Child Development, Parental Investments, and Community Social Support

Qianyao Ye *

Xiamen University

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Abstract

I examine how neighborhoods shape child development by studying the role of community social support: the collective capacity to nurture, supervise, and invest in children. Using novel neighborhood data, I measure and incorporate this community input, alongside parental investments, into a dynamic skill production function for children aged 6–15. Leveraging variation from Chicago's public housing demolition, I find that community support significantly enhances both cognitive and socio-emotional skills, whereas parental investments primarily improve cognitive development. Counterfactual simulations indicate that raising community support in low-income neighborhoods to high-income levels reduces cognitive and socio-emotional skill gaps by 27 and 22 percent, respectively.

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1 Introduction

Child development is a dynamic process with far-reaching implications for lifetime outcomes (Heckman and Mosso, 2014). A large literature emphasizes that during early childhood, parental investments and the home environment play a central role (e.g., Cunha et al., 2010; Attanasio et al., 2020b,c). As children grow older, however, their daily experiences increasingly extend beyond the household into the surrounding neighborhood and community. This developmental shift suggests that the community environment may serve as an important additional input in the child development process. Consistent with this view, recent studies have documented substantial benefits of exposure to more advantaged neighborhoods for education, earnings, and family formation (Chetty et al., 2016; Chetty and Hendren, 2018; Chyn et al., 2025). Yet the specific community mechanisms underlying these neighborhood effects remain largely understudied.

This paper fills the gap by identifying a key environmental input: a community's capacity to support, supervise, and invest in children. This capacity manifests through behaviors such as intervening when children misbehave, keeping close ties with local families, and serving as positive role models. I refer to this capacity as community social support. This concept can be interpreted as one dimension of what sociologists term social capital or collective efficacy. I show that community social support is an important determinant of child development, providing the first robust evidence of this mechanism.

To understand the relative importance of community social support and parental investments in the development process, I consider them as two different inputs of a dynamic skill production function (Cunha and Heckman, 2008; Cunha et al., 2010). Child skill development depends on existing skill endowments, parental investments, and community support. I focus on two key dimensions of human development, cognitive and socio-emotional skills, among children aged 6 to 15. This framework allows me to directly compare the productivity of home and community inputs and to examine how the two skill dimensions interact over time.

A fundamental challenge in implementing this approach is the absence of a quantitative measure of community support in the literature. Therefore, this paper's first contribution is to develop such a metric. Although sociologists have long emphasized the importance of adult supervision and support within neighborhoods (Coleman, 1988; Sampson et al., 2002), economists have lacked reliable tools to quantify this input. Community social support is not directly observable, and it is unclear which indicators capture it and how noisy those indicators are. This measurement difficulty has partly limited empirical work on its role in child development.

I address this challenge using data from the Project on Human Development in Chicago Neighborhoods (PHDCN), which, to the best of my knowledge, has not previously been used in economics research. The PHDCN Community Survey polled a random sample of adults in each of Chicago's 343 neighborhood clusters on various features of their community. Rather than relying on any single, noisy proxy, I identify a set of complementary indicators of community social support from the Community Survey and exploit their covariance structure to extract the underlying construct. I implement a latent factor framework that jointly models community support, parental investments, and child skills. This approach separates true signal from measurement error, makes efficient use of multiple indicators, and respects the ordinal nature of the survey items without imposing arbitrary cardinal distances between response options. The resulting measure shows substantial variation across neighborhoods and demographic groups.

To construct parental investments and child outcomes, I use the PHDCN Longitudinal Cohort Study, which follows seven cohorts (ages 0–18) and their caregivers in 80 clusters across three waves. I focus on the 6-, 9-, 12-, and 15-year-old cohorts and the first two waves for consistent measures of parental investments and child skills. I then link each child to the community support factor derived from the independent Community Survey. The PHDCN's paired community and home data provide an ideal setting to characterize the productivity of both community and home inputs.

Building on a robust measurement system, the second contribution of this paper is to integrate community social support into the human capital production function framework and to estimate its causal effects alongside parental investments. This framework extends the standard model, which typically includes only parental inputs, allowing us to quantify the relative importance of community support. Identifying these effects is challenging because both community support and parental investments are potentially endogenous, as parents' residential and investment decisions may respond to unobservable shocks in their child's development. For example, parents may move to neighborhoods with stronger support networks or invest more at home after an adverse event. Failing to address this endogeneity would bias the estimates of their true effects.

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 community social support. My analysis focuses on children whose homes were *not* demolished. The displacement of residents from public housing units disrupted existing networks and social bonds, thereby negatively impacting the community support of the remaining neighborhood residents. I compare the outcomes of children in neighborhoods that experienced demolitions to those in other neighborhoods with public housing. The demolition decisions primarily stemmed from deteriorating building conditions and escalating management problems, issues that were prevalent across U.S. public housing developments in the 1990s (U.S. National Commission On Severely Distressed Public Housing, 1992). To the extent that these factors are not correlated with community support or unobserved determinants of child development, this design provides plausibly exogenous variation in community support.

For robustness, I implement a second design exploiting the randomness in the timing of demolitions, comparing children in neighborhoods demolished early against those demolished later. The estimates remain consistent. In addition, I conduct a series of robustness checks to assess the exclusion restriction assumption. The results suggest that demolition does not change the school environment or peer composition. I also control for post-demolition criminal activities, and the estimated effects remain unaffected. [1]

Identification of parental investments relies on variation driven by household economic constraints. I instrument investments using household resources and female labor market shocks, capturing how shifts in budget constraints and the opportunity cost of time drive investment decisions (see, e.g., Cunha et al., 2010; Attanasio et al., 2020c).

My results reveal that community social support and parental investments play important yet distinct roles in the development process. First, community support is a significant determinant of both cognitive skills and socio-emotional skills. Specifically, a one standard deviation (SD) increase in community support improves cognitive skills and socio-emotional skills by 0.13 and 0.14 units, respectively. [2]

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 0.40-unit increase in cognitive skills. [3] While previous literature finds positive impacts of parental investments on socio-emotional skills in early childhood

[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. However, the scale of demolition after 1999 (about 16,000 units) was much larger than the demolition studied in this paper (about 700 units), so the crime-related effects can be less relevant here and do not impact the estimates of the production function.

[2]The scale of the community support latent factor is normalized to one of the measures: "the likelihood that neighbors would do something about kids skipping school." Based on the measurement system estimates, a 1.31 SD increase in community support shifts the average response from "likely" to "very likely." Based on the neighborhood survey, a 1 SD increase in community support corresponds to a $50,000 increase in neighborhood mean household income.

[3]A 0.9 SD increase in parental investments is equivalent to caregivers encouraging the child to read from less than once a month to about once a month. Further improving the frequency from about once a month to a few times a month is equivalent to a 2.03 SD increase.

(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.

Finally, using the estimated skill production functions, I conduct counterfactual experiments to assess how improvements in parental investments and community social support could reduce developmental disparities between high- and low-income neighborhoods. Raising community support in low-income areas to the level observed in high-income ones substantially mitigates the widening of socio-emotional skill gaps over time. It narrows the gap by 22 percent in the first period and over 30 percent in the long run. For cognitive outcomes, increasing either community support or parental investments initially decreases the gap by about one quarter. However, their long-term effects diverge: community support continues to generate larger cumulative gains, ultimately reducing the gap by over 40 percent. This amplifying effect arises from community support's positive influence on socio-emotional skills, which in turn reinforce cognitive development.

These findings suggest that while parental investments are more directly effective for cognitive skills, the wider disparity in community support across neighborhoods (see Section A.4) creates greater potential for reducing inequality along this dimension. They also underscore the relevance of real-world initiatives such as the U.S. Joint Economic Committee's Social Capital Project, which promotes community mentoring programs and investments in shared public spaces like libraries and parks as ways to strengthen local networks and support child development.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data. Section 4 presents the latent factor model and discusses identification issues, while Section 5 details the measurement system and estimation procedure. Section 6 outlines the empirical strategy addressing endogeneity. Section 7 reports the main findings, followed by robustness analyses in Section 8. Section 9 presents counterfactual experiments, and Section 10 concludes.

2 Related Literature

This paper builds upon several strands of literature. First, it relates to the neighborhood effect literature. Chetty and Hendren (2018) identify substantial effects of childhood exposure to better neighborhoods on earnings, college attendance rates, and fertility and marriage patterns using data from residential movers. Experiments such as Moving to Opportunity and the Gautreaux Assisted Housing Program also underscore the benefits of moving children to more favorable neighborhoods (Chetty et al., 2016; Chyn et al., 2025).

While the neighborhood effects are well documented, their underlying mechanisms remain insufficiently understood. Previous research has pointed to several mechanisms, including peer interactions, social networks, access to schools, and crime (e.g., Agostinelli et al., 2020; List et al., 2020; Laliberté, 2021; Damm and Dustmann, 2014). This paper adds to this literature by focusing on an understudied yet critical mechanism: community social support.

Community social support refers to the local and collective capacity of adults within a neighborhood to monitor, guide, and support children. This construct can be viewed as a dimension of the broader sociological concepts of social capital and collective efficacy. Although sociologists have long recognized the importance of this community-level input for human development (Coleman, 1988; Sampson et al., 2002), it has received much less attention in the economics literature, with notable exceptions such as Goldin and Katz (1998). As Durlauf and Fafchamps (2003) argue, two persistent challenges have constrained economics research on social capital: reliable measurement and identification of its causal effects.

Recent work has advanced measurement. Chetty et al. (2022a) and Chetty et al. (2022b), for example, use Facebook data to construct measures of economic connectedness, social cohesion, and civic engagement, showing that economic connectedness is strongly associated with upward mobility. Taking a different approach, this paper focuses on the kind of in-person community connections that directly shape children's local environments with detailed survey data from Chicago neighborhoods. I apply a latent factor model to construct a credible measure of community support. Crucially, this paper moves beyond documenting associations. It provides causal estimates of community support's impact on child skills by exploiting quasi-experimental variation from public housing demolitions.

The paper's focus on the determinants of child skills also relates to the child development literature. This body of work has a rich history of exploring how inputs like the home environment and parental investments shape a child's human capital (Todd and Wolpin, 2003, 2007; Del Boca et al., 2014). Cunha and Heckman (2008) and Cunha et al. (2010) advance the field by introducing a dynamic latent factor model to address measurement error and distinguish between cognitive and non-cognitive skills across developmental stages. Recent studies extend this framework by developing new identification and estimation methods (Agostinelli and Wiswall, 2025; Attanasio et al., 2020c), applying it to uncover mechanisms behind experimental interventions (Heckman et al., 2013; Attanasio et al., 2020b), and modeling richer developmental dynamics (Attanasio et al., 2020a). Others disaggregate parental inputs, examining different types of investments and their complementarities (Caucutt et al., 2025).

Despite these advances, few studies incorporate factors beyond the home environment

(Agostinelli et al., 2020, 2025). This literature has largely treated community conditions as background characteristics rather than productive inputs. This paper is the first to incorporate both parental investments and community social support into the skill production function, offering a more comprehensive framework for understanding the determinants of child development.

Lastly, because this paper uses quasi-experimental variation from public housing demolitions for identification, it contributes to the literature on the impacts of public housing policy. Previous research has investigated the direct consequences of living in public housing projects (Currie and Yelowitz, 2000; Oreopoulos, 2003). 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 their academic outcomes, labor market outcomes, and criminal behaviors. While this paper relates to the impacts of public housing demolition on children, it focuses on children whose homes were not demolished, a group that has not been studied before. In doing so, this paper reveals a new dimension of the effects of public housing policy.

3 Data

3.1 Primary Dataset

The primary data source is the Project on Human Development in Chicago Neighborhoods (PHDCN), a large-scale study of children, families, and communities across the city of Chicago. The city is divided into 343 neighborhood clusters (each covering about two to three census tracts and roughly 8,000 residents). To the best of my knowledge, this is the first time that PHDCN has been used in economics research.

Two key components of the PHDCN are used in this paper: the Community Survey and the Longitudinal Cohort Study (LCS). The Community Survey interviewed 8,782 adults across all 343 neighborhood clusters in 1995. A three-stage sampling design ensured representation within clusters, with a target sample size of 50 in the 80 clusters included in the LCS and 20 in the remaining clusters (see Section A.2.1). In addition to providing basic demographic information, respondents evaluated neighborhood environments across a wide range of dimensions, including a set of questions used to capture community social support.

Respondents reported on the likelihood of neighbors intervening if children skipped school, defaced buildings, or displayed disrespectful behaviors. They also indicated whether parents generally know each other and their children's friends, whether adults know and look out for local children, and whether children can look up to adults in the neighborhood. Responses were recorded on a five-point scale, ranging from very likely/strongly agree to very unlikely/strongly disagree. Taken together, these indicators capture the extent of informal monitoring and cooperative norms within a community, reflecting its capacity to invest in and support child development. The data reveal substantial geographic variation in this capacity (see Appendix Figure A8).

While the Community Survey provides detailed information on the community environment, the second key component, the LCS, complements it with child and household information. It follows seven cohorts of children (ages 0, 3, 6, 9, 12, 15, and 18). Data were collected in three waves: 1994-1996, 1997-1999, and 2000-2001. The LCS employed a stratified three-stage sampling design to ensure variation across neighborhoods by socioeconomic status and racial/ethnic composition (see Section A.2.1). It covered 80 neighborhood clusters.

The LCS provides rich information on child development, parental investments, and household demographics. However, 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 for the oldest cohort (age 18) in waves 2 and 3, and the investment measures for other cohorts in wave 3 are less comprehensive. To ensure measurement consistency across different periods, I restrict the sample to children in the 6-, 9-, 12-, and 15-year-old cohorts observed in the first two waves.

Cognitive skills are measured through both standardized assessments and interviewer-rated tasks. Standardized tests include reading scores from the Wide Range Achievement Test (WRAT) and word definition scores from the Wechsler Intelligence Scale for Children (WISC). In addition, interviewers evaluated children's attention span and their comprehension of interview questions, providing complementary indicators of cognitive processing. Socio-emotional skills are measured using the Child Behavior Checklist, covering dimensions such as withdrawn problems, anxiety/depression, somatic complaints, social and thought problems, attention deficits, rule-breaking, and aggression.

Parental investments are measured using a broad set of indicators, as listed in Table 3. These include the frequency with which the primary caregiver encouraged the child to read, helped with homework, and praised accomplishments, along with the availability of books, board games, tapes or CDs, sports equipment, dictionaries, and encyclopedias in the household.

Table 1 reports descriptive statistics for respondents in the Community Survey. Respondents are, on average, 43 years old, and 59 percent are female. The sample is racially diverse, with 25 percent identifying as Hispanic and 39 percent as Black. The average educational attainment is slightly above 12 years. Income levels are modest: over 60 percent of respondents report annual household income below $30,000, and nearly one-third fall below $15,000.

Table 2 presents characteristics of the households and children in the Longitudinal Cohort Study.[4] The sample has equal representation of boys and girls. Forty-seven percent identify as Hispanic and 34 percent as Black. The average income per capita is about $6,000 and parental education levels are moderate, with fewer than half of parents having attended college.

Table 1: Respondent Characteristics in the Community Survey

Variable	Obs	Mean	Std. Dev.
Age	7956	42.58	16.64
Female	7634	0.59	0.49
Hispanic	7634	0.25	0.43
Black	7634	0.39	0.49
U.S.-born	8622	0.85	0.36
Married	7634	0.37	0.48
Years of Education	7634	12.32	3.12
Annual Household Income			
Below $15,000	7634	0.32	0.47
Below $30,000	7634	0.62	0.49
Below $60,000	7634	0.89	0.32

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.

3.2 Secondary Datasets

I supplement the PHDCN with several secondary sources to construct the instrumental variables discussed in Section 6, as well as to include additional control variables for various robustness checks.

Since the empirical design relies on variation from public housing demolitions, I requested data from the Chicago Housing Authority through the Freedom of Information Act. The dataset includes names, addresses, the number of units, and demolition dates for public housing projects. I focus on public housing units that were demolished in 1995, aligning with the collection of community support measures. In total, there were 728 units demolished in that year.

[4]Household characteristics for the analysis sample (ages 6 to 15) are reported in Table 6.

Table 2: Child and Household Characteristics in the Longitudinal Cohort Study

Variable	Obs	Mean	Std. Dev.
Child Characteristics			
Age	5930	8.32	5.76
Female	6187	0.50	0.50
Hispanic	6200	0.47	0.50
Black	6200	0.34	0.48
Household Characteristics			
Number of siblings	6083	1.96	1.63
Income per capita ($1,000)	5741	5.98	5.30
PC is married	5497	0.55	0.50
Number of years PC at current address	5461	5.30	6.32
Mother with higher education	5920	0.42	0.49
Father with higher education	5360	0.36	0.48
U.S.-born family	5302	0.46	0.50

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.

One of the instruments used for parental investments is labor market shocks. I proxy labor market shocks using the national growth rate in full-time female employment by education group, calculated from the Current Population Survey between 1996 and 1997. For control variables, I use 1990 U.S. Census data to provide neighborhood characteristics, including average educational attainment, racial composition, and unemployment rate. I also use the Homicides in Chicago Dataset for additional crime measures, which includes homicide counts at the census tract level from 1965 to 1995.

4 The Human Capital Accumulation Process

The paper examines the roles of community social support and parental investments in the human capital accumulation process. I focus on two dimensions of development: cognitive skills and socio-emotional skills, and model the development process using a dynamic skill production framework, as shown in the following equations:

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

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

where i, r, and t represent individuals, neighborhoods, and time periods, respectively. $\theta^c_{ir,t}$ and $\theta^s_{ir,t}$ denote cognitive and socio-emotional skills, $I_{ir,t}$ parental investments, $CS_{ir,t}$

community support, and $\boldsymbol{X_{ir,t}}$ a vector of demographic variables, detailed in Section 6.2.3. $\epsilon_{ir,t}$ 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 community support $CS_{ir,t}$. The first challenge lies in measuring the inputs and the outputs in the skill production functions. Unlike readily quantifiable metrics such as height or income, skills, parental investments, and community support are not directly observable. Measuring community support is particularly challenging because it involves a complex social process—such as informal monitoring and neighborhood support networks—that are rarely documented in standard household surveys or administrative data. Common proxy variables, such as blood donation or voter turnout (Guiso et al., 2004; Nannicini et al., 2013), may not fully capture the dimension of community support that matters for child development. Moreover, using a single proxy introduces measurement error bias, as it is likely an error-ridden measure of the true underlying construct.

The PHDCN dataset allows me to identify a rich set of complementary indicators that capture these inputs and outputs more accurately. I extend the traditional dynamic factor framework in the child development literature (Cunha and Heckman, 2008; Cunha et al., 2010; Attanasio et al., 2020b,c) by introducing community support as an additional latent factor alongside parental investments and child skills. I develop a measurement system that links the observed indicators to these underlying latent factors and estimate the distribution of these latent factors. This approach addresses the measurement error issue, efficiently leverages all available measurements, and respects the ordinal nature of certain survey items without imposing arbitrary distances between adjacent response options. Section 5 provides further details on the specification and estimation of the latent factor model.

The second challenge is the endogeneity of parental investments and community support. Both factors can be correlated with unobserved shocks to child development. Appendix A.1 outlines a structural model of parental investment and neighborhood choice to formalize this issue. For instance, parents may increase their investments in response to a child's health shock. Similarly, parents who observe their children exposed to adverse neighborhood influences may choose to relocate to an area with stronger social support networks. More generally, residential sorting means community support can be correlated with other unobserved neighborhood characteristics that also influence child development. Failure to address the endogeneity issue could lead to biased estimates. Therefore, identification requires exogenous variation in parental investments and community support. I use an instrumental variable approach.

Parents' investment decisions and residential choices depend on their preferences for child skill development, their budget constraints, and their beliefs about 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. In addition, to generate exogenous variation that shifts community support, I use public housing demolitions as an instrument. Further details on the instruments are provided in Section 6.

This paper does not estimate the structural economic model outlined in Appendix A.1, 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 first outline the specification and identification of the measurement system for skills, parental investments, and community social support. I then describe the key features of the community support measure. Finally, I summarize the three-step estimation procedure.

5.1 Specification of the Measurement System

The measurement system uses a combination of categorical and continuous indicators. Measures of community support and parental investments are exclusively categorical and are treated as ordinal rather than cardinal values, to avoid imposing arbitrary distances between response options. Skill measures are predominantly continuous, except for two categorical indicators capturing a child's attention span and comprehension of interview questions. Table 3 lists all measurements used in the analysis.

To determine the dimensionality of the latent constructs and guide the allocation of indicators, I first conduct an exploratory factor analysis (EFA). The EFA supports the extraction of one factor for each construct—community social support, parental investments, cognitive skills, and socio-emotional skills. Detailed results are provided in Appendix A.2.2.

5.2 Confirmatory Factor Analysis

I estimate the measurement system using confirmatory factor analysis (CFA). The intuition behind the CFA is straightforward: although each observed indicator is a noisy measure of an underlying construct, the joint covariance structure across multiple indicators enables the recovery of the latent factors. To anchor the scale of each latent factor and to ensure comparability of the dynamic skill factors over time (Agostinelli and Wiswall, 2025), I normalize one reference measurement per factor: intervention on children skipping school for community support, frequency of reading encouragement for parental investments, the reading scores for cognitive skills, and the Withdrawn CBCL subscale for socio-emotional skills.

The full model specification and normalization assumptions are discussed in Appendix A.2.3, and the estimated measurement parameters are reported in Appendix A.2.4. Table 3 summarizes the assignment of measurements to factors and their signal-to-noise ratios. The signal-to-noise ratio assesses the degree of information contained in a measurement relative to the measurement errors.[5]

As seen in Table 3, there is significant variation in the signal-to-noise ratio across these measures. For example, *Number of books in house for SP's age* has about 66% of the variance due to signal, while only 14% of the variance is due to signal for *Frequency PC helped SP with homework, past year*. Nearly all measurements have a signal-to-noise ratio far from 100%. This highlights 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] Computation details are provided in Appendix A.2.4.

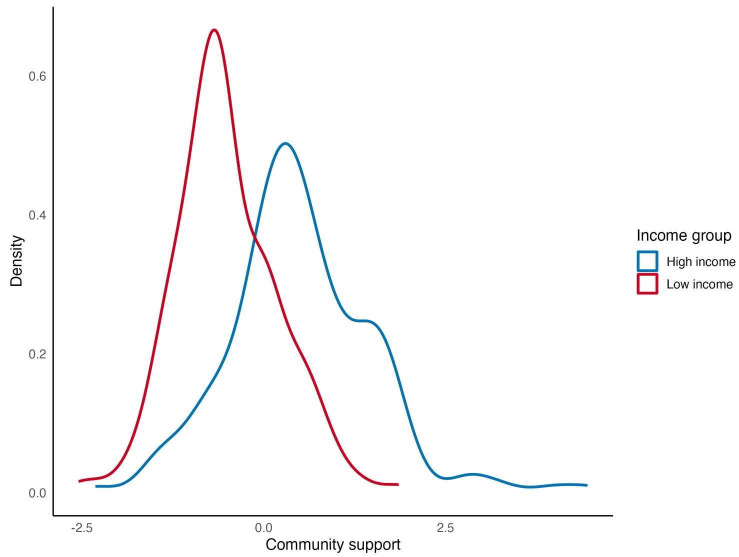
Table 3: Measurement System

Latent factor	Measurement	Signal
Community Support	Adults know who local children are	0.49
	Adults watch out for children	0.50
	Children look up to adults in the neighborhood	0.32
	Neighbors do something about kids defacing building	0.57
	Neighbors do something about kids skipping school	0.60
	Neighbors scold a kid for not showing respect	0.46
	Parents generally know each other	0.52
	Parents know their children's friends	0.49
Parental investments	Frequency PC encouraged SP to read, past month	0.23
	Frequency PC helped SP with homework, past year	0.14
	Frequency PC praised SP about accomplishment, past month	0.21
	Number of board games for SP's age	0.43
	Number of books in house for SP's age	0.66
	Number of books in the house	0.64
	Number of tapes, CDs, or records for SP's age	0.15
	SP has any sports equipment?	0.26
	SP has dictionary at home for use?	0.37
	SP has encyclopedia at home for use?	0.39
Cognitive skills, w1	WISC: Word definition scores	0.98
	WRAT: Reading scores	0.66
Socio-emotional skills, w1	CBCL: Aggressive behavior	0.63
	CBCL: Anxiety/depression	0.60
	CBCL: Attention problems	0.69
	CBCL: Rule-breaking behavior	0.50
	CBCL: Social problems	0.47
	CBCL: Somatic complaints	0.27
	CBCL: Thought problems	0.60
	CBCL: Withdrawn problems	0.43
Cognitive skills, w2	Attention duration levels	0.24
	Comprehension of interview questions	0.46
	WISC: Word definition scores	0.60
	WRAT: Reading scores	0.59
Socio-emotional skills, w2	CBCL: Aggressive behavior	0.59
	CBCL: Anxiety/depression	0.67
	CBCL: Attention problems	0.72
	CBCL: Social problems	0.36
	CBCL: Thought problems	0.43
	CBCL: Withdrawn problems	0.52

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.

5.3 Characterization of Community Social Support

Figure 1: Distribution of Community Social Support by Neighborhood Income



Notes: This figure displays the distribution of neighborhood-level community support by neighborhood income.

Figure 1 displays the distribution of the standardized community social support factor across neighborhoods, categorized by income level (see Appendix Figure A8 for the spatial distribution across the city). Neighborhoods with a 1990 census median income above the sample average are classified as high-income. The figure clearly shows that high-income neighborhoods, on average, exhibit higher levels of community support compared to their low-income counterparts. Yet, the substantial overlap indicates that community support captures a dimension of neighborhood quality distinct from economic resources.

To better characterize community support, I utilize respondent data from the Community Survey to explore correlations between community support and various neighborhood characteristics in 1995. Table 4 shows that community support is higher in neighborhoods with a higher average age, larger shares of White, U.S.-born, and married residents, as well as higher average income. The female share and average years of education are not significantly correlated with neighborhood community support after controlling for other characteristics.

Beyond neighborhood-level averages, access to community support can vary with an individual's demographic background, even within the same community. To examine this within-neighborhood variation, I analyze the correlation between community support and a set of individual-level demographic characteristics using a fixed-effects model:

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

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 (U.S.-born natives vs. immigrants, proxied by whether English is regularly spoken in the household), age (above vs. below the median), educational attainments (high school graduates vs. non-high school graduates), household incomes (above vs. below the median), and marital status (married vs. single).

Table 4: Correlation Between Community Support and Neighborhood Characteristics

Variables	Community support
Average age	0.04***
	[0.03, 0.06]
Female share	0.42
	[-0.12, 0.96]
White share	0.76***
	[0.46, 1.06]
U.S.-born share	1.02***
	[0.40, 1.64]
Married share	1.12***
	[0.55, 1.69]
Average years of education	-0.03
	[-0.11, 0.05]
Average household income ($5,000)	0.10***
	[0.05, 0.15]
Observations	343

Notes: This table presents the coefficient estimates from a multivariate regression of neighborhood-level community support on the neighborhood characteristics listed above, with robust asymptotic 90% confidence intervals shown in brackets. 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 individual characteristics are significantly correlated with community support. Community support tends to be higher among residents who are aged 40 and above, U.S.-born natives, married, and have household incomes exceeding the median. Interestingly, while neighborhoods with higher proportions of White residents on average have higher levels of community support, the influence of race diminishes within a neighborhood, a pattern likely related to residential racial segregation.

The fixed effects estimates indicate that about 80 percent of the variation in community support arises within neighborhoods, underscoring the need to capture heterogeneity at a more granular level than the neighborhood average. Among the observed individual characteristics, immigration status emerges as the most predictive factor of access to community support. This finding aligns with prior work documenting class-based disparities in social support and unequal access between immigrants and natives (McPherson et al., 2001; Völker et al., 2008; Behtoui, 2022).

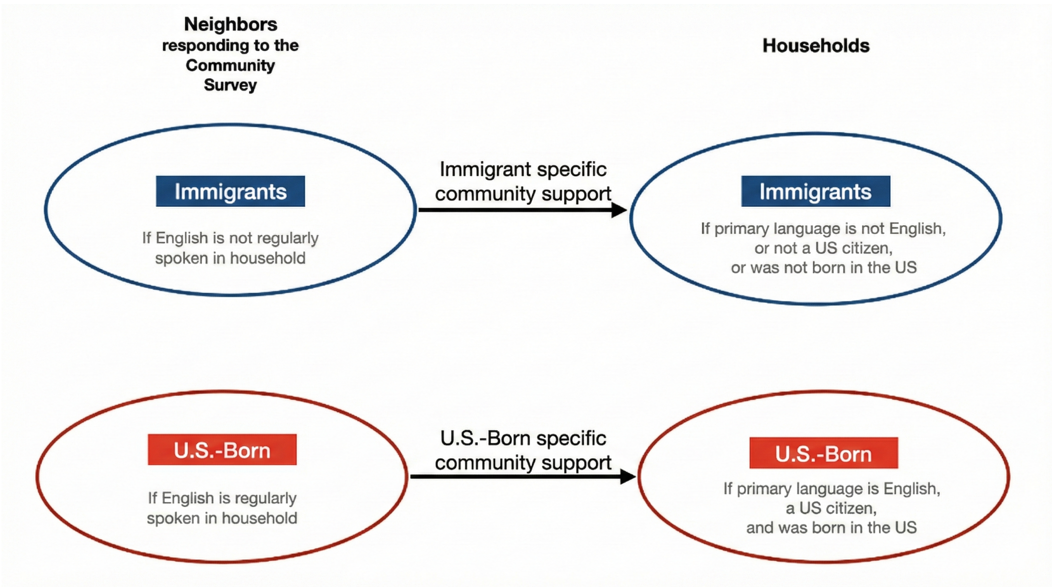
Table 5: Correlation Between Community Support and Individual Characteristics

Variables	Community support
Above median age	0.07**
	[0.03, 0.12]
Female	0.00
	[-0.04, 0.04]
White	-0.04
	[-0.10, 0.03]
U.S.-born	0.12***
	[0.05, 0.19]
Married	0.06**
	[0.01, 0.10]
HS graduate	0.01
	[-0.05, 0.06]
High income	0.08***
	[0.03, 0.13]
Neighborhood fixed effects	Yes
Observations	5,500

Notes: This table presents the coefficient estimates from a multivariate regression of individual-level community support on the individual characteristics listed above, controlling for neighborhood fixed effects. Robust asymptotic 90% confidence intervals are reported in brackets. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1

Building on these results, I construct a community support 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 U.S.-born natives. A respondent is classified as an immigrant if English is not regularly spoken in their household; otherwise, they are classified as a native. I then calculate the average of individual factor scores at the neighborhood level for each group. This means each neighborhood has both an immigrant-specific community support measure and a native-specific community support measure. I then 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.[6] Figure 2 illustrates the assignment process.

Figure 2: Constructing Community Support Tailored to Immigrants and U.S.-born

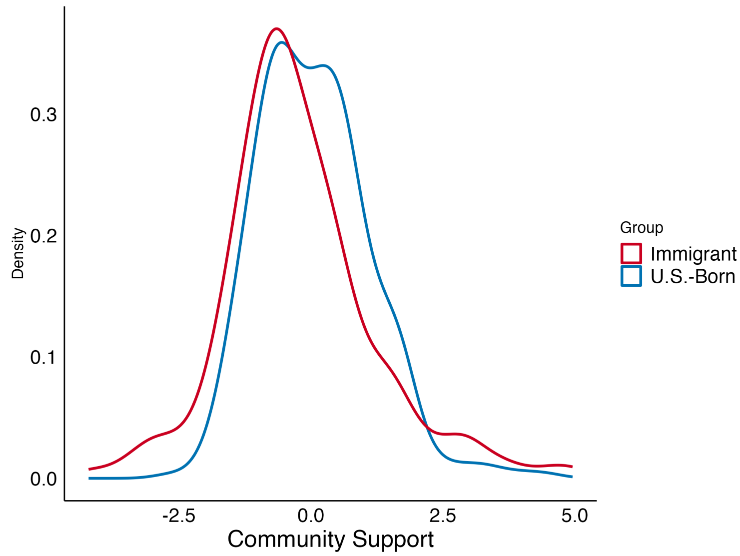


Notes: This figure illustrates the process of assigning a community support measure to households based on their immigration status after obtaining the factor scores of respondents in the Community Survey.

Figures 3 and 4 provide further insight into the community support differences between immigrants and U.S.-born natives. Figure 3 shows that, on average, natives enjoy a higher level of community support than immigrants, which aligns with our regression estimates. However, the scatter plot in Figure 4 reveals important heterogeneity; it shows that there are neighborhoods where immigrants possess a higher level of community support than their native counterparts, as indicated by observations above the 45-degree line. This heterogeneity underscores the value of measuring community support at a granularity below the neighborhood to capture group-specific patterns.

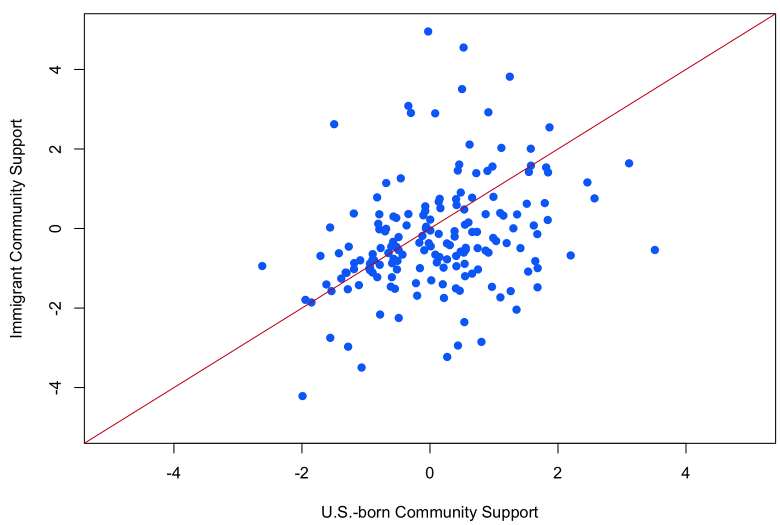
[6] The Longitudinal Cohort Study provides more detailed demographic information about parents, allowing for more accurate classification compared to what is available in the Community Survey. Using either the father's or mother's information alone for classification yields consistent results.

Figure 3: Distribution of Neighborhood-Level Community Support: Immigrants vs. U.S.-Born



Notes: This figure shows the distribution of neighborhood-level community support separately for immigrants and U.S.-born individuals. Community support is calculated using the average factor scores of all immigrant and U.S.-born respondents within each neighborhood.

Figure 4: Comparing Immigrant and U.S.-Born Community Support Within Neighborhoods



Notes: This figure compares neighborhood-level community support between immigrants and U.S.-born individuals. Each point represents one neighborhood, with values calculated using the average factor scores of immigrant and U.S.-born respondents in that neighborhood.

I assess whether the community support factor is measured consistently across immigrant and U.S.-born groups by testing for measurement invariance. The results show that imposing equality restrictions on thresholds, factor loadings, and intercepts does not materially worsen model fit. Changes in approximate fit indices (ΔCFI, ΔRMSEA, ΔRMSR) remain well within the recommended cutoffs, indicating that the factor structure is comparable across groups. This allows differences in estimated factor scores to be interpreted as substantive variations in community support rather than artifacts of measurement. Full test statistics and model comparisons are reported in Appendix A.2.5.

5.4 Estimation

I adopt a three-step estimation procedure. 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. The measurement systems accommodate both continuous and categorical indicators, and the parameters are estimated using a diagonally weighted least squares (DWLS) estimator. Additional details on the DWLS estimator are provided in Appendix A.2.4.

In the second step, I estimate factor scores for all latent factors based on the measurement parameters using the maximum likelihood estimator. After estimating the community support factor scores for all Community Survey respondents, I aggregate them to the neighborhood level by respondents' immigration status. These factor scores are then assigned 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 inherent in using estimated factors instead of the true latent factors. 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.

To obtain confidence intervals and critical values for the test statistics, I bootstrap 1000 samples clustered at the neighborhood level and repeat the entire process for each draw.

6 Empirical Design

6.1 Institutional Background

Public housing, operated and managed by the Chicago Housing Authority (CHA), provides affordable housing to low-income households. The CHA is one of the largest public housing authorities in the United States. Following the construction of large high-rise projects in the 1950s and 1960s, many buildings quickly deteriorated due to design flaws and poor maintenance. By the early 1990s, the national scale of this issue led to the establishment of the federal HOPE VI program, which advocated for the demolition and redevelopment of failing social housing projects.

Chicago received more HOPE VI funding than any other city, demolishing about 20,000 public housing units in the 1990s and 2000s (Sink and Ceh, 2011; Almagro et al., 2023). While most demolitions occurred after 2000 under the CHA's carefully coordinated "Plan for Transformation," the initial wave in the 1990s was shaped by a variety of initiatives, safety concerns, and management crises.

Some closures followed sudden infrastructure failures, such as burst pipes in several high-rise buildings of the Robert Taylor Homes in 1999 (Jacob, 2004; Chyn, 2018), while others were triggered by the chronic deterioration of basic systems, as in the Addams, Brooks, Loomis, and Abbott (ABLA) Homes. Residents there had long endured heating breakdowns, and when the CHA unexpectedly received a $200,000 HOPE VI planning grant in 1995, the funds were used to advance the demolition of ABLA high-rises instead of rehabilitating them (Bennett et al., 2015). Other sites, such as the Henry Horner Homes, were cleared following tenant-led lawsuits against the CHA for neglect and mismanagement. Unforeseen events and logistical challenges—including financial constraints and legal disputes involving tenant organizations—often produced outcomes that were uneven and unpredictable (Hunt, 2009).

Following the closure of their buildings, 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 households with children, it was 4.4 kilometers (Thomas Kingsley et al., 2003; Jacob, 2004).

The plan for demolished neighborhoods was to revitalize the public housing sites. However, the redevelopment process had been slow. For example, 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 Community Social Support

Public housing communities fostered informal networks that organized babysitting, neighborhood watches, food sharing, and mutual aid to provide childcare, safety, and everyday support (Venkatesh, 2000). Ben Austen vividly describes these dynamics in *High-Risers*: "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, p. 139).

The demolition of these housing projects fractured these networks of care and monitoring, weakening the parental support and local norms that had long sustained families in the neighborhood (Venkatesh, 2000). As residents were displaced, parents lost connections with one another, reducing access to information and support. Children who remained in the neighborhood had fewer adults who knew them and could provide guidance. The severance of these relationships weakened the social norms, trust, and sanctions that had previously governed community members' behaviors (Coleman, 1988; Pettit, 2004). Therefore, I leverage public housing demolition as an instrumental variable for the disruption of community social support.

I focus on the first wave of demolitions in 1995, which involved 728 public housing units. I define treatment neighborhoods as those with a demolished public housing building or located within one kilometer of one. This radius captures the area where daily social networks were most likely centered and affected by the demolition of public housing structures. Figure 5a highlights these designated treatment areas in dark blue. [7]

My analysis focuses on children who were not displaced but remained in neighborhoods affected by demolition, to isolate the impacts of community support disruption rather than those of relocation. I compare them to children in other neighborhoods that contained public housing but did not experience demolition in 1995. [8] This sample selection addresses concerns about the non-random placement of public housing. As discussed above, the initial wave of demolitions was largely driven by worsening building conditions and management challenges. If these factors are unrelated to community support or unobserved determinants of child development, the demolitions provide plausibly exogenous variation in community support.

I present the characteristics of treatment and this control group (control group (1)) at wave 1 in Table 6. The table is balanced, with no statistically significant differences between

[7] See Appendix A.2.1 for more details on treatment areas and dates.

[8] To avoid contamination from subsequent demolitions, I exclude neighborhoods with demolitions in 1996–1997 from the control group, since most children were assessed by 1998. I verify that estimates are not driven by later demolitions and report the robustness results in Appendix A.3.

the control and treatment groups. I also test for joint significance of all the characteristics on the treatment variable, and cannot reject the null hypothesis.

As a further robustness check for potential correlations between demolition and unobserved neighborhood characteristics, I implement a second design that leverages the quasi-random timing of demolitions across neighborhoods. As noted, the initial demolitions were often triggered by unforeseen events or logistical challenges, such as heating system breakdowns and pipe bursts (Jacob, 2004; Chyn, 2018). This alternative design uses a different control group: children living in neighborhoods where public housing was demolished in later years (1998–2010). Since the primary child outcomes were assessed by 1998, these later-demolished sites can serve as a non-exposed counterfactual for the main analysis period. Figure 5b highlights treatment neighborhoods in dark blue and these alternative control neighborhoods in light blue. While this design reduces the sample size, it offers stronger plausibility for exogeneity and confirms that the results remain very similar to the main design. Section 8 presents these results in detail. As shown in Table 6, the treatment and alternative control groups (control group (2)) are well-balanced across all observed characteristics.

The exclusion restriction assumption is that the demolition affects children in the treatment group only through community support and parental investments. Robustness checks in Section 8 suggest that demolition does not change the school environment or peer composition. To address the concern that demolition may affect criminal activities, I also control for post-demolition crime rates. The results remain unaffected (see Section 8 for further discussion).

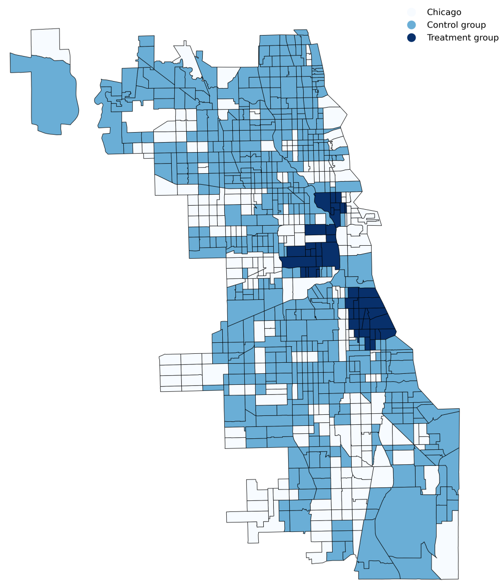
6.2.2 Instruments for Parental Investments

Parents' investment decisions depend on the budget constraints they face. This dependence suggests two natural candidates for instruments: household resources and labor market shocks.[9] As in Cunha et al. (2010) and Attanasio et al. (2020c), household income is a relevant instrument because greater income relaxes the budget constraint and allows parents to increase investments. The key question is whether income satisfies the exclusion restriction. From an economic perspective, household income is not itself a direct input in the production function. The concern is that it may still be correlated with unobserved inputs. Given that I also control for maternal educational attainment[10] and the child's

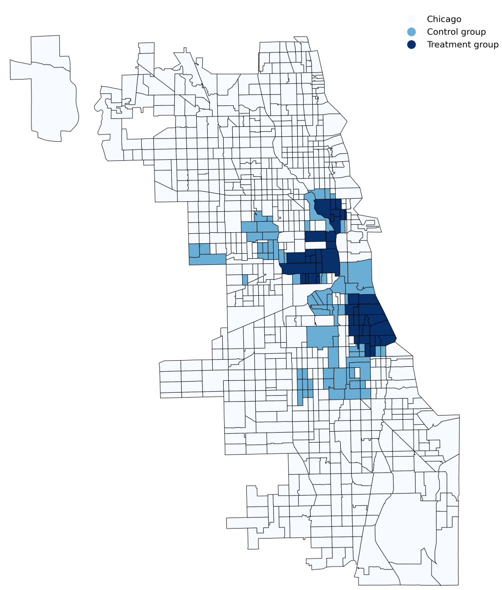
[9] Some studies instead exploit variation in the prices of investment goods as instruments for parental investments (Attanasio et al., 2020b,c), but such data are unavailable for this sample, and within-city price variation is likely limited.

[10] Results are robust to additionally controlling for paternal education (see Appendix A.3).

Figure 5: Treatment and control neighborhoods in Chicago



(a) Neighborhoods with public housing as the control group



(b) Neighborhoods with later-demolished public housing as the control group

Notes: Treatment neighborhoods are those with public housing developments that were demolished. Panel (a) uses all other neighborhoods with public housing as the control group. Panel (b) restricts the control group to neighborhoods with public housing demolished in later years, forming the robustness sample.

Table 6: Balance Table

Variable	Control group (1)	Control group (2)	Treatment group	Difference (1) [p value]	Difference (2) [p value]
Child characteristics					
Cognitive skills	-0.649	-0.774	-0.759	-0.110	0.016
	(1.099)	(1.075)	(1.018)	[0.462]	[0.925]
Socio-emotional skills	0.045	0.042	0.064	0.019	0.022
	(0.649)	(0.639)	(0.586)	[0.839]	[0.824]
Gender	0.505	0.511	0.563	0.059	0.052
	(0.500)	(0.501)	(0.499)	[0.213]	[0.314]
Age	10.217	9.999	10.435	0.218	0.435
	(3.375)	(3.472)	(3.238)	[0.333]	[0.112]
Hispanic	0.497	0.392	0.471	-0.026	0.079
	(0.500)	(0.489)	(0.502)	[0.917]	[0.773]
Black	0.292	0.456	0.437	0.145	-0.019
	(0.455)	(0.499)	(0.499)	[0.558]	[0.945]
Household characteristics					
Number of siblings	2.166	2.351	2.241	0.075	-0.109
	(1.580)	(1.719)	(1.422)	[0.687]	[0.608]
Income per capita ($1,000)	6.418	5.280	5.139	-1.279	-0.141
	(5.144)	(4.817)	(4.555)	[0.194]	[0.900]
PC is married	0.610	0.508	0.471	-0.139	-0.037
	(0.488)	(0.501)	(0.502)	[0.128]	[0.715]
Number of years PC at current address	5.628	6.567	6.418	0.789	-0.149
	(6.176)	(7.833)	(6.320)	[0.205]	[0.855]
Father with higher education	0.340	0.298	0.287	-0.052	-0.011
	(0.474)	(0.458)	(0.455)	[0.545]	[0.908]
Mother with higher education	0.438	0.409	0.368	-0.070	-0.041
	(0.496)	(0.492)	(0.485)	[0.481]	[0.711]
Immigrant family	0.550	0.337	0.471	-0.078	0.134
	(0.498)	(0.473)	(0.502)	[0.719]	[0.574]
F test statistic of joint significance				0.36	0.78
[p value]				[0.98]	[0.67]
Observations				1,730	449

Notes: This table reports summary statistics of child and household characteristics for the analysis sample. Control group (1) refers to neighborhoods with public housing, and control group (2) to those where public housing was demolished later. 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 in square brackets for the test of equality of means, obtained by regressing each characteristic on a treatment dummy with standard errors clustered by neighborhood. The F test statistic and the p-value for the joint significance test are from regressing the treatment variable on all baseline characteristics and clustering standard errors by neighborhood. 'PC' stands for the primary caregiver. 'Higher education' refers to at least some college. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.

initial conditions, it is plausible to treat income as conditionally exogenous.

The second instrument is labor market shocks. A positive shock is relevant because, conditional on household income, parents are more likely to increase labor supply and reduce time and effort devoted to their child. I proxy labor market shocks using the national growth rate in full-time female employment by education group between 1996 and 1997.[11] This variation should not affect the production function directly, other than through its effect on parental investments.

6.2.3 Empirical Specification of the Production Function

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

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

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

where i, r, t represent individuals, neighborhoods, and time periods, respectively. $\theta^{c}_{ir,t}$ and $\theta^{s}_{ir,t}$ denote cognitive skills and socio-emotional skills, $I_{ir,t}$ is parental investments, $CS_{ir,t}$ is community support, $\epsilon_{ir,t}$ is a shock to the production function. $\boldsymbol{X_{ir,t}}$ is a vector of household and pre-demolition neighborhood characteristics, including the child's age, maternal educational attainment, the number of siblings, the neighborhood's average household income, the share of high school graduates, the homicide rate, the racial composition, and the unemployment rate, included to improve estimation precision and robustness.

7 Results

This section presents the empirical results. As discussed in Section 5, log skills are expressed in the units of their reference measurements, while log parental investments and log community support are standardized to have mean zero and a standard deviation of one. I begin with the first-stage estimates for parental investments and community support, which confirm the relevance of the instruments. I then turn to the reduced-form estimates, as the effects of demolitions and household resources on child development are of independent interest. Finally, I present the estimated production functions for cognitive and socio-emotional skills. Confidence intervals are based on 1,000 bootstrap replications, accounting for the neighborhood cluster structure. For the reported test statistics, p-values are also computed using bootstrap methods.

[11] An alternative would be to use wage rates by education group, but these are not available for 1996–1997.

7.1 Estimates of the Investment Functions

Table 7 presents the estimates of the investment functions. The first column shows the estimates for parental investments, and the second column reports the results for community support. I use demolition, household income, and employment growth in the female labor market by educational attainments as exclusion restrictions.

Table 7: Estimates of the Investment Functions

	Community support	Parental investments
Demolition	-1.30**	-0.01
	[-1.63, -0.76]	[-0.10, 0.12]
Household resources	0.02	0.06**
	[-0.01, 0.04]	[0.05, 0.09]
Employment growth	2.70	-8.71**
	[-2.83, 7.34]	[-12.34, -6.38]
Test of joint significance: F-statistic (p-value)		
Demolition, resources, employment	31.01 (0.00)	67.83 (0.00)
Rank test (p-value)		0.01
Observations	1590	1610

Notes: 90% confidence intervals (CI) are reported in brackets. ** indicates that the 95% CI does not cross 0; * indicates that the 90% CI does not cross 0. 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 community support and parental investments equations.

Consistent with our hypothesis, demolition has a negative impact on community support but no direct effect on parental investments. This supports the idea that displacing residents disrupts existing networks and norms, thereby eroding neighborhood community support. For parental investments, a $10,000 increase in household income is associated with a 0.06 standard deviation (SD) increase, reflecting the importance of budget constraints. Conversely, a one percentage point increase in female employment growth—representing a higher opportunity cost of time—is associated with a 0.08 SD decline.[12]

Turning to instrument strength, I first test the joint significance of the three instruments in both investment functions. The F-statistic is 67.83 for parental investments and 31.01 for

[12] The employment growth variable is measured as a proportion (e.g., 1 for 100% growth).

community support, with p-values of 0 in both cases. I also implement a rank test, which evaluates 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 community support and parental investments equations (Blundell et al., 1998; Robin and Smith, 2000). The rank test has a p-value of 0.01, providing further evidence that the instruments are strong for both investments.

7.2 Estimates of the Reduced Forms

Table 8 presents the reduced form estimates of the instruments' effects on skill development. Living in a demolished neighborhood reduces log cognitive skills and log socio-emotional skills by 0.12 and 0.17 units. Conversely, every \$10,000 increase in household resources is linked to a 0.03 increase in log cognitive skills. The corresponding effect on socio-emotional skills is much weaker and not different from zero.

To validate these results, I next use a fixed effects model to examine the treatment effects of demolition. Specifically, I regress skill outcomes on individual, neighborhood, and time fixed effects (represented by the "Post" dummy variable), as well as an interaction term for the demolition treatment in the post-period. The results presented in Table 9 demonstrate that, even after accounting for all permanent neighborhood and individual effects, both cognitive and socio-emotional skills show a significant decline. The decline closely mirrors the reduced form estimates in Table 8, providing reassurance that the demolition instrument does not pick up unobserved time-invariant neighborhood attributes.

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 extend beyond this group, as displaced children 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) likewise document negative impacts of moving to a different neighborhood among those who moved at an older age, likely driven by the disruption effects. These potential adverse consequences should therefore be carefully considered when designing relocation experiments.

7.3 Estimates of the Production Functions

Table 10 reports production function estimates for cognitive and socio-emotional skills. The first and third columns present Ordinary Least Squares (OLS) estimates, while the second and fourth columns show instrumental variable (IV) estimates. All specifications

Table 8: Estimates of the Reduced Form

	Cognitive skills	Socio-emotional skills
Demolition	-0.12**	-0.17**
	[-0.15, -0.03]	[-0.26, -0.13]
Household resources	0.03**	0.00
	[0.01, 0.04]	[-0.02, 0.01]
Employment growth	-1.54	-0.84
	[-2.48, 2.06]	[-2.65, 3.99]
Observations	1655	1453

Notes: 90% confidence intervals (CI) are reported in brackets. ** indicates that the 95% CI does not cross 0; * indicates that the 90% CI does not cross 0. 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, maternal educational attainment, the number of siblings, the neighborhood's average household income, the share of high school graduates, the homicide rate, racial composition, and the unemployment rate.

Table 9: Fixed Effects Estimates

	Cognitive skills	Socio-emotional skills
Treatment * Post	-0.25***	-0.21***
	[-0.37, -0.12]	[-0.30, -0.12]

Notes: Asymptotic ninety percent confidence intervals are presented in brackets, allowing for clustering at the neighborhood level. Significance levels are indicated as follows: $***p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

include the same set of control variables: the child's age, maternal educational attainment, the number of siblings, the neighborhood's average household income, the share of high school graduates, the homicide rate, the racial composition, and the unemployment rate.

Table 10: Estimates of the Production Functions

	Cognitive skills w2		Socio-emotional skills w2	
	OLS	IV	OLS	IV
Community support	0.00	0.13**	0.05**	0.14**
	[-0.02, 0.04]	[0.02, 0.19]	[0.02, 0.09]	[0.10, 0.30]
Parental investments	0.02	0.40**	0.03*	0.00
	[-0.04, 0.03]	[0.15, 0.46]	[0.00, 0.06]	[-0.20, 0.09]
Cognitive, w1	0.65**	0.55**	0.10**	0.07**
	[0.51, 1.10]	[0.51, 0.75]	[0.07, 0.25]	[0.04, 0.18]
Socio-emo., w1	0.12**	0.08**	0.85**	0.87**
	[0.05, 0.19]	[0.04, 0.15]	[0.72, 0.95]	[0.78, 0.96]
Observations	1468	1468	1335	1335

Notes: 90% confidence intervals (CI) are reported in brackets. ** indicates that the 95% CI does not cross 0; * indicates that the 90% CI does not cross 0. 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, maternal educational attainment, the number of siblings, the neighborhood's average household income, the share of high school graduates, the homicide rate, racial composition, and the unemployment rate.

The OLS estimates indicate no significant correlation between community support and cognitive skills, but a positive correlation with socio-emotional skills. However, once endogeneity is addressed through the IV approach, community support becomes an important determinant of both cognitive and socio-emotional skills. A one standard deviation (SD) increase in log community support raises log cognitive skills by 0.13 units and log socio-emotional skills by 0.14 units. To illustrate, a 1.31 SD increase in log community support corresponds to shifting responses to the question "How likely would neighbors do something about kids skipping school" from "likely" to "very likely".[13] As another illustration, Table 4 shows that a 1 SD increase in log community support is correlated with a $50,000 increase in the neighborhood's average household income.

For parental investments, the OLS estimates suggest no statistically significant associa-

[13]This example is based on the measurement system estimates; analogous interpretations can be drawn for other survey items measuring community support.

tion between parental investments and the skill outcomes. In contrast, if we treat parental investments as endogenous, the IV estimates suggest that their effect on cognitive skills becomes both large and significant. 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 adverse shocks in the development process. A one SD increase in log parental investments improves log cognitive skills by 0.4 units. [14] In contrast, parental investments show no significant effect on socio-emotional skills at this stage.

Taken together, the results highlight that parental investments are particularly effective in fostering 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 shape these skills may be more limited as children grow older.

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. Across both OLS and IV estimates, a one-unit increase in log cognitive skills raises future log cognitive skills by 0.55–0.65 units. Persistence is even stronger for socio-emotional skills: a one-unit increase today translates into roughly 0.9 units in the future. Second, skills are cross-productive. A one-unit increase in log cognitive skills raises log socio-emotional skills by about 0.1 units. The impacts of socio-emotional skills on cognitive skills are similar, with a productivity of 0.08–0.12 units. These patterns of self-productivity and cross-productivity are consistent with findings from the broader child development literature.

8 Robustness Check

To assess the stability of my main findings, I conduct a series of robustness checks. First, I test the sensitivity of our results to alternative sample definitions by restricting the analysis to neighborhoods that only experienced demolitions and to non-moving residents. Second, I investigate potential alternative channels, specifically changes in the local crime and school environments, to ensure the results are not driven by these confounding factors. Finally, I confirm the validity of our research design by accounting for demolitions that occurred after the primary treatment period.

[14] Based on the measurement system estimates, a 0.9 SD increase in log parental investments is equivalent to caregivers encouraging the child to read from less than once a month to about once a month. Further improving the frequency from about once a month to a few times a month is equivalent to a 2.03 SD increase.

8.1 Analysis of Neighborhoods with Demolitions Only

To test the robustness of the main findings, I restrict the sample to a more comparable set of neighborhoods. Specifically, the sample is limited to only those neighborhoods that eventually experienced demolition, using later-demolished areas as a control group for those demolished earlier. On this restricted sample, I re-estimate both the reduced-form fixed-effects model and the skill production function.

The fixed effects estimates in Table 11 indicate that, even after accounting for unobserved neighborhood and individual heterogeneity, demolition leads to declines in both cognitive and socio-emotional skills. Reassuringly, the magnitudes of these effects are similar to those in Table 9, strengthening the credibility of the original results.

Because this restriction substantially reduces the sample size, it weakens the instrumental variables and renders inference unreliable. To preserve the sample with minimal changes, I impute missing values for the household income instrument, which is the single largest source of missingness. I use two approaches: (i) simple mean imputation, replacing missing values with the sample mean of household income, and (ii) regression-based imputation, where all other analysis variables are used to predict missing values for household income.[15]

Table 12 compares the production function estimates from the baseline model (Table 10) with those from the restricted sample using both imputation methods. The results are highly stable and quantitatively similar across specifications. Overall, this stability suggests that our main findings are robust and not driven by unobserved differences between neighborhoods with and without demolitions.

Table 11: Fixed Effects Estimates

	Cognitive skills	Socio-emotional skills
Treatment * Post	-0.21*	-0.29**
	[-0.37, -0.06]	[-0.45, -0.14]

Notes: Asymptotic ninety percent confidence intervals are presented in brackets, allowing for clustering at the neighborhood level. Significance levels are indicated as follows: $***p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[15] Variables used for prediction include cognitive and socio-emotional skills, community support, parental investments, demolition, employment growth, the child's age, parents' educational attainment, the number of siblings, the neighborhood's average household income, the share of high school graduates, the homicide rate, racial composition, and the unemployment rate.

Table 12: Production Functions Estimates (restricted to neighborhoods with demolitions)

	Cognitive skills, w2			Socio-emotional skills, w2		
	Full sample	Small sample	Small sample	Full sample	Small sample	Small sample
Community support	0.13**	0.13*	0.14*	0.14**	0.14**	0.15**
	[0.02, 0.19]	[0.00, 0.27]	[0.00, 0.29]	[0.10, 0.30]	[0.07, 0.41]	[0.06, 0.39]
Parental investments	0.40**	0.33**	0.41**	0.00	-0.09	-0.07
	[0.15, 0.46]	[0.16, 0.47]	[0.15, 0.50]	[-0.20, 0.09]	[-0.23, 0.07]	[-0.29, 0.03]
Cognitive, w1	0.55**	0.56**	0.53**	0.07**	0.06*	0.07*
	[0.51, 0.75]	[0.47, 0.71]	[0.46, 0.71]	[0.04, 0.18]	[0.00, 0.15]	[0.00, 0.15]
Socio-emo., w1	0.08**	0.09**	0.07**	0.87**	0.80**	0.79**
	[0.04, 0.15]	[0.02, 0.14]	[0.02, 0.14]	[0.78, 0.96]	[0.70, 0.96]	[0.69, 0.95]
Imputation	No	Mean imputation	Regression imputation	No	Mean imputation	Regression imputation
Observations	1468	405	405	1335	397	397

Notes: 90% confidence intervals (CI) are reported in brackets. ** indicates that the 95% CI does not cross 0; * indicates that the 90% CI does not cross 0. 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, maternal educational attainment, the number of siblings, the neighborhood's average household income, the share of high school graduates, the homicide rate, racial composition, and the unemployment rate.

8.2 Analysis of Non-Moving Residents

I observe household mobility between wave 1 and wave 2, with about a quarter of households moving during this period. Mobility rates do not differ significantly between the treatment and control groups. Still, stayers remain fully exposed to the decline in community support, whereas movers may partly avoid it. To address this, I conduct a robustness check restricting the sample to non-movers. As shown in Table 13, the estimates are consistent with the main results (Table 10), indicating that mobility does not substantially affect the findings.

8.3 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,

Table 13: Production Functions Estimates (restricted to non-moving residents)

	Cognitive skills w2		Socio-emotional skills w2	
	OLS	IV	OLS	IV
Community support	0.01	0.14**	0.04**	0.14**
	[-0.01, 0.06]	[0.02, 0.27]	[0.02, 0.09]	[0.09, 0.32]
Parental investments	0.00	0.44**	0.03**	0.02
	[-0.07, 0.02]	[0.12, 0.52]	[0.01, 0.07]	[-0.18, 0.19]
Cognitive, w1	0.72**	0.58**	0.09**	0.08**
	[0.53, 1.27]	[0.51, 0.78]	[0.07, 0.30]	[0.03, 0.21]
Socio-emo., w1	0.12**	0.09**	0.82**	0.85**
	[0.04, 0.23]	[0.05, 0.19]	[0.67, 0.92]	[0.69, 0.94]
Observations	1088	1088	971	971

Notes: 90% confidence intervals (CI) are reported in brackets. ** indicates that the 95% CI does not cross 0; * indicates that the 90% CI does not cross 0. 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, maternal educational attainment, the number of siblings, the neighborhood's average household income, the share of high school graduates, the homicide rate, racial composition, and the unemployment rate.

school type, school resources, and peer composition. In waves 1 and 2 of the PHDCN, primary caregivers rated their children's education and provided information on school type (public vs. private). I also collect school-level information from the National Center for Education Statistics (NCES) and use data from 1993-1997 to examine the effects of demolition on school-level characteristics. The pupil–teacher ratio serves as a proxy for school resources, while the share of low-income students is used as a measure of peer composition.

I use a fixed effects 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 schools when examining pupil-teacher ratio and low-income student share. $Y_{k,t}$ is one of the four outcomes, and $D_{k,t}$ equals 1 if unit k is treated in year t.[16] λ_k denotes school/individual fixed effects, ψ_t denotes time fixed effects, and $\epsilon_{k,t}$ is the error term.

Table 14 presents the estimates for these four regressions. Observations are at the school/individual-by-year level. All dependent variables, except for *public school*, are standardized to have a mean of zero and a standard deviation of one. *Public school* is a dummy variable; 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.

While the share of low-income students remains unaffected, demolition may cause non-displaced children to lose some friends. If only the average quality of friends (proxied by low-income share) matters, the number of friends lost may not influence the estimates. To test whether the loss of friends biases the results, I conduct an additional robustness check.

Ideally, we would measure the friendships of cohort members directly, but this information was not collected, and we lack data on which schools they attended. As a proxy, I rely on neighborhood-level data and construct a same-race friend share measure based on the principle of homophily. Specifically, using NCES school data, I compute the racial composition of children in each neighborhood and assign this share to cohort members based on their own race.

The *Peer* columns in Table 15 present the results controlling for both pre- and post-demolition friend shares. The estimates remain robust: while the point estimates for community support and parental investments shift modestly, the changes are small relative

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

to the original 95% confidence intervals.

Table 14: School Environment

Dependent variables:	(1) Education rating	(2) Public school	(3) Pupil-teacher ratio	(4) Low-income share
Treatment * Post	-0.073 [-0.477, 0.331]	-0.037 [-0.085, 0.011]	-0.016 [-0.045, 0.013]	-0.058 [-0.168, 0.051]
Observations	3390	3486	1903	1709

Notes: This table presents the fixed effects 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. Asymptotic ninety percent confidence intervals are presented in brackets, accounting for clustering at the neighborhood level. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.

8.4 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, the existing literature primarily examines the impacts of post-1999 demolition on crime. Aliprantis and Hartley (2015) and Sandler (2017) find that demolition reduces crime in affected neighborhoods, with concentrated declines in violent offenses, including homicide and gunfire incidents. However, the scale of demolition after 1999 (about 16,000 units) is much larger than the demolition studied in this paper (about 700 units). Therefore, the estimated effects may not necessarily apply to our case.

Nevertheless, I include post-treatment crime in the production function to test if my estimates are affected. The only available post-treatment crime data at a meaningful level of granularity is the homicide count by census tracts in 1995, sourced from the *Homicides in Chicago, 1965-1995* dataset. Given that violent crimes such as homicide were the most affected by later large-scale demolitions, the homicide count should capture any post-treatment changes in crime, if present. Table 15 shows that the estimates with post-treatment crime included remain similar to those of the main specification in Table 10. Additional results using interpolated homicide data for 1996–1997 also yield consistent findings.[17]

[17] Results are available upon request.

Table 15: Production Functions Estimates (with additional controls)

	Cognitive skills, w2		Socio-emotional skills, w2	
	Crime	Peer	Crime	Peer
Community support	0.08*	0.16**	0.13**	0.18**
	[0.01, 0.19]	[0.05, 0.27]	[0.11, 0.33]	[0.13, 0.41]
Parental investments	0.34**	0.23**	0.00	0.04
	[0.15, 0.45]	[0.07, 0.37]	[-0.22, 0.10]	[-0.16, 0.16]
Cognitive, w1	0.60**	0.60**	0.07**	0.10**
	[0.50, 0.76]	[0.52, 0.77]	[0.04, 0.18]	[0.04, 0.19]
Socio-emo., w1	0.08**	0.10**	0.88**	0.75**
	[0.04, 0.15]	[0.06, 0.18]	[0.78, 0.96]	[0.65, 0.87]
Post-demolition crime	-0.03		-0.01	
	[-0.08, 0.04]		[-0.07, 0.14]	
Pre-demolition peer		0.00		0.00
		[-0.01, 0.01]		[-0.01, 0.01]
Post-demolition peer		0.00		0.00
		[-0.01, 0.01]		[-0.01, 0.01]
Observations	1468	1166	1335	1070

Notes: 90% confidence intervals (CI) are reported in brackets. ** indicates that the 95% CI does not cross 0; * indicates that the 90% CI does not cross 0. 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, maternal educational attainment, the number of siblings, the neighborhood's average household income, the share of high school graduates, the homicide rate, racial composition, and the unemployment rate. Additional model-specific control variables are listed in the table.

9 Using the Estimates: Counterfactual Experiments

I present the distributions of skills, parental investments, and community support by neighborhood income in Appendix A.4. Children from high-income neighborhoods possess stronger cognitive and socio-emotional skills than their peers from low-income neighborhoods. They also benefit from greater parental investments, and experience higher levels of community support. Understanding the determinants of skill formation helps us design effective interventions to reduce inequalities in human capital accumulation.

Using the production function estimates, I perform two counterfactual experiments to narrow the skill gap between children from high- and low-income neighborhoods. [18] The first experiment raises community support in low-income neighborhoods to the level observed in high-income neighborhoods. This scenario mirrors real-world initiatives aimed at strengthening community support. For example, the Joint Economic Committee's Social Capital Project in the U.S. has recommended policies like community mentoring programs and investments in infrastructure such as libraries and parks to foster neighborly connections (Joint Economic Committee, 2021).

Figure 6 displays the impacts of a permanent increase in community support on the socio-emotional skill gap between children from high- and low-income neighborhoods. [19] Each period corresponds to three years. The blue line shows that, absent intervention, the skill gap widens over time. The red line shows that while the intervention does not halt this widening, it significantly flattens the trajectory. The socio-emotional skill gap narrows by 22% in the first period and by 31% in the final period.

Figure 7 shows the impacts of two interventions on the cognitive skill gap: a permanent increase in community support, or a permanent increase in parental investments.[20] While both interventions reduce the cognitive gap by approximately 27% initially, their long-term effects diverge. The community support intervention becomes progressively more powerful, ultimately reducing the gap by 43% compared to 36% for the parental investment intervention. This amplifying effect is driven by community support's positive impact on socio-emotional skills, which in turn cross-productively boost cognitive development.

Taken together, these results highlight that while parental investments are estimated to be more effective for cognitive skills, larger inequality in the distribution of community

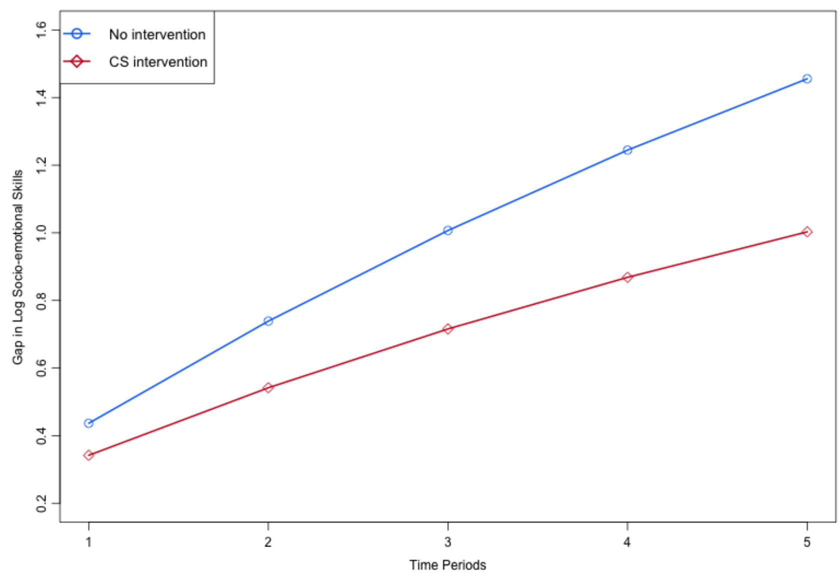
[18] The same production function estimates are applied to both groups, with parameters assumed to be constant over time.

[19] The experiment is equivalent to a 0.88 SD increase in log community support.

[20] The parental investment intervention corresponds to a 0.28 SD increase in log parental investments. This experiment is only performed for cognitive skills since parental investments are not effective for socio-emotional skills.

support creates more scope for improvement along this dimension.[21] As a result, interventions targeting community support can play an especially powerful role in reducing skill inequality.

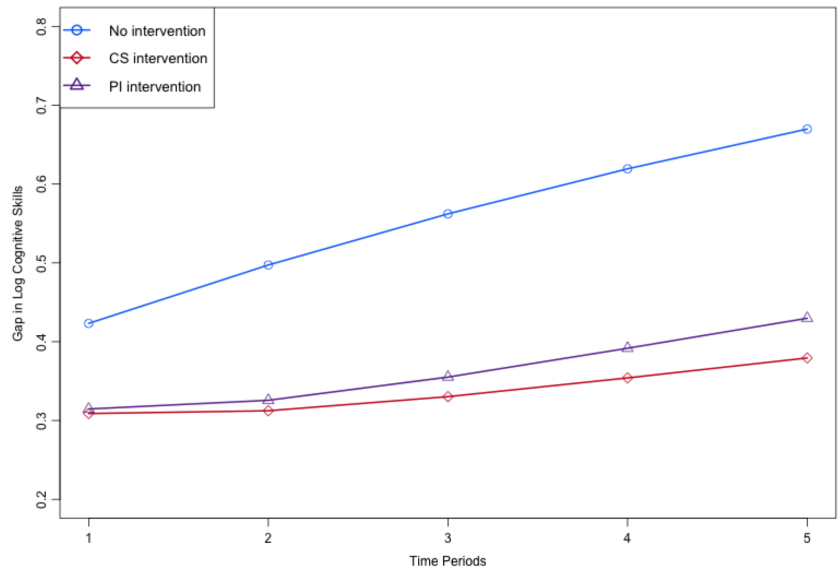
Figure 6: Impacts of an Increase in Community Support on the Socio-emotional Skill Gap



Notes: This figure shows the effects of permanent improvements in community support on the socio-emotional skill gap between children in high- and low-income neighborhoods. The blue line with circles shows the gap with no intervention. The red line with diamonds represents an intervention raising community support in low-income neighborhoods to high-income neighborhoods. Each time period represents three years

[21]See Appendix A.4 for distributions.

Figure 7: Impacts of an Increase in Community Support or Parental Investments on the Cognitive Skill Gap



Notes: This figure shows the effects of permanent improvements in community support or parental investments on the cognitive skill gap between children in high- and low-income neighborhoods. The blue line with circles shows the gap with no intervention. The red line with diamonds represents an intervention raising community support in low-income neighborhoods to high-income neighborhoods. The purple line with triangles shows the effect of raising parental investments to high-income levels. Each time period represents three years.

10 Conclusion

This paper studies a previously overlooked channel through which neighborhoods shape child development: a community's capacity to supervise, guide, and invest in children, which I refer to as community social support. I incorporate this form of support into a dynamic skill production function to jointly analyze its role alongside parental investments for children aged 6 to 15.

I begin by developing a robust measure of community social support using a novel neighborhood survey from the Project on Human Development in Chicago Neighborhoods. Leveraging a latent factor approach, I identify a set of indicators to quantify this specific form of community input. This approach highlights substantial variation in community support both across and within Chicago neighborhoods.

Next, I establish the causal effects of both community support and parental investments, addressing endogeneity through an instrumental variable approach. The results reveal distinct roles for the two key inputs. Community support significantly boosts both cognitive and socio-emotional skills. Parental investments are highly effective for cognitive skills, exhibiting effects three times larger than community support in this domain, but show a limited impact on socio-emotional skills during this school-age period. This suggests that the window for parents to foster socio-emotional skills may narrow after early childhood, highlighting the neighborhood's importance at this stage.

Finally, counterfactual experiments demonstrate the potential of neighborhood-level interventions to reduce developmental inequality. Specifically, raising community support in low-income areas to high-income levels proves effective, narrowing the gap in socio-emotional and cognitive skills by 22% and 27% in the short run, and increasing to 31% and 43% in the long run. While a similar experiment increasing parental investments yields comparable initial effects, raising community support has an amplified long-run effect. This arises because community support positively influences socio-emotional skills, which then recursively reinforce cognitive development over time.

Overall, the findings underscore the complementary roles of family and community in fostering human capital. While policies that enhance household resources or parenting practices remain important, reducing inequality in child development also requires community-based initiatives. These community-based initiatives are necessary for two reasons. First, the data reveal a much wider disparity in community support than in parental investments across neighborhoods, implying a greater scope for policy to close these gaps. Second, community support directly strengthens socio-emotional skills, an area where parental influence appears to be less pronounced as children grow older. Therefore, policies that expand mentoring programs, enhance shared public spaces, and strengthen neighborhood institutions can play a crucial role in promoting equal opportunities in child development.

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A Appendix

A.1 Theoretical Framework

This section develops a simple two-period model of parental decision-making to formalize the empirical challenges in estimating a skill production function. Household i chooses consumption $C_{i,t}$, parental investments $I_{i,t}$, and a residential location $R_{i,t}$ from the choice set $\mathcal{N}$, which includes 343 neighborhoods in Chicago. The household derives utility from current consumption, the child's future human capital $H_{i,t+1}$, and a vector of neighborhood amenities $\boldsymbol{Q}_{R_{i,t}}$.[22] 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 $p_{i,t}$ is the price of investments, $d_{R_{i,t-1}, R_{i,t}}$ is the moving cost, $m_{R_{i,t}}$ is rent, $w_{i,t}$ is the wage rate, and $y_{i,t}$ is non-labor income. Time is normalized to one. Since parental investments include both time and goods, $p_{i,t}$ reflects both wage rate and the prices of goods like books and educational toys.

The skill production functions are given by:

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

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

where $\theta^c_{i,t}$ and $\theta^s_{i,t}$ denote cognitive and socio-emotional skills, $I_{i,t}$ represents parental investments, $CS_{i,R_{i,t}}$ is community support, $\boldsymbol{X}_{i,t}$ 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 choices can be derived from this model:

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

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

These equations show that decisions depend on current skill endowments, amenities,

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

moving costs, and rents across all neighborhoods, as well as investment prices, wages, income, and household characteristics. Importantly, they also depend on shocks unobserved by the researcher. This creates endogeneity: for example, if a child falls ill or faces negative influences from current neighborhood, parents may respond by adjusting investments or relocating, confounding OLS estimates of the effects of investments and community support.

At the same time, the dependence of 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. Conditional on the income effect, a stronger labor market increases the cost of allocating time and effort to children, reducing parental investments. Conversely, higher household income relaxes the budget constraint, enabling parents to make more investments.

A.2 Data and Measurement Details

This appendix details the data sources, sampling design, and measurement system. The measurement section presents an exploratory factor analysis (EFA), which guides the specification of the measurement model in Table 3. It also reports the factor loadings for each indicator and provides the results of measurement invariance tests of community support between immigrant and U.S.-born groups.

A.2.1 Additional Notes on Data

Demolition and Treatment Data Data on buildings demolished between 1995 and 2010 were obtained from the Chicago Housing Authority. Using the Census Geocoder, these addresses were geocoded to their corresponding census tracts, which were then matched to neighborhood clusters using a crosswalk provided by the PHDCN. The "notice to proceed" date was selected as the treatment date because it marks the moment when the certainty of demolition begins to disrupt core community functions. Upon official confirmation, the long-term reciprocity needed for neighbors to watch each other's children or share resources rapidly declines. This creates the "atmosphere of perpetual change" where, as Austen (2018) observes, it becomes difficult to sustain the informal ties through which support and protective services are exchanged.

Sampling Design of the LCS The LCS used a three-stage sampling strategy. In the first stage, all 343 neighborhood clusters were cross-classified by two variables based on census information: racial-ethnic mix (seven categories) and socio-economic status (three levels).

80 neighborhood clusters were chosen through stratified random sampling. In the second stage, block groups were randomly selected from the aforementioned 80 neighborhood clusters, and all dwelling units within these blocks were included. In the final stage, households with children within the target age cohorts were selected and interviewed.

Sampling Design of the Community Survey 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 were 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.

A.2.2 Exploratory Factor Analysis

I assume a dedicated measurement system where each measurement proxies for only one latent factor to ensure transparent interpretation. I conduct EFA to determine the number of factors and the assignment of measurements to these factors.

The number of factors to extract is determined using Kaiser's eigenvalue rule (Kaiser, 1960) and Horn's parallel analysis (Horn, 1965). Kaiser's eigenvalue rule recommends retaining factors with eigenvalues greater than 1. It suggests extracting two factors from each of the following sets: skill measures at wave 1, skill measures at wave 2, parental investment measures, and community support measures. Horn's parallel analysis compares the eigenvalues from the actual data to those from a random dataset with the same number of variables and observations. Factors are retained as long as the eigenvalue from the actual data exceeds the corresponding eigenvalue from the random data. In this case, Horn's parallel analysis confirms the results from Kaiser's eigenvalue rule for all factor sets.

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 community support.

Having determined the number of factors to extract, I now assign the measurements to them. For parental investments and community support, I use all available measures, as each exhibits reasonably high correlations with its respective extracted factor.

For skills in wave 1 and wave 2, I implement an EFA with quartimin rotation by first estimating the factor loadings and then rotating them. The factor loadings are rotated

Table A16: Estimated Rotated Loadings on Child Development Measures in Wave 1

Measures	Factor 1	Factor 2
WRAT: Reading test scores	0.00	**0.93**
WISC: Word definition scores	0.01	**0.86**
CBCL: Withdrawn problems	**0.66**	-0.06
CBCL: Aggressive behavior	**0.79**	0.10
CBCL: Somatic complaints	**0.53**	-0.16
CBCL: Anxiety or depression	**0.78**	-0.05
CBCL: Social problems	**0.68**	0.05
CBCL: Thought problems	**0.77**	0.03
CBCL: Attention problems	**0.83**	0.02
CBCL: Rule-breaking behavior	**0.72**	-0.07

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

Table A17: Estimated Rotated Loadings on Child Development Measures in Wave 2

Measures	Factor 1	Factor 2
WRAT: Reading test scores	0.00	**0.83**
WISC: Word definition scores	-0.03	**0.83**
Attention duration levels	0.07	**0.42**
Comprehension of interview questions	0.08	**0.52**
CBCL: Withdrawn problems	**0.75**	-0.09
CBCL: Aggressive behavior	**0.76**	0.04
CBCL: Anxiety or depression	**0.82**	-0.06
CBCL: Social problems	**0.57**	0.13
CBCL: Thought problems	**0.69**	-0.02
CBCL: Attention problems	**0.83**	0.07

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

such that measures predominantly load on one factor, thereby satisfying the need for a dedicated measurement system. [23] Table A16 reports the rotated factor loadings for child development measures in wave 1. The estimates clearly suggest two distinct groups. The first two measures (reading and vocabulary) load heavily on the second factor, which is identified as cognitive skills. The remaining measures from the CBCL predominantly load on the first factor, which is labeled as socio-emotional skills. A similar pattern emerges in Table A17. The first four measures covering reading, vocabulary, attention, and comprehension load heavily on the second factor, while the CBCL measures load predominantly on the first. Based on these patterns, I use the CBCL measures to represent socio-emotional skills and all other measures to represent cognitive skills in both waves.

A.2.3 Confirmatory Factor Analysis

Our measurement system for skills, parental investments, and community support uses a mix of categorical and continuous variables. Specifically, measures for community support and parental investments are exclusively categorical. Skill measures are predominantly continuous, except for two categorical items related to a child's attention duration and comprehension of interview questions.

To model the relationship between the observed measurements and the latent factors, I employ a confirmatory factor analysis framework. Let m_{jki} denote the jth observed measurement for latent factor k and individual i. When m_{jki} is categorical, I 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 the literature usually assumes that the latent factor θ_{ki} is 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 captures the relationship between the continuous latent item m^*_{jki} and the observed item m_{jki}:

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

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

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

For continuous measurements, the observed measurement m_{jki} is equivalent to the latent item m^*_{jki}, $m^*_{jki} = m_{jki}$, and the relationship is directly specified as:

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

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. [24] Since latent factors have no inherent scale or location, we need normalization assumptions to set the scale and location.

To set the scale of the latent factors, I fix the factor loading of a designated reference measurement m_{1ki} to be one, $\lambda_{1k} = 1$ for factor k. Specifically, for community support, the designated reference measurement is *how likely your neighbors would do something about kids skipping school*. For parental investments, I use the measurement *frequency that the primary caregiver helped the child with homework*. As pointed out by Agostinelli and Wiswall (2025), maintaining a consistent scaling of latent factors is essential to ensure that dynamic latent factors are comparable over time. Therefore, for cognitive skills and socio-emotional skills, I use the same reference measurements across waves to ensure comparability over time. I use the *Wide Range Achievement Test score* for cognitive skills and the *Withdrawn Sub-scale of the Child Behavior Checklist* for socio-emotional skills.[25]

In terms of the location of the latent factors, I normalize the means of the log community support and log parental investments to be zero. For the dynamic latent factors (skills), I allow the means to change over time to avoid potential bias in the production function estimates (Agostinelli and Wiswall, 2025). Instead, I constrain the intercepts of the reference measurements (the *Wide Range Achievement Test score* and the *Withdrawn Sub-scale*) to be zero over time. [26] This constraint assumes that the mapping from these reference measurements to their respective latent factors is invariant with respect to a child's age. Any observed growth in the measures is only attributed to the growth of the underlying latent factors.

Additional assumptions are necessary to identify the measurement system with categorical measures. Since thresholds and intercepts cannot be jointly identified, I normalize the intercepts for all categorical items to zero. As neither the latent item nor the latent factor

[24] 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 measures are continuous, as done in Cunha et al. (2010) and Attanasio et al. (2020c).

[25] All continuous skill measures have been standardized, with the reference measurements in waves 1 and 2 standardized using the same means and standard deviations.

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

has a scale, I normalize the residual variances $V(\epsilon_{jki})$ to be one and obtain the variance of latent items as $V(m^*_{jki}) = \lambda^2_{jk} V(ln\theta_{ki}) + 1$. [27]

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. [28] Lastly, I assume the mapping from the latent factors to the measures is separable, as is common in this literature.

A.2.4 Measurement System Estimation

This section provides additional details on the estimation of the measurement systems for the 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. The mixed nature of the indicators requires different correlation estimators. When only continuous variables are involved, Pearson correlations are calculated. For categorical items, I use polychoric correlations, and for mixed-variable pairs, I use polyserial correlations. To obtain these correlations, I first estimate the thresholds for each item from its 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. 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 stable than WLS with small and

[27] An alternative is to set the variance of the latent items m^*_{jki} to be one for all associated categorical measurements, obtaining the residual variances as $V(\epsilon_{jki}) = 1 - \lambda^2_{jk} V(ln\theta_{ki})$.

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

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.

Table A18 presents the estimated factor loadings for all measures. In this dedicated measurement system, each measure relates exclusively to one latent factor. Additionally, as elaborated in Section A.2.3, I normalize the factor loading of one measure for each latent factor to one.

With these measurement system estimates, we can compute the signal-to-noise ratio (presented in Table 3), which assesses the degree of information contained in a measurement relative to the measurement errors. It is computed by

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

A.2.5 Measurement Invariance Between Immigrant and U.S.-Born Groups

I assess measurement invariance between immigrant and U.S.-born groups. Given that the community support measure is tailored to an individual's immigration status, it is crucial to confirm that the evaluation metrics are consistent for both immigrants and U.S.-Born. In essence, we want to test if immigrant and U.S.-Born respondents assess community support in the same way. Otherwise, disparities between the two groups could be attributed to differences in measurement rather than substantive variations in community support.

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 A18: Estimates of Factor Loadings

Measures	Latent factors					
	Community Support	Parental investments	Cognitive skills, w1	Socio-emo. skills, w1	Cognitive skills, w2	Socio-emo. skills, w2
Neighbors do something about kids skipping school	1.00	0	0	0	0	0
Neighbors do something about kids defacing bldg	0.94	0	0	0	0	0
Neighbors scold a kid for not showing respect	0.76	0	0	0	0	0
Children look up to adults in the neighborhood	0.56	0	0	0	0	0
Adults watch out for children	0.81	0	0	0	0	0
Parents know their children's friends	0.81	0	0	0	0	0
Adults know who local children are	0.81	0	0	0	0	0
Parents generally know each other	0.85	0	0	0	0	0
Frequency PC encouraged SP to read, past month	0	1.00	0	0	0	0
Frequency PC praised SP about accomplishment, past month	0	0.95	0	0	0	0
SP has any sports equipment?	0	1.09	0	0	0	0
Number of books in the house	0	2.43	0	0	0	0
Frequency PC helped SP with homework, past year	0	0.74	0	0	0	0
SP has dictionary at home for use?	0	1.40	0	0	0	0
SP has encyclopedia at home for use?	0	1.45	0	0	0	0
Number of books in house for SP's age	0	2.55	0	0	0	0
Number of tapes, CDs, or records for SP's age	0	0.76	0	0	0	0
Number of board games for SP's age	0	1.59	0	0	0	0
WRAT: Reading scores	0	0	1.00	0	0	0
WISC: Word definition scores	0	0	0.96	0	0	0
CBCL: Withdrawn problems	0	0	0	1.00	0	0
CBCL: Aggressive behavior	0	0	0	1.72	0	0
CBCL: Somatic complaints	0	0	0	0.77	0	0
CBCL: Anxiety/depression	0	0	0	1.11	0	0
CBCL: Social problems	0	0	0	2.28	0	0
CBCL: Thought problems	0	0	0	2.38	0	0
CBCL: Attention problems	0	0	0	1.58	0	0
CBCL: Rule-breaking behavior	0	0	0	1.45	0	0
WRAT: Reading scores	0	0	0	0	1.00	0
WISC: Word definition scores	0	0	0	0	1.01	0
Attention duration levels	0	0	0	0	0.73	0
Comprehension of interview questions	0	0	0	0	1.20	0
CBCL: Withdrawn problems	0	0	0	0	0	1.00
CBCL: Aggressive behavior	0	0	0	0	0	1.07
CBCL: Anxiety/depression	0	0	0	0	0	1.14
CBCL: Social problems	0	0	0	0	0	0.84
CBCL: Thought problems	0	0	0	0	0	0.92
CBCL: Attention problems	0	0	0	0	0	1.18

Notes: This table presents the estimated factor loadings for all measures of community support, parental investments, cognitive skills, and socio-emotional skills in both waves. For each latent factor, one loading is normalized to one.

Table A19 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 et al., 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 $\Delta RMSR > 0.010$.[29] Based on these cutoffs, I cannot reject the null that community support is measured with the same metric between the immigrant group and the U.S.-Born group. This allows me to interpret the differences as actual variations in community support.

Table A19: Measurement Invariance Test

	df	χ^2	RMSEA	CFI	RMSR
Baseline model	40	4294.191	0.157	0.946	0.085
Threshold invariance	56	4331.571	0.133	0.945	0.087
Threshold and loading invariance	63	4377.116	0.126	0.945	0.088
Threshold, loading, and intercept invariance	70	4614.801	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.

A.3 Additional Robustness Checks

Subsequent demolition Additional demolition activities occurred after 1995. To avoid contamination in the control group, the main analysis excludes neighborhoods that experienced demolitions in 1996–1997, as most outcomes were measured by 1998. Since a few treatment neighborhoods also experienced demolitions during 1996–1997, I perform a robustness check. I control for these subsequent demolitions and exclude children living in neighborhoods with 1998 demolitions whose outcomes were measured after those demolitions occurred. This approach ensures the results are not confounded by exposure to later demolition waves. The results in Table A20 remain consistent, confirming that the original estimates are not driven by subsequent demolition activity.

[29] 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.

Father's educational attainments The main specification includes only maternal education because data on fathers' education contain substantially more missing values. Table A21 reports results from specifications that include fathers' education as an additional control. The estimates remain robust, suggesting that the findings are not sensitive to the exclusion of fathers' educational attainment.

Table A20: Production Functions Estimates

	Cognitive skills, w2	Socio-emotional skills, w2
Community support	0.10**	0.10**
	[0.03, 0.17]	[0.07, 0.25]
Parental investments	0.37**	-0.09
	[0.15, 0.43]	[-0.21, 0.10]
Cognitive, w1	0.55**	0.10**
	[0.49, 0.71]	[0.03, 0.17]
Socio-emo., w1	0.08**	0.85**
	[0.04, 0.16]	[0.77, 0.97]
Demolition 1996	0.02	-0.38**
	[-0.27, 0.23]	[-0.53, -0.04]
Demolition 1997	0.07	0.17
	[-0.12, 0.33]	[-0.05, 0.34]
Observations	1450	1317

Notes: 90% confidence intervals (CI) are reported in brackets. ** indicates that the 95% CI does not cross 0; * indicates that the 90% CI does not cross 0. 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, maternal educational attainment, the number of siblings, the neighborhood's average household income, the share of high school graduates, the homicide rate, racial composition, and the unemployment rate. Additional model-specific control variables are listed in the table.

Table A21: Production Functions Estimates

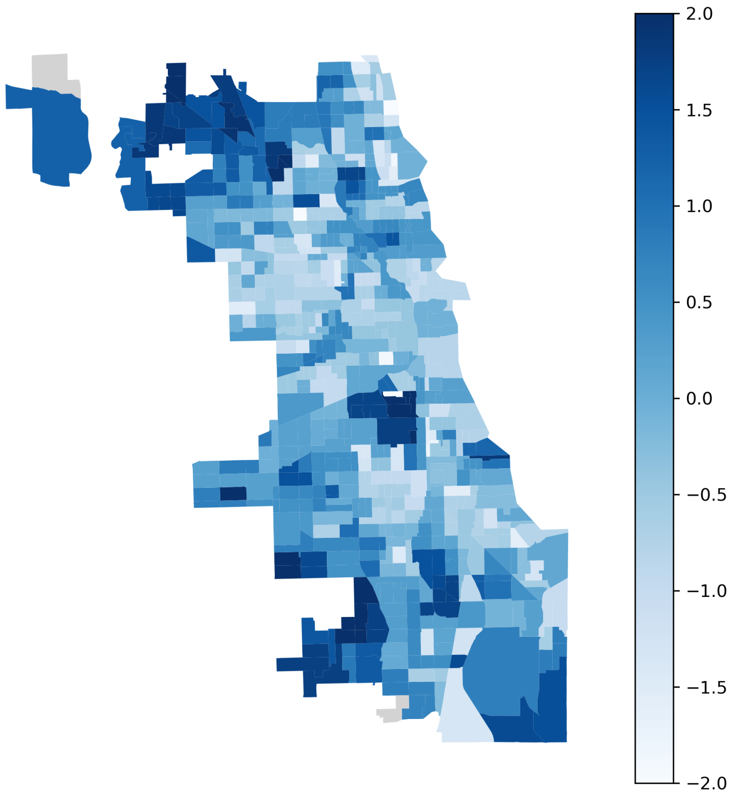
	Cognitive skills, w2	Socio-emotional skills, w2
Community support	0.11**	0.15**
	[0.02, 0.18]	[0.12, 0.30]
Parental investments	0.36**	0.05
	[0.15, 0.47]	[-0.21, 0.12]
Cognitive, w1	0.57**	0.08**
	[0.49, 0.73]	[0.05, 0.20]
Socio-emo., w1	0.09**	0.80**
	[0.05, 0.17]	[0.69, 0.92]
Father education	0.02	0.01
	[-0.06, 0.06]	[-0.05, 0.09]
Observations	1308	1191

Notes: 90% confidence intervals (CI) are reported in brackets. ** indicates that the 95% CI does not cross 0; * indicates that the 90% CI does not cross 0. 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, maternal educational attainment, the number of siblings, the neighborhood's average household income, the share of high school graduates, the homicide rate, racial composition, and the unemployment rate. Additional model-specific control variables are listed in the table.

A.4 Descriptive Patterns

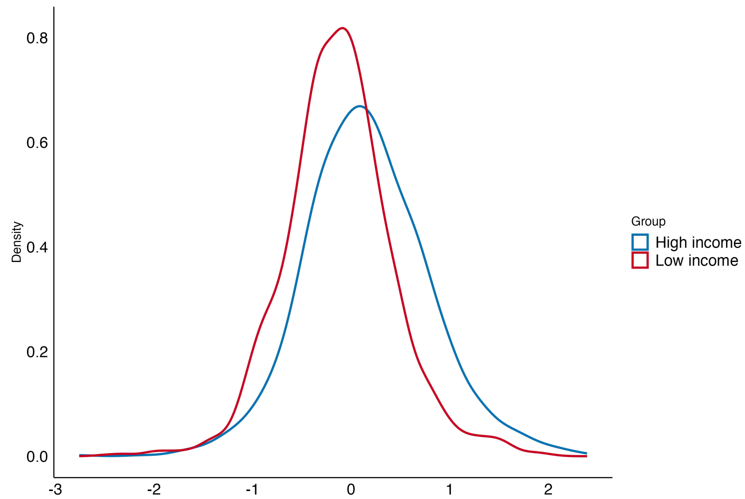
This section characterizes the distribution of key variables. Figure A8 first presents the spatial variation of community social support across Chicago neighborhoods. Figures A9 through A12 then display the distributions of skills, parental investments, and community support by neighborhood income. Both cognitive and socio-emotional skills are residualized with respect to children's age. All variables are standardized to a mean of zero and a standard deviation of one. The distributions reveal that, on average, children in high-income neighborhoods exhibit higher levels of both cognitive and socio-emotional skills than their peers in low-income neighborhoods. They also benefit from greater parental investments and community support. Furthermore, the disparity in community support between high- and low-income neighborhoods is larger than the corresponding disparity in parental investments.

Figure A8: Spatial Distribution of Community Social Support

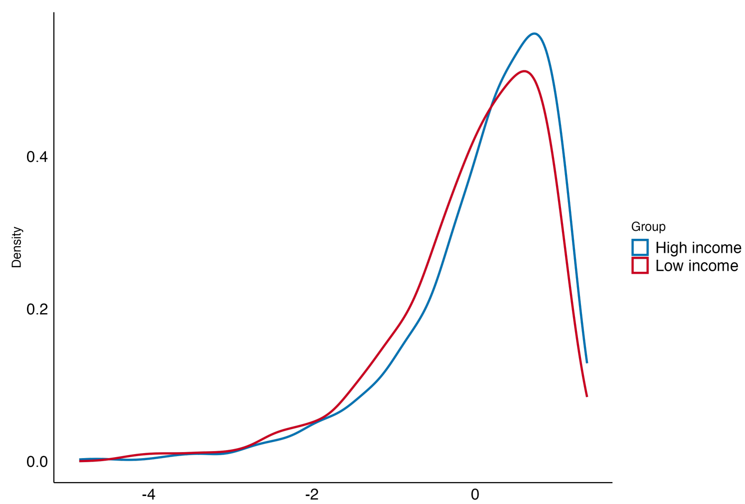


Notes: This figure illustrates the spatial variation of estimated Community Social Support across Chicago's 343 neighborhood clusters. The values represent standardized latent factor scores (see Section 5 for construction details). For visualization purposes, scores are censored at ± 2. Gray areas indicate clusters without data available. White areas inside the map boundaries denote independent municipalities excluded from the sampling frame.

Figure A9: Distribution of Skills in Wave 1 by Neighborhood Income



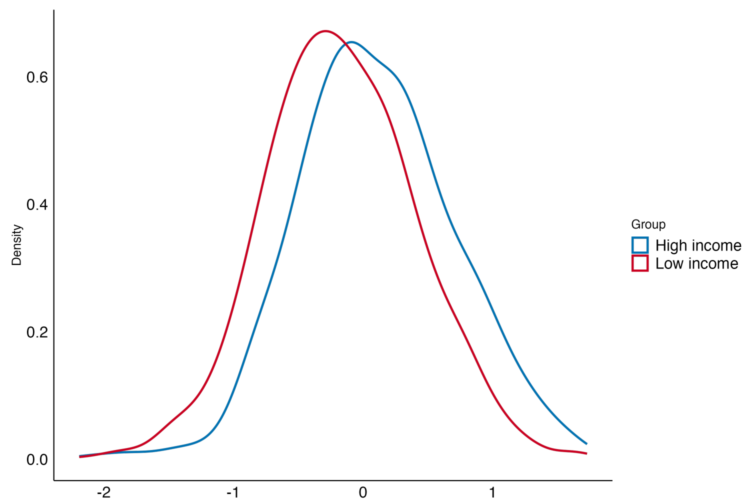
(a) Cognitive Skills



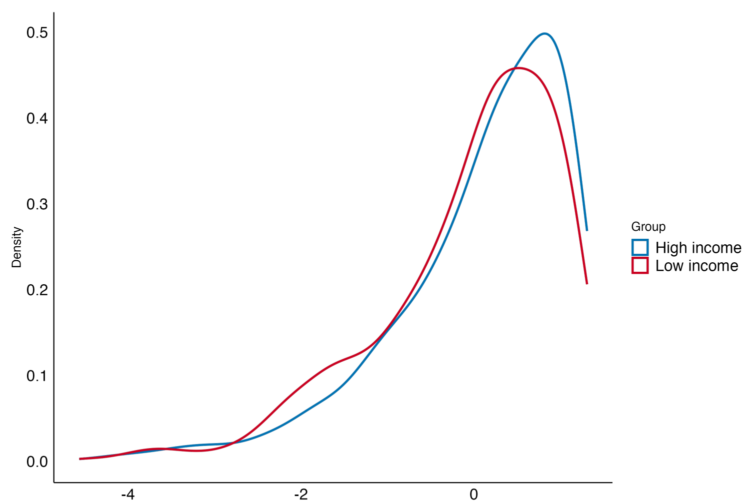
(b) Social-emotional Skills

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

Figure A10: Distribution of Skills in Wave 2 by Neighborhood Income



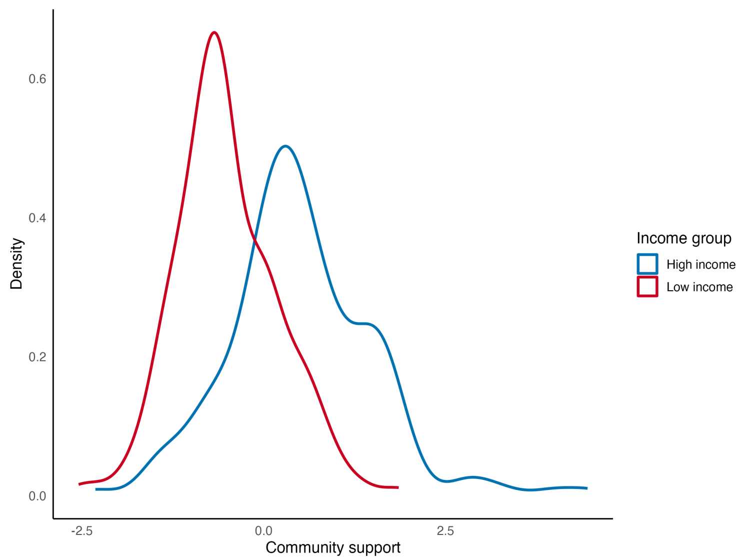
(a) Cognitive Skills



(b) Social-emotional Skills

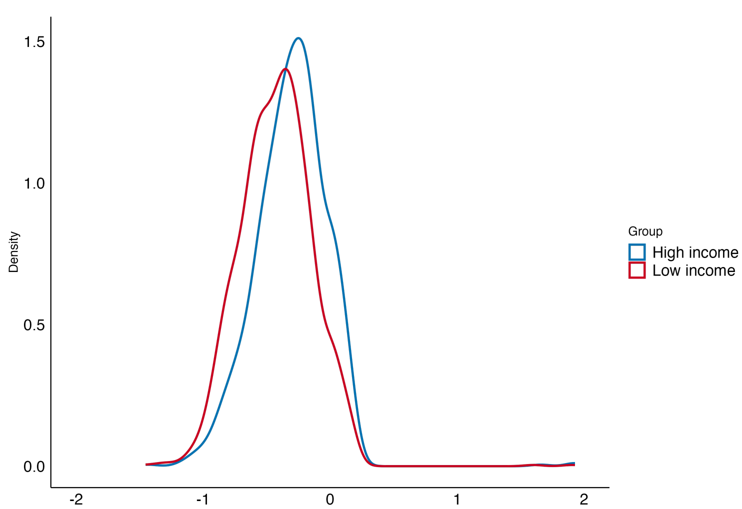
Notes: This figure illustrates the distributions of skills in wave 2 by neighborhood income. The top panel represents cognitive skills, while the bottom panel represents socio-emotional skills.

Figure A11: Distribution of Community Support by Neighborhood Income



Notes: This figure illustrates the distribution of community support by neighborhood income.

Figure A12: Distribution of Parental Investments by Neighborhood Income



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