Child Development, Parental Investments, and Social Capital

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Abstract

This paper examines the impact of social capital on child development. It is innovative in measuring social capital at the individual level by using a latent factor model and a novel neighborhood survey from the Project on Human Development in Chicago Neighborhoods. Social capital reflects neighborhood connectedness and neighbors' engagement in child support and monitoring. I study the roles of social capital and parental investments in skill development within a unified framework and estimate a dynamic skill production function for children aged 6-15. Leveraging a natural experiment from the Chicago public housing demolition, I find that social capital is important for both cognitive and socio-emotional skills. Parental investments are effective for cognitive skills during these ages. Counterfactual experiments suggest that increasing social capital levels in low-socioeconomic-status (SES) neighborhoods to those in high-SES neighborhoods could reduce the skill gap between high-SES and low-SES children by 25% for cognitive skills and 80% for socio-emotional skills.

JEL Codes: I24, I28, J13, J24, R23

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1 Introduction

Childhood development is critical for lifetime outcomes and is shaped by factors both within and beyond the home environment. On the one hand, previous research has established the important role of parental investments in child development (Cunha et al., 2010; Attanasio et al., 2020b,c). On the other hand, children increasingly interact with the broader world around them as they grow older, especially with people in the same neighborhood. Recent studies and experiments, such as Moving to Opportunity, have shed light on the benefits of exposure to a better neighborhood: improved educational attainments, better labor market outcomes, and reduced single parenthood rates (Chetty et al., 2016; Chetty and Hendren, 2018a; Chyn et al., 2022). However, the question of how neighborhoods affect child development remains under-studied.

This paper explores one aspect of neighborhoods: social capital. Social capital refers to the social trust, norms, and connections that enable a community to act together and pursue shared objectives effectively (Putnam, 1995). In this paper, I exploit a neighborhood survey to measure social capital at the individual level. The idea that social capital is important in the creation of human capital dates back to Coleman (1988), who finds that proxies for measuring social capital are positively correlated with educational attainments. More broadly, social networks and contacts influence a wide range of outcomes, including health, human capital, labor market opportunities, and a region's economic mobility (Carrell et al., 2011; Beaman, 2012; List et al., 2020; Barrios Fernández et al., 2021; Chetty et al., 2022).

I analyze the effects of social capital and parental investments within a unified framework, focusing on two dimensions of human capital: cognitive skills and socio-emotional skills. I estimate a dynamic skill production function with the following key inputs: a child's current endowment of cognitive and socio-emotional skills, parental investments, and social capital. Through this unified framework, I can compare the roles of social capital and parental investments in shaping different dimensions of human capital and explore how these dimensions interact over time.

This paper makes two major contributions: measuring social capital at the individual level and identifying its causal impacts on child development. Measuring social capital is acknowledged as challenging, primarily because of the lack of data available to capture its complexity. Furthermore, even when measurements are available, these imperfect proxies often contain measurement errors that can introduce serious bias in the estimates. I overcome this challenge by combining a novel dataset with a latent factor model.

I utilize data from the Community Survey of the Project on Human Development in

Chicago Neighborhoods (PHDCN). To the best of my knowledge, this is the first time that PHDCN has been used in economic research. The Community Survey divides the whole city of Chicago into 343 neighborhood clusters, each comprising approximately 8,000 residents. Within these clusters, a random sample of 20 to 50 adults is surveyed to provide insights into various aspects of their communities. Consequently, this survey offers a valuable opportunity for a comprehensive characterization of social capital across the entire city of Chicago. The measures used to construct social capital capture the extent of connectedness within each neighborhood and the level of neighborly involvement in supporting and supervising children.

On top of the variation observed across neighborhoods, social capital measures also display substantial variation within a neighborhood based on respondents' demographic information. In particular, an individual's access to social capital within a neighborhood is most significantly influenced by whether they are native-born or not. On average, natives enjoy a higher level of social capital. However, there are also neighborhoods where immigrants possess more social capital than natives. Therefore, it is crucial to account for these individual-level variations in social capital to precisely estimate its impacts. This paper is innovative in constructing an individual-level social capital measure that varies with each respondent's immigration status.

To estimate the production functions, I not only need to measure social capital but also skills and parental investments, which share measurement challenges with social capital. Fortunately, the Longitudinal Cohort Study of the PHDCN provides information on the children and their primary caregivers in 80 out of the 343 neighborhood clusters. This study follows seven cohorts, ranging in age from 0 to 18, along with their primary caregivers, over three waves spanning from 1994 to 2001. To construct measures for skills and parental investments, I utilize data collected on child development measures and various parenting activities and resources. For most of my analysis, I focus on the 6, 9, 12, and 15-year-old cohorts, using data in the first two waves to maintain consistency and comparability in the measurements.

With access to rich information on neighborhood and home environments, as well as child development, I propose a latent factor model of social capital, parental investments, and skills, following the approach of Cunha and Heckman (2008) and Cunha et al. (2010). I develop a measurement system that links the observed measures to latent factors and estimate the distribution of these factors. This approach allows me to efficiently utilize all available measurements for each latent factor and account for measurement errors.

The second contribution of this paper is to establish the causal link between social capital and child skill development and compare its role with parental investments. Identifying the causal effects is challenging due to the potential endogeneity of social capital and parental investments. Endogeneity arises when parents' location choices and investment decisions respond to unobservable shocks to child development. For example, parents might move to a neighborhood with better support or increase their investment levels if they observe their children being negatively influenced by the neighborhood or falling ill. Failing to address such endogeneity can mask the true effects of social capital and parental investments.

I address endogeneity with an instrumental variable approach. I leverage a natural experiment resulting from public housing demolition in Chicago, exploiting both the occurrence and the timing of demolition to identify the effects of social capital. My analysis focuses on children whose homes were *not* demolished. With a significant number of residents being displaced from public housing units, existing networks and social bonds were disrupted, negatively impacting the social capital of residents staying in those neighborhoods. I compare the outcomes of children living in neighborhoods with demolitions to children in other neighborhoods with public housing. The decision to demolish public housing primarily stemmed from deteriorating building conditions and escalating management problems, issues that were prevalent in public housing across the U.S. in the 1990s (U.S. National Commission On Severely Distressed Public Housing, 1992). To the extent that these physical conditions or management problems are not correlated with social capital or unobserved variables affecting child development, this design provides exogenous variation in social capital.

As a robustness check for the potential correlation between demolition and unobserved neighborhood characteristics, I implement a second design by exploiting the randomness in the timing of demolitions across neighborhoods. In the initial wave of demolition examined in this paper, demolitions were largely driven by unforeseen events or logistical challenges, such as heating system breakdowns, pipe bursts, and lawsuits (Jacob, 2004; Chyn, 2018). I designate an alternative control group composed of children living in neighborhoods with public housing to be demolished in later years. Naturally, this design results in a smaller sample size, but it is reassuring to observe that the estimates of the production function remain similar in both settings.

To identify the impacts of parental investments, I use household resources as an instrument, following Attanasio et al. (2020c). I also use female labor market shocks as an additional instrument, which is proxied by the employment growth by educational attainments in the female labor market. These instruments reflect the impacts of budget constraints on investments.

The exclusion restriction assumption is that demolition, household resources, and labor market shocks affect children only through social capital and parental investments, conditional on household characteristics. Robustness checks suggest that demolition does not change the school environment or peer composition. I also control for post-demolition criminal activities, and the results remain unaffected. [1]

My results reveal that social capital and parental investments play important yet distinct roles in the development process. First, I find that social capital is an important determinant of both cognitive skills and socio-emotional skills. Specifically, a one standard deviation (SD) increase in social capital improves cognitive skills and socio-emotional skills by 0.16 and 0.19 SD, respectively. [2] The positive impacts of social capital are particularly pronounced among long-term residents, young children, Black or Hispanic individuals, and children from low socioeconomic status (SES) backgrounds. This evidence sheds light on a channel through which neighborhoods influence child outcomes, helping to open the black box of neighborhood impacts.

Second, parental investments are primarily effective in developing cognitive skills but not socio-emotional skills for children aged 6-15. A one SD increase in parental investments translates into a 0.42 SD in cognitive skills. [3] While previous literature finds positive impacts of parental investments on socio-emotional skills in early childhood (Cunha et al., 2010; Attanasio et al., 2020a), the results here suggest that the windows of opportunity for parents to foster socio-emotional skills may be limited.

The positive impacts of social capital and parental investments become more evident with the instrumental variable estimates compared to the Ordinary Least Square estimates. This finding highlights the importance of addressing the endogeneity problem, as parents seem to respond positively in terms of investment levels and neighborhood choices to negative shocks in the development process, consistent with results in Cunha et al. (2010), Attanasio et al. (2020b), and Attanasio et al. (2020c).

Third, in line with the child development literature, I find that the current stock of

[1] This paper focuses on the initial wave of demolitions in 1995. The existing literature primarily investigates the impacts of post-1999 demolition on crime due to data limitations. Aliprantis and Hartley (2015) and Sandler (2017) find that demolition reduces criminal activities in the demolished neighborhoods. It should be noted that the scale of demolition after 1999 (about 16,000 units) is much larger than the demolition studied in this paper (about 700 units), so the impacts of demolition on crime can be less relevant here and do not impact the estimates of the production function.

[2] The scale of the social capital latent factor is normalized to be the same as one of the measures: "the likelihood that neighbors would do something about kid skipping school." Based on the measurement system estimates, a 1.25 SD increase in social capital on average shifts the likelihood from "likely" to "very likely." Based on the neighborhood survey, a 1 SD increase in social capital is correlated with a $50,000 increase in the average household income in a neighborhood.

[3] A 0.7 SD increase in parental investments is equivalent to increasing the frequency that primary caregivers encourage the child to read from less than once a month to about once a month. Further improving the frequency to a few times a month is equivalent to a 1.55 SD increase.

skills nurtures future skill development, and the two dimensions of human capital exhibit cross-productivity. These lagged effects become more persistent with older children aged 12 to 15, compared to their impacts on younger children aged 6 to 9. These results imply that early-year interventions should be followed up to sustain impacts in later years, and intervention targeting either dimension of human capital can be beneficial.

In essence, a better understanding of the development process provides us with tools to design interventions that can effectively reduce inequality in human capital accumulation. Building upon these results, I conduct two counterfactual experiments where I raise social capital and parental investments for children residing in low-SES neighborhoods to the levels observed in high-SES neighborhoods. [4]

Increasing social capital proves effective in narrowing the skill gap between high- and low-SES children, reducing the gap in cognitive skills by 25% and socio-emotional skills by 80%. Remarkably, a sustained increase in social capital has the potential to completely close the socio-emotional skill gap. Initiatives such as the Social Capital Project, which advocates for community mentoring programs and investments in infrastructure like libraries and parks to enhance neighborly connections, are already underway. These efforts to foster social capital in disadvantaged communities can be vital in reducing inequality.

Conversely, increasing parental investments leads to a significant reduction, specifically a 36% decrease, in the cognitive skills gap. It also prevents the gap from widening further. Various childhood interventions have been developed to enhance parental investments, ranging from providing households with income transfers to arranging home visits with parenting guidance. These interventions serve as valuable tools in the pursuit of reducing inequality and expanding opportunities.

The paper is structured as follows. In Section 2, I provide an overview of the related literature. Section 3 describes the data used in the paper. Section 4 presents the latent factor model and discusses the identification challenges. In Section 5, I elaborate on the measurement of the latent factors and the estimation procedure. Section 6 introduces the empirical design aimed at addressing the endogeneity issue. Section 7 presents the estimation results, while Section 8 provides robustness checks. Section 9 illustrates the impacts of counterfactual experiments. Finally, Section 10 concludes.

[4] These experiments represent a 0.7 SD increase in social capital and a 0.32 SD increase in parental investments for low-SES households.

2 Literature Review

This paper builds upon and contributes to four strands of literature. First, this paper relates to the neighborhood effect literature. Chetty and Hendren (2018a) identifies substantial effects of childhood exposure to better neighborhoods on earnings, college attendance rates, and fertility and marriage patterns using data from residential movers. Altonji and Mansfield (2018) uses group characteristics to control for selection and evaluates the contribution of schools and associated neighborhoods to student outcomes, including high school graduation and college enrollment. Experiments such as the Moving to Opportunity experiment and the Gautreaux Assisted Housing Program also underscore the benefits of moving children to more favorable neighborhoods (Chetty et al., 2016; Chyn et al., 2022).

This paper contributes to the neighborhood effect literature by shedding light on the mechanisms underlying the neighborhood impacts. Chetty and Hendren (2018b) finds that some neighborhood characteristics, including social capital, school quality, and income inequality, are strongly correlated to childhood exposure effects. This paper establishes the causal link between social capital and child outcomes. My results align with Chetty et al. (2016), which finds that the effects of moving to a better neighborhood are more pronounced in younger children than in older youths or adults, as observed in the Moving to Opportunity Experiment. This paper complements other studies investigating various channels of neighborhood effects, including peer interactions (Agostinelli et al., 2020), social networks (List et al., 2020), and crime (Damm and Dustmann, 2014).

Second, this paper relates to the child development literature. Prior studies have explored the role of the home environment and parental investments in the skill production function (Todd and Wolpin, 2003, 2007). Del Boca et al. (2014) estimate a structural model of parental investments with a production function for cognitive skills embedded. Cunha and Heckman (2008) estimate a dynamic latent factor model to account for measurement errors in parental investments and skills. They explore how the role of parental investments differs for two dimensions of human capital, cognitive skills, and non-cognitive skills, across childhood stages. Cunha et al. (2010) and Attanasio et al. (2020c) estimate a more general nonlinear technology of the skill production function. Agostinelli and Wiswall (2016) addresses several identification and estimation challenges associated with the latent factor approach. Attanasio et al. (2020a) explores richer dynamics of production functions for health, cognitive, and socio-emotional skills. Attanasio et al. (2020b) estimate the production functions and parental investment functions with data obtained from randomized trials to examine the channels through which the intervention affects child outcomes. This paper stands out as the first in the literature to incorporate parental investments and social capital into the production function.

The third relevant strand of literature is on the impacts of social capital. Coleman (1988) introduces the concept of social capital to embody relations among people and emphasizes its importance in the creation of human capital. More generally, social networks and contacts matter for education, health, and labor market outcomes (Carrell et al., 2011; Beaman, 2012; List et al., 2020; Barrios Fernández et al., 2021). Durlauf and Fafchamps (2003) provide a literature review of empirical research on social capital, and point out two common issues faced by researchers in this field. First, social capital is often assessed using proxies, and measurement issues are a concern. Second, while most studies examine the correlations between social capital and the outcome of interest, they cannot establish its causal role. More recently, Chetty et al. (2022) tackles the first problem using Facebook data to measure and analyze three dimensions of social capital at the ZIP code level: economic connectedness, social cohesion, and civic engagement. They show that economic connectedness is strongly correlated with economic mobility. This paper is innovative in measuring social capital at the individual level using data from a neighborhood survey in Chicago and a latent factor model to address measurement errors. I also provide causal estimates of social capital's impacts on child skills through plausibly exogenous variations from a natural experiment.

Lastly, this paper relates to the public housing literature. Jacob (2004) studies the short-run impacts of Chicago public housing demolitions on children who were displaced, while Chyn (2018) investigates the long-run impacts on academic outcomes, labor market outcomes, and criminal behaviors. There are also studies directly examining the impacts of living in public housing projects (Currie and Yelowitz, 2000; Oreopoulos, 2003). While this paper explores the impacts of public housing demolition on children, it focuses on children whose homes were not demolished, a unique group that has not been previously studied.

3 Data

3.1 Primary Dataset

The primary dataset used in this paper is the Project on Human Development in Chicago Neighborhoods (PHDCN). To the best of my knowledge, this is the first time that PHDCN has been used in economics research. PHDCN covers the entire city of Chicago, with the city being divided into 343 neighborhood clusters. As a comparison, there are 847 census tracts and 77 community areas in Chicago. Therefore, a typical neighborhood cluster includes two to three census tracts and is nested within a community area, with an average population of approximately 8,000 residents.

Two key components of the PHDCN are utilized in this paper. The first component is the Longitudinal Cohort Study (LCS), which follows seven cohorts of children. The cohorts include those at birth (0), 3, 6, 9, 12, 15, and 18 years of age. There are three waves of study, 1994-1996, 1997-1999, and 2000-2001. The LCS uses a three-stage sampling strategy. In the first stage, all 343 neighborhood clusters are cross-classified by two variables based on census information: racial-ethnic mix (seven categories) and socio-economic status (three levels). 80 neighborhood clusters are chosen through stratified random sampling. In the second stage, block groups are randomly selected from the aforementioned 80 neighborhood clusters, and all dwelling units within these blocks are included. In the final stage, households with children within the target age cohorts are selected and interviewed.

The LCS collected information on various child development measures, parental investment measures, and household demographics. However, it is worth noting that skill development measures for the youngest cohorts (ages 0 and 3) cannot be compared to those for the older cohorts. Additionally, there are no parental investment measures available for the oldest cohort (age 18) in wave 2, and the investment measures for other cohorts in wave 3 are less comprehensive. To ensure measurement consistency across different periods, I have chosen to limit my sample for the production function estimates, focusing on children within the 6, 9, 12, and 15-year-old cohorts in the first two waves.

Cognitive skills are assessed using a combination of measures, including (1) reading test scores obtained from the Wide Range Achievement Test (WRAT), (2) word definition scores derived from the Wechsler Intelligence Scale for Children (WISC), (3) attention duration levels, and (4) the child's comprehension of interview questions.

Socio-emotional skills, on the other hand, are measured through scores obtained from the sub-scales of the Child Behavior Checklist, encompassing various dimensions, including withdrawn problems, anxiety or depression, somatic complaints, social problems, thought problems, attention problems, rule-breaking behavior, and aggressive behavior.

Parental investments in wave 2 are characterized by a comprehensive range of items, as elaborated in Table 3. These investments can be broadly categorized into three domains. The first domain relates to the resources provided to the child such as the number of books, board games, puzzles, musical instruments, and sports equipment. The second domain captures the time spent with the child, including the frequency of family activities, helping and checking with homework, school visits, and communication with teachers. The last domain pertains to parents' involvement in their children's social circles, including their familiarity with their child's friends, connections with other parents, frequency of discussions with their child regarding behavior, and enforcement of rules.

The second component, the Community Survey, conducted in 1995, involves household interviews with residents aged 18 and older. A three-stage sampling strategy was employed. Firstly, block groups were randomly sampled within each of the 343 neighborhood clusters. Secondly, dwelling units were randomly selected from the chosen blocks. Lastly, one adult resident was randomly chosen from these selected dwelling units. All neighborhood clusters are represented in this survey. However, for the 80 neighborhood clusters that were selected for LCS, the target sample size was 50, while for the remaining neighborhood clusters, the target sample size was 20. In total, 8,782 adults participated in the Community Survey.

In addition to providing basic demographic information, the respondents assessed neighborhood environments in multiple dimensions such as the organizational and political structure of communities. Importantly for this project, the Community Survey provides various measures for social capital. Respondents were queried about the likelihood of neighbors taking action in cases of children skipping school, children defacing buildings, and neighbors reprimanding children for disrespectful behaviors. They were also asked whether they agreed that parents generally know their children's friends, whether parents generally know each other, whether adults generally know who local children are, whether adults would watch out for children, and whether children can look up to adults in the neighborhood. Responses are in five categories, ranging from very likely/strongly agree, likely/agree, neither likely nor unlikely/neither agree nor disagree, unlikely/disagree, to very unlikely/strongly disagree.

In Table 1 and Table 2, I present descriptive statistics on the household characteristics using the LCS for the whole sample and the respondent characteristics using the Community Survey, respectively.

3.2 Secondary Datasets

I requested data related to public housing from the Chicago Housing Authority through the Freedom of Information Act. The dataset includes names, addresses, the number of units, and demolition dates for the demolished housing projects. For my research, I specifically focus on public housing units that were demolished in 1995, coinciding with the collection of social capital measures. In total, there were 728 units demolished in that year.

The labor market statistics are from the Current Population Survey (CPS). I use the number of full-time employed females by educational attainments in 1996 and 1997 to

Table 1: Child and Household Characteristics in the Longitudinal Cohort Study

Variable	Obs	Mean	Std. Dev.
Child Characteristics			
Age	5930	8.319	5.757
Female	6187	0.502	0.5
Hispanic	6200	0.465	0.499
Black	6200	0.343	0.475
Other races	6226	0.195	0.397
Household Characteristics			
Number of siblings	6083	1.96	1.632
Income per capita ($1,000)	5741	5.975	5.301
PC is cohabiting	5522	0.68	0.467
Number of years PC at current address	5461	5.3	6.323
Mom with higher education	6226	0.395	0.489
Dad with higher education	6226	0.305	0.461
Native family	5302	0.457	0.498

Notes: "PC" stands for "primary caregivers". "Higher education" refers to at least some college education. The statistics are computed using the entire sample from the Longitudinal Cohort Study.

Table 2: Respondent Characteristics in the Community Survey

Variable	Obs	Mean	Std. Dev.
Age	7957	42.584	16.635
Female	7635	0.59	0.492
Hispanic	7635	0.251	0.434
Black	7635	0.394	0.489
Other races	7635	0.355	0.478
Native	8624	0.845	0.362
Married	7635	0.374	0.484
Years of Education	7635	12.314	3.118
Annual Household Income			
Below $15,000	7635	0.321	0.467
Below $30,000	7635	0.621	0.485
Below $60,000	7635	0.885	0.319

Notes: The Community Survey records annual household income in discrete categories. This table presents the distribution of respondents' income across three groups: below $15,000, below $30,000, and below $60,000.

compute the percentage change between 1996 and 1997. The percentage change is at the national level and is a proxy for labor market shock. In addition, I use 1990 census data to measure neighborhood characteristics, including below poverty line share, high school graduate share, racial composition, unemployment rate, and homicide rate. Additional crime measures are from the Homicides in Chicago Dataset which include homicide counts at the census tract level from 1965 to 1995.

4 The Human Capital Accumulation Process

The main objective of this paper is to investigate the roles of social capital and parental investments in the human capital accumulation process. I focus on two dimensions of human capital: cognitive skills and socio-emotional skills, and I estimate the skill production function for both. The skill production functions are defined as the following:

$$\theta^c_{ir,t+1} = f(\theta^c_{ir,t}, \theta^s_{ir,t}, I_{ir,t}, SC_{ir,t}, \boldsymbol{X_{ir,t}}, \epsilon_{ir,t}),$$

$$\theta^s_{ir,t+1} = g(\theta^c_{ir,t}, \theta^s_{ir,t}, I_{ir,t}, SC_{ir,t}, \boldsymbol{X_{ir,t}}, \eta_{ir,t}),$$

where i, r, and t represent individuals, neighborhoods, and time periods, respectively. $\theta^c_{ir,t}$ and $\theta^s_{ir,t}$ are cognitive and socio-emotional skills, $I_{ir,t}$ are parental investments, $SC_{ir,t}$ is social capital, and $\boldsymbol{X_{ir,t}}$ is a vector of demographic variables, discussed in more details later. $\epsilon_{ir,t}$ and $\eta_{ir,t}$ are shocks to the production function, unobserved by researchers.

There are two primary challenges in identifying the causal impacts of parental investments $I_{ir,t}$ and social capital $SC_{ir,t}$. The first challenge lies in measuring the inputs and the outputs of these production functions. Skills, parental investments, and social capital are unobservable. Measuring social capital is particularly challenging due to its complexity and the absence of comprehensive measurements. Although the PHDCN offers a range of measurements on social capital, parental investments, and skills, using any single measurement can introduce estimation bias because they are imperfect proxies and contain measurement errors.

In line with the literature in child development (Cunha and Heckman, 2008; Cunha et al., 2010; Attanasio et al., 2020b,c), I model social capital, parental investments, and skills as latent factors. I develop a measurement system that links the observed measurements to these underlying latent factors and estimate the distribution of these latent factors. Section 5 provides more detailed information on the specification and the estimation of this measurement system and the latent factor model.

The second challenge arises from the potential correlation between shocks and parental investments and social capital. I outline a structural economic model of parental investment decisions and neighborhood choice to fix ideas in Appendix A.1. The key insight of this model is that parents' decisions regarding investments and residential choices, which in turn determine the level of social capital they experience, can be correlated with shocks to child development that are unobservable to researchers. For instance, parents may become aware of adverse events affecting their children, such as illness, prompting them to increase their investments in child well-being. Similarly, parents may notice negative influences on their children stemming from their current neighborhood and opt to relocate to an area with stronger social support networks, aiming to assist their children in navigating challenging circumstances. More generally, social capital can be correlated with unobserved neighborhood characteristics that matter for child development due to sorting. Failure to address the endogeneity issue could lead to a spurious correlation between these input variables and child outcomes. Therefore, identification requires exogenous variations in parental investments and social capital. I utilize an instrumental variable approach.

Parents' investment decisions and residential choices depend on their preferences for child skill development, their budget constraints, and their beliefs on the effectiveness of inputs in the development process. The dependence on the budget constraint provides two natural candidates for instruments, labor market shocks and household resources. To generate exogenous variations that shift social capital, I consider public housing demolitions as an instrument and exploit the timing of demolitions across neighborhoods. I provide more details of the instruments in Section 6.

This paper does not estimate the structural economic model mentioned above, as done in Del Boca et al. (2014). While I am not able to explicitly simulate the impacts of potential intervention, the estimates presented here do not rely on strong assumptions on households' behaviors, such as assuming full knowledge or accurate beliefs about the production function.

5 Measurement System

In this section, I begin by discussing the theory and specification of the measurement system for skills, parental investments, and social capital. Following that, I make full use of the Community Survey to provide a detailed characterization of social capital, and construct an individual-level social capital variable that varies with an individual's immigration status. I then present the results of the measurement invariance test to confirm that the measurement metrics are the same for both immigrants and natives. Finally, I discuss the three-step estimation process.

5.1 Confirmatory Factor Analysis

The measurements for social capital and parental investments are all categorical, while the measurements for cognitive skills and socio-emotional skills are a mixture of continuous and categorical variables.

Let m_{jki} denote the jth available measurement related to latent factor k for individual i. When the observed measurement m_{jki} is categorical, we assume it is a manifestation of a continuous latent item m^*_{jki}. The latent item m^*_{jki}, in turn, has a semi-log relationship with the latent factor θ_{ki}, as we consider the latent factor θ_{ki} to be strictly positive.

$$m^*_{jki} = \alpha_{jk} + \lambda_{jk} ln\theta_{ki} + \epsilon_{jki},$$

where α_{jk} is the intercept, λ_{jk} is the factor loading, ϵ_{jki} is the measurement error.

The threshold model below captures the relationship between the continuous latent item m^*_{jki} and the observed item m_{jki}:

$$m_{jki} = \begin{cases} 1 & \text{if } m^*_{jki} < \tau_{1,jk}, \\ 2 & \text{if } m^*_{jki} \in [\tau_{1,jk}, \tau_{2,jk}], \\ ... & \\ n & \text{if } m^*_{jki} > \tau_{n-1,jk}, \end{cases}$$

where $\tau_{n,jk}$ is the n^{th} threshold.

For continuous measurements, the observed measurement m_{jki} is the latent item m^*_{jki}, so $m^*_{jki} = m_{jki}$, and

$$m_{jki} = \alpha_{jk} + \lambda_{jk} ln\theta_{ki} + \epsilon_{jki}.$$

I assume that the measurement errors are mean zero, independent of the latent factors, and independent of each other. The measurement errors follow a normal distribution and the latent factor follows a log-normal distribution. [5] Since there is no inherent scale or location of the latent factors, we need normalization assumptions to set the scale and location.

[5]These assumptions are more restrictive than necessary for identification. It is possible to allow measurement errors to be correlated with each other as long as there is one measure whose error is independent of those of other measures of the same factor. The latent factor can follow a mixture of normal distributions if all measurements are continuous, as done in Cunha et al. (2010) and Attanasio et al. (2020c).

First, I set the scale of the latent factors to be equal to the unit of one of the measurements, and denote this reference measurement as the 1^{st} measurement. This is equivalent to setting the factor loading of m_{1ki} to be one, i.e., $\lambda_{1k} = 1$ for factor k. Specifically, for social capital, I set the factor loading of the measurement "how likely your neighbors would do something about kids skipping school" to be one. For parental investments, I set the measurement "frequency that the primary caregiver helped the child with homework" to be one. As pointed out by (Agostinelli and Wiswall, 2016), maintaining a consistent scaling of latent factors is essential to ensure that dynamic latent factors are comparable over time. In this context, cognitive skills and socio-emotional skills are dynamic, and I use the same reference measurements in waves 1 and 2. For cognitive skills, I use the Wide Range Achievement Test score as the reference measurement, while for socio-emotional skills, the Withdrawn sub-scale of the Child Behavior Checklist (CBCL) is used as the reference measurement.

In terms of the location of the latent factors, it is natural to set the mean of the log of latent factors to be zero. Therefore, the means of log social capital and the means of log parental investments are constrained to be zero. However, for dynamic latent factors, i.e. cognitive skills and socio-emotional skills, it is important to allow them to change over time. Imposing the log skills to be mean zero across all time periods can lead to bias in the production function (Agostinelli and Wiswall, 2016). Consequently, I constrain the intercept of the Wide Range Achievement Test score, and the intercept of the Withdrawn Sub-scale to be zero over time, [6] assuming the mapping from these reference measurements to the related factors are invariant to the child's age. The observed growth in the measurements is only attributed to the growth of the related factors.

Further assumptions are required to identify the measurement system with categorical measures. Since the thresholds and the intercepts cannot be jointly identified, I normalize all the intercepts to be zero for categorical items. As neither the latent item nor the latent factor has a scale, I normalize the variance of the latent items m^*_{jki} to be one for all associated categorical measurements, obtaining the residual variances as $V(\epsilon_{jki}) = 1 - \lambda^2_{jk} V(ln\theta_{ki})$. [7]

For a measurement system with one latent factor, at least three measurements per factor are required for identification. With more than one latent factor in a measurement system, we require fewer measurements per factor. I assume a dedicated measurement system, where each measurement only proxies one factor. Although not necessary for identification, this assumption aids in interpreting the latent factor. [8] Lastly, I assume

[6] This constraint is equivalent to normalizing the means to be the means of the reference measurements.

[7] An alternative is to set the residual variances $V(\epsilon_{jki})$ to be one and obtain the variance of latent items as $V(m^*_{jki}) = \lambda^2_{jk} V(ln\theta_{ki}) + 1$.

[8] As long as there is one measure loading exclusively on one factor, other measures are allowed to relate

the mapping from the latent factors to the measures is separable. Cunha, Heckman, and Schennach (2010) consider a more general case where the mapping is non-separable. They demonstrate that non-parametric identification of the joint distribution of the latent factors and the measurement errors can be achieved with at least three measures.

5.2 Specification of the measurement system

I first conduct an exploratory factor analysis to investigate how many factors we can extract from the measurements and determine how to allocate each measurement to the factors. The explanatory factor analysis supports the extraction of one factor for each of the following latent factors: social capital, parental investments, cognitive skills, and socio-emotional skills. I then estimate the measurement system. The results of the exploratory factor analysis and measurement system are presented in Appendix A.2.1 and A.2.2.

I report the assignment of measurements to factors and the signal-to-noise ratio in Table 3 below. The signal-to-noise ratio assesses the degree of information contained in a measurement relative to the measurement errors. It is computed by

$$s_j^{\ln\theta_k} = \frac{\left(\lambda_{jk}\right)^2 \operatorname{var}\left(\ln\theta_k\right)}{\left(\lambda_{jk}\right)^2 \operatorname{var}\left(\ln\theta_k\right) + \operatorname{var}\left(\epsilon_{jk}\right)},$$

where I assume that the j^{th} measure of latent factor θ_k can be written as

$$m_{jki} = \alpha_{jk} + \lambda_{jk} ln\theta_{ki} + \epsilon_{jki},$$

for continuous variables, and

$$m^*_{jki} = \alpha_{jk} + \lambda_{jk} ln\theta_{ki} + \epsilon_{jki},$$

for categorical variables. I make the normalization assumption that $var(m^*_{jki}) = 1$ for identification.

The last column in Table 3 reports the signal-to-noise ratio for each of the measurements involved in the measurement system. There is significant variation in the signal-to-noise ratio. For example, *Number of books in house for SP's age* has about 52% of the variance due to signal, while only 5% of the variance is due to signal for *Frequency PC visited school or talked to teacher, last 3 months*. It should also be noted that except for *WRAT: Reading test scores*, all other measurements have a signal-to-noise ratio far from 100%. This highlights

to several factors.

the importance of using the latent factor approach. Without properly accounting for the measurement error issues, using these measurements will lead to biased estimates.

5.3 Characterization of Social Capital

Figure 1: Distribution of Social Capital by Neighborhood SES

Notes: This figure displays the distribution of neighborhood-level social capital by neighborhood socioeconomic status.

Figure A15 illustrates the distribution of social capital based on socioeconomic status (SES). The classification of high and low SES relies on neighborhood characteristics from the 1990 census, including the median income, the share of high school graduates, the unemployment rate, and the homicide rate. It is clear that high SES neighborhoods, on average, exhibit higher levels of social capital compared to their low SES counterparts.

To understand what characteristics are correlated with the social capital level in a neighborhood, I use the Community Survey. I utilize respondent characteristics from the Community Survey to explore the correlation between social capital and various neighborhood characteristics in 1995. Table 4 illustrates a positive correlation between social capital levels and neighborhood characteristics such as a higher average age, a larger share of White or U.S.-born native residents, greater rates of married residents, and a higher average income. In contrast, the female share and the average years of education are not correlated with the social capital level in a neighborhood.

Even within the same community, access to social capital can vary with an individual's demographic background. To better characterize social capital, I examine the correlation between social capital and a set of demographic characteristics at the individual level. I use the following fixed-effect model to examine within-neighborhood variation.

Table 3: Measurement System

Latent factor	Measurement	Signal
Social capital	Neighbors do something about kids skipping school	0.598
	Neighbors do something about kids defacing bldg	0.566
	Neighbors scold a kid for not showing respect	0.461
	Children look up to adults in the neighborhood	0.317
	Adults watch out for children	0.497
	Parents know their children's friends	0.493
	Adults know who local children are	0.495
	Parents generally know each other	0.517
Parental investments	Frequency PC helped SP with homework, past year	0.341
	Frequency PC encouraged SP to read, past month	0.332
	Frequency PC spoke with SP about day, past month	0.379
	Frequency PC praised SP about accomplishment, past month	0.357
	Frequency SP encouraged in hobbies, past month	0.330
	Frequency SP included in family activities, past month	0.377
	Frequency PC visited school or talked to teacher, last 3 months	0.049
	Frequency PC checked SP's homework completed	0.302
	SP has any sports equipment?	0.281
	Any musical instruments SP can use?	0.179
	Number of books in the house	0.498
	Number of books in house for SP's age	0.516
	Any books belong to SP?	0.220
	Number of board games for SP's age	0.456
	Number of tapes, CDs, or records for SP's age	0.125
	Any puzzles for SP's use?	0.249
	SP has dictionary at home for use?	0.252
	SP has encyclopedia at home for use?	0.309
	At least saw 2 of SP's friends last week	0.066
	Number of SP's friends PC knows by sight or name	0.156
	Frequency PC frequency PC talks with SP about behavior	0.079
	Frequency PC able to enforce rules, past year	0.109
Cognitive skills, w1	WRAT: Reading test scores	0.999
	WISC: Word definition scores	0.630
Socio-emotional skills, w1	CBCL: Withdrawn problems	0.428
	CBCL: Aggressive behavior	0.626
	CBCL: Somatic complaints	0.266
	CBCL: Anxiety or depression	0.601
	CBCL: Social problems	0.468
	CBCL: Thought problems	0.603
	CBCL: Attention problems	0.686
	CBCL: Rule-breaking behavior	0.503
Cognitive skills, w2	WRAT: Reading test scores	0.598
	WISC: Word definition scores	0.609
	Attention duration levels	0.236
	Comprehension of interview questions	0.456
Socio-emotional skills, w2	CBCL: Withdrawn problems	0.564
	CBCL: Aggressive behavior	0.570
	CBCL: Somatic complaints	0.269
	CBCL: Anxiety or depression	0.694
	CBCL: Social problems	0.347
	CBCL: Thought problems	0.435
	CBCL: Attention problems	0.690

Notes: This table shows the measures allowed to load on each latent factor, as well as the fraction of the variance in each measure that is explained by the variance in signal. 'w1' refers to wave 1, and 'w2' refers to wave 2. 'PC' refers to the primary caregiver and 'SP' refers to the child. 'WRAT' refers to the Wide Range Achievement Test, 'WISC' refers to the Wechsler Intelligence Scale for Children, and 'CBCL' refers to the Child Behavior Checklist.

$$lnSC_{jk} = \beta_0 + \mathbf{X_{jk}}'\Gamma + \lambda_k + \epsilon_{jk},$$

where j and k index individual respondents for the Community Survey, and the neighborhoods they are in, respectively. λ_k are neighborhood fixed effects. $\mathbf{X_{jk}}$ is a vector of dummy variables, including gender (female vs. male), race (white vs. non-white), immigration status (natives vs. immigrants, proxied by if English is regularly spoken at the household), age (above the median age 40 vs. below), educational attainments (high school graduates vs. non-high school graduates), household incomes (above median income vs. below median income), and marital status (married vs single).

Table 4: Correlation Between Social Capital and Neighborhood Characteristics

Variables	Social capital
Average age	0.048***
	(0.008)
Female share	0.407
	(0.313)
White share	0.705***
	(0.169)
Native share	1.185***
	(0.364)
Married share	1.242***
	(0.333)
Average years of education	0.002
	(0.045)
Average household income ($5,000)	0.100***
	(0.027)
Observations	343

Notes: This table presents the coefficient estimates from a multivariate regression of neighborhood-level social capital on the neighborhood characteristics listed above, with robust standard errors shown in parentheses. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1

The results in Table 5 reveal that conditional on neighborhood fixed effects, four characteristics display significant correlations with social capital. Social capital tends to be higher among residents aged 40 and above, U.S.-born natives, married couples, and those with household incomes exceeding the median. Interestingly, while neighborhoods with higher proportions of White residents on average have levels of higher social capital, the influence of race diminishes within a neighborhood, likely due to residential racial segregation.

It is worth noting that an individual's immigration status is the most predictive factor for their access to social capital. The results are consistent with existing studies that highlight class-specific differences in social capital and unequal access between immigrants and natives (Völker et al., 2008; Behtoui, 2022). Therefore, it is important to capture the heterogeneity in social capital at the individual level.

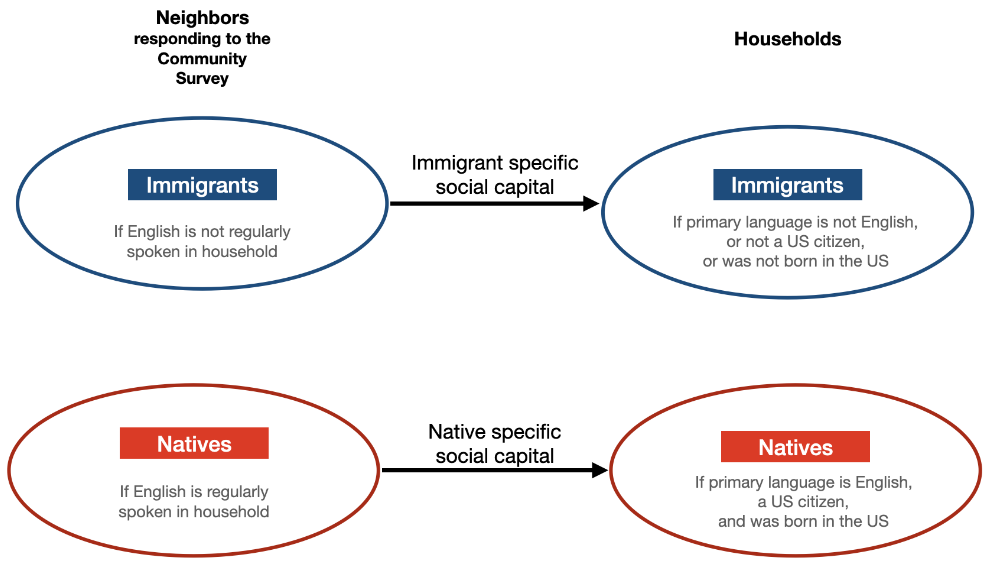
Table 5: Correlation Between Social Capital and Individual Characteristics

Variables	Social capital
Above median age	0.069**
	(0.029)
Female	0.007
	(0.027)
White	-0.033
	(0.038)
Native	0.160***
	(0.042)
Married	0.057**
	(0.028)
HS graduate	-0.023
	(0.034)
High income	0.120***
	(0.032)
Neighborhood fixed effects	Yes
Observations	5,490

Notes: This table presents the coefficient estimates from a multivariate regression of individual-level social capital on the individual characteristics listed above, controlling for neighborhood fixed effects. The robust standard errors are shown in parentheses. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1

Building on these results, I construct a social capital measure that varies by the immigration status of children and their households. Specifically, after obtaining estimated factor scores for all respondents in the Community Survey, I categorize them into two groups: immigrants and natives. A respondent is classified as an immigrant if English is not regularly spoken in their household; otherwise, they are classified as a native. Based on these classifications, I calculate the average of individual factor scores at the neighborhood level. In other words, each neighborhood has both an immigrant-specific social capital measure and a native-specific social capital measure. Then I assign the immigrant-specific measure to immigrant households and the native-specific measure to native households. The classifications for the households are based on whether at least one parent is an immigrant. Parents are identified as natives if they primarily speak English, are US citizens, and were born in the US.[9] Figure 2 illustrates the assignment process.

Figure 2: Constructing Social Capital Tailored to Immigrants and Natives

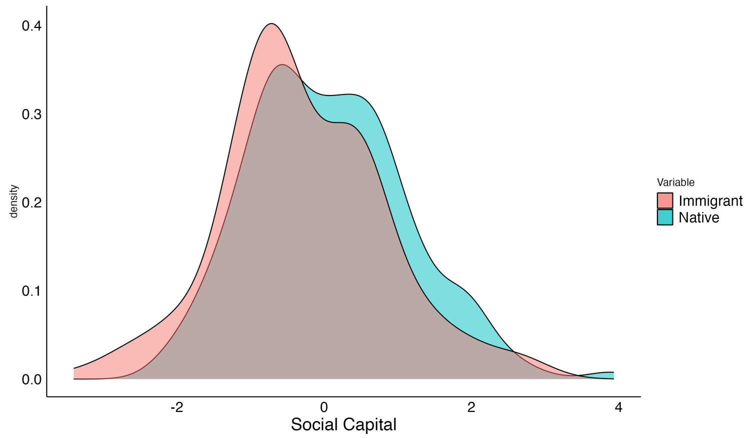


Notes: This figure illustrates the process of assigning a social capital measure to households based on their immigration status after obtaining the factor scores of respondents in the Community Survey.

Figure 3 depicts the distribution of social capital by immigrants and natives. The figure aligns with the regression estimates, indicating that, on average, natives enjoy a higher level of social capital than immigrants. Figure 4 plots each neighborhood's social capital measure for immigrants and natives. The scatter plot reveals that there are neighborhoods where immigrants have a higher level of social capital than natives, as indicated by observations above the 45-degree line.

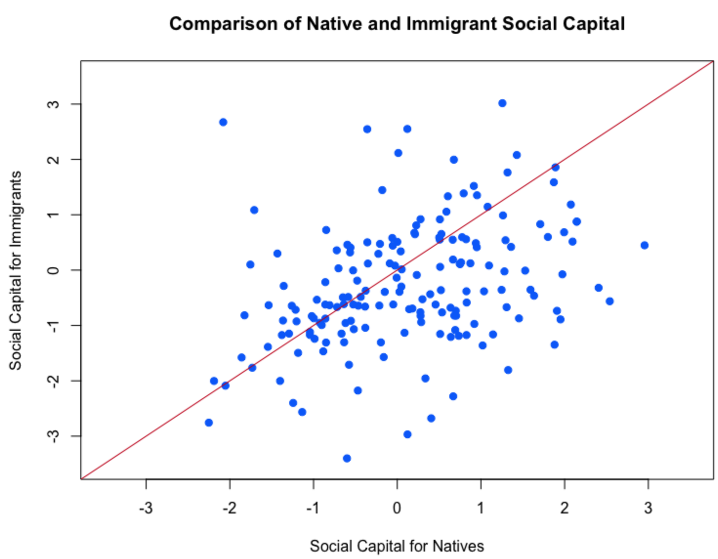
[9]The Longitudinal Cohort Study provides more detailed demographic information about parents, allowing for more accurate classification compared to what is available in the Community Survey. Utilizing either the father's or mother's information alone for classification does not yield different results.

Figure 3: Social Capital Across Immigrant and Native Groups



Notes: This figure displays the distribution of social capital by immigrants and natives at the neighborhood level, using the average factor scores for all immigrant respondents and all native respondents within each neighborhood, respectively.

Figure 4: Social Capital Comparison: Immigrants vs. Natives in Neighborhoods



Notes: This figure displays the immigrant and native specific social capital levels of each neighborhood, using the average factor scores for all immigrant respondents and all native respondents within each neighborhood.

5.4 Measurement Invariance

I assess measurement invariance between immigrant and native groups. Given that the social capital measure is tailored to an individual's immigration status, it is crucial to confirm that the evaluation metrics are consistent for both immigrants and natives. In essence, immigrant and native respondents should assess social capital in the same way. Otherwise, disparities between the two groups could be attributed to differences in measurement rather than substantive variations in social capital.[10]

Psychometrics has developed tests for measurement invariance (Wu and Estabrook, 2016). The idea is to compare the baseline model with a series of models that impose restrictions on equal intercepts, factor loadings, or thresholds between groups. The model fits are evaluated, and if more restricted models have similar fits, then invariance is established.

The baseline model puts the least stringent requirements on invariance. It only requires the same number of factors and the same pattern of zero and non-zero loadings across groups. Then three levels of invariance are considered. First, I restrict the thresholds to be invariant between groups. Second, I impose identical restrictions on the factor loadings, on top of threshold invariance. This means that the measurements relate to the factor in the same ways, and we can compare the variance between groups. Lastly, intercepts, factor loadings, and thresholds are all restricted to be invariant across groups. In other words, the means of the latent factors are comparable across groups.

Table 6 compares the model fits with various statistics. Tests based on $\Delta\chi^2$ are sensitive to sample size and model complexity, and can have a high Type I error (Mueller, 1999; Sass, Schmitt, and Marsh, 2014). For these reasons, alternative tests based on approximate fit indices such as Δcomparative fit index (ΔCFI) are recommended (Cheung and Rensvold, 2002). Chen (2007) proposes cutoff values for rejecting measurement invariance: $\Delta RMSEA > 0.015, \Delta CFI < -0.010$, and $\Delta RMSR > 0.010$.[11] Based on the ΔCFI, I cannot reject the null that social capital is measured with the same metric between the immigrant group and the native group. This allows me to interpret the differences as actual variations in social capital.

5.5 Estimation

I adopt a three-step estimation procedure as follows. First, I estimate the measurement systems for all latent factors. I recover the mean and covariance of latent factors, the intercepts, and the factor loadings based on the observed covariance and mean of the measurements. Pearson correlations are calculated for any two continuous variables. When categorical items are involved, I rely on polychoric correlations between categorical

[10] I also test measurement invariance between control and treatment groups. Test results are reported in Appendix A.2.3.

[11] The RMSEA is defined as $\sqrt{(\chi^2 - df)\,/df(n-1)}$, where df is the degrees of freedom and n is the sample size. The CFI is defined as $(\delta_{\text{Null Model}} - \delta_{\text{Alternative Model}})\,/\delta_{\text{Null Model}}$, where $\delta = \chi^2 - df$. The RMSR represents the square root of the difference between the residuals of the sample covariance matrix and the hypothesized model.

Table 6: Measurement Invariance Test

	df	χ^2	RMSEA	CFI	RMSR
Baseline model	40	4285.205	0.157	0.946	0.085
Threshold invariance	56	4322.539	0.133	0.945	0.087
Threshold and loading invariance	63	4368.153	0.126	0.945	0.088
Threshold, loading, and intercept invariance	70	4603.012	0.123	0.942	0.093

	Relative Fit to the Baseline model			
	p-value ($\Delta\chi^2$)	Δ RMSEA	Δ CFI	Δ RMSR
Threshold invariance	0	-0.024	-0.001	0.002
Threshold and loading invariance	0	-0.031	-0.001	0.003
Threshold, loading, and intercept invariance	0	-0.034	-0.004	0.008

Notes: RMSEA stands for the root mean squared error of approximation, CFI for the comparative fit index, and RMSR for the root mean square residual.

items and polyserial correlations between categorical and continuous items. To obtain these correlations, I first estimate the thresholds for each item from the univariate marginal distribution, and then compute the correlations between any two items using maximum likelihood.

The correlations obtained from this procedure, denoted as $(\hat{\rho})$, encompass Pearson correlations, polychoric correlations, and polyserial correlations between all pairs of measurements. Let the model-implied covariance matrix be $\rho(B)$, with B representing the measurement parameters, including the covariance of latent factors and the factor loadings. The estimator $\hat{B}$ is obtained from the Weighted Least Square (WLS) estimator:

$$F_{WLS} = [\hat{\rho} - \rho(B)]' W^{-1} [\hat{\rho} - \rho(B)],$$

where W is a consistent estimator of the asymptotic covariance matrix of $(\hat{\rho})$, as proposed by Muthén (1978). I adopt a modified approach, the Diagonally Weighted Least Squares estimator (DWLS), suggested by Muthén (1993). DWLS uses the diagonal of W as the weight matrix. It is computationally more practical and more stable than WLS with small and medium sample sizes (Maydeu-Olivares, 2001). DWLS also performs better statistically than maximum likelihood for categorical variables with fewer than 5 categories Rhemtulla et al. (2012). The mean of latent factors and intercepts can be obtained from the observed mean of measurements.

In the second step, I estimate factor scores for all latent factors based on the measurement parameters obtained in the previous steps. Empirical Bayes Modal approach is used to estimate the factor scores for each individual in the dataset. This step yields social capital factor scores for all Community Survey respondents. Subsequently, I aggregate these social capital factor scores to the neighborhood level by respondents' immigration status. Then, I assign these factor scores to children and their parents based on their neighborhoods and immigration status, as described in Section 5.3.

The last step corrects for the estimation error in the factor scores to account for the fact that we are using the estimated factors instead of the actual ones. Following the correction method proposed by Heckman et al. (2013) and used in Attanasio et al. (2020b), I correct the estimates of the reduced forms and the first stages, and then use a minimum distance estimator to recover the structural parameters.

I bootstrap 1000 samples with the neighborhood as the cluster and repeat this entire process 1000 times to obtain confidence intervals and critical values for test statistics.

6 Empirical Design

6.1 Institutional Background

Public housing provides low-income households with affordable housing and has been widespread across the city. It is operated and managed by the Chicago Housing Authority (CHA) with federal support. In the 1950s and 1960s, a series of large projects and high-rise buildings were built. Founded in 1937, the CHA has been the third-largest public housing authority in the United States since the 1990s. Applications for public housing units are competitive, and there are long waiting lists.

However, due to serious design flaws and bad maintenance, public housing soon began deteriorating. For example, the Addams, Brooks, Loomis, and Abbott (ABLA) Homes, one of the demolished sites studied in this paper, experienced obvious physical decline since the 1970s. In the 1980s, the ABLA heating system regularly broke down during the winter months (Bennett et al., 2015). The poor conditions of public housing were not unique to Chicago but were observed in other cities as well. In 1992, more than 80,000 public housing units in the United States were identified by a national commission as renovation or demolition needed (U.S. National Commission On Severely Distressed Public Housing, 1992). In response, the Housing and Urban Development established the HOPE VI program, advocating for the demolition of failed social housing projects in the country.

The HOPE VI program provided local authorities with funding to redevelop and revitalize public housing sites. Chicago received more HOPE VI funding than any other city and demolished more than 20,000 public housing units in the 1990s and 2000s (Sink and Ceh, 2011; Almagro et al., 2023). About 80% of these demolitions took place after 2000 under the CHA's "Plan for Transformation", where demolition and redevelopment were carefully planned.

In contrast, the initial wave of demolitions studied in this paper stemmed from various initiatives and unpredicted factors. In particular, the timing of demolitions was often driven by unforeseen events or logistical challenges, including financial challenges and legal disputes involving tenant organizations (Hunt, 2009). This unpredictability could generate plausible randomness in the closure timing. For example, the bursting of pipes in 1999 within several high-rise buildings in the Robert Taylor Homes caused an emergent evacuation and subsequent demolition (Jacob, 2004; Chyn, 2018). Similarly, residents in the ABLA Homes had long suffered from a broken heating system, and getting a $200,000 HOPE VI planning grant in 1995 promoted the demolitions of high-rise buildings (Bennett et al., 2015). The Henry Horner Homes were demolished as residents filed a class-action lawsuit against the CHA for neglect and mismanagement. The involvement of tenant groups in negotiations with the CHA introduced a significant degree of unpredictability into the demolition process.

Residents in the demolished buildings were relocated and provided with two options: (1) use a Section 8 voucher to rent housing in the private market, with all the moving expenses covered by the CHA, and (2) transfer to a different public housing unit. Buron and Popkin (2016) found that over 50% of former residents used a voucher to rent private housing and moved to diverse types of neighborhoods, while nearly 30% ended up in a public housing unit. The average distance between new and original residences for households receiving Section 8 vouchers was 8.4 kilometers, and for all households with children, it was 4.4 kilometers (Thomas Kingsley et al., 2003; Jacob, 2004).

The plan for demolished neighborhoods is to redevelop and revitalize the public housing sites. One of the key objectives is to replace low-income housing with mixed-income housing that includes public housing units, affordable units, and market-rate units. However, the redevelopment process had been slow. Washington Park Homes did not start rebuilding until 2017, more than two decades after its first demolition, due to various financing problems (Cholke, 2017). As documented in Almagro et al. (2023), 38 percent of the demolished public housing sites remained vacant and undeveloped in 2010. Among the redeveloped land, the majority was used for residential housing.

6.2 Empirical Strategy

6.2.1 Instruments for Social Capital

Following Putnam (1995), I consider social capital as the features of social life - networks, norms, and trust - that enable community members to act together effectively in pursuit of shared objectives.

As a large number of residents in the neighborhoods were displaced, the existing networks and ties that had once thrived were undermined. Parents may have lost connections with other parents who were displaced, resulting in reduced access to information and parental support. Meanwhile, children who remained in the neighborhood had fewer adults who were familiar with them and available for guidance. The severance of these relationships weakens the social norms, trust, and sanctions that had previously governed community members' behaviors (Coleman, 1988; Pettit, 2004).

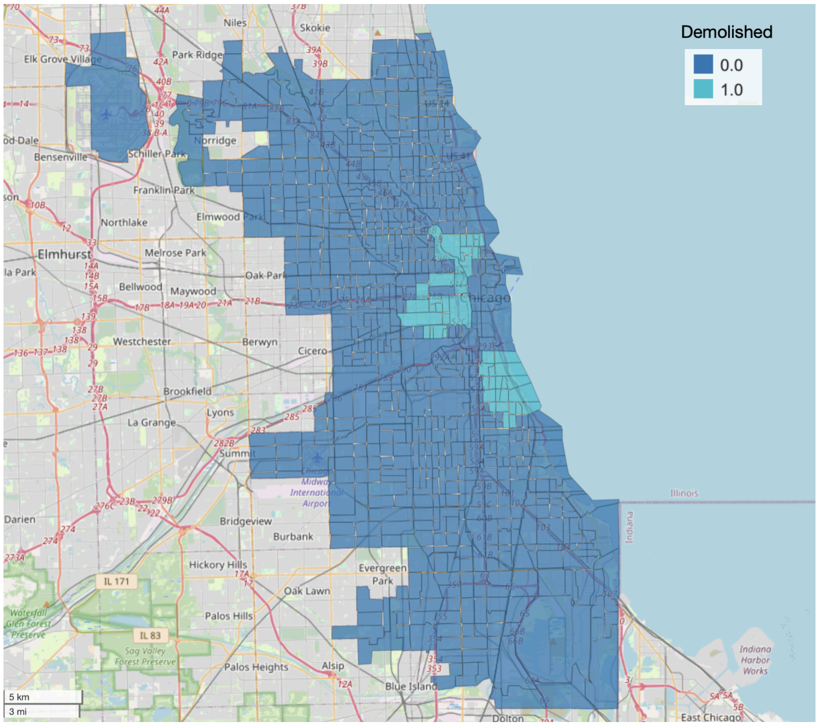
Interviews with community residents shed light on the positive social aspects of public housing, benefiting both public housing residents and those outside of it. Upon knowing the plans to demolish the Robert Taylor Homes, the owner of a local small store responded directly and clearly, "These people are poor. I give them credit and I let them pay me when they can, and they bring their business to me. You think Jewel[a large grocery chain] would do that?" (Venkatesh, 2001) This response illustrates the strong sense of mutual support and trust within public housing communities.

Ben Austen, who closely observed residents in the public housing units, beautifully captures what these communities meant in his book "High-Risers: Cabrini-Green and the Fate of American Public Housing": "They watched one another's children, shopped together, shared food, stepped up when a family lost a loved one or was in need" (Austen, 2018). It was a network of care and trust that can play a crucial role in child development. With the demolition, the loss of direct monitoring, dependable parental support, and shifts in prevailing norms could negatively impact the children who remained in the neighborhood.

I focus on demolitions in 1995 that involved a total of 728 public housing units. Considering the spillover effects of adjacent neighborhoods, I defined treatment neighborhoods as those with demolished public housing buildings, or neighborhoods adjacent to a demolished building (within 1 km). The map depicted in Figure 5 highlights neighborhoods that experienced demolition and those adjacent to a demolished building in light blue.

My analysis focuses on children whose homes were *not* demolished. I compare the outcomes of the children living in treatment neighborhoods to children living in all other neighborhoods with public housing. This selection is made to address concerns about the

Figure 5: Map of Demolished Neighborhoods



Notes: This map highlights the entire city of Chicago in dark blue and the neighborhoods with demolitions or neighborhoods adjacent to a demolished building (within 1 km) in light blue.

non-random locations of public housing. As discussed above, the decision to demolish public housing was largely driven by worsening building conditions and increasingly challenging management issues. If these physical conditions and management problems are uncorrelated with social capital or unobservable factors influencing child development, this design offers exogenous variation in social capital.

As a robustness check for the potential correlation between demolition and unobserved neighborhood characteristics, I implement a second design by leveraging the randomness in the timing of demolitions across neighborhoods. As previously noted, the initial demolitions were largely driven by unforeseen events or logistical challenges, such as heating system breakdowns, pipe bursts, and lawsuits (Jacob, 2004; Chyn, 2018). I designate an alternative control group composed of children living in neighborhoods with public housing to be demolished in later years. Naturally, this design results in a smaller sample size. I use the bigger control group for the analysis below, but also present the estimates using the smaller control group in Section 8 as a robustness check. It is reassuring to observe that the estimates of parameters in the production function remain similar in both settings.

I present the characteristics of treatment and control groups at the baseline before demolition in Table 7. The table is balanced, with no statistically significant differences between the control and treatment groups. I also test for joint significance of all the baseline characteristics on the treatment variable, and can not reject the null hypothesis.

The exclusion restriction assumption is that the demolition affects children in the treatment group only through social capital. [12] I control for pre-demolition neighborhood characteristics to improve estimation precision. These characteristics include the neighborhood's percentage of residents living below the poverty line, the average household income, the share of high school graduates, the homicide rate, racial composition, and the unemployment rate. Robustness checks in Section 8 suggest that demolition does not change the school environment or peer composition. I also control for post-demolition criminal activities, and the results remain unaffected, as presented in Section 8.

6.2.2 *Instruments for Parental Investments*

Parents' investment decisions depend on the budget constraints they face. Such dependence gives us two natural candidates for instruments, household resources and labor market shocks. As used as an instrument in Attanasio et al. (2020c), household resources is a relevant instrument because it relaxes the budget constraint and allows parents to make higher investments. The remaining question is whether it is excluded from the production function. From an economic point of view, household income is not a direct input in the production function. The concern is household income might be correlated with unobserved inputs in the production function. Given that I also include parents' educational attainments and the child's initial condition, it is plausible that income is conditionally exogenous.

The second instrument I use is labor market shocks. A positive shock is a relevant instrument because parents are more likely to increase time at work and reduce time and effort devoted to their child, conditional on household incomes. I use the percentage change in female employment by educational attainments from 1996 to 1997 as a proxy for labor market shocks. [13] The change is at the national level. It should not enter the production function directly, other than through parental investment.

The instrumental variable approach is commonly used in the literature to address the endogeneity concern with parental investments. Variations in the prices of investment goods are used in Attanasio et al. (2020b) and Attanasio et al. (2020c). In theory, one could potentially use the prices of books, puzzles, and other educational materials as instrumental

[12] Strictly speaking, demolition can also have an impact on children through parental investments and I don't impose any restrictions on this. Parental investments are allowed to be endogenous and I discuss the relevant instruments in Section 6.2.2.

[13] Alternatively, I could use the wage rate as a proxy, but wage rates by educational attainments from 1996 to 1997 are not available.

Table 7: Balance Table

Variable	Control group (1)	Control group (2)	Treatment group	Difference (1) [p value]	Difference (2) [p value]
Child characteristics					
Cognitive, wave 1	-0.036	-0.156	-0.062	-0.026	0.094
	(0.993)	(0.969)	(0.914)	[0.837]	[0.495]
Socio-emotional, wave 1	-0.007	-0.043	0.072	0.079	0.115
	(0.999)	(1.008)	(0.831)	[0.497]	[0.363]
Age	11.437	11.265	11.827	0.390	0.562
	(4.211)	(4.244)	(3.964)	[0.257]	[0.136]
Female	0.494	0.491	0.526	0.032	0.035
	(0.500)	(0.500)	(0.501)	[0.455]	[0.457]
Hispanic	0.524	0.523	0.442	-0.082	-0.082
	(0.500)	(0.500)	(0.498)	[0.749]	[0.771]
Black	0.297	0.371	0.474	0.177	0.103
	(0.457)	(0.483)	(0.501)	[0.479]	[0.706]
Other races	0.182	0.106	0.084	-0.097	-0.021
	(0.386)	(0.308)	(0.279)	[0.129]	[0.787]
Household characteristics					
Number of siblings	2.168	2.313	2.289	0.121	-0.024
	(1.662)	(1.731)	(1.634)	[0.475]	[0.894]
Income per capita ($1,000)	5.815	4.753	4.627	-1.188	-0.126
	(5.041)	(4.397)	(4.833)	[0.257]	[0.910]
PC is cohabiting	0.690	0.655	0.538	-0.153	-0.118
	(0.462)	(0.476)	(0.500)	[0.212]	[0.366]
Number of years PC at current address	5.698	6.314	7.999	2.301	1.684
	(6.304)	(7.316)	(10.572)	[0.128]	[0.295]
Moved out in wave 2	0.277	0.244	0.289	0.012	0.045
	(0.448)	(0.430)	(0.455)	[0.635]	[0.257]
Mom with higher education	0.363	0.314	0.312	-0.051	-0.003
	(0.481)	(0.465)	(0.465)	[0.569]	[0.978]
Dad with higher education	0.264	0.200	0.214	-0.050	0.015
	(0.441)	(0.400)	(0.412)	[0.446]	[0.834]
Immigrant family	0.594	0.511	0.518	-0.076	0.007
	(0.491)	(0.500)	(0.502)	[0.738]	[0.978]
F test statistic of joint significance				0.34	0.62
[p value]				[0.986]	[0.817]
Observations	2,903	776	154	3,057	930

Notes: Columns 1, 2, and 3 display means and standard deviations in parentheses for control group 1, control group 2, and the treatment group, respectively. Columns 4 and 5 present p-values for the test of equality of means, derived by regressing each characteristic on a treatment dummy variable and clustering standard errors by neighborhood. The F test statistic and the p-value for the joint significance test are derived by regressing the treatment variable on all baseline characteristics and clustering standard errors by neighborhood. All characteristics are from wave 1 unless specifically noted for wave 2. 'PC' stands for the primary caregiver. 'Higher education' refers to at least some college.

variables in this context. However, as far as I am aware, such data are not available, and I suspect that there is significantly less variation across different neighborhoods, given that this paper concentrates on Chicago.

6.2.3 *Empirical Specification of the Production Function*

I consider a log-linear specification of the production function as follows:

$$ln\theta^{p}_{ir,t+1} = \delta^{p}_{0} + \delta^{p}_{1} ln\theta^{c}_{ir,t} + \delta^{p}_{2} ln\theta^{s}_{ir,t} + \delta^{p}_{3} lnI_{ir,t} + \delta^{p}_{4} lnSC_{ir,t} + \boldsymbol{X_{ir,t}\Gamma^{p}_{1}} + \epsilon^{p}_{ir,t},$$

$$p \in \{c, s\}$$

where i, r, t represent individuals, neighborhoods, and time periods, respectively. $\theta^{c}_{ir,t}$ and $\theta^{s}_{ir,t}$ are cognitive skills and socio-emotional skills, $I_{ir,t}$ are parental investments, $SC_{ir,t}$ is social capital, $\epsilon_{ir,t}$ is a shock to the production functions. $\boldsymbol{X_{ir,t}}$ is a vector of pre-demolition household and neighborhood characteristics, including the child's age, parental educational attainments, the number of siblings, the neighborhood's percentage of residents living below the poverty line, the average household income, the share of high school graduates, the homicide rate, racial composition, and the unemployment rate.

Cunha and Heckman (2008) consider a similar linear production technology. Other specifications employed in the literature include the Cobb-Douglas (Attanasio et al., 2020b) and the Constant Elasticity of Substitution (Cunha et al., 2010; Attanasio et al., 2020c).

7 Results

This section presents the empirical results. Log skills, log parental investments, and log social capital have been standardized. I start with the estimates of the first stages for parental investments and social capital, which supports the validity of the instruments. Then, I present the reduced form estimates since the impacts of demolition and household resources on child development are interesting by themselves. Next, I show the estimates of the production functions of cognitive skills and socio-emotional skills. The heterogeneity analysis of different subgroups follows. Finally, I use the production function estimates to conduct three counterfactual experiments. I report the confidence intervals that are computed from 1,000 bootstrap repetitions with the cluster structure taken into account. For the test statistics presented, I compute the p-values using bootstrap. It is important to note that the bootstrap confidence intervals are not symmetric around the point estimates because the bias-correction procedure explained in the estimation process is nonlinear.

7.1 Estimates of the Investment Functions

Table 8 presents the estimates of the investment functions. The first column shows the estimates for parental investments, and the second column shows the estimates for social capital. I use demolition, household income, and employment growth in the female labor market by educational attainments as exclusion restrictions.

Table 8: Estimates of the Investment Functions

	Parental investments	Social capital
Demolition	-0.116	-1.219
	[-0.249, 0.01]	[-1.637, -0.572]
Household resources	0.063	0.017
	[0.051, 0.085]	[-0.008, 0.035]
Employment growth	-7.407	2.72
	[-11.95, -3.177]	[-2.324, 8.307]
Cognitive, w1	0.144	0.012
	[0.065, 0.167]	[-0.054, 0.048]
Socio-emo., w1	0.065	0.004
	[0.02, 0.09]	[-0.028, 0.054]
Rank test (p-value)		0.023
Test of joint significance: F-statistic (p-value)		
Demolition, resources, employment	74.917 (0.000)	25.091 (0.002)
Observations	1639	1548

Notes: Ninety-five percent confidence intervals are presented in brackets. Both the confidence intervals and the p-values are computed by 1,000 bootstrap replications of the entire estimation process, taking into account clustering at the neighborhood level. The rank test assesses the null hypothesis that the smallest eigenvalue of the 2×2 matrix $\beta'\beta$ is zero, where β is the 3×2 matrix of coefficients on demolition, household resources, and employment growth in the social capital and parental investments equations.

Consistent with the previous hypothesis, parental investments respond positively to household income, reflecting the impacts of budget constraints. A higher employment growth in the female labor market has negative impacts on investments as it induces a higher cost of investments conditional on household incomes. Demolition has no impact on parental investments. However, demolition has a negative impact on social capital. As previous residents were displaced in the demolished neighborhoods, the existing social networks and norms were affected, hurting the basis of social capital.

Turning to the test statistics, I first test the joint significance of the three instruments in both investment functions. The F-statistic is 74.917 for parental investments and 25.091 for social capital, both with a p-value of 0. I further implement a rank test. The rank test is a test of the null hypothesis that the smallest eigenvalue of the 2×2 matrix $\beta'\beta$ is zero, where

β is the 3×2 matrix of coefficients on demolition, household resources, and labor market shock in the social capital and parental investments equations (Blundell et al., 1998; Robin and Smith, 2000). The rank test has a p-value of 0.023, suggesting that these instruments are strong for both investments.

It is also interesting to note that parental investments respond positively to both cognitive skills and socio-emotional skills in the previous period. In particular, parental investments are two times more responsive to cognitive skills than socio-emotional skills. The positive response could help account for the widening skill gap as children age. Higher initial skill levels encourage more parental investments, which contribute to improved future development, as will be demonstrated in the production function estimates.

7.2 Estimates of the Reduced Forms

I first use a fixed effect model to understand the treatment effects of demolition on skill development. Specifically, I regress skill outcomes on individual fixed effects, neighborhood fixed effects, time fixed effects (represented by the "Post" dummy variable), and the interaction between the demolition treatment and the "Post" period. The results presented in Table 9 demonstrate that, even after accounting for all permanent neighborhood and individual effects, we still see a decline in both cognitive and socio-emotional skills. The decline closely mirrors the magnitudes observed in the reduced form estimates in Table 10 below, providing reassurance that the demolition instrument does not pick up unobserved neighborhood effects.

Table 9: Fixed Effect Estimates

	Cognitive skills	Socio-emotional sills
Treatment * Post	-0.295	-0.275
	[-0.430, -0.160]	[-0.393, -0.158]
Observations	3912	3484

Notes: Ninety-five percent confidence intervals are presented in brackets, accounting for clustering at the neighborhood level. Observations are at the individual * time period level.

Previous research has focused on the impacts of being displaced from the demolished buildings on children (Jacob, 2004; Chyn, 2018). This is the first paper that investigates the consequences of demolition on children who were not displaced. However, the implications of this research extend beyond this particular group, as children who were displaced may also suffer, and in some cases, even more so, due to the loss of their established social networks and connections. Chetty et al. (2016) also document the negative impacts of moving to a different neighborhood among those who moved at an older age, probably due to the disruption effects. Therefore, such adverse impacts should be taken into consideration when relocation experiments are designed.

Table 10 presents the reduced form estimates that help us understand the impacts of all instruments and previous skill development on current skill development. The impacts of demolition on skill development are negative: living in a demolished neighborhood reduces log cognitive skills by 0.22 standard deviations (SD), and log socio-emotional skills by 0.238 SD. The estimates also suggest that every $10,000 increase in household resources improves log cognitive skills by 0.031 SD. In comparison, the impacts on socio-emotional skills are much weaker and not different from zero. Both cognitive and socio-emotional skills exhibit persistent effects.

Table 10: Reduced Form Estimates

	Cognitive skills	Socio-emotional skills
Demolition	-0.22	-0.238
	[-0.317, -0.127]	[-0.421, -0.173]
Household resources	0.031	0.018
	[0.02, 0.044]	[-0.002, 0.035]
Employment growth	-2.368	-0.002
	[-5.098, 1.348]	[-3.764, 6.142]
Cognitive, w1	0.595	0.116
	[0.505, 0.668]	[0.069, 0.206]
Socio-emo., w1	0.09	0.579
	[0.072, 0.144]	[0.5, 0.634]
Observations	1482	1333

Notes: Ninety-five percent confidence intervals are presented in brackets. Confidence intervals are computed by 1,000 bootstrap replications of the entire estimation process, taking into account clustering at the neighborhood level. All models include the same set of control variables: the child's age, parental educational attainments, the number of siblings, the neighborhood's percentage of residents living below the poverty line, the average household income, the share of high school graduates, the homicide rate, racial composition, and the unemployment rate.

7.3 Estimates of the Production Functions

In Table 11, I report the production function estimates of cognitive skills and social-emotional skills. The first and the third columns are Ordinary Least Square (OLS) estimates, which ignore the endogeneity of parental investments and social capital. The second and the fourth columns are instrumental variable (IV) estimates that address the endogeneity issues. All four models include the same set of control variables: the child's age, parental educational attainments, the number of siblings, the neighborhood's percentage of residents living below the poverty line, the average household income, the share of high school graduates, the homicide rate, racial composition, and the unemployment rate.

Table 11: Estimates of the Production Functions

	Cognitive skills w2		Socio-emotional skills w2	
	OLS	IV	OLS	IV
Social capital	0.003 [-0.026, 0.049]	0.158 [0.067, 0.381]	0.03 [-0.012, 0.102]	0.190 [0.104, 0.547]
Parental investments	0.056 [0.025, 0.081]	0.421 [0.191, 0.616]	0.043 [0.003, 0.084]	0.156 [-0.159, 0.406]
Cognitive, w1	0.613 [0.518, 0.701]	0.547 [0.478, 0.663]	0.112 [0.066, 0.203]	0.106 [0.05, 0.215]
Socio-emo., w1	0.074 [0.051, 0.12]	0.064 [0.045, 0.125]	0.558 [0.475, 0.611]	0.574 [0.496, 0.637]
Observations	1616	1482	1460	1333

Notes: Ninety-five percent confidence intervals are presented in brackets. Confidence intervals are computed by 1,000 bootstrap replications of the entire estimation process, taking into account clustering at the neighborhood level. All models include the same set of control variables: the child's age, parental educational attainments, the number of siblings, the neighborhood's percentage of residents living below the poverty line, the average household income, the share of high school graduates, the homicide rate, racial composition, and the unemployment rate.

The OLS estimates suggest that social capital has no impact on either cognitive skills or socio-emotional skills. However, when I instrument social capital with the demolition treatment to address the endogeneity issue, social capital becomes important for both cognitive and socio-emotional skills. A one SD increase in log social capital leads to a 0.16 SD increase in log cognitive skills and a 0.19 SD increase in log socio-emotional skills. With estimates from the measurement system, I can interpret what a one SD increase in log social capital means in terms of each of the measurements.[14] For instance, a 1.25 SD increase in log social capital corresponds to a shift in the response to the question "How likely would neighbors do something about kids skipping school" from "likely" to "very likely". On the other hand, Table 4 shows that a 1 SD increase in log social capital is correlated with a $50,000 increase in the average household income in a neighborhood.

In terms of the effects of parental investments, the OLS estimates suggest that it has positive impacts on both dimensions of skills, although the coefficient estimates are small. However, if we consider parental investments as endogenous, and use household resources and female labor market shocks as instruments, the coefficients get much larger. This pattern is consistently found in other studies (Cunha et al., 2010; Attanasio et al., 2020b,c), indicating the importance of addressing endogeneity in parental investments. Parents seem to respond positively to the negative shocks in the development process. In the case of cognitive skills, the estimates suggest that one SD increase in log parental investments improves log cognitive skills by 0.42 SD. [15] While addressing the endogeneity issue gives a larger estimate of the effects of parental investments on socio-emotional skills, the estimate is small compared to that for cognitive skills and is insignificant.

The results highlight that parental investments are much more effective in producing cognitive skills. Although prior research has shown the beneficial effects of parental investments on socio-emotional skills in early childhood (Cunha et al., 2010; Attanasio et al., 2020a), the current findings suggest that the opportunities for parents to cultivate these skills may be fleeting.

The skill dynamics are also interesting because they are informative about the potential efficacy of interventions. First, skills are self-productive and display fairly high persistence at this stage. From both the OLS and IV estimates, a one SD increase in log cognitive skills improves future log cognitive skills by 0.5 to 0.6 SD. The persistence levels are similar in both dimensions. A one SD increase in log socio-emotional skills translates into approximately 0.6 SD in future log socio-emotional skills. Second, skills display cross-productivity. A one SD increase in log cognitive skills improves log socio-emotional skills by about 0.11 SD. The impacts of socio-emotional skills on cognitive skills are slightly weaker but still significant, with a productivity of 0.06 to 0.07 SD for each SD increase. The self-productivity and cross-productivity reported in this study are consistent with

[14] The standard deviation of log social capital is 0.8.

[15] The standard deviation of log parental investments is 0.34. Using the estimates of factor loadings in the measurement system, I can back up the implied change in the measurements. For example, a 0.7 SD increase in log parental investments is equivalent to increasing the frequency that primary caregivers encourage the child to read from less than once a month to about once a month. Further improving the frequency to a few times a month is equivalent to a 1.55 SD increase.

findings in the child development literature (e.g., Cunha et al., 2010; Attanasio et al., 2020b, Attanasio et al., 2020c).

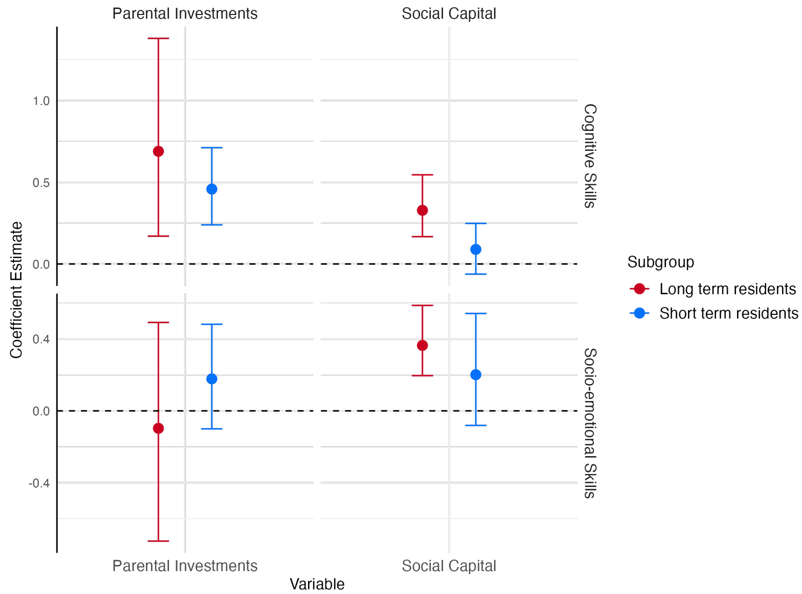
7.4 Heterogeneity Analysis

I plot the production function estimates and their 90% bootstrap confidence intervals by years of residency, age, gender, race, and neighborhood socioeconomic status. Figure 6 illustrates the different patterns of parental investments and social capital for long-term and short-term residents. Long-term residents refer to those who have stayed in the neighborhood for more than the median duration (5 years) as of wave 1. While parental investments have positive impacts on cognitive skills for both groups, social capital is only positive for long-term residents in terms of both cognitive and socio-emotional skills. These results are consistent with the idea that long-term residents may have a stronger network than short-term residents, and therefore benefit more from it.

Figure 7 shows the estimates for two age groups: those of 6 - 9 years old, and those of 12 - 15 years old. Parental investments are effective for both groups in terms of cognitive skills. However, social capital's positive impacts on both cognitive and socio-emotional skills are driven by the younger group. Estimating the self-productivity parameters by age groups is also of interest, as it sheds light on the window of opportunity. The persistence in cognitive skills is twice as large for the older cohort compared to the younger cohort (0.42 vs. 0.2). Similarly, the persistence is also stronger in socio-emotional skills (0.71 vs. 0.44) for the older cohort compared to the younger cohort.

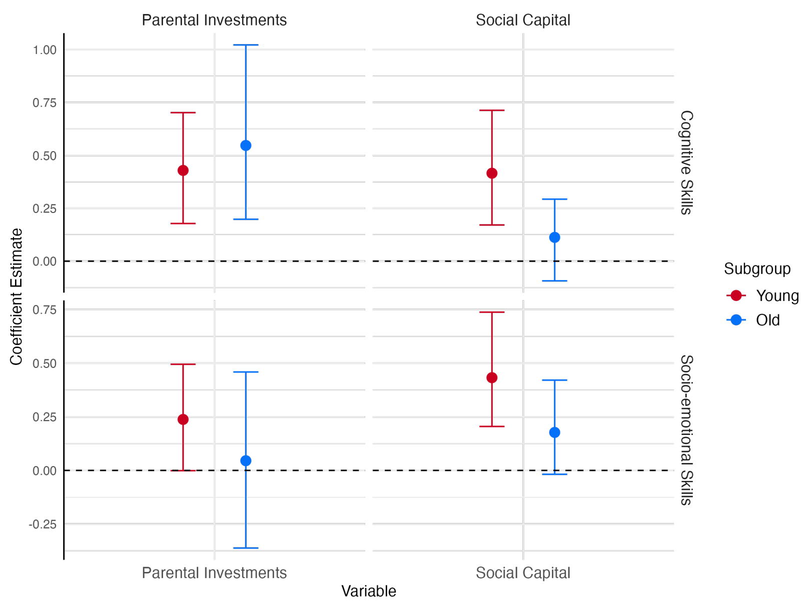
When it comes to gender, Figure 8 once again shows a similar impact of parental investments on cognitive skills across females and males. The role of social capital is stronger for males on cognitive skills, but the reverse is true for social-emotional skills. Figure 9 displays estimates by races: Black or Hispanic residents and White residents. In this case, both parental investments and social capital have larger effects on Black or Hispanic residents than the other group. Lastly, Figure 10 presents estimates by neighborhood SES. The positive impacts of parental investments are observed in both high- and low-SES neighborhoods. Social capital has positive impacts on the low SES group. Its impacts on the high SES group are not precisely estimated.

Figure 6: Estimates by Years Lived in the Neighborhood



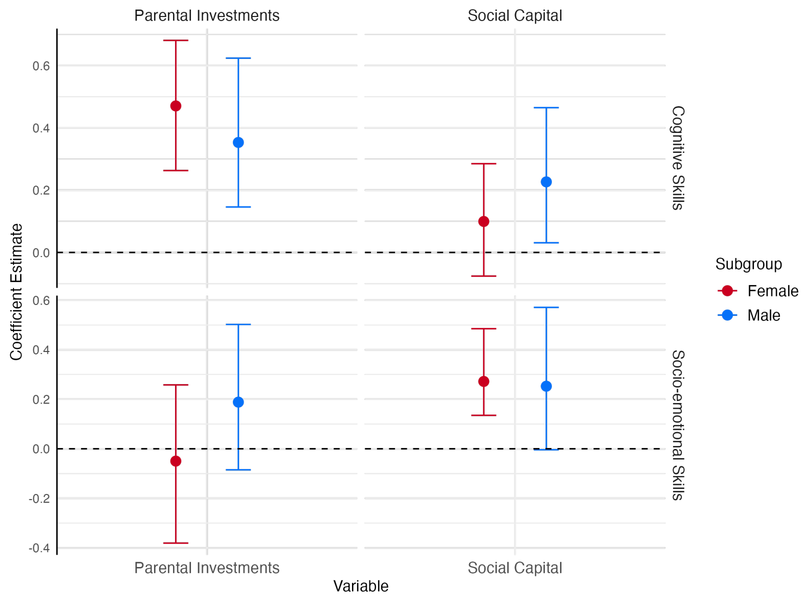
Notes: This figure presents the production function estimates of parental investments and social capital, along with their 90% bootstrap confidence intervals, categorized by years of residency. 'Long-term residents' refers to those who have stayed in the neighborhood for more than the median duration (5 years) as of wave 1. The top panel is for cognitive skills, while the bottom panel is for socio-emotional skills.

Figure 7: Estimates by Cohorts



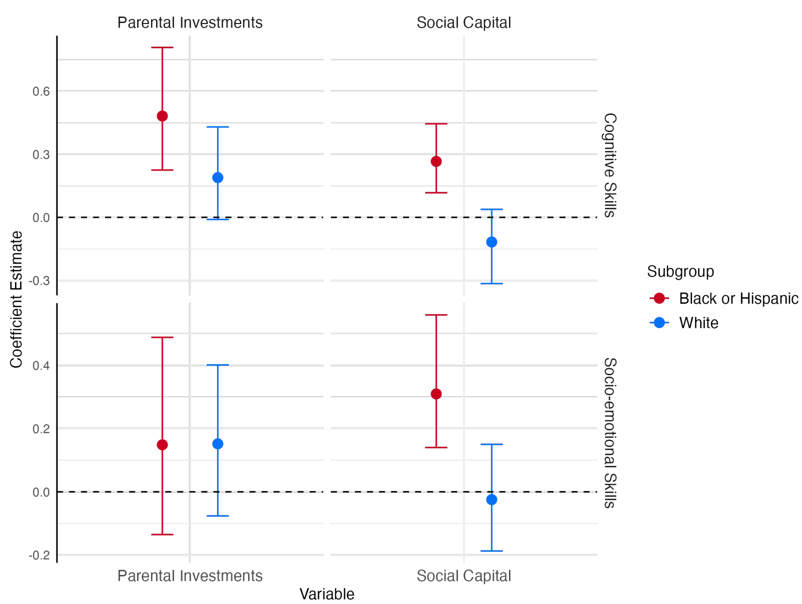
Notes: This figure presents the production function estimates of parental investments and social capital, along with their 90% bootstrap confidence intervals, categorized by age groups. 'Young' refers to ages 6 - 9, and 'Old' refers to ages 12 - 15. The top panel is for cognitive skills, while the bottom panel is for socio-emotional skills.

Figure 8: Estimates by Gender



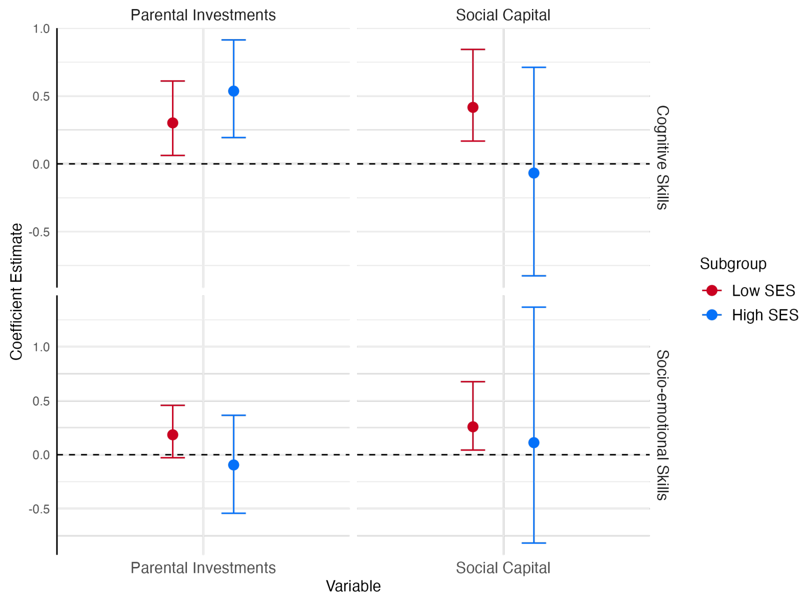
Notes: This figure presents the production function estimates of parental investments and social capital, along with their 90% bootstrap confidence intervals, categorized by gender. The top panel is for cognitive skills, while the bottom panel is for socio-emotional skills.

Figure 9: Estimates by Race



Notes: This figure presents the production function estimates of parental investments and social capital, along with their 90% bootstrap confidence intervals, categorized by race. The top panel is for cognitive skills, while the bottom panel is for socio-emotional skills.

Figure 10: Estimates by Neighborhood SES



Notes: This figure presents the production function estimates of parental investments and social capital, along with their 90% bootstrap confidence intervals, categorized by neighborhood socioeconomic status. The top panel is for cognitive skills, while the bottom panel is for socio-emotional skills.

8 Robustness Check

8.1 School Environment

Demolition may change the school environment, even for children who were not displaced. I investigate several aspects of the school environment, including school quality, school type, school resources, and peer composition. In wave 1 and wave 2 of the PHDCN, primary caregivers rated their children's education and provided information on school types (public vs. private). I also collect school-level information from the National Center for Education Statistics from 1990-1997. I use the pupil-teacher ratio as a proxy for school resources and low-income student share as a measure of student composition.

I use a fixed effect specification to investigate whether there are changes in the school environment.

$$Y_{k,t} = \gamma_0 + \gamma_1 D_{k,t} + \lambda_k + \psi_t + \epsilon_{k,t},$$

where k represents individuals when examining school type and education rating, and it represents schools when examining pupil-teacher ratio and the share of low-income students. $Y_{k,t}$ is one of the four outcomes, and $D_{k,t}$ takes a value of 1 if unit k is treated in year t.[16] λ_k is school/individual fixed effects, ψ_t is time fixed effects, and $\epsilon_{k,t}$ is the error

[16]Schools are treated if they are located in neighborhoods with demolitions.

term.

Table 12 presents the estimates for these four regressions. Observations are at the school/individual * year level. All dependent variables, except "public school", are standardized to have a mean of zero and a standard deviation of one. Public school is a dummy variable and about 80 percent of students in the sample attend public schools. None of these outcomes show significant changes due to demolition, and the estimated changes are small relative to their respective mean values.

Table 12: School Environment

	(1)	(2)	(3)	(4)
Dependent variables:	Education rating	Public school	Pupil-teacher ratio	Low-income share
Demolition	0.034	-0.027	0.006	-0.094
	[-0.184, 0.252]	[-0.060, 0.006]	[-0.025, 0.037]	[-0.216, 0.027]
Observations	4,038	4,186	3,612	3,152

Notes: This table presents the fixed effect estimates of demolition on four outcomes: education rating, school type, pupil-teacher ratio, and share of low-income students. Observations are at the school/individual * year level. All dependent variables, except "public school", are standardized to have a mean of zero and a standard deviation of one. Public school is a dummy variable. Ninety-five percent confidence intervals are presented in brackets, accounting for clustering at the neighborhood level.

8.2 Crime

One potential concern when using demolition as an instrument is whether it also affects criminal activities, thus influencing child development through the crime channel. Unfortunately, due to data limitations, existing literature primarily focuses on the impacts of post-1999 demolition on crime. Aliprantis and Hartley (2015) and Sandler (2017) find that demolition reduces criminal activities in the demolished neighborhoods, with a concentrated decrease in violent crimes, including homicide and shots fired. However, it should be noted that the scale of demolition after 1999 (about 16,000 units) is much larger than the demolition studied in this paper (about 700 units). Additionally, the estimated impacts represent the average effects of demolition on crime over the sample period from 1999 to 2011 and may not necessarily apply to our case.

Nevertheless, I include post-treatment crime in the production function and test if my estimates are affected. The only available post-treatment crime data at a meaningful granularity is the homicide count for census tracts in the year 1995, sourced from the 'Homicides in Chicago, 1965-1995' dataset. Given that violent crimes, such as homicide, are the most affected by later large-scale demolitions, the homicide count should effectively capture any changes in post-treatment crime, if they exist. Table 13 shows that the estimates are very similar to those of the main specification in Table 11 when post-treatment crime is not accounted for.

Table 13: Production Functions Estimates (controlling for post-demolition crime)

	Cognitive skills w2		Socio-emotional skills w2	
	OLS	IV	OLS	IV
Social capital	0.005	0.155	0.032	0.187
	[-0.028, 0.05]	[0.016, 0.303]	[-0.013, 0.1]	[0.081, 0.498]
Parental investments	0.057	0.35	0.043	0.053
	[0.025, 0.082]	[0.186, 0.612]	[0.003, 0.085]	[-0.144, 0.394]
Cognitive, w1	0.613	0.562	0.112	0.098
	[0.518, 0.701]	[0.478, 0.669]	[0.067, 0.202]	[0.041, 0.217]
Socio-emo., w1	0.073	0.078	0.557	0.609
	[0.051, 0.12]	[0.044, 0.123]	[0.475, 0.611]	[0.498, 0.637]
Post-demolition crime	-0.01	-0.023	-0.007	-0.008
	[-0.023, 0.003]	[-0.033, 0.01]	[-0.026, 0.01]	[-0.034, 0.019]
Observations	1616	1482	1460	1333

Notes: Ninety-five percent confidence intervals are presented in brackets. Confidence intervals are computed by 1,000 bootstrap replications of the entire estimation process, taking into account clustering at the neighborhood level. All four models include the same set of control variables: the child's age, parental educational attainments, the number of siblings, the neighborhood's percentage of residents living below the poverty line, the average household income, the share of high school graduates, racial composition, the unemployment rate, the homicide rate before demolition, and homicide counts after demolition.

8.3 Analysis on Neighborhoods with Demolitions Only

The analysis sample in the main text is based on neighborhoods with public housing, considering the possibility that neighborhoods with public housing might differ from those without it. In this section, I further restrict the analysis sample to include only neighborhoods that experienced demolition. While this restriction reduces the sample size significantly, it is reassuring to note that there are no substantial differences in the estimates reported in Table 14 compared to the main results presented in Table 11.

Table 14: Production Functions Estimates (restricted to neighborhoods with demolitions)

	Cognitive skills w2		Socio-emotional skills w2	
	OLS	IV	OLS	IV
Social capital	0.04	0.161	0.075	0.299
	[-0.017, 0.148]	[0.064, 0.542]	[-0.012, 0.246]	[0.155, 0.796]
Parental investments	0.085	0.405	0.035	0.063
	[0.035, 0.116]	[0.124, 0.749]	[-0.012, 0.076]	[-0.323, 0.249]
Cognitive, w1	0.481	0.618	0.109	0.123
	[0.391, 0.618]	[0.415, 0.674]	[0.034, 0.195]	[0.044, 0.253]
Socio-emo., w1	0.077	0.079	0.479	0.539
	[0.041, 0.152]	[0.039, 0.176]	[0.386, 0.606]	[0.447, 0.684]
Observations	481	439	466	430

Notes: Ninety-five percent confidence intervals are presented in brackets. Confidence intervals are computed by 1,000 bootstrap replications of the entire estimation process, taking into account clustering at the neighborhood level. All four models include the same set of control variables: the child's age, parental educational attainments, the number of siblings, the neighborhood's percentage of residents living below the poverty line, the average household income, the share of high school graduates, the homicide rate, racial composition, and the unemployment rate.

9 Using the Estimates: Counterfactual Experiments

I present the distributions of skills, parental investments, and social capital by neighborhood SES in Appendix A.3. It is evident that children from high-SES neighborhoods tend to possess stronger cognitive and socio-emotional skills than their peers in low-SES neighborhoods. They are also more likely to experience greater social capital and more parental investments. Gaining a deeper insight into the development process allows for the creation of effective interventions aimed at reducing disparities in human capital accumulation.

Using the estimates from the production function, I perform two counterfactual experiments to narrow the skill gap between children from high-SES neighborhoods and those from low-SES neighborhoods. [17] The first one involves fostering social capital in low-SES neighborhoods to the level observed in high-SES neighborhoods. Various initiatives aimed at promoting social capital are currently underway. For example, the Joint Economic Committee's Social Capital Project in the U.S. has provided Congress with recommendations for enhancing social capital (Joint Economic Committee, 2021).

[17] The same production function estimates are applied to both children from high-SES neighborhoods and children from low-SES neighborhoods. The production function is assumed to have the same parameters over time.

These recommendations encompass initiatives to revitalize civil society, which include the establishment of community mentoring programs, as well as investments in infrastructure that facilitate neighborly connections, such as the development of libraries and parks. This experiment would contribute to understanding how these recommendations could impact child development.

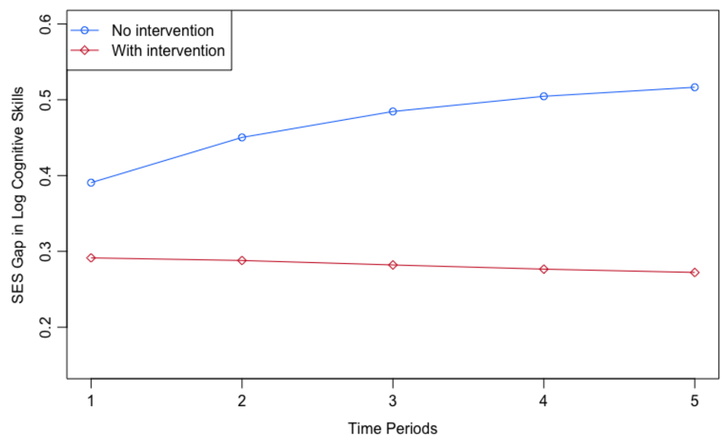
Figure 11 shows the impacts of a permanent increase in social capital on the skill gap between children from high-SES neighborhoods and those from low-SES neighborhoods. [18] The top and bottom panels display the gap in log cognitive skills and log socio-emotional skills, respectively. Each period corresponds to three years. The blue lines illustrate that, in the absence of any intervention, the skill gaps would continue to grow for both cognitive and socio-emotional skills. In contrast, the red lines indicate a declining trend in these gaps with such intervention. Notably, even in the first period with the intervention, the cognitive skill gap is reduced by 25%, and the socio-emotional skill gap is reduced by 80%. Children from low-SES neighborhoods successfully catch up in socio-emotional skills since period 2.

A similar experiment is conducted for parental investments. Figure 12 illustrates the effects of raising parental investments permanently in low-SES neighborhoods to the level observed in high-SES neighborhoods on cognitive skills. [19] This intervention closes the skill gap by 36% in the first period and stops the skill gap from further increasing. Childhood interventions, such as providing households with income transfers and arranging home visits with parenting guidance, are valuable tools to mitigate inequality and expand opportunities.

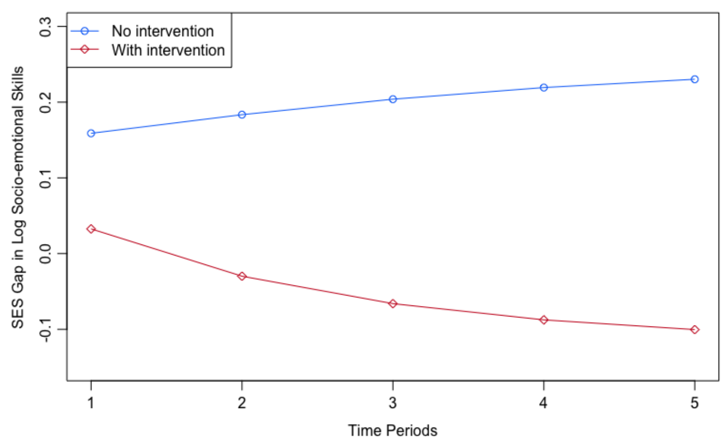
[18] The experiment is equivalent to a 0.7 SD increase in log social capital.

[19] The experiment is equivalent to a 0.32 SD increase in log parental investments. This experiment is only performed for cognitive skills since parental investments are not effective for socio-emotional skills.

Figure 11: Impacts of a Permanent Increase in Social Capital on SES Skill Gaps



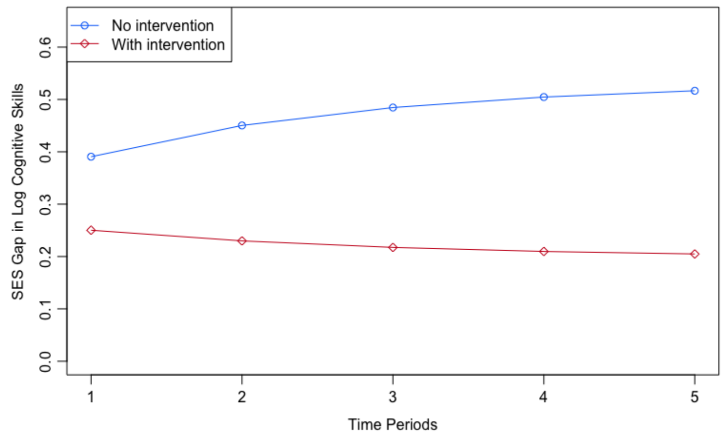
(a) Cognitive Skills



(b) Social-emotional Skills

Notes: This figure illustrates the impacts of a permanent increase in social capital on the skill gap between children in high-SES and low-SES neighborhoods. The red line represents the skill gap in the case of an intervention where social capital in low-SES neighborhoods is raised to the level observed in high-SES neighborhoods. The blue line represents the skill gap in the absence of this intervention. Each period corresponds to three years. The top panel is for cognitive skills, while the bottom panel is for socio-emotional skills.

Figure 12: Impacts of a Permanent Increase in Parental Investments on SES Skill Gaps



Notes: This figure illustrates the impacts of a permanent increase in parental investments on the cognitive skill gap between children in high-SES and low-SES neighborhoods. The red line represents the skill gap in the case of an intervention where parental investments in low-SES neighborhoods are raised to the level observed in high-SES neighborhoods. The blue line represents the skill gap in the absence of this intervention. Each period corresponds to three years.

10 Conclusion

This paper explores a new aspect of neighborhoods that impacts child development: social capital. I study the roles of social capital and parental investments in the dynamics of skill development, estimating dynamic skill production functions for cognitive skills and socio-emotional skills in children aged 6 to 15. Using the Community Survey from the Project on Human Developments in Chicago Neighborhoods, I provide a comprehensive characterization of social capital and employ a factor model to measure it at the individual level. I account for the potential endogeneity of social capital and parental investments and identify the impacts of social capital through a natural experiment resulting from public housing demolition in Chicago.

I obtain several important results. First, I find that social capital is important for both cognitive skills and socio-emotional skills. A one standard deviation increase in social capital improves cognitive skills and socio-emotional skills by 0.16 and 0.19 standard deviations, respectively. The positive impacts of social capital are particularly pronounced among long-term residents, children aged 6 to 9, Black or Hispanic individuals, and children from low socioeconomic status neighborhoods. This evidence helps open the black box of neighborhood effects.

Second, parental investments are primarily effective for cognitive skills during middle childhood. Every one standard deviation increase in parental investments translates into a 0.42 standard deviation increase in future cognitive skills. Although earlier studies have highlighted the positive effects of parental investments on socio-emotional skills during early childhood (Cunha et al., 2010; Attanasio et al., 2020c), the findings presented here indicate that the window for nurturing these skills may be limited.

Third, I find evidence of self-productivity and cross-productivity for both dimensions of skills. The self-productivity is stronger for children aged 12 to 15. These findings emphasize the importance of continuing early-year interventions to maintain their long-term impact, and underscore the potential benefit of interventions aimed at enhancing either aspect of human capital.

Lastly, I conduct two counterfactual experiments where I increase social capital and parental investments for children in low-SES neighborhoods to the levels observed in high-SES neighborhoods. Increasing social capital effectively narrows the skill gap between high- and low-SES children, reducing the cognitive skills gap by 25% and the socio-emotional skills gap by 80%. Conversely, elevating parental investments decreases the cognitive skills gap by 36%.

Understanding the skill development process is crucial for effective interventions. As demonstrated in this paper, conventional field experiments, such as promoting suitable parenting and providing income transfers, are effective ways to enhance development, especially cognitive skills during middle childhood. Nevertheless, by uncovering the important role of social capital in child development, we can envision more innovative neighborhood-level interventions that yield broader community benefits. Initiatives such as introducing community mentoring programs and investing in infrastructure that encourages neighborly connections can serve as potent tools for fostering social capital and, in turn, reducing inequality in skill development.

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A Appendix

A.1 Theoretical Framework

This section presents a simple model to illustrate the decision-making process of parents and the potential issues I face when estimating the production function. In this two-period model, household i makes decisions on consumption $C_{i,t}$, parental investments $I_{i,t}$, and residential area $R_{i,t}$ from a choice set $\mathcal{N}$. The choice set consists of 343 neighborhoods in Chicago. The household derives utility from current consumption, the future human capital level $H_{i,t+1}$, and a vector of current neighborhood amenities $\boldsymbol{Q}_{R_{i,t}}$.[20] Parents maximize their utility subject to the budget constraint and the skill production functions. Human capital is a function of cognitive skills θ^c and socio-emotional skills θ^s: $H_{i,t} = H(\theta^c_{i,t}, \theta^s_{i,t})$.

$$\max_{C_{i,t}, I_{i,t}, R_{i,t} \in \mathcal{N}} U(C_{i,t}, H_{i,t+1}, \boldsymbol{Q}_{R_{i,t}}),$$

s.t.

$$C_{i,t} + p_{i,t} I_{i,t} + d_{R_{i,t-1}, R_{i,t}} + m_{R_{i,t}} = w_{i,t} + y_{i,t},$$

where i and t represent individuals and time periods, respectively. $p_{i,t}$ is the price of investments, $d_{R_{i,t-1}, R_{i,t}}$ is the moving cost that depends on the locations households move from and to, $m_{R_{i,t}}$ is the rent payment, $w_{i,t}$ is the wage rate, and $y_{i,t}$ is non-labor income. Total time is normalized to be 1. As the parental investments include both time and monetary investments, the price $p_{i,t}$ depends on the wage rate and the prices of goods such as books and puzzles.

The skill production functions are defined as follows:

$$\theta^c_{i,t+1} = f(\theta^c_{i,t}, \theta^s_{i,t}, I_{i,t}, SC_{i,R_{i,t}}, \boldsymbol{X}_{i,t}, \epsilon_{i,t}),$$

$$\theta^s_{i,t+1} = g(\theta^c_{i,t}, \theta^s_{i,t}, I_{i,t}, SC_{i,R_{i,t}}, \boldsymbol{X}_{i,t}, \eta_{i,t}),$$

where $\theta^c_{i,t}$ and $\theta^s_{i,t}$ are cognitive skills and socio-emotional skills, $I_{i,t}$ represents parental investments, $SC_{i,R_{i,t}}$ is social capital, $\boldsymbol{X}_{i,t}$ is a vector of household characteristics, and $\epsilon_{i,t}$ and $\eta_{i,t}$ are shocks to the production function, unobserved by researchers.

Parental investments and neighborhood choice can be derived from this model:

$$R_{i,t} = R(\theta^c_{i,t}, \theta^s_{i,t}, \{\boldsymbol{Q}\}, \{d\}, \{m\}, p_{i,t}, w_{i,t}, y_{i,t}, \boldsymbol{X}_{i,t}, \epsilon_{i,t}, \eta_{i,t}), \tag{1}$$

$$I_{i,t} = I(\theta^c_{i,t}, \theta^s_{i,t}, \{\boldsymbol{Q}\}, \{d\}, \{m\}, p_{i,t}, w_{i,t}, y_{i,t}, \boldsymbol{X}_{i,t}, \epsilon_{i,t}, \eta_{i,t}). \tag{2}$$

[20]In this appendix, I use bold letters to represent vectors.

Equations 1 and 2 indicate that these choices depend on the current skill endowments, as well as neighborhood amenities, moving costs, and rents across all neighborhoods in the choice set $\mathcal{N}$. They also depend on investment prices, wage rates, household incomes, household characteristics, and shocks. Since these shocks are not observed by researchers, the responses to these shocks raise concerns about endogeneity. For instance, parents may observe their children falling ill or receiving negative influences from the neighborhood. In response, they might change their investment levels or relocate to a neighborhood with better support. These potentially endogenous responses could obscure the true effects of parental investments and social capital.

On the other hand, the dependence of these choices on wage rates and household incomes gives rise to natural candidates for instrumental variables. Specifically, labor market shocks, as captured by the wage rates in the model, represent the opportunity costs of parental investments. A better labor market can increase the cost of allocating time and effort to the child. Conversely, a higher household income relaxes the budget constraint, enabling parents to make more investments.

A.2 Measurement System

In this appendix, I provide additional details about the measurement system for skills, parental investments, and social capital. I start by presenting the results of the exploratory factor analysis (EFA), which guide the specification of the measurement system in Table 3. Following this, I report the estimates of the factor loadings for each measurement equation.

A.2.1 Exploratory Factor Analysis

I develop a dedicated measurement system where each measurement proxies for only one latent factor, to make the interpretation more transparent. I conduct EFA to determine the number of factors to be extracted and the assignment of measurements to factors.

I use Kaiser's eigenvalue rule (Kaiser, 1960) and Horn's parallel analysis (Horn, 1965) to investigate the extractable number of factors. Kaiser's eigenvalue rule recommends retaining factors with eigenvalues greater than 1. Applying this rule, two factors can be extracted from the skill measures at wave 1, from the skill measures at wave 2, and from the social capital measures, while four factors can be extracted from the parental investment measures. Horn's parallel analysis compares the eigenvalues derived from the actual data to those derived from a random dataset that parallels the actual dataset in terms of variables and the observation number. It retains the i-th factor as long as the i-th eigenvalue from the actual data is larger than the i-th eigenvalue from the random data. Horn's parallel analysis mostly aligns with Kaiser's eigenvalue rule but suggests the extraction of two factors from the parental investment measures.

Table A15: Estimated Rotated Loadings on Child Development Measures in Wave 1

Measures	Factor 1	Factor 2
WRAT: Reading test scores	-0.004	**0.926**
WISC: Word definition scores	0.01	**0.859**
CBCL: Withdrawn problems	**0.658**	-0.059
CBCL: Aggressive behavior	**0.788**	0.101
CBCL: Somatic complaints	**0.527**	-0.163
CBCL: Anxiety or depression	**0.779**	-0.052
CBCL: Social problems	**0.681**	0.049
CBCL: Thought problems	**0.774**	0.031
CBCL: Attention problems	**0.826**	0.024
CBCL: Rule-breaking behavior	**0.715**	0.072

Notes: This table presents the rotated factor loadings of child development measures in wave 1 on two factors using quartimin rotation.

In summary, this step of the EFA suggests that the data are sufficiently rich to support the model used in the main text, which assumes two dimensions of skills in both wave 1 and in wave 2, as well as one dimension each for parental investments and social capital.

Table A16: Estimated Rotated Loadings on Child Development Measures in Wave 2

Measures	Factor 1	Factor 2
WRAT: Reading test scores	-0.004	**0.926**
WISC: Word definition scores	0.01	**0.859**
CBCL: Withdrawn problems	**0.658**	-0.059
CBCL: Aggressive behavior	**0.788**	0.101
CBCL: Somatic complaints	**0.527**	-0.163
CBCL: Anxiety or depression	**0.779**	-0.052
CBCL: Social problems	**0.681**	0.049
CBCL: Thought problems	**0.774**	0.031
CBCL: Attention problems	**0.826**	0.024
CBCL: Rule-breaking behavior	**0.715**	0.072

Notes: This table presents the rotated factor loadings of child development measures in wave 2 on two factors using quartimin rotation.

Having determined the number of factors to extract, I now proceed to assign measurements to factors. For parental investments and social capital, I use all available measures as they each exhibit reasonably high correlations with the extracted factor. For skills in wave 1 and wave 2, I implement an EFA with quartimin rotation by first estimating the factor loadings in a measurement system and then rotating these factor loadings. The factor loadings are rotated such that measures predominantly load on one factor, thereby satisfying the need for a dedicated measurement system. [21] Table A15 reports the rotated factor loadings for child development measures in wave 1. The estimates clearly suggest two distinct groups of measures. The first two measures about reading and vocabulary load heavily on the second factor, identified here as cognitive skills. The remaining measures from the CBCL predominantly load on the first factor, which is labeled as the socio-emotional skills. A similar pattern emerges in Table A16. The first four measures covering reading, vocabulary, attention, and comprehension heavily load on the second factor, while the CBCL measures predominantly load on the first factor. Based on these classifications, I use the CBCL measures to measure socio-emotional skills and all other measures to assess cognitive skills in both waves.

A.2.2 Measurement System Estimates

Table A17 presents the estimated factor loadings for all measures. In this dedicated measurement system, each measure relates exclusively to one of the latent factors. Additionally, as elaborated in the main text, I normalize the factor loading of one measure for each latent factor to one.

A.2.3 Measurement Invariance Between Treatment and Control Groups

As explained in the main text, I exploit demolition to identify the impacts of social capital. Specifically, I consider the neighborhoods with demolition as the treatment group, while the remaining neighborhoods with public housing as the control group. One potential concern is whether demolition may change how residents evaluate social capital. If this is the case, the difference in social capital may reflect different metrics used by the control and treatment groups. To investigate this possibility, I conduct a test of measurement invariance between the two groups.

I provide more details on the measurement invariance test in Section 6. Table A18 shows the p-value for $\Delta\chi^2$ test, ΔRMSEA, ΔCFI, and ΔRMSR. It is important to note that the $\Delta\chi^2$ test is not recommended due to its potential for high Type I error, as highlighted in previous studies (Mueller, 1999; Sass et al., 2014). Based on the change in other fit indices, we cannot reject the hypothesis of measurement invariance.

[21] Various rotation methods are available. Quartimin rotation is an oblique rotation method that allows factors to be correlated.

Table A17: Estimates of Factor Loadings

Measures	Latent factors: Social capital	Parental investments	Cognitive skills, w1	Socio-emo. skills, w1	Cognitive skills, w2	Socio-emo. skills, w2
Neighbors do something about kids skipping school	1.000	0	0	0	0	0
Neighbors do something about kids defacing bldg	0.973	0	0	0	0	0
Neighbors scold a kid for not showing respect	0.877	0	0	0	0	0
Children look up to adults in the neighborhood	0.728	0	0	0	0	0
Adults watch out for children	0.911	0	0	0	0	0
Parents know their children's friends	0.908	0	0	0	0	0
Adults know who local children are	0.909	0	0	0	0	0
Parents generally know each other	0.930	0	0	0	0	0
Frequency PC helped SP with homework	0	1.000	0	0	0	0
Frequency PC encouraged SP to read	0	0.987	0	0	0	0
Frequency PC spoke with SP about day	0	1.054	0	0	0	0
Frequency PC praised SP about accomplishment	0	1.023	0	0	0	0
Frequency SP encouraged in hobbies	0	0.984	0	0	0	0
Frequency SP included in family activities	0	1.052	0	0	0	0
Frequency PC visited school or talked to teacher	0	0.380	0	0	0	0
Frequency PC checked SP's homework completed	0	0.941	0	0	0	0
SP has any sports equipment?	0	0.907	0	0	0	0
Any musical instruments SP can use?	0	0.724	0	0	0	0
Number of books in the house	0	1.208	0	0	0	0
Number of books in house for SP's age	0	1.230	0	0	0	0
Any books belong to SP?	0	0.803	0	0	0	0
Number of board games for SP's age	0	1.157	0	0	0	0
Number of tapes, CDs, or records for SP's age	0	0.605	0	0	0	0
Any puzzles for SP's use?	0	0.854	0	0	0	0
SP has dictionary at home for use?	0	0.859	0	0	0	0
SP has encyclopedia at home for use?	0	0.952	0	0	0	0
At least saw 2 of SP's friends last week	0	0.442	0	0	0	0
Number of SP's friends PC knows by sight or name	0	0.677	0	0	0	0
Frequency PC frequency PC talks with SP about behavior	0	0.481	0	0	0	0
Frequency PC able to enforce rules, past year	0	0.566	0	0	0	0
WRAT: Reading test scores	0	0	1.000	0	0	0
WISC: Word definition scores	0	0	0.972	0	0	0
CBCL: Withdrawn problems	0	0	0	1.000	0	0
CBCL: Aggressive behavior	0	0	0	3.257	0	0
CBCL: Somatic complaints	0	0	0	0.626	0	0
CBCL: Anxiety or depression	0	0	0	1.721	0	0
CBCL: Social problems	0	0	0	0.938	0	0
CBCL: Thought problems	0	0	0	0.784	0	0
CBCL: Attention problems	0	0	0	1.742	0	0
CBCL: Rule-breaking behavior	0	0	0	1.046	0	0
WRAT: Reading test scores	0	0	0	0	1.000	0
WISC: Word definition scores	0	0	0	0	0.996	0
Attention duration levels	0	0	0	0	0.059	0
Comprehension of interview questions	0	0	0	0	0.082	0
CBCL: Withdrawn problems	0	0	0	0	0	1.000
CBCL: Aggressive behavior	0	0	0	0	0	1.901
CBCL: Somatic complaints	0	0	0	0	0	0.563
CBCL: Anxiety or depression	0	0	0	0	0	1.719
CBCL: Social problems	0	0	0	0	0	0.323
CBCL: Thought problems	0	0	0	0	0	0.289
CBCL: Attention problems	0	0	0	0	0	1.216

Notes: This table presents the estimated factor loadings for all measures of social capital, parental investments, cognitive skills, and socio-emotional skills in both waves.

Table A18: Measurement Invariance Test

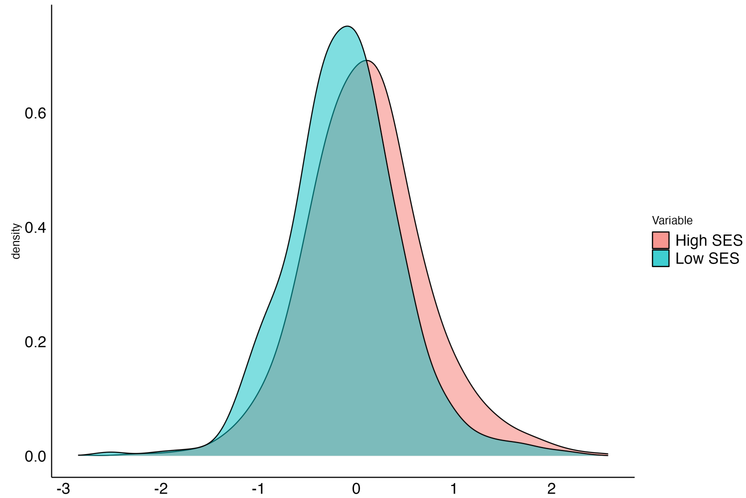
	df	chisq	RMSEA	CFI	RMR/RMSR
Baseline model	40	4214.997	0.156	0.946	0.084
Threshold invariance	56	4227.104	0.131	0.946	0.085
Threshold and loading invariance	63	4256.313	0.124	0.946	0.086
Threshold, loading, and intercept invariance	70	4295.452	0.118	0.945	0.087
		Relative Fit to the Baseline model			
		p-value ($\Delta\chi^2$)	ΔRMSEA	ΔCFI	ΔRMR
Threshold invariance		0.105	-0.025	0	0.001
Threshold and loading invariance		0.004	-0.032	0	0.002
Threshold, loading, and intercept invariance		0.001	-0.038	-0.001	0.003

Notes: RMSEA stands for the root mean squared error of approximation, CFI for the comparative fit index, and RMSR for the root mean square residual.

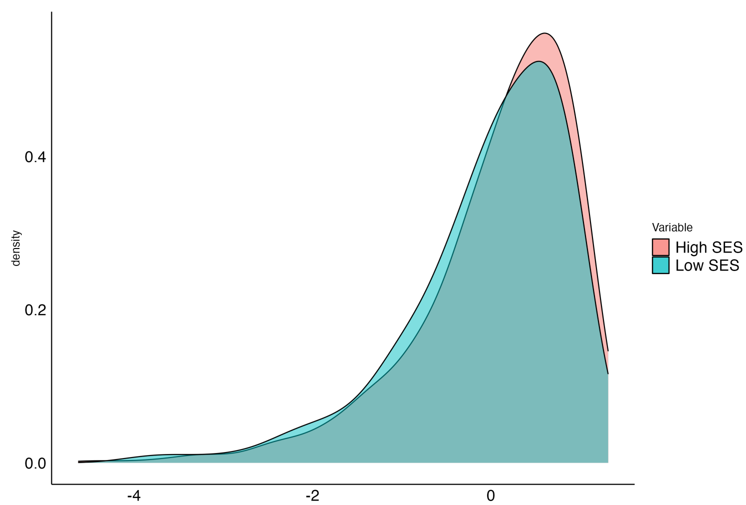
A.3 Inequality in Skills, Parental Investments, and Social Capital

This section presents the distributions of skills, parental investments, and social capital by neighborhood SES in Figures A13, A14, A15, and A16. Both cognitive skills and socio-emotional skills are residualized by the children's ages. All variables are standardized to have a mean of zero and a standard deviation of one. From these distributions, it's evident that children in high SES neighborhoods on average have higher cognitive skills and socio-emotional skills compared to their peers in low SES neighborhoods. They also benefit from higher levels of social capital and parental investments.

Figure A13: Distribution of Skills in Wave 1 by Neighborhood SES



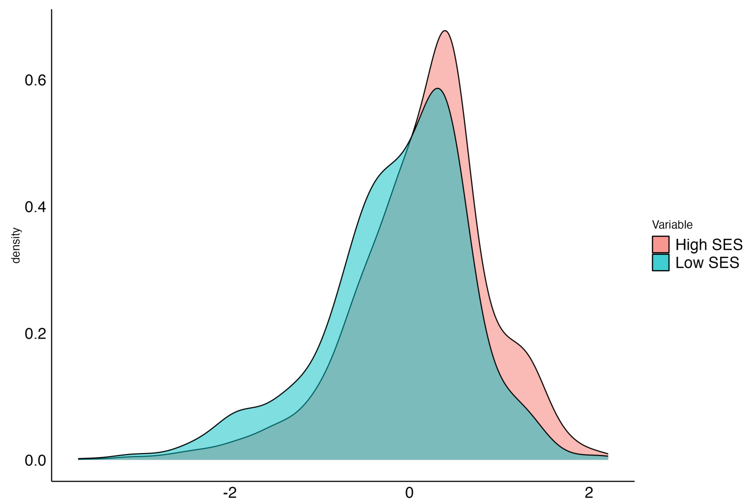
(a) Cognitive Skills



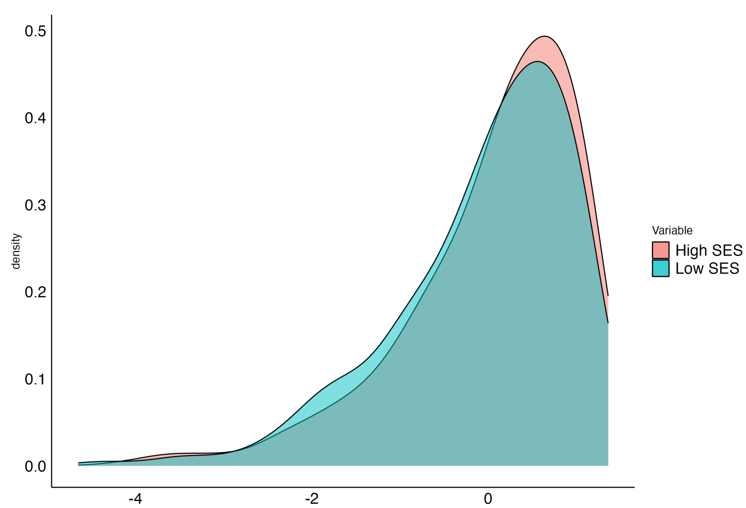
(b) Social-emotional Skills

Notes: This figure illustrates the distributions of skills in wave 1 by neighborhood socioeconomic status. The top panel represents cognitive skills, while the bottom panel represents socio-emotional skills.

Figure A14: Distribution of Skills in Wave 2 by Neighborhood SES



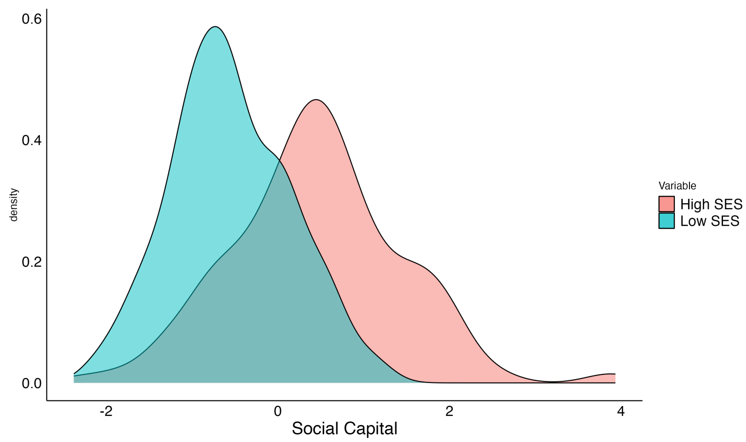
(a) Cognitive Skills



(b) Social-emotional Skills

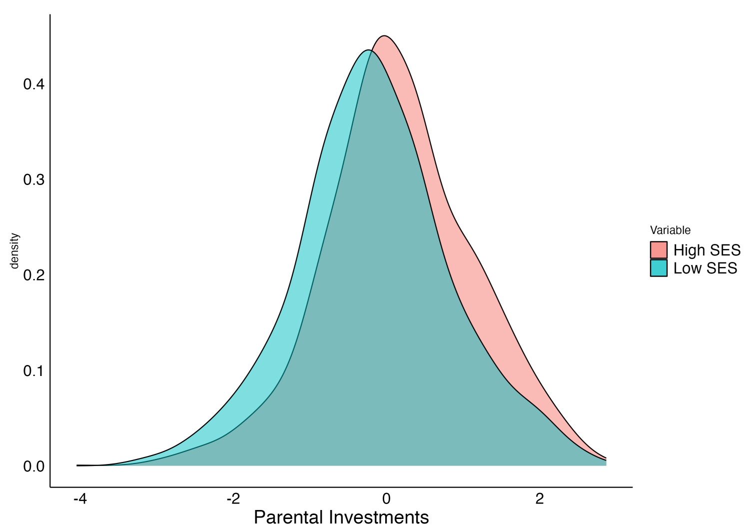
Notes: This figure illustrates the distributions of skills in wave 2 by neighborhood socioeconomic status. The top panel represents cognitive skills, while the bottom panel represents socio-emotional skills.

Figure A15: Distribution of Social Capital by Neighborhood SES



Notes: This figure illustrates the distribution of social capital by neighborhood socioeconomic status.

Figure A16: Distribution of Parental Investments by Neighborhood SES



Notes: This figure illustrates the distribution of parental investments by neighborhood socioeconomic status.