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EARLY CHILDHOOD EDUCATION

WHAT DO WE KNOW AND WHAT SHOULD WE DO?

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Executive Summary

When children start school, they do so with differing experiences, influenced by their early home environments, parenting, care arrangements, and neighborhoods. The result is widely varying levels of school readiness by age five.[1] These differences in school readiness have led many to conclude that providing children with a high-quality pre-K experience would help them do better in school and reduce current educational and income disparities.

The Biden Administration included a proposal for universal pre-K in the Build Back Better (BBB) bill.[d] Although the bill was not enacted, the issue remains important for both states and the federal government. Forty-six states now have pre-K programs, although they vary in what they provide (Potts, 2023). Additionally, pre-K enrollment and access is limited among lower-income families. In 2019, 42% of three- and four-year-old's in families earning under 185% of the poverty threshold were enrolled in pre-K, as compared to 54% of children in higher-income families (Irwin et al., 2021).

But exactly how large are disparities in school readiness, what's driving them, and how much difference do they make for children's long-term success? Does access to pre-K lead to greater success in school and help to close existing disparities that often persist until later in a child's life? Should programs be universal or targeted to a specific disadvantaged subgroup? And what do we know about how to make programs more effective?

In this paper, we review the major findings from the existing pre-K literature evaluating the effectiveness of such programs. Although researchers have found sizeable impacts of pre-K programs based on studies of small samples of very disadvantaged children born over 50 years ago, with some exceptions, they have often not found such effects when evaluating scaled-up, public programs serving today's children. Additionally, most studies of recent cohorts of children have only been able to look at the short-run effects of the programs. What we would like to explore is both the short and the longer-term effects of pre-K in a scaled-up public program serving today's children.

One common observation is that pre-K programs are very heterogeneous and that quality matters. It has been harder to say what we mean by "quality," but without attention to what goes on in the classroom and to the early-care work force, an expansion of pre-K could fail to produce any meaningful results. Another issue is targeting. Most of the existing research finds that pre-K programs benefit disadvantaged children more than the advantaged. But programs that serve low-income children may turn out to be of lower quality than those with universal eligibility and a broader political constituency.

In addition to reviewing the existing literature, we add to it by using longitudinal data from a large-scale microsimulation model to look at current gaps in school readiness by family income, race and ethnicity, and gender. We then show how those school readiness gaps reverberate throughout a child's educational career, leading to disparate outcomes later in life, and providing some insight into the mechanisms that explain why early interventions may have long-term effects. In brief, we find that:

- Children born to lower-income families (i.e., less than 200% of poverty) are less likely to be school ready. There are large gaps in school readiness by race and ethnicity although these are partially due to the disproportionate number of Black or Hispanic families in poverty.
- Across all racial groups, girls are more likely to be school ready at age five than boys. These gender gaps are most evident for children from low-income families. By the time they are adults, whatever influence the gender gap had at younger ages seems to disappear with women falling behind men on various measures of economic (although not educational) success.
- Children who are school ready at age five are more likely than other children to be successful in school through adolescence, to graduate from high school, to receive a BA degree, and to have higher lifetime earnings. However, some of these effects occur because these children come from more advantaged backgrounds to begin with and

cannot be attributed to their school readiness alone.

- After adjusting for these so-called "selection effects," we still find that school readiness matters for long-term outcomes, although to a much lesser degree after we control for as many confounding variables as the data will allow.
- We then draw on the existing literature on state-based programs to make assumptions about how much difference a pre-K program might make in addressing the lack of school readiness at age five. We simulate how these assumed effects at age five would translate into longer-term effects for the children who received the program compared to those who did not. We find that a universal pre-K program for all children might:
  - Increase BA attainment by 1.1 percentage points or 4.3%.
  - Increase annual earnings at age 30 by $962 or 2.8%.
  - Increase lifetime earnings by $15,756 or 2.4%.
- We also simulate the effects of a targeted program that would serve lower-income (below 200% FPL) children only. The absolute effects on BA attainment and earnings are just a bit higher than those for all children, but the relative increases are much higher for poorer children due to this group's lower baseline education and earnings. Specifically, we find that a targeted pre-K program for low-income children might:
  - Increase BA attainment by 1.3 percentage points or 8.2%.
  - Increase annual earnings at age 30 by $963 or 3.6%.
  - Increase lifetime earnings by $16,327 or 3.1%.
- In addition, because more advantaged children are excluded in a targeted program, their education and earnings are not affected with the result that education and income disparities between groups are further reduced. A targeted program does more to reduce racial disparities for similar reasons.
- While girls tend to be more school ready than boys at age five, the impact of a pre-K program for girls vs. boys depends on the metric being studied. In the case of earnings at age 30, the intervention favors girls. For lifetime earnings, it favors boys. But this is likely because adult women spend more time out of the labor force and if we had a measure of parenting skills to add to earnings at age 30, it might still favor girls.
- Finally, we examined which measures of school readiness matter most for later success and find that cognitive abilities are more important than behavioral measures, and that math skills are much more important than reading.

No one study can provide a full picture of the effects of pre-K, and we urge caution in relying on any one estimate, including ours, to answer the questions posed above. The research community has rightly emphasized the importance of identifying the causal effects of any intervention. The policy and practice communities are more focused on the variation in the quality of existing programs. The two together may explain why estimates of the impacts of pre-K vary. Pre-K in 2020 has different effects than pre-K in 1960. Pre-K in Boston has different effects than pre-K in Tennessee. Not only do programs vary, but so do the children who are enrolled, and the alternative care arrangements they would have experienced in the absence of a formal pre-K program. The limitations of the data and analysis in any one study and the heterogeneity of the programs being evaluated requires some humility in coming to firm conclusions. Nonetheless, in our conclusions, we offer our best current judgements about the implications of all of this research for policy.

A Review of the Literature on the Short-Run Impact of Pre-K

The research on the effectiveness of early childhood education is extensive. In what follows, we distinguish between small-scale demonstrations and large-scale publicly financed programs, between evidence for all children and specifically for disadvantaged children, and between short-term and longer-term effects. We also distinguish between studies that focus on relatively recent cohorts of children and those that studied earlier cohorts who grew up in very different environments as compared to today's children.

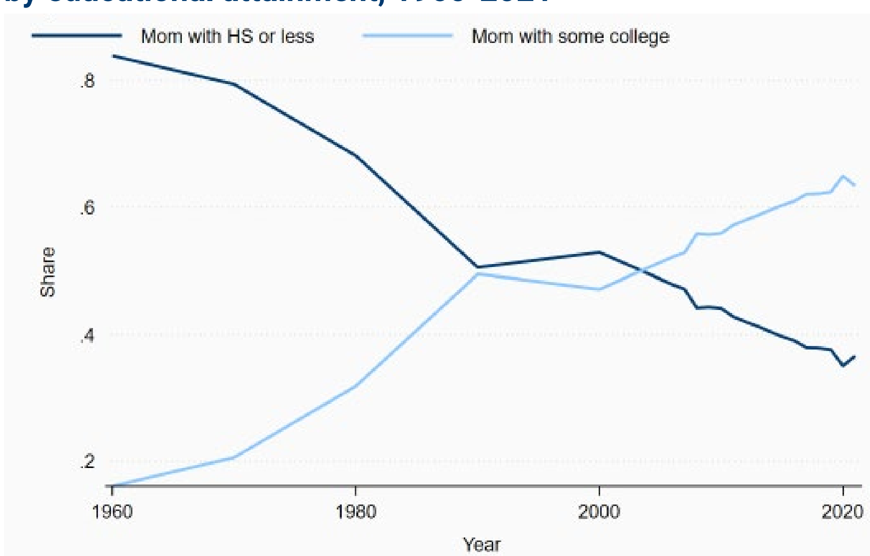
SMALL-SCALE DEMONSTRATION PROGRAMS

One of the most famous examples of a successful program is the Perry Preschool Project in Michigan, a high-quality preschool program targeted to children from disadvantaged backgrounds, which produced large effects on educational attainment, earnings, criminal activity, and other important life outcomes sustained well into adulthood. The results from the program are striking – the treatment group's high school graduation rate was 20 percentage points higher than the control group's rate. At age 27, the treatment group members were 26% less likely to have received government assistance. At age 40, the treatment group had 42% higher median monthly income than the control group (Schweinhart et al., 2005). Recent research has even found positive effects for a second generation, i.e. the children of the original participants (García et al., 2021). Similar to Perry, the Abecedarian Project in North Carolina showed long-term benefits for the children that participated, including higher rates of high school completion, higher wages, and better health outcomes measured at age 40 (Campbell et al., 2014). The results from these programs have been used to argue for much more investment in pre-K and have shaped public discourse around early education.

However, applying conclusions from these earlier programs to the present day should be done with caution. First, these specific programs were pilot or demonstration programs with very small sample sizes, very high-quality staff, and very intensive treatment – meaning that children were in the program for a long time (five years in the case of Abecedarian and two years in the case of Perry). The programs had generous funding and offered wrap-around services to the children and their families, including health care and home visits. For these reasons, they are a different animal than today's large-scale public programs such as Head Start. Put differently, quality matters and scaling up small-scale, well-funded programs to serve far more children is challenging. One needs to stay focused on the quality of the teachers, the curriculum, class size, time spent in the classroom, parent engagement, and other factors.

FIGURE 1

Share of mothers with children five and under by educational attainment, 1960-2021



SOURCE: Brookings Instituion analysis of the 1% census sample from years 1960-2000 and 1% American Community Survey sample from years 2005-2021. Downloaded from IPUMS USA, University of Minnesota, www.ipums.org

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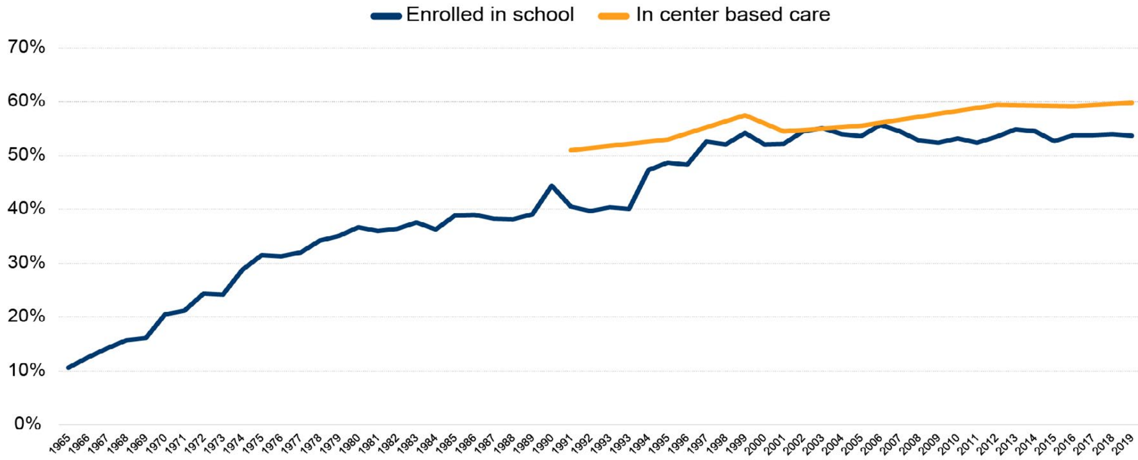
FIGURE 2

Share of three- and four-year olds enrolled in school and center based care, 1965-2019



Source: U.S. Census Bureau, CPS Historical Time Series Data on School Enrollment, Table A-2; U.S. Department of Education, National Center for Education Statistics (NCES). Table 202.40.

Note: Data for time series of children enrolled in school comes from the Census Bureau and presents the share of three- and four-year olds enrolled in school. Data showing trend in center based care enrollment comes from NCES. The share of children in center based care is shown for select years from 1991-2019. Center based care includes day care centers, nursery schools, prekindergarten, preschools, and Head Start programs.

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A second limitation of these evaluations is that the children in the programs were born over 50 years ago and much has changed in the last half century: especially mothers' educational attainment (shown in Figure 1), the proportion of young children in out-of-home care (see Figure 2), the ages of mothers when they had their first child, and the generosity of the safety net (DeParle & McGarvey, 2022).

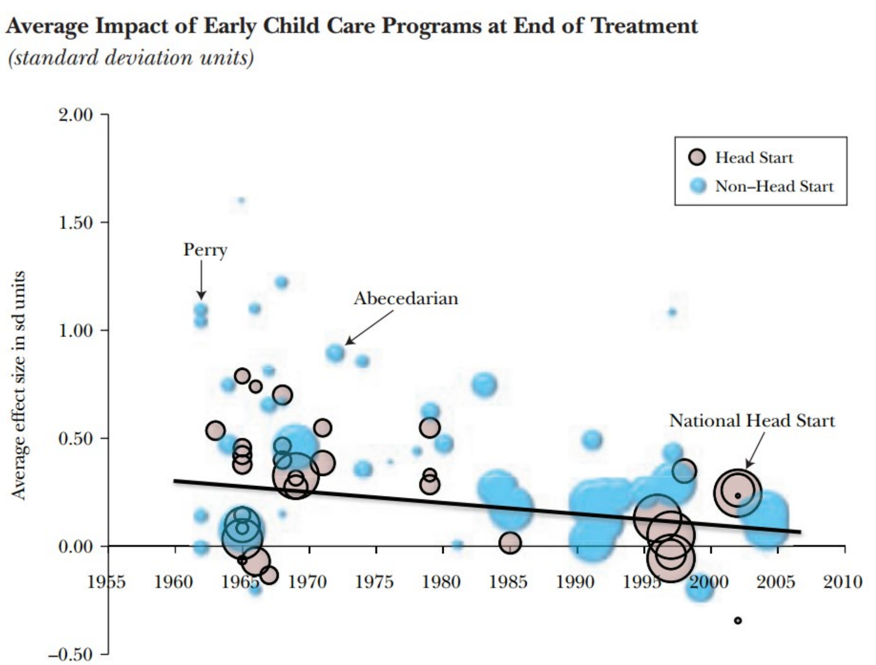
Mothers' educational attainment has been shown to be highly correlated with children's early cognitive development (Harding et al., 2019; Jackson et al., 2017; Reardon, 2011). With better-educated mothers, children are likely to receive higher-quality early care at home. With more children enrolled in out-of-home care, those in pre-K may not be experiencing a very different level of care than the children to whom they are being compared in various studies, diminishing any possible treatment effects. As Duncan and Magnuson put it, "the distinctions between early education and other kinds of center-based childcare programs have blurred" (Duncan & Magnuson, 2013). Indeed, there is evidence that gaps in children's early behavioral skills have narrowed since 1998 (Reardon & Portilla, 2016). In researcher jargon, whatever the internal validity of the research on these high-quality programs, such as Perry and Abecedarian, their external validity remains an issue.

SHORT-TERM IMPACT OF CONTEMPORARY PROGRAMS

While advocates believe that pre-K programs have positive effects, and there is some evidence to support this view, a number of studies have not supported this contention. For example, a study of the Tennessee Voluntary pre-K program (TNVPK) found that children who were enrolled in the program in 2009 and 2010 actually had worse academic and behavioral outcomes (Durkin et al., 2022).

More importantly, Head Start, a large, federally funded pre-K program for low-income children ages three to five years old that is operated by local non-profit organizations across the country, has been the subject of a relatively recent and rigorous evaluation. That evaluation found small initial positive impacts that completely faded out by the end of third grade (Puma et al., 2012). On social-emotional measures, some children (middle class white children, for example) that participated in Head Start actually were worse off than the controls.[2] Given this evidence alone, it would be hard to argue for spending a large sum on universal pre-K. To be sure, there has been some criticism of the Head Start Impact Study, suggesting that after correcting for some flaws in the way the study was conducted, it had positive effects on school readiness (Feller et al., 2016; Kline & Walters, 2015).[3] Moreover, numerous quasi-experimental or well-controlled studies relying on longitudinal datasets find positive, long-term impacts on health, education, and earnings for those who participated in the program (Deming, 2009; Garces et al., 2002; Ludwig & Miller, 2007). Additionally, some state programs, such as the ones in Tulsa, Oklahoma, and Boston, Massachusetts have had more positive effects and we will return to these examples and a discussion of the long-term evidence later.

FIGURE 3



SOURCE: Duncan, Greg J., and Katherine Magnuson. 2013. "Investing in Preschool Programs." Journal of Economic Perspectives, 27 (2): 109-32. Copyright American Economic Association; reproduced with permission of the Journal of Economic Perspectives.

NOTE: Figure 3 shows the distribution of 84 program-average treatment effect sizes for cognitive and achievement outcomes, measured at the end of each program's treatment period, by the calendar year in which the program began. Reflecting their approximate contributions to weighted results, "bubble" sizes are proportional to the inverse of the squared standard error of the estimated program impact. There is a weighted regression line of effect size by calendar year.

One reason that some programs work, and others don't, is because quality matters. Attempts to scale up small or localized programs to serve a much larger number of children may not be successful without very careful attention to such issues as teacher quality and pay, curriculum, the availability of services such as health care and nutrition, the duration of the program, class size, and the engagement of parents. Yet structural features of the environment that can be directly regulated, such as group size, teacher-child ratios, and teacher education do not seem to correlate very directly with the type of teacher-child interactions that make a program impactful (Morrissey et al., 2014). There is some evidence that a more academically oriented program has bigger impacts than one that is focused on "the whole child" (Duncan et al., 2022).

To summarize, the big impacts found in some earlier programs have not held up in recent years, most likely for two main reasons: changes in children's environments and changes in the programs themselves. The results are nicely illustrated in Figure 3 from Duncan and Magnuson (2013) showing how the estimated short-run effects of early care programs have fallen over the period 1960 to around 2007 and the big gaps in effectiveness between the two model programs (Perry and Abecedarian) and Head Start.

A Review of the Literature on Longer-Term Impacts

Even though the short-run impacts of pre-K appear to be small at best, its longer-term effects could be bigger and more significant. The hypothesis here is that getting a solid academic and behavioral foundation in early childhood may not pay immediate dividends but does affect later life outcomes such as education, crime, teen pregnancy, or earnings. Many researchers call these "sleeper effects" or "the secret sauce."

Several studies have suggested that such sleeper effects exist. Deming (2009) for example looks at families in which one sibling was enrolled in Head Start and another was not and uses this to look at the longer-term effects of Head Start using longitudinal data. He finds that the program had substantial effects for children treated in 1984-1990. Using a similar approach, Bauer & Schanzenbach, 2016 find substantial effects of pre-K on high school graduation rates and the likelihood of pursuing higher education for children who participated in Head Start from 1974-1994.[4] A recent study by Bailey et al. (2021), uses the roll-out of Head Start over a 15-year period to demonstrate large effects of the program on high school and college completion for children born in the 1960s up to the mid-1970s. Other studies have similarly found that Head Start has played some role in improving children's life chances – at least for earlier cohorts of low-income children (Garces et al., 2002; Ludwig & Miller, 2007). The question remains, however, whether these earlier cohorts are a good stand-in for today's children and exactly what is producing these longer-term effects. One study by Pages et al. (2020) that extended Deming's (2009) analysis to look at later cohorts of children found no or negative effects on adult outcomes.[5]

On the other hand, at least one recent evaluation has found longer-term effects from a state-based public pre-K program. A 2022 paper by Gray-Lobe et al. uses admissions lotteries to study the impact of a large-scale public preschool in Boston, Massachusetts. They find that pre-K had positive impacts on a variety of long-term outcomes, including: "college enrollment and persistence, grade progression and high school graduation, SAT and state achievement test scores, and behavioral outcomes related to truancy, suspension, and juvenile incarceration" (Gray-Lobe et al., 2022). Evaluation evidence like this which shows some fade-out of early test score advantages for those in pre-K but positive effects on later outcomes suggests that the impact of early childhood intervention might work through poorly understood (likely non-cognitive) channels and show up later in life. The findings for Boston are striking. Of course, Boston is not a typical state; it has a much more successful education system than most other states (Wong, 2016). Should we believe the results from Massachusetts or the ones from Tennessee? Or is Tulsa, Oklahoma with positive effects identified in still other research more typical than either one? One way to treat such findings is to assume that any effects are going to depend heavily on quality and on the backgrounds of the children enrolled and to not assume that any one estimate gives the full picture.

In sum, the research evidence is somewhat mixed. In an effort to produce a consensus statement in 2017, a distinguished group of early childhood researchers noted that not all pre-K programs are equally effective and that the greatest improvements in learning have been seen among economically disadvantaged children and dual language learners. They went on to add that the most effective programs have a well-implemented evidence-based curriculum, effective teachers in orderly but active classrooms, and are followed by elementary-school (K-3) experiences that build on any gains in pre-K. Effective programs also emphasize continuous improvement, often through research-practice partnerships (Phillips et al., 2017). In an impressively comprehensive and very recent review of the literature Greg Duncan and his co-authors conclude that "existing research on early childhood education fails to answer fundamental questions about what works for whom and why" (Duncan et al., 2022).

So, questions remain about if and why any positive effects persist into adulthood. And is it cognitive or noncognitive skills that matter most? Which outcomes are most likely to be affected and through what pathways or mechanisms?

Using the Social Genome Model to Predict Longer-Term Effects

This section of the paper describes our own attempts, using the Social Genome Model, to add to the literature on these kinds of questions. Those less interested in new analysis can jump to our conclusions. The main findings of the analysis are summarized above in the Executive Summary.

The Social Genome Model (SGM), developed by the Brookings Institution, Child Trends, and the Urban Institute, can be used to predict longer-term outcomes from shorter-term effects and can illuminate the pathways relating the two. It is a data-rich model stretching from birth to adulthood that allows analysts to examine how circumstances and actions at developmentally significant life stages, including early childhood, reverberate through a person's life. The model can be used to simulate how policies and programs targeting young people ultimately affect adult outcomes such as lifetime earnings. A detailed description of the model is available in the technical documentation and user's guide, developed by the Urban Institute and Child Trends (Werner et al., 2022). Here we provide an abbreviated version.

In the case of contemporary pre-K programs, by definition, we can only measure their short-term effects unless we wait another 30 or more years to see what happens to the children they are serving. Although some researchers might favor such patience, policy makers cannot wait that long; they would rather have some evidence than none at all. In addition, advocates could reasonably argue that bypassing an entire generation of children to see what works is morally unacceptable. It was these dilemmas that motivated us to use a simulation model to explore the longer-term effects associated with the programs available to today's children.

Another motivation for using a simulation approach is an interest in understanding mechanisms of impact. Some recent studies suggest that the quality of the education children receive once they enter the formal education system is critical to success. Johnson and Jackson (2019) show that impacts on educational attainment and other adult outcomes were larger for preschool students who were later exposed to better-funded public schools. Researchers call this "dynamic complementarity" meaning that the acquisition of skills is a cumulative process. One must learn to read, for example, before one can use reading as a tool to learn other topics. Conversely, if the children who did not receive an early intervention later "catch up" to those who did, then the timing of skill acquisition may be less important. In addition, what may matter most, in practice, is the sequencing and integration of the educational process from one level or grade to the next. Some children end up repeating what they learned in preschool in kindergarten or first grade while others, lacking such an experience, may not be able to take advantage of K-3. With a mixed delivery system, and with different children having very different early experiences, getting the sequencing and integration right is particularly challenging for educators.[6]

As we detail later, our simulations suggest that cognitive skills are more important than behavioral skills, and that math is far more important than reading in predicting longer-term success. This suggests paying more attention to pre-K programs that have emphasized these skills. The evaluation of one math-oriented pre-K program by MDRC found that combined with supplemental math instruction in kindergarten, and compared to children who attended regular pre-K programs, a focus on math not only improved math scores but also other outcomes as well. Based on this evaluation and other literature, MDRC concludes that "early math enrichment experiences can lead to lasting gains for children across a variety of outcome domains, even years later. The findings suggest that high-quality early math instructional practices could make a difference, particularly for children with the greatest need" (Kolnik Mattera et al., 2021).

Simulation models not only allow us to explore the longer-term impacts of contemporary programs, they also have more validity than some earlier studies since they are based on large and representative national datasets. Further, by comparing different strategies or programs in terms of their estimated effects on lifetime earnings, we can also rank strategies and programs more readily by using this single metric as at least a rough indicator of the relative benefits of an intervention which can then be compared to its costs and to competing strategies for improving upward mobility. Those other strategies could include providing families with more income, better health care or better housing.[7] Finally, the model can very easily and cheaply accommodate different assumptions about the short-term effectiveness of a program and about the relationships that are the primary drivers of any longer-term effects. This flexibility permits comparing the impacts of very different assumptions about the success of a program, whom it targets, and the mechanisms by which it works. It forces users to confront how and why a change at age five might affect later life outcomes and makes those assumptions explicit – assumptions that might or might not be correct, but which can be modified if and when better research or data become available. Below we describe the current data and structure of the model, and then its current limitations, recognizing that the model could be improved.

DATA

The SGM uses data from three nationally representative longitudinal surveys: The Early Childhood Longitudinal Study, Birth Cohort (ECLS-B); the Early Childhood Longitudinal Study, Kindergarten Cohort (ECLS-K); and the National Longitudinal Survey of Youth–1997 (NLSY-97). The model consists of a matched panel dataset of around 400,000 observations, which was created by linking the ECLS-K and NLSY-97, and is also informed by data from the ECLS-B. The model and its underlying data are structured around key developmental stages from birth to adulthood: Circumstances at birth, Prekindergarten (completed at age 5), Early elementary school (completed at age 8), Middle childhood (completed at age 11), Early adolescence (completed at age 15), Adolescence (completed at age 19), Transition to adulthood (completed at age 24), and Adulthood (completed at age 30). The model also predicts lifetime earnings based on relationships estimated using data from another simulation model, called DYNASIM, developed by the Urban Institute and used by the federal government.

DEFINING SUCCESS IN THE SOCIAL GENOME MODEL

At each life stage, the model includes variables that measure key developmental outcomes and their primary drivers. The model draws on theory (mainly developmental psychology and human capital theory), findings from previous literature, and expert opinion. It is also based on data availability, and statistical tests of explanatory importance.

The model draws on indicators of success at each life stage. These indicators are summarized in Table 1. To be considered successful or "on track" at a particular life stage, a child must cross a threshold value for all of the indicators of success at that stage.[8] The threshold is typically not falling more than one standard deviation below the mean on a particular indicator except in cases where another more intuitively meaningful threshold makes sense.[9]

THE STRUCTURE OF THE MODEL

The relationships in the model are estimated using a set of nested multivariate regressions in which success at each stage depends on earlier success plus a group of potentially confounding variables. For a full description of the model, see Werner et al. (2022). This means that we control for a very large number of variables when doing simulations of the effects of one variable on later ones, thus estimating net effects.

THE LIMITATIONS OF THE MODEL

The Social Genome Model has some limitations. First, it is not a causal model. As just described, it is based on a set of multiple regressions in which the most important confounding variables are included. Still, there could be some unobservable bias in the results. Our tests of the model's results (regression coefficients reporting the effects of, say, education on earnings) against more rigorous academic research that uses experimental or quasi-experimental methods give us some confidence that any biases related to this fact are small. Still, to pretend that the social science community fully un-

TABLE 1

Measures of success at each life stage in the Social Genome Model

Circumstances at Birth	Prekindergarten (age 5)	Early Elementary (age 8)	Middle Childhood (age 11)
• Birthweight • Mother's age at first birth • Parents marital status • Family income-to-needs ratio	• Internalizing and externalizing behavior • Math and reading scores • Interpersonal skills • Health • Parent-child relationship	• Internalizing and externalizing behavior • Math and reading scores • Self-control • Health • Parent-child relationship	• Internalizing and externalizing behavior • Math and reading scores • Self-control • Health • Peer relationships
Early Adolescence (age 15)	**Adolescence (age 19)**	**Transition to Adulthood (age 24)**	**Adulthood (age 30)**
• Delinquency index • ASVAB score • Health • Mental health	• Delinquency index • GPA • HS Degree • Health • Mental health	• Income-to-needs ratio • Health • Mental health	• Income-to-needs ratio • Health • Mental health

SOURCE: Identifying Pathways for Upward Mobility, Urban Institute, 2021 (Table A.1).

derstands what causes some individuals to be more successful in adulthood than others, or that our model is the last word on this topic, would be wrong.

Another limitation is the fact that most of the data in the model come from matching two (sometimes three) longitudinal data sets.[10] There is for this reason an attenuation bias toward zero in the coefficients related to the seam in the data at age 15 which stems from matching kids from the ESLS-K to those in the NLSY-97. Based on multiple runs of the model, the Brookings Institution, Child Trends, and Urban Institute team of researchers believe that this downward bias is more worrisome than any bias related to unobservable characteristics.

A third weakness is that we do not have estimates of statistical significance although given the very large sample sizes this should not be a major concern. On the other hand, for any variable to be included in the main model, it had to add significantly to the explanatory value of the model.

A fourth weakness is the fact that most of the model's equations are linear. If one believes that an intervention has diminishing (or possibly increasing) returns in whatever variable is being shifted in a positive direction, this will overstate (understate) the effects. For example, suppose that more education improves earnings but at a diminishing rate. Then the model underestimates the degree to which a program is likely to reduce disparities in earnings.

Partly because of these limitations, we rely heavily in this paper on the model's descriptive data, drawing on the life cycle framework it provides. Later, we report two simulations we have conducted with the model as a way to illustrate its potential for estimating the longer-term effects of a policy intervention on later outcomes such as educational attainment and achievement, adult earnings, and a measure of lifetime earnings. The model limitations we have just discussed suggest to us (although we could be wrong) that if anything our estimates of the long-term effects of pre-K are conservative, primarily because of the seam in the data and the linear structure of the model.

Who is School Ready?

In this section, we take advantage of the rich data in the model to assess the school readiness of different subgroups at age five. We first describe how school readiness is measured and then, based on those measures, how school readiness varies among different subgroups.

MEASURING SUCCESS AT AGE FIVE

In the prekindergarten life stage, the model considers the following seven variables.

- Internalizing behavior
- Externalizing behavior
- Math scores
- Reading scores
- Interpersonal skills
- Health
- Parent-child relationship

All of these variables are from The Early Childhood Longitudinal Study, Kindergarten Class of 1998-99 (ECLS-K), which focuses on children's early school experiences beginning with kindergarten and following them through middle school. The base-year data were collected in the fall and spring of the 1998–99 school year when the sampled children were in kindergarten.

The seven variables measured in the pre-K life stage are condensed into five metrics. The cutoffs for success or "school readiness" for these five metrics are shown in Table 2. For test scores and behavior measures, the cutoff for being school ready is not falling below one standard deviation below the mean. For the other three variables, the cutoffs correspond with critical values on a non-standardized scale.[11] To be considered school ready, a child must be above the cutoff value on all measures.

HOW SCHOOL READINESS VARIES FOR DIFFERENT GROUPS

Using the data from the model, and our definition of "school readiness," we find that more than 60% of the children are school ready while almost 40% are not. White children are most likely to be school ready (70%) while Black children are least likely (50%) with Hispanic children in between (53%). There are quite striking differences by gender with girls being much more likely to be school-ready than boys, as shown in Figure 4.

TABLE 2

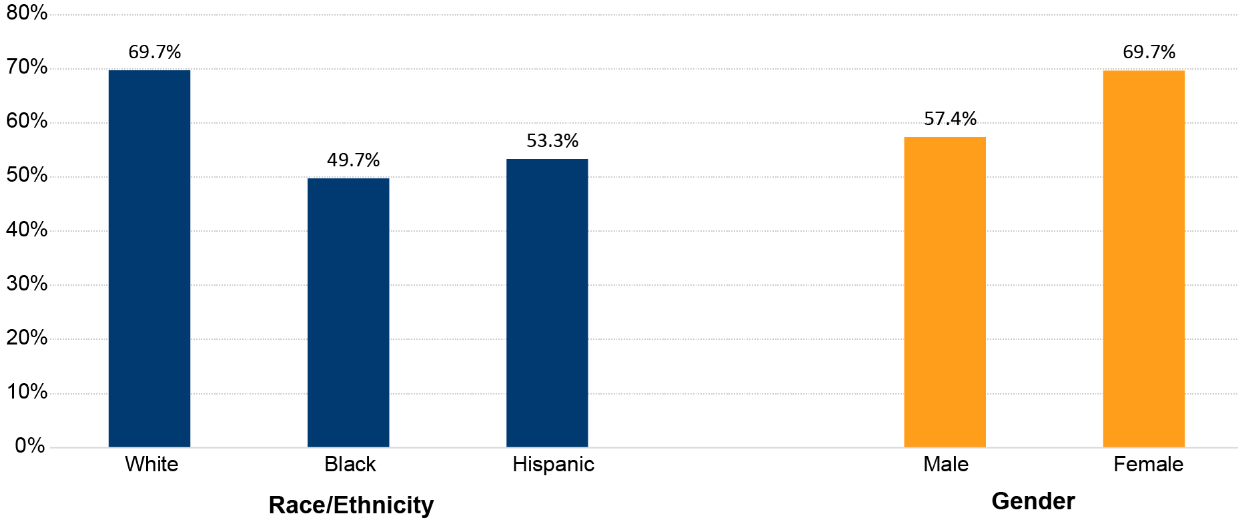
Cutoffs used to define school readiness at the pre-K life stage

Variable	Cutoff	Scale equivalent for cutoffs
Combined Internalizing and externalizing behavior	≥ -1 SD	N/A
Combined math and reading scores	≥ -1 SD	N/A
Interpersonal skills	≥ -.728 SD	At least 2.6 of 4
Health	≥ -1.57 SD	At least "good"
Parent-child relationship	≥ -1.876 SD	At least 3 of 4

SOURCE: Social Genome Model 2.1: Technical Documentation and User's Guide. Urban Institute and Child Trends, 2022.

FIGURE 4

Share of children who are school ready at age five by race/ethnicity and gender



Source: Social Genome Model 2.1. Brookings Institution, Child Trends, Urban Institute. 2022.

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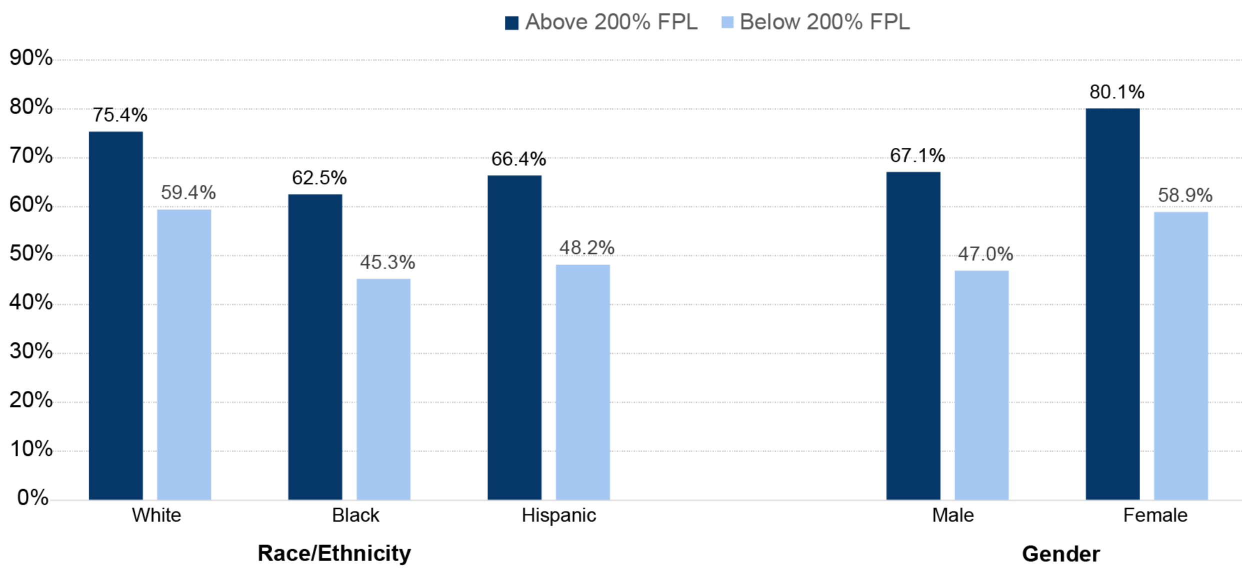
FIGURE 5

Share of children who are school ready at age five among those above vs. below 200% FPL at birth, by race/ethnicity and gender



Source: Social Genome Model 2.1. Brookings Institution, Child Trends, Urban Institute. 2022.

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The gaps by race/ethnicity and gender are not as large as those between children born into lower-income (below 200% FPL) and higher-income (above 200% FPL) families, as shown in Figure 5. In fact, what Figure 5 shows is that some of the racial gaps are due to the fact that Black and Hispanic children are more likely to be from lower-income families. Once we control for this, there are smaller differences by race/ethnicity and also by gender.

WHAT'S DRIVING SCHOOL READINESS?

As the last figure makes clear, school readiness is highly correlated with poverty. It's also correlated with other aspects of a child's home environment, such as their mother's education, whether they have married parents, and whether they were born at a healthy birth weight (defined as above 5.5 pounds), as Figure 6 shows.

SCHOOL READINESS PREDICTS LATER SUCCESS

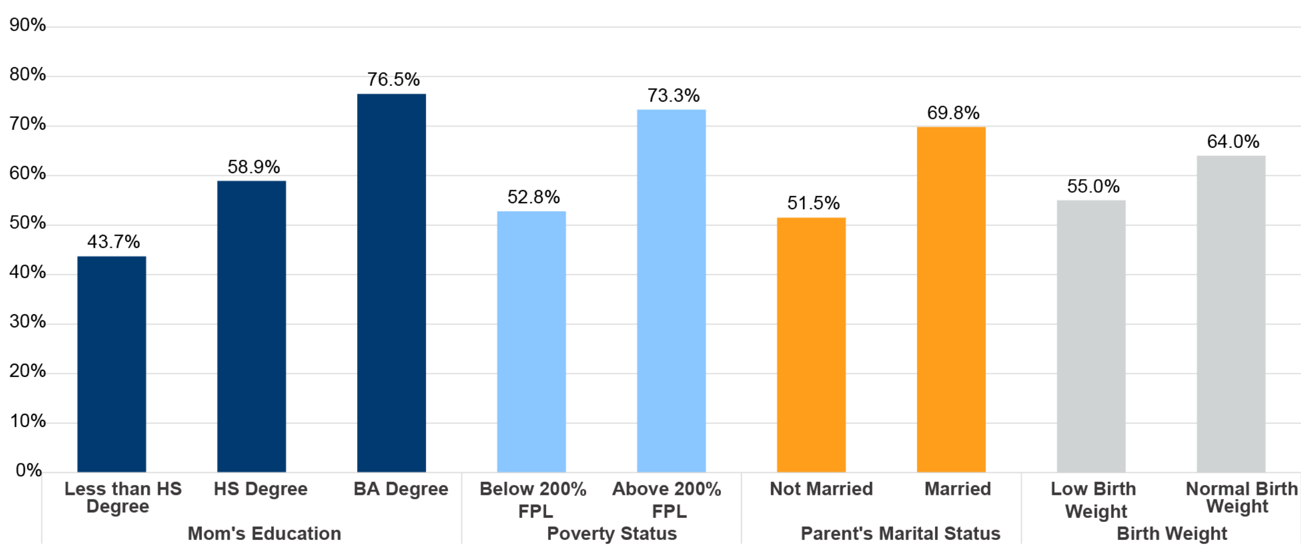
Not only does school-readiness vary with a child's background characteristics, but it is also correlated with later success in school and throughout a child's life span. Figure 7 shows how success at each life stage cumulates into more success at a later life stage.[12] The metrics used to define "success" (or being "on track") at each life stage can be seen on the left-hand side of the figure. What we find is that being school ready is associated with a child's reading and math scores as well as their behavior near the end of elementary school (at age eight) and that those successes create a higher probability that children will get through adolescence without committing a crime, will graduate from high school, go on to graduate from college, and have higher earnings at age 30 and higher lifetime earnings. Note that 78% of children who are school ready at age five – vs. only 40% of those who were not school ready – are "successful" by age eight. So, school readiness almost doubles a child's chances of being successful in elementary school.

By following the pathways shown in Figure 7, one can see how success at any one life stage reverberates, in a cumulative fashion, on success at later life stages. The fact that successes cumulate and lead to later successes is a critical insight and one that is given empirical content in the SGM.

The SGM follows in the spirit of earlier research that has shown that early success leads to later success. Cunha and Heckman (2007) have described the phenomena as "skills beget skills." It has also been called "dynamic complementarity" (Johnson & Jackson, 2019). The cumulative accretion of such skills continues throughout the school years and beyond. Still, as many behavioral scientists have emphasized, the early years are especially important because this is when the brain is developing most rapidly, when good habits and secure relationships are most likely to be

FIGURE 6

Share of children who are school ready at age five by birth circumstances



Source: Social Genome Model 2.1.
Brookings Institution, Child Trends. Urban Institute 2022.

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formed, and when it is easiest and least costly to prevent later problems (National Research Council, 2000).

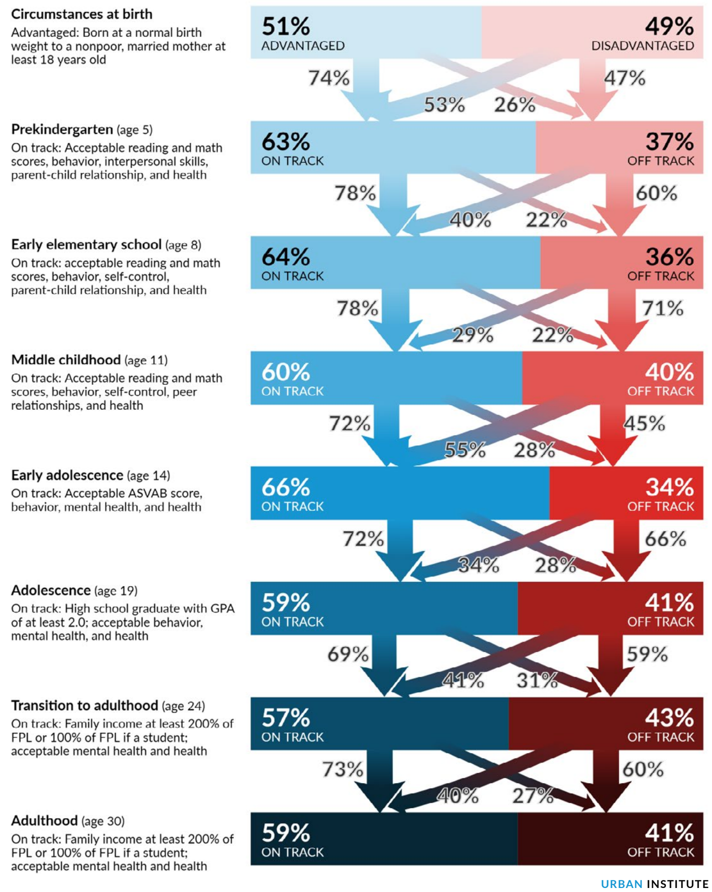
Table 3 shows **unadjusted** differences in BA attainment, mean earnings at age 30, and lifetime earnings by whether or not a child was school-ready at age five.

We should emphasize that all of the foregoing figures are based on descriptive data in which we are simply comparing later outcomes for children who were or were not school ready at age five. As emphasized in our analysis of what's driving these differences in school readiness, it's highly correlated with socioeconomic status (SES), especially mother's education.[13]

Comparing children who are school ready to those who are not tells us that school readiness is very predictive of later outcomes. It does not tell us whether a program to improve school readiness will work or not because the program cannot change a child's family income, their parents, their health, their race or ethnicity, gender, or other variables that affect later outcomes. Still, it's useful to know how much and why school readiness matters and for whom – and the SGM is especially useful for that purpose.

In the final section of this paper, we do control for most of the relevant differences by simulating the effects of a change in school readiness by itself on later outcomes.[14] Because we had to make assumptions about the short-run effects of a pre-K program and cannot control for everything that matters, our estimates should be viewed with caution. They suggest quite modest effects on long-term outcomes – more modest than many of the studies reviewed above.

FIGURE 7



Source: Social Genome Model.

TABLE 3

Difference in adulthood outcomes for school-ready vs. not school-ready children

	School-Ready	Not School-Ready	Absolute Difference	Percentage Difference
BA Attainment	31%	19%	12 p.p.	38.7%
Earnings at Age 30	$35,493	$30,837	$4,656	13.1%
Lifetime Earnings	$689,172	$589,776	$99,396	14.4%

SOURCE: Social Genome Model 2.1. Brookings Institution, Child Trends, the Urban Institute. 2022.
NOTE: The figures in this table are based solely on descriptive data which shows later-life outcomes for children who were or were not school ready at age five. Lifetime earnings are discounted. Undiscounted lifetime earnings would be approximately twice as large.

Simulating the Effects of Pre-K Programs on Long-Term Outcomes

In order to estimate the long-term impacts of pre-K, we use a range of estimates drawn from the existing research literature about the short-term effects of a pre-K program (Table 4) and then predict longer-term effects using the model. It would be very easy to substitute other assumptions about short-term effects and to then use the model to simulate longer-term effects.

We conduct two simulations: one for a universal program and one for a program targeted on low-income children (below 200% FPL). Our colleagues at Child Trends have independently done a similar analysis with results that are parallel to ours.[15]

ESTIMATES OF SHORT-RUN EFFECTS

For this simulation, we drew on studies that estimate the short-term impacts of well-known pre-K programs. We drew from the estimated effects highlighted in these studies to simulate an improvement in math and reading scores as well as internalizing and externalizing behavior to better understand the impact on longer-term outcomes. Most of the estimates of the short-term effects of pre-K on outcomes such as test scores or behavior range from about 0.1 standard deviations to about 0.4 with effects on cognitive metrics typically larger than those on behavioral measures in the very short run. We looked to the following programs as a guide in estimating our effect sizes for this simulation: a universal pre-K program in Tulsa, Oklahoma,[16] another program in New Jersey,[17] and the National Head Start program.[18]

TABLE 4

Estimated increase in cognitive and non-cognitive measures at age five

Variable	Effect Size Simulated
Math scores	+ .35 SD
Reading score	+ .35 SD
Internalizing behavior	+ .15 SD
Externalizing behavior	+ .15 SD

NOTE: Estimated effect sizes simulated are based on studied short-term effects of well-known pre-K programs. Higher SD change for internalizing and externalizing behavior indicates less negative behavior when simulated using the SGM.

Additionally, our colleagues at Child Trends reviewed additional studies on programs and interventions that serve preschool-age children and estimated similar cognitive and non-cognitive effect sizes (Moore et al., 2022). And a meta-analysis conducted by Duncan & Magnuson, 2013 shows similar average treatment effect sizes for cognitive outcomes as those we assumed for this simulation.

Table 4 shows the effect sizes we simulated based on studied short-term effects as described above.

RESULTS FROM THE SIMULATIONS

The first simulation of a universal program imagines an increase in test scores and behavior for all children by the amounts described in Table 4. It shows that this improvement in school-readiness had an effect on children in early elementary school, and in middle and high school, which was sustained throughout the child's life. As mentioned above, our colleagues at Child Trends, using a similar approach, have looked at these intermediate effects throughout the life course in much more detail (Moore et al., 2022).

The intervention led to a small improvement in high school graduation rates, and a 1.1 percentage point increase in BA attainment. Earnings at age 30 increased on average by $962 and lifetime earnings by $15,756 (see Table 5 for results). With less than 100% take-up, clearly the effects would be smaller. In addition, because many children are already enrolled in preschool today, any marginal effects of expanding pre-K would be smaller still.

TABLE 5

Results from simulating the effects of a universal pre-K program on long-term outcomes

	Before	After	Difference	Percent Increase
HS Degree Attainment	73%	73.5%	0.5 p.p	0.6%
AA Attainment	10.7%	10.9%	0.2 p.p	1.8%
BA Attainment	26.6%	27.8%	1.1 p.p	4.3%
Earnings at Age 30	$33,491	$34,452	$962	2.8%
Lifetime Earnings	$652,698	$668,454	$15,756	2.4%

SOURCE: Social Genome Model 2.1. Brookings Institution, Child Trends, the Urban Institute. 2022.

TABLE 6

Results from simulating the effects of a targeted pre-K program on long-term outcomes

	Before	After	Difference	Percent Increase
HS Degree Attainment	61.8%	62.5%	0.6 p.p	1.1%
AA Attainment	9.8%	10.1%	0.2 p.p	3.1%
BA Attainment	14.7%	15.9%	1.3 p.p	8.2%
Earnings at Age 30	$27,139	$28,102	$963	3.6%
Lifetime Earnings	$518,859	$535,186	$16,327	3.1%

SOURCE: Social Genome Model 2.1. Brookings Institution, Child Trends, the Urban Institute. 2022.

TABLE 7

Change in adulthood outcomes for universal vs. targeted programs

	Universal		Targeted (<200% FPL)	
	Difference	Percent Increase	Difference	Percent Increase
HS Degree Attainment	0.5 p.p.	0.6%	0.6 p.p.	1.1%
AA Attainment	0.2 p.p.	1.8%	0.2 p.p.	3.1%
BA Attainment	1.1 p.p.	4.3%	1.3 p.p.	8.2%
Earnings at Age 30	$962	2.8%	$963	3.6%
Lifetime Earnings	$15,756	2.4%	$16,327	3.1%

SOURCE: Social Genome Model 2.1. Brookings Institution, Child Trends, the Urban Institute. 2022.

When we look at these results for different subgroups, we find that their relative effects (in terms of percent gains from baseline) are largest for children living in poverty and for minorities. The gender story is more complicated, with the intervention favoring boys on some measures and girls on others. When earnings at age 30 is examined, the gains from the intervention for women come close to the gains for men on an absolute basis and eclipse the gains to men on a percentage basis. However, in terms of lifetime earnings, men tend to benefit more than women on both an absolute and a percentage basis. This fact can be attributed primarily to the loss of earnings women experience during the child-bearing years (and ignores possible effects on their parenting skills).

We also ran the simulation to target children in families with incomes under 200% of the federal poverty line (FPL), still using the effect sizes presented in Table 4. Table 6 presents the results of the targeted simulation on select adulthood outcomes.

The direct comparison of the impacts of the universal vs. targeted programs is shown in Table 7 for select adulthood outcomes. While the per person absolute effects are only slightly higher for the targeted program, the percentage change is significantly higher on all measures. (The similarity of the absolute gains reflects the fact that the SGM is basically a linear model.) More importantly, disparities between more and less advantaged groups are reduced by a larger amount in a targeted program due to the fact that the intervention now has no impact on the more advantaged groups (See the Appendix for more details.)

Conclusions

Efforts to improve long-term opportunities for less advantaged children have understandably focused on early childhood as a period when the right kind of intervention is most likely to have its biggest impacts. Our own simulation model is consistent with positive effects for this group. However, the conclusion that pre-K benefits measured in the past hold equal promise for today's children may be undermined by the fact that most of today's children are in some kind of early care, that their parents are much better educated than in the past, and that families have access to better health care and nutrition. It may also be undermined by the fact that separating out the effects of preschool from the other factors that affect longer-term outcomes is difficult.

That said, in this final section, we want to offer our own conclusions.

First, targeted programs are more cost-effective.
The biggest impacts of pre-K are for the most disadvantaged – children with less educated moms, living in poverty, and lacking a second parent to help with both raising children and earning a living. To ensure the largest return on investment, a targeted rather than a universal program would be best. However, there are arguments for a universal program related to greater ease of administration, quality of the resulting programs, positive peer effects, lack of stigma and social cohesion.[19] One potential compromise is a universal program with an income-based fee structure for parents or prioritizing creating the necessary infrastructure and staffing in poor communities.

Second, quality matters.
As many people have emphasized, the quality of a program matters and quality requires resources, good management, recruiting and training good teachers and staff, using an evidence-based curriculum, and ensuring that interactions between adults and children in a classroom are warm, responsive, stimulating, and age-appropriate (Phillips et al., 2017). Efforts to improve quality in both childcare and pre-K programs have proven difficult, but many believe that success will depend on investing in the early care work force which needs professional training, career ladders, and better pay.[20]

Third, the focus needs to be on the entire early care and learning environment.
The shortage of early care workers, due at least in part to poor pay, means that pre-K and child care centers are often competing for the same people. Given the critical need for child care among working parents, an expansion of pre-K that ended up cannibalizing child care centers would not make sense. We should think about child care and pre-K as simply different forms of early care and focus on making whatever care is provided better and more affordable, whether it is called pre-K or child care. We also need to worry about the alignment of pre-K with the K-3 years.

Fourth, parents matter, too.
Whatever the effects of pre-K on child development, there is still another reason to support early childhood education and care: its effects on families and on a parent's ability to work and to bring additional income into the family (Sawhill & Holzer, 2022). That additional income, all by itself, can enhance children's future prospects if spent in ways that enrich or stabilize their lives (Cabrera et al., 2022). Especially among disadvantaged children, a mother's employment can mean the difference between a child living in a better or worse neighborhood, having adequate nutrition or not, and having a parent who is anxious and depressed vs one who is secure and nurturing. Offsetting the effects of greater income, of course, is less time to care for children.

Fifth, in today's world, education is needed and should be valued more than ever.
There is a broad consensus in the U.S. that everyone should have access to a good education. Almost no one debates whether children should be enrolled in school at public expense by age five; the debate is about whether we should extend schooling to a slightly earlier age. Given the importance of education in a modern economy and the fact that the majority of parents are employed and supportive of investments in education, extending educational opportunities to three- and four-year-old's might be a good idea, even if the long-term effects were quite modest.

Appendix: Additional Simulation Results

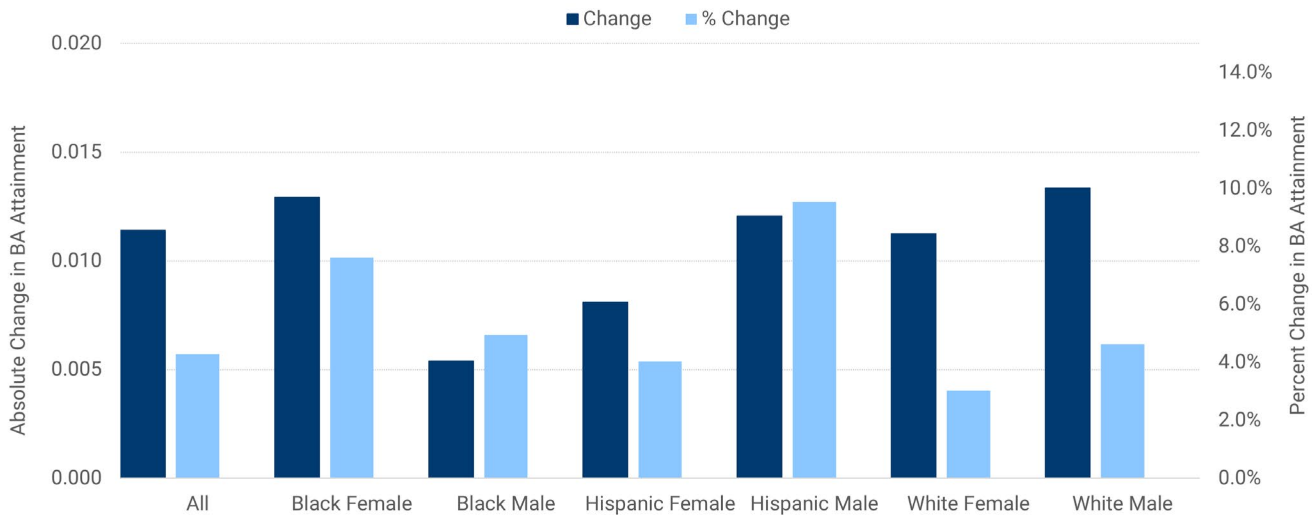
In Figures A-1 through A-6, the effects of a universal and a targeted pre-K intervention on three adult outcomes are estimated and broken out in more detail by demographic group. Some highlights include:

- In terms of lifetime earnings, men tend to benefit more than women on both an absolute and a percentage basis regardless of whether the program is targeted. This is likely because of the loss of earnings women experience during their child-bearing years. However, when earnings at age 30 are examined, the gains from the intervention for women come close to the gains for men on an absolute basis and eclipse the gains for men on a percentage basis.
- Hispanic men are consistently one of the largest beneficiaries of the intervention. This result can be attributed to the fact that Hispanics tend to benefit significantly from both cognitive and behavioral interventions. Hispanic men in particular have the highest positive impact from behavioral interventions.
- Black men also have significant positive benefits from behavioral interventions, and on a percentage basis the gains for Black men nearly matches that for Hispanic men. However, Black men do not derive as much benefit from the cognitive interventions as their Hispanic counterparts, especially in math.

As expected, Black and Hispanic children tend to benefit more in the long-term in relative terms from the targeted intervention given that they have lower baseline cognitive and behavioral scores.

FIGURE A-1

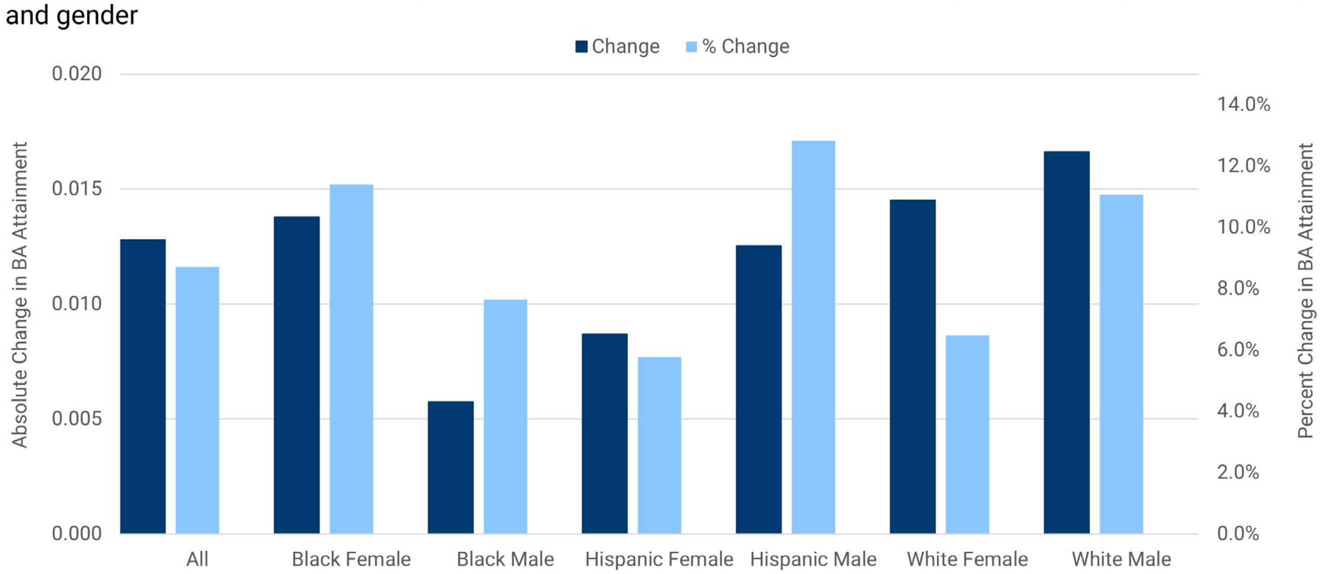
Universal pre-K intervention: Change in BA attainment for all children, by race/ethnicity and gender



Source: Social Genome Model 2.1. Brookings Institution, Child Trends, Urban Institute. 2022.

FIGURE A-2

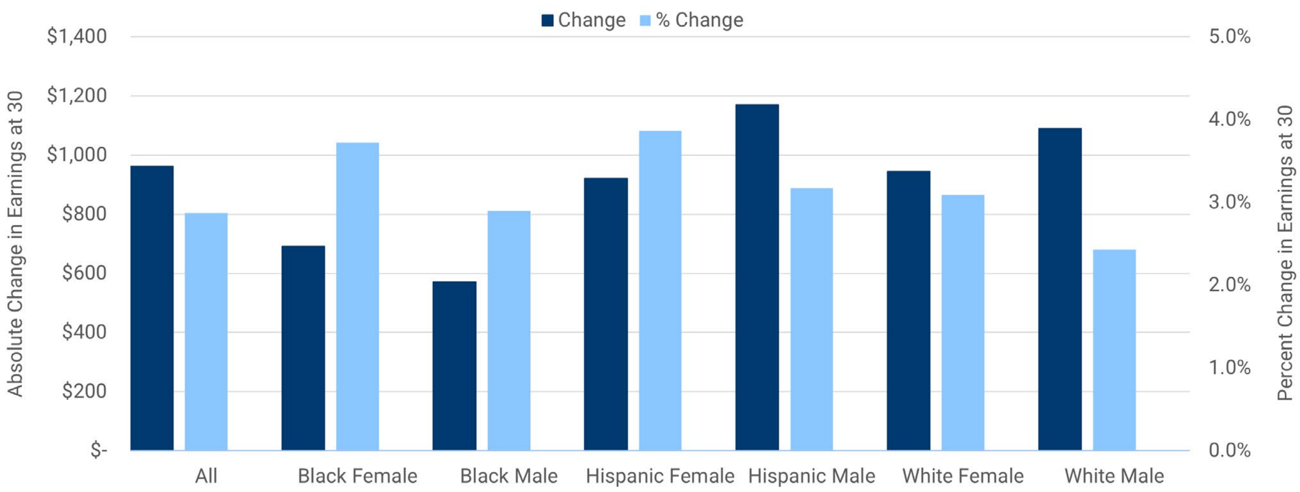
Targeted pre-K intervention: Change in BA attaintment for low-income children (<200% FPL), by race/ethnicity and gender



Source: Social Genome Model 2.1. Brookings Institution, Child Trends, Urban Institute. 2022.

FIGURE A-3

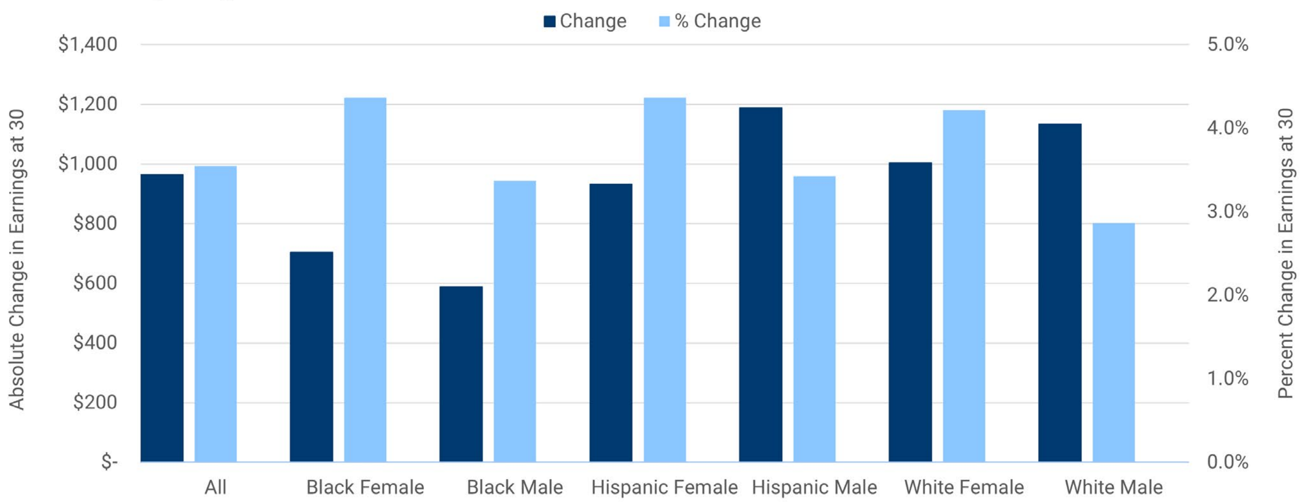
Universal pre-K intervention: Change in earnings at age 30 for all children, by race/ethnicity and gender



Source: Social Genome Model 2.1. Brookings Institution, Child Trends, Urban Institute. 2022.

FIGURE A-4

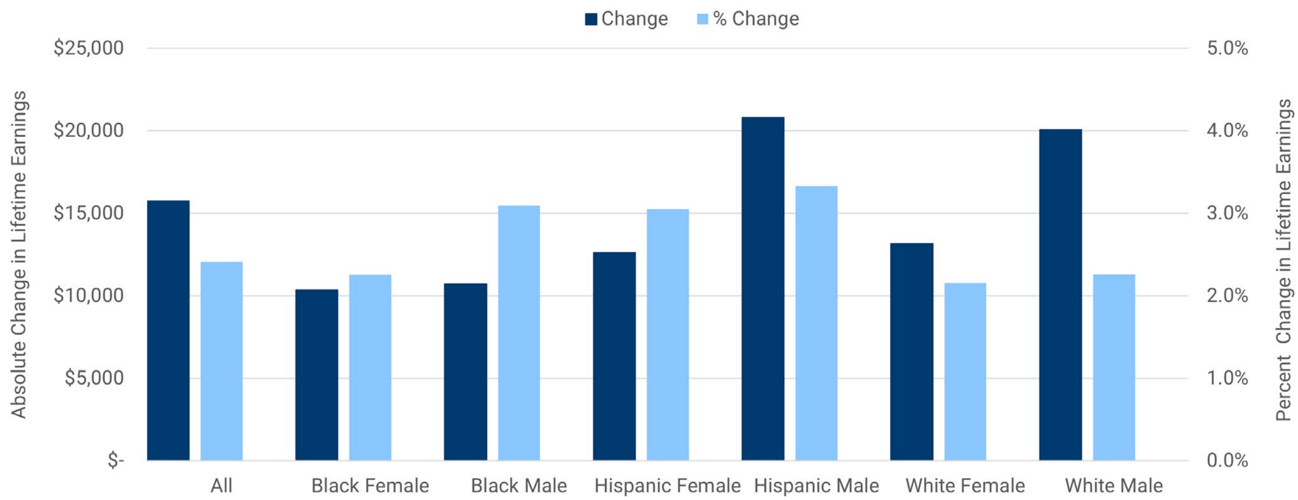
Targeted pre-K intervention: Change in earnings at age 30 for low-income children (<200% FPL), by race/ethnicity and gender



Source: Social Genome Model 2.1. Brookings Institution, Child Trends, Urban Institute. 2022.

FIGURE A-5

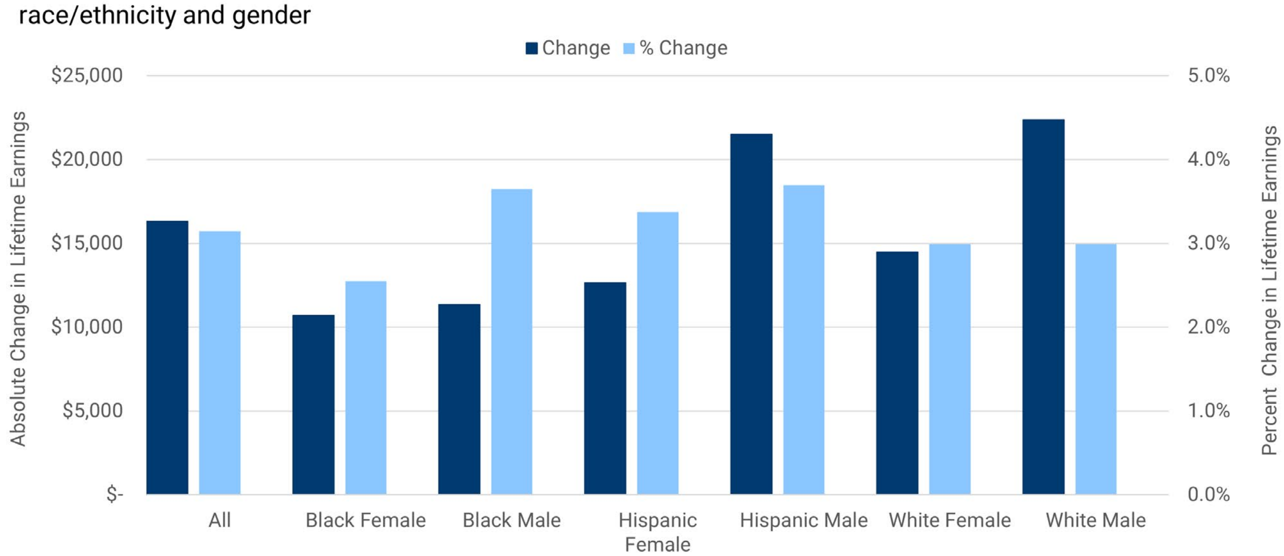
Universal pre-K intervention: Change in lifetime earnings for all children, by race/ethnicity and gender



Source: Social Genome Model 2.1. Brookings Institution, Child Trends, Urban Institute. 2022.

FIGURE A-6

Targeted pre-K intervention: Change in lifetime earnings for low-income children (<200% FPL), by race/ethnicity and gender



Source: Social Genome Model 2.1. Brookings Institution, Child Trends, Urban Institute. 2022.

Table A-1 provides additional details of the likely long-run effects of a universal pre-K program for each subgroup of the population based on the short-run effects assumed in the text of this paper. Table A-2 provides the same information but for a program targeted to lower-income children (under 200% of FPL). Because the SGM is essentially a linear model, the differences between the two on most absolute measures is very small or nonexistent. But if there are decreasing returns to (or other nonlinearities) related to improving education, these similarities may be an artifact of the model.

TABLE A-1

Results from simulating the effects of a universal pre-K program on long-term outcomes, broken down by poverty status and race/ethnicity and gender

		All	Below 200% FPL at Birth	Above 200% FPL at Birth	Black Women	Black Men	Hispanic Women	Hispanic Men	White Women	White Men
HS Degree Attainment	Without Pre-K	73.0%	61.8%	83.7%	73.4%	55.6%	71.3%	63.2%	79.9%	74.3%
	With Pre-K	73.5%	62.5%	84.0%	73.6%	56.5%	71.7%	63.9%	80.2%	74.8%
	Difference	0.5 p.p.	0.6 p.p.	0.3 p.p.	0.2 p.p.	0.9 p.p.	0.4 p.p.	0.7 p.p.	0.3 p.p.	0.4 p.p.
AA Attainment	Without Pre-K	10.7%	9.8%	11.5%	11.3%	5.0%	14.3%	7.4%	12.5%	10.4%
	With Pre-K	10.9%	10.1%	11.7%	11.6%	5.2%	14.9%	7.8%	12.5%	10.5%
	Difference	0.2 p.p.	0.2 p.p.	0.2 p.p.	0.2 p.p.	0.2 p.p.	0.6 p.p.	0.4 p.p.	0.1 p.p.	0.1 p.p.
BA Attainment	Without Pre-K	26.6%	14.7%	38.0%	17.0%	10.9%	20.1%	12.7%	37.3%	28.9%
	With Pre-K	27.8%	15.9%	39.0%	18.3%	11.5%	20.9%	13.9%	38.4%	30.2%
	Difference	1.1 p.p.	1.3 p.p.	1.0 p.p.	1.3 p.p.	0.5 p.p.	.8 p.p.	1.2 p.p.	1.1 p.p.	1.3 p.p.
Earnings at Age 30	Without Pre-K	$33,491	$27,139	$39,535	$18,559	$19,695	$23,875	$36,878	$30,523	$44,891
	With Pre-K	$34,452	$28,102	$40,494	$19,250	$20,266	$24,798	$38,048	$31,467	$45,981
	Difference	$962	$963	$960	$691	$571	$922	$1,170	$944	$1,090
	Percent Increase	2.8%	3.6%	2.4%	3.7%	2.9%	3.9%	3.2%	3.1%	2.4%
Lifetime Earnings	Without Pre-K	$652,698	$518,859	$780,051	$459,094	$346,600	$413,595	$624,404	$610,857	$887,661
	With Pre-K	$668,454	$535,186	$795,264	$469,449	$357,331	$426,219	$645,216	$624,020	$907,740
	Difference	$15,756	$16,327	$15,213	$10,355	$10,731	$12,624	$20,812	$13,163	$20,079
	Percent Increase	2.4%	3.1%	1.9%	2.3%	3.1%	3.1%	3.3%	2.2%	2.3%

SOURCE: Social Genome Model 2.1. Brookings Institution, Child Trends, Urban Institute. 2022.
NOTE: Lifetime earnings are discounted. Undiscounted lifetime earnings would be approximately twice as large.

TABLE A-2

Results from simulating the effects of a targeted (<200% FPL) pre-K program on long-term outcomes for low-income children, by race/ethnicity and gender

		All	Black Women	Black Men	Hispanic Women	Hispanic Men	White Women	White Men
HS Degree Attainment	Before	61.8%	69.4%	50.3%	67.5%	58.5%	66.1%	58.8%
	After	62.5%	69.6%	51.3%	68.0%	59.3%	66.7%	59.5%
	Difference	0.6 p.p.	0.3 p.p.	1.0 p.p.	0.5 p.p.	0.8 p.p.	0.6 p.p.	0.7 p.p.
AA Attainment	Before	9.8%	11.3%	4.0%	13.8%	6.1%	11.9%	10.1%
	After	10.1%	11.5%	4.2%	14.5%	6.5%	12.0%	10.3%
	Difference	0.2 p.p.	0.2 p.p.	0.2 p.p.	0.6 p.p.	0.4 p.p.	0.1 p.p.	0.1 p.p.
BA Attainment	Before	14.7%	12.1%	7.5%	15.1%	9.8%	22.4%	15.0%
	After	15.9%	13.5%	8.1%	15.9%	11.0%	23.8%	16.7%
	Difference	1.3 p.p.	1.4 p.p.	0.6 p.p.	0.9 p.p.	1.3 p.p.	1.5 p.p.	1.7 p.p.
Earnings at Age 30	Before	$27,139	$16,119	$17,477	$21,338	$34,700	$23,784	$39,516
	After	$28,102	$16,823	$18,066	$22,270	$35,889	$24,787	$40,650
	Difference	$963	$704.3	$589	$932	$1,189	$1,003	$1,134
	Percent Increase	3.6%	4.4%	3.4%	4.4%	3.4%	4.2%	2.9%
Lifetime Earnings	Before	$518,859	$419,549	$311,190	$374,741	$582,311	$484,617	$748,453
	After	$535,186	$430,260	$322,548	$387,393	$603,828	$499,108	$770,838
	Difference	$16,327	$10,711	$11,359	$12,652	$21,517	$14,491	$22,385
	Percent Increase	3.1%	2.6%	3.7%	3.4%	3.7%	3.0%	3.0%

SOURCE: Social Genome Model 2.1. Brookings Institution, Child Trends, Urban Institute. 2022.
NOTE: Lifetime earnings are discounted. Undiscounted lifetime earnings would be approximately twice as large.

THE RELATIVE IMPORTANCE OF DIFFERENT MEASURES OF SCHOOL READINESS FOR LATER OUTCOMES

In addition to simulating the effects of a universal and targeted pre-K program, we simulated the effects of increasing each measure of school readiness by 0.2 standard deviations to gain some insight into which of them make the most difference for later success.

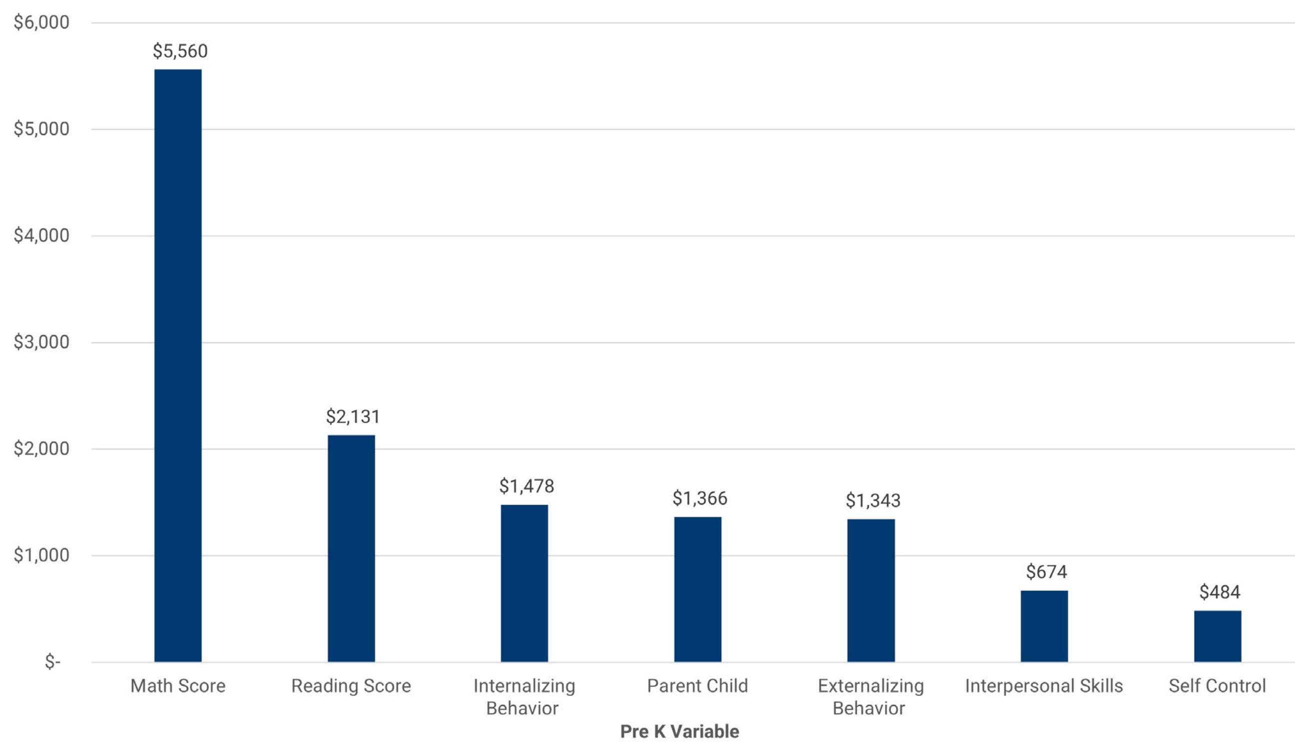
As the figure below shows, math scores at age five have by far the largest relative impact on lifetime earnings. Both Brookings and the Urban Institute have found this and continue to study its implications.

If all variables are increased by 0.2 SD, total lifetime earnings increase by $13,035 or 2.0%.

Cognitive variables account for 59% of the increase, with pre-K math score being by far the most important.

FIGURE A-7

Impact on lifetime earnings of a 0.2 standard deviation improvement in pre-K outcomes



Endnotes

1 Throughout this report we use the term "school readiness" as a benchmark for success at the pre-K life stage. The definition of school readiness is that at age five, the child enters school (kindergarten) with the academic preparedness, behavior, and capacity to sustain interpersonal relationships, and physical health that would lead them to thrive.

2 According to the Head Start impact study: "Over the years of the study, there were negative social-emotional impacts for the three-year-old cohort children not in the lowest quartile, although for differing outcomes and from different reporters. In kindergarten, teachers reported more aggressive behavior and peer problems for Head Start children, and at the end of 3rd grade, parents reported that Head Start children not in the lowest quartile were more likely to be withdrawn than their counterparts" (Head Start Impact Study. Final Report., 2010).

3 Researchers suggest that as the result of the cross-over of children between treatment and control conditions and because of the availability of programs other than Head Start to the controls, the results may be flawed (Bauer, 2019). Others might argue that these flaws are the current reality. There will always be competing programs and parents who are especially skilled at getting their children into a program.

4 The child cohort used by Deming (2009) was 1984-1990 and that used by Bauer & Schanzenbach, 2016 was more recent, 1974-1994.

5 Note that Miller et al. (2019) also found few effects on adult outcomes. Pages et al. (2020) contains an especially useful summary of various studies in the appendix. What their appendix tables, and our brief review, illustrate is the difficulty of finding consensus.

6 Our previous work with the Social Genome Model suggests that no one intervention can be the magic bullet that improves children's lives. Instead, children gained the most when they received effective interventions throughout their childhood years into adolescence and adulthood. We assumed that any cumulative effects were additive. But if they are complementary – if early skills make the learning later skills easier – then we have underestimated the effects of early education. Conversely, if they are substitutes for each other, then we have overestimated the effects (Sawhill & Karpilow, 2014).

7 Another approach is the Marginal Value of Public Funds (MVPF), which was developed and is used by Policy Impacts (run by Nate Hendren of Harvard). The MVPF measures the benefit of a policy relative to its costs and thus "serves as a unifying metric that can be calculated for any type of government (or private) spending" (What Is the MVPF?, n.d.). See Hendren & Sprung-Keyser (2020) and Finkelstein & Hendren (2020) for the MVPF in use.

8 In addition to the variables used in the model to determine on track status, there are additional main model variables and context variables measured at each life stage. For a full list of the variables in the model, see the 2.1 SGM technical documentation (Werner et al., 2022).

9 See Table A.1 in "Identifying Pathways for Upward Mobility" for full list of cutoffs used to define on track at each life stage (Acs et al., 2021).

10 As noted in the technical guide to the model, "Most of the results from ordinary least squares regressions reflect a causal effect, not ability bias; that is to say, higher earnings are the result of additional education and not reflective of underlying, innate ability that contributes to both higher educational attainment and higher earnings. The ability bias in such estimates is small and likely compensated by a bias in the opposite direction caused by measurement error (Card, 2001)" (Werner et al., 2022).

11 See SGM technical appendix for the cutoffs used to determine school readiness (Werner et al., 2022).

12 The cutoff for each metric of success at each life stage can be found in the Urban Institute's "Identifying Pathways for Upward Mobility" report (Acs et al., 2021).

13 These children's experiences have been tracked until the end of middle school (about age 15) by the ECLS-K. For later outcomes in adolescent or adulthood, we have had to use another data source, the National Longitudinal Survey of Youth, 1997 cohort, and a data matching algorithm to track success after age 15. For this reason, one must be more caution with interpreting the correlation between outcomes across the seam. In addition, one can argue about our specific measures of success and about whether this particular cohort of children born in the early to mid 1990s are representative of today's children. The unfortunate fact is that any data source that tracks children into adulthood will, of necessity be tracking the experiences of an earlier cohort of children. If the adults are currently age 30, they were, by definition, born in 1993.

14 The ideal way to avoid this kind of selection bias would be to conduct a Randomized Controlled Trial (RCT). But doing a RCT that follows children from age five into adulthood would take a long time, would be subject to sample attrition, and would lead to results that might lack external validity. Robustness checks to validate the SGM against external research suggests that problems with internal validity due to model misspecification are small but that the need to match two data sets to get a full longitudinal panel leads to additional measurement error that biases the model's coefficients downwards.

15 For more detail, see Moore et al., 2022.

16 The Tulsa Universal Pre-K Program offers voluntary pre-K to all four-year-old children in the state. The authors studied children attending the program in the 2002-2003 school year. The authors found effect sizes ranging from +.38SD to +.79SD on cognitive outcomes (applied problem solving and letter-word identification, respectively), observed in the child's kindergarten year (Gormley et al., 2005).

17 At the time of the study, the New Jersey Abbott Program served three- and four-year-old children in the lowest-poverty districts in the state. The authors studied children who completed their four-year-old year in the program in school year 2004-2005. We looked to the estimates for literacy and math for children in the fifth grade who completed two years of the pre-K program. The authors estimated effect sizes of +.22SD for literacy and +.29SD for math for these children (Barnett et al., 2013).

18 For non-cognitive effect sizes, we rely on some estimates from the Head Start Impact Study, which ran from fall 2002 through 2008. For the three-year-old cohort, the study found a range of favorable impacts on social-emotional outcomes observed at age four and in kindergarten, first grade, and third grade. These effects ranged from .11SD increase in social skills at age four to a decrease of .21SD in hyperactive behavior at the end of the three-year-old Head Start year (Puma et al., 2012).

19 Fuller et al. (2020) find that pre-K programs in New York City that are in higher-income neighborhoods and have fewer black students have higher quality classrooms and teaching practices. (Cascio, 2023) finds that attending a targeted preschool program produced smaller gains for poor children than attending a state-funded universal program.

20 See (Allen & Kelly, 2015) on the state of the early childcare work force. See Weiland and Yoshikawa (2013) on why Boston pre-K worked. See Mashburn et al. (2008) for the finding that there are weak associations between structural factors and child learning.

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