Annenberg Institute
BROWN UNIVERSITY

EdWorkingPaper No. 26-1561

Local Signals in a Global Tournament: Information Frictions, Optimism, and College Completion

Zach Weingarten
Yale School of Management

Jere R. Behrman
University of Pennsylvania

Andrew Postlewaite
University of Pennsylvania

Families frequently receive local signals about children's skills, such as class rank in high school, yet the college market in which most students ultimately compete is much broader. Using nationally-representative data, we show that student effort, parental investment, and beliefs about college degree attainment all respond predominantly to local ranks as opposed to global ranks, despite both strongly predicting college completion. We develop and estimate a dynamic model separating optimistic beliefs, information frictions, and peer interactions. Counterfactual-policy experiments show that more-precise information, provided sufficiently early, raises skill accumulation and college completion. Eliminating optimism has the opposite effects on all outcomes.

VERSION: August 2026

Suggested citation: Weingarten, Zach, Jere Behrman, and Andrew Postlewaite. (2026). Local Signals in a Global Tournament: Information Frictions, Optimism, and College Completion. (EdWorkingPaper: 26-1561). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/0pd3-d028

Local Signals in a Global Tournament: Information Frictions, Optimism, and College Completion*

Zach Weingarten
Yale School of Management

Jere R. Behrman
University of Pennsylvania

Andrew Postlewaite
University of Pennsylvania

August 21, 2026

Abstract

Families frequently receive local signals about children's skills, such as class rank in high school, yet the college market in which most students ultimately compete is much broader. Using nationally-representative data, we show that student effort, parental investment, and beliefs about college degree attainment all respond predominantly to local ranks as opposed to global ranks, despite both strongly predicting college completion. We develop and estimate a dynamic model separating optimistic beliefs, information frictions, and peer interactions. Counterfactual-policy experiments show that more-precise information, provided sufficiently early, raises skill accumulation and college completion. Eliminating optimism has the opposite effects on all outcomes.

JEL Codes: J24, I20, D83, D91

Keywords: Class Ranks, Information Frictions, Belief Distortions, Human-Capital Accumulation, Academic Competition

*We are grateful to Josh Kinsler for detailed feedback that greatly improved the paper. We also thank Micah Baum, Qinyou Hu, and Viviana Rodriguez for helpful comments.
Contact information: Weingarten: Yale School of Management, zach.weingarten@yale.edu. Behrman: University of Pennsylvania, jbehrman@upenn.edu. Postlewaite: University of Pennsylvania, apostlew@upenn.edu.

1 Introduction

As early as kindergarten, children are ranked and compared—against their classmates, their school-district peers, and state and national benchmarks (Denning, Murphy and Weinhardt, 2023). From the start of schooling, these comparisons shape how students and parents assess academic potential and make educational decisions. Yet the information readily available to families is fundamentally local. Students observe where they stand within their school-grade cohort, and parents infer academic potential from performance relative to nearby peers. The competition that ultimately matters, however, is often much broader. Admission to selective state universities is determined in statewide, if not national, markets, while admission to the most-selective universities is determined in a national or global one (Hoxby, 2009). When peer quality differs across schools, local comparisons may be weakly aligned with children's standings in the broader competitive landscape, altering student efforts, parental investments in their children (hereafter "investments"), and subsequent college-related outcomes.

In this paper, we study how local comparisons shape beliefs and investments even though the returns to education are determined in broader markets. We focus on high school, when students and parents receive repeated feedback about academic standing and make effort and investment decisions just as college expectations begin to shape educational trajectories. Our central focus is whether beliefs and behavior are more sensitive to local academic rank than its predictive power for long-run outcomes justifies, and whether that sensitivity reflects biased beliefs, a rational response to noisy information about latent academic potential, or both. To fix ideas, we use "information friction" to mean that families do not observe the child's latent academic potential and must infer it from local rank together with a noisy private signal. A friction in this sense makes beliefs imprecise rather than wrong on average, and it implies that relying on local rank may be the correct Bayesian response. We separately use "belief distortion" to mean a bias in beliefs about the child's academic potential that persists at any level of signal precision. In our framework, this bias takes the form of average optimism, or upward-biased beliefs.

To quantify the behavioral and long-run consequences of possible information frictions and belief distortions in high school, we combine reduced-form evidence from the National Longitudinal Study of Adolescent to Adult Health (Add Health) with a dynamic model of belief formation, student effort, parental investment, and college-going and completion. Add Health is especially well-suited for our research focus for several reasons. Its school-based design includes information on course grades for each school-grade cohort, allowing us to construct a measure of students' local class ranks. The in-home interviews in Add Health also include a standardized cognitive assessment—the abridged version of the Peabody Picture

Vocabulary Test (PPVT)—that places students in the broader (i.e., *global*) age-specific academic-potential distribution. A further key advantage of these data is that Add Health collects information on expectations, investments, and efforts from both children and parents. Additionally, the longitudinal design allows us to link these high-school measures to college completion and other outcomes more than a decade later.

The reduced-form evidence reveals large gaps between perceived educational prospects and realized educational attainment. Roughly 50 percent of students report in high school that they will "certainly" graduate from college, compared to the 35 percent who ultimately do. Even among students in the bottom decile of local class rank, who rarely complete college, nearly 30 percent believe they will earn college degrees. Parents display similar patterns of optimism, with 46 percent reporting that they would be "very disappointed" if their child did not graduate from college.

In the spirit of Elsner and Isphording (2017), we first examine the roles of local and global ranks using a within-school-grade empirical framework that compares students in the same school-grade cohort who differ in local academic standing and broader cognitive rank. We show that expectations are strongly tied to local academic standing and only weakly related to broader cognitive rank. Moving from the bottom to the top of the local-rank distribution raises student effort by 84 percent of a standard deviation, parental investment by 31 percent of a standard deviation, and reported certainty about college completion by 27–42 percentage points. An analogous movement in the global-rank distribution is associated with substantially smaller effects: student effort increases by 18 percent of a standard deviation, parental investment rises by 15 percent of a standard deviation, and expectations increase by only 4–5 percentage points. Yet the relative importance of local rank is much smaller for realized educational attainment, as well as for other long-run outcomes such as prestige, income, marital status and partner's schooling attainment. Both local and global ranks predict long-run outcomes, and their predictive power is nearly identical at the margin of graduating from an elite university. Local comparisons therefore appear to shape beliefs and behaviors in ways that are disproportionately high relative to realized returns, consistent with evidence that parents assess children's academic potentials relative to local peers (Kinsler and Pavan, 2021).

Although the reduced-form evidence is consistent with belief distortions and information frictions, several alternative mechanisms could also generate an apparent over-reliance on local signals. We address this concern through a series of robustness exercises and find little support for these alternatives. The large response to local rank does not appear to reflect preferences for social status, as parental investment does not respond disproportionately at the top or bottom of the local-rank distribution. The estimates are also robust to controlling for latent non-cognitive skills—constructed from multiple survey measures related to depressive symptoms—which tempers the concern that families respond to local rank because it proxies for non-cognitive traits such as motivation or self-determination. Moreover, the findings are not driven by families who correctly anticipate that their children will stay close to home in adulthood and face more-local labor markets. Furthermore, the discrepancy between beliefs and realized educational attainment is not driven by major intervening shocks that we observe between high school and possible college completion, including the death of a family member, parental incarceration, or unplanned pregnancies. Finally, the emphasis on local relative to global ranks does not seem to be driven by the relative weights on local versus global ranks in the realization of other long-run outcomes—such as occupational prestige, income in adulthood, marital status, and partner's schooling attainment—because for those outcomes, as for college completion, the relative predictive power of local ranks is much smaller than in the students' and parents' expectations of college completion.

With this belief-based interpretation in mind, we develop and estimate a model that separates several mechanisms that are confounded in the reduced-form empirical evidence—optimism, information frictions, competitive pressures within school-grade cohorts, and a possible gap between the true contribution of local academic performance to college readiness and what families perceive that contribution to be. The model builds on dynamic frameworks of skill formation in which household inputs and children's efforts shape the evolution of children's skills (Cunha and Heckman, 2007; Del Boca, Flinn and Wiswall, 2014; Attanasio, Meghir and Nix, 2020; Agostinelli et al., 2026), and translates the observed gaps among beliefs, behaviors, and realized outcomes into economically meaningful distortions. In the model, students and parents observe local academic standing and receive noisy private information about broader academic potential. Because global academic potential—that is, latent academic potential—is imperfectly observed, families may rationally rely heavily on local comparisons when forecasting future college success, while also being optimistic on average. In the model, parents choose investments and students choose efforts each period based on these perceived returns to skill accumulation and college completion. At the same time, the choices of other families in the same school-grade cohort generate local competitive pressures that further shape these decisions. Families may also misperceive how much local academic performance contributes to college readiness, which shapes both the effort and investment choices made during high school and the decision of whether to apply to college at all. Disentangling each of these mechanisms from one another allows us to quantify how local comparisons affect efforts and investments, and to evaluate how families would respond to information policies that make underlying academic potential more salient.

Credibly estimating the magnitude of these information frictions is further complicated by the fact that we observe an imperfect measure of global academic potential. The PPVT-based rank is a noisy proxy for the latent skills relevant for college-going, and treating it as error-free would conflate measurement error faced by the econometrician with the uncertainty faced by families. Specifically, ignoring this measurement error would overstate the information frictions families face and understate how informative the signals they receive actually are. We thus embed an explicit measurement-error structure into the model and estimate it jointly with the other parameters. Because families were not informed of the PPVT scores, error in our proxy cannot shape their beliefs or actions. As a result, measurement error and signal noise enter through two distinct channels of the model, allowing us to separately identify the two.

We estimate the model by indirect inference, targeting more than 500 moments in the simulated data that include first-order outcomes, such as college completion and dropout rates, as well as regression-based moments that summarize how local and global ranks predict investments, efforts, beliefs, and educational attainments. We match coefficient estimates from school-grade fixed-effect regressions that align with the reduced-form specifications, allowing the model to reproduce both the levels of key outcomes and the empirical relationships among academic ranks, family choices, and long-run educational attainments.

The estimates reveal systematic differences between perceived and realized academic prospects, as well as substantial information frictions. Parents and children both overestimate the child's academic potential by about 30 percent of a standard deviation. At the same time, both parents and children receive highly noisy private signals about academic potential. The variance of the noise in these signals is roughly four to eight times the variance of the latent academic potential they are meant to measure. Although parents receive more-precise signals, both members of the household rationally respond to this uncertainty by relying more heavily on local rank when forming beliefs about current academic potential and the likelihood of college completion. Because investments and efforts also respond to the choices of other families in the same school-grade cohort, these individual belief distortions generate equilibrium spillovers in which changes in one family's information environment affect not only its own choices, but also the peer environment faced by other families. The estimates further indicate that this over-response does not reflect an inflated perceived return to local rank at the college-admissions stage.

In counterfactual-policy experiments, we examine how improved information changes the paths of investments and efforts across high school, the accumulation of human capital before college, and eventual degree attainment, including completion at elite institutions. We conduct five experiments, each designed to isolate a separate mechanism in the model. The first corrects families' optimism and ensures that expectations about period-specific academic potential are unbiased. The second maintains families' optimism but eliminates information frictions related to the private signal of academic potential.[1] The third combines

[1] This experiment is related to information interventions that provide parents with clearer signals about children's academic performance (Dizon-Ross, 2019). In our setting, the information revelation affects both parent and student decisions dynamically and changes the equilibrium peer environment.

these two changes to examine how distinct channels of information revelation interact with one another in equilibrium. The fourth provides perfect information to families only in grades 11 and 12 to infer how much of the gains from information revelation depend on the dynamics of skill accumulation. The fifth shifts attention away from high-school information frictions and instead provides families and colleges with perfect information at the postsecondary application stage.

These exercises reveal three key findings. First, upward-biased beliefs encourage parental investments and student efforts throughout school, raising academic potential by the end of high school. This translates into more students being academically-prepared for college and subsequently obtaining college degrees at a higher rate.

Second, children and parents face large information frictions that, when eliminated, generate substantial improvements in long-run educational attainment. Providing precise information about the child's academic potential improves the allocation of environmental inputs toward students with high academic potential, and because the skill-formation technology features additional complementarities between skill and inputs, this reallocation raises aggregate skill accumulation. We find that shutting off information frictions entirely increases end-of-high-school academic potential by about 42 percent of a standard deviation, increases college completion by about 9 percentage points, and reduces the dropout rate by 5 percentage points. In additional experiments that vary the precision provided to families, we find that these gains are highly convex, with small reductions in signal noise doing very little and large improvements in outcomes emerging only once most of the friction is removed.

Third, the timing of information revelation can be nearly as important as the revelation itself. When families are given precise information about the child's academic potential only during the final two years of high school, the long-run gains are largely attenuated. Relative to the same policy implemented from the start of high school, the delayed version delivers only about a quarter of the academic-potential gains, and college and elite completion remain close to their baseline levels. These results indicate that information revealed near the college-application margin generates little additional benefit, and that dynamic complementarities in human-capital accumulation make the timing of accurate information nearly as important as whether families receive it at all.

Related literature. This paper contributes to several strands of the literature. We first relate to the literature on ordinal rank in education. A large body of work shows that a student's rank within a local cohort, holding own achievement fixed, causally affects later academic performance, college-going, and long-run earnings (Elsner and Isphording, 2017; Murphy and Weinhardt, 2020; Cicala, Fryer and Spenkuch, 2018;

Denning, Murphy and Weinhardt, 2023; Chang, Padilla-Romo and Peluffo, 2026).[2] Existing explanations for these effects emphasize mechanisms such as preferences over rank (Tincani, 2024), peer interactions (Bertoni and Nisticò, 2023), and parental responses to students' relative standing (Kinsler and Pavan, 2021; Megalokonomou and Zhang, 2024). We contribute a belief-based channel in which local rank provides a salient signal that students and parents use to infer academic potential. In contrast to work that emphasizes the reduced-form effects of ordinal rank on later outcomes, we study how contemporaneous local rank in high school shapes the beliefs of both students and parents, how those beliefs affect efforts and investments during a period when college-going decisions are particularly salient, and how outcomes can improve when information access improves under simulated counterfactual policy experiments.

Our work also relates to the literature on subjective expectations and educational choice. Building on the broader literature on measuring subjective expectations (Manski, 2004), researchers have used expectations data to show that perceived returns to schooling (Jensen, 2010), beliefs about own academic potential and outcomes across alternative fields of study (Arcidiacono, Hotz and Kang, 2012; Zafar, 2013; Stinebrickner and Stinebrickner, 2012; Wiswall and Zafar, 2015; Arcidiacono et al., 2025), and parents' beliefs about the productivity of investments (Boneva and Rauh, 2018; Attanasio, Boneva and Rauh, 2022) each affect educational behavior. A more closely related strand in developing contexts shows that parents' beliefs about their children's academic potential are often biased, that these beliefs impact parental investments (Dizon-Ross, 2019), and that providing clearer information about child and school performance can improve educational choices and outcomes (Andrabi, Das and Khwaja, 2017). Closest to our paper, Kinsler and Pavan (2021) show that parents of primary-school children assess their children relative to local school peers rather than to children of the same age more broadly.[3] We extend this evidence to secondary school and show that the same local-signal distortion is present not only in parental beliefs but also in students' own expectations. Our contribution is to study both sets of beliefs jointly, within the same household, and to trace how they affect behavior before college entry.

Our framework also builds on the literature on skill formation and dynamic models of household investment in children. In this literature, parental investments and child efforts are costly inputs into a dynamic production function for human capital (Todd and Wolpin, 2003, 2007; Cunha and Heckman, 2007; Cunha, Heckman and Schennach, 2010; Del Boca, Flinn and Wiswall, 2014; Attanasio, Meghir and Nix, 2020; Agostinelli et al., 2026; Del Boca et al., 2026). We embed belief formation into this framework, incorporating both optimism about the child's latent academic potential and imperfect information about

[2] For a broader review of this literature, see Delaney and Devereux (2022).

[3] Indeed there is evidence that parents make investments in their children prior to formal schooling, for example during the first two years of life, with reference to the distribution of outcomes for other children in the same communities (Wang et al., 2024).

that academic potential. Relatedly, Compte and Postlewaite (2004) study a model in which confidence affects performance, implying that biased beliefs may influence behavior not only through perceived returns but also through performances themselves. In our model, parents and children choose investments and efforts based on perceived—rather than true—academic potential, where beliefs are shaped by local standing, noisy private information, and high levels of optimism. Because our focus is on the competitive nature of high-school performance, the framework further decomposes the observed behavioral patterns into a within-household component arising from distorted beliefs, information frictions, and an equilibrium component arising from peer interactions within the school-grade cohort.

Finally, our work also relates to the literature on information frictions and college-going. Hoxby and Avery (2013) show that many academically-qualified students make application decisions that are misaligned with their broader opportunities, and subsequent studies show that low-cost information interventions can shift these decisions (Bettinger et al., 2012; Hoxby and Turner, 2015; Dynarski et al., 2021). We study an earlier margin—family behaviors early in high school—and quantify how information frictions compound through effort, investment, and skill formation before college decisions are made. When students and parents infer academic potential primarily from local rank, choices of effort, investment, and eventual college-going can be miscalibrated well before the college-application stage. By embedding this mechanism into an equilibrium framework, we are able to study counterfactual information policies that change what families know before college-application decisions are made.

The rest of the paper is organized as follows. Section 2 describes the Add Health data and the construction of the analytic sample. Section 3 presents reduced-form evidence on family beliefs, information frictions, and responses to local and global academic rank. Section 4 develops the structural model. Section 5 describes the identification assumptions, estimation strategy, and structural estimates. Section 6 presents the counterfactual policy experiments and their corresponding implications. Section 7 concludes.

2 Data

2.1 The National Longitudinal Study of Adolescent to Adult Health

This paper uses the rich panel data of the National Longitudinal Study of Adolescent to Adult Health (Add Health). Add Health is particularly well-suited to our study because it contains information on high-school students' college expectations, effort choices, and parental investments, while also allowing us to locate each student within both their local school-grade cohort standing and the broader (*global*) academic-potential distribution. Its longitudinal design allows us to follow respondents into adulthood and observe whether they complete college, and whether they earn a degree from an elite institution, as well as other long-run outcomes, including occupational prestige, income, marital status, and their partner's schooling attainment.

We use the first four waves of Add Health. Wave I, conducted during the 1994–1995 academic year, surveyed 90,118 middle- and high-school students in a nationally-representative sample of schools. We restrict the analysis to students who were in high school at the time of the Wave I interview, since these are the students for whom local academic standing is most relevant for college admissions and related effort decisions. This is also the group of students for whom we have the most confidence that they actually receive signals (e.g., via semester-wise academic transcripts) about their local standing. Because the survey was school-based, Add Health provides in-school information on the full student body within sampled schools.[4] We use students' self-reported grades in English, math, history, and science over the previous semester to construct a grade point average (GPA) for each student, and then assign each student a percentile rank within the academic distribution of the school-grade cohort. We interpret this measure as closely capturing the local academic standing that students and parents observe through report cards, transcripts, and other routine school feedback.[5] Throughout the paper, we refer to this GPA percentile rank as the student's *local rank*.

The Wave I in-school survey also includes an administrator questionnaire that provides information about the school environment. Using these data, we identify whether a school tracks students into separate academic pathways, a feature that speaks to the extent to which students are segregated into groups of academically stronger or weaker peers.[6] The data do not, however, allow us to observe the specific track to which an individual student is assigned. The administrator survey also provides information on other school characteristics that are useful for descriptive analyses.[7]

[4] All students present the day of the in-school survey were interviewed. Under the assumption that survey date is orthogonal to student academic potential, we capture a sample that is representative of the overall school population. However, it is worth emphasizing that the attendance-based survey design may impact our ability to construct the full distribution of academic potential. In particular, if chronically-absent students are not missing at random from the survey, we systematically omit students at the very bottom of the distribution. This missingness would understate some students' constructed local rank.

[5] The fact that grades are self-reported introduces the possibility that students inflate their grades upwards, introducing survey bias. To investigate this, we repeat our main empirical exercises using local rank constructed from transcript-level data available for a subset of respondents—approximately 70 percent of our in-home analytic sample. Table A5 shows that the main estimates are consistent across measures of local rank. The two rank measures also have a correlation of 0.75. Still, we prefer self-reported rank because the in-school survey covers the near-universe of students at each school, whereas transcripts are available only for a fraction of the students in the in-home subsample, generating a noisier within-cohort percentile. Additionally, because local rank is a within-cohort percentile, any common upward bias in reporting is differenced out in our empirical strategy.

[6] We construct this as a school-level indicator equal to one if the administrator reports that students are sorted by academic potential or achievement in 9th-, 10th-, 11th-, or 12th-grade English.

[7] Some of these characteristics include school size, the share of non-White students, the school's region in the United States, the share of teachers who are non-White, the share of first-year teachers, and the share of teachers who hold at least a master's degree.

The longitudinal component of Add Health was constructed by selecting a stratified sample of adolescents from the school-based sample for an in-home interview and administering companion surveys to their parents. The Wave I in-home sample included 20,745 adolescents. As part of the in-home interview, all respondents completed an abridged version of the Peabody Picture Vocabulary Test (PPVT), a standardized assessment of verbal skills and language development.[8] We use each student's raw PPVT score to construct an age-specific percentile rank. Unlike the GPA percentile, this measure is not defined relative to the student's school or grade. Instead, because Add Health is nationally representative, the PPVT percentile captures where a student's cognitive performance falls in the broader, national age-specific distribution. Throughout the paper, we use this measure as the student's *global rank*.[9] Importantly, neither students nor their parents were informed of the student's PPVT performance. Any associations between parental beliefs, student beliefs, or subsequent behavior and measured global rank therefore reflect other signals of academic potential observed by students and their families but unobserved by researchers. Helpful for our design, Add Health also administered a second PPVT examination in Wave III, approximately six years after Wave I, which we use to measure adolescents' skills around their college age.

The in-home survey also provides key information on parental investments and student efforts. To measure parental investments, we use ten binary questions answered by each child's mother about investment-related activities undertaken during the previous month, such as talking with the child about a personal problem or working together on a school project. We treat these responses as noisy measures of a latent parental investment factor and estimate that factor using the Bartlett scoring procedure (Heckman, Pinto and Savelyev, 2013).[10]

We similarly proxy for student efforts with a latent factor constructed from five variables: (1) a self-assessment of effort in school, based on the question "In general, how hard do you try to do your school work well?," with responses ranging from "I try very hard to do my best" to "I never try at all;" (2-3) two questions on the frequency with which the student has trouble getting homework done and trouble paying attention; and (4-5) whether the student had any unexcused absences in the past year and whether

[8] Although this assessment only measures one aspect of a child's cognitive skills, validation studies show that PPVT scores are strongly correlated with standard academic-skills assessments, including the Wechsler Intelligence Scale for Children-Revised among primary school-aged children (Altepeter and Handal, 1986) and the Wechsler Adult Intelligence Scale-Revised among adults (Altepeter and Johnson, 1989). Therefore, we interpret the PPVT as a good proxy for broader academic potential, while recognizing that it does not capture all dimensions of cognitive skills.

[9] Although we treat the PPVT score as a measure of latent global academic potential, its low-stakes nature, in addition to it being the abridged version of an examination that primarily measures verbal skills, means that it is likely a noisy proxy for the underlying skills we are interested in. We discuss the implications of this measurement error for both the reduced-form estimates and the structural model in Appendix C.

[10] The corresponding factor loadings from this procedure are reported in Table A1.

the student had more than ten, an indicator for chronic absenteeism.[11] Together, these variables capture multiple dimensions of student effort and engagement, including self-reported effort, attentiveness, homework difficulties, and school attendance. We combine these five variables into a latent factor of student effort, again using the Bartlett scoring procedure.[12] Although Add Health conducted a follow-up survey one year after Wave I for the in-home sample members who were still in high school, no parent information was collected to construct a Wave II parental investment measure, there is asymmetric information about student effort, and we cannot construct a similar measure of local rank from the near-universe of students in a given school. For these reasons, we restrict our attention on family behaviors to Wave I.

The other Wave I measures central to our design are students' and parents' expectations about whether children will graduate from college. We use both variables as proxies for beliefs about future college attainment. For students, we use responses to the question, "On a scale from 'No chance' to 'It will happen,' what do you think are the chances that you will graduate from college?" and define an indicator equal to one if the student answers "It will happen" and zero otherwise. For parents, we use responses to the parent-survey question, "How disappointed would you be if your child did not graduate from college?" and define an indicator equal to one if the parent answers "Very disappointed" and zero otherwise.[13] As we show below, both students and parents appear overly optimistic about college completion.

Finally, we use Wave IV, when respondents are on average 28 years old, to measure educational attainment in adulthood, as well as some other measures of outcomes at that point of time, such as prestige, income and marital status. These data allow us to observe each respondent's highest degree completed and, in turn, whether the respondent earned a college degree. In addition, Add Health links respondents' de-identified colleges to Integrated Postsecondary Education Data System (IPEDS) data, which report the 25th and 75th percentile SAT scores of admitted students at each institution. We use these values to construct a median SAT score for each college—taken as the average of the two provided scores—and define an institution as "elite" if its median SAT score exceeds the 75th percentile of the college SAT distribution.

[11] We use this second indicator on attendance rather than the number of unexcused absences to avoid extreme influence from outliers. Although 69% of students report zero unexcused absences and the sample mean is two, some students report as many as 99 unexcused absences.

[12] The corresponding factor loadings from this procedure are reported in Table A2. Although we refer to this factor as student effort, we acknowledge that student effort is difficult to separate from student skill. Still, our analysis requires that, conditional on academic potential, the factor captures variation in engagement that responds to local standing. Given that our empirical exercises condition on the PPVT-based skill measure, the estimated coefficients on local-rank are net of skills, as measured by the PPVT. We therefore interpret the residual variation in this constructed variable as student effort.

[13] Following Loomes and Sugden (1986), disappointment occurs when realized outcomes fall below expectations. We therefore interpret a parent's report that they would be "very disappointed" if their child did not graduate from college as an indication that they hold very high beliefs about the likelihood that their child will complete college.

2.2 Analytic Sample

We restrict the sample to high-school respondents observed in Wave I who also have a valid measure of degree attainment in Wave IV. Because we are interested in peer effects, defined at the school-grade level, we also restrict the sample to Wave I schools that include at least five students in each of 9th, 10th, 11th, and 12th grades. In Table A3, we show that these sample restrictions do not impact the representativeness of the overall sample. In total, we obtain 5,423 observations across 48 high schools in the in-home sample. Table 1 summarizes the analytic sample and highlights two patterns that motivate the analysis.

First, both students and parents appear overly optimistic about students' college-completion prospects. In Column (1), 50% of students report in high school that graduating from college "will happen," yet only 35% ultimately earn a bachelor's degree. Parents display a similar pattern. In Panel B, 46% report that they would be very disappointed if their child did not graduate from college, which we interpret as evidence that many parents also expect their child to complete college.[14]

Second, local and global ranks appear to capture different aspects of student standing. We classify students as above the median when their local rank or global rank lies above the sample median. Students with above-median local rank have only modestly above-average global rank, and vice versa.[15] More importantly, students with above-median local rank are more likely than students with above-median global rank to report with certainty that they will graduate from college, and their parents are also more likely to expect them to earn bachelor's degrees. Parents of students with above-median local rank further report higher levels of investment, and these students exert more effort in high school and are more likely to complete a bachelor's degree.

These differences are striking because the group with above-median global rank appears more advantaged in several observed dimensions. In particular, they have more-educated mothers, higher household income, and are more likely to attend schools with tracking and with a higher share of teachers holding master's degrees. Yet students further to the right of the local rank distribution, and their parents, hold higher expectations about college completion, and those students exert more effort and are more likely to complete college. Rates of elite-college completion, however, are very similar across the two groups. In

[14] Although not the central focus of our paper, we do identify some descriptive evidence of gender- and race-based heterogeneity in expectations. Approximately 57 percent (43 percent) of boys (girls) believe with certainty that they will graduate from college, compared to 48 percent (56 percent) for White (non-White) children. Parents' beliefs differ less strongly across demographic groups: 45 percent (47 percent; 43 percent; 56 percent) of parents whose child is male (female; White; non-White) report that they would be very disappointed if their child did not complete college.

[15] Figure B1 provides a scatterplot of the sample with respect to local vs. global ranks. Defining a student as having high local (global) rank if their local (global) rank is above the sample average, we find that about 31 percent of students have high ranks in both measures and 30 percent have low ranks in both measures. More than 40 percent of the sample are high-rank in one dimension and low-rank in the other.

Table 1: Descriptive Statistics

	Analysis Sample (1)	Above-Median Local Rank (2)	Above-Median Global Rank (3)
Panel A: Child Characteristics			
Female	0.534	0.582	0.493
	(0.499)	(0.493)	(0.500)
Non-White	0.280	0.251	0.170
	(0.449)	(0.434)	(0.376)
Age (Wave I)	16.35	16.30	16.33
	(1.227)	(1.218)	(1.218)
Grade (Wave I)	10.39	10.43	10.48
	(1.102)	(1.097)	(1.103)
Effort (Wave I)	−0.000	0.205	0.093
	(1.000)	(0.986)	(0.952)
Local Rank	0.509	0.752	0.572
	(0.284)	(0.141)	(0.283)
Global Rank	0.511	0.569	0.755
	(0.287)	(0.289)	(0.143)
Expect Bachelor's with Certainty	0.503	0.607	0.536
	(0.500)	(0.489)	(0.499)
Highest Degree: HS Diploma	0.188	0.116	0.125
	(0.390)	(0.320)	(0.331)
Earned Bachelor's Degree	0.351	0.508	0.474
	(0.477)	(0.500)	(0.499)
Graduate from Elite College	0.058	0.097	0.099
	(0.233)	(0.296)	(0.298)
Panel B: Parental Characteristics			
Parental Investment	0.000	0.100	0.077
	(1.000)	(0.993)	(0.973)
Expect Bachelor's Degree for Child	0.459	0.530	0.470
	(0.498)	(0.499)	(0.499)
Mother College-Educated	0.247	0.296	0.311
	(0.431)	(0.457)	(0.463)
Mother Married	0.729	0.769	0.783
	(0.445)	(0.422)	(0.413)
(Log) Household Income	3.599	3.681	3.801
	(0.850)	(0.848)	(0.758)
Panel C: School Characteristics			
Tracking	0.644	0.656	0.688
	(0.479)	(0.475)	(0.463)
First-Year Teachers (%)	11.62	11.50	11.92
	(18.91)	(18.75)	(20.56)
Teachers with Master's (%)	53.78	53.42	55.84
	(22.71)	(22.81)	(22.47)
Non-White Teachers (%)	16.94	17.83	11.16
	(24.11)	(24.70)	(18.58)
Observations	5,423	2,723 (50%)	2,637 (49%)

Notes: This table reports summary statistics for the analytic sample. Column (1) reports means for the full sample of high-school respondents observed in the Wave I in-home survey with a valid measure of degree attainment in Wave IV. Columns (2) and (3) report means for respondents in column (1) with above-median local rank and above-median global rank, respectively. Local rank is the student's rank in the GPA distribution of the school-grade cohort. Global rank is the student's age-specific rank in the PPVT distribution. "Effort" and "Investment" are latent factors constructed using the Bartlett scoring procedure, as described in the text. "Expect Bachelor's with Certainty" is an indicator equal to one if the respondent reports in Wave I that graduating from college "will happen." "Graduate from Elite College" is an indicator equal to one if the respondent's highest completed degree was obtained from a college whose median SAT score lies above the 75th percentile of the college distribution in Add Health. Educational attainment is measured in Wave IV. "Expect Bachelor's Degree" in Panel B is an indicator equal to one if parents respond that they would be very disappointed if their child did not graduate from college. All other variables are measured in Wave I. Standard deviations are reported in parentheses.

fact, having a higher global rank is slightly more correlated with graduating from an elite university. Taken together, these patterns suggest that local rank is more closely associated with the formation of beliefs and the allocation of environmental inputs, while global rank captures a different dimension of advantage that is less directly reflected in these short-run outcomes.

3 Reduced-Form Analysis

This section presents the reduced-form evidence that motivates the structural model in Section 4.

3.1 Short-Run

We first estimate how local and global rank predict parental investment, student effort, and the expectations of students and parents, using specifications with Wave I school-grade fixed effects. These regressions compare students within the same school-grade cohort who differ in local standing and broader cognitive rank. This exercise allows us to document the relative sensitivity of beliefs and behaviors to local versus global signals. We then examine whether individual choices are correlated with the behaviors of peers in the same school-grade cohort. This second exercise provides descriptive evidence on the competitive pressures surrounding high-school achievement and on the peer environments that enter the structural model. Because peer choices are determined simultaneously, and because our survey data do not allow us to instrument for this simultaneity, we do not interpret these estimates of peer effects as causal.

3.1.1 Main Analysis

We exploit within-school-grade variation to study how local and global rank signals predict short- and long-run outcomes. Let y_{isg} denote the outcome of interest for some student i in school s and grade g. We estimate

$$y_{isg} = \beta_0 + \beta_1 p_i^{\mathcal{L}} + \beta_2 p_i^{\mathcal{G}} + \boldsymbol{\gamma}' \boldsymbol{x}_i + \alpha_{sg} + \varepsilon_{isg}, \tag{1}$$

where $p_i^{\mathcal{L}}$ is the student's GPA percentile rank within the school-grade cohort, $p_i^{\mathcal{G}}$ is the student's PPVT percentile rank in the national age-specific distribution, $\boldsymbol{x}_i$ is a vector of covariates that includes race, gender, and age, α_{sg} is a school-grade fixed effect, and ε_{isg} is a random disturbance term.[16]

[16] Notably, both ranks are measured with error, which we do not correct for in the reduced-form results. However, as discussed in Appendix C, classical error in the global-rank measure attenuates $\hat{\beta}_2$, meaning that the local-to-global ratio should be read as an upper bound. We address these concerns of measurement error directly in the structural model, where we separate the error observed only by the econometrician from the signal noise that enters families' decisions, and estimate both by matching the error-prone empirical moments.

The coefficients of interest are β_1 and β_2. In the spirit of Elsner and Isphording (2017), identification comes from comparing students in the same school-grade cohort who differ in local standing and broader cognitive rank. The included fixed effects restrict our comparison to students in the same grade and in the same school. Any cohort-level differences in achievement, peer composition, resources, or other shared features of the local environment are therefore absorbed in our estimation specification. Despite these features, we do not interpret β_1 or β_2 as causal effects of rank due to the fact that local rank is constructed from course grades, which are themselves produced by prior effort and investment. As a result, Equation 1 is subject to simultaneity bias and the coefficients are treated as descriptive moments. For investment, effort, and expectations, the relative magnitudes of β_1 and β_2 summarize how strongly beliefs and behavior respond to local versus global signals. Looking ahead, the structural model in Section 4 tackles this simultaneity directly by jointly determining ranks, beliefs, and endogenous child and parent choices in equilibrium, then targeting these respective coefficients as moments to match in estimation.

The estimates in Table 2 show that parents and students respond much more strongly to local rank than to global rank. In the full sample, moving a child from the bottom to the top of the local percentile-rank distribution is associated with an increase in parental investment (Panel A) by approximately 31 percent of a standard deviation—approximately twice the corresponding effect of global rank. When we estimate the model separately by grade, the coefficient estimate on local rank remains positive and fairly similar across grades, while the coefficient estimate on global rank is smaller and decreases as children age. Overall, these results suggest that parents place substantially greater weight on local academic standing than on broader rank-based measures when making investment decisions. Additionally, as their children progress through high school, parents place an increasing amount of weight on local signals of academic potential.

Panel B shows an even stronger role for local rank in shaping student effort. In the full sample, moving a student from the bottom to the top of the local percentile-rank distribution is associated with an increase in effort by 84 percent of a standard deviation. This is approximately five times the corresponding coefficient attached to global rank. When we estimate the model separately by grade, the role of local rank remains large throughout high school, though it declines somewhat in later grades. The coefficient estimate on global rank is much smaller in magnitude in every specification and also declines with age.[17] These findings suggest that students exert effort primarily in response to how they rank relative to their local peers rather than in response to broader measures of standing.

Although the evidence above shows that parents and students respond much more strongly to local

[17] One possible explanation for the declining coefficient estimates on global rank in Panels A and B is that local competition becomes more salient as students approach college-application and college-admissions ages.

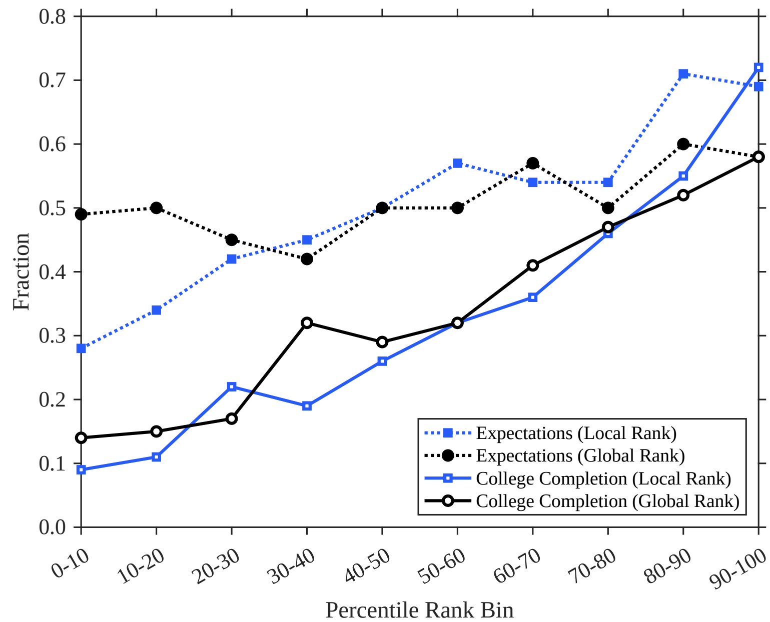
Table 2: The Effects of Local and Global Ranks on Short-Run Outcomes

	Analysis Sample (1)	Grade 9 (2)	Grade 10 (3)	Grade 11 (4)	Grade 12 (5)
Panel A: Parental Investment					
Local Rank	0.305	0.307	0.267	0.321	0.331
	(0.062)	(0.094)	(0.099)	(0.126)	(0.126)
Global Rank	0.152	0.290	0.177	0.069	0.079
	(0.043)	(0.105)	(0.086)	(0.097)	(0.128)
Observations	4,879	1,401	1,280	1,228	970
Panel B: Student Effort					
Local Rank	0.838	0.973	0.829	0.766	0.735
	(0.055)	(0.094)	(0.115)	(0.136)	(0.101)
Global Rank	0.176	0.248	0.178	0.113	0.139
	(0.087)	(0.112)	(0.139)	(0.165)	(0.115)
Observations	4,857	1,346	1,276	1,231	1,004
Panel C: Student College Expectations					
Local Rank	0.417	0.408	0.438	0.413	0.393
	(0.027)	(0.049)	(0.052)	(0.045)	(0.069)
Global Rank	0.042	0.011	0.001	0.110	0.042
	(0.028)	(0.057)	(0.055)	(0.059)	(0.072)
Observations	4,397	1,202	1,159	1,113	923
Panel D: Parent's College Expectations for their Child					
Local rank	0.273	0.232	0.288	0.276	0.309
	(0.024)	(0.044)	(0.050)	(0.058)	(0.058)
Global rank	0.053	0.044	0.073	0.081	0.023
	(0.025)	(0.066)	(0.047)	(0.051)	(0.067)
Observations	4,458	1,310	1,184	1,109	855

NOTES: This table reports estimates from regressions of short-run outcomes on local and global ranks. Panel A uses the parental investment factor, Panel B uses the student effort factor, Panel C uses an indicator equal to one if the respondent reports that graduating from college "will happen," and Panel D uses an indicator for whether the parent responds that they would be "very disappointed" if their child does not graduate from college. Column (1) reports estimates for the full analytic sample, which pools over grades 9 through 12. Columns (2)–(5) report estimates from the same specification estimated separately for students in each grade at Wave I. Local rank is the student's rank in the GPA distribution of the school-grade cohort, and global rank is the student's age-specific rank in the PPVT distribution. The dependent variables in Panels A and B are standardized latent factors constructed using the Bartlett scoring procedure. All specifications include controls for race, gender, and age. Column (1) includes school-grade fixed effects, while Columns (2)–(5) include school fixed effects. Standard errors clustered at the school level are reported in parentheses.

than to global signals of academic potential, this pattern does not by itself imply distorted beliefs. One alternative explanation is that families understand both signals correctly but attach greater value to local standing. For example, local rank may relate to social status in the school environment or shape peer interactions in ways that parents and students value directly. If so, the stronger response of environmental inputs to local rank reflects preferences rather than distortions. However, if local rank affects what families value rather than what they expect, it should not generate biased beliefs about college completion. A parent who places greater weight on local standing has no reason to form inaccurate expectations about whether a child will graduate from college. To shed light on this, we turn to belief measures directly. If beliefs

Figure 1: Expectations and Actual College Completion, by Local and Global Rank



NOTES: This figure plots students' beliefs about college completion and actual college completion by deciles of local and global ranks. The dashed lines show the fraction of students who report in Wave I that graduating from college "will happen," while the solid lines show the fraction who actually complete college by Wave IV. Local rank is the student's rank in the GPA distribution of the school-grade cohort, and global rank is the student's age-specific rank in the PPVT distribution. Each point reports the mean outcome within the corresponding percentile-rank decile.

respond more strongly to local rank than to global rank, then it is difficult to reconcile the aforementioned patterns with a pure preference channel.

Panel C shows that students' college expectations display the same strong sensitivity to local rank. In the full sample, moving a student from the bottom to the top of the local percentile-rank distribution raises the probability of reporting with certainty that they will graduate from college by 41.7 percentage points. The corresponding effect of moving from the bottom to the top of the global percentile-rank distribution is only 4.2 percentage points and is not statistically distinguishable from zero. This pattern is also broadly similar across grades 9 through 12. The results therefore suggest that the heightened reaction to local rank extends beyond investment and effort to the beliefs that guide those choices. Students who rank highly within their school-grade cohort are substantially more confident about completing college, even after controlling for broader cognitive standing. Again, this pattern is difficult to reconcile with a pure preference-based explanation in which local rank affects utility but does not affect expectations.

Figure 1 provides complementary visual evidence. The figure groups students into deciles of local and global rank and plots both their beliefs about college completion and their realized college-completion outcomes. To reduce the influence of signals that may arrive later in high school, such as college-application decisions or admissions outcomes, we restrict the figure to students in grades 9 and 10.

Two patterns stand out. First, beliefs rise strongly with local rank. Students who rank higher within their school-grade cohort are much more likely to report with certainty that they will graduate from college. By contrast, beliefs vary much less with global rank, as indicated by the relatively flat dashed black line. In fact, students near the top of the global percentile-rank distribution are only slightly more likely to expect college completion than students near the bottom, whereas expectations increase sharply across the local-rank distribution. This visual pattern mirrors the regression evidence that students place much greater weight on local standing than on broader measures of academic potential when forming expectations about future college success.

Second, realized college completion rises along both rank measures, but the relationship between beliefs and attainment differs sharply across them. Along the local-rank distribution, both expectations and completion increase with rank, but expectations substantially exceed realized completion at nearly every point, converging only at the top decile. On the other hand, along the global-rank distribution, realized completion rises substantially even though expectations are comparatively flat. Thus, students are not merely overoptimistic, but their expectations are also much more responsive to local rank, despite the fact that broader standing is also strongly predictive of eventual college completion. This visual evidence shows that students' expectations track local rank much more closely than realized completion does, even though global rank is also strongly predictive of completion. The reduced-form exercises alone cannot disentangle whether this reflects distortions or a rational response to noisy signals about children's academic potential. In Section 4, we separate these mechanisms explicitly using our structural model.

Returning to Table 2, Panel D shows a similar pattern for parents' expectations. Parents also place substantially greater weight on local, rather than global, rank when assessing the likelihood that their child will complete college. In the full sample, moving a child from the bottom to the top of the local percentile-rank distribution raises the probability that a parent reports being very disappointed if the child does not graduate from college by 27.3 percentage points, compared to only 5.3 percentage points for the global rank. This parallel between students and parents is important for the model that follows because it suggests that beliefs about college readiness shape both student effort and parental investment during high school.[18] More broadly, our results suggest that the belief distortions documented by Kinsler and Pavan (2021) among parents of primary-school students persist, and may even intensify, in secondary school. Moreover, these forces are not confined to parents but extend to students themselves.

[18] We also estimate versions of the student regressions that separately control for contemporaneous parental investment and find parental investment to be significant in some specifications, but its inclusion does not impact the coefficients on either rank measure.

In Figure B2, we examine whether the average short-run responses to rank documented above mask heterogeneity across school environments. In particular, parents and students may respond differently to local-rank signals depending on the average global skill level of the school they attend. In short, it may be the case that the same local rank conveys different information about broader academic potential depending on the average academic potential of one's peers. In this case, a pooled specification may conceal important differences in behavioral responses across school types. To investigate this, we divide schools according to whether their average student global academic potential is above or below the sample-wide mean and re-estimate Equation 1 separately for the two groups.

Figure B2 shows that the central pattern from Table 2 holds in both low- and high-performing schools. Across all four outcomes, local rank is a strong predictor of parental investment, student effort, and the college expectations of both students and parents, whereas the coefficient estimates on global rank are smaller and often imprecisely estimated. At the same time, the figure suggests some heterogeneity across school types. The local-rank coefficient estimate for student effort is somewhat larger in high-performing schools than in low-performing schools, while the coefficient estimate on global rank appears larger in low-performing schools. For parental investment and for both belief measures, however, the estimates are quite similar across the two groups, with substantial overlap in the confidence intervals. Overall, these results suggest that the strong role of local rank is not driven by one particular segment of the school-quality distribution.[19]

3.1.2 Robustness

We now present a series of robustness exercises to assess both the interpretation and the stability of the main results. The estimates of these robustness checks are reported in Table A7 through Table A10.

A first concern is that the short-run relationships we attribute to local rank may instead reflect students' underlying raw achievement irrespective of class rank, especially due to the fact that our baseline specification (Equation 1) does not directly control for course grades. Because local rank is constructed from grades in four core academic subjects, controlling for all observed grades would mechanically absorb much of the variation in rank itself. To test this possibility, we conduct a robustness exercise where we control directly for English and math grades. These two courses are observed for more than 95 percent of the sample and are especially relevant for future academic achievement, as they correspond closely to the

[19] We also investigate other margins of possible heterogeneity in Table A6. We find mixed evidence of heterogeneity across outcomes but largely find little deviation from our pooled results. For instance, non-White mothers do not appear to respond to global rank, and male students respond relatively more strongly to local rank.

verbal and quantitative skills tested on standardized college-entrance exams.[20]

The results are reported in Table A7. Controlling directly for English and math grades leaves the short-run estimates largely unchanged. The coefficient estimates on local rank remain similar in magnitude across outcomes, and the coefficient estimates on global rank are also largely unaffected. Therefore, the main patterns for parents and students appear to be driven by local comparisons and not absolute performance in core academic subjects.

Another concern is that the strong response to local rank may reflect not only beliefs about educational returns, but also a direct preference for relative standing. If parents value their child's local rank directly, then parental investment should exhibit pronounced nonlinearities at salient points of the local rank distribution rather than vary smoothly with rank. This is especially plausible when top positions offer visible distinctions or discrete rewards in school. For example, rank thresholds may determine eligibility for being honored at high-school graduation, which may be associated with higher status in the local community. In that case, parents may derive an additional utility premium from having a child near the top of the class, implying higher investment among students at the top of the local distribution. A similar argument can be made for parents' responses to their children being at the bottom of the local distribution.

To test for this, we augment Equation 1 to include separate indicators for specific positions in the local-rank distribution, namely the top 5, 10, and 15 percent, as well as the bottom 5, 10, and 15 percent. Panel A of Table A8 reports the results. We find no statistically significant effects for any of these indicators, nor do we observe meaningful changes in the coefficient estimates on local rank or global rank. This pattern suggests that parental investment does not respond disproportionately at the top or bottom of the local rank distribution. As a result, the evidence is less consistent with a direct preference for local rank and more consistent with a mechanism in which local rank affects investment through beliefs about future educational success.[21]

A third concern is that parents' expectations may not reflect beliefs about their children's academic potential, which should largely determine GPA, but instead beliefs about *non-cognitive* traits that affect persistence in degree completion, such as attitude, self-image, or motivation. To assess this, we use 19

[20] When constructing the local-rank and GPA measures, we impute missing course grades using valid English and math grades as predictors for missing social studies and science grades, which are missing for about 8 percent of the sample.

[21] Another possibility is that preferences are linear in class rank. Our previous test rules out kinks at the top and bottom of the local-rank distribution, but does not eliminate this competing explanation of linear preferences. To assess this possibility, we re-estimate Equation 1 with an additional interaction between local rank and centered school-level average cognitive skill. The idea is that, if local rank affects investment because it provides information about broader academic potential, then the effect of local rank may depend on the school's average skill level, whereas a direct linear preference for rank would generate a similar response to local rank across schools. In this specification, the interaction coefficient estimate is statistically insignificant and imprecisely estimated. We therefore do not find clear evidence that the local-rank effect varies with school average skill, but this test does not decisively rule out smooth linear preferences for rank. In general, however, we cannot reconcile an interpretation that local rank enters child and parent utility yet does not impact beliefs in light of our estimates on college-going expectations.

measures of depressive tendencies available in Wave I of Add Health to construct a latent factor for non-cognitive skills. We then re-estimate Equation 1 while controlling for this factor. The results are reported in Panel B of Table A8. In the pooled regression, the coefficient estimate on local rank is 0.278, compared to 0.273 in the main specification, while the coefficient estimate on global rank remains unchanged at 0.053. To the extent that this factor captures broader non-cognitive traits, these results suggest that parents' beliefs are still driven primarily by local rank and that this signal is interpreted mainly as conveying information about the child's academic potential.

A fourth concern is that some of the measures used to construct our parental investment latent factor—such as going to the movies—may capture contemporaneous consumption rewards for strong academic performance rather than investments that reinforce or compensate for skill development. To assess this, we construct a more parsimonious latent factor that excludes measures that could plausibly be interpreted as consolation prizes, namely whether the child's mother took the child to a movie, play, museum, concert, or sports event, or whether she played sports with the child directly. Panel C of Table A8 presents the results. Although the response to local rank is somewhat attenuated, the qualitative pattern is unchanged. Under this alternative specification, parents still respond to local academic potential at roughly 1.5 times the rate at which they respond to global academic potential.

Another concern is that families may rationally rely on local rank because the relevant market is itself local. If students in some places are likely to remain nearby as adults, then local rank may be especially informative about the peer group they will eventually face in the labor market. To assess this possibility, we use the Add Health Wave I contextual database to construct a measure of *county-level stickiness*, defined as the share of county residents aged 5 and over who lived in the same county five years earlier. We then create indicators for counties above the 50th, 75th, and 90th percentiles of the national "stickiness" distribution and re-estimate Equation 1 with interactions between these indicators and both rank measures. As shown in Table A9, the interactions between stickiness and local rank are statistically indistinguishable from zero across all outcomes and thresholds, and the local-rank coefficient estimates remain stable. Thus, families in counties where geographic mobility is rare do not place systematically greater weight on local rank. This pattern is difficult to reconcile with the view that families weight local rank according to the geographic scope of the relevant market, and is more consistent with local rank shaping beliefs about academic potential, regardless of whether the local market is actually the more relevant one.[22]

Additionally, the gap between the short-run response ratios and the corresponding long-run predictive relationships may not reflect information frictions in how families perceive these signals. Instead, families may form accurate expectations at the time of the Wave I survey, with later college outcomes distorted by large shocks that occur between high school and the age at which respondents would typically complete college. Omitting such shocks could lead us to overstate the role of information frictions. To assess this possibility, we examine four large shocks observed in Add Health—the death of a parent, the death of a sibling, the incarceration of a parent, and an unplanned pregnancy.[23] Using survey responses from Waves II and III, together with retrospective responses in Wave IV, we construct indicators for whether each event occurred after Wave I but before 2003, when respondents in our sample were about 24 years old on average and therefore largely beyond the age at which these shocks would affect standard college-going and completion decisions. Table A10 reports the results. Despite the fact that the shocks themselves are often predictive of college non-completion, their inclusion leaves the point estimates on local rank and global rank essentially unchanged.

A final concern we examine is that the PPVT may capture only a narrow dimension of cognitive skills—by virtue of being a verbal examination—whereas GPA reflects a more holistic notion. If so, families' reliance on local rank could be rational, as local rank would be the better signal of broader latent skills that govern long-run success in multiple outcomes. This would imply that local rank out-predicts global rank across a range of adult outcomes by roughly the same disproportionate margin observed for expectations. We thus compare the local-to-global ratio in expectations to the corresponding ratios in the predictive power of the two ranks for four adult outcomes distinct from degree attainment (estimated in Section 3.2): income in adulthood (measured in Wave IV), occupational prestige (measured in Wave IV), ever-married status (measured in Wave IV), and romantic partner's educational attainment (measured in Wave III).[24] Recall that the local-to-global ratios of children's and parents' expectations were approximately 9.9 and

[22] We conduct two additional checks using Wave IV outcomes. First, we regress adult log income on demographic characteristics, educational attainment, and PPVT score, excluding both local and global rank. We then add the residual from this regression to Equation 1 and interact it with local and global rank. Second, we repeat the exercise using an indicator for whether the respondent lives an above-median distance from their Wave I home in Wave IV, defined as more than 9.17 miles. In both cases, the interaction between the Wave IV proxy and local rank is statistically indistinguishable from zero. These results therefore do not provide any evidence that the weight placed on local rank is greater for students whose realized adult outcomes are more consistent with a local-market interpretation.

[23] Add Health does not report whether the birth was successful, but it does report when the pregnancy ended. We classify a pregnancy as unplanned if it ended at least 24 weeks after conception (which we interpret as a premature birth rather than an abortion) and the respondent reported that, upon learning of the pregnancy, they did not want the child.

[24] We measure occupational prestige by matching the Add Health SOC occupation code to the corresponding GSS/NORC occupational prestige score, a widely used index that ranks occupations on a 0–100 scale based on survey respondents' assessments of social standing (Nakao and Treas, 1994). We consider an occupation as "high" prestige if it is in the top 50 percent of the prestige distribution in Add Health.

5.2 (Table 2). Using the same empirical specification, the respective ratios for the four other long-run outcomes are 3.6, 2.0, −1.6, and 2.4, substantially lower than these ratios for expectations.[25] This pattern is difficult to reconcile with local rank being a more complete measure of the skills relevant for success in adulthood.

Taken together, these exercises suggest that our main findings are not driven by a direct preference for rank, omitted non-cognitive traits, the construction of the parental-investment factor, rational reliance on local labor markets, major life shocks that alter college-going behaviors, or local rank serving as a more complete proxy for the skills relevant to adult success. Across specifications, local rank remains the dominant predictor of beliefs, parental investments, and student efforts.

3.1.3 Peer Effects

Beyond the competitive pressures captured by local rank, we are also interested in whether parents and students respond to the broader local environment, in particular to the decisions of *other* parents and students in the same school-grade cohort. Accordingly, when y_{isg} denotes either parental investment or student effort, we also estimate

$$y_{isg} = \delta_0 + \delta_1 p_i^{\mathcal{L}} + \delta_2 p_i^{\mathcal{G}} + \delta_3 \bar{y}_{-i,sg} + \boldsymbol{\lambda}' \boldsymbol{x}_i + \alpha_g + \nu_i, \tag{2}$$

where $\bar{y}_{-i,sg}$ is the leave-one-out average outcome in student i's school-grade cohort. In this specification, δ_1 and δ_2 summarize the relationship between individual choices and local and global ranks, conditional on peer behavior, while δ_3 captures the association between an individual's choice and the choices of peers in the local cohort. Unlike Equation 1, here we include a grade fixed effect instead of a school-grade fixed effect, which is driven by the fact that the leave-one-out share is measured at the school-grade level, so a school-grade fixed effect would absorb nearly all of its variation. Similarly to our previous exercises, we do not interpret δ_3 as a causal peer effect. Because peer choices are determined simultaneously within cohorts, this specification is intended to recover descriptive moments of within-cohort associations rather than causal peer effects. These moments, together with those derived from Equation 1, help discipline the equilibrium interactions in the structural model.

Table 3 shows that the main patterns from Table 2 are essentially unchanged once we account for average peer behavior within the school-grade cohort instead of controlling for school fixed effects. In both panels, local rank remains a strong predictor of parental investment and student effort, and its coefficient

[25] Both rank measures have coefficient estimates that are statistically indistinguishable from zero in the ever-married specification. We recover a coefficient of 0.039 (−0.024) attached to local (global) rank.

Table 3: Descriptive Evidence of Peer Effects for Parents and Students

	Analysis Sample (1)	Grade 9 (2)	Grade 10 (3)	Grade 11 (4)	Grade 12 (5)
Panel A: Parental Investment					
Local Rank	0.300	0.309	0.273	0.288	0.328
	(0.064)	(0.085)	(0.096)	(0.123)	(0.123)
Global Rank	0.199	0.286	0.210	0.159	0.168
	(0.036)	(0.091)	(0.076)	(0.092)	(0.107)
Average Parental Investment	0.333	0.335	0.479	0.018	0.327
	(0.059)	(0.122)	(0.081)	(0.191)	(0.098)
Observations	4,879	1,401	1,280	1,228	970
Panel B: Student Effort					
Local Rank	0.825	0.944	0.823	0.747	0.750
	(0.057)	(0.100)	(0.114)	(0.130)	(0.096)
Global Rank	0.192	0.256	0.175	0.175	0.145
	(0.079)	(0.098)	(0.120)	(0.138)	(0.104)
Average Student Effort	0.211	0.414	0.208	−0.209	0.221
	(0.094)	(0.147)	(0.171)	(0.231)	(0.143)
Observations	4,857	1,346	1,276	1,231	1,004

Notes: This table reports estimates from regressions of parental investment and student effort on local percentile and global ranks, and the leave-one-out average choice of peers in the same school-grade cohort. Panel A uses the parental investment factor, and Panel B uses the student effort factor. Column (1) reports estimates for the full analytic sample, which pools over grades 9 through 12. Columns (2)–(5) report estimates from the same specification estimated separately for students in each grade at Wave I. Local rank is the student's rank in the GPA distribution of the school-grade cohort, and global rank is the student's age-specific rank in the PPVT distribution. "Average Parental Investment" and "Average Student Effort" denote leave-one-out averages within the school-grade cohort. The dependent variables in both panels are standardized latent factors constructed using the Bartlett scoring procedure. All specifications include controls for race, gender, and age, as well as grade fixed effects. Standard errors clustered at the school level are reported in parentheses.

estimate continues to exceed that of global rank by a wide margin. In the pooled sample, moving a child from the bottom to the top of the local percentile-rank distribution raises parental investment by 30 percent of a standard deviation, compared to 20 percent of a standard deviation for global rank. The discrepancy is even larger for student effort, where the corresponding effects are 83 percent of a standard deviation and 19 percent of a standard deviation.

The coefficient estimates on average parental investment and average student effort are generally positive in the pooled sample, indicating that individual choices are positively associated with the choices of peers in the local cohort. At the same time, these coefficient estimates are less stable across grades than the coefficient estimates on local rank, and in some cases they become small or even negative. For the purposes of our structural model below, the key takeaway is that peer behaviors may matter at the margin, but the dominant and robust pattern in the data is the much stronger role of local-rank signals.

Table 4: The Effects of Local and Global Rank on Long-Run Outcomes

	High School Diploma Only (1)	Ever Attend College (2)	Bachelor's Degree (3)	Elite Institution (4)
Local rank	−0.220	0.375	0.581	0.143
	(0.021)	(0.026)	(0.031)	(0.022)
Global rank	−0.168	0.249	0.236	0.097
	(0.025)	(0.030)	(0.031)	(0.017)
Observations	5,143	5,143	5,143	5,143

Notes: This table reports estimates from regressions of long-run educational outcomes on local rank and global rank. Column (1) uses an indicator equal to one if the respondent's highest completed degree is a high school diploma. Column (2) uses an indicator equal to one if the respondent ever attended college for at least one year. Column (3) uses an indicator equal to one if the respondent obtained a bachelor's degree. Column (4) uses an indicator equal to one if the respondent obtained a college degree from an elite institution. Local rank is the student's rank in the GPA distribution of the school-grade cohort, and global rank is the student's age-specific rank in the PPVT distribution. All specifications include controls for race, gender, and age, as well as school-grade fixed effects. Educational attainment is measured in Wave IV. Standard errors clustered at the school level are reported in parentheses.

3.2 Long-Run Analysis

Although parents and students respond most strongly to local-rank signals, this evidence does not by itself point to meaningful distortions. The strong reliance on local rank could arise through at least three distinct channels. First, families may be responding rationally to an information environment in which broad academic potential is noisily observed, whereas local rank is observed with greater precision. Second, parents and children may be optimistic on average about future attainment, thereby distorting their beliefs about future college attainment. Third, local rank may have a high return at the college-admissions stage, so that if colleges value local rank more than twice as much as global rank, families weighting it heavily would be a rational, forward-looking response. The reduced-form results shown before cannot separate the first two channels, which requires a structural model of choices and beliefs (see Section 4). The long-run analysis below provides evidence on the third channel. In particular, we extend Equation 1 to four long-run outcomes of interest: whether the child's highest degree is their high-school diploma, whether the student attends college for at least a year, whether the student obtains a four-year college degree, and whether the student obtains a four-year college degree from an elite institution.

Table 4 shows that both local rank and global rank predict long-run educational attainment, but local rank is more strongly associated with broad college-going and degree completion. In Column (1), moving a student from the bottom to the top of the local percentile-rank distribution reduces the probability that their highest completed degree is a high-school diploma by 22 percentage points, compared with a 16.8 percentage-point reduction for the global rank. In Column (2), the same change in local rank raises the probability of attending college for at least one year by 37.5 percentage points, relative to 24.9 percentage points for the global rank. The discrepancy is larger in Column (3), where moving from the bottom to the top of the local percentile-rank distribution raises the probability of obtaining a bachelor's degree by 58.1 percentage points, compared with 23.6 percentage points for the global rank.

At the same time, the gap between local and global rank is much smaller for obtaining a degree from an elite institution. In Column (4), moving from the bottom to the top of the local percentile-rank distribution increases the probability of obtaining a degree from an elite institution by 14.3 percentage points, while the corresponding effect for the global rank is 9.7 percentage points. These results suggest that local rank is more strongly associated with whether students attend college and complete a bachelor's degree, whereas global rank plays a more comparable role in predicting access to highly selective colleges. This pattern is consistent with the idea that local academic standing is especially important for the formation of beliefs and effort that shape broad college-going outcomes, while global rank has an increasingly important role for admissions to, and success at, more-competitive universities.

These findings, together with those in Table 2, suggest that parents and students place substantially more weight on local rank signals than long-run outcomes would justify. In the short-run results, the relative weight on local rank compared with global rank is about 2.0 for parental investment, 4.8 for student effort, 9.9 for student college expectations, and 5.2 for parent college expectations. However, among the long-run outcomes the corresponding ratios are much smaller: about 1.3 for not obtaining a high-school diploma, 1.5 for any college experience, 2.5 for bachelor's degree completion, and 1.5 for degree completion at an elite institution.[26] Altogether, despite the fact that local rank predicts later educational outcomes, the behavioral and belief responses documented above appear disproportionately strong. This gap is consistent with several distinct mechanisms, each of which carries a different policy implication. For one, family beliefs may be distorted, biasing the expectations parents and children hold about academic potential. Perhaps at the same time, the pattern may reflect a rational response to an environment in which broad academic potential is observed only through noisy signals, while information about local rank is conveyed clearly to families. The reduced-form cannot separate these mechanisms, which necessitates the development of a structural model that allows for both mechanisms and quantifies their relative contributions to the empirical patterns documented here.

[26] The comparison of these ratios is displayed visually in Figure B3.

4 Model

The reduced-form evidence suggests that parents and students respond strongly to local-rank signals, hold expectations that are high relative to later college attainment, and make choices that appear excessively sensitive to local standing. These patterns leave three issues unresolved. First, how large is the resulting wedge between family decisions and the decisions that would arise under unbiased beliefs? Answering this question requires an explicit counterfactual benchmark that takes into account the endogenous response of parents and children in equilibrium after beliefs are corrected. Second, to what extent do peer interactions amplify the family-belief distortions that drive the wedge? When one student over-exerts effort, the resulting increase in cohort effort can induce further responses from peers through social comparisons. Determining the importance of this amplification requires an equilibrium framework. Third, what are the effects of policy interventions that target optimism versus those that target information frictions? Because such interventions affect both individual beliefs and the peer environment, their consequences cannot be evaluated within the reduced-form framework alone. Distinguishing between these information-based mechanisms also requires us to take an explicit stance on the structure of information frictions and the source of optimism that families face.

The structural model developed below addresses these questions by combining the reduced-form moments with an equilibrium framework that disciplines the underlying mechanisms and allows us to conduct counterfactual-policy experiments. The model preserves two elements shown in Section 3. First, families possibly face information frictions because global academic potential is not directly observed and must instead be inferred from local rank and noisy private signals. Second, parents and children may be optimistic on average about children's future academic prospects. We capture this optimism as a belief distortion that shifts family expectations upward, while allowing the sensitivity of beliefs to local rank to continue to depend on signal precision. In addition, to place structure on the sequence of decisions made within-family each period, we impose a Stackelberg structure in which parents act as leaders and children as followers, following recent work in the child-development literature (Del Boca, Flinn and Wiswall, 2016; Del Boca et al., 2019; Agostinelli et al., 2026; Del Boca et al., 2026; Weingarten, Behrman and Postlewaite, 2026).

4.1 Environment, Measurement Error, and Information

Time is indexed by $t = 1, \ldots, 5$. Periods 1 through 4 correspond to grades 9 through 12, during which the parent—acting unilaterally—choose investment levels and children choose effort levels. At the end of period 4, the child decides whether to enroll in college, and college outcomes are realized in period 5.

Each student i is characterized by an evolving latent stock of human capital and a time-varying measure of local-class standing. Let θ_{it} denote latent-cognitive skill—our measure of human capital—in period t. We normalize the period-1 distribution of global academic potential to have mean zero and variance one. In later periods, the distribution of global academic potential is allowed to evolve with skill accumulation, so that θ_{it} has mean μ_t and standard deviation σ_t. For each period $t \leq 4$, let $\theta_{it}^{\mathcal{L}} \equiv \Phi^{-1}(p_{it}^{\mathcal{L}})$ denote the student's latent local standing within the school-grade cohort. Because local standing is constructed from within-cohort ranks, we normalize its distribution to have mean zero and variance one in every period. We assume that, for each t,

$$\begin{pmatrix} \theta_{it} \\ \theta_{it}^{\mathcal{L}} \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} \mu_t \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_t^2 & \rho\sigma_t \\ \rho\sigma_t & 1 \end{pmatrix} \right), \tag{3}$$

with the normalizations $\mu_1 = 0$ and $\sigma_1 = 1$.[27] The parameter $\rho \in (0, 1)$ governs the latent relationship between global academic potential and local standing. We impose a common value of ρ across periods and across schools to reduce the dimensionality of the model. Importantly, we do not calibrate ρ directly to the observed correlation between local and global ranks in Add Health, as both rank measures are observed with error, which we discuss below. Instead, we treat this data-driven correlation as a separate moment to match in estimation.

In the data, global rank is constructed from PPVT scores, which imperfectly proxy for latent academic potential. We invoke a classical measurement error structure and assume that the econometrician observes

$$\widetilde{\theta}_{it}^{\mathcal{G}} = \theta_{it} + \varepsilon_{it}^{\mathcal{G}}, \qquad \varepsilon_{it}^{\mathcal{G}} \sim \mathcal{N}(0, \sigma_m^2). \tag{4}$$

We then construct the simulated observed global percentile rank, $\widetilde{p}_{it}^{\mathcal{G}}$, by ranking $\widetilde{\theta}_{it}^{\mathcal{G}}$ within age groups. We treat measurement error in local rank analogously, where the family observes local standing but the researcher observes a noisy version in the survey data. Formally,

$$\widetilde{\theta}_{it}^{\mathcal{L}} = \theta_{it}^{\mathcal{L}} + \varepsilon_{it}^{\mathcal{L}}, \qquad \varepsilon_{it}^{\mathcal{L}} \sim \mathcal{N}(0, \sigma_{\mathcal{L}}^2). \tag{5}$$

The observed local percentile rank, $\widetilde{p}_{it}^{\mathcal{L}}$, is obtained by ranking $\widetilde{\theta}_{it}^{\mathcal{L}}$ within school-grade cohorts. Following Kuncel, Credé and Thomas (2005), we calibrate $\sigma_{\mathcal{L}}$ so that the correlation between realized (actual) and

[27] We calibrate the remaining distributional parameters for global academic potential using Add Health. For periods 2 through 4, the mean terms are 0.133, 0.208, and 0.327, respectively. The corresponding standard deviations are 0.983, 0.979, and 0.960.

observed (self-reported) local ranks is 0.76.[28] In estimation, in an effort to maintain consistency with the data used to construct the reduced-form moments, we compute the relevant simulated moments using $\tilde{p}_{it}^{\mathcal{L}}$ and $\tilde{p}_{it}^{\mathcal{G}}$.

In the model, families observe local standing $\theta_{it}^{\mathcal{L}}$ through routine school feedback—such as report cards and transcripts—but do not necessarily observe θ_{it} directly. Parents and children receive private information about the child's latent human capital. Although we do not take a stance on how this private information is translated to families, it could reasonably be given by other pieces of information that families receive throughout secondary schooling, such as their performance on standardized tests like the PSAT, or infrequent teacher feedback. We model this for agent $j \in \{P, C\}$, where P denotes the parent and C the child, as a period-t signal

$$q_{it}^{j} = \theta_{it} + \varepsilon_{it}^{j}, \qquad \varepsilon_{it}^{j} \sim \mathcal{N}(0, \sigma_j^2), \tag{6}$$

where σ_j governs the precision of the private signal. A larger σ_j implies noisier, and therefore less informative, private information. For simplicity, we impose a homogeneous σ_j, but acknowledge that a richer specification would allow for heterogeneity in signal precision on the basis of family characteristics.

4.2 Beliefs

In each period t, parent or child $j \in \{P, C\}$ combines current local rank $\theta_{it}^{\mathcal{L}}$ and the period-t private signal q_{it}^{j} to form beliefs about current academic potential. Parents and children use the Bayesian signal-extraction weights implied by the information structure in Equation 6, but may also hold beliefs that are optimistic on average. Because local standing is normalized to have mean zero and variance one in every period, whereas global academic potential has mean μ_t and standard deviation σ_t, the relevant signal-extraction problem can be written over deviations of global academic potential from its period-t mean. From Equation 3, the conditional distribution of global academic potential given local rank is

$$\theta_{it} \mid \theta_{it}^{\mathcal{L}} \sim \mathcal{N}\left(\mu_t + \rho\sigma_t\theta_{it}^{\mathcal{L}}, \sigma_t^2(1-\rho^2)\right). \tag{7}$$

Local rank therefore provides a prediction of global academic potential, while the private signal provides additional, albeit noisy, information about the same latent academic potential.

[28] Kuncel, Credé and Thomas (2005) also report a correlation between true high-school GPA and self-reported high-school GPA of 0.82. We rely on the more conservative correlation to reduce the likelihood that we misattribute measurement error to signal noise that families face.

Combining these two sources of information, expected cognitive skills in period t can be written as

$$\mathbb{E}^j[\theta_{it}] \coloneqq \hat{\theta}^j_{it} = \mu_t + \mu_j + \omega^j_{\mathcal{L},t}\theta^{\mathcal{L}}_{it} + \omega^j_{\mathcal{Q},t}(q^j_{it} - \mu_t), \tag{8}$$

where μ_j is a parent- or child-specific optimism term and

$$\omega^j_{\mathcal{L},t} = \frac{\rho\sigma_t\sigma^2_j}{\sigma^2_j + \sigma^2_t(1-\rho^2)}, \qquad \omega^j_{\mathcal{Q},t} = \frac{\sigma^2_t(1-\rho^2)}{\sigma^2_j + \sigma^2_t(1-\rho^2)}. \tag{9}$$

These weights are obtained from the posterior mean of θ_{it} given $\theta^{\mathcal{L}}_{it}$ and q^j_{it}.[29] As written, this belief rule is static and does not encompass a fully-dynamic learning problem. We argue that this modeling choice is a reasonable approximation because families are making inferences about an *evolving* state, rather than a fixed characteristic over time, so the value of carrying past signals forward is more limited than in a fixed-attribute setting. It is worth emphasizing that, although this inference problem is solved each period, latent skill persists through the technology of skill formation.

The limiting properties of these objects provide intuition for how the information frictions influence family decision-making. Recall that as σ^2_j rises, private signals become more imprecise. When this occurs, the posterior weight on the private signal ($\omega^j_{\mathcal{Q},t}$) falls toward zero, while the coefficient on local rank ($\omega^j_{\mathcal{L},t}$) rises toward $\rho\sigma_t$. In the limit, as $\sigma^2_j \to \infty$, the private signal becomes uninformative and beliefs collapse to the conditional expectation of global academic potential given local standing, shifted by the optimism term:

$$\hat{\theta}^j_{it} \to \mu_t + \mu_j + \rho\sigma_t\theta^{\mathcal{L}}_{it}. \tag{10}$$

In the opposite limit, as $\sigma^2_j \to 0$, the private signal perfectly reveals current human capital, so $\omega^j_{\mathcal{Q},t} \to 1$ and $\omega^j_{\mathcal{L},t} \to 0$. When $\mu_j = 0$, beliefs coincide with the Bayesian posterior implied by the objective signal structure. When $\mu_j > 0$, the parent or child is optimistic, and expectations are therefore biased upward.

4.3 Technology of Skill Formation

We adopt a simple linear technology of skill formation and write that cognitive skill evolves according to

$$\theta_{i,t+1} = \alpha_0 + \alpha_1\theta_{it} + \alpha_2 \ln I_{it} + \alpha_3 \ln e_{it} + \alpha_4\theta_{it} \ln I_{it} + \alpha_5\theta_{it} \ln e_{it} + \xi_{i,t+1}, \tag{11}$$

[29] We do not derive the posterior variance, as our utility specification features families having linear preferences over expected future skill (Equation 12). Alternative specifications could require the additional derivation of the posterior variance.

where $I_{it} > 0$ denotes parental investment, $e_{it} > 0$ denotes child effort, and $\xi_{i,t+1} \sim \mathcal{N}(0, \sigma_\xi^2)$ is an idiosyncratic production function shock. The parameters α_1, α_2, and α_3 capture the direct effect of current cognitive skills, parental investment, and student effort, respectively, in producing future cognitive skill. The terms $\alpha_4 \theta_{it} \ln I_{it}$ and $\alpha_5 \theta_{it} \ln e_{it}$ allow the marginal productivity of investment and effort to depend on the student's current skill.

The empirical counterparts to parental investment and student effort are standardized latent factor scores, rather than raw input quantities on the positive real line. To map the reduced-form evidence to the model, we interpret the investment and effort factors used in Section 3 as location-and-scale-normalized empirical proxies for $\ln I_{it}$ and $\ln e_{it}$.

4.4 Period Utility

Let a_{it}^j denote the period-t choice variable, where $a_{it}^P = I_{it}$ and $a_{it}^C = e_{it}$. Similarly, let $\bar{a}_{st}^j$ denote the corresponding average choice in school s and period t, so that $\bar{a}_{st}^P = \bar{I}_{st}$ and $\bar{a}_{st}^C = \bar{e}_{st}$.

Agent j's period utility depends on expected next-period cognitive skill, the cost of the current action, and the corresponding average action of others in the same school and period. We write period utility as

$$u_{it}^j = \lambda_i^j \, \mathbb{E}_t^j[\theta_{i,t+1}] - \frac{\kappa^j}{2} \left(a_{it}^j\right)^2 + \psi^j a_{it}^j \bar{a}_{st}^j, \tag{12}$$

where $\mathbb{E}_t^j[\theta_{i,t+1}]$ is formed using agent j's beliefs in Equation 8. The first term captures the parent's or child's valuation of higher future cognitive skill, the second captures the cost of the current action, and the third allows for peer effects, whereby the decision of agent j depends in part on the decisions of others in the same school and period. In both the parent's and the child's case, the current action is costly but raises the child's future cognitive skill through the production function in Equation 11. This creates a natural trade-off between costly actions today and higher expected returns tomorrow. This specification follows Del Boca, Flinn and Wiswall (2014) and subsequent work in the child development literature.

Families value the level of academic potential rather than local rank directly. This is consistent with our assumption that the outcomes families ultimately care about—college completion and elite completion—are governed by absolute readiness thresholds rather than by rank per se. Local rank still shapes behavior, but through beliefs about the level of academic potential rather than as a direct preference, consistent with the absence of rank-preference nonlinearities in Table A8.

We allow demographic heterogeneity in preferences for future cognitive skill along the same margins used in the reduced-form analysis. Let x_i^f denote an indicator equal to one if the child is female, and let

x_i^{nw} denote an indicator equal to one if the child is non-White. We parameterize preference heterogeneity as

$$\lambda_i^j = \lambda_0^j + \lambda_1^j x_i^f + \lambda_2^j x_i^{nw}, \qquad j \in \{P, C\}. \tag{13}$$

For simplicity, we assume the cost parameter κ^j is homogeneous within parent or child type.[30]

4.5 Recursive Formulation

Children act as followers under the Stackelberg structure. In each period $t \leq 4$, after observing parental investment I_{it}, child i chooses effort e_{it} to maximize current utility plus the expected continuation value. Let $V_t^C(\hat{\theta}_{it}^C, I_{it}, \bar{e}_{st})$ denote the child's value function. The child's problem is

$$V_t^C(\hat{\theta}_{it}^C, I_{it}, \bar{e}_{st}) = \max_{e_{it} > 0} \left\{ u_{it}^C + \beta \mathbb{E}_t^C \left[V_{t+1}^C(\hat{\theta}_{i,t+1}^C) \right] \right\}, \tag{14}$$

where $\beta \in (0, 1)$ is the common discount factor and $\mathbb{E}_t^C[\cdot]$ denotes expectations formed under the child's beliefs in Equation 8. Through Equation 11, higher effort today increases future cognitive skill and therefore raises continuation value.

Parents move first in each period and act as Stackelberg leaders. Parent i chooses investment I_{it} anticipating the child's best-response effort choice. Let

$$e_{it}^* = e_t^*(\hat{\theta}_{it}^C, I_{it}, \bar{e}_{st}) \tag{15}$$

denote the child's optimal effort policy implied by Equation 14. The parent's value function is

$$V_t^P(\hat{\theta}_{it}^P, \bar{I}_{st}, \bar{e}_{st}) = \max_{I_{it} > 0} \left\{ u_{it}^P + \beta \mathbb{E}_t^P \left[V_{t+1}^P(\hat{\theta}_{i,t+1}^P, \bar{I}_{s,t+1}, \bar{e}_{s,t+1}) \right] \right\}, \tag{16}$$

subject to Equation 15 and the technology of skill formation (Equation 11), where $\beta \in (0, 1)$ is again the common discount factor and $\mathbb{E}_t^P[\cdot]$ denotes expectations formed under the parent's beliefs in Equation 8. In estimation, we exogenously establish $\beta = 0.96$.

4.6 College Application, Admissions, and Completion

At the end of period 4, after parental investment and child effort have been chosen, period-5 cognitive skill is realized according to Equation 11. College completion depends on college readiness, which we

[30] This model is isomorphic to one that asserts homogeneity in preferences but allows for flexible heterogeneity across demographic margins for the cost parameters.

parameterize as

$$R_i = \theta_{i5} + \tau\theta_{i4}^{\mathcal{L}}. \tag{17}$$

The first component is incoming academic potential after high school. The second component allows local academic performance to enter college readiness directly. This term captures the fact that GPA rank summarizes transcript information and other possible dimensions of high-school achievement that are relevant for college admissions and completion but are not fully captured by the PPVT-based measure of academic potential. The τ term captures the weight that colleges place on local academic potential relative to global academic potential.[31]

Although families observe $\theta_{i4}^{\mathcal{L}}$, they do not observe θ_{i5} and thus do not observe true college readiness. Moreover, families may not know the true mapping from local academic performance to college readiness. We therefore allow beliefs about college readiness to depend on a perceived local-readiness return $\tilde{\tau}$, which may differ from the true return τ. We assume that $\tilde{\tau}$ is common between parents and children. Let

$$\tilde{R}_i^C \equiv \hat{\theta}_{i5}^C + \tilde{\tau}\theta_{i4}^{\mathcal{L}} \tag{18}$$

denote the child's perceived college readiness after period-4 choices have been made, where $\hat{\theta}_{i5}^C = \mathbb{E}_4^C[\theta_{i5}]$. The child then decides whether to apply to college. Let $d_i \in \{0, 1\}$ denote the application decision, where $d_i = 1$ if the child applies and $d_i = 0$ otherwise. The child's terminal value is

$$V_5^C(\tilde{R}_i^C) = \max_{d_i \in \{0,1\}} \mathbb{E}_4^C \left[\Gamma_i^C(d_i, \mathcal{C}_i, B_i)\right], \tag{19}$$

where $\mathcal{C}_i \in \{0, N, E\}$ denotes the admissions outcome, with 0 denoting no college, N denoting a non-elite college, and E denoting an elite college. The indicator $B_i \in \{0, 1\}$ denotes bachelor's degree completion.

The terminal payoffs for j are written as

$$\Gamma_i^j(d_i, \mathcal{C}_i, B_i) = d_i\Big[\gamma_A + \gamma_N^j \mathbb{1}\{\mathcal{C}_i = N, B_i = 1\} + (\gamma_N^j + \gamma_E^j)\mathbb{1}\{\mathcal{C}_i = E, B_i = 1\}\Big]. \tag{20}$$

Thus, no college application yields zero payoff, beginning college provides families with a fixed utility premium (γ_A) regardless of completion status, completing college yields a positive payoff, and completing

[31] The weight attached to each academic potential type is identified up to scale, so we normalize the weight attached to global academic potential to one.

at an elite college yields an additional premium.[32]

Conditional on applying, colleges form their own expectation of terminal college readiness using period-4 class rank and a period-5 admissions signal, which could capture other components of the submitted college application, such as SAT scores, personal essays, and teacher and counselor letters of recommendation. Specifically, let

$$q_i^A = R_i + \varepsilon_i^A, \qquad \varepsilon_i^A \sim \mathcal{N}(0, \sigma_A^2), \tag{21}$$

and define the college posterior mean as

$$\hat{R}_i^A \equiv \mathbb{E}\Big[R_i \mid \theta_{i4}^{\mathcal{L}}, q_{i5}^A\Big]\,. \tag{22}$$

Thus, because colleges receive transcripts directly, they observe the final class rank in high school together with a noisy signal of true terminal readiness when forming admissions decisions. Unlike parents and children, we assume that colleges hold unbiased beliefs about academic potential and are not subject to the optimism terms μ_P and μ_C. The admissions posterior therefore provides the undistorted benchmark against which children's application decisions are evaluated.

For simplicity, we assume that admissions are threshold-based. Let $\bar{a}_E$ denote the elite-college threshold and let $\bar{a}_N$ denote the non-elite threshold, with $\bar{a}_E > \bar{a}_N$. Conditional on $d_i = 1$, the admissions outcome is

$$\mathcal{C}_i = \begin{cases} E & \text{if } \hat{R}_i^A \geq \bar{a}_E, \\ N & \text{if } \bar{a}_N \leq \hat{R}_i^A < \bar{a}_E, \\ 0 & \text{if } \hat{R}_i^A < \bar{a}_N. \end{cases} \tag{23}$$

If $d_i = 0$, then $\mathcal{C}_i = 0$. This structure provides us with a parsimonious decision-rule for colleges that can be mapped to our limited college-age data. Implicit to this structure is an assumption that students are able to apply to both types of universities in a costless manner, and that there are no capacity constraints in admissions. This second assumption is reasonable because we collapse hundreds of universities into a single representative "elite" institution. As a consequence of this assumption, elite colleges do not endogenously update their threshold rule in response to distributional shocks to skills.

After admissions and enrollment, terminal readiness is revealed to the student. Given data limitations,

[32] The model cannot separately identify both a premium term (γ_A) and a drop-out penalty term. In estimation, a model with only the drop-out penalty term failed to rationalize the high rate of initial attendance in college. As a result, our preferred model features only γ_A.

we do not model the development of skills during college. Bachelor's completion is then given by

$$B_i = \mathbb{1}\{\mathcal{C}_i = N,\, R_i \geq \bar{a}_N\} + \mathbb{1}\{\mathcal{C}_i = E,\, R_i \geq \bar{a}_E\}. \tag{24}$$

Students who enroll but do not satisfy the relevant threshold drop out. Therefore, in our model, dropout occurs when a student enrolls in college based on imperfect information about college readiness, but realized readiness falls below the relevant completion threshold. Given the evidence presented in Section 3, we abstract from large later-life shocks—such as a parental death or an unplanned pregnancy—as drivers of this drop-out decision. Given our focus on information frictions and belief distortions, and the empirical evidence that these shocks do not meaningfully impact the role of information frictions in our setting, we avoid further complicating the model with their inclusion.

The parent's terminal value is defined analogously. Let $\tilde{R}_i^P \equiv \hat{\theta}_{i5}^P + \tilde{\tau}\theta_{i4}^{\mathcal{L}}$ denote the parent's perceived terminal college readiness after period-4 choices have been made, where $\hat{\theta}_{i5}^P = \mathbb{E}_4^P[\theta_{i5}]$. The parent's terminal value is

$$V_5^P(\tilde{R}_i^P) = \mathbb{E}_4^P\left[\Gamma_i^P(d_i^*, \mathcal{C}_i, B_i)\right], \tag{25}$$

where d_i^* is the child's optimal application decision.

As written, local rank plays two distinct roles in the terminal stage. First, through $\tilde{\tau}$, it shapes family beliefs about college readiness and therefore affects investment, effort, expectations, and application decisions. Second, through τ, it directly contributes to realized college readiness, reflecting information in high-school grades and transcripts that is relevant for admissions and completion beyond the PPVT-based skill measure. This distinction is important for counterfactual policy experiments, as information policies change families' beliefs about academic potential but do not mechanically eliminate the component of college readiness captured by local academic performance.

5 Identification and Estimation

5.1 Simulated Initial Conditions

We estimate the structural model by indirect inference, comparing moments generated from a simulated population of students to their empirical counterparts in Add Health. We simulate a large economy populated by $N = 20{,}000$ students who enter grade 9 at $t = 1$. Students are indexed by i and distributed across 48 high schools, indexed by h, matching the school count in our data. We assign students to schools so that the share of simulated students attending school h is the same as the corresponding share attending that school in Add Health.

For each student, we draw demographic characteristics $\boldsymbol{x}_i$, including indicators for female and non-White status, as well as age in 9th grade.[33] Within each school h, we first draw the observed PPVT-based measure of global academic potential,

$$\widetilde{\theta}_{i1}^{\mathcal{G}} \mid h \sim \mathcal{N}(\widetilde{\mu}_h, \widetilde{\sigma}_h^2), \tag{26}$$

where $\widetilde{\mu}_h$ and $\widetilde{\sigma}_h^2$ are the mean and variance of the observed PPVT-based measure among 9th-grade students in school h in Add Health. This preserves cross-school heterogeneity in the level and dispersion of observed academic potential.

We then draw the latent initial skill state θ_{i1} from the distribution implied by Equation 4. Specifically, $\widetilde{\theta}_{i1}^{\mathcal{G}}$ is treated as a noisy measure of latent academic potential, and the latent state used in the child's and parent's decision problem and skill-formation process is drawn conditional on this observed measure. Initial observed global rank, $\widetilde{p}_{i1}^{\mathcal{G}}$, is obtained by ranking $\widetilde{\theta}_{i1}^{\mathcal{G}}$ within age cells.

Conditional on the latent initial skill state, we draw initial local standing using the latent relationship between global academic potential and local standing (Equation 3). In particular, we draw a raw local-standing index that is correlated with standardized latent skill according to the estimated, common correlation parameter ρ. We then rank this index within each school to obtain the student's latent local rank, $p_{i1}^{\mathcal{L}}$, and transform it into the normalized local-standing measure, $\theta_{i1}^{\mathcal{L}} = \Phi^{-1}(p_{i1}^{\mathcal{L}})$. This latent local-standing object enters family beliefs and choices. To construct the simulated analogue of the observed local rank in Add Health, we add measurement error to $\theta_{i1}^{\mathcal{L}}$ and then rank the contaminated local-standing measure within school-grade cohorts, as described in Equation 5.

We then age the simulated cohort forward through grades 10, 11, and 12 according to the model. In each later grade, the latent skill state evolves through the skill-production technology, local standing is drawn from its latent relationship with global academic potential, and observed local and global ranks are constructed by applying the same measurement process used at baseline. Although Add Health observes each respondent in a single high-school grade at Wave I, the reduced-form moments pool students across grades. The simulated panel is therefore constructed to match the synthetic grade profile observed in the data.

[33] We match the 9th-grade age distribution in Add Health. In the simulation, 18 percent of students are age 14, 66 percent are age 15, and 16 percent are age 16.

5.2 Identification

Let $\Theta = (\Theta^B, \Theta^U, \Theta^K, \Theta^A, \Theta^E)$ denote the vector of parameters to be estimated. The belief parameters are $\Theta^B = \{\sigma_P, \sigma_C, \mu_P, \mu_C\}$, where σ_P and σ_C govern the precision of parent and child private signals, and μ_P and μ_C govern average optimism. The preference parameters are $\Theta^U = \{\lambda_k^P\}_{k=0}^2 \cup \{\lambda_k^C\}_{k=0}^2 \cup \{\kappa^P, \kappa^C\} \cup \{\psi^P, \psi^C\}$. The λ_k^j parameters govern the value that parents and children place on future skill, κ^P and κ^C govern the costs of investment and effort, respectively, and ψ^P and ψ^C govern the relevance of peer effects through school-grade average levels of investment and effort, respectively. The parameters governing the technology of skill formation (Equation 11) are $\Theta^K = \{\alpha_k\}_{k=0}^5 \cup \{\sigma_\xi\}$. The postsecondary education parameters are $\Theta^A = \{\gamma_A, \gamma_N^P, \gamma_E^P, \gamma_N^C, \gamma_E^C, \sigma_A, \bar{a}_N, \bar{a}_E, \tau, \tilde{\tau}\}$. The γ parameters govern payoffs from college enrollment and college completion, σ_A governs admissions-signal noise, $\bar{a}_N$ and $\bar{a}_E$ are the non-elite and elite thresholds, and τ and $\tilde{\tau}$ are the true and perceived returns to local performance in college readiness. Lastly, $\Theta^E = \{\rho, \sigma_m, \epsilon_P, \epsilon_C\}$, are the parameters related to latent measurement error and classification-error in subjective survey response data. The term ρ is the true correlation between local and global rank, whereas σ_m governs the level of noise faced by the econometrician when observing the proxy for global academic potential. The terms ϵ_P and ϵ_C are used only in simulation, capturing error in mapping continuous probabilities into binary measures of college completion certainty. These terms do not impact the child's or parent's decision problem.[34]

For each candidate value of Θ, we solve the dynamic Stackelberg problem conditional on school-grade peer environments. Although models of social interactions generally exhibit multiple equilibria, we circumvent this issue by imposing the equilibrium leave-one-out shares of parental investment and student effort observed in Add Health throughout estimation. Parents choose investment anticipating the child's effort response and integrating over the child's private signal.[35] Children observe parental investment and then choose effort given their own posterior beliefs. We simulate the resulting panel and compute the same moments in the simulated economy that we estimate in Add Health.

Let M denote the vector of empirical moments and let $M(\Theta)$ denote the corresponding vector of simulated moments. The estimator solves

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} \Big(M - M(\Theta)\Big)' W \Big(M - M(\Theta)\Big), \tag{27}$$

[34] For a full discussion of these two ϵ terms, see Appendix D.

[35] The parent observes their own posterior belief but not the child's private signal. We therefore compute the parent's expected value of each investment choice by integrating over the conditional distribution of the child's posterior belief, given the parent's current information. We approximate this integral via Gauss-Hermite quadrature (Judd, 1998).

where W is a fixed, positive semi-definite weighting matrix.[36] The moments are chosen to discipline the empirical patterns that motivate the model. These moments include the reduced-form coefficients on local and global rank, reduced-form analogues of the skill-formation technology, grade profiles, long-run educational attainment moments, and school-grade equilibrium averages of parental investment and student effort. We next describe how these moments identify the structural parameters.

Identification of Θ^B and Θ^U—The belief and preference parameters are primarily disciplined by the short-run moments in Table 2 and Table 3. These moments include coefficients on local and global rank in regressions for parental investment, student effort, student expectations, and parent expectations.[37] The relative responses of expectations to local and global rank discipline σ_P and σ_C, since signal precision governs how strongly parents and children rely on local standing when forming beliefs. The average levels of expectations relative to realized attainment discipline μ_P and μ_C.

Investment and effort moments discipline the preference and cost parameters. Holding beliefs fixed, the levels of investment and effort are informative about κ^P and κ^C, while their responses to perceived skill and future college prospects are informative about $\{\lambda_k^P\}_{k=0}^2$ and $\{\lambda_k^C\}_{k=0}^2$. The expectation moments help separate beliefs from incentives because they discipline subjective probabilities directly.

The model produces continuous subjective probabilities of bachelor's degree completion. To match the binary survey measures in Add Health, we convert these probabilities into binary survey analogues using a fixed cutoff, allowing reported expectations to differ from the threshold response through a symmetric classification error (see Appendix D for details). We then match both the grade-specific levels of these binary measures and their regression coefficients on local and global rank.

The parameters related to peer effects, ψ^P and ψ^C, are disciplined by the peer-behavior moments in Table 3 and by the school-grade means of investment and effort. These moments discipline the relationship between individual choices and the local peer environment, as well as the distribution of peer environments across schools and grades.

Identification of Θ^K—The parameters governing the technology of skill formation are disciplined by

[36] In practice, W is diagonal and block-normalized. We partition the moment vector into blocks $b \in \mathcal{B}$ and set $W_{kk} = \omega_b/|b|$ for moments k in block b, where ω_b is the block weight and $|b|$ is the number of moments in that block. The blocks are school-grade mean choices, short-run rank regressions, peer-behavior regressions, skill-input moments, grade profiles, long-run outcome regressions, and level moments. This normalization prevents large blocks from having disproportionate weight solely because they contain more moments. We fix W rather than estimate an optimal weighting matrix, as the full moment vector contains 511 moments and the unrestricted covariance matrix is high-dimensional. Estimated optimal weighting matrices can perform poorly in finite samples when the weighting matrix is itself estimated with error (Hansen, Heaton and Yaron, 1996; Altonji and Segal, 1996). For computation of the corresponding standard errors, we use the Delta method with the sandwich variance formula with the weighting matrix in Equation 27.

[37] In the simulated data, local rank is the empirical CDF of simulated local standing within the student's school-grade cell, and global rank is the empirical CDF of simulated global skill within the student's age cell.

moments relating terminal skill to students' initial academic potential and early high-school inputs. We use the transformed Wave III PPVT measure, $\Phi^{-1}(p_{i,5}^{\mathcal{G}})$, as the empirical analogue of terminal skill and regress it on the transformed Wave I PPVT measure, parental investment, student effort, and interactions between initial cognitive skill and each input. We estimate these regressions both with grade fixed effects and with school-grade fixed effects, matching the corresponding coefficient estimates in the simulated data.

These moments discipline how differences in initial academic potential and early environmental inputs translate into cognitive skill after the end of high school. The coefficient on initial cognitive skill is particularly informative about persistence, while the coefficients on parental investment and student effort identify the average productivity of each input. The interaction terms between initial cognitive skill and investment and effort identify whether the returns to these inputs vary with students' initial academic potential. The grade profile of cognitive skill provides an additional source of identification for the intercept and persistence of the skill-production process.

Identification of Θ^A—The terminal, college-stage parameters are disciplined by long-run educational outcomes and by the expectation moments. We match the levels of college attendance, bachelor's degree completion, and elite-college completion, as well as the coefficient estimates relating these outcomes to local and global rank. The inclusion of each of these moments forces the model to reproduce both average completion levels and the relationship between completion and the two types of rank.

The thresholds $\bar{a}_N$ and $\bar{a}_E$ are disciplined by the levels of non-elite and elite completion. The parameter τ is disciplined primarily by the extent to which long-run educational attainment varies with local rank, conditional on the short-run belief and behavior responses already disciplined by the expectation, investment, and effort moments. It captures the true contribution of local academic performance to college readiness. The parameter $\tilde{\tau}$ is disciplined by the sensitivity of expectations and environmental inputs to local rank. It captures the perceived contribution of local academic performance to college readiness. The admissions-signal variance σ_A is disciplined by the relationship between terminal readiness, rank, and college outcomes.[38] The payoff parameters γ_N^P, γ_E^P, γ_N^C, and γ_E^C govern the value of completing non-elite and elite college degrees, and are therefore disciplined by the investment, effort, and application choices needed to rationalize observed attainment. Lastly, the college-going premium parameter γ_A is disciplined by the model's ability to match college-going patterns.

Identification of Θ^E—The measurement-error parameters, ρ and σ_m, are disciplined in part by how ob-

[38] Note that a model without college-side information frictions, as written, would generate a dropout rate of 0 percent. The admissions noise term σ_A therefore helps rationalize the *ex-post* drop-out choices of students.

served local and global ranks relate to one another and to later outcomes. The observed local-global rank correlation, targeted in estimation, pins down the covariance of the two rank measures but cannot by itself separate the latent correlation ρ from the measurement error in global rank observed by the econometrician. To disentangle these two, we target global-rank coefficients on long-run outcomes, such as college completion, which establishes that the PPVT score—and by extension, the rank generated from it—provides a natural bound for σ_m. With the measurement error reasonably bounded, the observed correlation helps to identify the latent correlation, ρ. We discuss the identification of ϵ_P and ϵ_C in Appendix D.

5.3 Estimation Results and Model Fit

Table 5 reports the estimated structural parameters. The estimates illustrate that families make costly investment and effort choices using beliefs that are optimistic on average and strongly shaped by local-academic signals. Panel A shows that parents and children alike overestimate the child's academic potential by roughly 30 percent of a standard deviation. Both parents and children also receive noisy private signals of latent academic potential, with the child's signal about 35 percent noisier than the parent's. Local rank is therefore influential not because families lack information entirely, but because broader academic potential is observed with low precision and interpreted with upward-biased beliefs.[39]

The preference, peer-interaction, and skill-formation parameters determine how these belief distortions translate into behaviors and later outcomes. Parents and children both place substantial value on future skill, while investment and effort are costly. As a result, mistaken beliefs about academic potential distort realized actions, rather than only stated expectations. The positive peer-interaction parameters imply that investment and effort also respond to the behavior of others in the same school-grade cohort, creating an equilibrium channel through which individual belief distortions can affect the local environment.[40] Skill persistence then propagates these distortions dynamically, where belief errors affect current investment and effort choices that shape next-period skill accumulation, and future decisions are made from these distorted prior states.

Finally, the college-stage estimates separate the informational role of local rank from its true contribution to college readiness. The estimate of τ implies that 12th-grade local academic performance contains

[39] Using Equation 9, the model-implied ratio of the weight that agent j places on local standing relative to the private (global) signal is $\omega^j_{\mathcal{L},\mathcal{Q}} := \omega^j_{\mathcal{L}}/\omega^j_{\mathcal{Q}} = (\rho\sigma_j^2)/\sigma_t(1-\rho^2)$. Evaluated at the estimated correlation $\rho = 0.543$ and using $\sigma_t \approx 1$, this ratio is 3.3 for parents and 6.3 for children. The fact that $\omega^j_{\mathcal{L},\mathcal{Q}}$ is above one for both parents and children reflects the large reliance that both put on local rank when forming beliefs about academic potential.

[40] The magnitude of these estimates suggests that peer interactions are present but not the primary force behind family choices. In the model-fit moments, peer behavior predicts parental investment and student effort, but the local-rank gradient remains especially large, particularly for student effort. Together with the evidence in Table 3, these patterns suggest that social pressures are a secondary mechanism relative to the belief channel generated by local and global academic signals.

Table 5: Structural Parameter Estimates

Parameter	Estimate	Standard Error
Panel A: Beliefs and Information		
Parent optimism (μ_P)	0.278	0.009
Child optimism (μ_C)	0.293	0.009
Parent private-signal noise (σ_P)	2.082	0.090
Child private-signal noise (σ_C)	2.810	0.158
Panel B: Preferences		
Parent, intercept (λ_0^P)	4.710	0.133
Parent, female margin (λ_1^P)	3.632	0.104
Parent, non-White margin (λ_2^P)	−1.723	0.064
Child, intercept (λ_0^C)	5.660	0.113
Child, female margin (λ_1^C)	−0.589	0.040
Child, non-White margin (λ_2^C)	1.116	0.038
Panel C: Costs and Peer Interactions		
Parent investment cost (κ^P)	1.643	0.054
Child effort cost (κ^C)	2.377	0.058
Parent peer-investment interaction (ψ^P)	0.279	0.029
Child peer-effort interaction (ψ^C)	0.284	0.023
Panel D: Technology of Skill Formation		
Intercept (α_0)	0.121	0.005
Persistence (α_1)	0.601	0.007
Parental investment (α_2)	0.108	0.003
Child effort (α_3)	0.225	0.011
Skill-investment complementarity (α_4)	0.082	0.002
Skill-effort complementarity (α_5)	0.338	0.007
Shock standard deviation (σ_ξ)	0.218	0.016
Panel E: College Parameters		
Common attendance value (γ_A)	0.340	0.080
Parent payoff, non-elite (γ_N^P)	1.467	0.139
Parent payoff, elite (γ_E^P)	4.603	0.828
Child payoff, non-elite (γ_N^C)	1.029	0.051
Child payoff, elite (γ_E^C)	2.636	0.154
Admissions-signal noise (σ_A)	1.245	0.084
Non-elite threshold ($\bar{a}_N$)	0.367	0.015
Elite threshold ($\bar{a}_E$)	1.852	0.070
True local-rank return (τ)	0.937	0.063
Perceived local-rank return ($\tilde{\tau}$)	0.515	0.043
Panel F: Measurement-Error Parameters		
Latent local-global correlation (ρ)	0.543	0.008
PPVT measurement noise (σ_m)	0.408	0.025
Parent expectation reporting error (ϵ_P)	0.356	0.004
Child expectation reporting error (ϵ_C)	0.293	0.004

Notes: This table reports the estimated structural parameters from the simulated method-of-moments estimator described in Equation 27. Standard errors are computed using the Delta method based on a numerical Jacobian of the simulated moments at the estimated parameter vector. Panel A reports belief and information parameters from the belief rule in Equation 8. Optimism parameters are measured in standard deviation units of latent skills. Panels B and C report preference, cost, and peer-interaction parameters from the problems in Equation 14 and Equation 16. Panel D reports parameters of the skill-production technology in Equation 11. Panel E reports terminal-stage college-payoff and readiness parameters from Equation 20, Equation 17, Equation 18, Equation 23, and Equation 24. Panel F reports parameters governing rank measurement and the mapping from continuous subjective expectations to the binary expectation measures used in estimation.

substantial information about admissions and completion beyond measured cognitive skill. By contrast, the smaller estimate of $\tilde{\tau}$ implies that families understate the direct contribution of local academic performance to college readiness. This distinction supports our interpretation that the primary distortion operates through earlier beliefs about academic potential, rather than through an exaggerated perceived terminal return to class rank. Had the model instead recovered $\tau \leq \tilde{\tau}$, the reduced-form patterns could have been rationalized by families overvaluing local rank at the college-application stage, weakening the information-friction interpretation. Furthermore, information policies change how families interpret academic signals while holding fixed the true contribution of local academic performance to college readiness, so treating these channels separately is policy-relevant.

Before turning to our counterfactual policy experiments, we assess whether the estimated model reproduces the empirical patterns that discipline the main mechanisms. Although the estimation targets 511 moments, Table 6 reports the subset most relevant for the policy exercises. These include the local- and global-rank coefficients from the school-grade fixed-effect regressions, the pooled moments in the peer effects regressions, and the levels of college attendance, bachelor's degree completion, and elite-college completion. To summarize the large set of school-grade investment and effort moments, we report average investment and effort in the data and in the simulated economy, pooled across years.

Overall, the model reproduces the main empirical patterns that motivate the counterfactual analysis quite well. It generates the strong local-rank coefficient estimates in parental-investment and student-effort regressions, as well as the weaker role of global rank in the short-run choice equations. The model does a similarly good job of matching these coefficients in the student and parent belief regressions. It also captures the positive associations between individual actions and the behaviors of others in the local environment, which again disciplines the equilibrium-interaction channel. Notably, the model slightly under-predicts how strongly parents respond to other parents, as well as how strongly students respond to other students. The fit is less exact for terminal outcomes. It underpredicts college attendance but otherwise strongly matches non-elite and elite college completion. Table A11 shows the model's ability to replicate regressions that relate college-aged skills to 9th grade skills and investment. We obtain similar results but understate the role of lagged skills. One possibility that explains this attenuation is the fact that we enforce the same measurement error (σ_m) on the Wave III PPVT score embedded into the Wave I score.

Given the close overall fit between the simulated moments and their empirical counterparts, we next turn to counterfactual policy experiments. We interpret the model as a useful framework for studying how changes in information and belief formation affect family choices, skill accumulation, and eventual college outcomes.

Table 6: Evidence of Model Fit

	Data	Model
Panel A: Local and Global Rank Regressions		
Parental investment, local rank	0.305	0.342
Parental investment, global rank	0.152	0.115
Student effort, local rank	0.838	0.805
Student effort, global rank	0.176	0.229
Student college expectations, local rank	0.417	0.362
Student college expectations, global rank	0.042	0.080
Parent college expectations, local rank	0.273	0.254
Parent college expectations, global rank	0.053	0.062
Panel B: Peer-Behavior Moments		
Parental investment, local rank	0.300	0.344
Parental investment, global rank	0.199	0.111
Parental investment, peer investment	0.333	0.433
Student effort, local rank	0.825	0.806
Student effort, global rank	0.192	0.224
Student effort, peer effort	0.211	0.160
Panel C: Long-Run Outcome Regressions		
College attendance, local rank	0.375	0.333
College attendance, global rank	0.249	0.212
Bachelor’s completion, local rank	0.581	0.294
Bachelor’s completion, global rank	0.236	0.289
Elite completion, local rank	0.143	0.127
Elite completion, global rank	0.097	0.136
Panel D: College Attainment Levels		
College attendance	0.703	0.487
Bachelor’s completion	0.351	0.379
Elite completion	0.058	0.083
Panel E: Average Choices		
Parental investment	−0.004	−0.115
Student effort	0.005	0.004

Notes: This table compares selected empirical moments used in estimation with the corresponding moments in the simulated economy at the estimated parameter vector. Panel A reports coefficients on local and global rank from regressions with school-grade fixed effects. Panel B reports pooled peer-behavior moments from regressions that include the leave-one-out average choice in the school-grade cohort. Panel C reports coefficients from long-run outcome regressions. Panel D reports college-attainment levels. Panel E reports average parental investment and student effort, averaging across the school-grade moments used in estimation.

6 Counterfactual Information Interventions

We use the estimated model to study how outcomes change when families receive better information about academic potential. The counterfactuals are designed to isolate the two belief distortions emphasized by the model. The first removes average optimism by setting the parent and child optimism parameters, μ_P and μ_C, equal to zero. The second provides families with perfect information about global academic potential by eliminating the private signal noise terms, i.e., setting σ_P and σ_C equal to zero. The third combines these two changes and therefore gives families unbiased and perfect information about the child’s latent academic potential. To determine the importance of the timing of information revelation, the fourth counterfactual repeats the second policy experiment—providing families with exact signal precision—only in grades 11 and 12, after earlier high-school investment and effort decisions have already been made. Lastly, we consider a college-stage information counterfactual in which families correctly perceive the direct role of local academic performance in college readiness, setting $\tilde{\tau} = \tau$, and colleges observe readiness without admissions-signal noise, setting σ_A to zero.

The inclusion of peer effects in our structural framework requires that we solve each counterfactual as a new equilibrium, because any policy that changes beliefs also changes the local peer environments. We therefore treat the school-grade levels of parental investments and student efforts as equilibrium objects embedded into a separate fixed-point algorithm under each counterfactual policy regime.[41] Doing so allows the counterfactuals to incorporate both the direct effect of improved information on choices and the equilibrium spillovers generated by the responses of peers at the parent- and child-level.

Table 7 reports the results of the counterfactual-policy experiments. The baseline column reports the final simulated model fit from estimation. The remaining columns change the informational environment and report effects from the resulting equilibria. The table highlights three key takeaways. First, as shown in Policy I, biased beliefs have large consequences for both motivation and household resource allocation. Second, as shown in Policies II through IV, improved information about academic potential can have meaningful effects on skill accumulation and college completion, especially when the information revelation occurs early. Third, as shown in Policy V, information at the college stage improves sorting and completion, but cannot undo the consequences of earlier information frictions. Below, we discuss each policy experiment in greater detail.

Policy I.—The first counterfactual removes average optimism by setting $\mu_j = 0$ for both parents and children, while leaving signal precision (σ_j) unchanged. Doing so reduces average parental investments by about 16 percent of a standard deviation and average student efforts by about 30 percent of a standard deviation. Terminal academic potential falls by 16 percent of a standard deviation, and college completion falls by nearly 5 percentage points. Our results therefore imply that biased beliefs can be beneficial even when inaccurate.

Policy II.—The second counterfactual eliminates private-signal noise by setting $\sigma_j = 0$ for $j \in \{P, C\}$, giving families perfect information about the student's latent academic potential while maintaining the biased optimism term. By Equation 9, as σ_j approaches zero, the relative weight placed on the private signal, $\omega^j_{\mathcal{Q},t}/\omega^j_{\mathcal{L},t}$, explodes and families no longer rely on local rank to infer academic potential. We find that

[41] In general, the existence of peer effects introduces the possibility of multiple equilibria. We employ an equilibrium-selection rule by using the baseline peer shares (those observed in Add Health) as the starting point in the fixed-point algorithm in all counterfactual policies. The counterfactual-policy results are therefore interpreted as being conditional on this starting point.

Table 7: Simulated Effects from Counterfactual Policy Experiments

		Counterfactual-Policy Experiments				
	Baseline	I. No Optimism ($\mu_j = 0$)	II. Perfect Info ($\sigma_j = 0$)	III. No Optimism + Perfect Info ($\mu_j = \sigma_j = 0$)	IV. Late Info Grades 11–12 ($\sigma_j = 0, t \geq 3$)	V. No College Distortions ($\tilde{\tau} = \tau, \sigma_A = 0$)
Period-5 Academic Potential	0.310	0.142	0.727	0.610	0.424	0.326
Parental Investment	−0.112	−0.272	0.101	−0.001	−0.066	−0.115
Student Effort	0.002	−0.296	0.268	0.027	0.070	0.017
College Completion	0.379	0.331	0.462	0.433	0.397	0.478
Elite College Completion	0.083	0.065	0.127	0.119	0.090	0.101
Dropout	0.108	0.144	0.055	0.075	0.098	0.000

Notes. This table reports simulated outcomes from the estimated model under each counterfactual-policy experiment. The baseline column reports the final simulated model fit from estimation. In the column headers, $j \in \{P, C\}$ indexes parents and children. All counterfactual columns solve for the equilibrium peer environment in school-grade average parental investments and student efforts. In the late-information counterfactual, grades 9 and 10 are held fixed at their baseline simulated actions, while the counterfactual equilibrium is solved over grades 11 and 12. Parental investments and student efforts are pooled averages of log choices across periods. Period-5 academic potential is measured at the terminal college stage.

providing families with perfect information, which represents a large-scale information revelation policy, increases terminal academic potential by 42 percent of a standard deviation, raises college completion by about 9 percentage points, increases elite-college completion by 4 percentage points, and reduces dropout by 5 percentage points. Average parental investment and student effort also rise by 20 and 26 percent of a standard deviation, respectively. These effects show that information frictions affect not only expectations, but also the allocation of effort and investment during high school. When families observe academic potential perfectly, they choose inputs that are better aligned with students' true skill, and these improved choices accumulate dynamically through the skill-formation process.

The size of these effects reflects both the magnitude of the information friction and the dynamic role of information in the model. When families observe academic potential with greater precision, they choose effort and investment that are better aligned with the student's true academic potential. Because skill formation is cumulative, these improved choices compound across high-school grades. In Figure B4 through Figure B9, we examine how each of these six outcomes changes under increasingly-improved levels of precision. Across each of our main outcomes, the response is highly nonlinear. Small reductions in signal noise generate little to no movement in average outcomes. The gains become much larger only once a substantial share of the information friction is removed, producing a convex pattern for academic potential, investments, efforts, and college-completion outcomes. For example, a 50 percent reduction in the noise faced by families improves terminal academic potential by 4 percent of a standard deviation, whereas a 70 percent reduction improves academic potential by 14 percent of a standard deviation.

Policy III.—Combining the bias-correction policy with perfect information shows that correcting both sources of information imperfection simultaneously improves outcomes relative to the baseline and Policy I, but substantially attenuates the gains made under Policy II. Relative to the no-optimism counterfactual (Policy I), the addition of perfect information produces a pronounced recovery: college completion rises from 33 to 43 percent, terminal academic potential rises from 0.14 to 0.61 units of a standard deviation on average, elite-college completion rises from 7 to 12 percent, and the dropout rate falls from 14 to 7 percent. This finding underscores the competing roles of the two main mechanisms in the model. Improved information reallocates effort and investment toward students with higher true (*global*) academic potential, raising skill accumulation and college completion. Removing optimism, however, dampens the overall level of investment and effort, which limits the gains that occur due to better access to information.

Policy IV.—We find that the timing of information revelation strongly determines its effectiveness. In the fourth counterfactual, families receive the perfect-information intervention only in grades 11 and 12, keeping grades 9 and 10 fixed at their baseline simulated actions. Relative to the same policy implemented throughout high school, terminal academic potential is substantially lower, falling from 0.73 to 0.42 units of a standard deviation. Average parental investment and student effort are also lower, declining from 0.10 to −0.07, and from 0.27 to 0.07, respectively. College completion rises only modestly relative to the baseline, from 38 to 40 percent, while elite-college completion increases only from 8 to 9 percent and the dropout rate falls only from 11 to 10 percent. Together, these results suggest that the gains from providing families with better information about academic potential are concentrated in the earlier years of adolescence, when improved beliefs are able to compound dynamically.

Policy V.—Finally, we consider a policy that removes information distortions only at the college-admissions stage. In this counterfactual, families correctly perceive the role of local academic performance in college readiness, i.e., $\tilde{\tau} = \tau$, and colleges observe readiness without any noise ($\sigma_A = 0$). This policy increases college completion by about 10 percentage points and mechanically eliminates dropout, but it has little effect on academic potential. The model's final academic potential is nearly unchanged relative to the baseline, increasing by only 0.02 units of a standard deviation, because parental investment and student effort remain largely unaffected by the policy. These results highlight that such a late-stage intervention primarily improves sorting between students and colleges by helping students avoid enrolling in colleges where they are unlikely to complete, but it arrives too late to meaningfully change the earlier investment and effort decisions that improve college readiness.

Heterogeneity.—Table A12 shows that the main policy responses hold across school types. The patterns in Panel A persist when we restrict to either low- or high-performing schools, defined as the bottom or top quartile of initial academic potential. In both settings, eliminating optimism lowers investments, efforts, skills, and completion, while perfect information generates gains in terminal academic potential and college completion. Providing information only in 11th and 12th grade continues to generate much smaller improvements than providing the same information throughout high school. Although many of the levels differ across school types, the counterfactual responses point to the same underlying mechanisms.

7 Conclusions

This paper investigates the roles of local versus global ranks in shaping families' beliefs about children's college-completion potentials. Using rich panel data, we show that parents and children respond primarily to local rank, as opposed to global rank. Local rank distorts families' beliefs and leads to large gaps between expected college attainment and realized college attainment. In order to decompose the possibly competing mechanisms that drive families' decisions during high school, we develop and estimate a dynamic model of child development with several information frictions embedded into the decision problems. We allow families to be optimistic about their children's latent skills, to receive noisy signals about those skills, and to have misaligned beliefs about the roles of local ranks in the college admissions process.

Our estimates suggest that families overestimate children's academic potentials by about 30 percent of a standard deviation. They also face sizable noise in signals of academic potential, resulting in an over-reliance on local rank when forming expectations about children's academic potential. In counterfactual-policy experiments, we show that the effects of information distortions are potentially ambiguous, depending on the type of distortion being targeted. Optimism increases parental investments and student efforts, which dynamically generate higher cognitive skills by the end of high school. Providing families with precise information about children's latent academic potential generates large gains in terminal academic potential, which translate into higher college attainment and lower dropout rates. The model also demonstrates that the timing of information revelation matters nearly as much as the revelation itself. Providing improved information to families only in grades 11 and 12 leads to a substantial attenuation in the cognitive and postsecondary gains. Overall, our results show that information distortions generated by local-academic signals can shape educational trajectories long before students enter the postsecondary market, and that the effects of information interventions in high school depend on whether the policy eliminates a friction or corrects a distortion.

References

Agostinelli, Francesco, Matthias Doepke, Giuseppe Sorrenti, and Fabrizio Zilibotti. 2026. "It takes a village: The economics of parenting with neighborhood and peer effects." *Journal of Political Economy*, 134(1): 313–365.

Altepeter, Thomas S, and Kathleen A Johnson. 1989. "Use of the PPVT-R for intellectual screening with adults: A caution." *Journal of Psychoeducational Assessment*, 7(1): 39–45.

Altepeter, Tom, and Paul J Handal. 1986. "Use of the PPVT-R for intellectual screening with school-aged children: a caution." *Journal of Psychoeducational Assessment*, 4(2): 145–154.

Altonji, Joseph G, and Lewis M Segal. 1996. "Small-sample bias in GMM estimation of covariance structures." *Journal of Business & Economic Statistics*, 14(3): 353–366.

Andrabi, Tahir, Jishnu Das, and Asim Ijaz Khwaja. 2017. "Report cards: The impact of providing school and child test scores on educational markets." *American Economic Review*, 107(6): 1535–1563.

Arcidiacono, Peter, Esteban Aucejo, Arnaud Maurel, and Tyler Ransom. 2025. "College attrition and the dynamics of information revelation." *Journal of Political Economy*, 133(1): 53–110.

Arcidiacono, Peter, V Joseph Hotz, and Songman Kang. 2012. "Modeling college major choices using elicited measures of expectations and counterfactuals." *Journal of Econometrics*, 166(1): 3–16.

Attanasio, Orazio, Costas Meghir, and Emily Nix. 2020. "Human capital development and parental investment in India." *The review of economic studies*, 87(6): 2511–2541.

Attanasio, Orazio, Teodora Boneva, and Christopher Rauh. 2022. "Parental beliefs about returns to different types of investments in school children." *Journal of Human Resources*, 57(6): 1789–1825.

Bertoni, Marco, and Roberto Nisticò. 2023. "Ordinal rank and the structure of ability peer effects." *Journal of Public Economics*, 217: 104797.

Bettinger, Eric P, Bridget Terry Long, Philip Oreopoulos, and Lisa Sanbonmatsu. 2012. "The role of application assistance and information in college decisions: Results from the H&R Block FAFSA experiment." *The Quarterly Journal of Economics*, 127(3): 1205–1242.

Boneva, Teodora, and Christopher Rauh. 2018. "Parental beliefs about returns to educational investments—the later the better?" *Journal of the European Economic Association*, 16(6): 1669–1711.

Chang, Eunsik, Maria Padilla-Romo, and Cecilia Peluffo. 2026. "Persistent Effects of Early Academic Rank on Cognitive and Noncognitive Outcomes." National Bureau of Economic Research Working Paper 35267.

Cicala, Steve, Roland G Fryer, and Jörg L Spenkuch. 2018. "Self-selection and comparative advantage in social interactions." *Journal of the European Economic Association*, 16(4): 983–1020.

Compte, Olivier, and Andrew Postlewaite. 2004. "Confidence-enhanced performance." *American Economic Review*, 94(5): 1536–1557.

Cunha, Flavio, and James Heckman. 2007. "The technology of skill formation." *American economic review*, 97(2): 31–47.

Cunha, Flavio, James J Heckman, and Susanne M Schennach. 2010. "Estimating the technology of cognitive and noncognitive skill formation." *Econometrica*, 78(3): 883–931.

Del Boca, Daniela, Christopher Flinn, and Matthew Wiswall. 2014. "Household choices and child development." *Review of Economic Studies*, 81(1): 137–185.

Del Boca, Daniela, Christopher Flinn, and Matthew Wiswall. 2016. "Transfers to households with children and child development." *The Economic Journal*, 126(596): F136–F183.

Del Boca, Daniela, Christopher Flinn, Ewout Verriest, and Matthew Wiswall. 2026. "Parenting with patience: Parental incentives and child development." *Journal of Political Economy*, 134(1): 210–284.

Del Boca, Daniela, Christopher J Flinn, Ewout Verriest, and Matthew J Wiswall. 2019. "Actors in the child development process." National Bureau of Economic Research.

Delaney, Judith M, and Paul J Devereux. 2022. "Rank effects in education: What do we know so far?" *Handbook of Labor, Human Resources and Population Economics*, 1–24.

Denning, Jeffrey T, Richard Murphy, and Felix Weinhardt. 2023. "Class rank and long-run outcomes." *Review of Economics and Statistics*, 105(6): 1426–1441.

Dizon-Ross, Rebecca. 2019. "Parents' beliefs about their children's academic ability: Implications for educational investments." *American Economic Review*, 109(8): 2728–2765.

Dynarski, Susan, Carmello J Libassi, Katherine Michelmore, and Stephanie Owen. 2021. "Closing the gap: The effect of reducing complexity and uncertainty in college pricing on the choices of low-income students." *American Economic Review*, 111(6): 1721–1756.

Elsner, Benjamin, and Ingo E Isphording. 2017. "A big fish in a small pond: Ability rank and human capital investment." *Journal of Labor Economics*, 35(3): 787–828.

Hansen, Lars Peter, John Heaton, and Amir Yaron. 1996. "Finite-sample properties of some alternative GMM estimators." *Journal of Business & Economic Statistics*, 14(3): 262–280.

Heckman, James, Rodrigo Pinto, and Peter Savelyev. 2013. "Understanding the mechanisms through which an influential early childhood program boosted adult outcomes." *American economic review*, 103(6): 2052–2086.

Hoxby, Caroline, and Christopher Avery. 2013. "The Missing" One-Offs": The Hidden Supply of High-Achieving, Low-Income Students." *Brookings Papers on Economic Activity*, 1–50.

Hoxby, Caroline M. 2009. "The changing selectivity of American colleges." *Journal of Economic perspectives*, 23(4): 95–118.

Hoxby, Caroline M, and Sarah Turner. 2015. "What high-achieving low-income students know about college." *American Economic Review*, 105(5): 514–517.

Jensen, Robert. 2010. "The (perceived) returns to education and the demand for schooling." *The Quarterly Journal of Economics*, 125(2): 515–548.

Judd, Kenneth L. 1998. *Numerical methods in economics.* MIT Press.

Kinsler, Josh, and Ronni Pavan. 2021. "Local distortions in parental beliefs over child skill." *Journal of Political Economy*, 129(1): 81–100.

Kuncel, Nathan R, Marcus Credé, and Lisa L Thomas. 2005. "The validity of self-reported grade point averages, class ranks, and test scores: A meta-analysis and review of the literature." *Review of educational research*, 75(1): 63–82.

Loomes, Graham, and Robert Sugden. 1986. "Disappointment and dynamic consistency in choice under uncertainty." *The Review of Economic Studies*, 53(2): 271–282.

Manski, Charles F. 2004. "Measuring expectations." *Econometrica*, 72(5): 1329–1376.

Megalokonomou, Rigissa, and Yi Zhang. 2024. "How good am I? Effects and mechanisms behind salient rank." *European Economic Review*, 170: 104870.

Murphy, Richard, and Felix Weinhardt. 2020. "Top of the class: The importance of ordinal rank." *The Review of Economic Studies*, 87(6): 2777–2826.

Nakao, Keiko, and Judith Treas. 1994. "Updating occupational prestige and socioeconomic scores: How the new measures measure up." *Sociological methodology*, 1–72.

Stinebrickner, Todd, and Ralph Stinebrickner. 2012. "Learning about academic ability and the college dropout decision." *Journal of Labor Economics*, 30(4): 707–748.

Tincani, Michela. 2024. *Heterogeneous Peer Effects and Rank Concerns in the Classroom.* Centre for Economic Policy Research.

Todd, Petra E, and Kenneth I Wolpin. 2003. "On the specification and estimation of the production function for cognitive achievement." *The Economic Journal*, 113(485): F3–F33.

Todd, Petra E, and Kenneth I Wolpin. 2007. "The production of cognitive achievement in children: Home, school, and racial test score gaps." *Journal of Human capital*, 1(1): 91–136.

Wang, Fan, Esteban Puentes, Jere R Behrman, and Flavio Cunha. 2024. "You are what your parents expect: Height and local reference points." *Journal of econometrics*, 243(1-2): 105269.

Weingarten, Zach, Jere R Behrman, and Andrew Postlewaite. 2026. "A Dynamic Model of the Economic Returns to Adolescent Social Skills."

Wiswall, Matthew, and Basit Zafar. 2015. "Determinants of college major choice: Identification using an information experiment." *The Review of Economic Studies*, 82(2): 791–824.

Zafar, Basit. 2013. "College major choice and the gender gap." *Journal of Human Resources*, 48(3): 545–595.

Online Appendix

A Additional Tables

Table A1: Factor Loadings—Parental Investment

	Factor Loading
Gone shopping	0.194
Played a sport	0.115
Gone to a religious service	0.096
Talked about someone you're dating	0.259
Gone to a movie/play	0.196
Talked about personal problem	0.299
Had serious argument about behavior	0.088
Talked about school/grades	0.478
Worked on school project	0.259
Talked about other school things	0.501

NOTES. This table reports factor loadings from the one-factor model used to construct the parental investment measure. The ten indicators are binary measures from the Wave I parent survey capturing whether the mother engaged in each activity with the child during the previous week. The estimated loadings are used to form the parental investment factor score using the Bartlett scoring procedure.

Table A2: Factor Loadings—Student Effort

	Factor Loading
Trouble getting homework done	0.636
Trouble paying attention in school	0.628
1+ Unexcused Absences	0.101
10+ Unexcused Absences	0.075
Tries to do schoolwork well	0.102

NOTES. This table reports factor loadings from the one-factor model used to construct the student effort measure. The five indicators are Wave I measures of student effort and engagement, including self-reported difficulty getting homework done, difficulty paying attention in school, unexcused absences, chronic unexcused absences, and how hard the student tries to do schoolwork well. All measures are coded so that higher values relate to higher levels of effort. The estimated loadings are used to form the student effort factor score using the Bartlett scoring procedure.

Table A3: Descriptive Statistics Across Sample Criteria

	Full HS Sample (1)	Wave IV Restriction (2)	Analytic Sample (3)
Panel A: Child Characteristics			
Female	0.502	0.534	0.534
Non-White	0.294	0.279	0.280
Age (Wave I)	16.40	16.36	16.35
Grade (Wave I)	10.42	10.40	10.39
Any Unexcused Absence	0.678	0.689	0.688
GPA	2.745	2.773	2.768
Global Rank	0.500	0.512	0.511
Expect Bachelor's with Certainty	0.496	0.503	0.503
Highest Degree: HS Diploma	0.187	0.187	0.188
Earned Bachelor's Degree	0.354	0.354	0.351
Graduate from Elite College	0.058	0.058	0.058
Panel B: Parental Characteristics			
Talked about personal problem	0.421	0.427	0.427
Expect Bachelor's Degree for Child	0.461	0.459	0.459
Mother College-Educated	0.243	0.248	0.247
Mother Married	0.722	0.731	0.729
(Log) Household Income	3.582	3.606	3.599
Panel C: School Characteristics			
Tracking	0.647	0.648	0.644
First-Year Teachers (%)	11.43	11.59	11.62
Teachers with Master's (%)	54.41	53.64	53.78
Non-White Teachers (%)	17.46	16.93	16.94
Observations	7,260	5,495	5,423
Number of Schools	53	53	48

NOTES: This table compares the analytic sample to the broader high-school in-home sample to assess representativeness. Column (1) reports means for all respondents observed in the Wave I in-home survey who were in high school in Wave I. Column (2) restricts to those with a valid measure of degree attainment in Wave IV. Column (3) further restricts to schools with at least five students in each of grades 9 through 12, yielding the analytic sample used throughout the paper. To keep measures comparable across columns, we report variables defined identically regardless of sample, including some of the components underlying the parental investment and student effort factors (e.g., "Talked about personal problem," "Any unexcused absence") rather than the standardized factors themselves, which are constructed on the analytic sample directly. Global rank is the student's age-specific rank in the PPVT distribution. GPA is the grade point average across self-reported English, math, history, and science courses. "Expect Bachelor's with Certainty" is an indicator equal to one if the student reports in Wave I that graduating from college will happen," and "Expect Bachelor's Degree for Child" is an indicator equal to one if the parent reports they would be very disappointed if their child did not graduate from college. "Graduate from Elite College" is an indicator equal to one if the respondent's highest completed degree was obtained from a college whose median SAT score lies above the 75th percentile of the college distribution in Add Health. Educational attainment is measured in Wave IV. All other variables are measured in Wave I.

Table A4: Sensitivity of Controls on Short-Run Outcomes

	No Controls (1)	+ Demographics (2)	+ Grade FE (3)	+ School FE (4)
Panel A: Parental Investment				
Local rank	0.397	0.309	0.293	0.316
	(0.062)	(0.064)	(0.065)	(0.063)
Global rank	0.207	0.269	0.237	0.153
	(0.041)	(0.041)	(0.040)	(0.043)
Observations	4,881	4,879	4,879	4,879
Panel B: Student Effort				
Local rank	0.858	0.825	0.821	0.848
	(0.056)	(0.059)	(0.059)	(0.056)
Global rank	0.213	0.217	0.201	0.175
	(0.077)	(0.077)	(0.081)	(0.087)
Observations	4,859	4,857	4,857	4,857
Panel C: Student College Expectations				
Local rank	0.453	0.420	0.417	0.417
	(0.026)	(0.026)	(0.026)	(0.027)
Global rank	0.009	0.079	0.066	0.045
	(0.036)	(0.029)	(0.029)	(0.029)
Observations	4,398	4,397	4,397	4,397
Panel D: Parent College Expectations				
Local rank	0.312	0.312	0.308	0.267
	(0.025)	(0.027)	(0.026)	(0.025)
Global rank	−0.050	0.004	−0.010	0.060
	(0.049)	(0.065)	(0.068)	(0.026)
Observations	4,458	4,458	4,458	4,458

NOTES: This table reports estimates from regressions of short-run outcomes on local and global rank. Each column introduces a new set of control. Demographic controls include gender, race, and age controls. Column (3) adds grade fixed effects. Column (4) adds school fixed effects. Panel A uses the parental investment factor, Panel B uses the student effort factor, Panel C uses an indicator equal to one if the respondent reports that graduating from college "will happen," and Panel D uses an indicator for whether the parent responds that they would be "very disappointed" if their child does not graduate from college. Local rank is the student's rank in the GPA distribution of the school-grade cohort, and global rank is the student's age-specific rank in the PPVT distribution. The dependent variables in Panels A and B are standardized latent factors constructed using the Bartlett scoring procedure. Standard errors clustered at the school level are reported in parentheses.

Table A5: Results with Transcript-Level Local Rank

	Analysis Sample (1)	Transcript Sample (2)	Transcript Sample (3)
Panel A: Parental Investment			
Transcript-Based Rank			0.283
			(0.073)
Local rank	0.305	0.348	
	(0.062)	(0.069)	
Global rank	0.152	0.180	0.182
	(0.043)	(0.054)	(0.059)
Observations	4,879	3,385	3,385
Panel B: Student Effort			
Transcript-Based Rank			0.836
			(0.084)
Local rank	0.838	0.836	
	(0.055)	(0.065)	
Global rank	0.176	0.148	0.103
	(0.087)	(0.103)	(0.113)
Observations	4,857	3,383	3,383
Panel C: Student College Expectations			
Transcript-Based Rank			0.318
			(0.043)
Local rank	0.417	0.422	
	(0.027)	(0.035)	
Global rank	0.042	0.021	0.031
	(0.028)	(0.038)	(0.042)
Observations	4,397	3,036	3,036
Panel D: Parent College Expectations			
Transcript-Based Rank			0.255
			(0.038)
Local rank	0.273	0.273	
	(0.024)	(0.031)	
Global rank	0.053	0.071	0.062
	(0.025)	(0.035)	(0.037)
Observations	4,458	3,128	3,128

NOTES: This table compares estimates using self-reported and transcript-based local rank. Panel A uses the parental investment factor, Panel B uses the student effort factor, Panel C uses an indicator equal to one if the respondent reports that graduating from college will happen," and Panel D uses an indicator for whether the parent responds that they would be very disappointed" if their child does not graduate from college. Column (1) reports baseline estimates for the full analytic sample, reproducing Table 2. Columns (2) and (3) restrict to respondents with available transcript data, retroactively constructed in Wave III of Add Health. Column (2) uses local rank constructed from self-reported grades and Column (3) uses local rank constructed from transcript grades. Local rank is the student's rank in the GPA distribution of the school-grade cohort, transcript-based rank is the analogous percentile constructed from transcript grades, and global rank is the student's age-specific rank in the PPVT distribution. The dependent variables in Panels A and B are standardized latent factors constructed using the Bartlett scoring procedure. All specifications include controls for race, gender, and age, as well as school-grade fixed effects. Standard errors clustered at the school level are reported in parentheses.

Table A6: The Effects of Local and Global rank on Short-Run Outcomes by Subgroup

	Analysis Sample (1)	Male (2)	Female (3)	White (4)	Non-White (5)	Tracking (6)	No Tracking (7)	High SES (8)
Panel A: Parental Investment								
Local rank	0.305	0.312	0.292	0.338	0.157	0.333	0.246	0.322
	(0.062)	(0.087)	(0.084)	(0.072)	(0.100)	(0.061)	(0.138)	(0.125)
Global rank	0.152	0.143	0.133	0.253	−0.121	0.187	0.076	0.199
	(0.043)	(0.080)	(0.077)	(0.055)	(0.112)	(0.044)	(0.091)	(0.102)
Observations	4,879	2,265	2,614	3,528	1,351	3,171	1,708	2,000
Panel B: Student Effort								
Local rank	0.838	0.964	0.745	0.978	0.438	0.888	0.739	0.964
	(0.055)	(0.092)	(0.072)	(0.057)	(0.095)	(0.143)	(0.107)	(0.101)
Global rank	0.176	0.070	0.278	0.066	0.552	0.143	0.240	0.331
	(0.087)	(0.141)	(0.089)	(0.100)	(0.132)	(0.111)	(0.130)	(0.165)
Observations	4,857	2,203	2,654	3,549	1,282	3,168	1,689	2,028
Panel C: Student College Expectations								
Local rank	0.417	0.463	0.371	0.453	0.309	0.439	0.374	0.447
	(0.027)	(0.039)	(0.039)	(0.027)	(0.071)	(0.031)	(0.055)	(0.046)
Global rank	0.042	−0.007	0.088	0.065	−0.015	0.017	0.089	0.071
	(0.028)	(0.040)	(0.044)	(0.028)	(0.072)	(0.033)	(0.052)	(0.052)
Observations	4,397	2,056	2,340	3,251	1,119	2,893	1,504	1,825
Panel D: Parent College Expectations								
Local rank	0.273	0.273	0.273	0.274	0.222	0.297	0.221	0.384
	(0.024)	(0.040)	(0.037)	(0.028)	(0.047)	(0.033)	(0.036)	(0.051)
Global rank	0.053	0.088	0.036	0.059	0.037	0.052	0.055	−0.004
	(0.025)	(0.043)	(0.038)	(0.028)	(0.067)	(0.034)	(0.037)	(0.053)
Observations	4,458	2,101	2,354	3,325	1,108	2,970	1,488	1,476

Notes. This table reports estimates from regressions of short-run outcomes on local and global rank, estimated separately by subgroup. Panel A uses the parental investment factor, Panel B uses the student effort factor, Panel C uses an indicator equal to one if the respondent reports that graduating from college "will happen," and Panel D uses an indicator for whether the parent responds that they would be "very disappointed" if their child does not graduate from college. Column (1) reports estimates for the full analytic sample, which pools over grades 9 through 12. Columns (2) and (3) report estimates separately for male and female students, Columns (4) and (5) report estimates separately for White and non-White students, Columns (6) and (7) report estimates separately for students attending schools with and without academic tracking, and Column (8) restricts to families with (log) income in the top quartile in Add Health. Local rank is the student's rank in the GPA distribution of the school-grade cohort, and global rank is the student's age-specific rank in the PPVT distribution. The dependent variables in Panels A and B are standardized latent factors constructed using the Bartlett scoring procedure. All specifications include controls for race, gender, and age, except where a control is omitted because it is collinear with the subgroup restriction. We control for an indicator for missing income in Column (8). All specifications include school-grade fixed effects. Standard errors clustered at the school level are reported in parentheses.

Table A7: Short-Run Results, Controlling for Raw Academic Achievement

Panel A: Parental Investment	
Local rank	0.373
	(0.105)
Global rank	0.147
	(0.043)
Observations	4,879
Panel B: Student Effort	
Local rank	0.728
	(0.110)
Global rank	0.166
	(0.086)
Observations	4,857
Panel C: Student College Expectations	
Local rank	0.408
	(0.069)
Global rank	0.043
	(0.029)
Observations	4,397
Panel D: Parent College Expectations	
Local rank	0.291
	(0.043)
Global rank	0.048
	(0.025)
Observations	4,458

NOTES: This table reports estimates from regressions of short-run outcomes on local and global ranks, controlling directly for English and math course grades. Panel A uses the parental investment factor, Panel B uses the student effort factor, Panel C uses an indicator equal to one if the respondent reports that graduating from college "will happen," and Panel D uses an indicator for whether the parent reports that they would be "very disappointed" if the child does not graduate from college. Local rank is the student's rank in the GPA distribution of the school-grade cohort, and global rank is the student's age-specific rank in the PPVT distribution. The dependent variables in Panels A and B are standardized latent factors constructed using the Bartlett scoring procedure. All specifications include controls for race, gender, age, English grade, and math grade, as well as school-grade fixed effects. Standard errors clustered at the school level are reported in parentheses.

Table A8: Robustness Checks of Parental Investment and Expectations

Panel A: Nonlinearities in Local Rank						
	Top 5% (1)	Top 10% (2)	Top 15% (3)	Bottom 5% (4)	Bottom 10% (5)	Bottom 15% (6)
Local rank	0.288	0.287	0.275	0.319	0.293	0.389
	(0.062)	(0.062)	(0.065)	(0.063)	(0.069)	(0.108)
Global rank	0.150	0.150	0.149	0.150	0.153	0.153
	(0.044)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Location Indicator	0.067	0.032	0.039	0.056	−0.024	0.055
	(0.052)	(0.055)	(0.052)	(0.069)	(0.048)	(0.046)
Observations	4,879	4,879	4,879	4,879	4,879	4,879
Panel B: Non-Cognitive Skill Control						
	Original Estimate (1)	Analysis Sample (2)	Grade 9 (3)	Grade 10 (4)	Grade 11 (5)	Grade 12 (6)
Local rank	0.273	0.278	0.251	0.283	0.287	0.305
	(0.024)	(0.025)	(0.043)	(0.049)	(0.055)	(0.056)
Global rank	0.053	0.053	0.043	0.075	0.083	0.018
	(0.025)	(0.026)	(0.064)	(0.046)	(0.051)	(0.065)
Observations	4,458	4,446	1,305	1,183	1,106	852
	Original Estimate (1)	Analysis Sample (2)	Grade 9 (3)	Grade 10 (4)	Grade 11 (5)	Grade 12 (6)
Panel C: Parsimonious Investment Measure						
Local rank	0.305	0.249	0.244	0.166	0.262	0.282
	(0.062)	(0.060)	(0.097)	(0.107)	(0.123)	(0.126)
Global rank	0.152	0.166	0.298	0.195	0.106	0.072
	(0.043)	(0.044)	(0.097)	(0.093)	(0.101)	(0.129)
Observations	4,879	4,879	1,401	1,280	1,228	970

Notes. This table reports robustness checks for the parental investment and parent college-expectations regressions. Panel A re-estimates the parental investment equation after adding a control and interaction for the stated local-rank indicator. Panel B re-estimates the parent college-expectations equation after controlling for a latent factor of non-cognitive skills constructed from 19 Wave I measures of depressive tendencies. Panel C re-estimates the parental investment equation using a more parsimonious investment factor that excludes activities that may reflect contemporaneous consumption rewards rather than investment. Column (1) reports the original estimate from the baseline specification in Table 2. Column (2) reports the corresponding robustness estimate for the pooled analytic sample. Columns (3)–(6) report the same robustness specification estimated separately for students in grades 9 through 12 at Wave I. Local rank is the student's rank in the GPA distribution of the school-grade cohort, and global rank is the student's age-specific rank in the PPVT distribution. The dependent variables in Panels A and C are standardized latent factors of parental investment constructed using the Bartlett scoring procedure. The dependent variable in Panel B is an indicator equal to one if the parent reports that they would be "very disappointed" if their child did not graduate from college. All specifications include controls for race, gender, and age. The pooled specifications include school-grade fixed effects, and the grade-specific specifications include school fixed effects. Standard errors clustered at the school level are reported in parentheses.

Table A9: Results with Interactions for Local Stickiness

		County-Level Stickiness Percentile		
	Original	50th	75th	90th
	(1)	(2)	(3)	(4)
Panel A: Parental Investment				
Local rank	0.305	0.305	0.271	0.286
	(0.062)	(0.094)	(0.075)	(0.069)
Global rank	0.152	0.178	0.175	0.173
	(0.043)	(0.065)	(0.048)	(0.049)
Stickiness		−0.069	−0.073	−0.644
		(0.152)	(0.143)	(0.277)
Stickiness × Local rank		−0.002	0.129	0.161
		(0.118)	(0.131)	(0.111)
Stickiness × Global rank		−0.030	−0.041	−0.050
		(0.089)	(0.104)	(0.073)
Observations	4,879	4,858	4,858	4,858
Panel B: Student Effort				
Local rank	0.838	0.877	0.869	0.843
	(0.055)	(0.065)	(0.056)	(0.055)
Global rank	0.176	0.100	0.131	0.167
	(0.087)	(0.124)	(0.097)	(0.096)
Stickiness		−0.195	−0.161	−0.280
		(0.110)	(0.164)	(0.126)
Stickiness × Local rank		−0.067	−0.103	−0.001
		(0.100)	(0.121)	(0.173)
Stickiness × Global rank		0.157	0.178	0.083
		(0.151)	(0.159)	(0.163)
Observations	4,879	4,858	4,858	4,858
Panel C: Student College Expectations				
Local rank	0.417	0.430	0.432	0.422
	(0.027)	(0.037)	(0.029)	(0.029)
Global rank	0.042	0.023	0.018	0.047
	(0.028)	(0.042)	(0.034)	(0.033)
Stickiness		0.026	−0.002	−0.059
		(0.062)	(0.068)	(0.116)
Stickiness × Local rank		−0.025	−0.058	−0.036
		(0.053)	(0.065)	(0.080)
Stickiness × Global rank		0.046	0.105	−0.009
		(0.059)	(0.068)	(0.037)
Observations	4,397	4,376	4,376	4,376
Panel D: Parental College Expectations				
Local rank	0.273	0.242	0.276	0.280
	(0.024)	(0.037)	(0.028)	(0.025)
Global rank	0.053	0.094	0.072	0.051
	(0.025)	(0.063)	(0.030)	(0.030)
Stickiness		0.063	0.186	−0.010
		(0.078)	(0.095)	(0.201)
Stickiness × Local rank		0.058	−0.027	−0.072
		(0.051)	(0.058)	(0.068)
Stickiness × Global rank		−0.082	−0.072	0.004
		(0.055)	(0.070)	(0.052)
Observations	4,458	4,438	4,438	4,438

Notes. This table reports estimates from regressions of short-run outcomes on local rank, global rank, an indicator for high local stickiness, and the interactions of that indicator with each rank measure. The underlying stickiness measure is the share of county residents aged 5 and over who lived in the same county five years earlier, measured in the 1990 Census and merged to respondents' Wave I residences. In Columns (2)–(4), the stickiness indicator equals one if the respondent's county lies at or above the 50th, 75th, and 90th percentile of the stickiness distribution, respectively. Column (1) reproduces the baseline estimates from Table 2. Panel A uses the parental investment factor, Panel B uses the student effort factor, Panel C uses an indicator equal to one if the respondent reports that graduating from college "will happen," and Panel D uses an indicator for whether the parent reports being "very disappointed" if their child does not graduate from college. Local rank is the student's rank in the GPA distribution of the school-grade cohort, and global rank is the student's age-specific rank in the PPVT distribution. The dependent variables in Panels A and B are standardized latent factors constructed using the Bartlett scoring procedure. All specifications include controls for race, gender, and age, as well as grade fixed effects. Standard errors clustered at the school level are reported in parentheses.

Table A10: The Relationship Between ranks and Incomplete College, with Large Shocks

	(1)	(2)
Local rank	−0.206	−0.200
	(0.031)	(0.031)
Global rank	0.013	0.018
	(0.028)	(0.028)
Parent Death		−0.015
		(0.033)
Sibling Death		0.032
		(0.045)
Parent Incarceration		0.165
		(0.067)
Unplanned Pregnancy		0.097
		(0.023)
Observations	5,143	5,143

NOTES: This table reports estimates from regressions of incomplete college on local rank and global rank. Incomplete college is an indicator equal to one if the respondent attended college but did not obtain a bachelor's degree by Wave IV. Column (1) reports the baseline specification. Column (2) adds indicators for large shocks occurring after Wave I and before 2003: the death of a parent, the death of a sibling, the incarceration of a parent, and an unplanned pregnancy. Local rank is the student's rank in the GPA distribution of the school-grade cohort, and global rank is the student's age-specific rank in the PPVT distribution. All specifications include controls for race, gender, and age, as well as school-grade fixed effects. Standard errors clustered at the school level are reported in parentheses.

Table A11: Model Fit—Moments Related to the Technology of Skill Formation

	Data		Model	
	Grade FE	School-Grade FE	Grade FE	School-Grade FE
Initial skills	0.596	0.543	0.160	0.162
Investment, grade 9	0.001	0.000	0.143	0.151
Effort, grade 9	0.025	0.028	0.077	0.073
Initial skills × investment	0.014	0.011	0.069	0.069
Initial skills × effort	0.011	0.010	0.099	0.098
School-Grade FE	✗	✓	✗	✓

NOTES: This table compares empirical and simulated moments from the reduced-form analogue of the terminal skill-formation technology. Each entry is the coefficient from a regression of terminal cognitive skill on initial cognitive skill, grade-9 parental investment, grade-9 student effort, and interactions between initial cognitive skill and each input. Terminal and initial cognitive skills are measured using the inverse-normal transform of the corresponding global PPVT rank. Columns (1) and (3) include grade fixed effects; Columns (2) and (4) include school-grade fixed effects. Columns (1)–(2) report the data moments used in estimation and Columns (3)–(4) report the corresponding simulated moments at the estimated parameter vector.

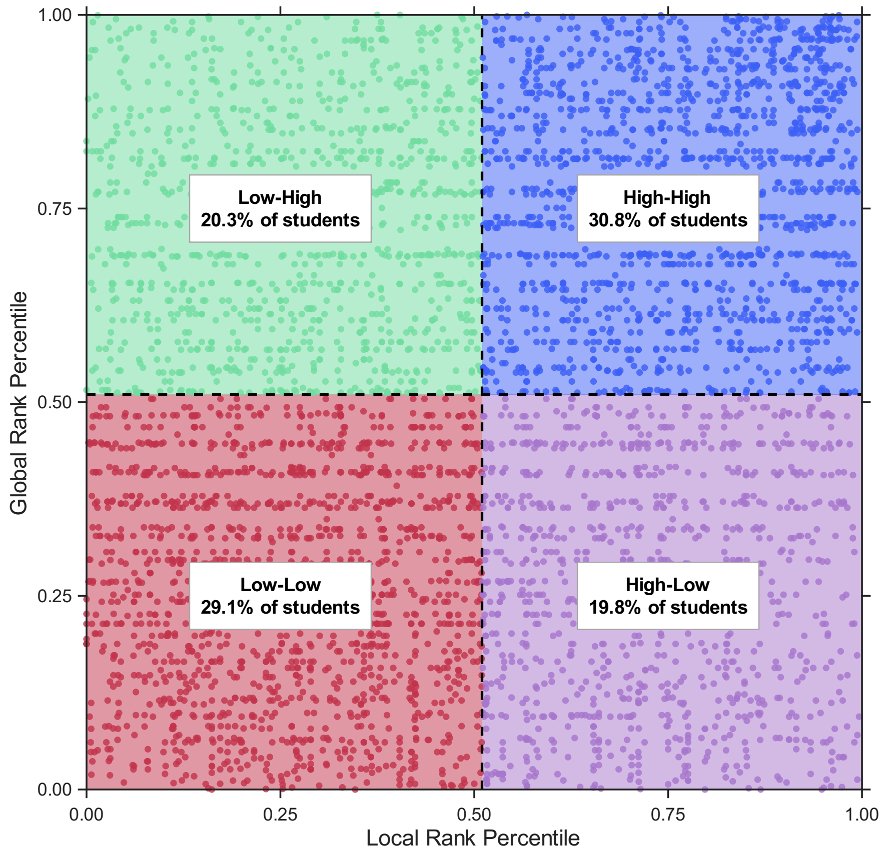
Table A12: Simulated Effects from Counterfactual Policy Experiments

		Counterfactual-Policy Experiments				
	Baseline	I. No Optimism ($\mu_j = 0$)	II. Perfect Info ($\sigma_j = 0$)	III. No Optimism + Perfect Info ($\mu_j = \sigma_j = 0$)	IV. Late Info Grades 11–12 ($\sigma_j = 0, t \geq 3$)	V. No College Distortions ($\tilde{\tau} = \tau, \sigma_A = 0$)
Panel A: All Schools						
Period-5 Academic Potential	0.310	0.142	0.727	0.610	0.424	0.326
Parental Investment	−0.112	−0.272	0.101	−0.001	−0.066	−0.115
Student Effort	0.002	−0.296	0.268	0.027	0.070	0.017
College Completion	0.379	0.331	0.462	0.433	0.397	0.478
Elite College Completion	0.083	0.065	0.127	0.119	0.090	0.101
Dropout	0.108	0.144	0.055	0.075	0.098	0.000
Panel B: Low-Performing Schools						
Period-5 Academic Potential	0.314	0.140	0.710	0.579	0.423	0.322
Parental Investment	−0.099	−0.252	0.134	−0.026	−0.050	−0.098
Student Effort	0.002	−0.305	0.278	0.023	0.070	0.007
College Completion	0.377	0.332	0.456	0.419	0.392	0.476
Elite College Completion	0.078	0.062	0.121	0.111	0.083	0.096
Dropout	0.111	0.150	0.061	0.085	0.103	0.000
Panel C: High-Performing Schools						
Period-5 Academic Potential	0.336	0.160	0.806	0.704	0.470	0.356
Parental Investment	−0.097	−0.259	0.134	−0.058	−0.046	−0.105
Student Effort	0.001	−0.289	0.334	0.131	0.082	0.021
College Completion	0.390	0.341	0.476	0.450	0.413	0.481
Elite College Completion	0.088	0.067	0.135	0.137	0.098	0.114
Dropout	0.104	0.136	0.044	0.060	0.085	0.000

Notes. This table reports simulated outcomes from the estimated model under each counterfactual-policy experiment. The baseline column reports the final simulated model fit from estimation. In the column headers, $j \in \{P, C\}$ indexes parents and children. All counterfactual columns solve for the equilibrium peer environment in school-grade average parental investments and student efforts. In the late-information counterfactual, grades 9 and 10 are held fixed at their baseline simulated actions, while the counterfactual equilibrium is solved over grades 11 and 12. Parental investments and student efforts are pooled averages of log choices across periods. Period-5 academic potential is measured at the terminal college stage. Low-performing schools are the bottom 25 percent of schools in the baseline initial academic-potential distribution, while high-performing schools are the top 25 percent.

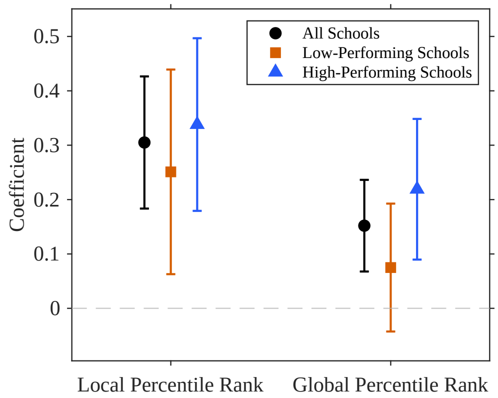
B Additional Figures

Figure B1: Two-Dimensional Distribution of Student Ranks

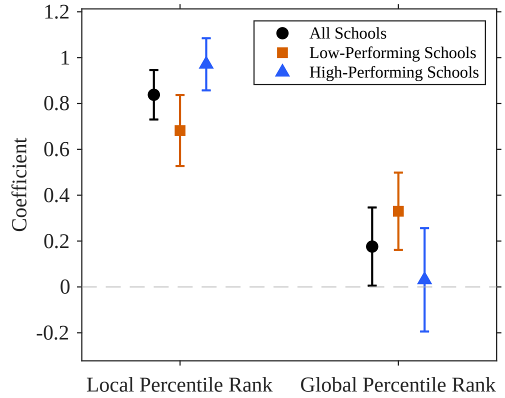


Notes: This figure plots students' local rank (x-axis) against students' global rank (y-axis), each measured along $[0, 1]$, with 1 the highest percentile ranking. Quadrants are split according to above-average (approximately 0.51) in each given rank.

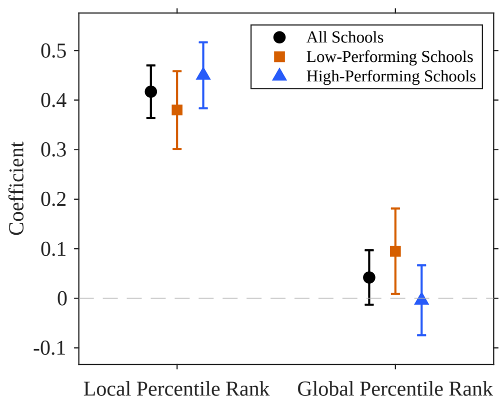
Figure B2: The Effects of Local and Global rank, by School Type



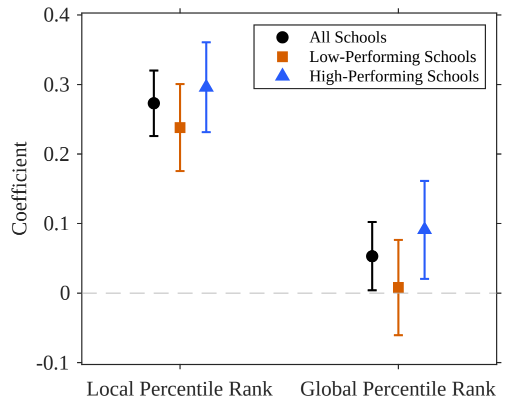
(a) Parental Investment



(b) Student Effort



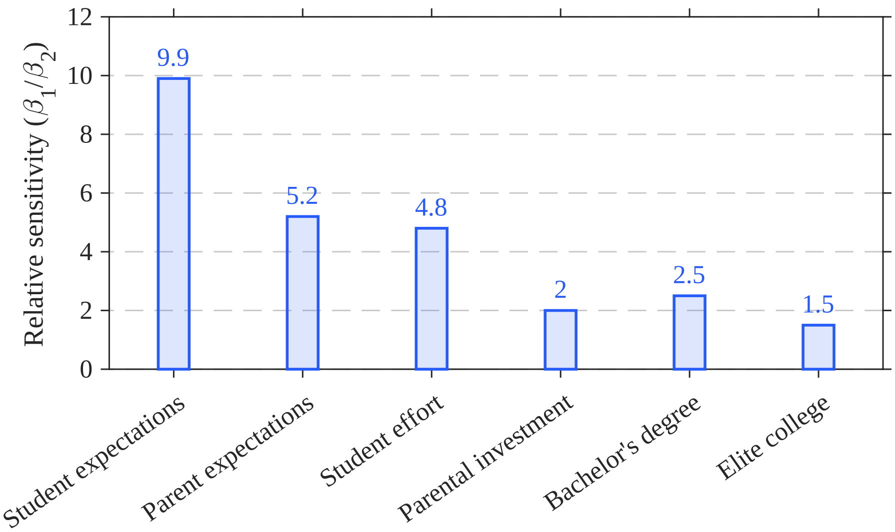
(c) Student College Expectations



(d) Parent College Expectations

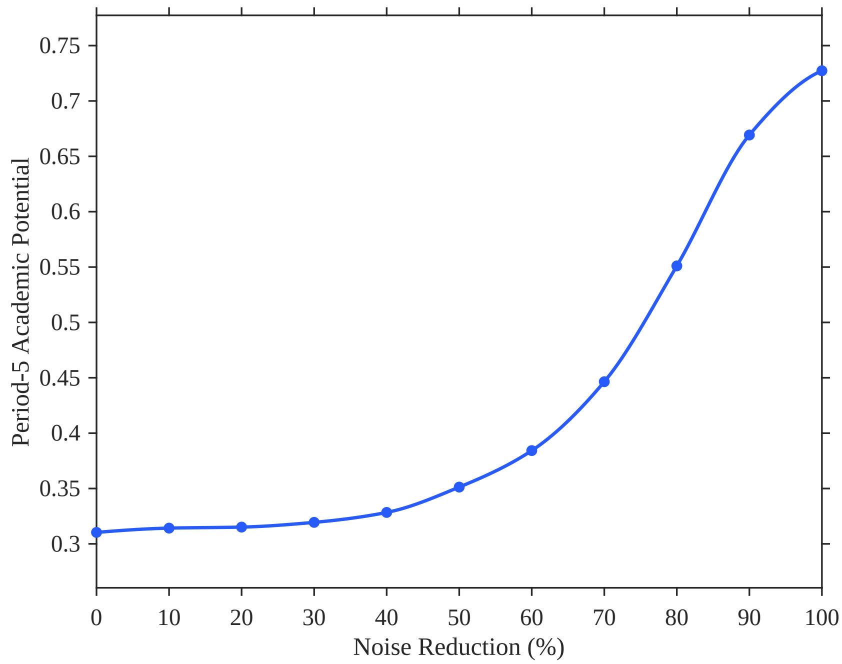
Notes. This figure reports coefficient estimates and 95 percent confidence intervals from regressions of short-run outcomes on local rank and global rank, estimated separately for all schools, low-performing schools, and high-performing schools. Panel (a) shows parental investment, Panel (b) student effort, Panel (c) student college expectations, and Panel (d) parent college expectations. Local rank is the student's rank in the GPA distribution of the school-grade cohort, and global rank is the student's age-specific rank in the PPVT distribution. The parental investment and student effort measures are standardized latent factors constructed using the Bartlett scoring procedure. All specifications include controls for race, gender, and age, as well as school-grade fixed effects.

Figure B3: Relative Sensitivity to Local and Global rank



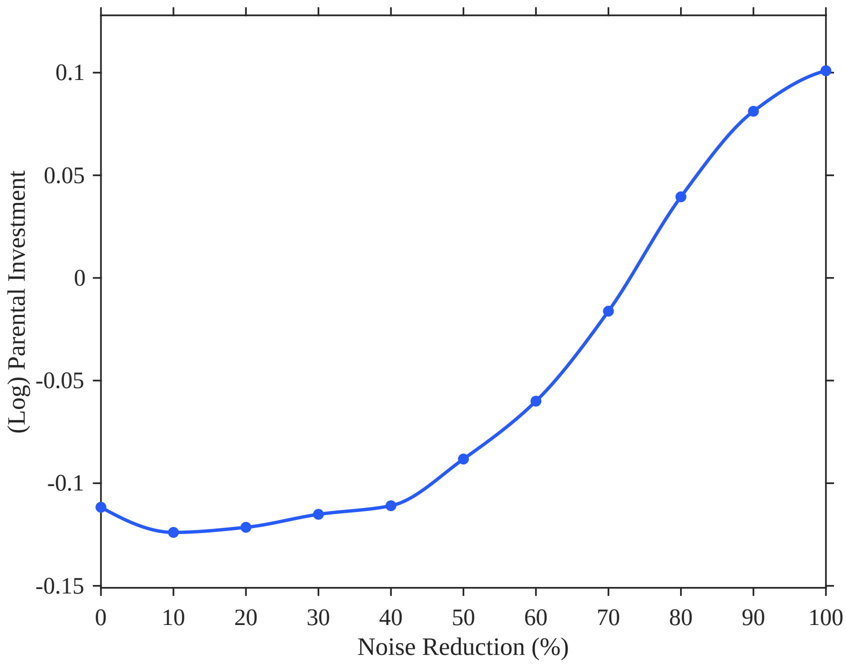
NOTES: This figure plots the ratio of the estimated coefficient on local rank (β_1 in Equation 1) to the estimated coefficient on global rank (β_2 in Equation 1) for each outcome. Local rank is the student's rank in the GPA distribution of the school-grade cohort, and global rank is the student's age-specific rank in the PPVT distribution. Ratios above one indicate that the outcome is more sensitive to local rank than to global rank. The first four bars use estimates for short-run outcomes, specifically beliefs and input choices, while the final two bars use estimates for long-run educational attainment.

Figure B4: Average Change in Period-5 Academic Potential, by Noise-Reduction Fraction



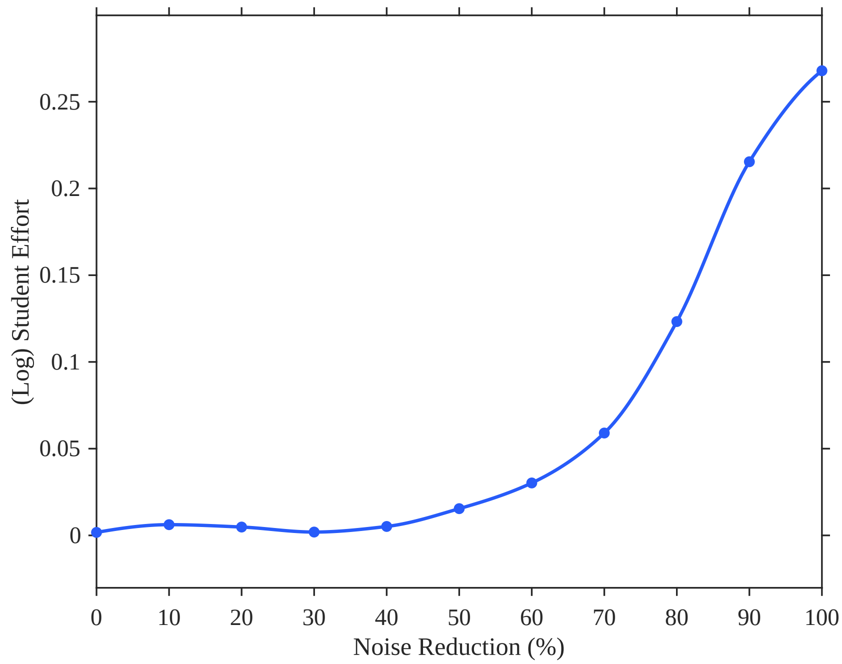
NOTES: This figure plots simulated period-5 academic potential as a function of the fraction of private-signal noise eliminated, ranging from 0% (baseline) to 100% (Counterfactual II). Academic potential is the mean of the latent cognitive skill distribution at the terminal college stage. Optimism parameters μ_P and μ_C are held at their estimated values throughout. Each point is solved as a new equilibrium using the fixed-point procedure described in Section 6. The sample corresponds to all schools in the simulated economy.

Figure B5: Average Change in Parental Investment, by Noise-Reduction Fraction



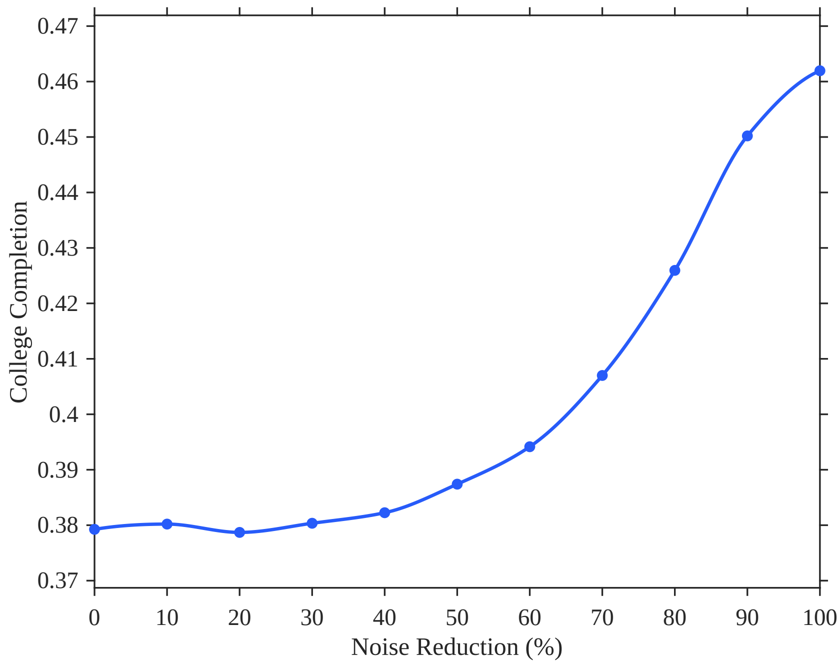
NOTES: This figure plots simulated average (log) parental investment as a function of the fraction of private-signal noise eliminated, ranging from 0% (baseline) to 100% (Counterfactual II). Optimism parameters μ_P and μ_C are held at their estimated values throughout. Each point is solved as a new equilibrium using the fixed-point procedure described in Section 6. The sample corresponds to all schools in the simulated economy.

Figure B6: Average Change in Student Effort, by Noise-Reduction Fraction



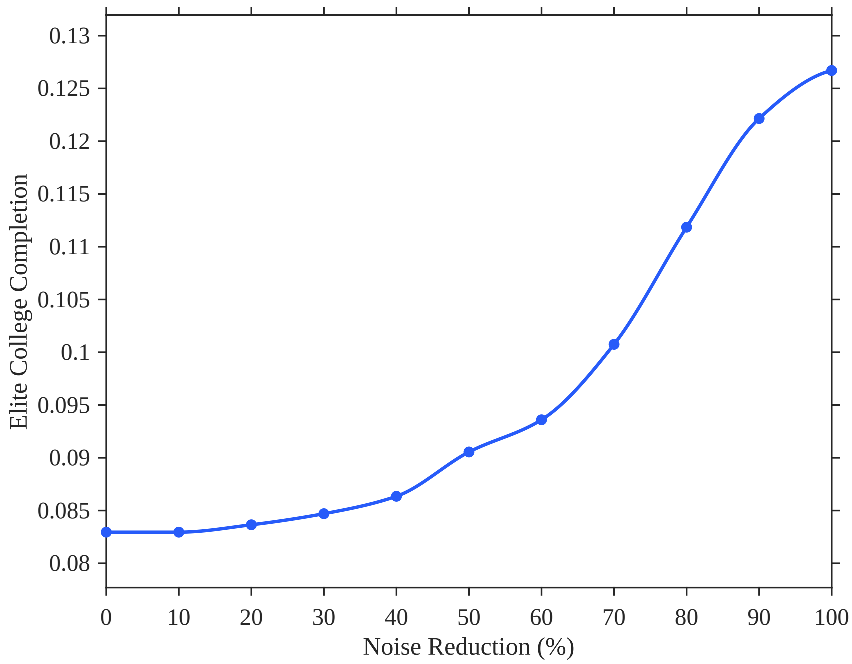
NOTES: This figure plots simulated average (log) student effort as a function of the fraction of private-signal noise eliminated, ranging from 0% (baseline) to 100% (Counterfactual II). Optimism parameters μ_P and μ_C are held at their estimated values throughout. Each point is solved as a new equilibrium using the fixed-point procedure described in Section 6. The sample corresponds to all schools in the simulated economy.

Figure B7: Average Change in College Completion, by Noise-Reduction Fraction



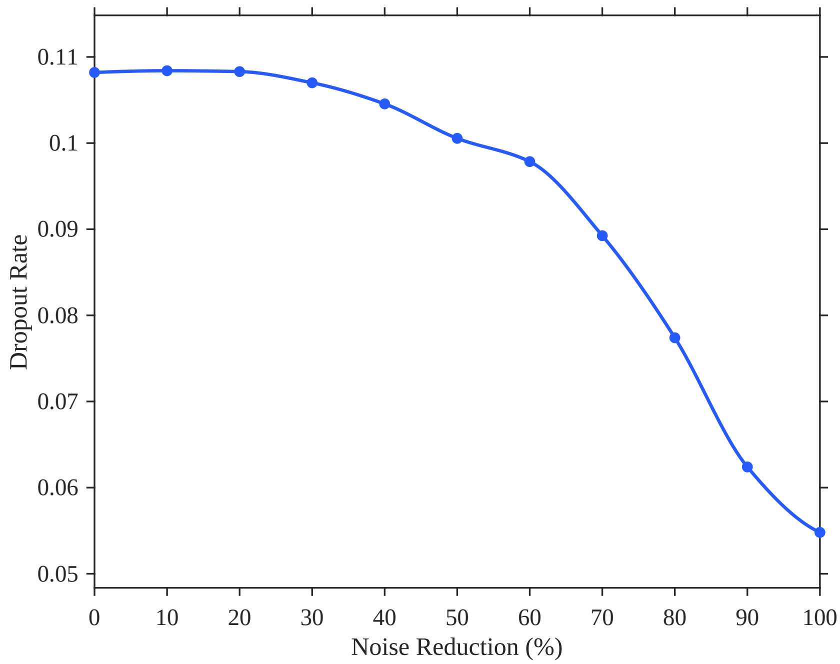
NOTES: This figure plots simulated fraction of college completion as a function of the fraction of private-signal noise eliminated, ranging from 0% (baseline) to 100% (Counterfactual II). Optimism parameters μ_P and μ_C are held at their estimated values throughout. Each point is solved as a new equilibrium using the fixed-point procedure described in Section 6. The sample corresponds to all schools in the simulated economy.

Figure B8: Average Change in Elite College Completion, by Noise-Reduction Fraction



NOTES: This figure plots simulated fraction of elite college completion, defined as the set of colleges with average SAT performance above the 75th percentile in the data, as a function of the fraction of private-signal noise eliminated, ranging from 0% (baseline) to 100% (Counterfactual II). Optimism parameters μ_P and μ_C are held at their estimated values throughout. Each point is solved as a new equilibrium using the fixed-point procedure described in Section 6. The sample corresponds to all schools in the simulated economy.

Figure B9: Average Change in Dropout Rates, by Noise-Reduction Fraction



NOTES: This figure plots simulated rate of college dropout as a function of the fraction of private-signal noise eliminated, ranging from 0% (baseline) to 100% (Counterfactual II). Optimism parameters μ_P and μ_C are held at their estimated values throughout. Each point is solved as a new equilibrium using the fixed-point procedure described in Section 6. The sample corresponds to all schools in the simulated economy.

C Discussion of Measurement Error

Our reduced-form analysis uses each student's age-specific rank in the PPVT distribution as a proxy for latent global academic potential. Although the PPVT is a validated, standardized assessment that is strongly correlated with broader cognitive skills, it does not capture every dimension of academic potential. Any single test score may also contain noise arising from testing conditions, the abridged format of the assessment, or the fact that the PPVT measures verbal skills rather than other important skills, such as math skills or logical reasoning. We therefore interpret the observed global rank as a noisy proxy for the latent academic-potential object relevant for college-going outcomes.

Notably, this measurement issue is faced *only* by the econometrician, not by families. Students and parents were not informed of the student's PPVT performance, so any error in the PPVT-based rank cannot, by construction, alter the information environment facing families. In short, families cannot respond to a score they do not observe. The PPVT-based rank is instead an econometrician-constructed proxy for broader academic-potential signals that families may receive through other channels.

As a reduced-form benchmark, let $p_i^{\mathcal{G},*}$ denote latent global academic potential rank and let $p_i^{\mathcal{G}}$ denote the observed one based on the PPVT score. We write

$$p_i^{\mathcal{G}} = p_i^{\mathcal{G},*} + u_i, \tag{C.1}$$

where u_i is mean-zero classical measurement error. In the baseline specification,

$$y_{isg} = \beta_0 + \beta_1 p_i^{\mathcal{L}} + \beta_2 p_i^{\mathcal{G}} + \boldsymbol{\gamma}'\boldsymbol{x}_i + \alpha_{sg} + \varepsilon_{isg}, \tag{C.2}$$

classical measurement error in $p_i^{\mathcal{G}}$ attenuates $\hat{\beta}_2$ toward zero. Because local rank $p_i^{\mathcal{L}}$ and latent global academic potential $p_i^{\mathcal{G},*}$ are positively correlated, this attenuation can also increase the estimated coefficient on local rank.[1] Thus, under the classical measurement-error benchmark, the reduced-form ratio $\hat{\beta}_1/\hat{\beta}_2$ should be interpreted as an upper-bound estimate of the relative sensitivity of outcomes to local versus global academic standing.

This concern does not overturn the qualitative pattern in the data. For student effort and both belief measures, the local-rank coefficients are several times larger than the corresponding global-rank coefficients. Measurement error in the PPVT would have to be substantial to fully explain these gaps. Additionally, the PPVT-based rank is highly informative, as it predicts college completion and strongly predicts elite

[1] When observed global rank imperfectly absorbs the contribution of latent global potential, part of that variation may be attributed to local rank.

college completion. Therefore, the concern is not that the PPVT is pure noise, but that it is an imperfect proxy for global academic potential.

The structural model incorporates this concern directly. The parameter σ_m governs measurement error in the econometrician's observed global-skill proxy, while the signal-noise parameters σ_P and σ_C govern the private information available to parents and children. Relevant for identification, these parameters enter through distinct channels. Measurement error in the PPVT-based proxy affects how strongly observed global rank is related to latent academic potential in the simulated moments, yet it does not affect beliefs or choices. Signal noise, on the other hand, affects beliefs and therefore the choices of investment and effort, but does not alter the econometrician's rank measurement. The local-global rank correlation, the long-run predictive power of observed global rank, and the expectation and choice gradients together discipline these distinct sources of noise.

We emphasize one final caveat. Separating measurement error from information frictions relies on the assumption that measurement error is classical and that the calibrated reliability of the local-rank measure matches closely to the value established in the literature. Subject to those assumptions, the model allows PPVT measurement error to attenuate observed global-rank gradients without mechanically attributing all of the local-global gap in beliefs and behavior to information frictions.

D Incorporating Error into Subjective Probabilities

D.1 Overview

The model generates continuous subjective probabilities of college completion for both parents and children. The data, however, record expectations through coarse survey responses. Students report whether graduating from college "will happen," while parents report whether they would be "very disappointed" if the child did not graduate from college. We treat these responses as noisy binary measures of the continuous beliefs that enter family decision-making.

Let p_{it}^C and p_{it}^P denote the model-implied subjective probabilities of bachelor completion for child i and parent i when the child is in period t (grade $t+8$). The latent survey response is positive when this probability exceeds one half:

$$d_{it}^{C,*} = \mathbb{1}\{p_{it}^C \geq 0.5\}, \tag{D.1}$$

$$d_{it}^{P,*} = \mathbb{1}\{p_{it}^P \geq 0.5\}. \tag{D.2}$$

The threshold is fixed rather than chosen to match the empirical reporting shares. As a result, the levels of reported expectations remain informative moments for the estimation.

To allow for the coarseness of the survey measures, we let the observed report differ from the latent threshold response with symmetric probability ϵ_j, for $j \in \{P, C\}$:

$$\Pr(d_{it}^j = 1 \mid d_{it}^{j,*}) = \epsilon_j + (1 - 2\epsilon_j) d_{it}^{j,*}, \qquad \epsilon_j \in [0, 0.5). \tag{D.3}$$

Equivalently,

$$\mathbb{E}[d_{it}^j \mid p_{it}^j] = \epsilon_j + (1 - 2\epsilon_j)\mathbb{1}\{p_{it}^j \geq 0.5\}. \tag{D.4}$$

The simulated moments use this conditional expectation rather than drawing additional reporting shocks. This keeps the reporting layer smooth and separate from the household decision problem.

The reporting-error parameters are included strictly to improve the model's ability to replicate regression coefficients related to beliefs. These parameters do not enter household beliefs, choices, skill accumulation, or college outcomes. Parents and children choose investments and efforts using the continuous probabilities p_{it}^P and p_{it}^C. Thus, ϵ_P and ϵ_C only determine how those probabilities are observed through the binary expectation variables.

D.2 Identification

The classification-error parameters are identified from the expectation moments separately from optimism. If s_j^* denotes the latent share of type-j agents whose subjective completion probability exceeds one half, the *observed* positive-report share is

$$\epsilon_j + (1 - 2\epsilon_j)s_j^*. \tag{D.5}$$

Holding latent beliefs fixed, symmetric reporting error attenuates the coefficients in reported-expectation regressions by the factor $(1 - 2\epsilon_j)$. For agent $j \in \{P, C\}$, the parameter ϵ_j is disciplined by how sharply the reported expectation responds to local and global rank.

Optimism enters earlier by shifting the perceived skill distribution that generates the continuous probabilities p_{it}^j. Therefore, optimism is disciplined by both the level of reported expectations and the investment and effort moments, especially given that choices respond to the continuous beliefs themselves and not to reporting error.