Modeling Equal Opportunity

ISABEL V. SAWHILL AND RICHARD V. REEVES

We examine the themes of equal opportunity, intergenerational mobility, and inequality. We address the normative and definitional questions of selecting measures of mobility and summarize the current state of intergenerational mobility in the United States and abroad. We introduce a new microsimulation model, the Social Genome Model (SGM), which provides a framework for measuring success in each stage of the life cycle. We show how the SGM can be used not only to understand the pathways to the middle class, but also to simulate the impact of policy interventions on rates of mobility.

Keywords: Social Genome Model, mobility, opportunity

The Horatio Alger ideal of upward mobility has a strong grip on the American imagination (Reeves 2014). But recent years have seen growing concern about the distance between the rhetoric of opportunity and the reality of intergenerational mobility trends and patterns.

The related issues of equal opportunity, intergenerational mobility, and inequality have all risen up the agenda, for both scholars and policymakers. A growing literature suggests that the United States has fairly low rates of relative income mobility, by comparison to other countries, but also wide variation within the country. President Barack Obama has described the lack of upward mobility, along with income inequality, as "the defining challenge of our time." Speaker Paul Ryan believes that "the engines of upward mobility have stalled."

But political debates about equality of opportunity and social and economic mobility often provide as much heat as light. Vitally important questions of definition and motivation are often left unanswered. To what extent can "equality of opportunity" be read across from patterns of intergenerational mobility, which measure only outcomes? Is the main concern with absolute mobility (how people fare compared to their parents)—or with relative mobility (how people fare with regard to their peers)? Should the metric for mobility be earnings, income, education, well-being, or some other yardstick? Is the primary concern with upward mobility from the bottom, or with mobility across the spectrum?

In this paper, we discuss the normative and definitional questions that guide the selection of measures intended to capture "equality of opportunity"; briefly summarize the state of knowledge on intergenerational mobility in the United States; describe a new microsimulation model designed to examine the process of

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mobility—the Social Genome Model (SGM); and how it can be used to frame and measure the process, as well as some preliminary estimates of the simulated impact of policy interventions across different life stages on rates of mobility.

The three steps being taken in mobility research can be described as the what, the why, and the how. First, it is important to establish what the existing patterns and trends in mobility are. Second, to understand why they exist—in other words, to uncover and describe the "transmission mechanisms" between the outcomes of one generation and the next. Third, to consider how to weaken those mechanisms—or, put differently, how to break the cycles of advantage and disadvantage.

CONCEPTS AND DEFINITIONS

Amartya Sen, the Nobel Prize-winning economist, famously argued that since everyone favors equality of one sort or another, the key question is: equality of what (Sen 1979)? In particular, what do we mean by *equality of opportunity*? Assuming we can approximate opportunity in some way, do we really want equality of it, or just more equality than we have right now? And how will we determine the acceptable level? Should we focus on opportunities or outcomes, on intergenerational or intragenerational mobility, on absolute or relative mobility, on incomes or some other measure of adult outcomes?

Opportunities or Outcomes?

First, are we interested in opportunities or outcomes? It hardly needs saying that the two are not the same. Individuals are born with different initial endowments and into different family environments that, in the absence of radical social engineering, constrain or enhance their opportunities. Individual preferences matter as well. An opportunity—say, for a college education—may be equally available to Fred and Bob. If Fred chooses to take up the opportunity and Bob chooses not to, their life outcomes—say, in earnings—may differ too.

Understanding how far inequalities of outcome reflect inequalities of opportunity or merely inequalities of abilities or preferences is, of course, a difficult task. For one thing, we need a robust way to measure whether an opportunity is within an individual's opportunity set. More difficult still, we need a way to determine whether an individual's abilities and preferences—say, to go to college—are a reflection of their background, rather than fixed, individually based attributes.

In short, "perfect" mobility rates—with no statistical association at all between background and outcomes—would be an unreasonable as well as unrealistic goal for a number of reasons. On the other hand, we are a long way from worrying about the problems related to perfect mobility. In our view, it is safe to say that current mobility patterns reflect real differences in substantive opportunities which ought to be tackled.

Intragenerational or Intergenerational?

Individuals will move up and down the income ladder during their own lifetime, especially during the prime working-age years. Typically, incomes will rise during the course of one's career and taper down during retirement. Positive and negative income shocks are also possible along the way, especially from unemployment. The movement of an individual along the income distribution during his or her lifetime is defined as intragenerational mobility.

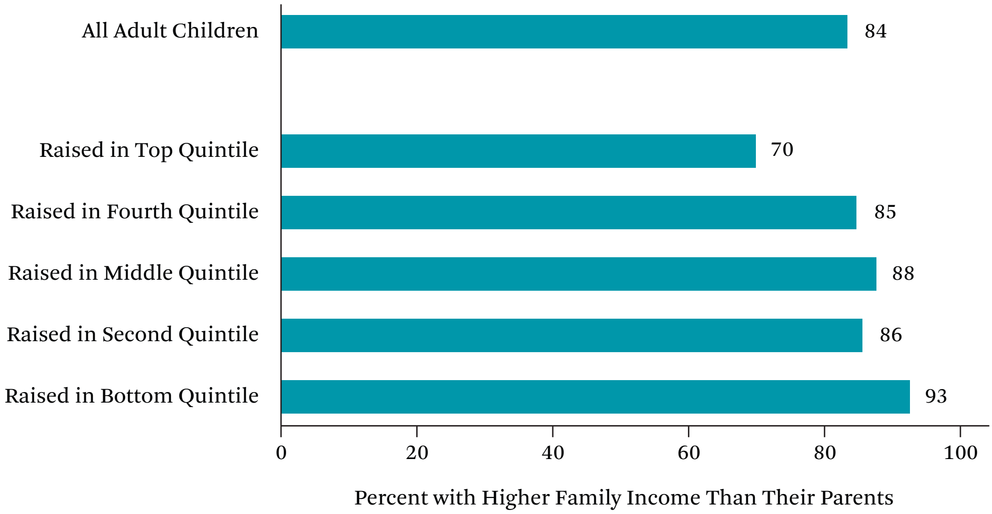
By contrast, intergenerational mobility compares the outcome of an individual with the outcome of their parents, in terms of rank position, income, or another measure. Typically, the comparison is between the parents' income at midlife and the child's adult income at roughly the same point, say the mid-thirties.

Our focus in this paper is on intergenerational mobility, but we recognize that both are important. The two kinds of mobility are also empirically related: the extent to which parental outcomes influence the adult outcomes of their children will depend in part on the ability of each generation to move up during their lifetimes.

Relative or Absolute Mobility?

A related and important distinction is between relative and absolute mobility. Relative mobility is a measure of how far the income rank of parents influences the income rank of children. A society with high relative mobility is

Figure 1. American Children Whose Family Income Exceeds Parents' Family income



Source: Economic Mobility Project 2012.

one with a limited association between the income rank of parents and the (adult) income rank of their children. By contrast, absolute mobility rates are all about real dollar amounts, rather than rank positions (on the distinction between relative and absolute mobility, see Katharine Bradbury and Robert Triest in this volume).

Most people have been upwardly mobile in the absolute sense: 84 percent of U.S. adults, according to the latest estimates, based on an analysis of the Panel Study of Income Dynamics (PSID) for the Economic Mobility Project at the Pew Charitable Trusts (Economic Mobility Project 2012). Those raised in families toward the bottom of the income distribution are the most likely to overtake their parents' income status, as figure 1 shows.

Of course both kinds of mobility matter, though for somewhat different reasons. One version of the American Dream is of growing prosperity for the overwhelming majority, and this is captured well by absolute mobility rates. The two key drivers here are the rates of economic growth and the distribution of that growth.

In theory at least, it is possible to have a society with high relative mobility but low absolute mobility, or vice versa. In practice, societies will display a different mix. Postwar America, for example, was an engine of absolute mobility, fueled by strong and broadly shared economic growth (Economic Mobility Project 2012). But relative mobility rates remained flat, as we discuss.

Policymakers will likely balance the need to promote both kinds of mobility, and some scholars are exploring innovative ways to combine aspects of both kinds of mobility into a single measure (Genicot and Ray 2013). But it is important to be clear which kind of mobility a particular policy is attempting to improve, so that the efficacy of the policy can be judged against the appropriate benchmark. In the end, most people want both growth and shared prosperity but also fluidity and meritocratic fairness.

Mobility of What?

The array of possibilities here is kaleidoscopic: income, wages, education, well-being, and occupational status. The truth is that all of them matter, and it is instructive to examine mobility patterns in each, and indeed on other dimensions (Graham and Nikolova 2013). An important item on the mobility research agenda is deepening our understanding of the interactions between mobility on these different dimensions. We also need to keep a range of successful outcomes in mind. For instance, a person from an affluent background might receive a great education and choose a career that is stimulating to them, high in status but low in earnings: they become the curator of a small arts museum, perhaps. In income terms, they may be downwardly mobile, but in all the other dimensions they may have risen up the ladder.

It is important to bear this diversity in mind, but at the same time we need to select some concrete dimensions to focus our research efforts. And though achievements on the various dimensions do not go together lock-step, they do cluster together quite strongly. In most cases, education, wages, income, status, and well-being will point in the same direction (Haskins and Sawhill 2009).

We follow most researchers in the field by focusing on income as an outcome and, in particular, on household income. Income is a powerful predictor of other outcomes in terms of health, employment, housing, family formation, and so on. It is also what Joseph Fishkin describes as an "instrumental good"—in other words, one that can be fairly easily converted into other goods, including opportunity-enhancing ones such as education (2014). Income is also easier to measure on a comparable basis than many other constructs.

Because most recent research, including our own, has focused on relative intergenerational income mobility (RIIM), we now briefly review the evidence for this particular measure of opportunity.

RELATIVE INTERGENERATIONAL INCOME MOBILITY: THE EVIDENCE

Taken as a whole, the United States has fairly low rates of RIIM. Rates appear to have been flat for at least the last few decades (Chetty, Hendren, Kline, and Saez 2014). However, there is significant geographical variation within the United States in mobility patterns —as least as much, it seems, as between the United States and other nations (Chetty, Hendren, Kline, Saez, and Turner 2014). These geographical variations are visible both between fairly large areas, such as commuting zones, but also at a smaller, neighborhood level.

There are sharp differences in mobility patterns by race, with African Americans in particular having a much worse mobility pattern than white Americans (Mazumder 2012, 2014). There are modest differences in mobility patterns for women and men, which we do not address here but are examined by a number of scholars (Isaacs, Sawhill, and Haskins 2008).

There are also marked gaps in mobility patterns at different levels of education, as well as for different family structures experienced during childhood. Other papers in this collection provide a detailed picture of these patterns (see articles in this volume by Timothy Smeeding, Katherine Magnuson, Patrick Sharkey, and Eric Rosengren).

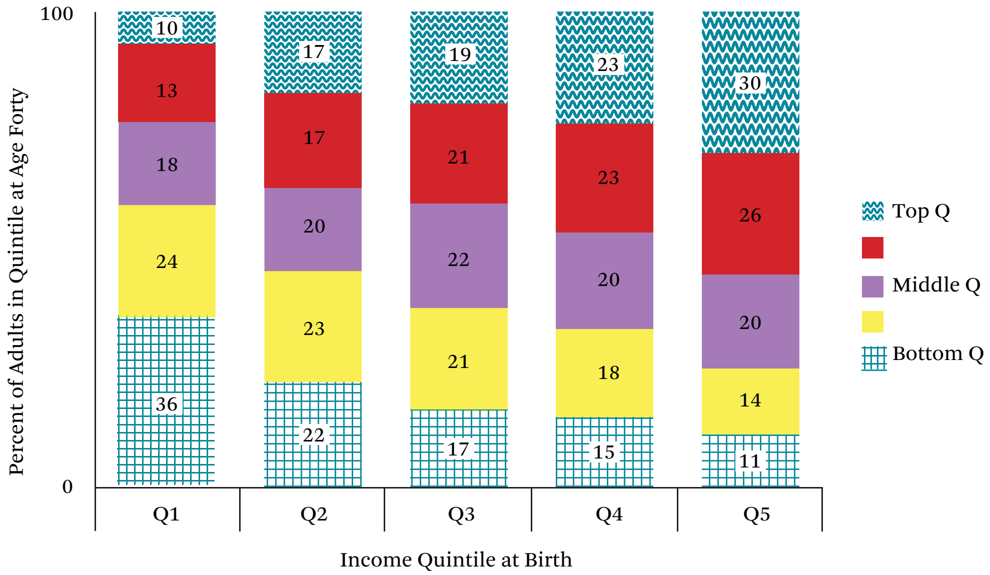
Current Overall Picture on Mobility

A standard technique for assessing intergenerational mobility is sorting children and their parents into their respective income distributions and plotting the results. This procedure generates a social mobility transition matrix. Such matrices can then be conditioned to capture differences by individual characteristics, for example, race, gender, education, etc. If a society has "perfect" mobility, then—regardless of conditioning—children whose parents are in the lowest quintile of the parent income distribution are as likely to end up in the lowest quintile of the child income distribution as they are to end up in any other quintile. An alternative approach—developed in particular by the economist Bhashkar Mazumder—is rank directional mobility, which tracks an individual's position on the whole income rank compared to their parents' rank (Bhattacharya and Mazumder 2011).

Still another way to measure the degree of mobility is to estimate the relationship between parental and child incomes or earnings around age thirty-five or forty, a measure referred to as intergenerational elasticity (IGE). It reflects both the correlation between the economic status of parent and child and any change in the distribution of these economic outcomes between the two generations.

In addition, different sources of data can be

Figure 2. Social Mobility Matrix, United States Overall



Source: Reeves 2014.

used, including longitudinal surveys such as the PSID or the National Longitudinal Survey of Youth (NLSY), Social Security data, or tax records. Again, each has its strengths and weaknesses (Winship and Owen 2013).

The United States exhibits a high degree of intergenerational income "stickiness," especially at the top and the bottom of the income distribution. Using the dataset constructed from the NLSY79 for the SGM, figure 2 shows that children born to families at the bottom of the income distribution (that is, whose parents' income falls in the bottom quintile) have a 36 percent probability of remaining stuck there in adulthood—far more than the "ideal" 20 percent. Likewise, children on the opposite end of the spectrum have a 30 percent chance of remaining in the highest income quintile. The difference is similarly more than twofold between the odds of a child born in the top quintile ending up in one of the top two quintiles (the "comfortable middle class") as an adult and one born in the bottom quintile (56 percent versus 23 percent). Other studies using different datasets find similar results; most of those using the PSID find lower rates of mobility (Isaacs, Sawhill, and Haskins 2008).

International Variations

Comparing cross-generation trends across countries is inevitably difficult. However, the broad picture that emerges from these comparisons is fairly clear and consistent: within economically developed countries, mobility rates are highest in Scandinavia and lowest in the United States, UK, and Italy, with Australia, Western Europe, and Canada lying somewhere in between. Table 1 provides a list of the most recent, reliable income elasticity coefficients for a range of nations (Blanden 2014).

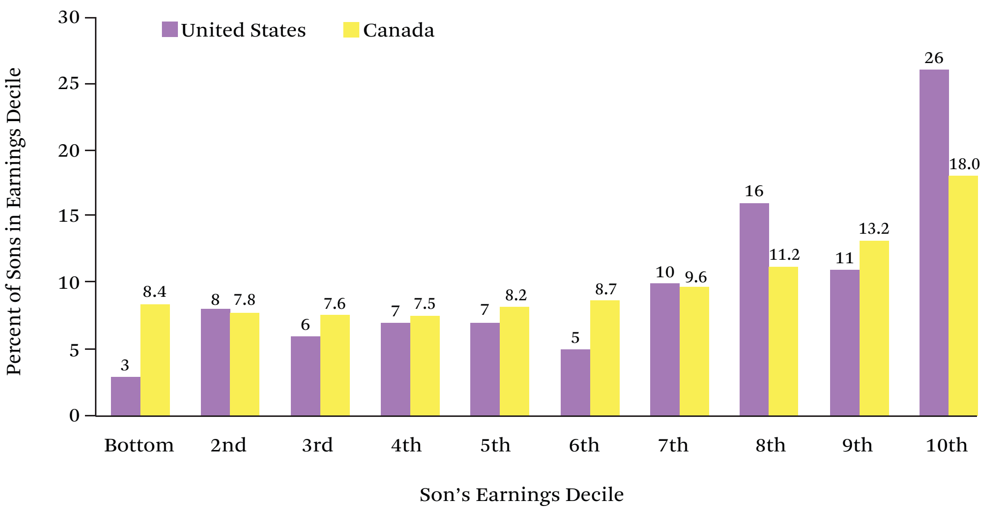
Given the huge differences on a whole range of factors between nations—not least population size and diversity—these comparisons can only take us so far. It is instructive to look at close neighbors, too, and scholars such as the economist Miles Corak have conducted a number of studies comparing the United States to Canada. Overall, Canadian rates of mobility appear to be higher. One analysis compares intergenerational earnings persistence by earnings decile in the United States and Canada and finds greater persistence in the United States, especially at the top and bottom of the distribution (see figures 3 and 4) (Corak 2010).

Table 1. Preferred Estimates of Income Mobility

Country	Elasticity	Country	Elasticity
Brazil	0.52 (0.011)	New Zealand	0.25 (0.09)
United States	0.341 (0.0004)	Germany	0.24 (.053)
UK	0.37 (0.05)	Sweden	0.24 (0.011)
Italy	0.33 (0.026)	Canada	0.23 (0.01)
France	0.32 (0.045)	Finland	0.20 (.020)
Spain	0.29 (0.03)	Denmark	0.14 (0.004)
Norway	0.25 (0.006)	Japan	0.31 (0.043)
Australia	0.25 (.080)	South Africa	0.48 (0.045)

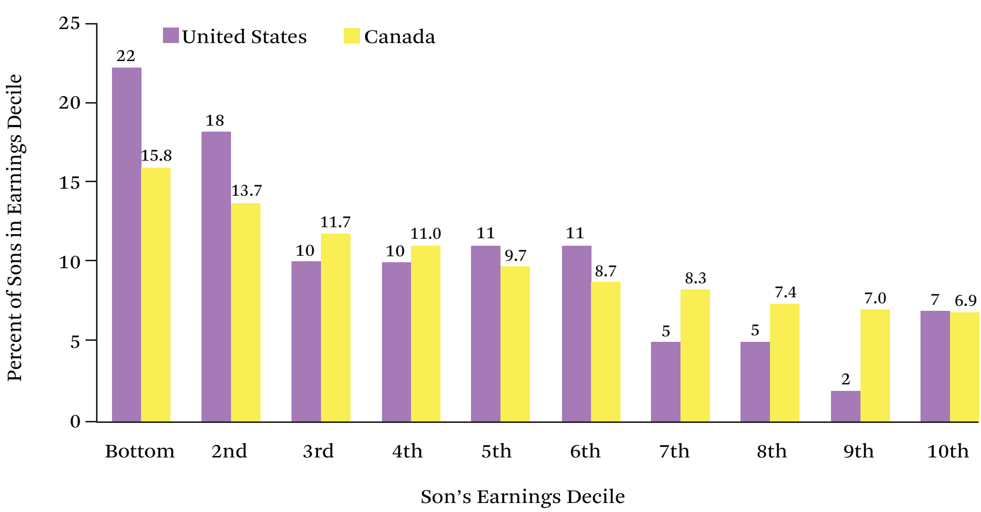
Source: Blanden 2014.

Figure 3. Earnings Decile of Sons Born to Top-Decile Fathers



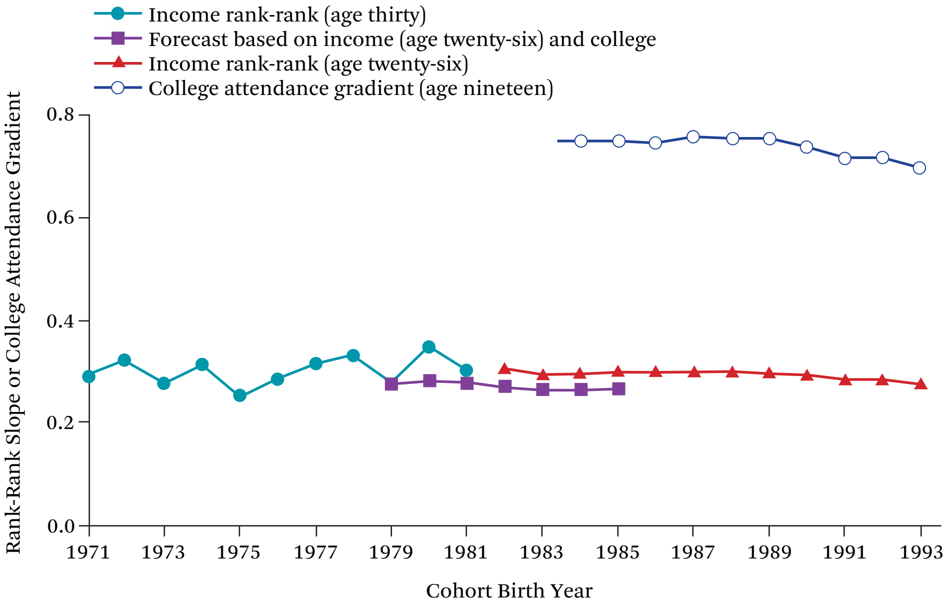
Source: Corak 2010.

Figure 4. Earnings Decile of Sons born to Bottom-Decile Fathers



Source: Corak 2010.

Figure 5. Intergenerational Mobility Estimates



Source: Chetty, Hendren, Kline, Saez, and Turner 2014.

Time Trends

In a comprehensive series of recent studies, making innovative use of administrative records of income, the economist Raj Chetty and his colleagues probe both geographical variations in mobility (see below) and long-term trends. Their conclusion is that RIIM rates are flat (Chetty, Hendren, Kline, and Saez 2014).

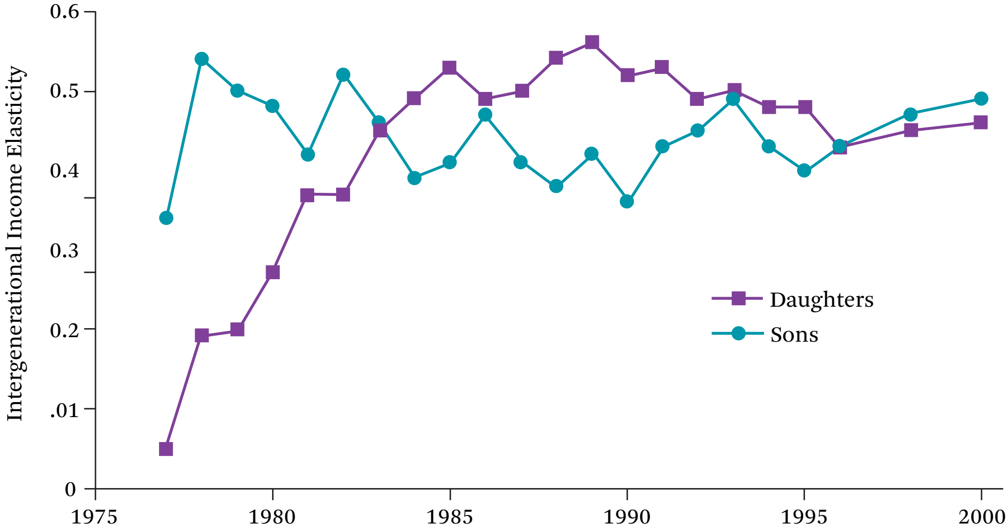
Raj Chetty and coauthors estimate a rank-rank specification, each child ranked within their birth cohort according to his or her mean family income at age twenty-nine to thirty, and each set of parents ranked according to their mean family income over the five years when the child is fifteen to nineteen years old. Regressing child rank on parent rank shows "no trend" across birth cohorts (that is, 1971–1974, 1975–1978, or 1979–1982); see figure 5. The authors also use college attendance and college quality as alternative outcome measures of mobility and come to a similar conclusion: "Intergenerational mobility is stable (or improving slightly)."

These findings echo the results of earlier research on time trends. Tom Hertz examined cohorts of children born between 1952 and 1975 and observed as adults between 1977 and 2000 included in the PSID. Using several distinct methodologies to correct for respondent attrition, he found "no clear long-run linear trends in the IGE of family income or family income per person" (Hertz 2007, 46). Chul-In Lee and Gary Solon used the same underlying dataset and come to a similar conclusion (2009). Although data limitations prevented them from ruling out a modest trend, their analysis of IGEs for sons and daughters—they analyze the two separately—suggests "intergenerational income mobility in the United States has not changed dramatically over the last two decades." Figure 6 shows the IGEs for sons and daughters who reached adulthood (age twenty-five) between 1977 and 2000.[1]

Although the evidence on mobility trends over time suggests a degree of stability, improving rates of intergenerational mobility is by definition a long-term endeavor. So it is important to be alert to contemporary signals of

1. The results for daughters show some decrease in mobility early in the 1980s, in contrast to the discussed findings, but this result may be anomalous.

Figure 6. Intergenerational Income Elasticities



Source: Lee and Solon 2009.

a potential improvement or worsening in mobility rates in the decades ahead. In particular, it is worth looking at growing inequalities in income, educational attainment, family structure and parenting, and by neighborhood. Most of these are covered in other papers in this volume, so our treatment here is brief.

Income inequality has been rising in recent decades. The extent of the rise is strongly determined by the selection of income measure (in particular, the difference between pre-tax and pre-transfer income and post-tax and post-transfer income). There is certainly a strong intuitive claim in the idea of a positive relationship between inequality and immobility, not least because, as Isabel Sawhill has said elsewhere, "when the rungs of the ladder are far apart, it becomes more difficult to climb the ladder. . . . Inequality in one generation may mean less opportunity for the next generation to get ahead and thus still more inequality in the future" (quoted in Froomkin 2010; quoted also in Krueger 2012).

So far, however, no definitive evidence suggests that rising inequality has led to declining intergenerational mobility (Chetty, Hendren, Kline, and Saez 2014). This could be because the primary driver of income inequality is the gap between the top of the distribution and the majority of the population, which may not influence mobility rates in the population more broadly (Burtless 2014). It is also possible that income inequality has been pulling downwards on mobility rates, but that other forces—such as declining teen pregnancy or crime rates, or rising high school graduation rates—have been pulling in the opposite direction. Or, it could simply be a matter of time.

Some evidence does exist for growing gaps in levels of educational attainment by parental income background, in the early years, through K–12, and into higher education (see articles by Katherine Magnuson, Greg Duncan, and Richard Murnane in this volume; see also Reardon 2011; Bailey and Dynarski 2011). Most of these are covered by other contributors to this collection; suffice for us to say that to the extent that educational attainment predicts adult outcomes, rising gaps by background could, prima facie, result in lower rates of intergenerational mobility. From the perspective of relative mobility, gaps in attainment are of course more important than the overall levels. If higher education rates rise, but rise disproportionately among the affluent, the effects on RIIM are likely to be negative. Evidence is good, for example, that differences in higher educational attainment by income background have had a strong, negative influence on intergenerational mobility in the UK in recent years (Blanden, Gregg, and Macmillan 2007).

In the areas of family and parenting, significant gaps have opened up in rates of marriage, intentional childbearing, and family stability by social and economic background. These gaps are the principal subject of Isabel Sawhill's latest book, *Generation Unbound: Drifting into Sex and Parenthood Without Marriage*, in which she writes that "family formation is a new fault line in the American class structure" (Sawhill 2014, 76). Again, it is too early to say whether these trends will have an impact on intergenerational mobility. But given the relationship between family structure and outcomes, there is certainly cause for concern (Cooper et al. 2011; McLanahan 2011).

Gaps are also large in terms of parental engagement and parenting skills along income, race, and educational axes. Work by the economist James Heckman and colleagues shows that parents provide vital "scaffolding" around the skill development of their children (Cunha and Heckman 2008; Cunha, Heckman, and Schennach 2010). Research by the psychologists Ross Thompson, Ariel Kalil, and others shows how supportive, nurturing parenting styles can blunt the impact of poverty and underpin the development of positive skills and outlook (Kalil 2014; Thompson 2014). Our own research suggests that narrowing parenting gaps would have a positive impact on certain outcomes, including high school graduation rates (Reeves and Howard 2013a).

In addition to growing gaps in income, education, family structure, and parenting, individuals are increasingly sorting themselves into different communities in America. Neighborhoods have become somewhat less segregated along race lines in recent decades, though from high levels, but rates of segregation by economic status have risen (Sharkey 2013a). The sociologist Patrick Sharkey provides suggestive evidence that cities with higher rates of economic segregation have lower rates of intergenerational mobility. As he concludes: "The degree to which the poor live apart from the rich is a more robust predictor of economic mobility than the overall amount of inequality within a metropolitan area. In other words, what matters is not just the size of the gap between the poorest and richest residents of a metro area, but how the richest and poorest are sorted across different communities" (Sharkey 2013b, 1).

Scholarly efforts to discover and describe the "transmission mechanisms" by which inequalities transfer from one generation to the next should help to identify the most dangerous gaps, and so point the way to the most fruitful areas for policy intervention. It is for these purposes that the SGM has been developed. In the next section, we describe the model and put it to work, estimating the effects of a range of interventions on patterns of intergenerational mobility.

WHY ISN'T THERE MORE MOBILITY? A LOOK INSIDE THE BLACK BOX USING THE SOCIAL GENOME MODEL

Much of the literature on intergenerational mobility has relied on a simple mobility matrix or a summary statistic such as the IGE. The most common measure of mobility is the relationship between the income of a parent and the income of the child as an adult. This research literature leaves unanswered a number of important questions that work using the SGM is beginning to address:

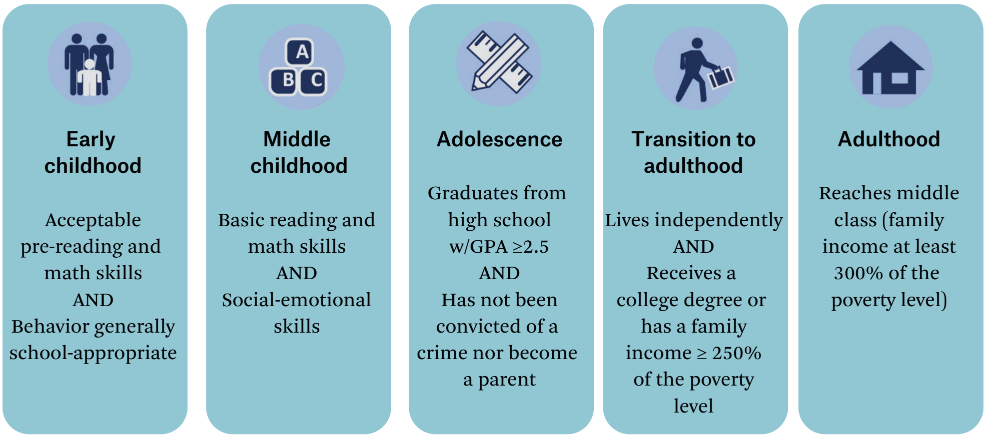
1. Is income a sufficient measure of a child's early background and later "success"?
2. Can we fill in the black box and show the pathways to adult success?
3. What might be done to improve social mobility?
4. How do we measure the effectiveness of alternative programs and policies aimed at this goal?

The SGM—originally developed at Brookings and now a partnership between Brookings, the Urban Institute, and Child Trends—is a first attempt to answer such questions.

The Conceptual Framework

The SGM is a life cycle model with five life stages (after circumstances at birth) with a corresponding set of success measures at the end of each life stage, as illustrated in figure 7. A

Figure 7. Stages of the Social Genome Model



Source: Sawhill and Karpilow 2014.

few brief points are worth making about the construction of the model.

First, the SGM is theoretically motivated by the long literature on human capital formation. Gaps in skills, in particular, help explain mobility patterns. An ongoing debate over the relative contribution of cognitive and "noncognitive" skills (variously labeled grit, persistence, prudence, conscientiousness, and so on) aside, agreement exists that both sets of skills matter, that the two sets are strongly interrelated, and that both are malleable—with noncognitive skills more malleable later, and certainly well into adolescence (Roberts et al. 2007; Heckman, Stixrud, and Urzua 2006).

The SGM includes measures of both cognitive and noncognitive skill acquisition at the end of middle childhood (ages ten to eleven) and at the end of adolescence (ages eighteen to nineteen). We also look at both achievement (for example, test scores, GPA) and attainment (for example, graduation from high school or college). Other measures of skill acquisition could, of course, be added, and factor analysis could be used to hunt for important latent variables (Heckman, Pinto, and Savelyev 2013). New work by James Heckman and others on character or noncognitive skills suggests that self-control (prudence) and persistence (grit) also matter for later success (Reeves and Howard 2013b). Currently, the model includes some direct measures of social-emotional development in childhood, and some rough behavioral proxies for these skills, such as involvement in crime, having a baby as a teenager, or being suspended from school.

Although the model attempts to measure human capital broadly, the core relationship is the one between education and earnings, in the tradition of the economists Gary Becker, Jacob Mincer, and later contributors to the human capital literature. Lessons from that literature include the following:

- The rate of return on education is in the neighborhood of 6 to 10 percent.
- Most of the results from ordinary least squares regressions (finding rates of return of around 6 percent) reflect a causal effect and not an ability bias (the ability bias in such estimates is small and likely compensated for by a bias in the opposite direction due to measurement error) (Card 2001; Ashenfelter and Rouse 1999).
- Rates of return have increased for recent cohorts, probably because of a lag in the response of supply to demand (Goldin and Katz 2008).
- Marginal returns may differ from average returns and depend on who is being targeted by an intervention (Carneiro, Heckman, and Vytlacil 2011).

- The "rate of return to education" is heterogeneous across skill sets, and depends on labor market demand (Owen and Sawhill 2013).
- Rates of return vary by subgroup, with African Americans experiencing higher returns than whites, natives experiencing higher returns than immigrants, and youth experiencing higher returns than the elderly (Henderson, Polachek, and Wang 2011).

Gaps in skills are likely to overlap strongly, though not perfectly, with gaps in educational achievement. Indeed, much of the effect of education on mobility rates may be mediated through cognitive ability, and vice versa. Higher levels of education are clearly associated with significantly higher rates of upward mobility. Children who go on to achieve a college degree regardless of their parents' income are more likely to make it to the top income quintile, whereas those who complete only high school have significantly worse mobility patterns (see paper by Timothy Smeeding in this volume).

Another ongoing debate is over the extent to which skills are heritable, rather than learned. For the purposes of the present discussion, it is enough to endorse Jo Blanden's view that "genes play an important role in generating intergenerational transmissions. But they . . . are not the whole story" (2014, 20).

Second, the SGM is a dynamic model, allowing changes in one life stage to be passed through to the next. As James Heckman has famously stated, success begets success. The process of human capital formation is cumulative, and rates of return vary with the level of prior skill development. Although the process of human development begins in the home and is greatly influenced by the quality of parenting, the process continues through the school years (Garcia and Heckman 2014). Also, cognitive and noncognitive skills may be complementary. The children in the Perry Preschool Project, for example, did better in high school because the noncognitive skills they acquired early on helped them focus and stay out of trouble. James Heckman calls this capacity-building "self-productivity." It is one reason why the economists Flavio Cunha and James Heckman find that later-stage interventions designed to remediate early-stage deficiencies are more costly than earlier ones (Cunha and Heckman 2008).

Relatedly, the full benefits of early-stage interventions will not materialize without some investment during later stages. The economists Janet Currie and Duncan Thomas, for example, show that participants in the Head Start program lose some of their performance advantage over nonparticipants after returning to their disadvantaged home environments (Currie and Thomas 1995). The Chicago Longitudinal Study, which tracked children in a preschool program, also found that adolescent and adult-stage benefits were greater for children that received extended interventions through sixth grade; later investment helped the children capitalize on earlier investment (Reynolds et al. 2011). As noted in more detail later in this paper, one advantage of the SGM's life-cycle, cumulative approach is that it can capture the effects of sustained intervention throughout childhood and adolescence.

Third, the SGM incorporates multiple social, personal, and economic indicators, as suggested by research evidence, into each life stage. Circumstances at birth provide the most vivid illustration of the need for this multidimensional approach. Parents determine not only a child's genetic endowment but also the early home environment—and this is not merely, or even mostly, a question of income. The literature in sociology that has used a multiple measure of "class" or of various advantages and disadvantages at birth is extensive. Child's birth weight is included as a proxy for prenatal environment, which recent literature suggests can be critical to future development (Glover 2011). Maternal education plays a strong role in the model and gets at some mixture of genetic endowment and home environment. In addition, the model includes direct measures of the quality of parenting using the Home Observation for Measurement of the Environment Revisited (HOME) scale, which scores parents on the level of cognitive stimulation and emotional support they provide to their children. In the SGM, we sometimes use such a multidimensional measure, looking at a child's family income, maternal education, marital status, and weight at birth. At other times, we use conventional measures of family income.

Fourth, although individual earnings are a function of human capital accumulation, broadly defined, they do not, of course, depend only on human capital. Imperfections in the labor market (for example, discrimination or high rates of unemployment induced by a recession) may also determine how much a person can earn. In addition, many unobserved characteristics affect earnings. For these kinds of reasons, the ability of even well-specified earnings equations to explain a lot of the variance in individual earnings is limited.

Fifth, the SGM operationalizes a series of success measures for each life stage. These were selected after a review of the literature on child development and human capital, with particular attention paid to empirical evidence suggesting which measures were predictive of later success. Our other selection criteria were the availability of data on the measure and the advice of experts in the field.[2] Our final success measure is family income at age forty, in particular the proportion who become "middle class by middle age." For our purposes, if an individual's family income at age forty (middle age) is 300 percent or more of the family-size adjusted poverty threshold—roughly $68,000 for a family of four—they have cleared our adult success benchmark. This is necessarily a heavily normative formulation of what defines success. Some scholars prefer a measure of capacities (health and education, for example), or even of adult happiness over a measure of income (Sen 1992). The model could of course be used to explore a wide variety of outcomes: this is the one we have selected for our purpose of examining patterns of intergenerational mobility.

Sixth, the SGM must still be considered a work in progress. A number of improvements, additions, and extensions are currently being worked on or considered, including the following:

- a more detailed structural model for the long and critical life stage between ages ten and nineteen;[3]
- a labor market module based on an earnings function and several identities (relating, for example, income to earned and unearned sources and to the earnings and employment experience of different family members), as well as a series of equations that relate employment and earnings to the state of the labor market; and
- a family formation module, possibly by connecting the SGM to another model, FamilyScape, which is now a partnership between Brookings and Child Trends. FamilyScape models the process of family formation in detail, including the formation of a dyad, whether a couple has sex, whether they use birth control, become pregnant, have an abortion, marry or divorce, and whether a birth occurs and to what kind of parents. By linking the two—or by using the Urban Institute's Dynasim model—it might become possible to create a two-generation model.

Structure of the SGM

With the previously discussed conceptual framework in mind, we turn to a description of the model. The model is structured as a series of regression equations in which outcomes in each life stage are treated as dependent on outcomes in all prior life stages, plus some more contemporaneous variables. More specifically,

$$\mathit{Outcome} = \beta_0 + \beta_1 \mathit{CAB} + \beta_2 \mathit{Previous\ Stage\ Outcomes} + \varepsilon$$

where $\beta 1$ and $\beta 2$ are vectors of coefficients, *CAB* is the set of *Circumstances at Birth* variables, *Previous Stage Outcomes* is the set of outcomes

2. Some measures strongly suggested by theory or by other experts were simply not available or were not well measured enough to include in the model. Examples include paternal education and child health outcomes, which were poorly measured in our dataset.

3. Child Trends is developing the model, breaking the adolescent stage into multiple more detailed stages, and adding variables that capture additional information on peer relationships and educational progress.

from temporally prior stages (see figure 7), and ε is a random error term.[4] For all variables and equations used in the model, as well as an explanation of the model's structure, see the appendix.

The relationships between variables across life stages were estimated using ordinary least squares regression for continuous outcomes and a linear probability model for dichotomous outcomes. Other functional forms were tried and did not significantly affect the results.

The model tries to capture both the direct and indirect effects, via their effects on intermediate outcomes, of all prior outcomes in a child's life. For this reason, the equations for the later stages often contain many variables. For example, the equation predicting high school graduation contains twenty-five independent variables, representing a core set of demographic variables, measures of a child's birth circumstances (family structure, birth weight, income, maternal education), early childhood outcomes (cognitive and noncognitive), and middle childhood outcomes (cognitive and noncognitive). Because of the nested or recursive structure of the model, the coefficients capture both the direct effect of a variable and its indirect or mediated effect through its impact on some earlier life outcome. For example, the coefficient on school readiness reflects the effects of that variable (or any intervention affecting it) on later outcomes (for example, adult income) due to its effects on some earlier outcome (for example, reading at age ten) but also its effects on some less measurable aspect of a child's development that has a direct effect on incomes even after accounting for all of the intermediate outcomes. These direct effects are sometimes called sleeper effects. Because of this structure, it is possible to explore not only how much early outcomes are correlated with later ones but also through which paths.

Efforts are under way to test alternative specifications that allow for more interactions or better measures of these outcomes and to benchmark the parameters against external research findings from the most sophisticated literature on these topics. Not only does each equation include a different set of variables, but sixteen equations representing the many different outcomes are included in the model (see figure 7). These outcomes, or benchmarks of success, were selected based on a year-long review of the literature, the advice of other experts and practitioners, the availability of data, and sometimes an explicitly normative framing of desirable goals at each life stage (for example, a crime-free adolescence).

Regression models do not, of course, provide causal estimates of the kind of long-term relationships hypothesized in our model. For these reasons, but also because of measurement error and difficult specification issues, we do not want to argue that the model's parameters and any predictions based on them are necessarily correct or that one can make causal inferences based on them. Instead we hope that this fledgling effort to create a framework in which the process of mobility is made more explicit and some data attached to that process will lead to a better understanding of mobility that will encourage others to improve on our efforts.

Data

The SGM is constructed using two data sets from the Bureau of Labor Statistics' National Longitudinal Surveys. Our primary data set is the Children of the NLSY79 (CNLSY). It represents children born mainly in the 1980s and 1990s and is the source of our data for the birth, early and middle childhood, and adolescent stages. No respondent in the CNLSY is yet old enough to track through adulthood, so we impute their adult values with help from a second dataset, NLSY79.[5]

4. Because of the need to impute data for the two adult stages of the model, the actual specification for these two stages is different than in the case of the childhood stages. For a complete list of the variables used to measure outcomes at each life stage and some of the other control variables used in the model, see Winship and Owen 2013.

5. The NLSY79 followed Americans from the generation just before the CNLSY sample. To impute the adult-stage outcomes for the CNLSY respondents, we follow a two-step process. First, we use regression analysis of

The result is a longitudinal dataset in which synthetic individuals, part actual CNLSY data and part imputed data, pass through five life stages from birth to adulthood. This includes 5,783 children from the CNLSY, born between 1971 and 2009.[6]

SOCIAL GENOME MODEL AS A POLICY TOOL

The SGM has a number of advantages as a policy tool for studying social mobility. First, it provides an explicit framework for considering pathways to the middle class (Sawhill, Winship, and Grannis 2012). As noted earlier, the model divides the life cycle into five stages and identifies outcomes in each stage that are predictive of later outcomes and eventual economic success. This framework allows us to assess not only whether children are likely to be successful as adults but also whether they are likely to be successful middle schoolers, adolescents, or young adults. Allowing for these intermediate outcomes and the transitions between them, as the SGM does, is critical to understanding downward and upward mobility; we can test whether and how gaps in success persist or cumulate over time.

Second, although the model relies on certain metrics of success, it allows for flexibility in how success is defined. We currently use a family income of at least 300 percent of poverty by age forty, but other measures could be used. In addition, a user interested in a specific question, such as the proportion of African American children who are reading at grade level by age ten, or the number of poor children who graduate from college, or the number of adolescent boys who have ever been involved with the juvenile justice system, will be able to use the model to answer these and numerous similar questions.

Third, the SGM can take the results of rigorous evaluations of social programs, typically randomized controlled trials (RCTs), and estimate their simulated impact on longer-term outcomes. This allows for the "test driving" of policy experiments without the significant delay and expense of a real-world evaluation. For example, if we know how a preschool program affects school readiness at age five, we can use the SGM to estimate its effects on later outcomes, such as high school graduation rates or adult earnings, without having to wait thirty years and spend millions of dollars on a real-world evaluation of the program.

Fourth, the SGM enables decision-makers to compare the relative predicted effectiveness of different interventions using a standardized metric, such as discounted lifetime income, and then compare those results to the costs of the program. For instance, we show later in this paper that the predicted positive impact on lifetime income of a multistage intervention targeted at children living in families with incomes below 200 percent of the poverty line would more than pay for the intervention. The use of such cost-benefit analyses may lead to more informed decisions on where to invest the marginal dollar of public or philanthropic funds.

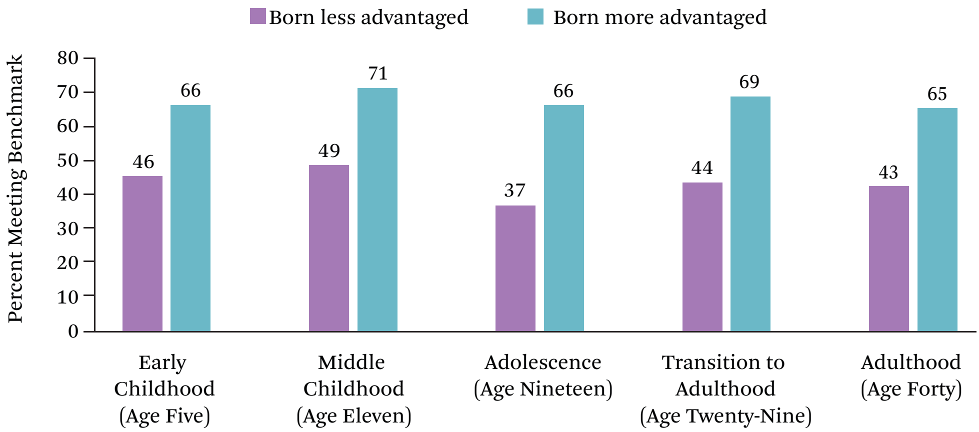
Fifth, the SGM can be used to look at the cumulative impacts of intervening not just once but multiple times and in multiple domains over a child's life. By design, many evaluations are limited to quantifying the short-run effect of a single, isolated intervention. But disadvantaged children may need more than a one-time boost whose effects may fade over

---

the NLSY79 to estimate the relationships between birth and adolescent values, and adult outcomes. Then we apply the regression coefficients, which summarize those relationships, to the birth and adolescent values in the CNLSY sample. This plug-in approach gives us predicted adult outcomes for each CNLSY respondent. This assumes that the CNLSY respondents will follow a similar life-trajectory to the older, NLSY79 respondents. As a result, our model does not incorporate possible cohort effects. Both the CNLSY and the NLSY79 also suffer from missingness because of attrition, nonresponse, and data entry error. We use imputation to fill in these gaps.

6. Because the CNLSY children were born to mothers who were living in the United States in 1978, we exclude children who immigrated after 1978, or were born to mothers who immigrated after 1978. Our data and model, then, are best viewed as applying to the entire set of children born to women living in the U.S. Child Trends, in conjunction with Brookings, retooled the model to use data from the 1997 National Longitudinal Survey of Youth (see Moore et al. 2014).

Figure 8. Success at Each Life Stage, Circumstances at Birth



Source: Authors' update to Sawhill, Winship, and Grannis 2012.

time. Perhaps they need a parenting program in infancy, a preschool experience as a toddler, a reading program in elementary school, and so forth (Sawhill and Karpilow 2014). The SGM can be, and—as will be discussed—has already been, used to evaluate such multiple intervention efforts.

Sixth, the SGM allows for examinations of the distributional implications of different policies. For many years, researchers have documented persistent gaps in success between men and women, whites and African Americans, and children of high-income parents and low-income parents. Because the SGM is based on a detailed representation of the demographic and economic characteristics of the U.S. population, it will allow us to measure and monitor these gaps not only at baseline but also after a targeted intervention. For example, we can simulate the predicted effect of a middle childhood education initiative on the black-white gap in success at adulthood.

Finally, the SGM can be used to set research priorities. Where the model's parameters or data are weak (discussed later in this paper), it is usually because insufficient resources have been devoted to collecting the right data or estimating the most important parameters. Currently, in characterizing the birth circumstances of children, we rely on data on the mother only, for example, her education attainment, age at child's birth, and so on. Ideally, we would include analogous data on the father, but the NLSY79 does not contain good data on such questions. This is just one example of a research gap that may be worth filling.

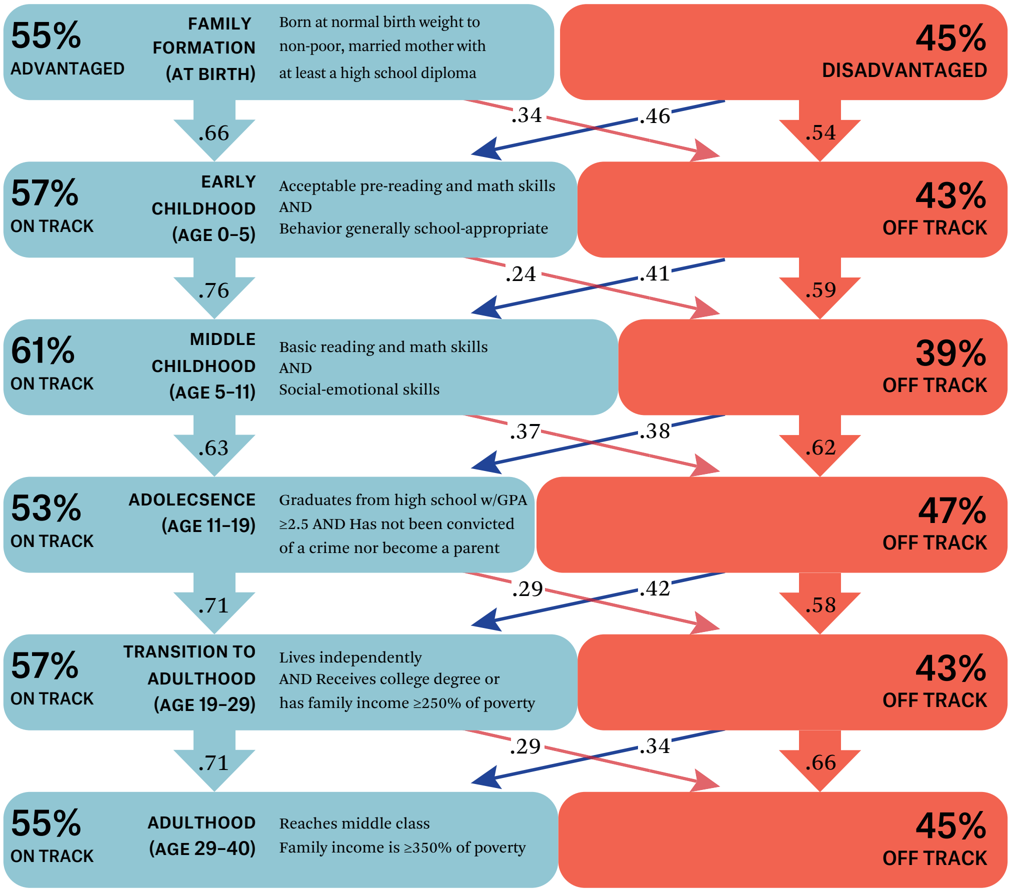
Use of the SGM

The SGM has been put to work as a policy tool in several previous papers (see, for instance, Sawhill and Karpilow 2014; Sawhill, Karpilow, and Venator 2014; and Moore et al. 2014).[7] Some of this work has been descriptive and documents how pathways to success vary systematically for different groups of children. Of particular concern, we document a significant and persistent gap between children born into disadvantaged and advantaged circumstances (Sawhill, Winship, and Grannis 2012).

As shown in figure 8, among children born of normal birth weight to married mothers who were not poor and had at least a high school education at the time of their child's birth (advantaged-at-birth), 66 percent can be expected to be ready to start kindergarten, versus only 46 percent otherwise. This gap never narrows—even by the end of adolescence, children who are less advantaged at birth are 29

7. For a full list, see the Social Genome Project website (http://www.social-genome.org).

Figure 9. Probability of Being On or Off Track



Source: Authors' update to Sawhill, Winship, and Grannis 2012.

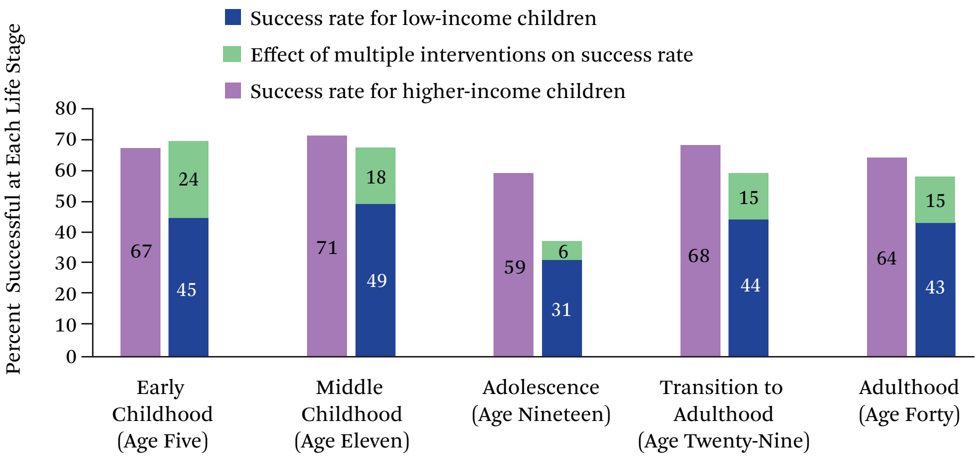
percentage points less likely to succeed as adults.[8] At age forty, the gap in the likelihood of being middle class between advantaged-at-birth and disadvantaged-at-birth children is 22 percentage points.

The model also confirms that success begets further success. Not only do children born advantaged retain a large advantage at the end of early childhood, but the pattern also persists in subsequent stages. In middle childhood, adolescence, and adulthood, those who succeeded in the previous stage are much more likely than those who did not to succeed again. For example, we find that 76 percent of children in our sample who are well prepared to start school are able to master basic skills by age eleven, compared with just 41 percent of children who were ill prepared (see figure 9). Acquiring these basic academic and social skills by age eleven further increases a child's chances of completing high school with good grades and risk-free behavior by a similar magnitude—which, in turn, further increases the chances that a young person acquires a college degree or the associated income. Success by age twenty-nine doubles the chances of being middle class by middle age.

Nevertheless, falling off the success track is

8. Here, we define success in adulthood as being middle class (income of at least 300 percent of poverty line) by middle age (age forty).

Figure 10. Success at Each Life Stage, Income at Birth



Source: Sawhill and Karpilow 2014.

not (necessarily) the end of the matter. Early failures need not be determinative; children can get back on track. A child who is not school ready has a similar chance of being middle class as another child who is school ready as long as he or she can get on track by age ten and stay on track. Moreover, a child from a disadvantaged background who does meet our metrics of success in each life stage has almost the same probability of being middle class by middle age as a child who started off more advantaged. The problem is that there are relatively few such children. These findings point to the importance of early interventions by government or parents that keep children on the right track.

Beyond these descriptive analyses, we have used the SGM to conduct two types of simulations. The first involves analyzing the effects of changing a particular set of parameters or variables to explore certain what-if questions. For example, what if disadvantaged children were as school ready as their more advantaged peers? The second type of simulation involves looking at the effects of a program intervention or set of interventions.

In one particular simulation, we use the model to show how much of the adult income gap between low- and high-income children might be closed with an illustrative set of well-evaluated programs at every life stage.[9] As shown in figure 10, we model the effects of five interventions targeted on children born to families with incomes less than 200 percent of the federal poverty line by adjusting outcome variables from early childhood to adolescence (see table 2).[10] Although each program has been evaluated independently, their cumulative and long-term impact has not. The program evaluation literature is extensive, but most of this literature only provides estimates of short-term impacts and does not permit

9. We define low-income as family income below 200 percent of the poverty line. High-income is defined as the complement—at least 200 percent of the poverty line (Sawhill and Karpilow 2014).

10. Only children born to families with incomes less than 200 percent of the federal poverty line receive the treatment—they make up the bottom two quintiles and approximately one-third of the middle quintile of the income distribution. This threshold was chosen because it was used as a means test for many of the programs on which we base our simulation. Modifying the targeting threshold (up to a point) does not yield substantively different results. Eliminating targeting completely—that is, allowing all children to reap benefits from each intervention—is inappropriate given that many higher-income children may already benefit from the programs included in our simulation, for example, high-quality preschool.

Table 2. Summary of Postbirth Interventions

Life Stage	Intervention Model	Description	Adjusted Variable	Effect Size
Early childhood	Home Instruction for Parents of Preschool Youngsters (HIPPY)	Biweekly home visits and group meetings to instruct and equip parents to be effective teachers for their children	*Reading* *Hyperactivity*	0.75 SD −0.68 SD
	Preschool	High-quality center-based preschool programs that provide educational services to children directly	*Reading* *Math* *Antisocial Behavior*	0.45 SD 0.45 SD −0.20 SD
Middle childhood	Social Emotional Learning (SEL)	Broad range of interventions that focus on improving behavioral, emotional, and relationship competencies	*Reading* *Math*	0.36 SD 0.27 SD
	Success for All (SFA)	School-wide reform program with a strong emphasis on early detection and prevention of reading problems	*Antisocial Behavior*	−0.22 SD
Adolescence	Talent Development (TD)	Comprehensive high school reform initiative aimed at reducing student dropout rates	*Reading* *Math*	0.32 SD 0.65 SD

Source: Sawhill and Karpilow 2014.

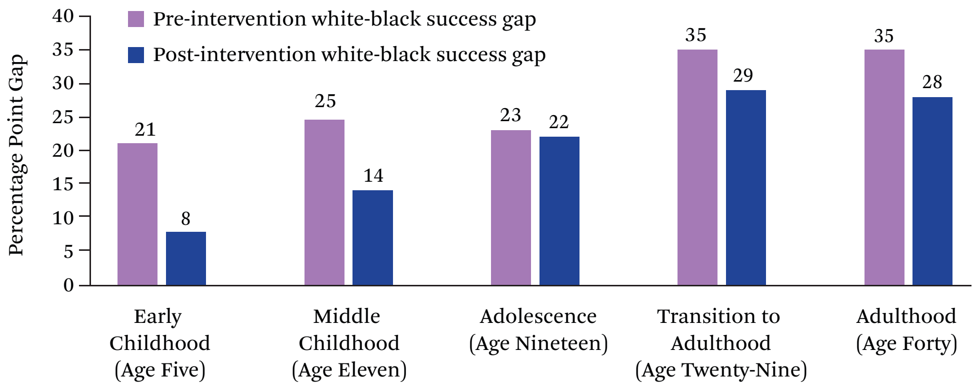
comparison of different intervention strategies based on their predicted effects on lifetime incomes. Our rationale for pursuing such a simulation is that if we want to see larger and longer lasting effects on adult outcomes, we may have to combine early childhood initiatives with interventions in elementary school, adolescence, and beyond.

The predicted results of intervening early and often are impressive. The baseline 20 percentage point gap in the share of low-income and high-income children reaching middle class by middle age shrinks to 6 percentage points after the multi-stage intervention, as shown in figure 10. When we measure the impact of the same set of interventions, targeted on low-income children, but look at how they affect racial gaps in success rates later in life, the results are less dramatic but still encouraging.[11] White-black gaps in success narrow in every stage of the life cycle, although large disparities still persist, especially in adolescence and adulthood (see figure 11).

These interventions also pass muster under a simple cost-benefit test. Table 3 shows the marginal lifetime income effect of each program, as well as its cost per child. We estimate the total cost per child for all of these programs is just over $20,000. The discounted lifetime income of the average participant in these programs would increase by more than $200,000. Looked at from a society-wide perspective, this much additional income would likely produce sufficient additional revenues

11. Again, success here is defined as reaching the middle class by middle age.

Figure 11. Gap in White-Black Success Rate



Source: Sawhill and Karpilow 2014.

Table 3. Costs and Estimated Benefits of Simulated Interventions

	Marginal Lifetime Income Effect	Cost per Child
HIPPY (ages three through five)	$43,371	$3,500
Preschool (ages three through five)	$45,651	$8,100
SFA and SEL (ages six through eleven)	$47,594	$8,100
Talent development (ages fourteen through eighteen)	$68,574	$1,400
Total	$205,190	$21,100

Source: Sawhill and Karpilow 2014.

to offset the costs of the programs. We caution once more that these predictions are only that. They are based on a model that is still quite primitive and has many limitations, as detailed in the following section.

Limitations of the SGM

These results suggest the SGM's utility to evaluators and policymakers. That said, the model has certain limitations, reflecting both the availability of data and the state of research in the field.

On the data front, no longitudinal data set follows children from birth to age forty and includes a rich set of variables about their outcomes at each life stage. This has necessitated a significant amount of imputation or simulation of outcomes, which has added to measurement error.

The model also lacks a module devoted explicitly to family formation and childbearing. Although marriage and childbearing are at work behind the scenes of our regressions, an improved model would make these factors explicit. In addition, good measures of childhood health are lacking in our data set.

With respect to the accuracy of the model parameters, the biggest concern is whether the regression coefficients can be considered causal estimates of the effects of different variables on the outcomes being measured. We make no claims to this effect. However, we investigated the reasonableness of the model by looking in particular at whether the returns to education predicted by the model are similar to those in the best external literature and found that they are. On the other hand, when we try to benchmark the model against some of the RCT evidence from long-term follow ups (for example, Perry Preschool), the model tends to underestimate some effects and overestimate others. This is likely due to an insufficiently specified model of child development and the limited variables available in the NLSY79 datasets. But it could also reflect the fact that the Perry Preschool Program was given to a particularly disadvantaged group that has no counterpart in today's environment, in which mothers are more educated and many children receive some form of out-of-home care. More work to benchmark the model against the best evidence available from external research is needed.

The Social Genome Model: Lessons and Next Steps

The SGM provides a tool for learning more about how—and why—a child's circumstances at birth are related to his or her eventual success in life, including adult incomes. It can also be used to simulate the potential effects of a variety of interventions designed to help less advantaged children climb the ladder. We find it encouraging that a set of well-evaluated programs appear, according to the current model at least, to make it possible to close a substantial portion of the gap in the lifetime incomes between children born into lower- and higher-income families. We stress, however, that the predicted effects do not represent causal estimates. The only way to get truly causal estimates is to do a RCT over thirty to forty years. This approach has three disadvantages. First, it bypasses an entire cohort of children while one waits for the results. Second, it assumes that the impacts of an intervention on today's children are the same as those found for a much earlier cohort of children growing up in a different historical period. Third, it does not permit one to aggregate the results of different evidence-based policies in one consistent framework or model. We believe a model-based prediction of the likely effects of multiple interventions in different life stages is better than nothing. We further believe that research is an evolutionary or cumulative process. The question is whether others in the field will find these predicted effects of some interest and whether this will catalyze new efforts to find better sources of data and more adequate models that better capture the complexity of childhood development and the potential of various interventions to change childhood trajectories. The current model has many inadequacies but it will take years, and the efforts of many different researchers, to improve on the kind of data and modeling that we hope will undergird the policy choices of the future.

CONCLUSION

The issue of intergenerational mobility is likely to be on the public agenda for the foreseeable future, especially against a background of weak growth rates in the economy and in median earnings and rising income inequality. In recent years, scholars have made considerable progress in describing the patterns of mobility in the United States. The main challenges now are to increase our understanding of the transmission mechanisms between the status of one generation and the next and to develop a policy agenda for promoting greater mobility.

APPENDIX

As explained, the Social Genome Model is a recursive set of equations of the form:

$$\mathit{Outcome} = \beta_0 + \beta_1 \mathit{CAB} + \beta_2 \mathit{Previous\ Stage\ Outcomes} + \varepsilon$$

The variables included and their definitions are presented in table A1, the regression coefficients in tables A2 through A4. As an example, take the equation predicting reading ability by age nine or ten:

$$\mathit{mcRead} = -0.199 + .039\mathit{gender} - .220\mathit{black} + .017\mathit{hispanic} - .083\mathit{otherRace} + .062\mathit{matEd2} + .125\mathit{matEd3} + .128\mathit{matEd4} - .005\mathit{cabMatAge} + .005\mathit{cabMatAge1} - 0.021\mathit{cabMarried} - .007\mathit{cabLbw} + .037\mathit{cabFamIncFpl} + .067\mathit{cabPpvt} + .003\mathit{cabParEmoSup} + .015\mathit{cabParCogStim} + .004\mathit{cabMomAfqt} + .111\mathit{ecMath} + .360\mathit{ecRead} + .016\mathit{ecAnti} + .067\mathit{ecHyper}$$

The variables at earlier stages work directly and indirectly to affect middle childhood reading. (The indirect effects cannot be read directly from the regression coefficients but can be calculated.) The predicted effect of early childhood reading on reading in middle childhood is substantial, even after controlling for a large number of background variables and other measures of early childhood readiness for school. To be exact, 1 standard deviation improvement in early childhood reading scores predicts a 0.36 standard deviation improvement in individual middle childhood reading scores.

To fully appreciate the way in which these regression coefficients are used it is important to understand the simulation process. As explained in greater detail in the *Guide to the Social Genome Model*, a number of steps are taken when doing a simulation. Briefly,

> We first take the effect sizes from a rigorous evaluation and apply them to the appropriate target population and relevant independent variable or variables in our model.
>
> We then compare a baseline run of the model with a postintervention run of the model in which, say, an enhanced reading score is allowed to affect subsequent outcomes. Because the predicted effect on later outcomes such as educational attainment or income are the difference between a preintervention baseline run and a postintervention run of the model, errors in the levels of the variables cancel out. However, the coefficients that are used to propagate an initial experimentally estimated effect size (for example, a change in reading scores) through the remainder of the model could be biased because the parameters used to predict later outcomes are estimated using conventional multivariate regression techniques. Most of the variables we shift as the result of an intervention are either an educational achievement or attainment variable. That fact led us to worry most about whether our coefficients were a biased estimate of the effect of some measure of education on earnings. The best external research suggests that the conventional regression-estimated effect of education on earnings does not include a lot of bias and that what bias exists may be compensated for by measurement error (see, for example, Ashenfelter and Rouse 1999). Our model predicts roughly a 7 percent rate of return on years of education.

The coefficients in tables A2 through A4 need to be interpreted with caution. They are used only to update an individual child's characteristics after an intervention has shifted one or more of that child's characteristics. As is typical in all large microsimulation models, the updating is done iteratively within the model *at the level of an individual observation with adjustment for individual errors postsimulation*. Given the iterative or recursive nature of the model, many of the individual coefficients are not readily interpretable because they work through multiple channels to affect a predicted value downstream from the intervention, typically with attenuated effects. In addition, given the large number of control variables in the model, many turn out to be insignificant and noisy. To understand the way in which they are used you need to fully understand the simulation process. Here, in a little more detail, is how it works (as explained in the technical guide to the model).

The Model's Structure

SGM predicts the thirty-three outcomes from early childhood through adulthood listed in table A1. Through adolescence, it does so using the *Circumstances at Birth* variables in table A1 plus all outcomes from intervening stages. So, for example, if we were predicting high school graduation, one of the outcomes in adolescence, the regression equation would include all of the *CAB* variables and all of the outcomes in early childhood (EC) and middle childhood (MC). The equation we estimate for each outcome through adolescence (*ADOL*) is as follows:

$$Outcome = \beta_0 + \beta_1 CAB + \beta_2 Previous\ Stage\ Outcomes + \varepsilon \qquad \text{Equation 1}$$

where β_1 and β_2 are vectors of coefficients, *CAB* is the set of *Circumstances at Birth* variables in table A1, *Previous Stage Outcomes* is the set of outcomes from temporally prior stages, and ε is the error term containing unobserved characteristics.

Beginning with *Transition to Adulthood* (*TTA*) outcomes, however, we must estimate different equations because of our reliance on NLSY79-

based imputations for measures in *TTA* and in adulthood. We are limited to predictor variables that are common to both datasets, which come from the *CAB* and *ADOL* stages. For *TTA* outcomes, we estimate using this calculation:

$$\begin{aligned} \textit{TTA Outcome} &= \beta_0 + \beta_1 CAB^* \\ &+ \beta_2 ADOL + \varepsilon \qquad \text{Equation 2} \end{aligned}$$

where the asterisk following *CAB* indicates the subset of *CAB* variables available in the NLSY79 and where *ADOL* is the set of adolescent outcomes.[12] For adulthood income, we estimate using this calculation:

$$\begin{aligned} \textit{Adult Income} &= \beta_0 + \beta_1 CAB^* + \beta_2 ADOL \\ &+ \beta_3 TTA + \varepsilon \qquad \text{Equation 3} \end{aligned}$$

where *TTA* is the set of *Transition to Adulthood* outcomes. EC and MC outcomes cannot directly affect *TTA* outcomes and adulthood income in these specifications, though they may indirectly affect them through the *ADOL* variables. The SGM may be shown in graphically as in figure 1 in the guide.

Process for Doing Simulations

To simulate the effect of any policy intervention, we use the following procedure:

1. Estimate coefficients for our regression equations.
2. Use those coefficients to create a synthetic baseline.
3. Adjust one or more variables to reflect the policy intervention.
4. Propagate the effects of that intervention through the model using the coefficients estimated in Step 1.
5. Calculate the effect of the intervention on later outcomes.
6. Calculate the effect on lifetime income.

Step 1. Estimating Coefficients

We estimate coefficients on our entire nationally representative samples of children in the CNLSY and adults in the NLSY79.[13] We conduct substantial imputation of missing values in both surveys, and we include cases with imputed values in these estimation samples. Continuous outcomes (all early and middle childhood outcomes, GPA, and the income measures) are estimated using OLS.[14] To account for the long right tail of income variables, we estimate them in logged forms which are converted back to their original metric when we report the results. Binary outcomes are estimated using a linear probability model.[15]

Step 2. Creating the Synthetic Baseline

Once we have estimated the model, we use the estimated coefficients and the actual values for the baseline characteristics to predict each of the outcomes for every individual in the target population. The target population can be defined either by the limited applicability of an intervention (for example, children who al-

12. The subset of CAB variables in the NLSY79 includes race, gender, maternal age, and maternal education.

13. We might prefer to newly estimate the coefficients on simulation-specific target populations each time. However, because our TTA and adulthood income equations must be estimated on NLSY79 data, and only limited pre-adolescent information is available in that data, it is not generally possible to restrict this data to target populations defined with respect to at-birth characteristics or early outcomes.

14. Continuous measures include all early and middle childhood outcomes, GPA, all income measures, and a number of adolescent variables including math and reading scores, self-esteem, frequency of religious service, and gender role attitudes.

15. Binary measures include high school graduation, teen birth, conviction, college graduation, marijuana use, other drug use, early sex, suspension, fighting, hitting, damaging property, participation in school clubs, and independence in ADOL and TTA. We confirmed that our results were similar using logistic regression models and chose linear probability models for the greater flexibility they have in the context of structural equation modeling.

ready attend preschool cannot be affected by an intervention that enrolls children in preschool) or because the effect size we use for a given policy is taken from a rigorous evaluation of a specific population and would require unacceptable assumptions to generalize (for example, the Nurse Family Partnership home visiting program generally has been available only to poor, first-time mothers).

For the fifteen continuous outcomes in EC, MC, and ADOL, we add the residual terms back to individuals' predicted values, which leaves each person's baseline value the same as their actual value.[16] We do so because we reassign each person the same residual when we implement the intervention later on. Doing so ensures that the only thing that changes between the baseline and policy estimates is the value of the outcome or outcomes that the policy intervention affects, and it leaves the simulated counterfactual as consistent with the actual baseline as possible. It also incorporates into the policy estimates potentially valuable information about individuals' unobserved characteristics.

For the twelve binary outcomes in adolescence, the linear probability models are used to produce predicted probabilities for each individual. These estimates are bound such that no individual may have a predicted probability less than 0 or greater than 1. To assign each person a dichotomous value, he or she is randomly assigned a number between 0 and 1. If their random number is less than their predicted probability, then the outcome is predicted to occur. If their random number is greater than or equal to their predicted probability, then their outcome is predicted not to occur. We retain the random number drawn for each person for the simulated counterfactual, again, in order to keep everything as consistent as possible with the baseline.

For TTA and adulthood outcomes, the creation of baseline values is somewhat different because of the necessity of relying on the NLSY79 to estimate coefficients. To impute TTA outcomes, we use actual CAB values from the CNLSY with the corresponding coefficients estimated from the NLSY79, but we use the *baseline* adolescent values rather than the actual values in the CNLSY data. For continuous adolescent outcomes, the baseline values are exactly the same as the actual values because we add residuals to the predicted values, but for dichotomous adolescent outcomes, the baseline values are those predicted from the procedure just described.[17]

To impute adult income, we again use actual CAB values from the CNLSY and baseline adolescent values, and we also use the baseline TTA values just estimated. All of these values are combined with the coefficients estimated from the NLSY79. Because we do not have actual TTA and adulthood outcomes, we do not have actual residual terms for each individual after estimating continuous baseline outcomes. We instead give everyone a residual that is randomly drawn from a normal distribution with mean zero and with standard deviation taken as the standard error of regression from the applicable NLSY79 equation. As with earlier stages, after predicting dichotomous outcomes using a linear probability model, we take a random draw to determine whether to assign individuals a 0 or a 1.

Step 3. The Intervention

To implement a policy intervention or what-if scenario, we must first make three important decisions: which metric or metrics are affected, for whom, and by how much. For what-if scenarios, this is simply a matter of specifying the change, such as "what if we equalized the middle childhood reading scores of poor and non-

16. GPA is restricted to be between 0 and 4 after prediction.

17. Those baseline values need not equal the actual values in the CNLSY because our predictions of dichotomous outcomes are imperfect. It might seem preferable to use the actual values here, but doing so would create inconsistencies in the postintervention run of the model—we might predict, in the postintervention run, some actual high school graduates, for instance, to be dropouts, which would mean that an intervention could be estimated to worsen outcomes among some youth.

poor children?" In that case we would just increase every poor child's reading score by the amount of the poor-nonpoor reading gap. For a policy intervention, we rely on the best-practice evaluations, preferably randomized controlled trials, of others to generate effect sizes. When determining an effect size, we err on the conservative side or simulate a range of possible effects to avoid a false sense of precision and to account for differences between metrics in our model and the evaluation studies.

We also use the data in the evaluation literature to determine which portion of our model's population should receive the effects of the program, looking at whether the evidence shows heterogeneous effects on particular subgroups. The comprehensive school reform program, Success for All, for example, was implemented in a variety of schools nationwide and showed a high degree of homogeneity of its effects in different schools; on the other hand, a program like Nurse Family Partnership, for which only low-income, first-time mothers are eligible, requires that we narrow our treatment group in the model.

After deciding on the target population and the appropriate effect size, we apply the intervention differently depending on whether it affects a continuous or dichotomous variable. If it is a continuous variable, we simply add the effect size to everyone in the target group. For interventions on dichotomous variables, we come up with effect sizes as a percentage change from baseline. For example, if some intervention increases high school graduation by 15 percent, we calculate how many extra individuals (N) in our data would need to graduate to increase the rate within the target population by 15 percent, randomly sort the individuals who were in the target group and had not graduated from high school, and then change the top N people from nongraduates to graduates.

Step 4. Propagating the Effects Through the Model

To simulate the effect of the changes we make in step 3 on subsequent life stages, we apply the estimated coefficients from step 1 to the simulated data, which have now been adjusted according to the effect size of the intervention being evaluated. In doing so, we implicitly assume that the only thing an intervention changes is a person's measured outcomes, and not the relationship between the different outcomes or unmeasured outcomes.

Every outcome prior to the intervention stage is unaffected, as is every outcome in the intervention stage we did not perturb directly as part of the intervention. We iterate though the subsequent stages and predict outcomes for each stage using earlier outcomes, which have been adjusted by the intervention. This ensures that the effect of the intervention is carried though the entire life course. For example, if we improved middle childhood reading, our postintervention data through middle childhood would be exactly the same as the preintervention baseline (except for middle childhood reading) but our adolescent data would be predicted using the increased reading scores and would reflect that change. To predict the *Transition to Adulthood* outcomes, we would use the newly predicted adolescent outcomes that include the effect of the intervention, and adulthood income would be predicted from these new adolescent outcomes as well the newly predicted *Transition to Adulthood* outcomes. As noted, to ensure that our effect size reflects only the impact of the intervention, continuous outcomes are assigned their same residual from step 2, and dichotomous outcomes are assigned a 0 or 1 based on the same random number from step 2.

Step 5. Calculating the Impact of the Intervention

When reporting how outcomes have changed based on an intervention which alters one or more earlier outcomes, we compare the preintervention simulated outcomes from step 2 to the postintervention simulated outcomes from step 4. For most outcomes, the pre- and post-values are used to calculate a percent change in each outcome as a result of the intervention. If a middle childhood intervention increases the high school graduation rate from 75 percent to 80 percent, then the effect size is to increase graduation by (80–75)/75 = 6.7 percent.

For our early and middle childhood outcomes, which are all measured in terms of standard deviations, we simply subtract the pre-value from the post-value.

Next, we assess how the intervention affected general measures of "success" at each life stage. The success measures are dichotomous variables corresponding to the definitions presented in table A1. We estimate success rates using the preintervention simulated outcomes for the individual components of success, and do the same using the postintervention simulated outcomes.[18]

Step 6. Calculating the Impact on Lifetime Income

Along with the effects on our outcomes and success measures, we also report the effect of our interventions on lifetime income. To get a preintervention estimate for lifetime family income, we first find the sample average family income at ages twenty-nine and forty. We calculate the slope between these two ages as follows:

$$\text{29-to-40 } slope = \left(\overline{Income_{40}} - \overline{Income_{29}}\right)/11 \qquad \text{Equation 4}$$

Assuming linear income growth for simplicity, we use an individual's family income at age twenty-nine and forty, with the average slope calculated in equation 4, to interpolate average income at every age between twenty-nine and forty. For example, the estimated mean income value at age thirty is $(\overline{Income_{29}}) + 1 * (29\text{–}40\ slope)$.[19]

The process of estimating income at ages before age twenty-nine and after age forty is slightly more complicated, but uses a similar approach. Each income (age twenty-two, age twenty-three, . . . , age sixty) is discounted from birth using a real discount rate of 3 percent. So discounted age forty income is $(\overline{Income_{40}})/1.03^{40}$. Finally, lifetime family income is the sum of every discounted income:

$$\text{discounted lifetime income} = \textstyle\sum_{i=22}^{62} (\overline{Income_i})/1.03^i \qquad \text{Equation 5}$$

To estimate the *change* in lifetime income that results from an intervention or what-if, this process is done with both pre- and post-income values. We subtract discounted lifetime income *pre* from discounted lifetime income *post* to get the mean change in lifetime income.

Caveats

As also explained in the *Guide to the Social Genome Model*, the researchers who built the model dealt with numerous methodological and data issues and attempted to validate the results against independent sources of data. It is worth noting that our predictions of adult household incomes accord very well with data from the CPS although both our values and CPS values are a little low relative to the PSID.

The model's choice of age ranges and life stage outcomes is motivated by human capital theory and some of the other literature on child development, including a literature review on the determinants of education and earnings, and consultations with other experts in the field. The predictions should not be interpreted as causal estimates of the long-term effects of an intervention.

The biggest data issue has been a seam in the data at the end of adolescence, requiring us to find variables capable of linking the CNLSY to the NLSY79 and imputing values for

18. Note that we do policy simulations that include income-to-needs at age twenty-nine and age forty separately from the simulations that include income measured continuously in dollars. We consider income-to-needs solely to construct the success measures for TTA and adulthood. The basic simulation equations do not include income-to-needs, and the simulation equations to predict income-to-needs do not include income.

19. We use mean incomes to compute the slope—as opposed to using individual incomes to compute individual-specific slopes—because some individual slopes are negative, which would complicate the estimation of stylized lifetime income effects. At the same time, our spline estimation prevents us from having to assume a linear growth rate, which would involve substantial under- and over-prediction of income at different points in the age profile.

the adult period. Many of the adolescent variables included in the model were imported to improve the linking of the CNLSY and the NLSY (that is, they are variables in both data sets that earlier analysis had showed were predictive of adult outcomes). This is the weakest part of the model, but our benchmarking of the model's predicted adult outcomes, such as college graduation and family income, against independent sources of data (for detailed tables of results, see the guide), reassured us that the model was doing an adequate job of making these predictions.

The Social Genome Model, originally developed at Brookings, is now a partnership between Brookings, the Urban Institute, and Child Trends. Anyone interested in an update to this work should check the SGM website (http://www.social-genome.org). Research teams at both the Urban Institute and Child Trends have recalibrated some of the parameters in the model and also run it on the NLSY97 in addition to the NLSY79. The results vary depending on the parameterization and the data used but are similar, giving us some confidence that the model's predictions are reasonably stable and not overly dependent on the exact specification and data used. We welcome ideas for further improvements. The current model should be viewed as a framework within which to look at the process of social mobility, and its limitations should be seen as a challenge to the research community to find better theory, data, and methods with which to estimate the longer-term effects of various interventions. Although RCTs are now the gold standard for estimating the causal impact of an intervention on some outcome of interest, for some purposes RCTs are simply not practical or feasible given the very long follow-up periods required to measure long-term outcomes and the ethical issues involved in bypassing an entire generation of children or relying on even cruder assumptions about likely long-term effects.

Table A1. Variable Definitions

Stage	Variable	
Circumstances at birth	*Gender*	A dichotomous variable indicating the sex of the individual. Males are the omitted category.
	Race	Dichotomous variables indicating whether the child is black, Hispanic, or other. The omitted category consists of white children.
	Maternal Educational Attainment	Dichotomous variables are included to indicate whether the individual's mother graduated from high school, attended some college, or obtained a bachelor's degree or more advanced degree. The omitted category is mothers who did not finish high school.
	Maternal Age at Time of Child's Birth	A continuous variable measuring the age of the mother (in years) at the time of the child's birth.
	Maternal Age at First Birth	A continuous variable measuring the age of the mother (in years) at the time of her first child's birth.
	Marital Status of Child's Parents at Time of Birth	A dichotomous variable indicating whether the child's mother was married when he or she was born. The omitted category includes those children whose mothers were not married, even if cohabitating, at the time of their birth.
	Family Income at Birth	This continuous variable is the log-transformed measure of the family's income as a percent of the federal poverty line in the year that the child was born.
	Low Birth Weight	A dichotomous variable indicating whether a child weighed 5.5 pounds or less when he or she was born. The omitted category consists of children who weighed more than 5.5 pounds at the time of birth.
	Mother's AFQT Score	The age-normed percentile score of the child's mother on the Armed Forces Qualifying Test, a general achievement test taken when the mothers were between sixteen and twenty-three.
	Parenting: Cognitive Stimulation	Standardized score on the HOME Inventory Cognitive Stimulation scale, measured when the child is younger than two.
	Parenting: Emotional Support	Standardized score on the HOME Inventory Emotional Support scale, measured when the child is younger than two.
	Early Verbal Ability	The age-standardized score of the child on the Peabody Picture Vocabulary Test (PPVT), measured when the child is three or four.
Early child-hood (age five)	*Math*	Age-standardized scores from the math section of the Peabody Individual Achievement Test (PIAT)
	Reading	Age-standardized scores from the reading recognition section of the Peabody Individual Achievement Test (PIAT)
	Antisocial Behavior	Age-standardized antisocial behavior subscale from the Behavior Problems Index (BPI). Scores are reverse coded so that higher is better.
	Hyperactivity	Age-standardized hyperactivity subscale from the Behavior Problems Index (BPI). Scores are reverse coded so that higher is better.

Table A1. (*cont.*)

Stage	Variable	
Middle childhood (age eleven)	*Math*	Age-standardized scores from the math section of the Peabody Individual Achievement Test (PIAT)
	Reading	Age-standardized scores from the reading recognition section of the Peabody Individual Achievement Test (PIAT)
	Antisocial Behavior	Age-standardized antisocial behavior subscale from the Behavior Problems Index (BPI). Scores are reverse coded so that higher is better.
	Hyperactivity	Age-standardized hyperactivity subscale from the Behavior Problems Index (BPI). Scores are reverse coded so that higher is better.
Adolescence (age nineteen)	*High School Graduation Status*	A dichotomous variable indicating whether the individual received a high school diploma by age nineteen. GED earners are not counted as high school graduates.
	Grade Point Average (GPA)	A continuous variable of average grade in the last year of high school. Ranges from 0 to 4.
	Criminal Conviction	A dichotomous variable indicating whether the individual was convicted of any charges other than minor traffic violations by age nineteen.
	Teen Parent	A dichotomous variable indicating whether the individual reported having a child by age nineteen.
	Lives Independently from parents	A dichotomous variable indicating whether the individual was living independently from his or her parents at age nineteen.
	Math	Age-standardized score on a test measuring mathematical ability: math section of the Peabody Individual Achievement Test (PIAT) at age thirteen or fourteen in the CNLSY and arithmetic reasoning section of the Armed Services Vocational Aptitude Battery (ASVAB), taken between ages fifteen and twenty-three, in the NLSY79.
	Reading	Age-standardized score on a test measuring verbal ability: reading recognition section of the Peabody Individual Achievement Test (PIAT) at age thirteen or fourteen in the CNLSY and word knowledge section in the Armed Services Vocational Aptitude Battery (ASVAB), taken between ages fifteen and twenty-three, in the NLSY79.
	Family Income	This continuous variable is the log-transformed measure of the family's income during early adolescence (ideally measured at age thirteen, fourteen, fifteen, or sixteen).
	Marijuana Use	This dichotomous variable indicates whether the individual reports having ever used marijuana (CNLSY) or having used marijuana in the past year (NLSY79).
	Other Drug Use	This dichotomous variable indicates whether the individual reports having ever used drugs other than marijuana or amphetamines (CNLSY) or having used drugs other than marijuana in the past year (NLSY79).
	Early Sex	This dichotomous variable indicates whether the individual reports having had sexual intercourse before age fifteen.

Table A1. (*cont.*)

Stage	Variable	
Adolescence (age nineteen) (*cont.*)	*Suspension*	This dichotomous variable indicates whether the individual was ever suspended from school.
	Fighting	This dichotomous variable indicates whether the individual reported getting in a fight at school or work in the past year.
	Hitting	This dichotomous variable indicates whether the individual reported hitting or seriously threatening to hit someone in the past year.
	Damaging Property	This dichotomous variable indicates whether the individual reported intentionally damaging the property of others in the past year.
	Self-Esteem Index	Age-standardized IRT score on the Rosenberg Self-Esteem Scale.
	Religious Service Attendance	This variable measures frequency of religious service attendance on a scale of 0 (none) to 5 (more than once a week).
	Gender Role Attitudes	This continuous variable is the mean of the individual's answers to five questions about how he or she views women.
	Participation in School Clubs	Dichotomous variable indicating whether the individual participated in clubs in high school such as band, choir, or sports.
Transition to adulthood (age twenty-nine)	*Family Income*	This continuous variable is the log-transformed measure of the family's income during the year the individual was twenty-nine years old.
	Family Income to Needs	This continuous variable is the log-transformed measure of the family's income as a percentage of the federal poverty during the year the individual was twenty-nine years old.
	College Completion	Dichotomous variable indicating whether the individual obtained a four-year degree or higher.
	Lives Independently from Parents	A dichotomous variable indicating whether the individual was living independently from his or her parents at age twenty-nine.
Adulthood (age forty)	*Family Income*	This continuous variable is the log-transformed measure of the family's income during the year the individual was forty years old.
	Family Income to Needs	This continuous variable is the log-transformed measure of the family's income as a percentage of the federal poverty during the year the individual was forty years old.

Source: Authors' compilation.

Outcome Prediction Regressions

Table A2. Early Childhood and Middle Childhood Outcomes

	ecMath (Math Scores at Age Five–Six)	ecRead (Reading Scores at Age Five–Six)	ecAnti (Antisocial Behavior at Age Five–Six)	ecHyper (Hyperactivity at Age Five–Six)	mcMath (Math Scores at Age Ten–Eleven)	mcRead (Reading Scores at Age Ten–Eleven)	mcAnti (Antisocial Behavior at Age Ten–Eleven)	mcHyper (Hyperactivity at Age Ten–Eleven)
gender	0.018904	0.121959	0.243874	0.250316	−0.17521	0.038797	0.199664	0.188864
black	−0.1297	0.189867	0.029594	0.138353	−0.21887	−0.22049	−0.13755	0.025035
hispanic	−0.05345	0.138821	0.17328	0.131733	−0.05843	0.016657	0.016501	0.108351
otherRace	−0.07385	0.014875	0.18553	0.206544	−0.04437	−0.083	−0.00747	0.079038
matEd2	0.045286	0.068779	0.159832	0.177408	0.021086	0.061652	0.097754	0.049561
matEd3	0.085451	0.16224	0.256458	0.218371	0.040429	0.125366	0.100238	0.062428
matEd4	0.27233	0.22564	0.225497	0.389272	0.106163	0.12769	0.131283	0.078281
cabMatAge	−0.00665	−0.00327	0.011978	0.028064	0.006491	−0.00462	0.009855	−0.00079
cabMatAge1	0.015769	0.016885	−0.0036	−0.01541	0.004796	0.004839	0.00236	−0.00238
cabMarried	0.01958	0.060694	0.057067	0.049981	−0.00469	−0.02089	0.070576	0.022167
cabLbw	−0.08772	−0.12214	−0.0041	−0.06236	−0.06551	−0.0069	−0.02757	−0.04688
cabFamIncFpl	0.028034	0.033313	0.04041	0.030402	0.014259	0.03694	0.028568	0.003854
cabPpvt	0.131849	0.120464	0.044706	0.086152	0.049762	0.067198	−0.00572	0.007036
cabParEmoSup	0.021463	−0.00431	0.079571	0.068624	0.006263	0.002864	0.024663	0.015364
cabParCogStim	0.035558	0.032731	0.087209	0.069281	0.022479	0.015397	0.03053	0.018971
cabMomAfqt	0.005807	0.006634	7.18E-05	0.000941	0.005355	0.004378	−0.00014	0.000926
ecMath					0.235293	0.111101	0.00483	0.054423
ecRead					0.210429	0.35917	0.034448	0.022756
ecAnti					0.021075	0.015506	0.37923	0.116345
ecHyper					0.061383	0.067465	0.116996	0.390312
intercept	−0.62215	−0.94848	−0.60819	−0.83881	−0.38751	−0.19916	−0.50863	−0.0991
R^2	0.1859	0.1609	0.0883	0.1245	0.3765	0.3788	0.312	0.2767

Source: Authors' compilation.

Table A3. Adolescent Outcomes

	adolHs (High School Graduation)	adolBirth (Teen Birth)	adolGpa (GPA)	adolConvict (Criminal Conviction)	adolMath (Math)
gender	0.024803	0.115033	0.170925	−0.10442	−0.11648
black	0.049503	0.058792	−0.01763	−0.06543	−0.11373
hispanic	−0.02278	0.105756	−0.02298	0.005076	−0.11182
otherRace	−0.07757	0.055014	0.101019	0.062903	−0.04973
matEd2	0.126889	−0.09987	0.058885	−0.04808	0.011075
matEd3	0.143189	−0.10562	0.11241	−0.06002	−0.02041
matEd4	0.135164	−0.0945	0.259241	−0.09323	0.04453
cabMatAge	0.00237	0.001717	0.008021	0.006745	−0.00376
cabMatAge1	0.002094	−0.00641	0.007525	−0.00116	0.012525
cabMarried	0.030465	−0.03232	0.065373	−0.07217	0.035966
cabLbw	0.016286	−0.02504	0.018336	0.001026	0.003882
cabFamIncFpl	0.024128	−0.01149	−0.00956	−0.00712	0.005731
cabPpvt	0.008314	0.004532	0.00468	0.001613	0.028337
cabParEmoSup	0.001671	−0.01433	0.001501	0.007185	−0.00818
cabParCogStim	0.001944	0.00096	0.003384	−0.00714	0.007666
cabMomAfqt	−8.20E-05	−0.00036	0.002433	−0.0005	0.002587
ecMath	0.015206	−0.00381	0.038993	−0.01095	0.092228
ecRead	0.017872	0.001541	0.019973	−0.01334	0.019441
ecAnti	0.028669	−0.00988	0.006853	−0.00909	−0.02211
ecHyper	−0.02054	−0.00268	0.002504	0.015657	0.022601
mcMath	0.019686	−0.01795	0.052673	0.015953	0.434562
mcRead	0.010927	−0.00848	0.025361	−0.00924	0.1378
mcAnti	0.041416	−0.0084	0.06057	−0.04414	0.033526
mcHyper	0.010812	0.001607	0.059541	−0.00964	0.029367
intercept	0.590778	0.277945	2.217064	0.213027	−0.2176
R^2	0.1853	0.1569	0.2041	0.08	0.5227

adolRead (Read)	adolInc (Family Income)	adolIndep (Lives Independently from Parents)	adolEarlySex (Early Sex)	adolSelfEsteem (Self-Esteem Index)	adolDamageProperty (Damaging property)
−0.00163	−0.07568	0.076161	−0.02195	−0.18152	−0.105427
−0.0536	−0.31361	−0.10737	0.0992123	0.37306	−0.002235
0.037953	−0.1913	−0.07389	0.0853673	−0.00244	0.0671071
−0.00326	−0.10793	0.00178	0.0072385	0.146987	0.0437333
0.060458	0.442045	−0.06683	−0.088935	0.090241	−0.013457
0.009684	0.525166	−0.04445	−0.090589	0.057126	−0.028812
−0.03386	0.637487	−0.08816	−0.097125	0.061526	−0.032128
−0.00508	−0.00254	−0.00356	0.0037966	−0.01467	−0.002869
0.002046	0.006047	−0.00628	−0.005946	0.000783	−0.001133
−0.02153	0.208944	0.012382	−0.090126	−0.02737	−0.018247
0.027088	−0.14555	−0.01927	0.0118362	−0.10647	0.0268664
0.011076	0.133832	−0.01639	−0.005894	0.050184	0.0039734
0.03287	−0.00106	−0.00222	0.0029939	0.068538	0.0010607
0.023159	0.017604	−0.01239	−0.011289	0.00163	0.0049936
0.007751	0.049571	−0.01573	0.0079626	0.033712	0.0172399
0.002345	0.007374	0.000167	−1.86E-05	−0.00154	0.000091
0.032299	0.031245	0.019216	−0.006427	0.055409	−0.009233
0.034626	0.049732	0.000647	0.0040184	−0.04187	0.0129152
−0.01699	0.047093	−0.00669	−0.000107	0.047196	0.0119009
0.008579	−0.02883	−0.00272	−0.001576	−0.00662	−0.001028
0.086172	0.031922	0.009537	−0.002214	0.056294	0.0164869
0.602254	−0.01854	−0.00531	−0.007706	0.094175	−0.007475
0.066184	0.002686	−0.03289	−0.038062	0.031148	−0.057882
0.010334	0.090584	−0.00867	−0.01155	0.039719	0.004114
0.004803	9.758433	0.476732	0.3637962	0.40817	0.3053755
0.5929	0.1902	0.0684	0.1051	0.064	0.0677

Table A3. (*Cont.*)

	adolFight (Fighting)	adolHit (Hitting)	adolSuspend (Suspension)	adolMarijuana (Marijuana Use)
gender	−0.04138	−0.10642	−0.072998	−0.03425
black	−0.00352	0.0006636	0.1908452	−0.112427
hispanic	−0.0023	0.0139355	0.0489738	0.0049473
otherRace	0.025721	0.0299238	0.0099518	0.0076051
matEd2	−0.03882	−0.029353	−0.010075	−0.05498
matEd3	−0.0335	−0.040134	−0.018638	−0.061095
matEd4	−0.03702	−0.076669	−0.030907	−0.111039
cabMatAge	−0.00883	−0.000381	−0.00161	−0.010786
cabMatAge1	−0.00018	−0.004298	−0.003171	−0.005836
cabMarried	−0.03439	−0.049229	−0.041558	−0.062936
cabLbw	0.00082	−0.003774	−0.020341	0.0163089
cabFamIncFpl	0.013045	0.0115596	0.0056989	−0.001649
cabPpvt	−0.00283	0.0039814	0.0064589	0.0098538
cabParEmoSup	0.004944	0.0102301	−0.013869	0.0108683
cabParCogStim	0.003752	0.0009732	−0.005689	0.0005094
cabMomAfqt	−0.00036	−0.000729	-8.83E-05	−0.000132
ecMath	0.000515	−0.012903	−0.004682	−0.00199
ecRead	−0.00317	0.0075674	0.0032331	−0.002805
ecAnti	0.000396	0.0061965	−0.016683	−0.01725
ecHyper	0.00228	−0.010879	0.0039318	0.0078014
mcMath	−0.00141	0.0164909	0.0201491	0.0206738
mcRead	−0.0039	0.0135147	−0.020177	0.0266279
mcAnti	−0.03497	−0.047741	−0.075529	−0.040784
mcHyper	−0.00433	−0.010546	−0.014604	−0.013897
intercept	0.411634	0.477741	0.3103284	0.9011838
R^2	0.0951	0.0667	0.1976	0.0851

Source: Authors' compilation.

adolOtherDrug (Other Drug Use)	adolHsClub (Participation in School Clubs)	adolRelServ (Religious Service Attendance)	adolGenderRole (Gender Role Attitudes)
−0.014831	0.0684602	−0.07729	0.2767102
−0.066028	0.0070092	−0.79484	0.087795
−0.029821	−0.040038	−0.29228	0.0179912
−0.039281	0.0539026	−0.19409	0.0577652
−0.003287	0.0769293	−0.22507	0.047796
0.0003134	0.0961848	−0.43521	0.0438276
−0.003107	0.1309736	−0.81985	0.0202436
−0.002775	−0.004496	0.002255	−0.007052
−0.000932	0.0027287	−0.01928	−0.000659
−0.01737	0.0087148	−0.39536	−0.060999
−0.012992	−0.101763	0.052724	0.0169083
0.0004384	0.0055832	0.009163	0.0118431
0.0013941	0.0242737	−0.02238	0.0243812
0.002561	−0.006408	0.08725	0.0040863
0.0040535	0.0150972	−0.04354	0.0058304
−1.64E-05	0.0011134	−0.00259	0.000722
0.0003128	0.0113636	0.0115	0.0054753
2.71E-06	0.0052319	−0.02538	−0.001583
−0.00195	0.0241237	−0.03895	0.0195944
0.002099	0.0008716	−0.00886	−0.000809
−0.009427	0.033854	0.073772	0.060716
0.0123686	−0.008071	−0.02128	0.0199537
−0.006421	0.0144231	0.00384	0.020834
−0.004974	0.033202	−0.08656	−0.017218
0.1918993	0.571242	4.240868	2.054974
0.0202	0.1117	0.0812	0.1235

Table A4. Transition to Adulthood and Adulthood Outcomes

	ttaIndep (Lives Independently from Parents)	ttaCollege (College Completion)	ttaFamIncC (Family Income)	ttaFamIncFpl (Family Income to Needs)	adFamIncC (Family Income)
gender	0.04271	−0.03504	−0.08409	−0.16236	−0.23956
black	−0.11764	0.055169	−0.29146	−0.28963	−0.2712
hispanic	−0.04498	0.021398	−0.0982	−0.1277	−0.11214
otherRace	0.011492	−0.05978	−0.16864	−0.18659	−0.19334
matEd2	−0.00915	0.003588	0.004699	0.039108	−0.01949
matEd3	0.006378	0.096953	0.007874	0.056443	−0.10301
matEd4	−0.00728	0.225878	0.036273	0.135453	−0.1517
cabMatAge	−0.00058	0.000358	−0.00266	−0.00344	0.002026
cabMatAge1	−0.00331	0.005675	0.002064	0.007334	−0.00263
adolHs	0.033018	−0.0336	0.250706	0.263997	0.324467
adolBirth	0.045465	−0.08679	0.000906	−0.14592	−0.00997
adolGpa	0.001137	0.047492	0.081715	0.077736	0.04358
adolConvict	−0.05633	−0.02659	−0.19122	−0.20671	−0.09461
adolMath	0.01032	0.083265	0.052919	0.049799	0.043631
adolRead	0.015016	0.004866	0.113087	0.136859	0.131804
adolInc	−0.00419	0.019118	0.099275	0.100026	0.057776
adolIndep	0.030774	0.083104	0.018737	0.02049	0.022916
adolEarlySex	−0.00747	−0.00807	−0.03016	−0.01835	−0.17068
adolSelfEsteem	0.005002	0.003086	0.035861	0.042474	−0.03015
adolDamageProp	0.000882	0.011632	0.036656	0.037795	−0.07891
adolFight	−0.00501	−0.02303	−0.04587	−0.06577	−0.03509
adolHit	0.011168	−0.02403	−0.02336	−0.01143	0.009642
adolSuspend	−0.01521	−0.03724	−0.08369	−0.07554	−0.04886
adolMarijuana	0.021901	−0.00993	0.03847	0.049251	0.062612
adolOtherDrug	−0.01063	−0.02059	0.030263	0.083292	−0.01885
adolHsClub	0.012369	0.072895	0.076333	0.079283	0.142804
adolRelServ	−0.00671	−0.01362	−0.03142	−0.02083	−0.02751
adolGenderRole	−0.01075	0.041859	0.022461	0.042922	0.152489
ttaIndep					0.382121
ttaCollege					0.13012
ttaFamIncC					0.377835
intercept	1.00811	−0.3200115	9.311073	−0.58669	5.287203
R^2	0.0553	0.2966	0.1623	0.2107	0.2351

Source: Authors' compilation.

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