The Scale and Nature of Neighborhood Effects on Children: Evidence from a Danish Social Housing Experiment

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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 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 beyond family background and 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

[1] For example, Ludwig 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 (2013) 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.

so using rich administrative data from Denmark along with data on the 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 experiment differs from MTO in that compliance is higher here (63% versus 48% in MTO), and the newly assigned housing unit can be in a neighborhood of higher or lower 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. The first is that the detailed administrative data uniquely enables us to explore the spatial scale at which we define neighborhoods. 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.[3] Instead, we can assess the role of neighborhood quality when measured using only that part of the neighborhood that is within a radius of a 2 minute walk up to a 15 minute walk from one's residence. 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

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

[3] This is particularly true for those living near a boundary of a defined geographic area, which is especially problematic when using small geographic units.

neighborhood quality and therefore the potential for attenuation bias. We have the unique ability to do this because we can use the various underlying individual-level measures available in the administrative data to construct neighborhood characteristics, rather than being constrained by administrative aggregates. Secondly, we can examine various measures of neighborhoods, including unemployment levels, income, and education.[4] Thirdly, we are able to examine the effect of these various neighborhood measures on a broad range of administrative outcomes, including matriculating at a upper secondary education institution, criminal arrest, drug possession, and whether the child received any mental health treatment.[5]

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 college attendance and, to a lesser extent, mental health are largely local, as estimates are both substantially smaller and statistically insignificant for neighborhood distances of 10 – 15 minute walks (larger than census tracts). 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 peers or other social networks that operate at a small geographic scale, while drug use is more impacted by factors that operate at a larger geographic scale.

[4] 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.

[5] 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.

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 addition, in other settings results are mixed. 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 that 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 defined locally are absent for larger definitions of neighborhood, and that how one measures neighborhood quality can have some impact on one's findings.

Overall, our results highlight that the scale of neighborhood effects may be quite small in practice and consistent with existing literature, heterogeneity in individuals matters for the role of neighborhood effects. These results have implications for housing policies more broadly. In particular, they suggest there may be benefits both 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.

It is important to note that any apartment located in a local area that exceeded a 40% rate of resident adult unemployment on January 1st of any given year is ineligible for assignment to urgent needs households for that year. This regulation implies that urgent need households are not allocated to the most disadvantaged residential sectors in Copenhagen. However, the wide definition of unemployment used by the municipality, coupled with the variation of social housing neighborhoods, neighbors within developments over time, and neighbors within local areas, implies that disadvantaged individuals are assigned to a wide range of environments in terms of relative locations in the city as well as neighbor composition.

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. That is because the existence of such preferences is deemed to be in direct contradiction with 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.[6]

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 as our the measure of assigned housing unit in this study. 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. 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 and residents typically receive a new housing unit that is approximately 1 hour walking (5.5 kilometers) distance from their previous neighborhood.

Data and Empirical Model

[6] 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. These data allow us to define individuals as living with biological parents, 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 as well as income and education. These data also provide some health outcomes as they relate to mortality as well as general and mental health doctors' visits. The main limitation of the data is managing its richness while focusing on relevant attributes for our research.

Our main sample of randomly assigned children to social housing incorporates 1,171 children that 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 15 min 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 individual outcomes. Perhaps unsurprisingly, children in our sample of newly assigned social housing are more likely to be non-western immigrants, live in single parent households, have unemployed parents, and live in lower income/education and higher crime families than their neighbors located within a 15 min walking distance of social housing. The standard deviation in column 4 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 our later measures of neighborhood quality are about 20-25% of mean values for education, unemployment and income indicating that neighborhoods do exhibit a substantial amount of variation in our measures of quality.

We note that the definition of neighborhood used in Table 1 is quite large as it is approximately equal to either a larger U.S. zip code or to five or six census tracts. Later models show results for various neighborhood sizes ranging from a two-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 likely to account for how often individuals

will interact with their neighbors and environment.[7] In addition, this walking distance definition overcomes concerns about nearby individuals located on opposite sides of administrative boundaries (e.g. census geographies, postal areas, etc.) not being considered 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 on 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 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.[8] To do so, we first use the individual attributes highlighted in

[7] 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.

[8] In addition, we also perform the standard balance test in which we regress each individual covariate on assigned neighborhood quality. Results are shown in appendix Table A1.

the row headings of Table 1 to predict each of our four outcomes for the entire population of children used in column two of Table 1. We conduct this test using pre-assignment neighbors and neighbor attributes to mitigate any concern that our sample of children newly assigned to the neighborhood would influence our measure of predicted outcomes. Specifically, we estimate equation 1 with a logit model and we do not include any measure of neighborhood in its estimation. 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 on a bivariate model with our index of neighborhood quality as the independent variable and $\hat{p}_i$ as the dependent variable for each waking 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 with child 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. 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 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. Subsequently, the 5 minute definition averages 2,835 neighbors, which is about equal to a Census block group. The 10 minute definition corresponds to 10,930 neighbors, which is closer to two Census tracts. Finally, the 15-minute definition averages 24,198 neighbors. We provide the full range of results when defining neighborhoods for each minute of walking distance graphically in Figure 2.

Our first set of results are provided in Table 2. Each panel represents one of our four outcomes of interest, while each column represents a different measure of neighborhood quality. Considering the opposite sign implied by unemployment relative to income and education, results are quite consistent across the first three columns for education and crime. Income is less precise when examining drug possession and mental health. These three measures of neighborhood are combined into a single index in column four. For our neighborhood quality index, results indicate a 6% increase in attending college for only the smallest definition of neighborhood (2 min walking distance) relative to the pre-assignment mean, which represents a TOT effect of 9.5% based on the average compliance rate of 63%. From the top left panel of Figure 2, one can see that impacts quickly decrease and become statistically insignificant once the neighborhood definition exceeds a 2 minute walking distance.

Results in the second panel 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 the third panel of Table 2 and the lower left panel of Figure 2 indicate there are large effects on drug possession that is consistent across neighborhood size when using unemployment or education

(or the index measure), but not using income as a measure of neighborhood quality. 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.

Finally, for the outcome indicating whether the child ever had a mental health visit, find localized effects of neighborhood quality---as measured by unemployment, education, or the index, but not income. Specifically, a one standard deviation improvement in the 2 min 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 min walks or larger.

In addition, in Appendix Figure A1 we show results using an alternative measure of neighborhoods based on transacted property values.[9] In these results, we estimate a hedonic regression model using sales price for all market based transacted homes in the neighborhood boundary 1 year before assignment. We implement a standard model with log sales price as the dependent variable and house attributes and time periods dummies as the right-hand side variables. The resulting residuals from this estimation model are then averaged to each walking distance definition of neighborhood as our measure of neighborhood quality. This provides a single-dimensional measure that captures how the market at large values the various neighborhood characteristics, irrespective of whether they are observed to us. 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 (5–15-minute walking distance). 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.

[9] House sale prices and house characteristics are obtained from Boliga Aps. 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.

Next, given the neighborhoods 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 ethnic majority. Effects on drug possession are again persistent across spatial neighborhood definitions, and are present only for ethnic minorities and boys. Finally, 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 neighborhood effects operate. In this study, we use administrative data from Denmark along with the random assignment of housing to families in urgent need to address these questions. Results indicate that a one standard deviation improvement in neighborhood quality 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. However, both effects are present only when neighborhood quality is defined as essentially one's own or close adjacent building. For example, estimated effects of neighborhood quality as defined by a 15 minute walk radius are a 1.1 percent and an 1.3 percent reduction for the same two outcomes, respectively, neither of which is statistically significant. Additionally, while we find no effect on adult violent and 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, and that this effect is roughly similar across a variety of neighborhood scales.

While it is clear that the neighborhood scale matters with respect to impact 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 additional evidence on the role of neighborhoods in shaping the adult outcomes of children. Moreover, 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. In addition, the results also provide insight into the main mechanisms at play. In particular, they 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 crime (%)	23.94	*42.69*	8.14	*2.44*
Family possession of narcotic drugs	4.95	*21.69*	1.45	*0.47*
B. Outcomes				
Education enrollment (%)	63.12	*48.27*	78.87	*8.20*
Crime (%)	27.92	*44.88*	12.20	*3.66*
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: Columns present means and standard deviations of characteristics and outcomes for children enrolled in class 0-8. "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 home at a certain point before social housing assignment. "At least 10 doctor visits" denotes that the child has had at least 10 contacts with doctors within the year preceding the year of social assignment. "Family education" denotes the average years of schooling of family members of at least 25 years old before social housing assignment. "Family unemployment" denotes the average unemployment rate within 5 years before social housing of all family members of at least 18 years old. "Family income" denotes the average rank in disposable income within 5 years before social housing among families with same composition. "Family crime" denotes that at least a member of the family has been charged for an offense to the penal code within 5 years before social housing. "Family possession" of narcotic drugs denotes that at least a member of the family has been charged for possession of narcotic drugs within 5 years before social housing. "Education enrollment" denotes that the child is enrolled in upper secondary education program between the date of first offered social housing and January 1, 2021. "Crime" denotes that the child is charged for offenses to the Penal Code in Denmark between the date of first offered social housing and January 1, 2021. "Possession of narcotic drugs" denotes that the child is charged for possession of narcotic drugs between the date of first offered social housing and January 1, 2021. "Mental illness" denotes that the child has contact with psychiatric treatment and care within the four years after the date of the first offered social housing apartment. Sample size for Neighborhood children within 15 min walk is the average size of this group and standard deviations indicate the variation across neighborhood averages.

Table 2: Average neighborhood effect on children

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 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 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 provided for Equation 2 with standard errors clustered by families in parentheses. Square brackets provide the p-value of our coefficient relative to a randomization exercise where each child in our sample is randomly assigned to the housing unit of other children in the same 6 month by housing unit size group 1,000 times. *$p<0.10$ *, $p<0.05$ **, $p<0.01$* *** Education denotes the standardized version of average years of schooling among family members of at least 25 years old. Unemployment denotes the standardized version of the unemployment rate of family members of at least 18 years old during the last 5 years before the date of first offered social housing. Income denotes the standardized version of the average rank in family disposable income during the 5 years preceding the year of first offered social housing. Neighbor quality denotes a summary index based on "Education", "Unemployment", and "Income" and is mean zero, standard deviation one.

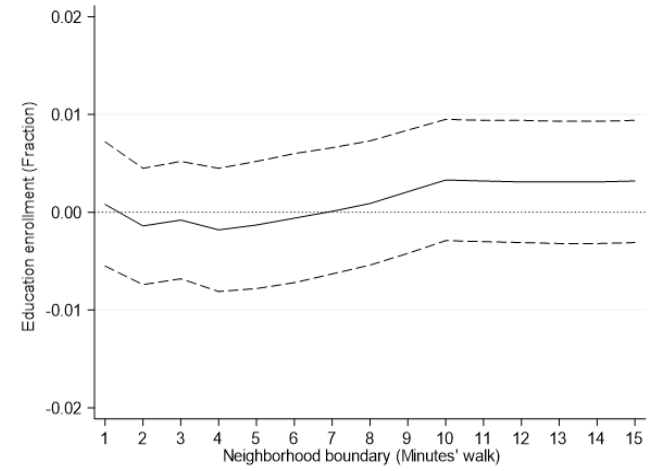
Table 3: Heterogeneity of neighborhood effect on children

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 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 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)

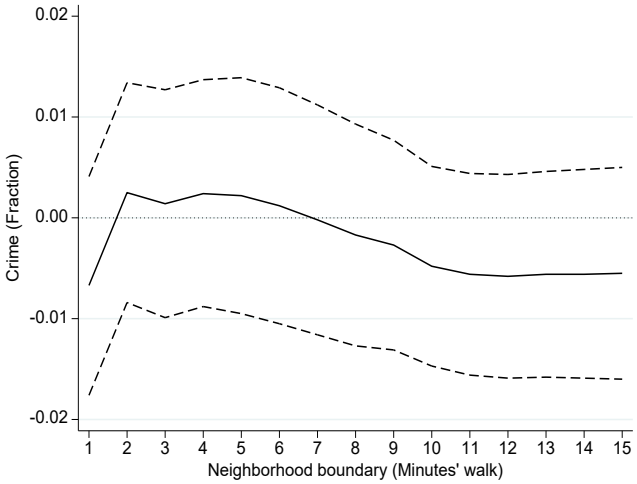
Notes: Ethnic majority includes assigned children with other origin than non-western. Ethnic minority includes assigned children with non-western origin. Sample size is 586 for females, 585 for males, 578 for ethnic majorities, 593 for ethnic minorities. All models include a summary index of neighbor quality based on "Education", "Unemployment", and "Income" which is mean zero, standard deviation one. Standard errors clustered by families in parentheses. *$p<0.10$ *, $p<0.05$ **, $p<0.01$ ****

Figure 1: Balance test of index of neighborhood quality

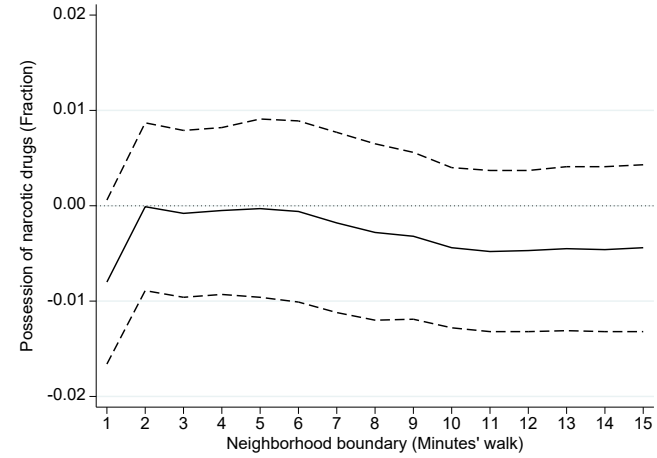
A. Correlation between neighborhood quality and expected education enrollment



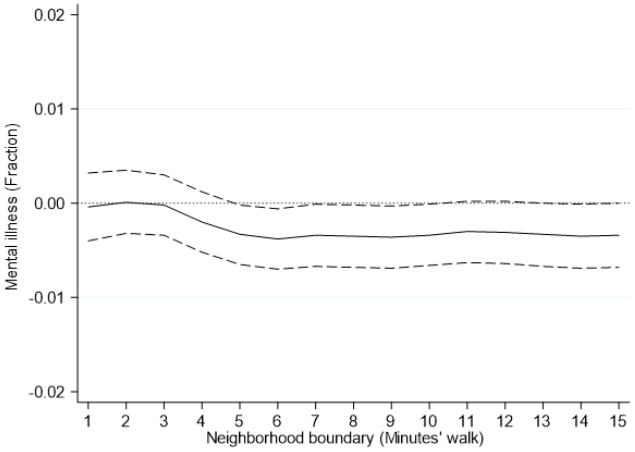
B. Correlation between neighborhood quality and expected crime



C. Correlation between neighborhood quality and expected possesion of narcotics



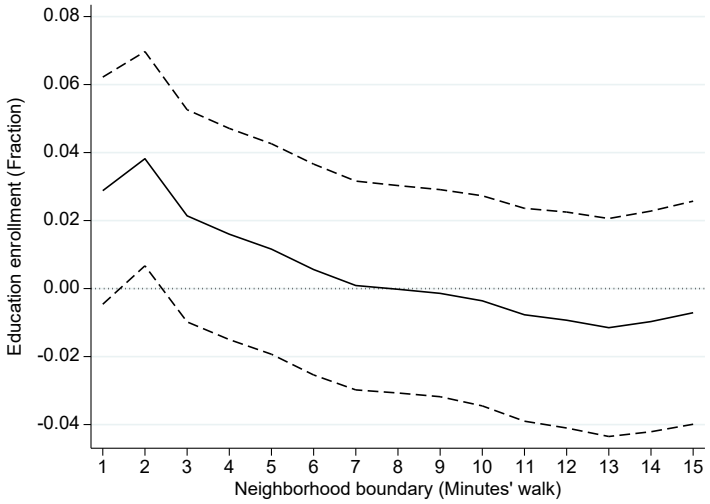
D. Correlation between neighborhood quality and expected mental illness



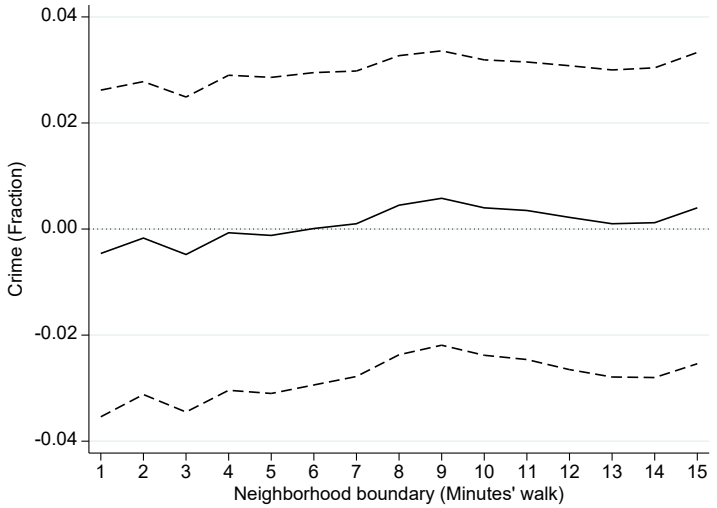
Notes: These figures are based on a series of bivariate estimations of $\hat{p}_i$ from Equation 1 on y_i for each corresponding definition of neighborhoods given by the geographic extent given by the minutes' walk given in the x-axis. Coefficient and corresponding confidence intervals are plotted for each outcome y_i given by panel headings.

Figure 2: Average neighborhood effect on children by neighborhood boundary

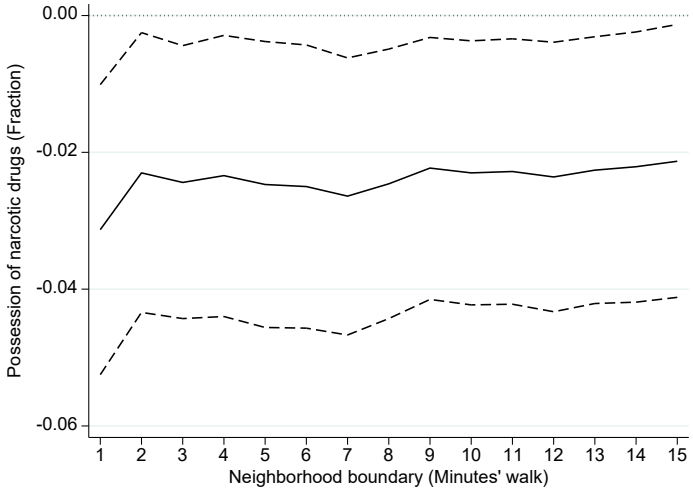
A. Effect on education enrollment



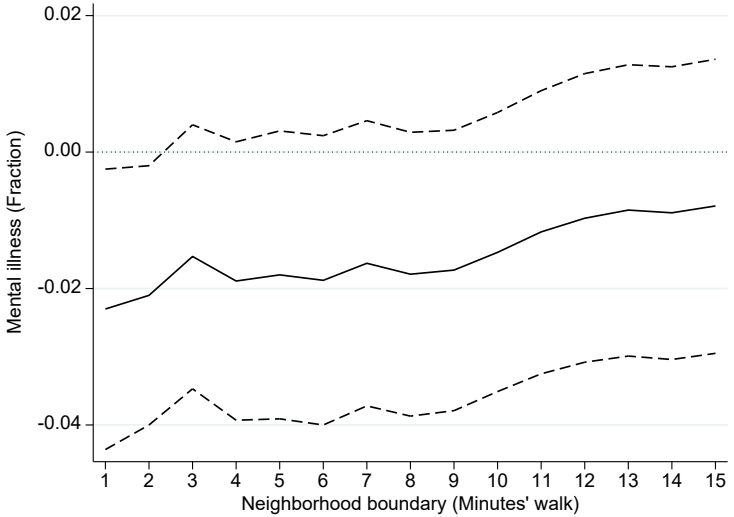
B. Effect on crime



C. Effect on possession of narcotic drugs



D. Effect on mental illness



Notes: These figures are based on estimation of Equation 2 and plots β on y_i for each corresponding definition of neighborhood size given by the geographic extent given by the minutes' walk given in the x-axis. All figures incorporate our index of neighborhood quality to measure neighborhood quality. Coefficient and corresponding confidence intervals are plotted for each outcome y_i given by panel headings.

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. $p<0.05$ **

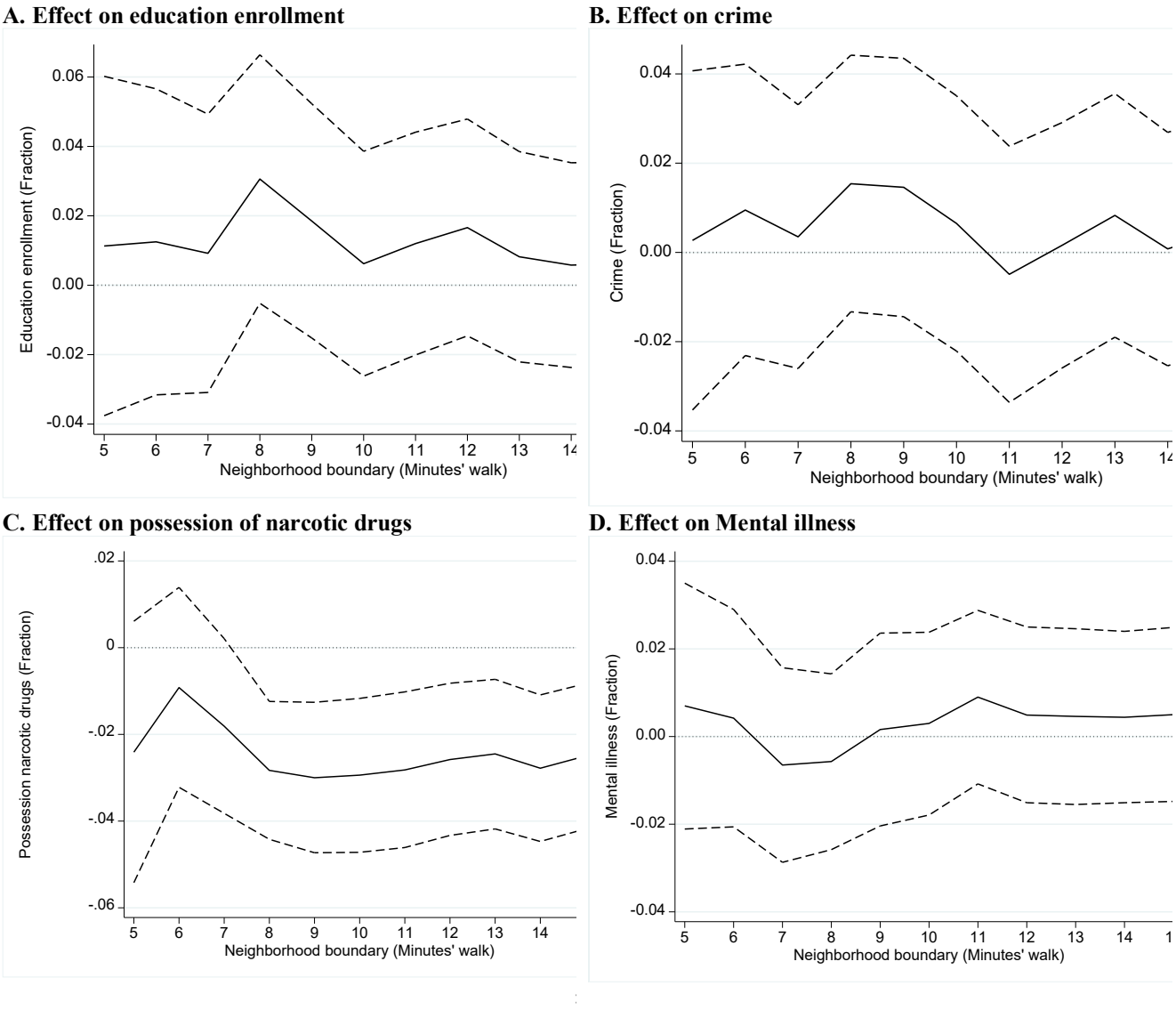


Figure A.1: Average effect of house property values on children by neighborhood boundary

Notes: These figures are based on estimation of Equation 2 and plots β on y_i for each corresponding definition of neighborhood size given by the geographic extent given by the minutes' walk given in the x-axis. All figures incorporate our property values based measure of neighborhood quality. Coefficient and corresponding confidence intervals are plotted for each outcome y_i given by panel headings