	2.62	2.62
Girl (%)	49.96	15	1.67	-1.93	2.41	2.48
Non-western origin (%)	50.64	2	-0.02	0.94	0.41	-0.27
Non-western origin (%)	50.64	5	0.94	-0.92	1.96	1.37
Non-western origin (%)	50.64	10	1.99	-2.14	3.02	2.92
Non-western origin (%)	50.64	15	2.60	-2.77	3.57**	3.80
Lives with both parents (%)	16.23	2	0.47	0.96	0.02	-0.18
Lives with both parents (%)	16.23	5	0.08	0.94	0.15	-0.22
Lives with both parents (%)	16.23	10	-0.43	0.12	-0.09	-0.32
Lives with both parents (%)	16.23	15	-0.54	-0.02	-0.15	-0.54
Placed out of home (%)	16.91	2	-0.45	-0.24	-0.44	-0.23
Placed out of home (%)	16.91	5	-0.70	0.31	-1.13	-0.79
Placed out of home (%)	16.91	10	-0.34	1.13	-1.03	-0.72
Placed out of home (%)	16.91	15	0.31	0.50	-0.79	-0.19
At least 10 doctor visits (%)	25.19	2	0.56	0.50	-0.37	-0.07
At least 10 doctor visits (%)	25.19	5	1.03	-0.94	1.31	1.21
At least 10 doctor visits (%)	25.19	10	1.67	-1.87	1.67	1.89
At least 10 doctor visits (%)	25.19	15	2.43	-1.60	1.34	2.37
Family education (years)	10.79	2	0.02	-0.05	0.10	0.06
Family education (years)	10.79	5	-0.04	-0.08	0.07	0.03
Family education (years)	10.79	10	-0.10	0.02	0.03	-0.04
Family education (years)	10.79	15	-0.12	0.02	0.04	-0.06
Family unemployment (%)	62.94	2	2.51	-0.94	0.44	1.64
Family unemployment (%)	62.94	5	1.73	-0.28	-0.24	0.82
Family unemployment (%)	62.94	10	-0.13	1.37	-1.15	-0.64
Family unemployment (%)	62.94	15	-0.52	1.74	-1.35	-0.85
Family income (0-100 scale)	27.04	2	-0.50	0.05	-0.18	-0.30
Family income (0-100 scale)	27.04	5	0.46	-0.81	0.35	0.59
Family income (0-100 scale)	27.04	10	0.25	-0.53	0.21	0.22
Family income (0-100 scale)	27.04	15	-0.02	0.19	-0.45	-0.29
Family crime (%)	23.94	2	-1.36	0.08	-1.11	-0.97
Family crime (%)	23.94	5	0.49	0.66	-1.57	-0.49
Family crime (%)	23.94	10	-0.30	-0.02	-2.11	-1.56
Family crime (%)	23.94	15	0.04	0.65	-2.53	-1.68
Family possession of narcotic drugs (%)	4.95	2	0.25	-0.72	0.31	0.50
Family possession of narcotic drugs (%)	4.95	5	0.43	-0.18	-0.11	0.22
Family possession of narcotic drugs (%)	4.95	10	0.13	-0.43	-0.26	-0.15
Family possession of narcotic drugs (%)	4.95	15	-0.30	0.17	-0.57	-0.61

Notes: Column “Mean” presents means of characteristics of assigned children. Columns “Income”, “Unemployment”, “Education”, and “Quality” present coefficients of regression of characteristic of assigned children on neighborhood quality measured before assignment.
p<0.05 **

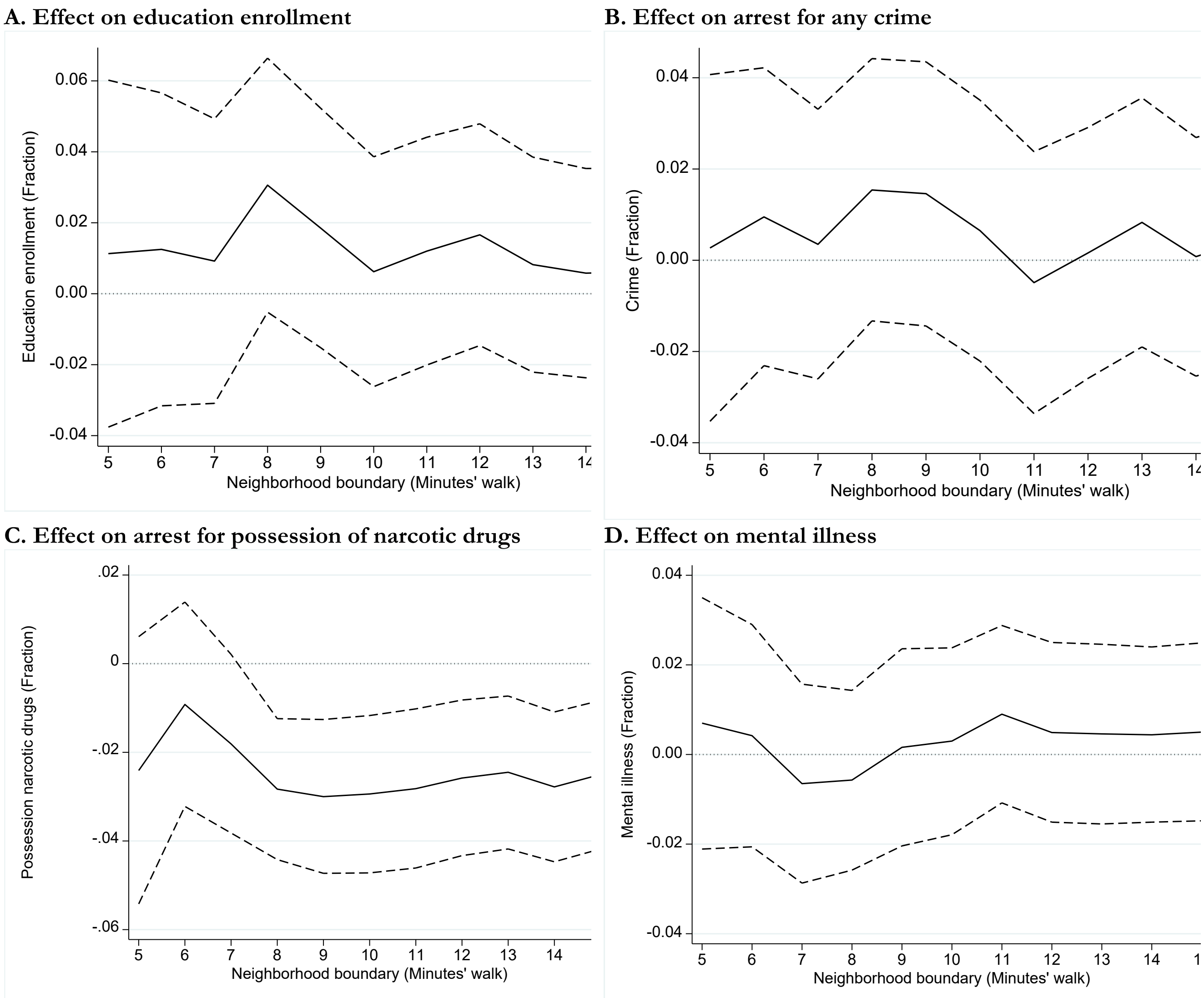


Figure A.1: Average effect of house property values on children by neighborhood boundary

Notes: These figures are based on estimation of Equation 2 in which the outcome is regressed on the property-values-based measure of neighborhood quality. Coefficients and corresponding confidence intervals are plotted for each geographic measure of neighborhood size shown on the x-axis.