Interrupting the Cycle: The role of Promise Neighborhood initiatives in creating access to opportunity

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Abstract

This study examined place-based, cradle-to-career approaches to community-level change such as Promise Neighborhoods and the indicators used to measure their impact. Key predictors from childhood were chosen for analysis to understand to what extent they contributed to educational attainment and economic mobility later in life. Data was used from the Child Development Supplement and Transition to Adulthood Supplement of the Panel Study of Income Dynamics (PSID) between the years of 1997 – 2019. Children who ranked higher in reading skills and social wellbeing achieved more years of education and higher incomes in early adulthood on average. However, the effects of neighborhood-level exposures included in the study such as safety and neighborhood quality proved to be largely inconclusive. Finally, subgroup analyses showed varying magnitude of effects across characteristics such as race, poverty level, and urbanicity.

Introduction

Racial differences in economic mobility have persisted for centuries and gaps continue to widen. Research on the causes of racial inequality points to discrimination and segregation as primary factors (Chetty et al., 2019) and enduring systemic racism has made it difficult to close the gap (Pratama, 2023). In addition, the concentration of Black, Brown, and Indigenous populations in high poverty neighborhoods has created cycles of intergenerational poverty that further exacerbate racial disparities. The result is that one's zip code can serve as a predictor of future life outcomes. As a result of the prevailing hypothesis that economic characteristics of neighborhoods affect economic mobility, In the 1990s, the Moving to Opportunity experiment was an attempt to test whether relocating low-income families to "opportunity neighborhoods" would improve economic outcomes (Shroder & Orr, 2012). In the years since Moving to Opportunity, even though the results were mixed (Shroder & Orr, 2012), policies have been introduced such as school choice and housing voucher programs in an effort to facilitate pathways to economic opportunity for low-income families. However, what if the opportunity moved to the neighborhood? Would investments in improving neighborhood quality, including neighborhood safety, higher quality schools, and better social services be a more effective use of resources to mitigate poverty transmission across generations?

During the Obama administration, a series of programs seeking to do just that were introduced to reverse the impacts of historic disinvestment, racial segregation through redlining, and the problem of under-resourced, high poverty schools. These place-based efforts sought to focus on the source as opposed to the symptom of racial and economic inequality by transforming neighborhoods into places of opportunity (Pettit et al., 2015). One of the cornerstone programs of this approach was the Department of Education's Promise Neighborhood Program, launched in 2010 by awarding planning grants to 21 place-based initiatives seeking to transform high poverty neighborhoods into opportunity neighborhoods (*U.S. Department of Education*, 2019). What followed has been a sustained investment for over a decade in the Promise Neighborhood program, accompanied by the expansion of similar community-level change initiatives seeking to improve outcomes for low-income families by expanding the unit of change from the individual to the community and systems-level.

Around the same time as the launch of the Promise Neighborhood initiative, an influential article in the Stanford Innovation Review by Kania and Kramer (2011) sought to understand and ultimately define the components of place-based initiatives seeking community-wide transformation. They coined the term “Collective Impact” to describe coordinated, cross-sector approaches that sought to affect population-level change. According to Kania and Kramer, what made the Collective Impact strategy unique and compelling was the systems-change orientation to solving the complex challenges facing high-poverty neighborhoods. As opposed to individual-level interventions (i.e. an afterschool program, tutoring program, and employment or housing program, etc.) operating in silos, the Collective Impact approach involve intentional collaboration, data sharing, shared accountability, and aligned goals. In addition, the engagement of philanthropy, the private sector, and policymakers at different levels also served to tackle the problem at the systems-level, with the theory that not only the direct beneficiaries of the intervention but also the community at large would experience the positive effects of community transformation.

Background

While Kania and Kramer’s article is credited with coining the term Collective Impact as well as spurring an increase in attention paid towards coordinated systems-change strategies as an alternative to isolated program-level interventions to address social inequality, the concept in practice is not new. In fact, one of several critiques of Kania and Kramer’s article points out that diverse community coalitions have long sought to bring about systems change through grassroots organizing and advocacy (Wolff, 2016). Moreover, the Collective Impact framework was not created based on the authors’ firsthand account of developing cross-sector collaboratives but on a relatively small number of their own observations. Kanie and Kramer released an updated article in 2021 to respond to critiques and update the Collective Impact framework to center equity and community voice (Kania et al., 2021).

Over the past decade, the Collective Impact approach has undoubtedly received increased attention from both the public and private sector. The Promise Neighborhood program has now awarded over $1 billion in grants to a total of 64 organizations (*U.S. Department of Education*, 2023). Early on in the program, significant investment had outpaced the research and evaluation of such programs with the Government Accountability Office (GAO) calling in 2014 for a national evaluation plan to measure program effectiveness and impact across sites (Nowicki, 2014). Since the GAO report, the Department of Education has created a more robust technical assistance resource for grantees and invested considerably in creating a more cohesive evaluation framework (*Promise Neighborhoods*, 2023).

The challenge faced by Promise Neighborhoods and Collective Impact initiatives is *how* to know they are having the desired effect and whether they are focusing on the right levers to achieve the type of population-level change they are seeking. The simple explanation for this is that individual-level interventions are easier to evaluate using traditional experimental methods. For example, a well-designed literacy program can construct a randomized control study or use quasi-experimental designs to measure its impact on individuals or groups where a counterfactual can also be observed (practically and ethically). However, it is much more difficult to detect effects at the population-level given that a counterfactual population cannot be easily constructed due to the large amount of variables that could be at play—even by employing quasi-experimental group pairings based on similar geographic and social characteristics (Newcomer et al., 2015). Further complicating the issue is that community-level change initiatives hope to impact both individuals receiving services as well as individuals and groups *not* receiving the direct intervention (so-called spillover effects). This means the traditional impact evaluation approaches are not feasible (Nichols, 2013). It is thus difficult to establish whether specific outcomes are attributable to the initiative itself or other factors and to what extent population-level change is occurring.

Recent meta-analyses have been conducted by scholars and research firms seeking to understand whether Collective Impact initiatives are achieving desired results and what challenges and opportunities exist (Congdon et al., 2021; Lin et al., 2020). There is a growing consensus that, while Collective Impact-style initiatives are promising, the evidence-base has not caught up to the growth in number of such initiatives. One possible explanation for the gap between research and practice is the lack of scholarly agreement on the core theory behind Collective Impact (Lin et al., 2020). Without consensus on process standards or measurement indicators, there is significant variation in implementation across sites. For example, Hanson (2013) points out that place-based initiatives such as Harlem Children's Zone (HCZ), one of the original models for Promise Neighborhoods, are designed specifically for the neighborhood they serve; therefore, exact replication in other contexts can prove difficult and, in fact, this is by design since context is so important.

The other challenge that makes it difficult to determine effects of community-level change initiatives is the unit of analysis. For example, while the Harlem Children's Zone states as its mission "to change the face of the entire neighborhood," it is unclear whether any changes at the population-level can be traced back to HCZ (Hanson, 2013). Research has shown that Harlem students who attended HCZ flagship charter schools tended to out-perform their peers, however potential bias in sampling, the relatively limited time frame of the study (one-year standardized test outcomes), and criticisms of charter school-only models complicate the capacity to draw conclusions.

Lin et al. (2020) conducted the most comprehensive meta-analysis of community-level change initiatives that I could find in my research by reviewing empirical studies that specifically targeted population-level change as an outcome measure. This distinction is significant given that many Collective Impact programs aspire to long term systems change goals, though only track individual-level data or focus on process measures (such as the level of stakeholder engagement, goal alignment, etc.) as indicators of effectiveness (Lin et al., 2020). In reviewing 25 studies across six youth-focused community-level initiatives, the authors cumulated overall promising results at both the individual and community levels. Again, notably present across programs was the emphasis placed not only on the intervention but also how it fit the specific community context. The conclusion emphasizes that most of the literature focuses on youth prevention programs (i.e. reducing violence, substance abuse, etc.) and that studies focused on other types of outcomes (such as education) are more limited.

Congdon, et al. (Congdon et al., 2021) also noted the differences in how community-level change initiatives approached both the focus of their intervention(s) as well as how measurement and evaluation was incorporated into their strategy. One recommendation offered is to use theory-based evaluation methods which build off of existing evidence and situate the initiative's focus within a causal chain of activities that lead to the desired outcomes (Congdon et al., 2021). This approach is expanded upon by Stachowiak et al. (2020) who discuss process tracing, which can combine qualitative and quantitative methods in order to understand the causal mechanisms that underlie a program or intervention. The advantage of this approach is the ability to test the program's theory of change and leverage the existing evidence-base to validate the interventions and methods chosen that have been proven elsewhere. The process tracing method results in strong internal validity of the evaluation, however, cannot be generalized outside of the program context (Stachowiak et al., 2020).

One of the other reasons that process tracing makes sense is that place-based initiatives focus on an array of population-change indicators, often referred to as cradle-to-career indicators that, together, link multiple protective factors together that can be influenced from birth to adulthood (StriveTogether, 2023). As more initiatives use these common measures, the evidence-base will grow. The federal Promise Neighborhood Program provides a predefined set of focus areas that include education and community-level indicators from which grantees are required to choose to focus their work (see Table 1) (*U.S. Department of Education*, 2019). In addition, private entities such as the StriveTogether network, which originated as a Collective Impact initiative called Strive Cincinnati and served as another form of inspiration for the Promise Neighborhood program, is now a national network and has published additional recommendations for community- and systems-level indicators (*A Guide to Racial and Ethnic Equity Systems Indicators*, 2020).

However, the variety of indicators available to also presents implementation and evaluation challenges. One challenge is time. It can be difficult to sustain multiple interventions from cradle-to-career such that outcomes in adulthood are manifested (Newcomer et al., 2015). The other challenge, as alluded to earlier, is the question of what mediating factors make a meaningful difference in education outcomes and economic mobility for children growing up at or near the poverty line. The multitude of community-level change indicators that can have an impact on cradle-to-career outcomes combined with varying amounts of research on each indicator prompted me to explore and also to empirically test select indicators to better understand their effects on a sample population and potentially inform recommendations for future study and practice.

The goal of this paper, thus, is to further examine the key population-level change indicators that Promise Neighborhoods, and Collective Impact initiatives more broadly, are influencing with the goal of systems change. The primary research question is: What are the individual and community-level predictors from childhood and adolescence that have an impact on educational attainment and economic mobility?

Literature Review

The research on the effects of poverty on economic mobility and educational outcomes is well documented and illustrates the complexity faced by initiatives that seek to mitigate the effects of growing up in poverty on outcomes later in life (Duncan et al., 2014, 2017, 2018). The widely cited Moving to Opportunity experiment led by the U.S. department of Housing and Urban Development (HUD) sought to demonstrate the extent to which neighborhood effects contributed to economic mobility. However, while families benefited across several dimensions of wellbeing, the effect of moving to low-poverty neighborhoods was not significant economically (Ludwig et al., 2012).

In a 2018 paper from the US Partnership on Mobility from Poverty, authors Acs, et. al. (Acs et al., 2018) argue that material factors alone (such as income) do not account for the differences in intergenerational economic mobility. However, family income does appear to make a difference if the timing of poverty takes place while children are youngest (Duncan et al., 2014). These papers, in addition to similar research on poverty and its effect on child development and outcomes later in life (Duncan et al., 2017; McKay et al., 2002; Turner et al., 2020) illuminate the myriad of factors that influence economic mobility. It is no wonder, then, that there is no one-size-fits-all approach to addressing the impact that poverty has on children and families, especially in neighborhoods with concentrated poverty. Place-based approaches such as Collective Impact and the Promise Neighborhood model have emerged as promising solutions to this challenge, however, much remains to be studied to understand the theory and practice behind these initiatives.

One of the limiting factors to fully understanding the factors in childhood that matter later in life, especially for a particular local population or context, is the lack of readily accessible data. Researchers (Brown et al., 2021) at the University of Minnesota sought to address this gap by using Minnesota Department of Education Statewide Longitudinal Education Data System (SLEDS) which traces key milestones from preschool through postsecondary education and workforce participation (*Minnesota Department of Education*, 2023). Using state-level longitudinal data allows for an in depth understanding of the factors beyond just socio-economic status that influence life trajectories. Findings from the Tracing Pathways study demonstrated the importance of academic factors as well as geographic location where K-12 education took place in influencing postsecondary wages and wage growth. These findings lead further questions about the connections between place-based factors, community-level factors and individual factors with respect to creating opportunity.

Research Methodology

Informed by cradle-to-career initiatives such as Promise Neighborhoods, my research used observational data to explore what predictors in childhood and adolescence influence educational attainment and economic mobility. Predictors selected for analysis were based on the focus areas of the federal Promise Neighborhood Program as well as the StriveTogether cradle-to-career network of community-level change initiatives. The research method included an original empirical analysis of panel data. Data used for this secondary analysis was from the Panel Study of Income Dynamics (PSID) where it is possible to further explore the predictive factors that correlate with economic mobility. Specifically, using OLS regression analysis, I modeled how individual and community factors in childhood and adolescence influence educational attainment and income later in life.

Variables selected for analysis included both individual-level factors (such as literacy skills and social wellbeing) as well as community-level factors such as the quality and safety of the neighborhood. By exploring the relationship between variables in childhood and adolescence and key outcomes later in life, the goal of this study was to better understand the individual and community factors that have the most significant impact. Findings from this research informed recommendations for how place-based population-level change initiatives can focus resources for optimal impact.

Data and Methods

As I have outlined thus far, the Promise Neighborhood movement is focused on addressing place-based poverty and its effect on child, family, and community wellbeing. In addition to understanding whether a particular initiative is working, community-level change initiatives must contend with the question of what levers will make the biggest difference in their community. To understand what childhood factors contribute to educational attainment and economic mobility, data from the Panel Study of Income Dynamics (PSID) was used. The PSID was chosen given both data accessibility and the survey's reputation as a key source of rich, nationally representative data on individuals over time. The population-level scope of the PSID allows for the application of findings to other contexts such as community-level change initiatives.

The sample used in this analysis includes all three waves of the initial Child Development Supplement (CDS) cohort (1997, 2002, and 2007) and six waves of the Transition to Adulthood (TAS) supplement (2009, 2011, 2013, 2015, 2017, and 2019). The CDS was developed to better understand how economic and social factors affected child development (Hofferth et al., 1997). The children in the CDS cohort were ages 0-12 in 1997, 5-17 in 2002, and 10-17 in 2007. When these children turned 18 (or in some cases, 17), they were included in the Transition to Adulthood (TAS) supplement which traced key milestones in early adulthood. In addition to observations from the CDS and TAS, the PSID Main Family File (MFF) was also used to capture household characteristics during childhood such as family income, parents' educational attainment and employment status, and urbanicity. The sample was restricted to CDS children who had both key outcome variables observed in the TAS between 2009 – 2019 and were not missing any key independent variables. Additional observations were then excluded (n=93) if they were missing any of the selected control variables. The resulting sample size used in the analysis included 1,125 children.

Demographically, the sample was 49.2%% White, 38.2% Black, 7.1% Hispanic, 1.1% Asian, <1% American Indian, and 4% other race. In addition, 52% of the sample were female. The PSID oversamples low-income and families of color and, as a result, there is a higher number of Black families than the population as a whole (14.9% of the U.S. population in 2020 identified as Black) (U.S. Census Bureau, 2020). In addition, 85.9% of the sample lived in an urban area growing up as determined by a measure of urbanicity used by the PSID. These characteristics mean that the sample selected for this analysis is more representative of the populations served by Promise Neighborhood initiatives.

In the 1997 CDS survey only, school administrators at the school where the child attended were surveyed. In the initial analysis, the 1997 school-based data was collected with the goal of understanding how systems indicators such as staff diversity and per-pupil funding were related to the key outcome variables. These school system indicators align with key Collective Impact goals such as school racial diversity and equitable education funding (*A Guide to Racial and Ethnic Equity Systems Indicators*, 2020). However, the sample size proved to be too small for the analysis to provide any real insights; therefore, the school-based variables were omitted from the final analysis. However,

Outcome Variables

Educational attainment and annual income were observed between the years 2009 and 2019, controlled by the respondent's age at the time of the observation. For both outcomes, the observations across each of the six years (2009, 2011, 2013, 2015, 2017, and 2019) were collapsed to construct a single composite variable by preserving the latest available observation. For example, if the most recent value was missing, the next most recent value was used. If that value was missing, the next most recent was used, and so on. This method produced a single, consolidated observation which allowed for the use of ordinary least squares (OLS) regression analysis. In addition to collapsing the observations into one variable, educational attainment was recoded into a continuous variable where an increase in 1 unit corresponds with a single year increase in education level. Using this scale, for example, a value of twelve signifies a high school graduate and a value of sixteen signifies a four-year college degree. Finally, only individuals between the ages of 22 to 28 at the time the education or annual income variables were observed were included in the sample.

As outlined in Table 2, the mean education level attained by the sample is 14.190 or just over 2 years of college. The subsample of Black respondents had a mean education level of 13.68 years and non-Black respondents on average attained 14.5 years of schooling. Children who grew up at 200% of the federal poverty level (FPL) or below averaged just over 13 years of education. Children above 200% FPL attained at least two years of college on average (14.58 years). The average education level attained by children who grew up in urban area was also over 14 years (14.271).

The annual income variable is a continuous variable consisting of the reported annual income of the respondent in the year prior to the year of the interview (i.e., the 2019 value consists of the annual income from 2018). Similar to the educational attainment outcome variable, income was also collapsed to construct a single observation. The sample was also limited to individuals with a minimum age of 22 and with an observed annual income of zero or greater. As described in Table 2, the mean annual income is $22,848 per year. The range of annual incomes in the sample is zero to $185,000, however, the median income is $18,720. The largest age group with earnings observed are 26-year-olds (n=394). For the subsample populations, the average income varies across groups. For example, black respondents reported an average income of $18,411 and white respondents' average income was $25,583. Children who grew up in low-income families had an average annual income of $17,431 as a young adult and urban children had an average income of $25,502.

Key Independent Variables

Four key independent variables were selected for analysis and included individual-level, community-level, and neighborhood-level exposures that align with Promise Neighborhood focus areas. Three of the four key independent variables selected were observed in the CDS between 1997 and 2005 from either child-level interviews, family-level interviews, or parent/caregiver (PCG) interviews. The fourth predictor variable was selected from the TAS supplement and observed between 2005 and 2019, however, was constrained to only include the value when the respondent was 17 or 18 years old.

Neighborhood quality. One of the central theories behind place-based antipoverty initiatives is the importance of the neighborhood environment. This is supported by evidence that community violence and crime contributes to higher levels of stress, even for individuals living in proximity to the violence but who are not direct victims themselves (Turner et al., 2020). In addition, the cumulative effects of trauma exposure in childhood have a strong negative relationship with academic outcomes and economic mobility more broadly (Turner et al., 2020). Chetty, et al. (Chetty et al., 2019) also provides evidence to support the relationship between neighborhood quality and economic mobility, specifically for Black males. In their study using American Community Survey data, findings suggested that Black males who live in low-poverty neighborhoods achieve a level of economic mobility that is close to parity with white children.

The PSID includes two indicators of neighborhood quality that can be used to understand how neighborhood-level factors in childhood mediate economic mobility and educational attainment. The first indicator is overall neighborhood quality for raising children. As a part of the CDS survey, parents/ caregivers are asked how they would rate their neighborhood as a place to raise children on a scale from one (excellent) to five (poor). A constructed variable was generated by taking the average neighborhood rating across three observations (1997, 2002, and 2007). Then, a binary variable was generated by recoding observations with a value between 1 and 3.4 as a high-quality neighborhood (value =1) and observations with an average neighborhood rating value greater than 3.4 as not a good neighborhood for raising kids (value=0). This strategy accounts for variation in neighborhood quality across survey years and the binary variable provides a clearer understanding of results.

Eighty-four percent of the full sample lived in high-quality neighborhoods. Seventy-five percent of Black respondents rated their neighborhoods as high quality while 92% of White respondents did. Seventy-three percent of families with incomes below 200% of the FPL rated their neighborhood as high quality as did 85.4% of urban families.

Neighborhood Safety. The other neighborhood-level exposure is a more specific measure of neighborhood safety, also reported by the parent/ caregiver. The survey asked parents/ caregivers how “safe is it to walk around alone in your neighborhood after dark.”

Response values to this question ranged from one to four with one being “completely safe” to four being “extremely dangerous”. Similar to the neighborhood rating variable, the neighborhood safety value was averaged across the three years it was observed (1997, 2002, and 2007). Then, a binary variable was constructed where a value of one indicated the child grew up in a “fairly safe” or “completely safe” neighborhood on average and a value of zero indicated that the family lived in a somewhat or “extremely dangerous” neighborhood. Eighty-four percent of the sample reported living in a fairly safe or completely safe neighborhood. The same was true for 73% of black respondents and 91% of white children. For children who grew up at or below 200% of FPL, 70% of parents reported their neighborhoods as safe and the average was 84% for urban families.

Social Wellbeing and Belonging. Social inclusion and sense of belonging to a supportive community are indicators that both the federal Promise Neighborhood program (*Promise Neighborhoods*, 2023) as well as the StriveTogether network (*A Guide to Racial and Ethnic Equity Systems Indicators*, 2020) include as recommended focus areas for community-level change initiatives. The PSID includes interview questions that survey a respondent’s social wellbeing across a variety of measures using the languishing/ flourishing scale (Stafford et al., 2008). The following questions were asked to understand the respondent’s sense of social wellbeing and belonging to community:

“In the last month, how often did you feel…

…That you had something important to contribute to society?”

…That you belonged to a community like a social group, your school, or your neighborhood?”

…That our society is becoming a better place?”

…That people are basically good?”

…That the way society works makes sense to you?”

Responses to these questions were recorded on a scale from one (“never”) to six (“every day”). Then, a subscale was generated to signify the respondent’s sense of overall social wellbeing by taking the average of all five responses. Responses were only included in this subscale if all were non-missing. The responses to the social wellbeing questions were recorded for sample respondents every two years between 2005 and 2019. In order to detect the relationship between social wellbeing and educational attainment and annual income later in life, the observations of this variable were consolidated to preserve the value at age 17 or 18 only, just as the child was entering the Transition to Adulthood supplement survey. The rationale being that detecting the individual’s social wellbeing just as they were completing high school is a good proxy for how well they felt supported by their community throughout adolescence.

Across the sample, 52% of respondents reported a score of 4 or higher, signifying feeling positively about each area of social wellbeing at least two or three times per week. Forty-six percent of black respondents experienced the same frequency of belonging and overall social wellbeing. The same was true for 47% of low-income children and 53% of urban children.

Reading Proficiency. Finally, reading proficiency was included as an individual-level variable given that K-12 education is a key focus area of the federal Promise Neighborhood program (Table 1). Research on the relationship between literacy skills and educational attainment suggests that efforts to improve academic skills such as reading and math are key ingredients to support the pathway from cradle-to-career (Crawford & Cribb, 2013). The University of Minnesota's Tracing Pathways study, mentioned earlier, also suggests that that proficiency in core subjects such as reading and math contribute to increased earnings later in life (Brown et al., 2021).

CDS children ages six and above were administered subtests of the Woodcock-Johnson Psycho-Educational Battery-Revised (WJ-R), which included two reading tests (Letter-Word Identification test and the Passage Comprehension test) used to assess literacy skills. The variable used in this analysis is the child's percentile rank compared to a normed sample of children matched by age. The percentile rank is used in this analysis because it enables the comparison of individuals across a range of ages and years that the test was administered (Duffy & Sastry, 2014). As would be expected, the mean percentile rank of the sample is just above 50%. Black children ranked near the 39th percentile, low-income children at the 37th percentile, and urban children at the 53rd percentile.

Controls

Controls include time invariant variables such as the child's race, sex, and whether the child's mother was married at birth. In addition, constructed variables were generated based on the child's parents' employment status in 2007, 2002, or 1997 (using the most recent observation), average family income (across three observations in 1996, 2001, and 2006), highest education level completed by either parent/ caregiver, and whether the child grew up in an urban or non-urban area. The natural log of average family income was ultimately used in the data analysis because of the nonlinear relationship with the outcomes of interest.

Analysis

By observing this cohort of children into young adulthood, it is possible to identify how key predictors in childhood and adolescence influence educational attainment as well as income in early adulthood. An ordinary least squares regression model was used to estimate the relationship between key childhood indicators (CH_i) on outcomes (O_i) in adulthood mediated by vector of controls X_i. O_i represents either educational attainment or income at the oldest age observed (between age 22 and 28). CH_i includes all four childhood exposures which were included in the analysis: neighborhood quality, neighborhood safety, belonging, and reading proficiency. In all models, the following controls are included: age at the time the outcome was observed, race, sex, and sociodemographic characteristics during childhood (mother's marital status at birth, parent's employment status, log of family income, parent's education level, and urban status). The following regression model was used:

$$O_i = \alpha_1 + \beta_1 CH_i + \beta_3 X_i + \varepsilon_i$$

I hypothesize that each key predictor will positively correlate with educational attainment and annual income. Statistical significance of each independent variable and the magnitude of their effects is central to the analysis seeking to understand the factors that contribute to educational attainment and income later in life. In order to interpret the relative magnitude of each key variable, standardized coefficients were used in the final analysis. In addition to an analysis of the whole sample, additional subsample analyses were conducted for Black children, children who grew up in a family with an average income less than 200% of the federal poverty level (FPL), and who grew up in an urban area.

Results

Table 4 and table 5 show the results of the regression analysis for both outcomes by key variable and subgroup (black, low-income, and urban). For both outcomes, the standardized coefficients were significant for just two of the four predictors (reading percentile and social wellbeing) on all but the urban subgroup in the annual income model. The effects of the neighborhood-level predictors were not significantly different than zero. For the educational attainment outcome, reading percentile rank was significant at $p<.01$ for all subgroups. Social wellbeing had the same level of significance across all subgroups except for black children (p.<.1). The effect of reading percentile rank on annual income was significant at $p<.01$ for black and low-income children, p.<.1 for the full sample, and not significant for urban children. Social Wellbeing had the same level of significance at p.<.01 for all but black children (p.<.05). The variability in magnitude of each coefficient across subgroups is further explored below.

Educational Attainment. Both reading ability in childhood and sense of social wellbeing at age 17 or 18 had significant effects on educational attainment according to this model. Adjusting for the effects of social wellbeing and controlling for other mediating factors (Table 4), a child's reading percentile rank mattered the most. For the full sample, the effect of a one standard deviation change in reading percentile rank (29 percentiles) is a .412 standard deviation change in years of education attained on average (approximately .74 years of education). In comparison, the effect of a one standard deviation change in social wellbeing is a .277 standard deviation change in educational attainment on average (.5 years of education).

The effect of reading skill ranking was largest for black and low-income children (.543 and .562 standard deviations respectively) compared to the full sample while urban children saw a smaller effect on average than the sample as a whole (.377 std. dev.). Social wellbeing had the lowest magnitude effect on average for black children (.131 std. dev.) and, across subgroups, the effect was half that of reading skills.

Annual Income. The correlation between each key independent variable and the natural log of annual income between the ages of 22 and 28 is reflected in Table 5. Significance and magnitude of each standardized coefficient across subgroups is more variable than with the educational attainment model. In this model, neighborhood ratings for the urban subsample do have a significant effect at p.<.1. However, the same group saw no significant effect of reading percentile ranking (p.>.1). The one similarity with the educational attainment model that holds true with the annual income model is that reading percentile rank, adjusting for social wellbeing, also had the largest effect magnitude for low-income children (.833 std. dev.). The next highest effect magnitude was reading percentile ranking for black children (.698 std. dev.).

Social wellbeing had a more consistent effect both in magnitude and significance across all groups. Significance for low income and urban children was p.<.01 while, for black children, the significance had a p-value of less than .05. For children who grew up at or below 200% of FPL, a one standard deviation increase in social wellbeing was correlated with a .657 standard deviation increase in annual income later in life on average, adjusting for reading percentile ranking and other controls. Social wellbeing among both black children and urban children were similar in effect size to that of the full sample (.554 std. dev.).

Discussion

This findings in this study suggest that reading skill level in childhood is associated with years of education as well as increased annual earnings, though significance varies across groups with respect to earnings. Higher reading skill levels (measured by percentile ranking) contribute to more years of education on average. These findings are consistent with other research on the relationship between academic skills in childhood and economic mobility (Brown et al., 2021; Crawford & Cribb, 2013). In addition, these findings support the focus of Promise Neighborhoods and community-level change initiatives on school and academic supports for low-income children and families (*Promise Neighborhoods*, 2023).

With respect to the key outcome of economic mobility as measured by increased annual earnings, findings suggest that increased reading ability is most strongly associated with higher earnings among black children and low-income children. This is consistent with findings from the Tracing Pathways study (Brown et al., 2021) which found that educational milestones (such as reading and math proficiency) accounted for a reduction in demographic inequities such as racial differences in wages.

Additionally, findings suggest that social wellbeing is a significant mediating factor for both educational attainment and earnings. This again supports the theory behind systems indicators such as the extent to which communities facilitate inclusion and belonging (*A Guide to Racial and Ethnic Equity Systems Indicators*, 2020). That social wellbeing was most significant for low-income children both in relation to educational attainment as well as earnings also supports recommendations in the Measuring Mobility from Poverty Report (Acs et al., 2018). In

Measuring Mobility, the authors suggest that, in addition to economic factors, “power and autonomy and being valued in community” should be considered as measures affecting economic mobility. In fact, programs or community initiatives could use similar psycho-social measures such as those used in the PSID survey to track change social wellbeing over time.

Findings from the PSID data used in my analysis show limited observable effects of neighborhood quality or neighborhood safety, as reported by the child’s parent or caregiver, on educational attainment or earnings. While some significance was detected for urban children whose parents reported living in a high-quality neighborhood, limitations in the data, as discussed further below, likely limit the validity of these findings. This somewhat mirrors the findings by Ludwig et al. (2012) with regards to the limited long-term effects of the Moving to Opportunity experiment on economic mobility. However, interestingly, the findings from Ludwig show that moving to opportunity neighborhood did have positive effect on social wellbeing which, in this study are significant predictors of economic mobility.

Ultimately, as the above statement demonstrates, the difficulty of untangling the myriad of factors that contribute to economic mobility confirms that more research is needed to understand how these variables interact and to what degree certain exposures or experiences can give low-income children a clearer path to opportunity. In addition, these findings support the continued need for research on the long-term effects of cradle-to-career initiatives and whether population-level change can be detected over time and attributed to community-level interventions.

Limitations

The data used in this analysis is not without limitations. The PSID oversamples low income and Black respondents compared to the national population. Thus, while the sample used in this analysis may mirror communities served by Promise Neighborhoods, it is not nationally representative. In addition, exclusion of individuals from the sample due to nonresponses or missing data introduces nonrandom elements that could affect results.

As with any observational study, omitted variable bias is a limitation that must be considered. Due to the myriad of interrelated factors that contribute to changes in educational attainment and income, it is possible that some factors were omitted from the analysis. This is especially true for the neighborhood-level variables. Due to self-selection into neighborhoods, it is possible that certain people, for a variety of reasons, may choose to live in one neighborhood over another. The reasons for a household's location are not captured in this study and could be more influential than the neighborhood itself.

In addition, measurement error must be taken into consideration due to the variation in how individuals respond to surveys. While the reading percentile rank is created from a validated measure of reading skills, the neighborhood-level variables and sense of belonging are self-reported by the respondent.

Conclusion

This study generally supports the assumptions made by Promise Neighborhood programs and similar community-level change initiatives that focus on academic achievement and social wellbeing as key strategies for supporting youth and families from cradle-to-career. This study also supports research on economic mobility that has found that factors beyond just family income contribute to economic mobility (Acs et al., 2018; Duncan et al., 2018). The positive effects of academic skills and high levels of social wellbeing and belonging are important to consider for community initiatives seeking to improve educational attainment and economic mobility within their populations.

In addition, these findings demonstrate the importance of understanding the interaction between demographic and socio-economic characteristics of children and families and the conditions in which social inequities can be mediated by program and policy-level interventions. In other words, finding the ingredients that work for a particular family or community to facilitate pathways to opportunity will require continued negotiation between research and practice. With the persistent effects of the pandemic that have exacerbated opportunity gaps, the importance of continuing to understand and develop the evidence base for Collective Impact and the Promise Neighborhood model could not be more evident.

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Tables & Figures

Table 1. National Promise Neighborhood indicators

Focus	Result
Academic	Children enter kindergarten ready to succeed in school
	Students are proficient in core academic subjects
	Students successfully transition from middle school grades to high school
	Youth graduate from high school
	High school graduates obtain a postsecondary degree, certification, or credential
Family and community supports	Students are healthy
	Students feel safe at school and in their community
	Students live in stable communities
	Families and community members support learning in Promise Neighborhood schools
	Students have access to 21st century learning tools

Source: Relevant *Federal Register* notices.

Table 2. Descriptive statistics for full sample (all variables)

VARIABLES	N	Mean	Std. Dev.	Min	Max
Key Dependent					
Education Level (years)	1,125	14.190	1.804	11	20
Annual Earnings	1,125	22,848.34	24,370.92	0	185,000
Log Annual Earnings	1,125	7.318	4.514	0	12.128
Key Independent					
High Neighborhood Quality	1,125	0.860	0.347	0	1
High Neighborhood Safety	1,125	0.840	0.367	0	1
Reading Percentile Rank	1,125	52.315	28.986	0	99
Social Wellbeing	1,125	3.563	1.294	1	6
Controls					
Female	1,125	0.521	0.500	0	1
Race					
Black	1,125	0.382	0.486	0	1
Hispanic	1,125	0.071	0.257	0	1
Asian	1,125	0.012	0.107	0	1
American Indian	1,125	0.003	0.052	0	1
Other	1,125	0.040	0.196	0	1
Unknown	1,125	0.002	0.042	0	1
Mother single at birth	1,125	0.332	0.471	0	1
Urbanicity	1,125	0.859	0.349	0	1
Log Family Income Avg.	1,125	10.780	0.805	7.688	13.950
Parents Education Level					
High School Diploma	1,125	0.291	0.454	0	1
Some College	1,125	0.297	0.457	0	1
Four-year Degree	1,125	0.172	0.377	0	1
Grad. School or more	1,125	0.125	0.331	0	1
At least one parent employed	1,125	0.890	0.313	0	1
Age (when education reported)	1,125	25.112	1.768	22	28
Age (when earnings reported)	1,125	25.195	1.740	22	28

Table 3. Subgroup descriptive statistics by key variable (standard deviations in parentheses)

Variable	Subgroup Means (std. dev. In parentheses)		
Key Dependent	Black	Low Income	Urban
Educational Attainment	13.685 (1.665)	13.298 (1.597)	14.271 (1.781)
Annual Income	18,411.25 (20,071)	17,421.57 (19,708.74)	23,502.77 (24,792.2)
Key Independent			
High Neighborhood Quality	.774 (.419)	.740 (.439)	.854 (.353)
High Neighborhood Safety	.732 (.443)	.699 (.459)	.835 (.371)
Reading Percentile Rank	38.934 (26.122)	37.339 (25.780)	53.459 (28.956)
Social Wellbeing	3.468 (1.380)	3.412 (1.384)	3.578 (1.303)

Table 4. Regression of Key Predictors in Childhood and Adolescence on <u>Educational Attainment</u> between ages 22-28 by subgroup

VARIABLES (standardized)	Full Sample	Black	Low-Income	Urban
High Neighborhood Quality	-0.00715	0.0205	0.0415	0.0113
	(0.0488)	(0.0644)	(0.0681)	(0.0524)
High Neighborhood Safety	0.0135	0.0343	-0.0112	-0.00838
	(0.0491)	(0.0643)	(0.0672)	(0.0531)
Reading Percentile Rank	0.412***	0.543***	0.562***	0.377***
	(0.0523)	(0.0883)	(0.0957)	(0.0559)
Social Wellbeing	0.277***	0.131*	0.252***	0.254***
	(0.0446)	(0.0702)	(0.0736)	(0.0477)
Observations	1,125	429	342	966
R-squared	0.353	0.259	0.268	0.344

Controls: Race, sex, log of family income, parent educational attainment, parent employment, urbanicity.

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Regression of Key Predictors in Childhood and Adolescence on Log of Annual Income at ages 22-28 by subgroup

VARIABLES (standardized)	Full Sample	Black	Low Income	Urban
High Neighborhood Quality	0.169	0.0359	0.0201	0.285*
	(0.147)	(0.196)	(0.215)	(0.160)
High Neighborhood Safety	0.0415	0.0623	-0.0721	0.0118
	(0.149)	(0.196)	(0.213)	(0.162)
Reading Percentile Rank	0.266*	0.698***	0.833***	0.0471
	(0.158)	(0.269)	(0.304)	(0.170)
Social Wellbeing	0.554***	0.530**	0.657***	0.552***
	(0.135)	(0.215)	(0.234)	(0.145)
Observations	1,125	429	342	966
R-squared	0.056	0.077	0.123	0.055

Controls: Race, sex, log of family income, parent educational attainment, parent employment, urbanicity.

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1