

Costs or Benefits? Why Students Specialize Across Skills and How Teachers Can Respond

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Abstract

Teachers' knowledge about which skills benefit their students is key to promoting student welfare. Parents hold useful insight about which skills benefit their child, but large class sizes and informal communication limit teachers' access to this information. In this paper, I give teachers information about parent preferences through a field experiment. I survey 3,404 parents across five private schools in India, measuring perceptions of their child's skill levels and preferences for improvement across nine academic, emotional, and social domains. I develop a structural model of multidimensional skill development to diagnose whether observed specialization primarily reflects differences in how hard skills are to learn (costs) or the value of skills (benefits). Parents vary in priorities but on average prefer improving weaknesses. Through the lens of the model, this pattern suggests that learning costs drive specialization. I elicit teachers' beliefs about parent preferences and find little alignment with actual parent views, even at the classroom level. I then randomize teacher access to parent survey data which shifts student specialization toward parent-prioritized skills, with larger effects where baseline teacher beliefs were most inaccurate. Structural estimation enables policy counterfactuals quantifying welfare gains from better cost-benefit alignment.

JEL: C93; D83; I21; I31; J24; O15

Keywords: parental preferences; skill development; socio-emotional skills; teacher beliefs; information frictions; education policy; India; field experiment

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1 Introduction

Educational policy has long focused on increasing the rate of students' skill growth, using outcomes such as test scores or teacher value-added as benchmarks for success (Rivkin et al., 2005; Hanushek and Woessmann, 2008; Glewwe and Muralidharan, 2016). Yet if students and families vary in what skills they value most, then choosing which skills to promote—the *direction* of skill growth—may be equally important for designing welfare-maximizing policy. For example, a student who aims to be a business leader may prefer to improve their teamwork and leadership skills over math and reading skills. This issue has grown in relevance as educational goals expand beyond foundational academic skills to include socio-emotional and other non-cognitive skills (Heckman et al., 2006; Kosse and Tincani, 2020; Deming and Silliman, 2025).

In this paper, I examine how teachers can better align the direction of student skill growth with those skills students and families value most. Teachers must allocate limited time and resources across many skills, and they often lack structured information about which skills benefit each student. These benefits depend on hard-to-observe features such as students' home environments, peer groups, and future aspirations. Teachers who lack this information often rely on observable skill levels to guide instruction, such as remedial education that targets weak skills, or gifted education that builds on students' strengths. This practice speaks to a long standing debate in education: should educators promote well-rounded or specialized students (Rosen, 1983; Câmara Leme et al., 2020; Mulhern et al., 2024; Kemper and Renold, 2024). Students' skill levels alone cannot resolve the quandary: Teachers targeting weak skills may be focusing on low-value (hence neglected) skills, or correctly targeting high-value skills that are weak because they are hard to learn.

Parents often have insight teachers need regarding what skills are high value for their children. However, information about students typically flows in the direction of schools to parents, both in standard operations (e.g., report cards and parent-teacher meetings) and in interventions (e.g., parental engagement programs and messaging campaigns)¹. This directional flow of information may leave teachers without structured information about what skills benefit each student, and may thus limit their ability to align instruction with student needs.

I address this challenge by increasing the flow of information from parents to teachers. I survey 3,404 parents and 242 teachers across five private schools in India (grades 1-10) to gather structured information on the skill-based needs of students. Parents assess their child's current **skill levels** on a scale of 0-100 across nine academic, emotional, and social domains. To capture specialization, I standardize skill levels within-student so that positive values indicate strengths and negative values indicate weaknesses. Parents then report **skill preferences** by ranking skills from most to least important to improve. I elicit teachers' *beliefs* about the skill preferences of parents and show that they are largely uncorrelated with actual parent views, even at the classroom level. Motivated by this misalignment, I randomize whether teachers receive access to their classroom's parent survey data (i.e., parent-reported skill levels and skill preferences) through a custom-built web portal.

¹See Hastings and Weinstein (2008); Andrabi et al. (2017); Bergman (2021); Bergman and Chan (2021); Berlinski et al. (2022) for examples of information interventions targeting parents.

To understand why this information matters, I develop a model that centers parents and teachers as key decision-makers. Parents maximize their child’s utility by choosing inputs to produce multiple skills: they balance the ease with which their children build each skill (costs) with the value of having that skill (benefits). Teachers, with aligned incentives, shift the effective costs of learning in the classroom, thereby changing the production function faced by parents. However, teachers must infer parents’ preferences from noisy signals. Time and effort may be shifted away from the highest-value margins when teachers misperceive what parents value, as I document in my context.

The model yields a simple insight: namely, whether parents prefer improving weak or strong skills helps diagnose why students specialize. This stems from a familiar economic principle—marginal benefits equal marginal costs for each skill when optimizing across skills. Consider first the case of pure cost-driven specialization, in which skills only vary with regard to how difficult they are to learn. Students thus specialize in skills that are easier to build. Because marginal benefits decrease, these easy-to-learn strengths offer little remaining value to improve further, and thus parents prefer to improve weaker skills. Conversely, if skills only vary with regard to how they are valued, students specialize in high-value skills; these skills incur increasing marginal costs and are thus more costly to further improve. Because marginal benefits must equal these high marginal costs, parents continue to prefer improvement in strong skills.

I use the data from the parent survey to examine if skill specialization is primarily cost- or benefit-driven in this setting. I regress skill preferences on skill levels to capture if parents prefer improving weak or strong skills. The slope, hereafter the **preference-level slope**, is negative when parents prefer improving weaker skills, and positive when they prefer improving stronger skills. Across students and within-skill, I find a strong negative preference-level slope for all nine skills. For a given skill, parents that perceive low skill levels for their child consistently rank that skill as more important to improve relative to other parents. This pattern is driven almost entirely by older grades: skill levels and skill preferences are nearly uncorrelated for primary grades and become increasingly negatively correlated by grade 10. Through the lens of the model, this implies costs (how easy or hard it is to learn skills) become increasingly important relative to benefits in determining specialization patterns as students age. This is consistent with dynamic complementarity in skill formation ([Cunha and Heckman, 2007](#)), where early gaps in skill levels lead to widening differences in the costs of acquiring new skills over time.

Within each student, I find parents predominantly want improvement in their children’s weaker skills, but this varies widely: many parents prefer for their children to improve strengths. In fact, when the preference-level slope is more positive, parents report greater satisfaction with their children’s progress in school. In the model, more positive alignment between marginal benefits and skill levels represents a case in which a student’s natural path of skill growth becomes more aligned with the direction that would raise utility fastest. This suggests that when parents see the direction of their child’s skill growth as aligned with what they value, they are more satisfied with their child’s progress. Supporting this interpretation, the preference-level slope is uncorrelated with parent satisfaction with school quality, suggesting that it reflects satisfaction with dynamic growth,

rather than static features of the school environment.

With regard to teachers, I ask them to rank the same nine skills for a typical student, and then for specific randomly sampled students in their class. Crucially, for the specific students, I also elicit teachers' beliefs about each parent's skill preferences. I find that teacher beliefs are largely uncorrelated with parents' actual preferences, both at the individual-student level and in classroom averages, and instead reflect teachers' own priorities—consistent with teachers projecting their own preferences onto parents. This misalignment highlights potential misallocation of teacher effort across skills and students.

Motivated by these findings, I design and implement a randomized experiment that provides teachers with access to parent-reported skill levels and skill preferences. Randomization occurs at the teacher level, with each treated teacher receiving individual login credentials to a custom-built website displaying information for students in their homeroom section.² This intervention acts in the context of my model as a production-side shock, leading teachers to lower the effective cost of improving parent-prioritized skills. The model yields three testable predictions: for students whose teachers were initially misaligned, treatment should (i) increase specialization in the parents' most preferred skill (i.e., empirically, raise skill levels), (ii) reduce the marginal benefit for that skill (i.e., lower the skill preference rank), and (iii) increase the within-student alignment between marginal benefits and skill levels (i.e., result in a more positive preference-level slope).

I find that providing parent preference information to teachers shifts their beliefs toward the true classroom average, but does not improve accuracy about individual parents. Averaging teacher beliefs across all parents in their class, treated teachers' beliefs become more aligned with actual classroom average preferences, with suggestive evidence of roughly 10 percentage point improvements in accuracy in identifying which category (academic, social, emotional) is most or least valued. However, teachers do not become better at predicting which specific parents hold these preferences. This pattern aligns with the model's policy logic: since teacher effort is applied at the classroom level, correctly identifying classroom-average preferences can increase the rate of welfare growth, even if teachers do not perfectly know individual values.

The experiment produces results consistent with the model predictions. First, giving teachers data concerning parents' assessment of their children's skill levels and skill preferences changed how students specialized. Average effects on skill levels are near zero, but this masks substantial heterogeneity by baseline teacher accuracy. When teachers initially held inaccurate beliefs about a parent's priorities, treatment increased skill levels in parents' most-preferred skills and decreased skill levels in their least-preferred skills. Conversely, when teachers were initially accurate, treatment reduced skill levels in parents' most-preferred skills and increased skill levels in their least-preferred skills. This result is consistent with teachers applying effort at the classroom level, reallocating effort away from students they already understood and toward students they previously misjudged. Second, parents' initial top priorities become less urgent to improve: for the

²In this setting, teachers are assigned one section of students during the 0-period (homeroom), where they are responsible for student guidance and are the point of contact for parents (e.g., they meet parents during parent-teacher meetings). Teachers then rotate into other classrooms throughout the day to teach specific subjects.

skill parents most wanted to improve at baseline, treated parents' endline skill preference falls by 0.26 ranks compared to control, implying that the marginal benefit declined. Third, treated students' skill levels become more aligned with parents' skill preferences: compared to the control, the preference-level slope increases by about 0.15 on average (from a base slope of -0.7) and by 0.26 in classrooms where parents most preferred improving academic skills. All three effects are strongest in treated classrooms where parents on average preferred improving academic skills; this result is consistent with teachers having more scope to shift efforts in the academic domain. Taken together, these findings show that providing teachers with structured information can act a production shock: in other words, teachers' classwide efforts are reoriented toward parents' most-preferred skills. Parents' perceived need for improvement in those areas is reduced, and specialization is shifted away from what is easiest to build and toward what parents value most.

To provide additional evidence that costs drive specialization in this setting, I structurally estimate the model using Bayesian methods. The model decomposes observed skill level ratios into two components: variation in how families value skills (benefits) and variation in how hard skills are to learn (costs). A key result is the ratio of cost variance to benefit variance, which measures the relative importance of production constraints versus preference heterogeneity in driving specialization. I find that production constraints vary approximately 21% more across families than do preferences for academic versus social-emotional skills. These structural estimates corroborate the reduced-form preference-level slope findings: observed specialization in this setting reflects primarily what students find easier to learn rather than what families value more. The estimated model also enables policy counterfactuals, though welfare gains from better aligning production costs with parental preferences are modest on average, at around one percent, suggesting most families are not far from their optimal skill mix given the production constraints they face.

The key contribution of the framework is diagnostic. Observing whether parents prefer improving weak or strong skills identifies if barriers to learning or perceived benefits are the primary driver of specialization. A teacher observing students struggle in math can use this diagnostic: for example, if parents consistently report preferring improvement in math, the diagnostic tells us that high barriers to learning math, not low perceived value, are driving the observed pattern. In this setting, I find that parents consistently prefer improving weaker skills; this observation points to uneven production costs as the primary driver of specialization. Consistent with costs driving specialization in this context, interventions in primary and secondary education tend to target production-side barriers: teacher training, additional school resources, and intensive instructional models that help students overcome learning difficulties ([Jackson et al., 2016](#); [Muralidharan and Sundararaman, 2013](#); [Burgess et al., 2023](#); [Fryer Jr, 2017](#)). In contrast, in contexts where individuals likely prefer further improving their strengths, such as in college or the labor market, the diagnostic suggests benefits drive specialization. In these settings, interventions accordingly tend to target the benefit side: such interventions may include providing students information about earnings across majors and occupations, role models demonstrating career opportunities in different fields, and career guidance counselors helping students to understand returns to specialization ([Jensen, 2010](#); [Wiswall and Zafar, 2015](#); [Porter and Serra, 2020](#); [Hoxby and Turner, 2015](#); [Conlon,](#)

2021).

Beyond identifying the source of specialization, this framework suggests how teachers can personalize education by providing instruction based on student-varying costs and benefits to skills. This represents a theory-guided complement to “Teaching at the Right Level”(Banerjee et al., 2017): personalize not only by skill levels, but also by values. This is particularly relevant for educational aims that go beyond foundational skill development and where level-based grouping may be sufficient if all parents similarly value basic literacy and numeracy. However, broadening educational goals to diversify or specialize skill development requires accounting for large variation in preferences over these skills. Providing teachers with structured information on parent preferences may help align instructional effort with welfare-maximizing aims.

Contributions to the Literature This benefits-vs-costs question is central but empirically underidentified in most educational settings, despite related evidence on the technology of skill formation and dynamic complementarity (Cunha and Heckman, 2007; Cunha et al., 2010), on the heterogeneous returns to cognitive and socioemotional skills (Heckman et al., 2006; Lindqvist and Vestman, 2011; Deming, 2017; Kosse and Tincani, 2020; Deming and Silliman, 2025), on parental preferences over teacher attributes (Jacob and Lefgren, 2007; Jackson, 2018), and on resource and productivity constraints in schools (Jackson et al., 2016; Muralidharan and Sundararaman, 2011, 2013; Burgess et al., 2023; Fryer Jr, 2017). The work of Cotton et al. (2025) is most closely related to my study: the authors structurally distinguish motivation from productivity as drivers of student study time and find that low productivity, rather than low motivation, predicts academic struggles³. My study complements this work by distinguishing costs from benefits as drivers of skill specialization across multiple dimensions, and by examining the supply side (i.e., teacher allocation) rather than the demand side (i.e., student effort). It also relates to literature on parental preferences and beliefs (Jacob and Lefgren, 2007; Dizon-Ross, 2019) and on information interventions that primarily inform parents (Hastings and Weinstein, 2008; Bergman, 2021; Bergman and Chan, 2021; Berlinski et al., 2022).

I contribute along five margins. First, I provide new measurements for the literature on parental preferences and beliefs by directly eliciting, for the same child, parents’ perceived skill levels and skill preferences for improvement across nine cognitive and socio-emotional dimensions (Jacob and Lefgren, 2007; Dizon-Ross, 2019). By linking skill levels to marginal benefits, I go beyond documenting preferences to provide a diagnostic for the underlying source of specialization. Second, I contribute to the literature on the technology of skill formation by providing a tractable framework to distinguish benefit- from cost-driven heterogeneity and by modeling teachers as endogenous cost-shifters who respond to information (Cunha et al., 2010). Third, I structurally estimate the model using Bayesian methods, leveraging teacher skill rankings as supply-side cost shifters to recover primitives governing skill formation. The estimated model enables policy counterfactuals compar-

³While Cotton et al. (2025) focus on why students do not complete homework (i.e., they examine motivation vs. productivity in converting time to learning), I examine why students specialize across skills (i.e., I examine costs vs. benefits driving comparative advantage). Their framework clarifies intensive margin decisions for a single skill; my framework clarifies extensive margin allocation across multiple skills.

ing alternative approaches to personalizing instruction. Fourth, my framework informs work on the heterogenous benefits to cognitive and non-cognitive skills by offering a way to interpret observed specialization, helping to understand when heterogeneous benefits are likely to be the more important driver of investment choices (Heckman et al., 2006; Lindqvist and Vestman, 2011; Deming, 2017; Kosse and Tincani, 2020; Deming and Silliman, 2025).

Fifth, I contribute to the literature on information interventions that primarily inform parents about their child’s behavior (Hastings and Weinstein, 2008; Bergman, 2021; Bergman and Chan, 2021; Berlinski et al., 2022). My experiment, however, reverses the typical information flow. I inform teachers about parent priorities that serve as a proxy for students’ marginal benefits to skill development, a parameter where parents are plausibly better informed, in contrast to academic levels where evidence shows parental perceptions can be inaccurate. Despite my limited statistical power, my experimental results provide validation that the structural model’s mechanisms operate in practice. This demonstrates that reducing uncertainty on the school side can be a powerful lever for change.

The paper proceeds as follows. Section 2 describes the Indian school context, including the process for recruitment and list of human capital dimensions. Section 3 presents the model of multidimensional skill formation distinguishing benefit- from cost-driven specialization and models teachers as key inputs to skill production. Section 4 describes the data from the parent survey and reports initial descriptives. Section 5 presents results on benefit- vs cost-driven specialization. Section 6 describes the teacher-facing information experiment and its implementation. Section 7 discusses the impact of information on teacher beliefs about parent priorities and section 8 reports impacts on key student outcomes. Section 9 structurally estimates the model and presents policy counterfactuals. Section 10 concludes.

2 Setting

2.1 Context

This study takes place in five private schools located across four states in India: Delhi (two schools), Gujarat, Punjab, and West Bengal. These schools serve middle to upper-middle-class families, with approximately 90% of students coming from families with household incomes above the national median. All schools span from Nursery to 12th grade; for this study we focus on students in grades 1-10.

Tuition fees range from approximately \$350 per year at the least expensive school to \$2,500 per year at the most expensive school—a range that covers the bulk of low- to middle-income private schools in the Indian context. This setting is not an outlier; in fact, it is quite representative of a large and growing segment of education in developing countries. Private schools have become increasingly prevalent across low-income countries with enrollment shares rising from 11 to 22 percent between 1990 and 2010 (Baum et al., 2014), and for India specifically to 39% in 2024 (UDISE+, 2024-25), representing about 100 million students.

Class sizes in these schools typically range from 30 to 40 students per classroom, creating significant challenges for teachers in providing individualized attention. They often have to balance the wide variation in parental values and expectations for their child as parents pay fees, and some cases, teacher compensation is explicitly tied to parental feedback. Across all five schools, parent-teacher meetings occur either twice a year (once per term), or monthly. These meetings provide opportunities primarily for teachers to share information about student progress with parents, but also for parents to share their perceptions with teachers. However, the format and content of these interactions vary widely. Most of the schools in this study provide report cards that focus primarily on academic subjects, with at least one school including non-cognitive skills on the report card.

Despite the regular occurrence of parent-teacher meetings, teachers face numerous information frictions that limit their ability to incorporate parent preferences into their decision-making. These include large class sizes, varying parental communication styles, and the difficulty of aggregating information from multiple parents. This context where parent input is valued, but potentially undersupplied due to structural constraints, provides an ideal setting to examine how structured information about parent preferences can influence teacher decision-making and student outcomes.

2.2 Sample and Recruitment

The recruitment process involved a self-directed search for schools interested in participating in a research study focused on understanding the varied needs of their students and accommodating parent perspectives through structured information aggregation. I conducted recruitment throughout 2023 and 2024, presenting the project as an opportunity for schools to better understand parent preferences and perceptions, allowing them to better align teaching practices with school aims. The recruitment process led to partnerships with five private schools across four states in India.

The study began with a pilot phase in October 2023 at the initial partner school in West Bengal. Following a successful implementation of the pilot, I conducted a full baseline survey at this school in March 2024. I launched the intervention by sharing information with treated teachers in July 2024. Concurrent with the implementation at the first school, I recruited additional schools throughout the summer of 2024. I successfully onboarded four more schools, conducting baseline surveys at these institutions in September and October 2024. Treated teachers at these schools received access to the website containing parent preference information in November 2024, marking the beginning of the intervention phase for these schools.

Figure 1: Study Timeline



Due to prior commitments, two schools were unable to continue their participation after the baseline phase. Although I collect and analyze endline data for all three remaining schools, I follow the pre-analysis plan in only estimating treatment effects using endline data for schools in which treatment compliance was above 15% (measured as the percent of treated teachers who view the website with parent data at least once). This threshold was set ex-ante to ensure that there was sufficient engagement with the intervention to potentially affect student outcomes. Despite regular reminders and school visits, this threshold was only surpassed by teachers in the initial partner school. As a result, the baseline sample includes 3404 parents surveyed in 242 classrooms across the five schools, and the final experimental sample includes 849 students across 106 classrooms in the initial partner school.

The reduction from baseline to endline within the partner school reflects the voluntary nature of survey completion rather than systematic attrition. Both baseline and endline surveys were administered during parent-teacher meetings, with participation incentivized only by informing parents that their responses would help teachers better target instruction for their child. Approximately one-quarter of the school's roughly 4,000 parents completed surveys at each wave, with substantial turnover in which families participated. To verify that this pattern does not threaten internal validity, I regress an indicator for having complete data (non-missing values for all baseline and endline outcomes) on treatment assignment and baseline covariates. Appendix Table [B.1](#) shows no significant relationship between treatment status and survey completion, nor do treatment effects on completion vary by parents' baseline skill preferences. This null result indicates that sample composition is balanced across treatment and control classrooms. Full descriptive statistics for the baseline and experimental samples are provided in Appendix Table [B.2](#).

2.3 Skill Dimensions

The study focuses on nine dimensions of human capital that encompass both cognitive and non-cognitive skills. The skills are divided into three broad categories: academic, social, and emotional skills. The nine skill dimensions are shown below in Table [1](#).

The set of skills was decided through an iterative process. The initial list contained 21 potential skill dimensions designed to be comprehensive in covering any skill a parent may care about. Skill dimensions were drawn from literature on educational frameworks, psychology, and through discussion with parents prior to the start of the study. Through pilot testing with parents and teachers, the list was narrowed to nine dimensions to balance time constraints of the survey with the comprehensiveness of the final list. The selection process prioritized dimensions that (1) were comprehensible to parents without specialized knowledge, (2) covered a range of both cognitive and non-cognitive domains, and (3) were potentially actionable by both teachers and parents. Parents were provided the exact image shown in Table [1](#) to promote consistency in parents' understanding of the dimensions. For each dimension, parents were asked to rate their child's current standing on a scale from 0 to 100 (skill levels), and then to rank the nine dimensions in order of importance for improvement (skill preferences), which we describe further in Section [4](#).

Table 1: Human Capital Dimensions

Category	Aspect	Explanation
Academic	Literacy skills	Reading, writing, speaking, and listening
Academic	Mathematical skills	Numeracy, quantitative reasoning, problem-solving
Academic	Scientific literacy	Understanding scientific concepts and processes
Social	Collaboration and teamwork skills	Ability to work effectively with others and contribute to group goals
Social	Interpersonal skills	Effective communication, conflict resolution, recognizing and responding to social cues
Social	Leadership and initiative	Taking charge, setting goals, motivating others
Emotional	Perseverance and growth mindset	Resilient in the face of challenges, belief in self-improvement
Emotional	Emotional self-awareness and regulation	Recognizing and managing emotions, thoughts, and behaviors
Emotional	Empathy for others	Understanding and valuing perspectives of others

Notes: Parents and teachers are asked to evaluate nine human capital dimensions for their students. Dimensions were chosen to cover a range of cognitive and non-cognitive skills. This exact table was shown to both parents and teachers in their respective surveys to promote consistency in understanding each dimension.

3 Model

To understand how teachers can better align the direction of student skill growth with what students and families value most, I develop a framework to distinguish whether differences in students' skill profiles are driven primarily by variation in benefits (in terms of satisfaction, money, etc.) for different skills or by production cost differences in producing them. Note we focus on two types of variation: (i) variation across students within a skill (why some students specialize in a given skill) and (ii) variation across skills within a student (why some skills are relatively strong or weak for a given student).

We proceed in two steps. First, I present a model in which parents maximize their child's utility by allocating a fixed budget towards producing multiple skills. Parents have full information about the costs and benefits to skills. I interpret the expansion path (the path of optimal bundles as the budget rises) as how skills would change over time, absent changes to the costs or benefits from skills. This yields two types of students: (A) students who would derive higher utility from more well-rounded profiles relative to the expansion path, and (B) students who would derive higher utility from more specialized profiles relative to the expansion path.

Second, I introduce teachers with aligned incentives who choose how to allocate their time and resources across students and skills. Teachers hold imperfect beliefs about parents' perceived benefits. When those beliefs are incorrect, on average, the path of skill growth as resources rise is misaligned with the direction that would raise utility fastest, motivating our information experiment. Critically, teachers shift the production frontier at the classroom-level. This allows us

to interpret the expansion path as the classroom production path, and the two types of students as those who would benefit from teachers shifting classroom production toward well-roundedness (type A) or specialization (type B).

3.1 Parents' Problem

Skills. Parents derive utility from their child's skill bundle $\mathbf{c} = (c_1, c_2) \in \mathbb{R}_+^2$, where c_1 and c_2 denote two distinct skill domains (e.g., cognitive and non-cognitive). We focus on two skills for simplicity, but the model extends naturally to three or more skills. We define the child's level of *specialization* (in skill 1, without loss of generality) as the ratio of the skill levels, $s_i := c_{1i}/c_{2i}$.

Preferences. Parent i has Cobb-Douglas utility⁴

$$U(c_{1i}, c_{2i}; \beta_i) = c_{1i}^{\beta_i} c_{2i}^{1-\beta_i}, \quad 0 < \beta_i < 1.$$

The marginal rate of substitution (MRS) between skills 1 and 2 is

$$\text{MRS}_{12,i} = \frac{\beta_i}{1 - \beta_i} \cdot \frac{c_{2i}}{c_{1i}} = \frac{\beta_i}{1 - \beta_i} \cdot \frac{1}{s_i}. \quad (1)$$

Budget and technology. Parents buy inputs (x_{1i}, x_{2i}) at prices (p_{1i}, p_{2i}) subject to $p_{1i}x_{1i} + p_{2i}x_{2i} \leq I_i$. Each skill is produced via single-input technologies with diminishing marginal products:

$$c_{1i} = a_{1i}x_{1i}^\theta, \quad c_{2i} = a_{2i}x_{2i}^\theta, \quad a_{ji} > 0, \quad 0 < \theta < 1.$$

Eliminating (x_1, x_2) yields a smooth, strictly concave frontier in (c_1, c_2) space:

$$p_{1i} \left(\frac{c_{1i}}{a_{1i}} \right)^{1/\theta} + p_{2i} \left(\frac{c_{2i}}{a_{2i}} \right)^{1/\theta} = I_i.$$

Feasible set. Let $\rho := 1/\theta > 1$ and define

$$\kappa_{1i} := a_{1i} \left(\frac{I_i}{p_{1i}} \right)^{1/\rho}, \quad \kappa_{2i} := a_{2i} \left(\frac{I_i}{p_{2i}} \right)^{1/\rho}.$$

⁴I use Cobb-Douglas preferences for transparency and tractability. All qualitative results (diagnostic, comparative statics) continue to hold under smooth, strictly increasing, and strictly quasi-concave preferences. The closed-form expression are specific to Cobb-Douglas.

The frontier becomes the constant-elasticity-of-transformation (CET) form⁵:

$$\left(\frac{c_{1i}}{\kappa_{1i}}\right)^\rho + \left(\frac{c_{2i}}{\kappa_{2i}}\right)^\rho = 1, \quad \rho > 1. \quad (2)$$

Marginal rate of transformation. Implicit differentiation of (2) yields the marginal rate of transformation (MRT) between skills:

$$\text{MRT}_{12} = \left(\frac{\kappa_{2i}}{\kappa_{1i}}\right)^\rho \left(\frac{c_{1i}}{c_{2i}}\right)^{\rho-1}. \quad (3)$$

Note that κ_{ji} fully captures the effective cost of producing skill j for parent i , and is exactly the intercept of the frontier on the c_j axis.

Equilibrium skill ratio. Utility maximization subject to (2) equates (1) and (3), giving the optimal skill ratio:

$$s_i^* := \frac{c_{1i}^*}{c_{2i}^*} = \underbrace{\left(\frac{\beta_i}{1-\beta_i}\right)^{1/\rho}}_{T_i} \underbrace{\frac{\kappa_{1i}}{\kappa_{2i}}}_{\lambda_i}. \quad (4)$$

This equilibrium condition is shown graphically in Figure 2A. The equation illustrates how the variation in skill ratios across parents can be decomposed into two components: variation in the *benefits tilt* $T_i = \left(\frac{\beta_i}{1-\beta_i}\right)^{1/\rho}$, which reflects how much more a parent values skill 1 relative to skill 2, and variation in the *costs tilt* $\lambda_i = \frac{\kappa_{1i}}{\kappa_{2i}}$, which reflects the relative costs or ease of producing skill 1 compared to skill 2.

Comparative statics. Consider the following elasticities of the optimal skill ratio with respect to the primitives:

$$\frac{\partial \ln s_i^*}{\partial \beta_i} = \frac{1}{\rho} \left(\frac{1}{\beta_i} + \frac{1}{1-\beta_i} \right) > 0, \quad \frac{\partial \ln s_i^*}{\partial \ln \kappa_{1i}} = 1, \quad \frac{\partial \ln s_i^*}{\partial \ln \kappa_{2i}} = -1.$$

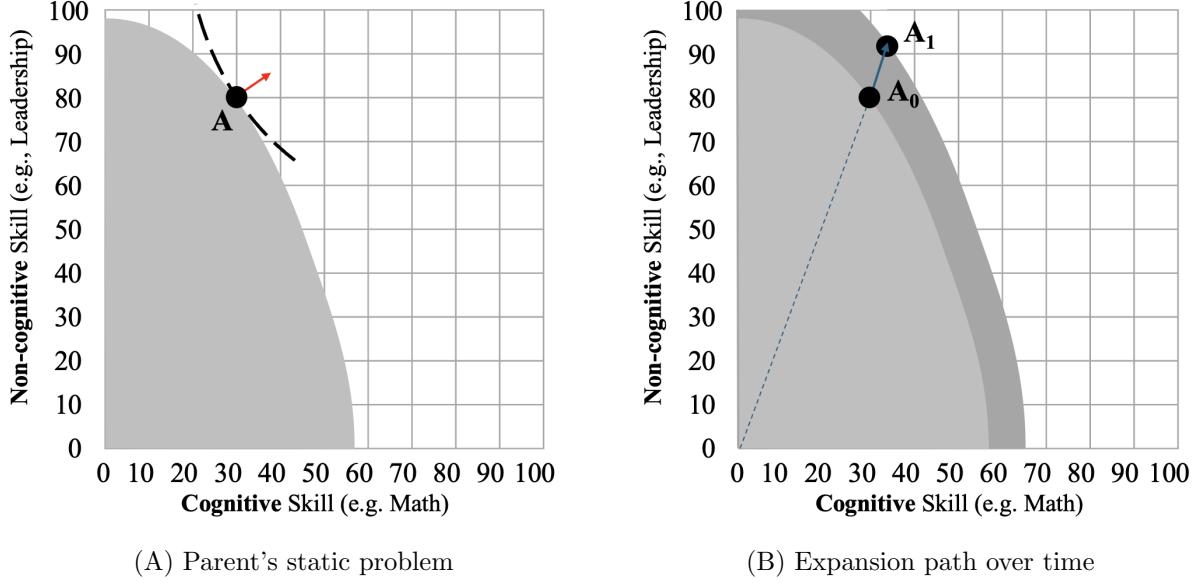
Thus, an increase in the relative benefit to skill 1 ($\beta_i \uparrow$), or a decrease in the relative cost of producing skill 1 ($\kappa_{1i} \uparrow$ or $\kappa_{2i} \downarrow$) raises the optimal specialization s_i^* .

Skill growth over time. In this model, parents' budgets consists of time, money, and other resources that they can invest in their child's skill development. Consider additional time (e.g. one more year) to spend on skill development. We model this as a *pure budget expansion*: in each period the family has more effective resources I_i . With homothetic preferences and the CET frontier, if *benefits* (β_i) and *costs* (κ_{1i}, κ_{2i}) are fixed, optimal levels scale up with income, but proportionally

⁵The CET frontier allows for non-unit elasticity of transformation between skills. Multi-output production functions with constant elasticity of transformation are widely used; this single-period CET mirrors the multistage production functions in Cunha and Heckman (2007, 2008); Cunha et al. (2010). We abstract from dynamic self-productivity and cross-period complementarity to focus on the question of whether observed heterogeneity is driven by relative costs (κ_{1i}, κ_{2i}) or by relative benefits (β_i).

so that specialization, $s_i^* = c_{1i}^*/c_{2i}^* = T_i\lambda_i$, remains constant. This is shown graphically in Figure 2B. The expansion path will allow us to distinguish two types of students, and will be key to understanding how teachers can influence skill growth over time.

Figure 2: Parent's Problem and Skill Growth



Two types: (A) Desire well-roundedness or (B) Desire specialization. Fix student i at $c_i = (c_{1i}, c_{2i})$ with specialization level $s_i = c_{1i}/c_{2i}$ and

$$\text{MRS}_{12,i} = \frac{\beta_i}{1 - \beta_i} \cdot \frac{1}{s_i}.$$

With β_i and $(\kappa_{1i}, \kappa_{2i})$ fixed, income growth moves the optimum with constant slope $(dc_2/dc_1)_I = 1/s_i$. Contrast this with the direction of *maximal utility growth*, which is normal to the indifference curve (or equivalently normal to the frontier), hereafter denoted as the *IC-normal* direction. The IC-normal has slope $1/\text{MRS}_{12,i}$, and is denoted in red in Figure 2A.

Without loss of generality, fix the weaker skill level to be on the horizontal axis so that $s_i < 1/2$. We define:

- **Type A:** expansion path is *steeper* than the IC normal,

$$\frac{1}{s_i} > \frac{1}{\text{MRS}_{12,i}} \iff \text{MRS}_{12,i} > s_i,$$

i.e., marginal utility puts more weight on the *weaker* skill 1 relative to the current level of specialization.

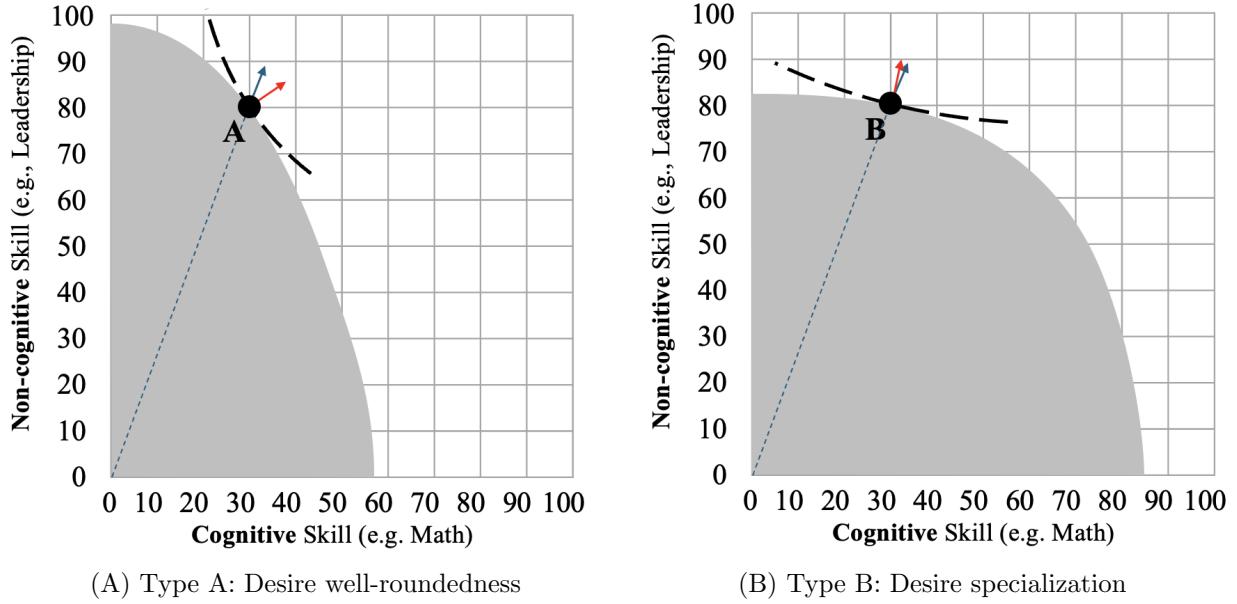
- **Type B:** expansion path is more *shallow* than the IC normal,

$$\frac{1}{s_i} < \frac{1}{\text{MRS}_{12,i}} \iff \text{MRS}_{12,i} < s_i,$$

i.e., marginal utility favors further improvement in the *stronger* skill relative to the current level of specialization.

Recall that $\text{MRS}_{12,i} = \beta_i / (1 - \beta_i) * s^{-1}$. Therefore, considering the in-between case where $\text{MRS}_{12,i} = s_i$ allows us to define the threshold ratio $s^\dagger(\beta_i) := \sqrt{\beta_i / (1 - \beta_i)}$. A student is of type A iff $s_i < s^\dagger(\beta_i)$ and of type B iff $s_i > s^\dagger(\beta_i)$. Intuitively, if the student is relatively weak in skill 1 (s_i small) but the parent places high value on skill 1 (β_i large), then the student is type A and would benefit from further well-roundedness. Conversely, if a student's relative weakness is not *too* weak relative to values ($1/2 > s_i > s^\dagger(\beta_i)$), then the student is type B and would benefit from further specialization. We show Type A and B graphically in Figure 3.

Figure 3: Type A and B Students



Note that type A and B can be applied to *either* students or skills. For a given student, type A (B) students derive more utility from improving weaker (stronger) skills. For a given skill, type A (B) skills are ones in which the largest utility gains would come from boosting the weaker (stronger) students in that skill.

Diagnostic for type A or B skills. We showed above that type A is characterized by environments in which higher marginal benefits are associated with relative weaknesses (low skill levels), and type B by environments in which higher marginal benefits are associated with relative strengths (high skill levels). Hence, we propose the **preference-level slope** as a sufficient

statistic for capturing this relationship between marginal benefits and relative levels. Consider the regression **across students** for a given skill (here, skill 1):

$$\text{MRS}_{12,i}^* = \alpha + \beta^{\text{RF}} s_i^* + \varepsilon_i, \quad (5)$$

with population slope

$$\beta^{\text{RF}} = \frac{\text{Cov}_i(s^*, \text{MRS}^*)}{\text{Var}_i(s^*)}. \quad (6)$$

Using the primitives from Section 3.1, optimal specialization is the product of the benefit and cost tilts so that

$$s_i^* = T_i \lambda_i, \quad \text{MRS}_{12,i}^* = T_i^{\rho-1} \lambda_i^{-1},$$

so

$$s_i^* \cdot \text{MRS}_{12,i}^* = T_i^\rho, \quad (7)$$

which cancels λ_i and separates *benefits* (T_i) from *costs* (λ_i). It follows that

$$\text{Cov}(s^*, \text{MRS}^*) = \text{Cov}(T_i \lambda_i, T_i^{\rho-1} \lambda_i^{-1}) = \mathbb{E}[T_i^\rho] - \mathbb{E}[T_i \lambda_i] \mathbb{E}[T_i^{\rho-1} \lambda_i^{-1}]. \quad (8)$$

Writing mean-zero deviations $\tilde{T}_i := T_i - \mathbb{E}[T]$ and $\tilde{\lambda}_i := \lambda_i - \mathbb{E}[\lambda]$, a first-order expansion around means yields

$$\beta^{\text{RF}} = \frac{(\rho - 1) \text{Var}(\tilde{T}) - \text{Var}(\tilde{\lambda})}{\text{Var}(\tilde{T}) + \text{Var}(\tilde{\lambda})}. \quad (9)$$

so that the sign and magnitude of the slope depends on the relative sizes of the variance in benefit and cost tilts. As dispersion in costs increases, the slope becomes more negative (Type A), and as dispersion in benefits increases, the slope becomes more positive (Type B).

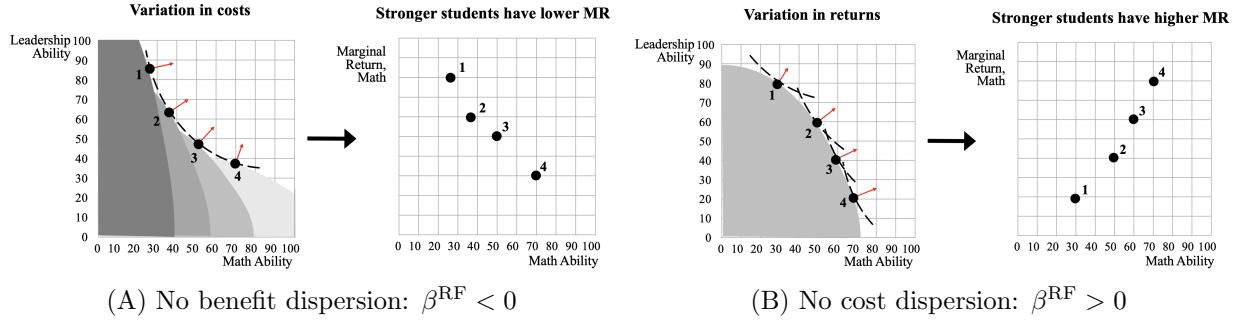
This derivation shows that asking whether a student or skill is closer to Type A or Type B is closely related to asking if relative strengths and weaknesses are primarily driven by dispersion in costs or benefits. Intuitively, Type A students that desire more well-rounded profiles exist in environments where weakness is due to high costs of production, not a low value for that skill. Type B students that desire more specialized profiles exist in an environment where the strengths are primarily due to high value for that skill, not ease of production

Extreme cases and interpretation. Two polar cases benchmark (9):

- (i) **No cost variation** ($\text{Var}(\tilde{\lambda}) = 0$): $\beta^{\text{RF}} = \rho - 1 > 0$ when heterogeneity is purely benefit-driven.
- (ii) **No benefit variation** ($\text{Var}(\tilde{T}) = 0$): $\beta^{\text{RF}} = -1$ when heterogeneity is purely cost-driven.

In intermediate cases $\beta^{\text{RF}} \in [-1, \rho - 1]$, and its sign/magnitude reveal the relative importance of benefit vs. cost dispersion. We display these benchmarks graphically in Figure 4.

Figure 4: Preference-level slope benchmarks



Diagnostic for Type A or B students. Similar to the within skill diagnostic, we can classify type A students as those that have high marginal benefits for improving weaker skills, and type B students as those that have high marginal benefits for improving stronger skills.

First we solve for the equilibrium skill mix for a given student, with more than two skills. Dropping the i subscript, let there be $J \geq 3$ skills with $\sum_j (c_j/\kappa_j)^\rho = 1$ and preferences $\prod_j c_j^{\beta_j}$. Fix skill 1 as an anchor and therefore for $j \neq 1$:

$$s_j^* = \frac{c_j^*}{c_1^*} = \left(\frac{\beta_j}{\beta_1} \right)^{1/\rho} \frac{\kappa_j}{\kappa_1} =: T_j \lambda_j, \quad \text{MRS}_{j1}^* = T_j^{\rho-1} \lambda_j^{-1},$$

where $T_j = (\beta_j/\beta_1)^{1/\rho}$ and $\lambda_j = \kappa_j/\kappa_1$ (full derivation in Appendix D). We consider the analogous regression **across skills for a given student** of the marginal rate of substitution on skill levels. A first order expansion around means $\mathbb{E}[T_j]$ and $\mathbb{E}[\lambda_j]$ yields a similar expression for the preference-level slope across skills for a given student:

$$\beta_j^{RF} := \frac{\text{Cov}_j(s^*, \text{MRS}^*)}{\text{Var}_j(s^*)} = \frac{(\rho-1)\text{Var}_j(\tilde{T}) - \text{Var}_j(\tilde{\lambda})}{\text{Var}_j(\tilde{T}) + \text{Var}_j(\tilde{\lambda})}.$$

Thus, the same logic applies: if the variation in costs dominates, the student is type A, the slope is negative, and they would benefit from more well-roundedness; if the variation in benefits dominates, the student is type B, the slope is positive, and they would benefit from more specialization.

3.2 Teachers Problem (Classroom-Level Targeting)

A teacher enters after the baseline parent problem. Each student arrives with an achievement bundle $c_0 = (c_{1,0}, c_{2,0})$ and with barriers to learning summarized by cost shifters $\kappa = (\kappa_1, \kappa_2)$. The teacher cannot change benefits β and does not choose inputs x ; instead, she can *lower effective costs* by changing κ , with the aim of maximizing students' utility.

Crucially, the teacher does not observe each student's true benefit parameters β_i or complete cost structure, which depend on hard-to-observe features such as home environment, peer groups,

and future aspirations. Instead, the teacher holds beliefs $\hat{\beta}_i$ about each student's marginal benefits to different skills. Parents are plausibly better informed about these benefits, but large class sizes and informal communication limit teachers' structured access to this information.

I model teachers as choosing a single classroom environment that shifts the frontier *for all students in the class*. Let $z := (\kappa_1, \kappa_2)$ summarize the classroom-level technology (intercepts of the CET frontier). Starting from z_0 , the teacher selects a class-wide change $\Delta z := z - z_0$ subject to a convex resource cost

$$\mathcal{C}(\Delta z) \leq B, \quad \mathcal{C}(0) = 0, \quad \nabla^2 \mathcal{C}(z) \succ 0.$$

Representative (target) student. Following the spirit of tracking/targeting models (e.g., [Duflo et al. \(2011\)](#)), we assume the teacher orients instruction toward a fixed percentile $\tau \in (0, 1)$ of the baseline distribution.⁶ Let $i(\tau)$ denote the student at percentile τ in the baseline specialization distribution (or, under symmetry, the median equals the mean). The teacher operates on beliefs $\hat{\beta}_{i(\tau)}$ about the representative student's benefit parameters. The teacher's objective is to improve the representative student $i(\tau)$:

$$\max_{\Delta z} U(c^*(z_0 + \Delta z; I_{i(\tau)}, \hat{\beta}_{i(\tau)}) ; \hat{\beta}_{i(\tau)}) \quad \text{s.t.} \quad \mathcal{C}(\Delta z) \leq B.$$

This delivers a simple, class-wide policy rule while making explicit which part of the distribution the teacher is targeting. (Section 3.2 briefly discusses student-specific levers; when feasible, such levers are weakly welfare-improving relative to any single-environment benchmark.)

First-order characterization. Write $z := (\ln \kappa_1, \ln \kappa_2)$ and let $c^*(z; I, \hat{\beta})$ be the parental optimum on production frontier given the teacher's beliefs about benefits. The 2×2 Jacobian

$$J(z; I, \hat{\beta}) := \frac{\partial c^*(z; I, \hat{\beta})}{\partial z} \quad \text{with entries} \quad J_{jk} = \frac{\partial c_j^*}{\partial \ln \kappa_k}$$

measures how the optimal outcomes respond to small cost/productivity shifts. For small moves, $\Delta c \approx J \Delta z$; for larger moves, the mapping is nonlinear, but the endpoint FOCs evaluate J at the chosen z^* .

The teacher chooses Δz subject to a convex *technology-space* budget $\mathcal{C}(\Delta z) \leq B$. When we use the quadratic form

$$\mathcal{C}(\Delta z) = \frac{1}{2} \Delta z^\top W \Delta z, \quad W \succ 0,$$

the symmetric, positive-definite matrix W is the cost curvature in technology space. Diagonal entries encode how expensive it is to relax costs for each skill, while off-diagonals allow for spillovers/complementarities in moving both costs at once (if $W = I$, all directions in z are equally costly).

⁶The role of τ is to capture an instructional target level; Duflo et al. study how x^* (a target) depends on the distribution and payoff curvature. Here we impose a simple, testable benchmark in which the teacher chooses a single classroom environment aimed at a chosen percentile; we focus on $\tau = 0.5$ (the median) for symmetry and transparency.

It is important to distinguish W from κ_i ; W captures how difficult it is for teachers to shift costs, whereas κ_i summarizes those very costs, capturing how difficult it is for parents to shift skill levels.

The KKT condition for the teacher's problem,

$$\max_{\Delta z} U\left(c^*(z_0 + \Delta z; I, \hat{\beta}); \hat{\beta}\right) \text{ s.t. } \mathcal{C}(\Delta z) \leq B,$$

is

$$\nabla_z U\left(c^*(z^*; I, \hat{\beta}); \hat{\beta}\right) \propto \nabla \mathcal{C}(\Delta z^*), \quad (10)$$

and, by the chain rule,

$$\nabla_z U = J(z^*; I, \hat{\beta})^\top \nabla_c U\left(c^*(z^*; I, \hat{\beta})\right).$$

Under quadratic costs, $\nabla \mathcal{C}(\Delta z^*) = W \Delta z^*$, so

$$\boxed{\Delta z^* \propto W^{-1} J^\top \nabla_c U} \quad (\text{move in } z \text{ along utility gain per technology-cost}).$$

Mapping back to outcomes,

$$\Delta c^* \approx J \Delta z^* \propto \underbrace{J W^{-1} J^\top}_{M(z^*; I, \hat{\beta}) \succ 0} \nabla_c U\left(c^*(z^*; I, \hat{\beta})\right).$$

Interpretation.

- $J^\top \nabla_c U$ takes utility gradient from outcome space to technology space—i.e., it captures which cost reductions raise utility fastest once parents re-optimize (under the teacher's beliefs).
- W^{-1} reweights that direction by how cheap each cost move is for the teacher.
- $M := JW^{-1}J^\top$ is the induced metric in outcome space: it tells us which outcome directions are cheapest to deliver, given both teacher costs (W) and skill level responsiveness (J) which is formed under the teacher's beliefs about benefits.

Hence the globally optimal change in outcomes points along the direction $M \nabla_c U$, i.e., the utility normal, weighted by the metric M that captures how costly different outcome moves are for the teacher operating on her beliefs.

Benchmark: symmetric teacher costs in outcome space. If the composite metric M is locally proportional to the identity (movements in outcome space are equally costly), the optimal class move aligns with the utility normal of the representative student under the teacher's beliefs:

$$\Delta c^* \parallel \nabla_c U\left(c^*(z^*; I_{i(\tau)}, \hat{\beta}_{i(\tau)})\right).$$

With $\tau = 0.5$ and a symmetric, single-peaked baseline distribution, this implies the classroom environment is chosen so that the *expansion path* for the median aligns with that student's IC-normal as perceived by the teacher. In our Cobb-Douglas/CET setting, this pins down the specialization

threshold $s^\dagger(\hat{\beta}) = \sqrt{\hat{\beta}/(1 - \hat{\beta})}$ as the classroom alignment point: if the teacher believes the median student is of Type A (desires more well-roundedness), the teacher should tilt technology toward the weaker skill (lower its cost); if Type B, the reverse.

Belief misspecification and the role of information. When the teacher’s beliefs $\hat{\beta}_{i(\tau)}$ diverge from the true benefit parameters $\beta_{i(\tau)}$, the chosen classroom environment Δz^* will be misaligned with students’ actual preferences. This misspecification can lead the teacher to misclassify the representative student’s type (Type A vs. B), allocating effort in directions that do not maximize student welfare. My experiment tests whether providing teachers with structured information about parent priorities—which serve as a proxy for students’ true benefit parameters—reduces this misalignment. Since the teacher applies a classroom-level policy, correcting beliefs about the representative (median) student potentially generates spillovers to other students in the class, though the direction and magnitude of these spillovers depend on each student’s position relative to the targeted type.

Remark on individual levers. If student-specific Δz_i (or student-time allocations) are feasible, then a menu $\{\Delta z_i\}$ weakly dominates any single Δz by allowing movement along each student’s own IC-normal. We treat the classroom-wide Δz as a policy benchmark: it is realistic when instruction and resources are common at the class level, and it gives sharp, testable directional predictions.

4 Data and Descriptive Statistics

4.1 Parent Survey Overview

The parent survey was administered on paper and took approximately 15-20 minutes to complete. Surveys were conducted before parent-teacher meetings, as this represented the point of greatest contact with parents. Participation was voluntary, and no compensation was offered to parents. Parents were told that the survey was being conducted to help the school better understand parent priorities and that their responses would be shared with the school and teachers either immediately (treated group) or at the end of the school year (control group). The survey was administered in English, but parents were allowed to ask for clarifications in their native language.

Motivated by the model in Section 3, the key components of the survey are the elicitation of parents’ ratings of their child’s current abilities (skill levels) and given where they perceive their child to be, their rankings of which skills are most important to improve (skill preferences). The survey also contained a rich set of parent demographics, with the full survey instrument provided in Appendix C. These measures allow us to analyze the relationship between perceived ability levels and improvement priorities, shedding light on whether observed specialization reflects production constraints or preference heterogeneity.

4.1.1 Skill Ratings

Parents were asked to rate their child's current abilities (Figure 5, Panel A) across each of the nine skill dimensions on a scale from 0 to 100, where 0 represents the “lowest level possible” and 100 represents the “highest level possible.” Respondents were explicitly instructed not to use 100 unless they believed their child had no room for improvement in that skill. This measure provides a quantitative assessment of perceived current ability levels and helps identify areas where parents perceive strengths and weaknesses in their child’s development.

Figure 5: Parent Survey Instrument

At present, how would you rate your child's...

Literacy skills	<input type="text"/>	<input type="text"/>	<input type="text"/>
Mathematical skills	<input type="text"/>	<input type="text"/>	<input type="text"/>
Scientific literacy	<input type="text"/>	<input type="text"/>	<input type="text"/>
Collaboration and teamwork skills	<input type="text"/>	<input type="text"/>	<input type="text"/>

(A) Skill Levels: 0–100 ratings of current abilities

Now consider the nine skills. Which is most important to improve? Please select one skill per column.

	1 SELECT ONE PER COLUMN (most important)	2	3	4	5	6	7	8	9 (least important)
Literacy skills	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Mathematical skills	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Scientific literacy	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Collaboration and teamwork skills	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Interpersonal skills	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Leadership and initiative	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Perseverance and growth mindset	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Emotional self-awareness and regulation	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Empathy for others	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

(B) Skill Preferences: 1–9 ranking of marginal improvement priorities

Notes: Panel A shows the 0–100 skill levels question; Panel B shows the 1–9 skill preference ranking framed as which improvement would benefit the child the most, conditional on current levels. Full wording in Appendix C.

The skill level measure is comparable to those used in other studies measuring subjective assessments of abilities (Dizon-Ross, 2019; Bergman, 2021) and allows for creating standardized measures of perceptions that can be compared across dimensions and between respondents.

4.1.2 Skill Preferences

In addition to perceived skill levels, parents were asked for their skill preferences: a ranking of the nine skills in order of importance for improvement, from most important (1) to least important (9) (Figure 5, Panel B). Parents also ranked the three broader categories (academic, social, and emotional skills) in order of importance for improvement. This forced-choice ranking methodology was designed to capture relative valuation, with the measure itself serving as a proxy for the marginal rates of substitution between different skill dimensions. In practice, since the survey was administered on paper, parents reported ties despite instructions to avoid them; we break these ties by assigning the average rank for the tied positions (e.g., if two skills are tied for 2nd place, both receive a rank of 2.5).

Asking parents to rank skills by importance offers several advantages over alternative approaches for measuring preferences for improvement. A natural alternative would be to ask parents to rate the importance of improving each skill on a Likert scale (e.g., 1–5). However, such ratings are subject to scale-use bias and often lead to ceiling effects (Chyung et al., 2020), making it difficult to discern true preference heterogeneity.

4.2 Demographics and Validation

Parent-reported skill levels display strong and systematic relationships with independently validated behavioral measures. I administered the Strengths and Difficulties Questionnaire (SDQ, Goodman (1997)), a widely-used behavioral screening tool, in the same parent survey. I find that the nine elicited skill levels correlate sensibly with SDQ subscales (Appendix Figure A.1). Higher scores on SDQ problem dimensions (emotional symptoms, conduct problems, hyperactivity, peer problems) are consistently associated with lower parent-reported skill levels across all nine dimensions, with magnitudes ranging from 1.6 to 5.1 points per standard deviation increase in the SDQ scale. Conversely, higher prosocial behavior scores predict 2.1 to 6.0 point increases in skill levels. The largest associations appear for self-awareness (up to -5.0 points for hyperactivity), perseverance (-5.1 points for hyperactivity), and empathy (+6.0 points for prosocial behavior), suggesting parents integrate diverse behavioral signals when assessing their children's capabilities. All coefficients are statistically significant at conventional levels. These patterns persist when controlling for school-by-grade fixed effects and are robust to using within-child standardized skill levels rather than raw levels. While I report raw skill level associations for interpretability, subsequent analyses employ within-student standardized measures, as the theoretical framework and experimental design focus on relative strengths across skills (specialization) rather than absolute levels.

The elicited skill preferences move sensibly with family characteristics and stated aspirations (Appendix Figure A.2). Higher-income households place relatively more weight on social skills and less on academic skills, fathers emphasize social and academic skills more and emotional skills less relative to mothers, and parents of children in higher grades prefer improving academic skills more and emotional skills less. I also examine how skill preferences vary with parents' aspirations for their child's future career, and find that parents who aspire for their child to be a mechanic or engineer place markedly higher priority on improving academics relative to those who aspire for their child to be a business leader. By contrast, priorities show no systematic relationship with child gender, birth order, or parental education. Together with the sensible demographic correlates of skill levels (Appendix Figure A.1), these validation exercises indicate that both the skill levels and skill preferences capture meaningful variation in parental perceptions rather than measurement error.

5 Preference-Level Slopes

Following Section 3, I define our empirical measure of the preference-level slope as the slope from regressing the skill preference rank assigned by parents on the corresponding standardized skill levels. We estimate two versions: (i) within a skill, across students (e.g., regressing math skill preference ranks on skill levels) and (ii) within a student, across skills (regressing the nine skill preference ranks on the nine skill levels for a given student).

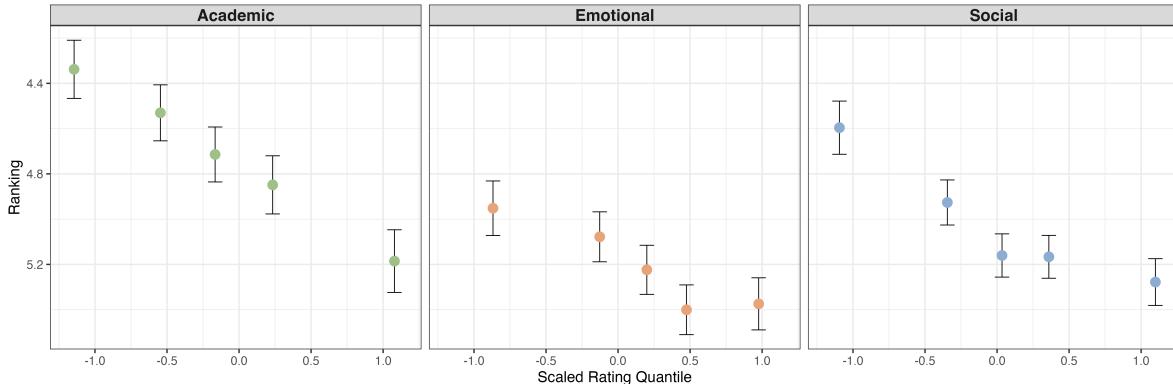
5.1 Within-Dimension Slopes (across students)

Before running regressions, I plot the raw data in Figure 6. The figure shows, for each skill, the average skill preference rank within quintiles of standardized skill levels. The y -axis is reversed so that higher values indicate higher priority (rank 1 = most important). Each point shows the mean rank within a quintile of skill levels, with 95% confidence intervals.

Maintaining the convention that higher skill preference ranks indicate higher priority I multiply the skill preference ranks by -1 so that higher values indicate lower priority (rank 1 = most important). The relationship between these transformed ranks and standardized skill levels is monotone and downward sloping for all three categories (academic, social, emotional). This is consistent with parents of students with relative weakness (negative skill levels) placing higher priority on improving that skill compared to parents of students for whom the skill is a relative strength (positive skill levels). In a pooled regressions across all dimensions, the slope is negative and precisely estimated: the slope is -0.40 (s.e. 0.024) implying that across students, a one-standard-deviation increase in the child's relative skill level is associated with a 0.46 decrease in the skill preference rank (less important to improve).

Allowing the slope to vary by skill shows that it is negative for every dimension, but that the steepness of the slopes vary. The negative slope is by far the steepest in mathematics, yet still substantial for other dimensions, and closer to zero for perseverance and science (Figure A.3). Aggregating to three categories gives an average negative slope of -0.42 (s.e. 0.037), and shows that they similarly vary by category: steepest for academic skills (-0.48 , s.e. = 0.050), similarly steep for social skills (-0.44 , s.e. = 0.047), and less steep for emotional skills (-0.35 s.e. 0.053) for emotional skills.

Figure 6: Average Parent Skill Preference Rank Within Skill Level Quintile



Notes: Figure shows average parent skill preference rank within quintiles of standardized skill levels, by category. Higher values on the y -axis indicate higher parental priority (rank 1 = most important). Points show quintile means; bars show 95% confidence intervals.

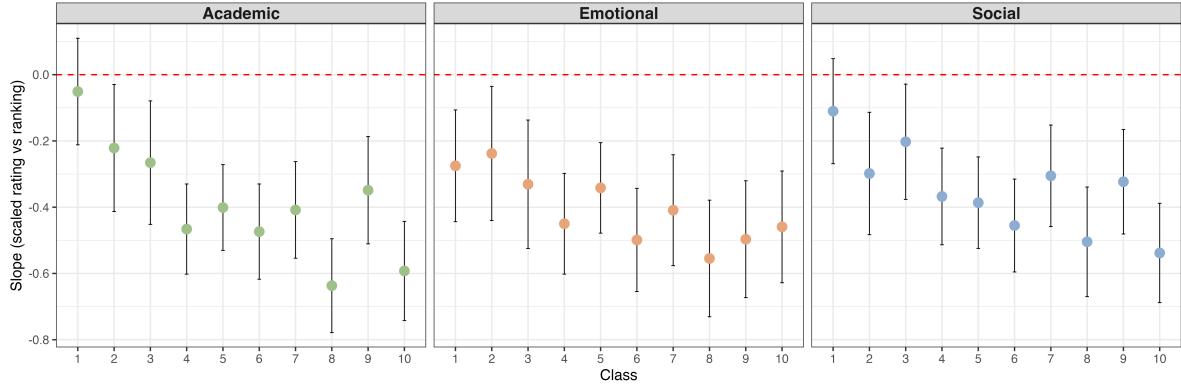
Through the lens of the model, these patterns imply that across students, variation in who specializes in a given skill is driven by differences in production constraints as opposed to differences in real or perceived benefits. I find that this is more true for academic skills than for social or

emotional skills, consistent with either (i) production constraints being relatively more dominant for academic skills, or (ii) variation in benefits being more dominant for social and emotional skills.

5.2 Heterogeneity by grade

Next, we examine whether the preference-level slope varies by grade. We estimate the slope separately for each grade and plot the results in Figure 7. The slope is negative in every grade, yet indistinguishable from 0 for classes 1 and 2, and increasingly negative reaching between -0.5 to -0.7 for grades 9-10. This pattern suggests that specialization driven by production constraints becomes more pronounced as children age, consistent with the idea that as children grow, the costs of improving weaker skills relative to stronger skills become more prominent drivers of specialization. This may reflect both increasing differentiation in the cost of producing skills as students age, or the benefits to skills becoming more similar as students approach upper secondary school.

Figure 7: Preference-Level Slope by Grade



Notes: Figure shows estimated preference-level slope by grade. Each point is the slope from a regression of skill preference ranks on skill levels, estimated separately for each grade-skill pair. Bars show 95% confidence intervals.

5.3 Within-Student Slopes (across dimensions)

I now turn to the within-student preference-level slopes, which measure how a child's skill levels relate to parents' skill preferences across dimensions. We estimate within-student preference-level slopes by regressing skill preference ranks on the associated skill levels, for each parent. The average within-student slope is *negative* (-0.43), with wide dispersion across students ($SD = 1.25$). This indicates that within a given child, skills that parents prefer to improve most tend to be those where they perceive their child to be weaker, consistent with specialization driven by production constraints rather than by differences in benefits.

I relate this slope to parental satisfaction to gauge whether observed specialization aligns with perceived benefits. I compare the preference-level slope to two satisfaction measures: (i) satisfaction with the child's progress and (ii) satisfaction with the school overall. Both are measured on a four-point scale from "completely satisfied" to "completely dissatisfied." Regressing an indicator for being completely satisfied on the within-student slope shows that more positive slopes (indicating

more aligned skill levels and skill preferences) are associated with higher satisfaction with the child's progress (coefficient 0.019, s.e.=0.008), but not with satisfaction with the school (coefficient 0.003, s.e. 0.010). The marginal effect is economically meaningful: going from the most negative slope observed (-3.15) to the most positive slope (3.54) raises the probability of being completely satisfied with the child's progress by 12.7 percentage points (baseline mean = 52%).

In the model, more positive within-student slopes indicate that the child's current mix of skills aligns more closely with the parent's marginal benefits-what they most want improved. Geometrically, this is what we expect when the child's natural expansion path is closer to the indifference-curve normal, so incremental learning goes in a direction that raises utility fastest. Practically, parents report higher satisfaction with their child's progress when observed specialization lines up with what they value, while the lack of correlation with satisfaction about the school suggests the slope captures a dynamic growth alignment rather than static school quality. These patterns reinforce the cost-side reading of the average negative preference-level slope in this setting and motivates the information experiment that follows.

6 Information Experiment

The cross-sectional evidence points to cost-side forces as a central driver of specialization. If so, a production-side shock that helps teachers target instruction where parents place the highest marginal value should shift students' portfolios toward parent-prioritized skills. We test these predictions in a teacher-facing information experiment.

6.1 Teacher Survey

The teacher survey was administered online at baseline and at endline using Qualtrics. It collected comprehensive information about teachers' professional backgrounds, pedagogical philosophies, and most importantly, their skill preferences for (i) a typical student, (ii) specific individual students in their class, and (iii) their beliefs about how parents would rank skill priorities for those same students. Descriptions of the full survey instrument is provided in Appendix C.

6.1.1 Teacher Demographics and Professional Background

The survey collected standard demographic and professional information including gender, education level, years of teaching experience, and tenure at the current school. This baseline information allows analysis of how teacher characteristics influence their beliefs about student development priorities and their responsiveness to information about parent preferences.

6.1.2 Teaching Philosophy and Self-Efficacy

To understand the context within which teachers make instructional decisions, the survey measured teachers' views on their professional responsibilities and their self-efficacy across different teaching domains.

Teachers rated the importance of various responsibilities (e.g., improving student academic achievement, incorporating parent priorities, managing student behavior) on a five-point scale from “Not important” to “Extremely important.” This provides insight into how teachers conceptualize their role and the relative weight they place on different aspects of their job.

A validated teacher self-efficacy scale was also included, with items such as “How much can you do to control disruptive behavior in the classroom?” and “How much can you do to motivate students who show low interest in school?” Teachers responded on a nine-point scale ranging from “Nothing (1)” to “A great deal (9).” This scale measures teachers’ beliefs about their ability to influence various student outcomes, which may mediate teachers’ responsiveness to information about parent preferences.

6.1.3 Rankings for Students

The core component of the teacher survey paralleled the parent skill preference questions, but with three distinct variations designed to assess alignment between teachers and parents, and to measure how teachers form beliefs about parent preferences. First, teachers ranked the nine skill dimensions for a typical student they encounter in their teaching. This provides a baseline measure of teachers’ general pedagogical priorities. Second, for six specific students, teachers provided skill preference rankings based on their own professional judgment about what each individual student needed most. Students were selected through stratified random sampling based on the parent survey. Two students were chosen from families prioritizing academic, social, and emotional skills, respectively.

The first two variants captured teachers’ own assessment of individual student needs. In cases where fewer than six students had parent survey data, all available students were included. The third variant is distinct in eliciting teachers’ *beliefs* about parent preferences: for the same six students, teachers were asked to predict how they believed each student’s parent would rank the skill development priorities. This measure enables direct comparison between teachers’ beliefs about parent skill preferences and parents’ actual stated skill preferences.

Teacher responses reveal several striking patterns in the baseline data. Teachers demonstrate remarkably poor calibration about individual parent preferences: the correlation between teacher beliefs about parent rankings and actual parent rankings is close to zero. More systematically, teachers appear to project their own professional priorities onto parents, which I discuss in more detail in Section 7. The teacher ranking data also shows that while parents tend to prioritize academic skills most highly, teachers’ own professional priorities tilt more toward social and emotional development. I show the full distribution of teacher rankings in Appendix Figure A.4. This preference divergence, combined with teachers’ poor beliefs about parent preferences, creates substantial scope for misalignment between classroom instruction and family priorities.

This baseline misalignment provides the foundation for testing whether structured information provision can improve teacher-parent alignment and ultimately shift student outcomes. The experimental design leverages the fact that teachers have systematically biased beliefs about parent preferences, making information provision potentially valuable even in a context where formal

communication channels already exist between teachers and families.

6.1.4 Pedagogical Strategies for Skill Development

In addition to uncertainty over parent preferences, teachers also face uncertainty about how to effectively develop the skills they prioritize. Therefore, the teacher survey included a component designed to elicit teachers' beliefs about effective pedagogical strategies for developing each of the nine skill dimensions. This component was informed by the literature on social and emotional learning (SEL) and evidence-based teaching practices.

For each of the six social and emotional skill dimensions, teachers were presented with four evidence-based teaching strategies, and were then asked to rank these strategies from most effective (1) to least effective (4) based on their professional judgment. A full list of the strategies presented is provided in Appendix Section [C](#).

This component of the survey enabled the creation of a second treatment in which teachers receive an aggregated report on the effectiveness of pedagogical strategies based on the collective responses of teachers within their school. As described in the experimental design section, this second treatment was cross-randomized with the first treatment, which provided teachers with information about parent skill levels and skill preferences.

6.2 Experimental Design

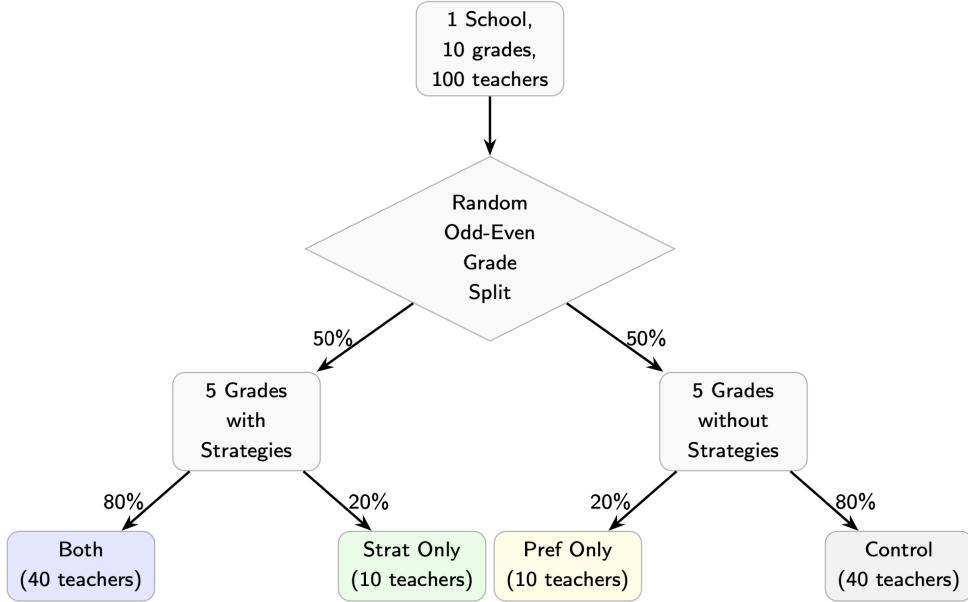
The experimental design addresses two key questions: (1) Do teachers update their beliefs and behaviors when provided with information about parent preferences? and (2) Does supplementing this preference information with concrete pedagogical strategies enhance teacher responsiveness? To answer these questions while minimizing spillover concerns, I employ a two-stage randomization design at the school-grade and teacher levels:

6.2.1 First Stage: Grade-Level Randomization

The first level of randomization occurs at the grade level within each school. Grades are randomly assigned to either receive or not receive pedagogical strategies for developing different skill dimensions. This design choice is motivated by the hypothesis that teachers primarily communicate with other teachers in their grade at the same school, making grade-level assignment a natural boundary to prevent spillover.

To further ensure the Stable Unit Treatment Value Assumption (SUTVA) holds, I implement an odd/even grade split, where odd-numbered grades (1, 3, 5, 7, 9) in a school are assigned to one condition and even-numbered grades (2, 4, 6, 8, 10) to the other. This spatial separation minimizes the risk of treatment contamination, as teachers in adjacent grades typically have fewer opportunities for professional interaction than teachers within the same grade.

Figure 8: Treatment Assignment



6.2.2 Second Stage: Teacher-Level Randomization

Within each grade, I then randomize at the classroom (teacher) level whether teachers receive information about parent preferences. This information includes aggregated data on how parents of students in their specific class rate their children's current abilities and rank the importance of improving each dimension.

To maximize statistical power for the primary comparison (receiving both treatments versus receiving neither), I employ an unbalanced randomization:

- In grades assigned to receive strategies: 80% of teachers are randomly selected to also receive parent information, while 20% receive only strategies
- In grades assigned not to receive strategies: 20% of teachers are randomly selected to receive parent information, while 80% receive neither treatment

This allocation results in approximately 40% of teachers receiving both treatments, 40% receiving neither, and 10% receiving each treatment alone, providing optimal power for the main comparison while still allowing for tests of individual treatment effects. I show the randomization achieved balance across teacher and student characteristics in Appendix Table [B.3](#).

6.3 Implementation Through Web Portal

The intervention is delivered through a custom-built web portal that provides teachers with access to treatment information in an intuitive, user-friendly format. To encourage proper implementation, we conducted demonstration sessions with all teachers, illustrating how the information tool could be used to understand parent preferences and potential ways to incorporate these insights into

their teaching approaches. These sessions focused on navigating the website, interpreting the visualizations of parent preferences, and connecting these preferences to pedagogical strategies. School administrators were appointed as points of contact to address any questions or challenges teachers might encounter while using the tool.

6.3.1 Access and Authentication

Each teacher receives individual login credentials via email, with access restricted to their assigned treatment condition. The portal uses secure authentication to ensure teachers can only view information relevant to their treatment status. This individualized access allows for precise tracking of teacher engagement with the intervention, including login frequency, pages viewed, and time spent on different components of the portal.

6.3.2 Interface and Content

The portal presents information through several organized tabs:

1. **Welcome:** Provides an introduction to the portal and navigation instructions, with content tailored to the teacher's treatment assignment
2. **Class Overview (Parent Information):** This tab provides a classroom overview. Each row corresponds to a student, and the columns show which skill category (academic, social, or emotional) each parent identified as most important for improvement, along with the parent's perceived skill levels for their child. The table is sorted by default so that rows are grouped by the parents' top skill priority. The skill category with the most parents prioritizing it is highlighted at the top, allowing teachers to quickly identify common themes in parent preferences within their class. A sample rendering is shown in Figure 9, Panel A.
3. **Student Reports (Parent Information):** This tab shows the full student-level reports. Each report includes the parent's skill levels (ratings of current abilities) across all nine dimensions, as well as the parent's skill preference ranking of which skills are most important to improve. The report features both tabular data and interactive visualizations to help teachers quickly grasp each student's unique profile. An example student report is shown in Figure 9, Panel B.
4. **Classroom Report (Parent Information):** Presents the same information as the student reports, but averaged at the classroom level. This summary enables teachers to see overall patterns in parents' perceptions and priorities.
5. **Strategies for Improvement (Strategy Information):** This tab summarizes the

Figure 9: Web-Portal Displays

Parents' most important skills to improve for each student

Ratings scored from 0-100.
Positive (green) numbers means better than average, and negative (red) numbers means worse than average.

Student	Most important skills	Parent rating
Christopher Harris	Emotional	52
Kylie Ferguson	Emotional	47
Bernadette Walsh	Emotional	60
Ruth Terry	Emotional	46
Amanda Ogden	Emotional	58
Stewart Langdon	Emotional	58
Heather Reid	Emotional	57
James Walker	Emotional	52
Emma Dyer	Academic	56
Gordon Sharp	Academic	59
Olivia Bond	Academic	37
Rachel Dyer	Academic	40
Tim Grant	Social	39
Joseph Rampling	Social	46
Joe Quinn	Social	42

(A) Class Overview

According to Bernadette Walsh's parent, the most important skill for them to improve is **collaboration and teamwork skills**.

Bernadette Walsh

Parent ratings: Scored from 0-100.

Ranking: How valuable it is to improve for this student. Lower rank = more important

Category	Ability	Parent rating	Ranking
Social	Collaboration and teamwork skills	33	1
Emotional	Empathy for others	77	2
Academic	Literacy skills	53	3
Emotional	Emotional self-awareness and regulation	31	4
Social	Leadership and initiative	39	5
Emotional	Perseverance and growth mindset	71	6
Academic	Mathematical skills	82	7
Academic	Scientific literacy	57	8
Social	Interpersonal skills	56	9

(B) Student Report

Notes: Panel A shows the class overview tab; Panel B shows an example student report. Names and numbers randomly generated, but visual layout is identical to the actual portal.

Figure 10: Example Strategies Report

Strategies for improving Interpersonal skills

Strategy	Average ranking	Share teachers ranked #1 (most effective)	Description
Classroom circles	2.3	35 %	In classroom circles, students and teachers form a physical circle for open discussions about a variety of topics including personal feelings, conflict resolution, or community building, aimed at fostering a supportive environment.
Role-playing exercises	2.3	29 %	Students take on roles in predefined scenarios, acting out interactions to explore interpersonal dynamics and learn through feedback. Scenarios can include various contexts from conflict resolution to collaborative tasks.
Service-Learning Projects	2.7	20 %	Involve students in group-based projects that address community needs, linking classroom objectives with real-world applications. Tasks include planning, executing, and reflecting on their projects.
Think-Pair-Share	2.7	16 %	Teachers pose a question. Students think independently, then pair up to discuss with a partner, providing feedback on each other's work. Finally, they share with the class, encouraging participation and collaborative problem-solving.

Notes: Example of the strategies report tab, showing pedagogical strategies for developing interpersonal skills. All six socio-emotional skills are included. Each has four associated pedagogical strategies. Numbers displayed are specific to the school, and are calculated based on teacher rankings of strategy effectiveness collected at baseline.

The portal's design facilitates easy interpretation of parent preferences through color-coded visualizations and clear tabular formats. For instance, skill dimensions are consistently color-coded by category (green for academic, orange for emotional, blue for social), and skill levels employ a red-yellow-green color scale to highlight areas of strength and opportunity. Skill preferences are presented as ranked lists to clearly communicate relative priorities.

In the strategies section, teachers can access specific, actionable pedagogical approaches for each non-cognitive skill. These strategies include brief descriptions and implementation guidance, along with indicators of how commonly other teachers ranked each strategy as most effective.

6.4 Treatment Implementation and Compliance

The information intervention was implemented through a custom-built web portal that provided teachers with individualized login credentials and access to their students' parent-reported skill levels and priority rankings. The platform tracked comprehensive usage data including login frequency, session duration, and specific content accessed.

Implementation proceeded differently across the five participating schools. While 242 teachers were initially assigned to treatment across all schools, practical challenges emerged that significantly affected compliance and data collection. Two schools withdrew from the study entirely before endline data collection. Two additional schools either failed to distribute login credentials to their teachers or achieved login rates below 15%.

The main results presented here focus on the one school (100 classrooms) that successfully implemented the intervention. Even in this successful implementation, compliance was limited: only 46% of treated teachers logged into the platform at least once during the intervention period. Among those who did access the platform, usage varied substantially, with some teachers making single brief visits while others engaged more systematically with the content.

Interestingly, the school's administration responded to the baseline parent survey results by implementing school-wide assemblies and developing lesson plans aimed at addressing the skill priorities identified in the parent data. This represents a form of treatment spillover that likely affected both treatment and control teachers within the school, potentially attenuating measured treatment effects while demonstrating the policy relevance of the parent preference information.

The low compliance rate and administrative response highlight important features of information interventions in educational settings. Teachers face multiple competing demands on their attention, and information provision alone may be insufficient without accompanying incentives or administrative support. Nevertheless, the experimental results suggest that even partial compliance can generate meaningful changes in student outcomes, consistent with the hypothesis that information about parent priorities can serve as a low-cost production shock that reallocates instructional effort toward high-value dimensions.

7 Teacher Beliefs and Updating

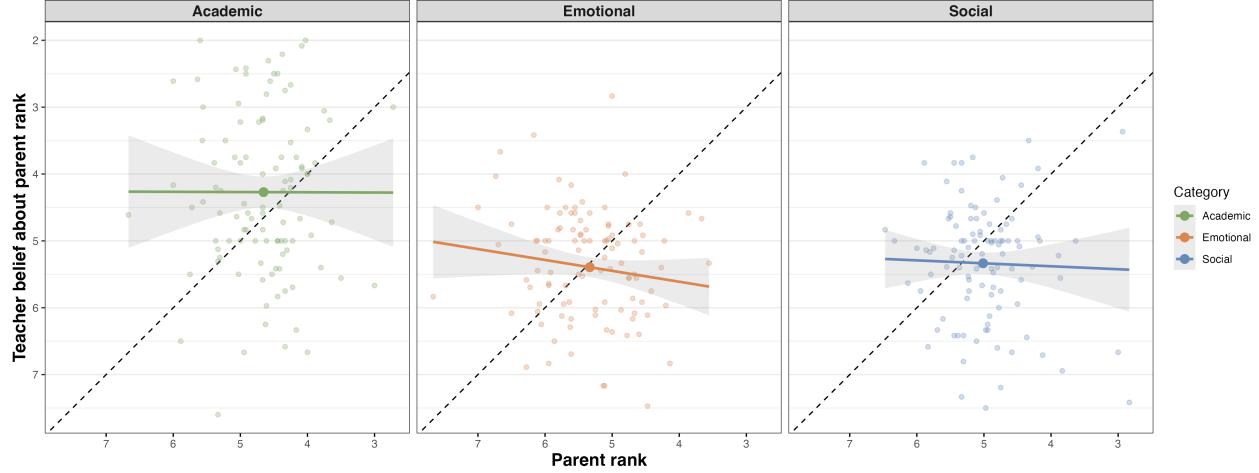
Before turning to treatment effects on student outcomes, I document two facts about teacher beliefs at baseline, and test whether the information intervention improved belief accuracy.

Baseline misalignment. Teachers were asked, for a random subset of students, to predict how that student's parent would rank the importance of improving the nine academic, emotional, and social skills (skill preferences).⁷ To reduce noise and focus on broad priorities, I group the nine skills into three categories (academic, social, emotional) and average skill preferences within each category. Figure 11 plots, for each classroom, the average parent skill preference rank (x-axis) against the average teacher belief about parents skill preference (y-axis) for the sampled students. At baseline, beliefs are essentially uncorrelated with truth: points scatter around a flat line. In other words, even in these relatively well-resourced schools with routine parent-teacher meetings, teachers had little signal about what parents most wanted improved.

Where do baseline beliefs come from? Projection. To probe how teachers form beliefs when they lack signal, Figure 12 keeps the same y-axis (average teacher belief about parents) but replaces the x-axis with the teacher's own skill preference ranking (averaged across the same students). A strong positive relationship emerges, indicating teachers project their own priorities onto parents. This is consistent with the model's misperception channel: in the absence of reliable information on parents' skill preferences, teachers substitute their own ranks for the parent's, creating scope for misallocation even when classroom effort is intended to reflect parental priorities.

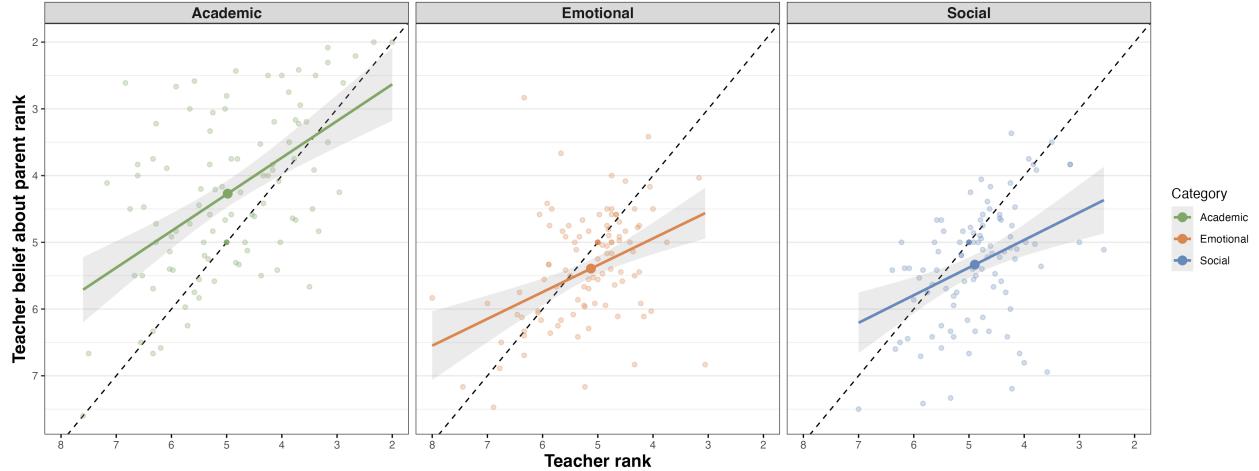
⁷Although ties were discouraged in the instructions, the parent survey was conducted on paper, so skill preference ranks allowed ties; teacher elicitation mirrored this.

Figure 11: Baseline Teacher Beliefs vs. Parent Skill Preferences (Class Averages)



Notes: $N_{\text{parent}} = 550$. $N_{\text{teacher}} = 103$. Each point represents one classroom, with skill preferences averaged across the sampled parents. For each classroom, six parents are sampled (two each from parents prioritizing academic, social, and emotional skills). If less than six parents completed the survey for a given classroom, all available students are included. The x-axis shows the average parent skill preference rank for each classroom; the y-axis shows each teacher's beliefs about parents' skill preferences averaged over the same students. Perfect accuracy would lie on the 45-degree line (dashed).

Figure 12: Baseline Teacher Beliefs vs. Teachers' Own Priorities (Class Averages)



Notes: $N_{\text{parent}} = 550$. $N_{\text{teacher}} = 103$. Each point represents one classroom, with skill preferences averaged across the sampled parents. For each classroom, six parents are sampled (two each from parents prioritizing academic, social, and emotional skills). If less than six parents completed the survey for a given classroom, all available students are included. The x-axis shows each teacher's own skill preferences for the sampled students; the y-axis shows each teacher's beliefs about parents' skill preferences for the sampled students. Perfect accuracy would lie on the 45-degree line (dashed).

Measuring accuracy. I operationalize accuracy with four binary outcomes: (i) *Exact Order Match* (teacher's full ranking equals the parent's, ties allowed); (ii) *Top Skill Match* (teacher in-

cludes at least one of the parent’s top-ranked categories among the top); (iii) *Bottom Skill Match* (analogous for the bottom); and (iv) *Top & Bottom Match* (both ends correct). I study accuracy at two levels: (a) student-level: does the teacher correctly predict an individual parent’s ranking?—and (b) classroom-average: does the teacher correctly identify the average parent’s priorities in her class?

Does information correct beliefs? First-stage evidence. Tables 2–4 report intent-to-treat effects of providing teachers the parent rankings and levels via the website (Section 6). The analysis is underpowered due to implementation constraints ($N = 94$ teachers), so I emphasize direction and magnitude.

Student-level accuracy. At the individual student level, point estimates are indistinguishable from zero and, if anything, slightly negative (Table 2). For example, the ITT on *Top Skill Match* is -0.0165 (s.e. 0.0675), with similar nulls for other outcomes. There is strong persistence in accuracy (baseline-to-endline), but no detectable treatment effect. This suggests that even with information, teachers did not reliably memorize or track each parent’s unique ranking for the sampled students.

Classroom-average accuracy. By contrast, when I aggregate to the classroom mean ranking (“what does the average parent in my class want?”), treatment effects turn positive and economically meaningful, though imprecise (Table 3). ITT estimates are on the order of 9–10 percentage points for *Top Skill Match* and *Bottom Skill Match* (e.g., $+0.0918$ and $+0.1017$), with similar magnitude for *Top & Bottom Match* ($+0.1028$). While not statistically significant, these effect sizes are large relative to control means (0.27–0.46), consistent with teachers updating their mental model of the typical parent in the class.

Heterogeneity by what parents value most. Table 4 splits classrooms by which category parents most often rank top. Patterns are intuitive: (i) in classrooms where academics is the top priority on average, teachers improve in pinning down the top category (ITT on *Exact Order Match* $+0.199$; *Top Skill Match* $+0.145$); (ii) where social or emotional skills are the top classroom priority, teachers become more accurate about the bottom category (ITT on *Bottom Skill Match* $+0.185$ for social; $+0.115$ for emotional). A natural reading is that information helped teachers correctly locate where academics sits in the average parent’s priority ordering—on top in some classes, lower in others.

At baseline, teacher beliefs about parent priorities were largely noise and heavily colored by projection. The intervention did not make teachers precise about each parent, but it nudged them toward a more accurate picture of the average parent in their class, especially about the relative place of academics. In the model, this matters because teacher policy is a classroom-level cost tilt: getting the class-average benefits right moves the frontier in the direction that better aligns growth with what families value, even if idiosyncratic values are harder to track.

Table 2: Treatment Effects on Teacher Accuracy about Specific Parents

Dependent Variables	Exact Order Match	Top Skill Match	Bottom Skill Match	Top & Bottom Match
	(1)	(2)	(3)	(4)
<i>Variables</i>				
Treated	-0.0111 (0.0291)	-0.0165 (0.0675)	-0.0194 (0.0774)	-0.0267 (0.0774)
Baseline Accuracy	0.2638*** (0.0662)	0.2845*** (0.0552)	0.2013*** (0.0546)	0.2746*** (0.0540)
<i>Statistics</i>				
Observations	482	482	482	482
R ²	0.07583	0.13548	0.07613	0.12501
Control Mean	0.1292	0.6667	0.6333	0.5542

Notes: Outcomes are parent-level indicators for whether a teacher's belief matches a given parents' ranking of skills (academic, emotional, social). *Exact Order Match* = 1 if the teacher's full ranking matches the parents' ranking, including ties (e.g., parent 1–2–2 requires teacher 1–2–2). *Top Skill Match* = 1 if the teacher identifies at least one of the parent's top-ranked skills as top. *Bottom Skill Match* = 1 if the teacher identifies at least one of the parent's bottom-ranked skills as bottom. *Top & Bottom Match* = 1 if both top and bottom categories are correctly identified. “Treated” indicates teachers who received information about parent rankings and levels. “Baseline accuracy (same outcome)” is the coefficient on the corresponding baseline measure of that outcome.

Standard errors in parentheses, clustered at the class level

Significance Codes: ***: 0.01, **: 0.05, *: 0.1

Table 3: Treatment Effects on Teacher Accuracy about Classroom Average

Dependent Variables	Exact Order Match	Top Skill Match	Bottom Skill Match	Top & Bottom Match
	(1)	(2)	(3)	(4)
<i>Variables</i>				
Treated	0.0351 (0.0988)	0.0918 (0.1452)	0.1017 (0.1376)	0.1028 (0.1224)
Baseline Accuracy	0.3613*** (0.1283)	0.2448** (0.1134)	0.2439** (0.1034)	0.3019*** (0.1071)
<i>Statistics</i>				
Observations	94	94	94	94
R ²	0.17440	0.09531	0.18254	0.15772
Control Mean	0.1450	0.4618	0.4122	0.2710

Notes: Dependent variables are indicators for the accuracy of teacher beliefs about parents' skill rankings (academic, emotional, social). Grade fixed effects included in all specifications. *Exact Order Match* = 1 if the teacher's full ranking matches the parents' ranking, including ties (e.g., parent ranking 1–2–2 requires teacher belief 1–2–2). *Top Skill Match* = 1 if the teacher identifies at least one of the parent's top-ranked skills as top. *Bottom Skill Match* = 1 if the teacher identifies at least one of the parent's bottom-ranked skills as bottom. *Top & Bottom Match* = 1 if both top and bottom categories are correctly identified. “Baseline accuracy” is the coefficient on the corresponding baseline measure of that outcome. “Treated” indicates whether the teacher received information about parent rankings and levels.

Clustered standard errors in parentheses

Significance Codes: ***: 0.01, **: 0.05, *: 0.1

Table 4: Treatment Effects on Teacher Accuracy about **Classroom Average** by Parent Top Priority

Dependent Variables	Exact Order Match	Top Skill Match	Bottom Skill Match	Top & Bottom Match
	(1)	(2)	(3)	(4)
<i>Variables</i>				
Treated: Parents' Top = Academic	0.1987 (0.1239)	0.1453 (0.1820)	-0.0025 (0.1693)	0.0639 (0.1585)
Treated: Parents' Top = Social	-0.0878 (0.1056)	0.0884 (0.1733)	0.1846 (0.1673)	0.1196 (0.1455)
Treated: Parents' Top = Emotional	-0.0396 (0.1020)	-0.0503 (0.2385)	0.1150 (0.2263)	0.1608 (0.2149)
Baseline Accuracy	0.3097** (0.1223)	0.2100* (0.1234)	0.2666** (0.1032)	0.3152*** (0.1094)
<i>Statistics</i>				
Observations	94	94	94	94
R ²	0.22938	0.10416	0.19377	0.16074
Control Mean	0.1450	0.4618	0.4122	0.2710

Notes: Dependent variables are indicators for the accuracy of teacher beliefs about the class average of parents' skill rankings (academic, emotional, social). Grade fixed effects included in all specifications. *Exact Order Match* = 1 if the teacher's full ranking matches the class average ranking, including ties (e.g., parents 1–2–2 requires teacher 1–2–2). *Top Skill Match* = 1 if the teacher identifies at least one of the parent's top-ranked skills as top. *Bottom Skill Match* = 1 if the teacher identifies at least one of the parent's bottom-ranked skills as bottom. *Top & Bottom Match* = 1 if both top and bottom categories are correctly identified. Rows labeled "Treated: Parents' Top = Academic/Social/Emotional" correspond to classrooms where the teacher received information about parent rankings and levels, estimated separately by the parents' top-ranked category. Coefficients are intent-to-treat effects relative to control classrooms in the same category. "Baseline accuracy" is the coefficient on the corresponding baseline measure of the same outcome.

Clustered standard errors in parentheses

Significance Codes: ***: 0.01, **: 0.05, *: 0.1

8 Student Outcome Results

We focus on three outcomes that map directly to the model:

(1) Skill levels increase for parents most preferred skill category when teachers were initially inaccurate. Panel 1 of Figure 13 shows that the average intent-to-treat (ITT) effect on parents' skill levels is close to zero. However, this masks important heterogeneity. Panel 2 plots the interaction between treatment and teachers' baseline inaccuracy. Teacher inaccuracy is calculated as the absolute difference between the teacher's belief about how a given parent ranks a skill and the parent's actual ranking. Therefore, the gap varies depending on the teacher-parent-skill triple, with higher gap indicating the teacher was more incorrect about how much that parent valued improving that skill. The coefficient on the interaction is +0.07 (s.e. 0.03) for the category parents rated most important and -0.09 (s.e. 0.03) for the least important, both statistically significant.

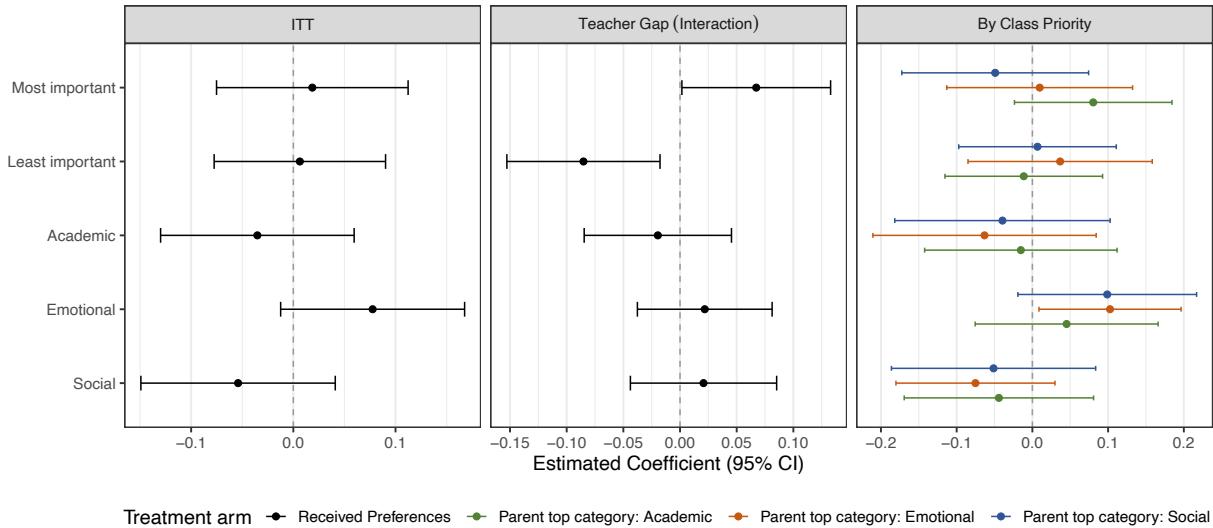
Panel 3 splits effects by which category parents, on average, valued most across the classroom. For example, "Parent top category: Academic" compares control to treated classrooms where par-

ents, on average, most preferred improving academic skills. Coefficients are larger when parents prioritized academics (0.08, s.e. 0.05) than social or emotional skills. This likely reflects that teachers can more readily reallocate effort in academics, that our belief updating analysis showed they learned more precisely where academics ranked, and that schools were already running universal social-emotional programming, making new information about academic preferences especially actionable.

Figure 14 visualizes heterogeneous treatment effects as a function of the baseline parent-teacher gap. Strikingly, when teachers were initially accurate (gap = 0), treatment effects run counter to the intended direction in both panels: skill levels decrease in parents' most important category (-0.25 SDs, s.e. 0.14, $p=0.09$, Panel 1) and increase in parents' least important category (0.30 SDs, s.e. 0.12, $p=0.02$, Panel 2). However, as baseline misalignment grows, effects reverse in the intuitive direction. For parents' most important category, treatment effects become positive around gap = 4 (the 75th percentile), though coefficients remain marginally significant at the 10% level. For parents' least important category, treatment effects turn negative at moderate gaps and become significantly so at higher levels of misalignment, reaching -0.39 SDs (s.e. 0.19, $p=0.04$) at gap = 8.

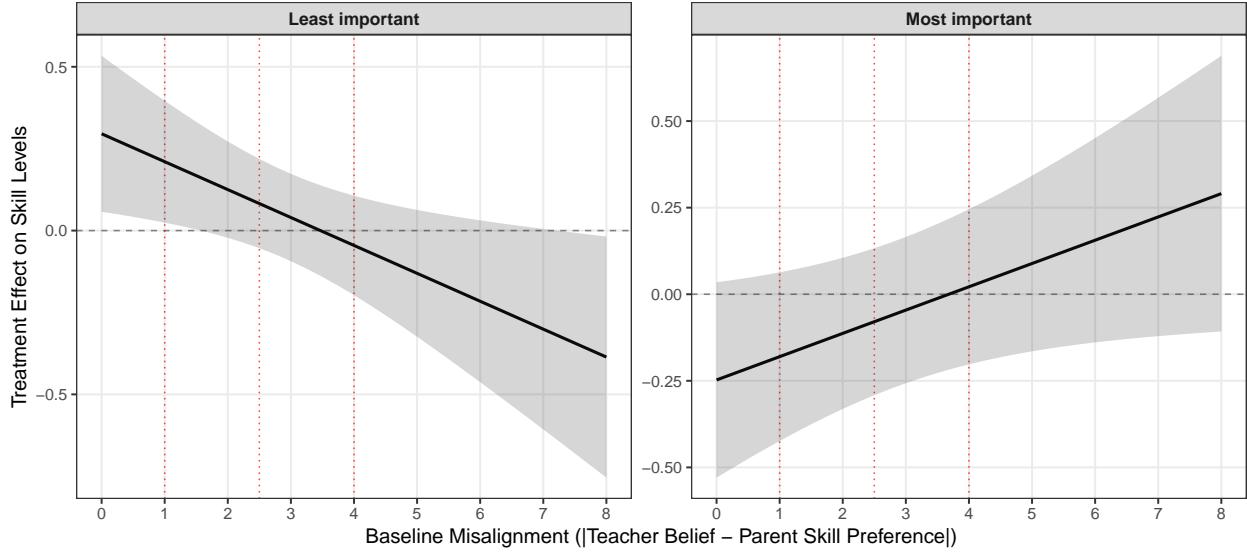
These patterns are consistent with classroom-level reallocation: teachers initially allocated effort toward students they thought they understood; upon learning the true distribution of parent priorities, they shifted effort toward previously misaligned students, sometimes at the expense of those they had correctly matched. Since most students fall in the middle of the gap distribution (median = 2.5), the average treatment effect masks offsetting movements—teachers reallocating from well-matched to poorly-matched students within the same classroom.

Figure 13: Treatment Effects on Skill Levels



Notes: $N = 823$ parents. Outcome is skill levels (standardized within-student). Estimates control for grade fixed effects; standard errors clustered at the classroom level. Panel 1 shows ITT effects; Panel 2 interacts treatment with the baseline teacher-parent gap (higher gap = teacher more incorrect); Panel 3 splits treatment by which category parents valued most. For example, “Parent top category: Academic” compares control to treated classrooms where parents’ average top priority was academic skills.

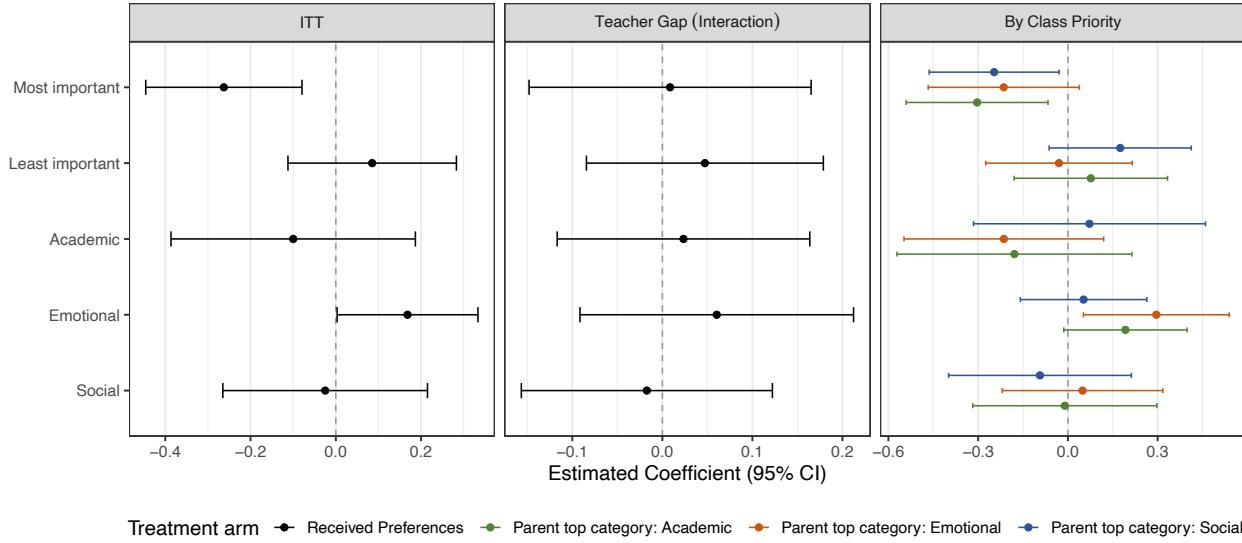
Figure 14: Treatment Effects by Baseline Teacher Accuracy



Notes: $N = 823$ parents. Treatment effects are for skill levels (standardized within-student). Treatment effects control for grade fixed effects with standard errors clustered at the classroom level. Panel 1 shows effects for the category parents rated least important; Panel 2 for the most important. The x-axis is the baseline teacher-parent gap (higher gap = teacher more incorrect). The solid line is the marginal effect of treatment estimated from a regression of the outcome on treatment, the gap, and their interaction; the shaded area is the 95% confidence interval. The red dashed lines show the 25th, 50th, and 75th percentiles of the gap distribution.

(2) Skill preferences fall for parents' most preferred skill category. Panel 1 of Figure 15 shows a clear average intent-to-treat (ITT) effect on parents' skill preferences; in treated classrooms, the skill parents had most preferred falls 0.26 skill preference ranks (s.e. 0.09, $p=0.006$) relative to control. This pattern is consistent with teachers, once informed of parent priorities, making it easier for students to develop those skills, and parents subsequently judging them less in need of work. Panel 2 plots treatment interacted with the baseline teacher-parent gap; the interaction coefficients are small and imprecise (-0.02 to 0.05), indicating that, unlike the skill levels outcome, parents' shift in rank orderings does not vary systematically with how wrong teachers were at baseline. Column 3 splits treated classrooms by the category parents prioritized most, on average. In line with the treatment effects for skill levels, the decreasing in skill preference rank is largest when parents' top priority was academics (-0.30 ranks, s.e. 0.12, $p=0.014$), somewhat smaller for social (-0.25 ranks, s.e. 0.11, $p=0.028$), and positive but only marginally significant for emotional (-0.21, s.e. 0.13, $p=0.099$). This suggests that teachers most effectively re-oriented classroom effort when the desired skills were academic, where they have more control and, as our updating analysis showed, learned most clearly how academics compared to other skills.

Figure 15: Treatment Effects on Skill Preference Ranks

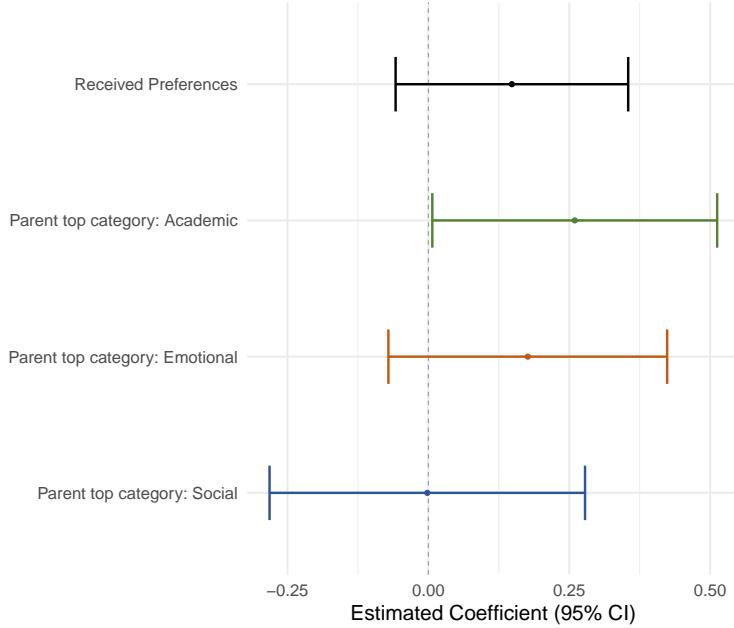


Notes: $N = 823$ parents. Skill preference ranks (1-9) multiplied by -1 so higher values indicate more preferred skills. Estimates control for grade fixed effects; standard errors clustered at the classroom level. Panel 1 shows ITT effects; Panel 2 interacts treatment with the baseline teacher-parent gap (higher gap = teacher more incorrect); Panel 3 splits treatment by which category parents valued most. For example, “Parent top category: Academic” compares control to treated classrooms where parents’ average top priority was academic skills.

(3) Preference-Level Slope shifts upward for treated students. Recall from Section 5 that we estimate the within-student preference-level slope by regressing each parent’s skill preference ranking on standardized skill levels; a more positive slope means the parent prefers improvement in skills to be stronger. Figure 16 shows that the average intent-to-treat (ITT) effect on this slope is positive though only marginally precise: +0.15 (s.e. 0.11, $p=0.162$). We are not able to interact treatment with the baseline teacher-parent gap for the preference-level slope outcome because the slope is estimated at the student level, not the student-skill level. However, as in our analysis of skill levels and skill preferences, we split treatment effects by which category parents prioritized most, on average, in their class.

Splitting treatment by parents’ modal top category show the effect is largest and statistically significant in academic-priority classrooms (+0.26, s.e. 0.13, $p=0.047$), essentially zero for social (-0.00, s.e. 0.14, $p=0.990$), and positive but imprecise for emotional (+0.18, s.e. 0.13, $p=0.165$). Together with the skill levels and skill preference results, this pattern suggests that when teachers learn parents’ priorities, and in particular academics, they reconfigure the classroom so it is easier for students to build the skills parents value, making students’ observed skill profiles better aligned with parental preferences rather than with underlying production cost constraints.

Figure 16: Treatment effect on preference-level slope



Notes: $N = 823$ parents. Estimates control for grade fixed effects; standard errors clustered at the classroom level. ITT effects at the top; Treatment effects split by which category parents valued most at the bottom. For example, “Parent top category: Academic” compares control to treated classrooms where parents’ average top priority is academic skills.

Taken together, these findings fit the framework: information to teachers acts as a production shock that selectively lowers the effective cost of building parent-prioritized skills. By reshaping the classroom environment rather than only tailoring instruction to individual students, teachers enable more progress where parents want gains (skill level improvements for prioritized categories), shift students’ overall skill profiles toward parental preferences (upward preference-level slope), and reduce parents’ perceived need for further improvement in those areas (downward skill preference rank movement). In short, providing teachers with clear signals of parental marginal valuations moves the whole classroom’s skill production away from what is merely easiest to build and toward what families value most.

9 Model Estimation

To provide additional evidence on the relative importance of costs versus benefits in driving specialization, I structurally estimate the model using Bayesian methods. The estimation leverages teacher skill rankings as supply-side cost shifters—teachers who emphasize certain skills should make those skills easier for students to produce. Since students are plausibly randomly assigned to teachers within grades, these rankings provide exogenous variation in production costs that can help separate cost from benefit heterogeneity. I extend the two-skill model in Section 3 to three skill categories (academic, social, emotional) to match the data structure. The full technical details

of the three-skill model are provided in Appendix Section E.

9.1 Estimation Methodology

The model includes demographics as covariates for both preferences (β_i) and production costs (κ_{ji}). Specifically, I allow class, parental education, household income, and teacher skill rankings to shift the ease of producing academic versus social-emotional skills. Teacher rankings enter only the cost equation (not preferences), providing an exclusion restriction that aids identification.

The model is estimated using Stan via Hamiltonian Monte Carlo, with 4 chains of 3,000 post-warmup draws each. I use skill levels and skill levels jointly: skill levels (s_{ij}) are increasing in benefits and decreasing in costs, while skill preferences (MRS_{ij}) are increasing in both benefits and costs, helping to separately identify the two sources of heterogeneity. Appendix E provides full technical details on priors, identification, and convergence diagnostics.

9.2 Main Results: Variance Decomposition

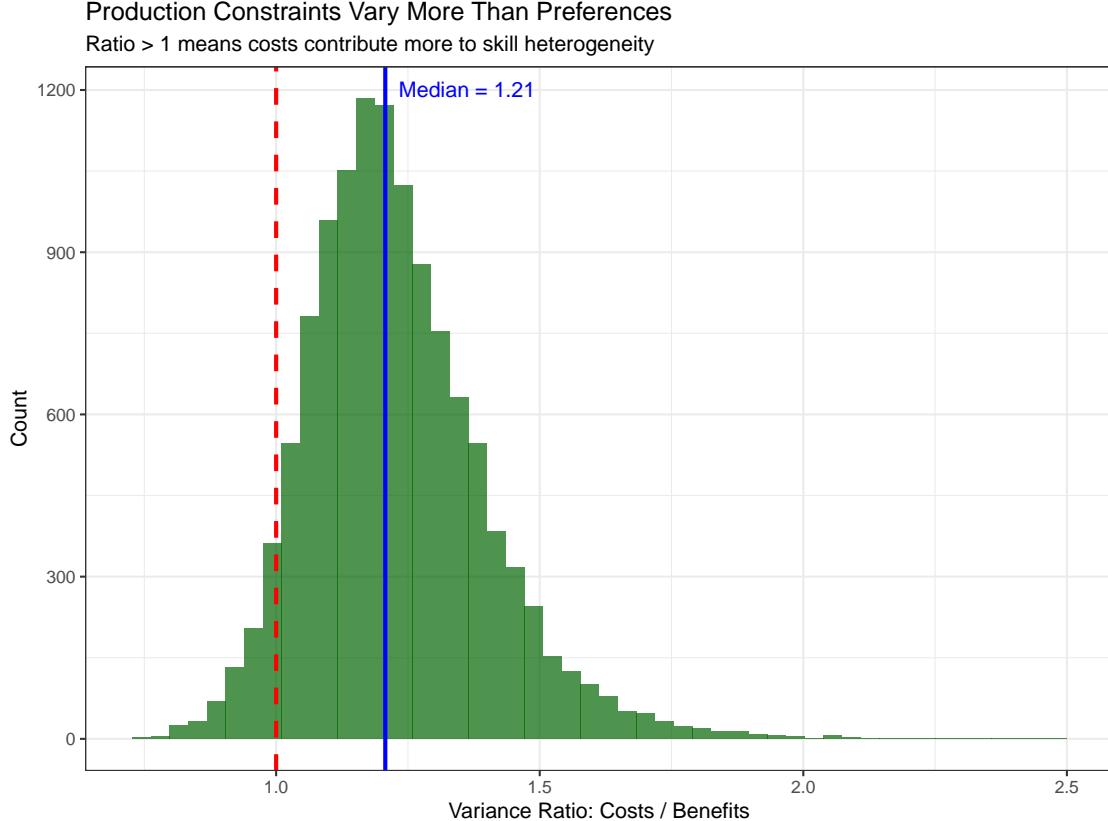
Recall from Section 3 that the equilibrium skill ratio decomposes as $s_i^* = T_i \cdot \lambda_i$, where $T_i = (\beta_i/(1-\beta_i))^{1/\rho}$ captures the benefits tilt (how much more a parent values skill 1) and $\lambda_i = \kappa_{1i}/\kappa_{2i}$ captures the costs tilt (how much easier it is to produce skill 1). Taking logs yields $\log s_i^* = \log T_i + \log \lambda_i$, so the variance of log skill ratios decomposes additively as

$$\text{Var}[\log s_i] = \text{Var}[\log T_i] + \text{Var}[\log \lambda_i] + 2\text{Cov}[\log T_i, \log \lambda_i].$$

The covariance term reflects identification challenges: while the mapping from (T_i, λ_i) to observables is one-to-one in theory, it is empirically weakly identified because the likelihood is nearly flat along ridges where $\log T_i + \log \lambda_i$ remains constant. Many (T_i, λ_i) pairs produce nearly identical predictions in finite, noisy data. Nevertheless, the ratio of the two variance components remains well-identified and directly measures the relative importance of cost versus benefit heterogeneity in driving specialization patterns.

Figure 17 presents the posterior distribution for this key quantity: the ratio of cost variance to benefit variance, $\text{Var}[\log \lambda_i]/\text{Var}[\log T_i]$. The median ratio is 1.21 (95% CI: [0.94, 1.62]), with 93.5% of posterior mass above 1.0. This indicates that production constraints vary approximately 21% more across families than do preferences for academic versus social-emotional skills, consistent with the reduced-form preference-level slope analysis in Section 5.

Figure 17: Posterior Distribution of Variance Ratio: Costs / Benefits



Notes: Distribution shows $\text{Var}[\log \lambda_i]/\text{Var}[\log T_i]$ across 12,000 posterior draws. Red dashed line marks equality (ratio = 1); blue solid line shows posterior median (1.21). Ratio > 1 implies production constraints vary more than preferences.

After controlling for demographics, unexplained residual variation in costs ($\sigma_{\ell 1}$) exceeds that in preferences ($\sigma_{\beta 1}$) by an even larger margin: the median ratio $\sigma_{\ell 1}/\sigma_{\beta 1} = 3.11$ (95% CI: [0.42, 70.59]), though with substantial uncertainty. Together, these estimates reinforce that observed specialization in this setting is primarily driven by what students find easier to learn rather than by what families value more.

9.3 Heterogeneity Across Subgroups

Table 5 examines whether the costs-versus-benefits balance differs by grade, income, or parental education. The variance ratio remains consistently above 1 across all subgroups, though with considerable overlap in credible intervals due to limited sample sizes within groups. The ratio is somewhat higher in early grades (median 1.48 for grade 3) than in upper grades (1.42 for grade 10), though differences are imprecise. Income and parental education show little systematic relationship with the ratio.⁸

⁸Wealthier and more educated families show slightly *lower* ratios (1.21–1.27 versus 1.17–1.18), potentially indicating that higher-resourced households face more uniform production costs, but these patterns are not statistically

Table 5: Variance Ratio by Demographic Subgroups

Subgroup	N	Median Ratio	95% CI	P(Costs > Benefits)
<i>By Grade (omitted: Grade 1)</i>				
Grade 2	132	1.43	[0.92, 2.81]	0.942
Grade 3	145	1.50	[0.92, 3.00]	0.948
:				
Grade 10	209	1.44	[0.93, 2.80]	0.949
<i>By Household Income (omitted: 0–5 Lakh)</i>				
5–10 Lakh	303	1.22	[0.93, 1.73]	0.934
10–15 Lakh	425	1.22	[0.94, 1.74]	0.933
Over 15 Lakh	779	1.28	[0.93, 1.91]	0.942
<i>By Mother's Education (omitted: Less than Secondary)</i>				
Secondary	146	1.19	[0.91, 1.70]	0.895
Bachelor's	500	1.25	[0.94, 1.78]	0.942
Graduate+	1131	1.26	[0.94, 1.80]	0.945

Notes: Each row shows the posterior median, 95% credible interval, and probability mass above 1 for $\text{Var}[\log \lambda]/\text{Var}[\log T]$ within the indicated subgroup. Full results for all grades and father's education in Appendix Table B.6.

The current estimation faces several limitations. First, teacher skill rankings—intended as supply shifters—do not enter significantly in the cost equation, likely reflecting weak instruments or insufficient sample variation within schools.⁹ As a result, the model primarily identifies the variance ratio from cross-sectional patterns in how parents' skill levels and skill preferences covary, supplemented by demographic controls. This reflects the fundamental identification challenge: many (T_i, λ_i) combinations produce similar skill ratios. Note that while the *ratio* of variances remains well-identified, decomposing *individual-level* contributions is not feasible without additional instruments or longitudinal data that could trace out expansion paths over time. Despite these constraints, the structural estimates corroborate the reduced-form findings: in this setting, production constraints—not preference heterogeneity—are the primary driver of why students specialize differently across skills.

9.4 Welfare Implications and Counterfactuals

The model framework opens a path toward quantifying welfare gains from policy interventions. In the model, utility-maximizing parents choose skill bundles subject to a production frontier determined by $(\kappa_{1i}, \kappa_{2i})$ and budget I_i . As shown in Section 3, when the ratio of costs $\lambda_i = \kappa_{1i}/\kappa_{2i}$ is set optimally, the skill ratio converges to a threshold $s^\dagger = \sqrt{\beta_i/(1 - \beta_i)}$ that equates the marginal rate of substitution with the expansion path. This threshold represents the aligned specialization level where incremental skill growth due to budget increases (e.g., skill growth over time) moves in the direction of steepest utility increase.

distinguishable.

⁹Teachers within the same school may hold similar views about skill importance, limiting cross-teacher variation in rankings. Future work could exploit teacher turnover or larger multi-school samples to strengthen this identification strategy.

Observed skill ratios $s_i^* = T_i \lambda_i$ deviate from this threshold whenever production costs $\lambda_i = \kappa_{1i}/\kappa_{2i}$ are misaligned with preferences. As shown in Section 3, the optimal cost ratio that would implement the aligned threshold is

$$\lambda_i^* = \frac{s_i^*}{T_i} = \left(\frac{\beta_i}{1 - \beta_i} \right)^{1/2-1/\rho}.$$

Counterfactual: Alignment between costs and benefits to skills. In this counterfactual, I quantify the potential welfare gains from reducing production-preference misalignment using a simple benchmark. Fix preferences β_i and the size of the production possibility set (budget I_i and overall frontier scale), and ask: how much would utility increase if each family faced production costs κ_i^* that perfectly aligned with their preferences? Formally, for each parent i , compute:

$$\Delta U_i = U(c^*(\kappa_i^*; I_i, \beta_i)) - U(c^*(\kappa_i^{\text{baseline}}; I_i, \beta_i)),$$

where $\kappa_i^* = (\kappa_{1i}^*, \kappa_{2i}^*)$ satisfies:

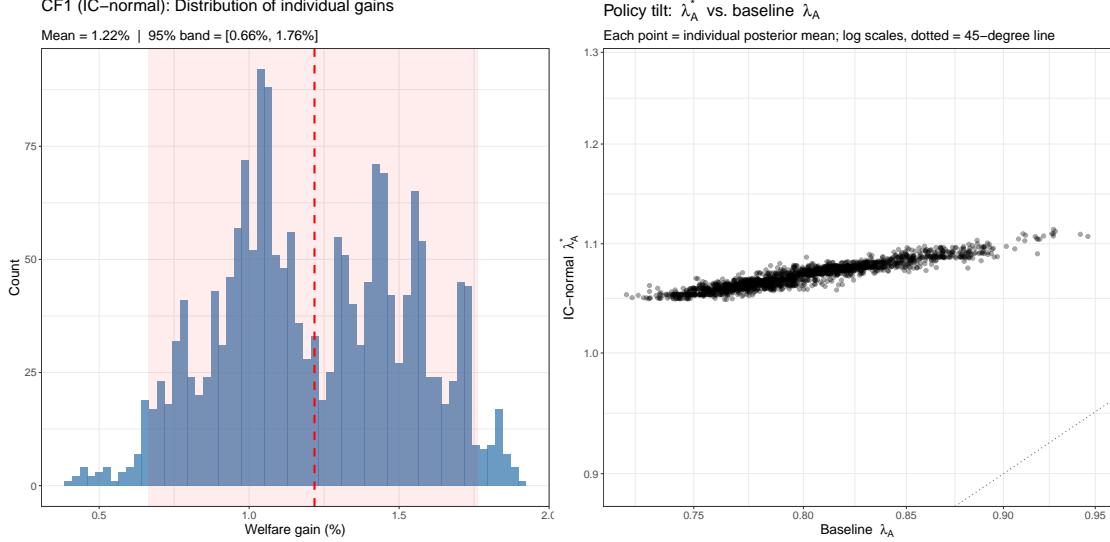
$$\kappa_{1i}^*/\kappa_{2i}^* = \lambda_i^* = \left(\frac{\beta_i}{1 - \beta_i} \right)^{1/2-1/\rho}.$$

This counterfactual captures the welfare gain from rotating the academic-vs-non-academic cost ratio just enough so that the indifference curve is locally orthogonal to the expansion path (Appendix D.5). Intuitively, λ_i^* aligns the cost side with what the family values, without expanding or contracting the overall production possibility set.

To isolate the effect of rotating the frontier, I impose a scale normalization on the frontier. The CET-consistent sum of cost terms remains constant, $\sum_j \kappa_{ji}^{-\rho}$ is held fixed for each i . This ensures that the overall size of the production possibility set is constant, while allowing the frontier to rotate. Under this normalization, I compute utility at the baseline and counterfactual cost parameters, with optimal choices in each case.

Figure 18 presents the distribution of welfare gains from this counterfactual. The gains are modest: average gains are on the order of one percent, with a long but thin upper tail. Overall, the small gains indicate that most families are not far from their aligned mix given these estimated preferences and production costs.

Figure 18: Distribution of Welfare Gains from Aligning Costs and Benefits



Notes: Panel 1 shows histogram of percentage welfare gains from the alignment of costs and benefits. Each observation is the mean of posterior draws for each family ($N = 1,851$). Panel 2 shows the baseline estimated $\lambda_A = \kappa_A/\kappa_N$ ratio for academic and non-cognitive skills against the counterfactual aligned ratio κ^* . The aligned ratio is defined based on β_i as described in Appendix Section D.5.

Three features of the estimated environment dampen the estimated welfare gains. First, posterior means for β_1 concentrate around 0.3–0.45, so the IC-normal target λ_i^* only moderately differs from baseline λ_i . Second, with $\rho = 1.5$, the optimal academic share depends on the degree of the preference tilt $(\beta_i/(1 - \beta_i)/\rho)$, muting the response to cost rotations. Finally, the Bayesian estimation smooths over extreme heterogeneity (Bayesian shrinkage), reducing the scope for large misalignments, and large welfare gains.

Taken together, these results suggest that while production-preference misalignment exists, it is not extreme for most families in this setting. Policies that better align production costs with parental preferences could yield modest welfare improvements on average, with large gains coming from stronger preference heterogeneity, steeper production tradeoffs (lower ρ), or interventions that expand the frontier rather than simply rotating it.

10 Conclusion

This paper develops and tests a simple but powerful idea: observed skill profiles may reflect either production costs (i.e., some skills are harder to build) or benefits (i.e., some skills are less valued). Distinguishing these forces matters for policy. If weaknesses mainly reflect high costs, the right lever is to shift the production frontier and make hard skills easier to learn; if they reflect low benefits, the lever is to change incentives or perceived payoffs. I show that a single statistic, namely, the preference-level slope, the relationship between a child’s current skill levels and the marginal value parents assign to them, can help diagnose which force dominates.

I find that, in the context of Indian private schools, the slope is negative on average: parents usually want gains where their child is weakest. This implies that production constraints rather than low benefits drive most observed specialization. Teachers, however, begin with beliefs about parent priorities that are largely uncorrelated with truth, instead mirror their own preferences.

A classroom-level randomized experiment shows that providing teachers with simple, structured information on parent-reported priorities acts as a production shock. Treated teachers become more accurate about average class priorities (especially where academics rank) and adjust the classroom environment, not just individual targeting. Students in treated classes gain more in the skills their parents value, parents then report lower need for improvement in those areas (rank moves), and preference-level slopes tilt upward, indicating that skill portfolios move away from what is easiest to produce and toward what families value most. Effects are strongest when average parental priority is academic; this is consistent with teachers having more scope to shift costs and effort in that domain.

These results offer a tractable way to diagnose and act on the “costs versus benefits” question in skill formation. Simple low-cost measures of skill levels and parental priorities can help school leaders decide whether to invest in lowering production costs or in changing incentives. They also show that teachers’ most powerful lever is classroom-level cost shifting: with better information about what families care about, they can redesign the shared learning environment to deliver value beyond what is easiest to teach.

Important limitations remain. The experiment took place in one country and school sector; further testing whether similar dynamics hold across other systems and grade levels is crucial. We also do not directly observe what teachers change—for example, they may change curriculum emphasis, grouping, feedback, or classroom routines—and schools themselves may have complementary levers, such as planning tools or resource supports once priorities are known. Finally, mapping which skills are genuinely easier or harder for teachers to improve will give a more complete picture of production constraints and guide better targeting.

Even with these caveats, my findings point to a promising path: namely, that education can be made more personally relevant by combining simple preference information with teachers’ ability to shape learning costs at the classroom level. Rather than focusing only on measured achievement, schools can better reflect what families value and align instruction with both skills and priorities, and help translate learning into higher long-run welfare.

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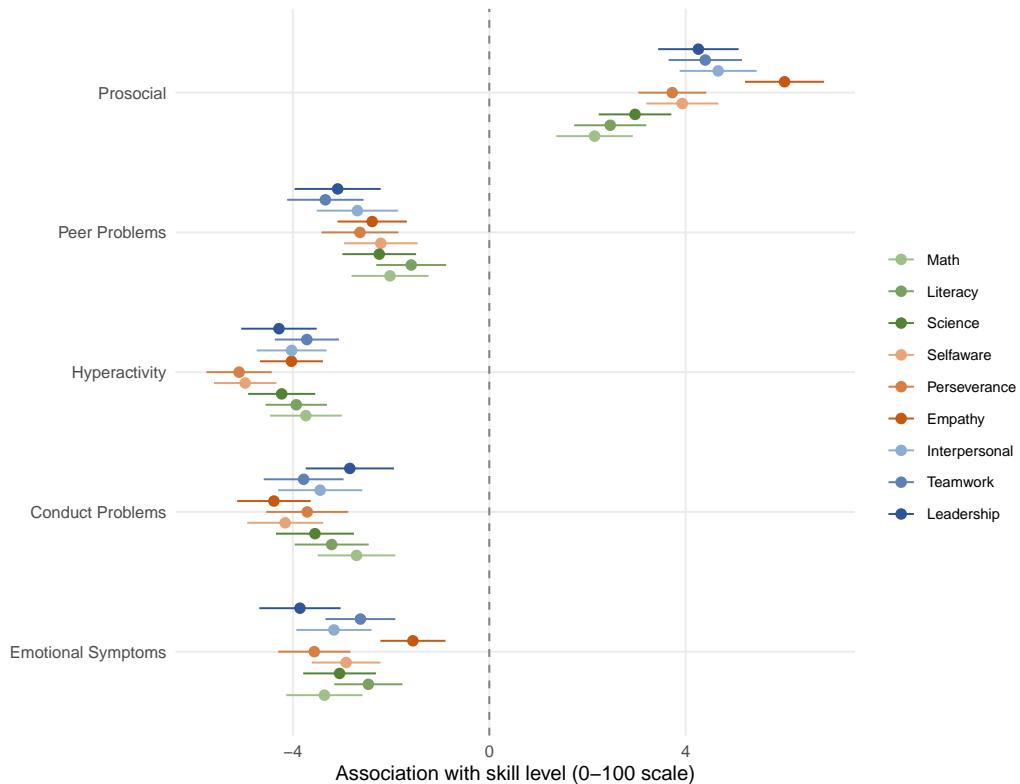
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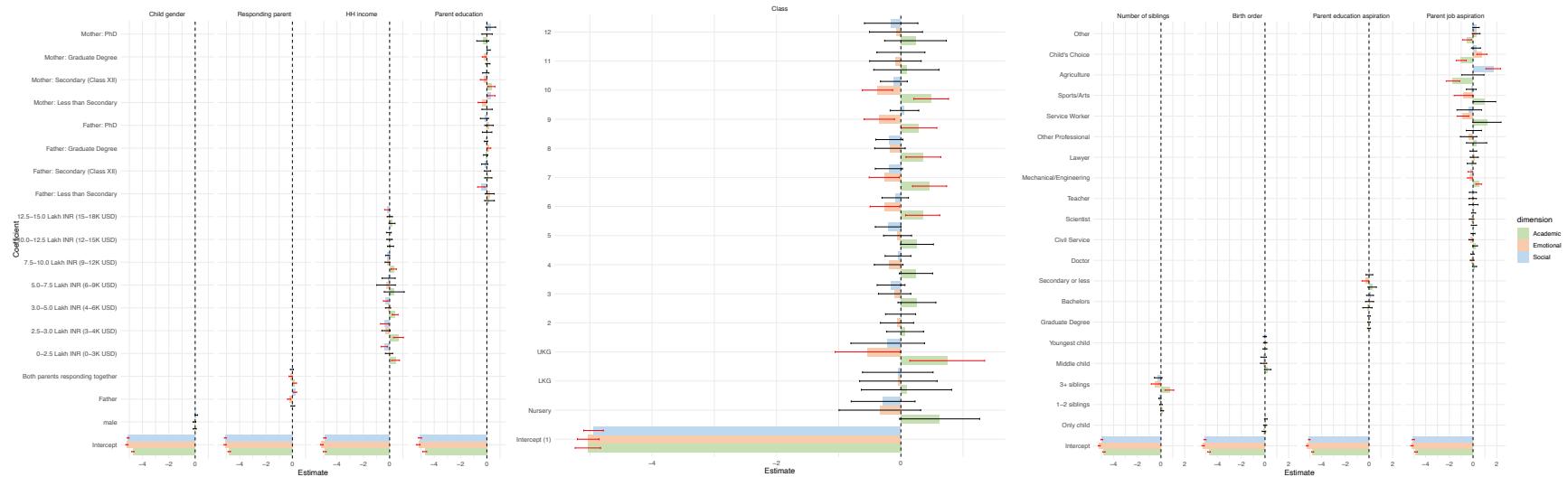
A Additional Figures

Figure A.1: Parent-Reported Skill Levels and Behavioral Measures



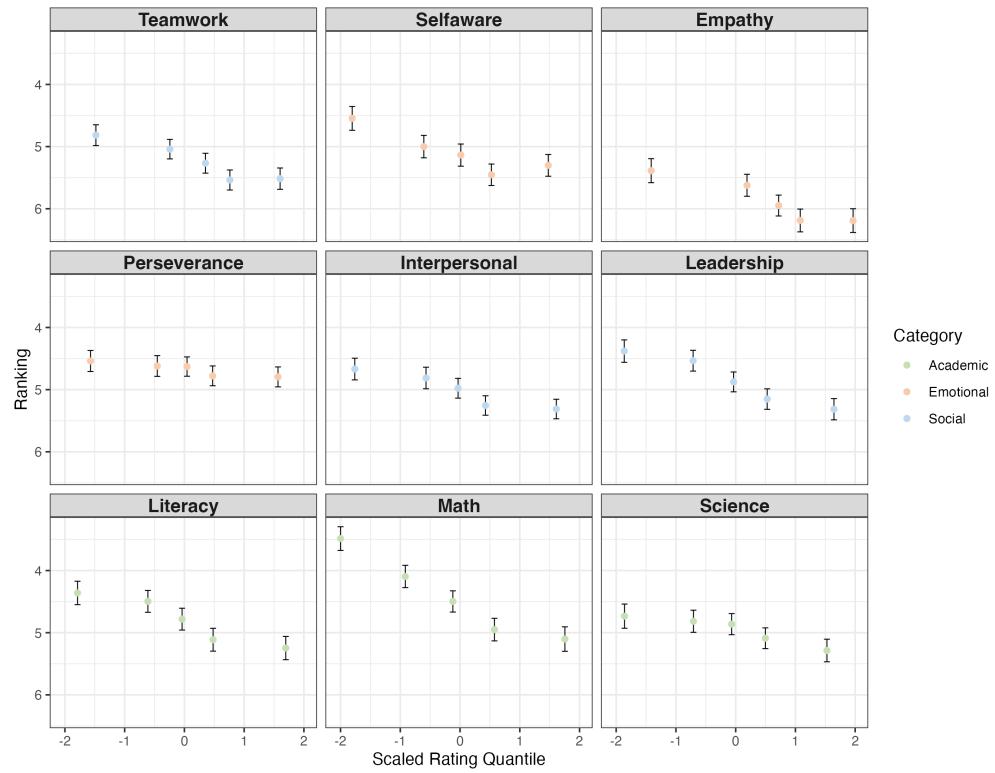
Notes: Coefficients from regressions of parent-reported skill levels (0-100 scale) on standardized Strengths and Difficulties Questionnaire (SDQ) subscales. Each SDQ subscale is constructed from five survey items and standardized across parents (mean 0 and standard deviation 1). Higher values on problem subscales (Emotional Symptoms, Conduct Problems, Hyperactivity, Peer Problems) indicate more difficulties; higher Prosocial scores indicate more prosocial behavior. Points show coefficient estimates; horizontal lines show 95% confidence intervals. All coefficients are statistically significant at the 5% level. Sample varies by skill dimension: $N=2,015\text{--}2,032$ students across 242 teachers.

Figure A.2: Skill Preferences by Family Characteristics



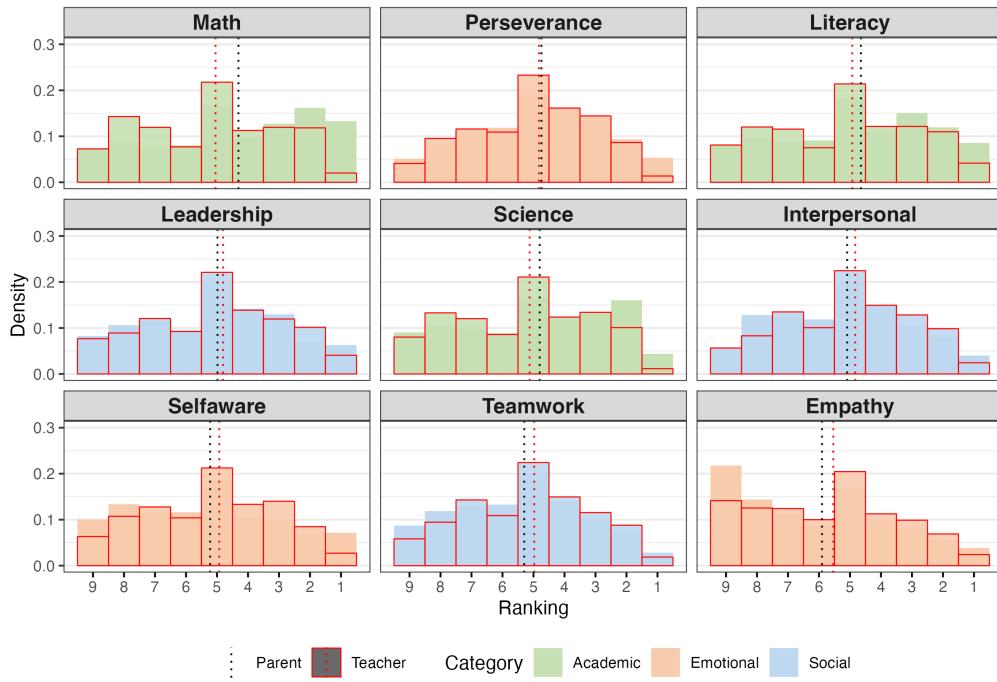
Notes: Coefficients from regressions of skill preference rankings on family characteristics. Skill preference rankings multiplied by -1 so that higher values indicate greater parental preference for the skill. N=3,404 students, 242 teachers. Points show coefficient estimates; bars show 95% confidence intervals.

Figure A.3: Average Skill Preference Rank by Skill Level Quintile (All Dimensions)



Notes: Higher values on the *y*-axis indicate higher parental priority (rank 1 = most important). Points show quintile means; bars show 95% confidence intervals.

Figure A.4: Teacher Versus Parent Skill Preference Rankings by Skill Dimension



Notes: $N = 1,273$ students, 242 teachers. Each panel shows the distribution of teachers' skill preference rankings for the specified skill dimension overlaid on the parent distribution. Dotted lines show the mean skill preference rank for each dimension. The x-axis is reversed so that the highest skill preference ranks (most important to improve) are on the right.

B Additional Tables

Table B.1: Treatment Effects on Survey Completion (Attrition Analysis)

Dependent Variable: Has Complete Data	(1)	(2)
<i>Variables</i>		
Treated	-0.0089 (0.0204)	0.0029 (0.0276)
Top Category: Social		0.0046 (0.0309)
Top Category: Emotional		-0.0114 (0.0306)
Treated × Social		-0.0402 (0.0426)
Treated × Emotional		0.0160 (0.0489)
<i>Statistics</i>		
Observations	26,256	26,256
R ²	0.05916	0.05966
Control Mean	0.2774	0.2774

Notes: The dependent variable equals 1 if a student has non-missing data for all four key outcomes (rating baseline, rating endline, ranking baseline, and ranking endline), and 0 otherwise. Column (1) tests whether treatment assignment predicts survey completion. Column (2) tests whether the treatment effect on completion varies by the parent's top-ranked category at baseline (reference category: Academic). "Treated" indicates teachers who received information about parent preferences. All specifications include class fixed effects, and standard errors are clustered at the teacher level. The null results indicate that attrition does not threaten the validity of the main analysis.

Standard errors in parentheses, clustered at the teacher level

Significance Codes: ***: 0.01, **: 0.05, *: 0.1

Table B.2: Descriptive Statistics of Parent Survey Sample

Demographic	Group	Full Sample (N=3404)	Main School (N=1460)	Completed Baseline and Endline (N=849)
Child Gender	Male	53.4	52.9	53.0
	Female	46.6	47.1	47.0
Child Age	4-8 years	26.3	25.8	35.3
	9-12 years	43.3	45.1	46.1
	13+ years	30.0	29.1	18.6
Class Level	Primary (1-5)	48.0	47.4	64.1
	Middle (6-8)	30.0	30.6	23.0
	Secondary (9-12)	22.0	22.0	13.0
Family Structure	Only child	40.0	53.1	54.0
	1-2 siblings	58.6	46.1	45.5
	3+ siblings	1.5	0.8	0.5
Responding Parent	Mother	44.6	50.9	51.2
	Father	30.8	37.0	38.2
	Both parents	24.6	12.0	10.6
Household Income	0-5.0 Lakh INR	19.3	9.6	9.1
	5.0-10.0 Lakh INR	17.1	12.1	13.9
	10.0-15.0 Lakh INR	22.0	21.8	23.5
	Over 15.0 Lakh INR	41.6	56.4	53.5
Mother Education	Below Bachelor's	11.0	4.1	4.2
	Bachelor's	28.0	29.3	25.3
	Graduate/PhD	61.0	66.6	70.5
Father Education	Below Bachelor's	11.2	2.3	3.0
	Bachelor's	30.9	29.2	28.0
	Graduate/PhD	57.9	68.5	69.0
Educational Aspiration	Bachelor's or less	5.5	3.9	3.5
	Graduate degree	42.5	36.9	34.4
	PhD	51.9	59.2	62.2
Job Aspiration	Academic/Professional	43.4	52.1	55.5
	Business	26.6	16.5	14.8
	Child's choice	2.0	3.3	3.2
	Other	44.3	42.1	38.5
Education Quality Satisfaction	Completely Satisfied	60.9	66.5	69.0
	Not Completely Satisfied	39.1	33.5	31.0
Child Progress Satisfaction	Completely Satisfied	52.4	54.6	57.0
	Not Completely Satisfied	47.6	45.4	43.0
Teacher Gender	Male	91.8	91.1	94.1
	Female	8.2	8.9	5.9
Teacher Education	Bachelor's	14.8	16.1	18.7
	Graduate/PhD	85.2	83.9	81.3
Years at School	1-5 years	39.6	21.4	18.9
	6+ years	60.4	78.6	81.1

Notes: All numbers are percentages unless noted. Household income in lakhs (100,000 INR); 1 USD ≈ 75 INR.

Table B.3: Balance Table: Parent and Child Characteristics by Treatment Status

Balance Table: Treatment vs Control Groups				
Comparison of baseline characteristics across experimental conditions				
Variable	Control Group	Treatment Group	Difference	P-value ¹
Skill Ratings				
Rating: Academic Skills	78.29 (12.71)	78.81 (13.13)	0.520	0.495
Rating: Emotional Skills	79.92 (12.62)	79.46 (13.14)	-0.460	0.544
Rating: Social Skills	77.79 (14.62)	77.86 (14.14)	0.073	0.931
Parent Rankings				
Parent Ranking: Academic	4.72 (1.78)	4.80 (1.92)	0.082	0.454
Parent Ranking: Emotional	5.27 (1.63)	5.20 (1.67)	-0.077	0.425
Parent Ranking: Social	5.02 (1.41)	5.00 (1.53)	-0.016	0.852
Aspirations & Contact				
Educational Aspirations	0.02/0.01/0.39/0.58	0.02/0.01/0.34/0.62		0.345
Job Aspirations	0.19/0.26/0.11/0.18/0.03/0.09/0.03/0/0/0/0.03/0.08	0.16/0.3/0.09/0.21/0.02/0.07/0.01/0.01/0/0/0.03/0.1		0.195
Teacher Contact	0.02/0.05/0.06/0.33/0.54	0.01/0.03/0.05/0.39/0.52		0.102
Demographic Characteristics				
Child Gender	0.46/0.54	0.47/0.53		0.791
Household Income	0.02/0.02/0.04/0.01/0.1/0.1/0.11/0.59	0.05/0.02/0.04/0.03/0.1/0.11/0.12/0.53		0.215
Mother's Education	0.01/0.03/0.28/0.63/0.05	0.02/0.03/0.3/0.62/0.04		0.590
Father's Education	0.01/0.01/0.3/0.61/0.07	0.01/0.02/0.29/0.63/0.05		0.503

¹ Standard deviations in parentheses for continuous variables. Proportions shown for categorical variables. P-values in bold red indicate significance at p < 0.05.

Notes: N = 823 parents. Standard deviations in parentheses below means. P-values from t-tests of difference in means between treatment and control, and a Pearson chi-squared test for categorical variables. Household income in lakhs (100,000 INR); 1 USD ≈ 75 INR.

Table B.4: Complier Characteristics

Characteristic	Complier Characteristics vs. Full Sample	
	Compliers	Full Sample
Average Age	45.03 (1.41)	44.07 (0.7)
Proportion Age 20-40	0.23 (0.09)	0.3 (0.04)
Proportion Age 41-50	0.52 (0.11)	0.48 (0.05)
Proportion Over 50	0.26 (0.14)	0.22 (0.07)
Proportion Class 1-3 ¹	0.55 (0.11)	0.3 (0.04)
Proportion Class 4-7	0.16 (0.08)	0.41 (0.05)
Proportion Class 8-10	0.29 (0.13)	0.29 (0.07)

¹ Highlighted rows show the largest differences between compliers and full sample, suggesting strongest treatment effect heterogeneity.
Note: Standard errors in parentheses. Complier characteristics estimated using 2SLS following Hull (2025).

Notes: Standard errors in parentheses. Complier characteristics estimated using 2SLS following Hull (2025).

Table B.5: Cost and Benefit Demographic Coefficients

Subgroup	Equation	Median	95% CI	Variable
Grade				
Grade 2	Academic Preference (beta1)	0.030	[-0.200, 0.270]	class_coarse2
Grade 3	Academic Preference (beta1)	0.035	[-0.195, 0.265]	class_coarse3
Grade 4	Academic Preference (beta1)	0.053	[-0.159, 0.260]	class_coarse4
Grade 5	Academic Preference (beta1)	0.179	[-0.028, 0.382]	class_coarse5
Grade 6	Academic Preference (beta1)	0.065	[-0.141, 0.277]	class_coarse6
Grade 7	Academic Preference (beta1)	0.130	[-0.076, 0.340]	class_coarse7
Grade 8	Academic Preference (beta1)	0.126	[-0.097, 0.344]	class_coarse8
Grade 9	Academic Preference (beta1)	0.101	[-0.118, 0.324]	class_coarse9
Grade 10	Academic Preference (beta1)	0.153	[-0.063, 0.360]	class_coarse10
Household Income				
5-10 Lakh INR	Academic Preference (beta1)	0.011	[-0.163, 0.181]	hh_income_coarse
10-15 Lakh INR	Academic Preference (beta1)	0.022	[-0.140, 0.178]	hh_income_coarse
Over 15 Lakh INR	Academic Preference (beta1)	0.002	[-0.140, 0.150]	hh_income_coarse
Mother Education				
Secondary (Class XII)	Academic Preference (beta1)	0.068	[-0.218, 0.350]	mother_education_coarse
Bachelors	Academic Preference (beta1)	0.084	[-0.170, 0.340]	mother_education_coarse
Graduate Degree	Academic Preference (beta1)	0.082	[-0.162, 0.329]	mother_education_coarse
Father Education				
Secondary (Class XII)	Academic Preference (beta1)	-0.087	[-0.375, 0.209]	father_education_coarse
Bachelors	Academic Preference (beta1)	-0.006	[-0.258, 0.249]	father_education_coarse
Graduate Degree	Academic Preference (beta1)	0.015	[-0.231, 0.260]	father_education_coarse
Teacher Ranking				
Academic	Academic Supply (lkA)	-0.005	[-0.680, 0.670]	ranking
Social	Academic Supply (lkA)	-0.006	[-0.561, 0.546]	ranking
Emotional	Academic Supply (lkA)	-0.006	[-0.457, 0.445]	ranking
Grade (Supply)				
Grade 2	Academic Supply (lkA)	-0.048	[-0.209, 0.108]	class_coarse2
Grade 3	Academic Supply (lkA)	-0.029	[-0.183, 0.125]	class_coarse3
Grade 4	Academic Supply (lkA)	-0.049	[-0.189, 0.095]	class_coarse4
Grade 5	Academic Supply (lkA)	-0.128	[-0.263, 0.011]	class_coarse5
Grade 6	Academic Supply (lkA)	-0.060	[-0.203, 0.078]	class_coarse6
Grade 7	Academic Supply (lkA)	-0.103	[-0.244, 0.038]	class_coarse7
Grade 8	Academic Supply (lkA)	-0.091	[-0.239, 0.059]	class_coarse8
Grade 9	Academic Supply (lkA)	-0.084	[-0.233, 0.065]	class_coarse9
Grade 10	Academic Supply (lkA)	-0.105	[-0.245, 0.040]	class_coarse10
Income (Supply)				
5-10 Lakh INR	Academic Supply (lkA)	-0.013	[-0.130, 0.102]	hh_income_coarse
10-15 Lakh INR	Academic Supply (lkA)	-0.018	[-0.124, 0.091]	hh_income_coarse
Over 15 Lakh INR	Academic Supply (lkA)	0.000	[-0.102, 0.096]	hh_income_coarse
Mother Ed. (Supply)				
Secondary (Class XII)	Academic Supply (lkA)	-0.036	[-0.229, 0.157]	mother_education_coarse
Bachelors	Academic Supply (lkA)	-0.048	[-0.218, 0.125]	mother_education_coarse
Graduate Degree	Academic Supply (lkA)	-0.046	[-0.214, 0.119]	mother_education_coarse
Father Ed. (Supply)				
Secondary (Class XII)	Academic Supply (lkA)	0.049	[-0.152, 0.241]	father_education_coarse
Bachelors	Academic Supply (lkA)	-0.003	[-0.177, 0.167]	father_education_coarse
Graduate Degree	Academic Supply (lkA)	-0.017	[-0.182, 0.151]	father_education_coarse
Siblings				
1 sibling	Academic Supply (lkA)	-0.003	[-0.015, 0.010]	siblings_cat
2+ siblings	Academic Supply (lkA)	0.005	[-0.016, 0.027]	siblings_cat

Notes: Each row shows the posterior median and 95% credible interval for coefficients from the hierarchical model. Academic Preference (beta1) refers to family preferences for academic skill development; Academic Supply (lkA) refers to teacher supply of academic instruction.

Table B.6: Variance Ratio by Demographic Subgroups

Subgroup	N	Median Ratio	95% CI	P(Costs > Benefits)
<i>By Grade (omitted: Grade 1)</i>				
Grade 2	132	1.43	[0.92, 2.81]	0.942
Grade 3	145	1.50	[0.92, 3.00]	0.948
Grade 4	221	1.44	[0.91, 2.78]	0.945
Grade 5	230	1.45	[0.94, 2.75]	0.953
Grade 6	207	1.45	[0.92, 2.91]	0.946
Grade 7	216	1.51	[0.92, 3.07]	0.951
Grade 8	163	1.46	[0.90, 2.90]	0.942
Grade 9	184	1.45	[0.93, 2.90]	0.948
Grade 10	209	1.44	[0.93, 2.80]	0.949
<i>By Household Income (omitted: 0–5 Lakh)</i>				
5–10 Lakh	303	1.22	[0.93, 1.73]	0.934
10–15 Lakh	425	1.22	[0.94, 1.74]	0.933
Over 15 Lakh	779	1.28	[0.93, 1.91]	0.942
<i>By Mother's Education (omitted: Less than Secondary)</i>				
Secondary (Class XII)	146	1.19	[0.91, 1.70]	0.895
Bachelor's	500	1.25	[0.94, 1.78]	0.942
Graduate Degree	1131	1.26	[0.94, 1.80]	0.945
<i>By Father's Education (omitted: Less than Secondary)</i>				
Secondary (Class XII)	134	1.18	[0.90, 1.73]	0.876
Bachelor's	571	1.24	[0.94, 1.77]	0.942
Graduate Degree	1074	1.28	[0.95, 1.85]	0.949

Notes: Each row shows the posterior median, 95% credible interval, and probability mass above 1 for $\text{Var}[\log \lambda]/\text{Var}[\log T]$ within the indicated subgroup.

C Survey Instruments and Demographic Questions

The parent survey collected a rich set of additional information that allows for heterogeneity analysis and provides context for understanding preference formation:

C.0.1 Demographic Information

- Family composition: Number of siblings, birth order, primary caregivers
- Parental education: Highest level attained by both mother and father
- Household income: Annual income in categorical brackets
- Parental occupation: Categorized into professional, clerical, sales, service, etc.
- Marital status: Married, unmarried, widowed, separated/divorced

C.0.2 Educational Aspirations and Expectations

- Highest level of education parents would ideally like their child to attain
- Occupational aspirations for when their child is 30 years old

These aspirational measures allow us to examine how longer-term goals align with preferences for immediate skill development priorities, building on recent work by [Eble and Escueta \(2023\)](#) that shows the importance of caregiver aspirations in educational investment and outcomes in resource-constrained settings.

C.0.3 Parent-Teacher Communication

- Frequency of parent contact with teachers (ranging from “rarely” to “daily or more”)
- Satisfaction with school and child’s progress

The communication frequency measure is particularly important for our analysis, as it allows us to test whether teachers have more accurate beliefs about parent preferences when they communicate more frequently with parents.

C.0.4 Child Well-being and Socio-emotional Assessment

The survey incorporated the Strengths and Difficulties Questionnaire (SDQ), a widely validated psychological assessment tool that measures:

- Emotional symptoms
- Conduct problems
- Hyperactivity/inattention

- Peer relationship problems
- Prosocial behavior

The SDQ provides an alternative measure of children's socio-emotional development that can be used both as an alternative outcome measure, and also to validate parent skill levels for emotional and social skills. It consists of 25 attributes, both positive and negative, with parents rating each attribute as "Not True," "Somewhat True," or "Certainly True."

C.0.5 Life Satisfaction

Parents were asked to place themselves on a ladder from 0 to 10, where 0 represents the worst possible life and 10 represents the best possible life. This measure allows us to examine whether parent preferences for different skill dimensions vary with overall life satisfaction.

D Model Derivations

D.1 Environment and CET technology

Outcomes and notation. Each child exits the grade with a two-dimensional skill vector $\mathbf{c} = (c_1, c_2) \in \mathbb{R}_+^2$, where c_1 denotes academic/cognitive skill and c_2 denotes non-cognitive skill.

Preferences and the MRS. Parent i has Cobb–Douglas utility

$$U(c_1, c_2; \beta_i) = c_1^{\beta_i} c_2^{1-\beta_i}, \quad 0 < \beta_i < 1.$$

The marginal utilities are

$$MU_1 = \frac{\partial U}{\partial c_1} = \beta_i c_1^{\beta_i-1} c_2^{1-\beta_i}, \quad MU_2 = \frac{\partial U}{\partial c_2} = (1 - \beta_i) c_1^{\beta_i} c_2^{-\beta_i}.$$

The marginal rate of substitution of skill 2 for skill 1 (the amount of c_2 the parent requires to compensate a one-unit loss of c_1 while holding utility constant) is

$$\text{MRS}_{12,i} = \frac{MU_1}{MU_2} = \frac{\beta_i}{1 - \beta_i} \frac{c_2}{c_1}. \quad (\text{D.11})$$

It will be convenient below to define the *taste index*

$$T_i := \left(\frac{\beta_i}{1 - \beta_i} \right)^{1/\rho} \iff \log T_i = \frac{1}{\rho} \log \left(\frac{\beta_i}{1 - \beta_i} \right),$$

where $\rho > 1$ will be the curvature parameter of the technology.

Technology and the CET frontier. Let parents purchase inputs e_1, e_2 at prices p_1, p_2 subject to a static budget $p_1 e_1 + p_2 e_2 \leq I$. Each skill is produced with diminishing marginal product from its own input:

$$c_1 = a_1 e_1^\theta, \quad c_2 = a_2 e_2^\theta, \quad a_j > 0, \quad 0 < \theta < 1.$$

Eliminating inputs using $e_j = (c_j/a_j)^{1/\theta}$ and substituting into the budget gives

$$p_1 \left(\frac{c_1}{a_1} \right)^{1/\theta} + p_2 \left(\frac{c_2}{a_2} \right)^{1/\theta} \leq I.$$

Let $\rho := 1/\theta > 1$ and define the *effective productivity-price* constants

$$\kappa_1 := a_1 \left(\frac{I}{p_1} \right)^{1/\rho}, \quad \kappa_2 := a_2 \left(\frac{I}{p_2} \right)^{1/\rho}. \quad (\text{D.12})$$

Dividing both sides by $I^{1/\rho}$ and rearranging yields the constant-elasticity-of-transformation (CET) frontier:

$$\left(\frac{c_1}{\kappa_1} \right)^\rho + \left(\frac{c_2}{\kappa_2} \right)^\rho = 1, \quad \rho > 1, \quad \kappa_1, \kappa_2 > 0. \quad (\text{D.13})$$

We collect relative technology/price/budget information in the *tilt* (relative supply parameter)

$$\lambda := \frac{\kappa_1}{\kappa_2} > 0, \quad (\text{D.14})$$

so that larger λ means skill 1 is relatively easier to produce (or relatively cheaper per efficiency unit), tilting the PPF toward c_1 .

The MRT along the CET. Let $F(c_1, c_2) := (c_1/\kappa_1)^\rho + (c_2/\kappa_2)^\rho - 1 = 0$ define the frontier (D.13). By definition, the MRT is the ratio of marginal costs (the absolute slope of the frontier). Totally differentiating gives

$$F_{c_1} dc_1 + F_{c_2} dc_2 = 0 \implies \frac{dc_2}{dc_1} = -\frac{F_{c_1}}{F_{c_2}}.$$

Compute the partial derivatives:

$$F_{c_1} = \rho \kappa_1^{-\rho} c_1^{\rho-1}, \quad F_{c_2} = \rho \kappa_2^{-\rho} c_2^{\rho-1}.$$

Hence the (absolute) marginal rate of transformation between the two skills is

$$\text{MRT}_{12} := -\frac{dc_2}{dc_1} = \left(\frac{\kappa_2}{\kappa_1}\right)^\rho \left(\frac{c_1}{c_2}\right)^{\rho-1} = \lambda^{-\rho} s^{\rho-1}, \quad s := \frac{c_1}{c_2}. \quad (\text{D.15})$$

Expression (D.15) shows how the frontier's marginal tradeoff depends both on curvature ρ and on the tilt λ : for a given skill ratio s , a higher λ (skill 1 relatively easier) rotates the PPF, lowering the amount of c_2 that must be sacrificed per unit increase in c_1 (a smaller MRT). The associated elasticity of transformation for the CET is $\sigma_T = 1/(\rho - 1) \in (0, \infty)$.

D.2 Optimal skill ratio

Equating the MRS (D.11) and the MRT (D.15) yields the *optimal skill ratio*

$$s^* := \frac{c_1}{c_2} = \left(\frac{\beta}{1-\beta}\right)^{1/\rho} \frac{\kappa_1}{\kappa_2} = T \lambda, \quad T := \left(\frac{\beta}{1-\beta}\right)^{1/\rho}. \quad (\text{D.16})$$

Evaluated at (c_1^*, c_2^*) , the MRS equals

$$\text{MRS}_{12}^* = T^{\rho-1} \lambda^{-1}. \quad (\text{D.17})$$

Multiplying gives the identity

$$s^* \cdot \text{MRS}_{12}^* = T^\rho. \quad (\text{D.18})$$

D.3 Within-dimension dispersion across students

Covariance formula. Let (T_i, λ_i) vary across students. Then (dropping the subscript i for convenience),

$$\text{Cov}(s^*, \text{MRS}^*) = \mathbb{E}[T^\rho] - \mathbb{E}[T\lambda] \mathbb{E}[T^{\rho-1}\lambda^{-1}]. \quad (\text{D.19})$$

Pure supply heterogeneity. If β is constant ($T \equiv \bar{T}$), then

$$\text{Cov}(s^*, \text{MRS}^*) = \bar{T}^\rho (1 - \mathbb{E}[\lambda] \mathbb{E}[\lambda^{-1}]) < 0, \quad (\text{D.20})$$

as by the Cauchy-Schwarz inequality, we have $\mathbb{E}[\lambda] \mathbb{E}[\lambda^{-1}] > \mathbb{E}[\sqrt{\lambda} * \sqrt{\lambda^{-1}}] = 1$.

Pure preference heterogeneity. If λ is constant, write $t := \beta/(1-\beta) > 0$ and note $T = t^{1/\rho}$. Then

$$\text{Cov}(s^*, \text{MRS}^*) = \mathbb{E}[t] - \mathbb{E}[t^{1/\rho}] \mathbb{E}[t^{1-1/\rho}] > 0, \quad (\text{D.21})$$

as by Jensen's inequality, we have that $\mathbb{E}[t^{1/\rho}] < \mathbb{E}[t]^{1/\rho}$ and $\mathbb{E}[t^{1-1/\rho}] < \mathbb{E}[t]^{1-1/\rho}$ (note $0 < 1/\rho < 1$ and $0 < 1-1/\rho$), so their product is less than $\mathbb{E}[t]$.

Reduced-form slope and variance comparison. Recall from (D.11)–(D.15) that the observed skill ratio and MRS are

$$s^* = T\lambda, \quad \text{MRS}^* = T^{\rho-1}\lambda^{-1},$$

where $T = (\frac{\beta}{1-\beta})^{1/\rho}$ captures preferences and $\lambda = \kappa_1/\kappa_2$ is the relative supply tilt. Across students, the reduced-form slope from regressing MRS* on s^* is

$$\beta^{\text{RF}} = \frac{\text{Cov}(s^*, \text{MRS}^*)}{\text{Var}(s^*)}. \quad (\text{D.22})$$

Exact formula. Let $\mu_{ab} := \mathbb{E}[T^a \lambda^b]$ denote mixed moments of the taste and technology parameters. From (D.22) we have that

$$\beta^{\text{RF}} = \frac{\mu_{\rho,0} - \mu_{1,1} \mu_{\rho-1,-1}}{\mu_{2,2} - \mu_{1,1}^2}. \quad (\text{D.23})$$

This expression is fully general.

D.3.1 Log-linearized approximate variance decomposition.

Reduced-form slope in levels (first-order derivation). Recall

$$s^* = T\lambda \quad \text{and} \quad \text{MRS}^* = T^{\rho-1}\lambda^{-1},$$

where $T := \left(\frac{\beta}{1-\beta}\right)^{1/\rho}$ is the *benefits tilt* and $\lambda := \frac{\kappa_1}{\kappa_2}$ is the *costs tilt*. Let $\bar{T} := \mathbb{E}[T]$, $\bar{\lambda} := \mathbb{E}[\lambda]$, and write small mean-zero fractional deviations

$$\tilde{T} := \frac{T - \bar{T}}{\bar{T}}, \quad \tilde{\lambda} := \frac{\lambda - \bar{\lambda}}{\bar{\lambda}}, \quad \mathbb{E}[\tilde{T}] = \mathbb{E}[\tilde{\lambda}] = 0.$$

Then $T = \bar{T}(1 + \tilde{T})$ and $\lambda = \bar{\lambda}(1 + \tilde{\lambda})$. A first-order expansion gives

$$s^* = T\lambda \approx \bar{T}\bar{\lambda}(1 + \tilde{T} + \tilde{\lambda}),$$

$$\text{MRS}^* = T^{\rho-1}\lambda^{-1} \approx \bar{T}^{\rho-1}\bar{\lambda}^{-1}(1 + (\rho-1)\tilde{T} - \tilde{\lambda}).$$

Centering by subtracting means (which differ from the above only by constants), the first-order fluctuations are

$$\hat{s} \approx \bar{T}\bar{\lambda}(\tilde{T} + \tilde{\lambda}), \quad \hat{m} \approx \bar{T}^{\rho-1}\bar{\lambda}^{-1}((\rho-1)\tilde{T} - \tilde{\lambda}),$$

where $\hat{s} := s^* - \mathbb{E}[s^*]$ and $\hat{m} := \text{MRS}^* - \mathbb{E}[\text{MRS}^*]$.

Assuming (for expositional clarity) that \tilde{T} and $\tilde{\lambda}$ are approximately uncorrelated,¹⁰ we obtain

$$\text{Cov}(\hat{m}, \hat{s}) \approx \bar{T}^\rho \left((\rho-1) \text{Var}(\tilde{T}) - \text{Var}(\tilde{\lambda}) \right),$$

$$\text{Var}(\hat{s}) \approx (\bar{T}\bar{\lambda})^2 \left(\text{Var}(\tilde{T}) + \text{Var}(\tilde{\lambda}) \right).$$

Hence, the reduced-form OLS slope of MRS^* on s^* is

$$\beta^{\text{RF}} = \frac{\text{Cov}(\hat{m}, \hat{s})}{\text{Var}(\hat{s})} \approx \underbrace{\bar{T}^{\rho-2}\bar{\lambda}^{-2}}_{\text{units factor}} \cdot \frac{(\rho-1)\text{Var}(\tilde{T}) - \text{Var}(\tilde{\lambda})}{\text{Var}(\tilde{T}) + \text{Var}(\tilde{\lambda})}.$$

The prefactor $\bar{T}^{\rho-2}\bar{\lambda}^{-2}$ is a units normalization. It rescales the dependent variable by a positive constant and does not affect the sign comparison. If we report the slope in normalized units (divide MRS^* by $\bar{T}^{\rho-1}\bar{\lambda}^{-1}$ and s^* by $\bar{T}\bar{\lambda}$), this prefactor is 1 and we get the variance-ratio form used in the main text:

$$\beta^{\text{RF}} \approx \frac{(\rho-1)\text{Var}(\tilde{T}) - \text{Var}(\tilde{\lambda})}{\text{Var}(\tilde{T}) + \text{Var}(\tilde{\lambda})} \tag{D.24}$$

where \tilde{T} and $\tilde{\lambda}$ are *fractional* (mean-normalized) deviations of the tilts. Relating tilts to primitives, $T = \exp(b/\rho)$ with $b = \log \frac{\beta}{1-\beta}$ and $\tilde{\lambda}$ corresponds to $\tilde{k} = \log \lambda - \mathbb{E}[\log \lambda]$; for small dispersion, $\text{Var}(\tilde{T}) \approx \frac{1}{\rho^2} \text{Var}(\tilde{b})$ and $\text{Var}(\tilde{\lambda}) \approx \text{Var}(\tilde{k})$, matching the appendix formulas.

We reparametrize the optimal skill ratio and MRS as:

$$s^* = T\lambda = \exp\left(\frac{1}{\rho}b + k\right), \quad \text{MRS}^* = T^{\rho-1}\lambda^{-1} = \exp\left(\frac{\rho-1}{\rho}b - k\right),$$

¹⁰When $\text{Cov}(\tilde{T}, \tilde{\lambda}) \neq 0$, the same steps yield a simple adjustment term; see above for the general formula.

where $b = \log \frac{\beta}{1-\beta}$ and $k = \log \lambda$. Define the linear indices

$$x := \frac{1}{\rho}b + k, \quad y := \frac{\rho-1}{\rho}b - k,$$

so that $s^* = e^x$ and $\text{MRS}^* = e^y$.

Write $b = \bar{b} + \tilde{b}$ and $k = \bar{k} + \tilde{k}$, with $\mathbb{E}[\tilde{b}] = \mathbb{E}[\tilde{k}] = 0$, $\sigma_b^2 := \text{Var}(\tilde{b})$, $\sigma_k^2 := \text{Var}(\tilde{k})$, $\sigma_{bk} := \text{Cov}(\tilde{b}, \tilde{k})$.

Then

$$x = \bar{x} + A\tilde{b} + B\tilde{k}, \quad y = \bar{y} + C\tilde{b} + D\tilde{k},$$

with coefficients

$$A = \frac{1}{\rho}, \quad B = 1, \quad C = \frac{\rho-1}{\rho}, \quad D = -1,$$

and means $\bar{x} = \frac{\bar{b}}{\rho} + \bar{k}$, $\bar{y} = \frac{\rho-1}{\rho}\bar{b} - \bar{k}$.

Second-order expansion. Using the second-order Taylor approximation $e^u \approx 1 + u + \frac{1}{2}u^2$ for small, centered u ,

$$\begin{aligned} e^x &= e^{\bar{x}} e^{A\tilde{b}+B\tilde{k}} \approx e^{\bar{x}} \left[1 + (A\tilde{b} + B\tilde{k}) + \frac{1}{2}(A\tilde{b} + B\tilde{k})^2 \right], \\ e^y &= e^{\bar{y}} e^{C\tilde{b}+D\tilde{k}} \approx e^{\bar{y}} \left[1 + (C\tilde{b} + D\tilde{k}) + \frac{1}{2}(C\tilde{b} + D\tilde{k})^2 \right]. \end{aligned}$$

Therefore the means are given as

$$\mathbb{E}[e^x] \approx e^{\bar{x}} \left[1 + \frac{1}{2}(A^2\sigma_b^2 + 2AB\sigma_{bk} + B^2\sigma_k^2) \right],$$

$$\mathbb{E}[e^y] \approx e^{\bar{y}} \left[1 + \frac{1}{2}(C^2\sigma_b^2 + 2CD\sigma_{bk} + D^2\sigma_k^2) \right].$$

For the variance, we use the first-order approximation

$$\text{Var}(e^x) \approx e^{2\bar{x}} \text{Var}(A\tilde{b} + B\tilde{k}) = e^{2\bar{x}} (A^2\sigma_b^2 + 2AB\sigma_{bk} + B^2\sigma_k^2).$$

$$\text{Var}(e^y) \approx e^{2\bar{y}} \text{Var}(C\tilde{b} + D\tilde{k}) = e^{2\bar{y}} (C^2\sigma_b^2 + 2CD\sigma_{bk} + D^2\sigma_k^2).$$

The covariance is

$$\begin{aligned} \text{Cov}(e^y, e^x) &\approx e^{\bar{x}+\bar{y}} \text{Cov}(A\tilde{b} + B\tilde{k}, C\tilde{b} + D\tilde{k}) \\ &= e^{\bar{x}+\bar{y}} \left(AC\sigma_b^2 + (AD + BC)\sigma_{bk} + BD\sigma_k^2 \right). \end{aligned}$$

Assembling the ratio. Recall the reduced-form slope is

$$\beta^{\text{RF}} = \frac{\text{Cov}(e^y, e^x)}{\text{Var}(e^x)}.$$

Thus,

$$\beta^{\text{RF}} \approx e^{\bar{y}-\bar{x}} \frac{AC \sigma_b^2 + (AD + BC) \sigma_{bk} + BD \sigma_k^2}{A^2 \sigma_b^2 + 2AB \sigma_{bk} + B^2 \sigma_k^2}.$$

Substituting A, B, C, D :

$$AC = \frac{\rho-1}{\rho^2}, \quad AD + BC = \frac{\rho-2}{\rho}, \quad BD = -1,$$

$$A^2 = \frac{1}{\rho^2}, \quad 2AB = 2/\rho, \quad B^2 = 1.$$

Hence

$$\beta^{\text{RF}} \approx e^{\bar{y}-\bar{x}} \frac{\frac{\rho-1}{\rho^2} \sigma_b^2 - \sigma_k^2 + \frac{\rho-2}{\rho} \sigma_{bk}}{\frac{1}{\rho^2} \sigma_b^2 + \sigma_k^2 + \frac{2}{\rho} \sigma_{bk}}. \quad (\text{D.25})$$

Simplifications.

- (i) The constant factor $e^{\bar{y}-\bar{x}}$ reflects a units normalization of the dependent variable in the reduced-form regression; rescaling MRS* by a positive constant rescales the slope by the same constant, so this term can be set to 1 without loss of generality.
- (ii) If \tilde{b} and \tilde{k} are approximately uncorrelated ($\sigma_{bk} \approx 0$), then this becomes the compact variance-comparison formula

$$\boxed{\beta^{\text{RF}} \approx \frac{\frac{\rho-1}{\rho^2} \sigma_b^2 - \sigma_k^2}{\frac{1}{\rho^2} \sigma_b^2 + \sigma_k^2}} \quad (\text{D.26})$$

which matches the presentation in the main text.

Equation (D.26) shows that the sign and magnitude of the reduced-form slope are governed by the relative dispersion of benefits and costs.

D.4 Within-student dispersion across skills

We observe $J \geq 3$ skills for the same parent. Let the CET frontier be

$$\sum_{j=1}^J \left(\frac{c_j}{\kappa_j} \right)^\rho = 1, \quad \rho > 1,$$

and preferences $U(\mathbf{c}; \boldsymbol{\beta}) = \prod_{j=1}^J c_j^{\beta_j}$ with $\beta_j > 0$ and $\sum_j \beta_j = 1$. Fix skill 1 as an anchor. For each $j \neq 1$, define the pairwise *skill ratio* and *MRS*:

$$s_j^* := \frac{c_j^*}{c_1^*} = \left(\frac{\beta_j}{\beta_1} \right)^{1/\rho} \frac{\kappa_j}{\kappa_1} =: T_j \lambda_j, \quad \text{MRS}_{j1}^* = T_j^{\rho-1} \lambda_j^{-1},$$

where $T_j := (\beta_j / \beta_1)^{1/\rho}$ and $\lambda_j := \kappa_j / \kappa_1$ are the *within-parent* benefit and cost tilts, respectively.

Key identity (within-parent). As in the two-skill case, technology cancels when we multiply:

$$s_j^* \cdot \text{MRS}_{1j}^* = \frac{\beta_j}{\beta_1} = e^{b_j}, \quad b_j := \log\left(\frac{\beta_j}{\beta_1}\right). \quad (\text{D.27})$$

Exact covariance expression. Let expectations and variances be taken across the $J-1$ non-anchor skills for this parent (denote them by $\mathbb{E}_j[\cdot]$, $\text{Var}_j(\cdot)$, etc.). Using (D.27) and the definitions above,

$$\begin{aligned} \text{Cov}_j(s^*, \text{MRS}^*) &= \mathbb{E}_j[s_j^* \text{MRS}_{1j}^*] - \mathbb{E}_j[s_j^*] \mathbb{E}_j[\text{MRS}_{1j}^*] \\ &= \mathbb{E}_j[e^{b_j}] - \mathbb{E}_j[e^{\frac{1}{\rho}b_j + k_j}] \mathbb{E}_j[e^{\frac{\rho-1}{\rho}b_j - k_j}], \end{aligned} \quad (\text{D.28})$$

where $k_j := \log \lambda_j = \log(\kappa_j / \kappa_1)$.

Second-order approximation (small dispersion across skills). Write $b_j = \bar{b} + \tilde{b}_j$ and $k_j = \bar{k} + \tilde{k}_j$ with within-parent means \bar{b}, \bar{k} and centered shocks $\mathbb{E}_j[\tilde{b}_j] = \mathbb{E}_j[\tilde{k}_j] = 0$. Define

$$\sigma_b^2 := \text{Var}_j(\tilde{b}), \quad \sigma_k^2 := \text{Var}_j(\tilde{k}), \quad \sigma_{bk} := \text{Cov}_j(\tilde{b}, \tilde{k}).$$

As in the cross-section derivation, set

$$x_j := \frac{1}{\rho}b_j + k_j, \quad y_j := \frac{\rho-1}{\rho}b_j - k_j, \quad \Rightarrow \quad s_j^* = e^{x_j}, \quad \text{MRS}_{1j}^* = e^{y_j}.$$

With coefficients $A = \frac{1}{\rho}$, $B = 1$, $C = \frac{\rho-1}{\rho}$, $D = -1$, a second-order expansion in (\tilde{b}, \tilde{k}) yields (cf. the general formula in the previous subsection)

$$\begin{aligned} \text{Cov}_j(s^*, \text{MRS}^*) &\approx e^{\bar{x}+\bar{y}} \left(AC \sigma_b^2 + (AD + BC) \sigma_{bk} + BD \sigma_k^2 \right) \\ &= e^{\bar{x}+\bar{y}} \left(\frac{\rho-1}{\rho^2} \sigma_b^2 + \frac{\rho-2}{\rho} \sigma_{bk} - \sigma_k^2 \right), \end{aligned} \quad (\text{D.29})$$

where $\bar{x} = \frac{\bar{b}}{\rho} + \bar{k}$ and $\bar{y} = \frac{\rho-1}{\rho}\bar{b} - \bar{k}$.

Within-parent reduced-form slope. The within-parent OLS slope from regressing MRS_{1j}^* on s_j^* across the $J-1$ pairs is

$$\beta_{\text{within}}^{\text{RF}} = \frac{\text{Cov}_j(s^*, \text{MRS}^*)}{\text{Var}_j(s^*)}.$$

Using the same expansion,

$$\text{Var}_j(s^*) \approx e^{2\bar{x}} (A^2 \sigma_b^2 + 2AB \sigma_{bk} + B^2 \sigma_k^2) = e^{2\bar{x}} \left(\frac{1}{\rho^2} \sigma_b^2 + \frac{2}{\rho} \sigma_{bk} + \sigma_k^2 \right).$$

Thus,

$$\beta_{\text{within}}^{\text{RF}} \approx e^{\bar{y}-\bar{x}} \frac{\frac{\rho-1}{\rho^2} \sigma_b^2 - \sigma_k^2 + \frac{\rho-2}{\rho} \sigma_{bk}}{\frac{1}{\rho^2} \sigma_b^2 + \sigma_k^2 + \frac{2}{\rho} \sigma_{bk}}. \quad (\text{D.30})$$

As before, the level constant $e^{\bar{y}-\bar{x}}$ is a units normalization and can be absorbed by rescaling the dependent variable.

Interpretation. Equation (D.29) (or (D.30)) shows that, *within a parent*, dispersion in tastes across skills (σ_b^2) pushes the covariance/slope positive, while dispersion in technology tilts across skills (σ_k^2) pushes it negative; the cross-covariance σ_{bk} enters with coefficient $(\rho - 2)/\rho$ and vanishes in the special case $\rho = 2$. Under approximate orthogonality of tastes and tilts across skills ($\sigma_{bk} \approx 0$), the sign reduces to a simple variance comparison:

$$\text{Cov}_j(s^*, \text{MRS}^*) \geq 0 \iff \frac{\rho - 1}{\rho^2} \text{Var}_j(\tilde{b}) \geq \text{Var}_j(\tilde{k}).$$

Empirically, this justifies running the within-parent regression of ranks on demeaned skill levels across skills (with an anchor), and interpreting the sign/magnitude as a diagnostic of whether the child's skill profile mirrors parental priorities (taste dispersion) or comparative advantage in production (supply dispersion).

D.5 Policy intervention: local analysis

Optimal local policy direction. Let $u(c_1, c_2) = c_1^\beta c_2^{1-\beta}$ and feasible (c_1, c_2) be summarized locally by instruments $z = (\ln \kappa_1, \ln \kappa_2)$ with $dc = H dz$, $H = \text{diag}(c_1, c_2)$. The policymaker solves

$$\max_{dz} \nabla u^\top H dz \quad \text{s.t.} \quad \frac{1}{2} dz^\top W dz \leq \mathcal{C}.$$

The Lagrangian yields $W dz = \lambda H^\top \nabla u$, hence $dz \propto W^{-1} H^\top \nabla u$ and $dc = H dz \propto M \nabla u$, $M := HW^{-1}H^\top \succ 0$. Under skill-symmetric costs in outcome space ($M \propto I$), $dc \propto \nabla u$, i.e., along the IC normal.

Budget expansion leaves s unchanged. With CET frontier $(c_1/\kappa_1)^\rho + (c_2/\kappa_2)^\rho \leq 1$ and Cobb–Douglas, the optimal levels are $c_1^* = \kappa_1 \beta^{1/\rho}$ and $c_2^* = \kappa_2 (1-\beta)^{1/\rho}$, so

$$s := \frac{c_1}{c_2} = \frac{\kappa_1}{\kappa_2} \left(\frac{\beta}{1-\beta} \right)^{1/\rho}.$$

Since $\kappa_i = a_i(I/p_i)^{1/\rho}$, a pure I increase scales both c_i by $I^{1/\rho}$ and leaves s unchanged: $ds/dI = 0$ and $d\text{MRS}/dI = 0$.

Total-differential derivation for the IC-normal step. Define $r := \frac{c_2}{c_1}$ and let the policymaker induce an outcome step *along the IC normal* (utility gradient). For Cobb–Douglas,

$$\nabla u \propto \left(\frac{\beta}{c_1}, \frac{1-\beta}{c_2} \right), \quad \Delta c_1 = \kappa \frac{\beta}{c_1}, \quad \Delta c_2 = \kappa \frac{1-\beta}{c_2}$$

for a small step size $\kappa > 0$. Using $r(c_1, c_2) = c_2/c_1$,

$$\frac{\partial r}{\partial c_1} = -\frac{c_2}{c_1^2} = -\frac{r}{c_1}, \quad \frac{\partial r}{\partial c_2} = \frac{1}{c_1}.$$

Hence the first-order change is

$$dr \approx \frac{\partial r}{\partial c_1} \Delta c_1 + \frac{\partial r}{\partial c_2} \Delta c_2 = -\frac{r}{c_1} \left(\kappa \frac{\beta}{c_1} \right) + \frac{1}{c_1} \left(\kappa \frac{1-\beta}{c_2} \right) = \frac{\kappa}{c_1^2} \left(\frac{1-\beta}{r} - \beta r \right).$$

Thus the sign of dr matches $\frac{1-\beta}{r} - \beta r$, which is positive if $r < \sqrt{\frac{1-\beta}{\beta}}$, negative if $r > \sqrt{\frac{1-\beta}{\beta}}$, and zero at $r^\dagger = \sqrt{\frac{1-\beta}{\beta}}$.

Dynamics and convergence to the threshold. Treat repeated tiny IC-normal steps as a continuous-time limit. Write $r = c_2/c_1$ and $s = 1/r$. From A.3,

$$\frac{dr}{d\tau} = K \left(\frac{1-\beta}{r} - \beta r \right) \quad \text{with } K > 0.$$

Then $s = r^{-1}$ satisfies

$$\frac{ds}{d\tau} = -\frac{1}{r^2} \frac{dr}{d\tau} = K \left(\beta s - (1-\beta) s^3 \right) \propto \frac{\beta}{s} - (1-\beta)s.$$

The unique positive fixed point is $s^\dagger = \sqrt{\frac{\beta}{1-\beta}}$. Linearization shows global (monotone for small steps) convergence toward s^\dagger .

Equilibrium κ -ratio implementing the fixed point. At the optimum under CET, $s = \lambda T$ with $\lambda := \kappa_1/\kappa_2$ and $T := (\beta/(1-\beta))^{1/\rho}$. To implement s^\dagger as the new optimum, choose

$$\boxed{\lambda^* = \frac{s^\dagger}{T} = \left(\frac{\beta}{1-\beta} \right)^{\frac{1}{2}-\frac{1}{\rho}}}.$$

Connection to endogenous technology choice/frontiers. In the framework of [Caselli and Coleman \(2006\)](#), firms pick (A_s, A_u) on a frontier characterized by a “height” B and curvature; the first-order conditions link the chosen bias A_s/A_u to factor ratios and relative wages, generating appropriate technology choices across endowments and a barrier parameter shifting the whole frontier.¹¹ Our quadratic budget on dz is a local reduced form of these frontier trade-offs for policy. The distinction is that we treat κ_i as policy levers, responding to student-specific values captured by β_i . In the the objective is fixed: maximize profit. The choice is for optimal technology in response to varying prices of labor inputs.

¹¹See [Caselli and Coleman \(2006\)](#) for the frontier concept and the way the FOCs pin down the choice of production frontier.

D.6 Teacher-driven supply and key identity

A teacher enters after parents form preferences β_i over skills. The teacher chooses effort, pedagogy, and materials to determine λ_i ; these may be shifted by observable shocks (e.g., randomized information, measured teacher priorities). Parents observe learning under this supply and report endline skill levels and skill preferences; thus reports lie on the PPF determined by λ_i and B_i .

From (D.16)–(D.17):

$$s_i^* = T_i \lambda_i, \quad \text{MRS}_{12,i}^* = T_i^{\rho-1} \lambda_i^{-1},$$

so

$$s_i^* \cdot \text{MRS}_{12,i}^* = T_i^\rho. \quad (\text{D.31})$$

Hence supply dispersion $\text{Var}(\log \lambda)$ attenuates the covariance of (s^*, MRS^*) relative to the Period 1 benchmark if treatment reduces misalignment between λ_i and T_i (e.g., reallocating classroom effort toward parent-valued skills) rotates the reduced-form slope upwards.

D.7 Empirical implementation and identification

Proxies. Let $r_{ij} \in [0, 100]$ and $m_{ij} \in \{1, \dots, 9\}$ denote parent i 's rating and importance rank for skill j . Set $\tilde{r}_{ij} := r_{ij} - \bar{r}_i$. Assume a monotone reporting function so that \tilde{r}_{ij} is a monotone proxy for s_{ij}^* . Parents rank by marginal utility, so m_{ij} is a monotone proxy for MRS_{ij}^* .

Baseline regression. Estimate

$$m_{ij} = \alpha + \beta \tilde{r}_{ij} + \xi_j + \varepsilon_{ij}, \quad (\text{D.32})$$

with heteroskedasticity-robust SEs and parent clustering when stacking skills; include dimension fixed effects ξ_j and, if desired, dimension-specific slopes.

Supply-side instruments. Treat teacher/classroom variables as *supply instruments* for \tilde{r}_{ij} :

- randomized information assignment at grade/teacher level;
- teacher “typical student” priorities (constructed indices);
- class-level aggregates of parent priorities (leave-one-out).

These shift λ_i but not β_i , identifying the supply-driven component of the slope. Over identified designs allow over-ID tests; report partial-F (or Bayesian analogs) and cluster at the classroom (or school \times grade) level.

Policy mapping. Posterior (or sampling) decompositions of $\text{Var}(b)$ and $\text{Var}(k)$ quantify whether skills are primarily shaped by benefits or costs. If the latter dominates, cost-side levers (pedagogy, time allocation, materials, class size, resources) should be prioritized; if the former dominates, alignment and benefit-side interventions are the natural lever.

E From the 2-Skill Framework to a 3-Category Estimable Model

This section shows, step by step, how the two-skill model (3.1) generalizes to three skill *groups* (academic, social, emotional), how the optimal skill ratios are derived, and how every term that appears in the Stan likelihood is obtained directly from the economic primitives.

E.1 Environment

Skills (now 3 categories). Parents end the decision period with category-level skills $\mathbf{c} = (c_A, c_S, c_E) \in \mathbb{R}_+^3$.

Preference parameters. Two taste weights govern trade-offs:

$$U(c_A, c_S, c_E) = c_A^{\beta_1} (c_S^{\beta_2} c_E^{1-\beta_2})^{1-\beta_1}, \quad \beta_1, \beta_2 \in (0, 1). \quad (\text{E.33})$$

- β_1 : academic vs. *non-academic* ($c_S^{\beta_2} c_E^{1-\beta_2}$);
- β_2 : social vs. emotional *within* the non-academic composite.

E.2 Marginal-rate-of-substitution (MRS) between Academic and Non-academic skills

Utility with nested Cobb–Douglas preferences.

$$U(c_A, c_S, c_E) = c_A^{\beta_1} (c_S^{\beta_2} c_E^{1-\beta_2})^{1-\beta_1}, \quad \beta_1, \beta_2 \in (0, 1). \quad (\text{D.1})$$

Collapse Social and Emotional into a single non-academic index. Fix the within-non-academic mix $s_{SE} = c_S/c_E$ (chosen optimally in the *inner* problem). Because s_{SE} is constant during the Academic vs Non-academic trade-off, the term in brackets is proportional to $c_N := c_S + c_E$; the proportionality factor does not affect marginal rates. Hence we can write the *outer* utility as

$$\boxed{U(c_A, c_N) = c_A^{\beta_1} c_N^{1-\beta_1}} \quad (\text{E.34})$$

Marginal utilities.

$$\frac{\partial U}{\partial c_A} = \beta_1 c_A^{\beta_1-1} c_N^{1-\beta_1} = \beta_1 \frac{U}{c_A}, \quad \frac{\partial U}{\partial c_N} = (1 - \beta_1) c_A^{\beta_1} c_N^{-\beta_1} = (1 - \beta_1) \frac{U}{c_N}.$$

MRS between Academic and Non-academic.

$$\boxed{\text{MRS}_{A,N} = \frac{\beta_1}{1 - \beta_1} \frac{c_N}{c_A} = \frac{\beta_1}{1 - \beta_1} \frac{1}{s_A}, \quad s_A := \frac{c_A}{c_N}} \quad (\text{E.35})$$

Equation (E.35) is the expression equated to the MRT in Section E.3 to solve for the optimal Academic share s_A^* .

Technology. Each category continues to have its *own* one-input Cobb–Douglas line: $c_j = a_j e_j^\theta$ ($0 < \theta < 1$). Combining them with the linear budget $p_1 e_1 + p_2 e_2 + p_3 e_3 \leq I$ again yields a *constant-elasticity-of-transformation* (CET) frontier

$$(c_A/\kappa_A)^\rho + (c_S/\kappa_S)^\rho + (c_E/\kappa_E)^\rho = 1, \quad \rho = \frac{1}{\theta} > 1.$$

Only the two *ratios* $\ell_1 = \log(\kappa_A/\kappa_S)$ and $\ell_2 = \log(\kappa_S/\kappa_E)$ matter for the frontier's shape (its absolute scale is absorbed by the budget).

E.3 MRT between Academic and Non-Academic

We start from the three-category constant-elasticity-of-transformation (CET) frontier with $\rho > 1$:

$$\left(\frac{c_A}{\kappa_A}\right)^\rho + \left(\frac{c_S}{\kappa_S}\right)^\rho + \left(\frac{c_E}{\kappa_E}\right)^\rho = 1 \quad (\text{E.36})$$

Collapse c_S and c_E into a single non-academic quantity while holding their *mix* constant. Fix a within-non-academic ratio

$$s_{SE} := \frac{c_S}{c_E} \quad (\text{taken as given during marginal changes}).$$

Write

$$c_S = \frac{s_{SE}}{1 + s_{SE}} c_N, \quad c_E = \frac{1}{1 + s_{SE}} c_N, \quad \text{where } c_N := c_S + c_E.$$

Insert these into (E.36); all terms containing c_N share the factor c_N^ρ . Collect them:

$$\left(\frac{c_A}{\kappa_A}\right)^\rho + \left(\frac{c_N}{\kappa_N}\right)^\rho = 1 \quad (\text{E.37})$$

with the **effective non-academic conversion factor**

$$\kappa_N(s_{SE}) = (1 + s_{SE}) \left(\frac{s_{SE}^\rho}{\kappa_S^\rho} + \frac{1}{\kappa_E^\rho} \right)^{-1/\rho}$$

(E.38)

Thus *for every fixed s_{SE}* the three-point frontier is algebraically equivalent to the two-point frontier (c_A, c_N) with parameters (κ_A, κ_N) .

Implicit differentiation: MRT_{A,N}. Let

$$F(c_A, c_N) = \left(\frac{c_A}{\kappa_A}\right)^\rho + \left(\frac{c_N}{\kappa_N}\right)^\rho - 1 = 0.$$

Total-differentiating while *holding s_{SE}* (and therefore κ_N) constant:

$$\frac{\partial F}{\partial c_A} dc_A + \frac{\partial F}{\partial c_N} dc_N = 0,$$

$$\frac{\partial F}{\partial c_A} = \rho \left(\frac{c_A}{\kappa_A} \right)^{\rho-1} \frac{1}{\kappa_A}, \quad \frac{\partial F}{\partial c_N} = \rho \left(\frac{c_N}{\kappa_N} \right)^{\rho-1} \frac{1}{\kappa_N}.$$

Hence the absolute slope is

$$|\text{MRT}_{A,N}| = \frac{dc_N}{dc_A} = \left(\frac{\kappa_N(s_{SE})}{\kappa_A} \right)^\rho \left(\frac{c_A}{c_N} \right)^{\rho-1} \quad (\text{E.39})$$

E.3.1 Optimal Academic-vs-Non-academic mix.

Recall that our preferences across categories give

$$\text{MRS}_{A,N} = \frac{\beta_1}{1 - \beta_1} \frac{c_N}{c_A}.$$

Set $\text{MRS}_{A,N} = |\text{MRT}_{A,N}|$ and define $s_A := c_A/c_N$:

$$\frac{\beta_1}{1 - \beta_1} \frac{1}{s_A} = \left(\frac{\kappa_N(s_{SE})}{\kappa_A} \right)^\rho s_A^{\rho-1}.$$

Multiply by s_A , take logs, divide by ρ , and exponentiate:

$$s_A^* = \exp \left[\frac{1}{\rho} \log \beta_1 + \log \left(\frac{\kappa_A}{\kappa_N(s_{SE})} \right) \right] \quad (\text{E.40})$$

Because $\kappa_N(s_{SE})$ in (E.38) depends on κ_S, κ_E and the within-non-academic mix s_{SE} , the optimal Academic share s_A^* incorporates *all three* technology parameters unless we impose a normalization such as $\kappa_S = \kappa_E$.

E.3.2 Estimation and identification

Why the baseline estimation sets $\kappa_S = \kappa_E$.

- Without panel data or exogenous price shocks the single cross-section of levels & preference ranks identifies β_1, β_2 precisely but cannot pin down $\ell_2 = \log(\kappa_S/\kappa_E)$ tightly—its effect overlaps almost one-for-one with β_2 inside s_{SE} .
- Normalising $\kappa_S = \kappa_E$ ($\ell_2 = 0$) therefore removes a weakly identified parameter and focuses statistical power on $\ell_1 = \log(\kappa_A/\kappa_S)$, which is central for detecting supply-side heterogeneity.
- If future data supply additional variation you can restore ℓ_2 by estimating it directly via (E.38) and (E.40); only a few lines of Stan code change.

Social vs. Emotional skills. Within the non-academic pair set $s_{SE} := c_S/c_E$ and equate MRS to MRT:

$$\frac{\beta_2}{1 - \beta_2} \frac{c_E}{c_S} = \left(\frac{\kappa_E}{\kappa_S}\right)^\rho \left(\frac{c_S}{c_E}\right)^{\rho-1}.$$

Substituting $s_{SE} = c_S/c_E$ yields,

$$\frac{\beta_2}{1 - \beta_2} \left(\frac{\kappa_S}{\kappa_E}\right)^\rho = s_{SE}^\rho.$$

If we impose the *normalisation* $\kappa_S = \kappa_E$ (i.e. no technological asymmetry *within* the non-academic block), then $\ell_2 = 0$ and (??) simplifies to the expression used in the baseline Stan specification:

$$\tilde{s}_{SE} = \exp\left[\frac{1}{\rho} \text{logit}\beta_2\right].$$

Why one tilt (ℓ_1) is enough for identification

- (a) Given three observed ratings, any common rescaling of $(\kappa_A, \kappa_S, \kappa_E)$ is absorbed by the unobserved budget B_i ; only *two* independent cost ratios remain.
- (b) Rank data depend on those ratios *only through the two mixes* s_A and s_{SE} . With a single cross-section, ℓ_2 is nearly collinear with β_2 inside (??). Estimating both leads to weak identification unless additional variation (panel data, price changes, supply shifters) is available.
- (c) Therefore the empirical benchmark sets $\ell_2 = 0$, keeps ℓ_1 free, and focuses on the contrast between *benefit heterogeneity* $\sigma_{\beta_1}, \sigma_{\beta_2}$ and *cost heterogeneity* σ_{ℓ_1} . Section ?? shows that allowing $\ell_2 \neq 0$ yields similar qualitative results but much wider posteriors.

A scale-free representation (g_A, g_S, g_E) Because only (s_A, s_{SE}) matter for choices, we pick a single convenient point on the CET frontier:

$$\underline{g}_A := 1, \quad \underline{g}_E := \frac{1}{s_A(1 + s_{SE})}, \quad \underline{g}_S := s_{SE} \underline{g}_E \tag{E.41}$$

Any feasible skill vector differs from $\mathbf{g} := (\underline{g}_A, \underline{g}_S, \underline{g}_E)$ only by a *common* positive multiplier. We let the parent-specific *budget scale* $B_i > 0$ supply that multiplier:

$$c_{ik} = B_i g_k.$$

E.3.3 Latent utilities for the ordered-probit

We show a numerically stable way to obtain the three category-specific latent utilities that feed the ordered-probit likelihood, using only log and logit transformations that Stan handles safely.

Raw marginal utilities. With nested Cobb–Douglas preferences

$$U(c_A, c_S, c_E) = c_A^{\beta_1} (c_S^{\beta_2} c_E^{1-\beta_2})^{1-\beta_1}, \quad \beta_1, \beta_2 \in (0, 1),$$

the marginal utilities factor as

$$MU_A = \beta_1 \frac{U}{c_A}, \quad MU_S = (1 - \beta_1)\beta_2 \frac{U}{c_S}, \quad MU_E = (1 - \beta_1)(1 - \beta_2) \frac{U}{c_E}.$$

Normalise by the common factor $(1 - \beta_1)$. Multiplying or dividing every MU_j by the same positive constant leaves rankings unchanged, so set

$$\widetilde{MU}_j := \frac{MU_j}{U(1 - \beta_1)} \quad (j = A, S, E).$$

Then

$$\widetilde{MU}_A = \frac{\beta_1}{1 - \beta_1} \frac{1}{c_A}, \quad \widetilde{MU}_S = \beta_2 \frac{1}{c_S}, \quad \widetilde{MU}_E = (1 - \beta_2) \frac{1}{c_E}.$$

Take logs and cancel parent-specific constants. Write $c_j = B_i g_j$ where B_i is parent i 's budget and g_j the *effective* skill output. After subtracting $\log B_i$, which is common to all three categories, we obtain

$$\begin{aligned} u_A &= \log\left(\frac{\beta_1}{1 - \beta_1}\right) - \log g_A, \\ u_S &= \log \beta_2 - \log g_S, \\ u_E &= \log(1 - \beta_2) - \log g_E \end{aligned} \tag{E.42}$$

E.3.4 Implementation of the model in Stan

Let

$$\theta_1 = \text{logit_beta1}, \quad \theta_2 = \text{logit_beta2}.$$

- $\log\left(\frac{\beta_1}{1 - \beta_1}\right) = \theta_1$.
- $\log \beta_2 = \theta_2 + \text{log1m_inv_logit}(\theta_2)$.
- $\log(1 - \beta_2) = \text{log1m_inv_logit}(\theta_2)$.

Using these identities avoids under- or overflow when β is very close to 0 or 1, while the $-\log g_j$ terms come straight from the rating equation $c_j = B_i g_j$.

These u_A, u_S, u_E are proportional to the (negative) ordering utilities used in the likelihood; their differences determine the probabilities of each category being ranked first, second, or third.

E.3.5 Mapping to observed data

Skill Levels. Parents report a cardinal score on each category, modelled as

$$r_{ik} \sim \mathcal{N}(B_i g_k, \sigma_{\text{rating}}^2) \quad (\text{E.43})$$

so ratings identify *both* B_i and the supply tilts ℓ_1, ℓ_2 .

Skill Preferences (ordered probit). Assume i.i.d. $\mathcal{N}(0, 1)$ noise on three latent utilities and a pair of cut-points $c_1 < c_2$. Observed ranks $\text{rank}_{ik} \in \{1, 2, 3\}$ (1 = most important) for person i and category k follow the ordered probit:

$$\begin{aligned} \Pr(\text{rank}_{ik} = 1) &= 1 - \Phi(c_2 - u_{ik}), \\ \Pr(\text{rank}_{ik} = 2) &= \Phi(c_2 - u_{ik}) - \Phi(c_1 - u_{ik}), \\ \Pr(\text{rank}_{ik} = 3) &= \Phi(c_1 - u_{ik}) \end{aligned} \quad (\text{E.44})$$

with u_{ik} equal to the corresponding expression in (E.42). To ensure identifiability, we parameterize the cutpoints as c_1 and $c_2 = c_1 + \Delta$ with $\Delta > 0$, preventing label-switching during MCMC sampling.

I chose to model skill preference ranks using an independent three-level ordered probit given that ties were allowed, in practice. If skill preference rankings were strictly ordered, a rank-ordered likelihood (Plackett-Luce, rank-probit, etc.) could be used instead.

E.3.6 Incorporating demographics

The model allows each individual-level parameter to vary with observed covariates \mathbf{X}_i . For parent i , the logit preferences, supply tilts, and log budget are:

$$\text{logit}(\beta_{1i}) = \gamma_{\beta1,0} + \mathbf{X}_{\beta1,i}^\top \boldsymbol{\gamma}_{\beta1} + \sigma_{\beta1} z_{\beta1,i}, \quad (\text{E.45})$$

$$\text{logit}(\beta_{2i}) = \gamma_{\beta2,0} + \mathbf{X}_{\beta2,i}^\top \boldsymbol{\gamma}_{\beta2} + \sigma_{\beta2} z_{\beta2,i}, \quad (\text{E.46})$$

$$\ell_{1i} = \gamma_{\ell1,0} + \mathbf{X}_{\ell1,i}^\top \boldsymbol{\gamma}_{\ell1} + \sigma_{\ell1} z_{\ell1,i}, \quad (\text{E.47})$$

$$\log B_i = \gamma_{B,0} + \mathbf{X}_{B,i}^\top \boldsymbol{\gamma}_B + \sigma_B z_{B,i}. \quad (\text{E.48})$$

where $z_{\beta1,i}, z_{\beta2,i}, z_{\ell1,i}, z_{B,i} \sim \mathcal{N}(0, 1)$ are independent standard normal draws. The γ_0 terms are intercepts, $\boldsymbol{\gamma}$ are covariate effect vectors, and σ parameters govern unexplained (residual) heterogeneity conditional on covariates.

Covariate selection. In the main specification, we include:

- **Preferences ($\mathbf{X}_{\beta1}, \mathbf{X}_{\beta2}$):** grade, household income, mother's education, father's education. These capture how observable family characteristics shift the relative value placed on academic versus social-emotional skills.

- **Supply ($\mathbf{X}_{\ell 1}$):** All preference covariates *plus* teacher skill rankings for academic, social, and emotional categories. Teacher rankings serve as an exclusion restriction—they enter the production technology but not preferences, providing exogenous variation in costs to aid identification.
- **Budget (\mathbf{X}_B):** household income and number of siblings, proxying for total resources available for skill investment.

The model is flexible: setting any $K = 0$ reduces to the baseline specification without covariates for that equation. All covariate matrices are constructed using dummy encoding for categorical variables, with reference categories omitted (e.g., Grade 1, lowest income bracket, less than secondary education).

E.3.7 Priors and normalization

Priors on intercepts and covariate effects. We use weakly informative priors centered at zero:

$$\begin{aligned}\gamma_{\beta 1,0}, \gamma_{\beta 2,0}, \gamma_{\ell 1,0} &\sim \mathcal{N}(0, 0.5^2), \\ \gamma_{B,0} &\sim \mathcal{N}(\log 75, 0.3^2), \\ \boldsymbol{\gamma}_{\beta 1}, \boldsymbol{\gamma}_{\beta 2}, \boldsymbol{\gamma}_{\ell 1} &\sim \mathcal{N}(\mathbf{0}, 0.5^2 \mathbf{I}), \\ \boldsymbol{\gamma}_B &\sim \mathcal{N}(\mathbf{0}, 0.3^2 \mathbf{I}).\end{aligned}$$

The budget intercept prior centers on $\log 75$, reflecting that parent ratings average around 75 on the 0–100 scale. Covariate effect priors are symmetric around zero, allowing demographics to shift parameters in either direction.

Priors on heterogeneity parameters. Standard deviations governing unexplained variation receive exponential priors:

$$\sigma_{\beta 1}, \sigma_{\beta 2}, \sigma_{\ell 1} \sim \text{Exponential}(2), \quad \sigma_B \sim \text{Exponential}(3), \quad \sigma_{\text{rating}} \sim \mathcal{N}(10, 5^2) \text{ truncated at } 0.$$

These priors are weakly informative, allowing substantial heterogeneity while penalizing extreme values. The rating noise prior centers on 10 points (on a 0–100 scale), consistent with measurement error in subjective assessments.

Cutpoint priors. The ordered probit cutpoints use:

$$c_1 \sim \mathcal{N}(0, 2^2), \quad \Delta := c_2 - c_1 \sim \text{Exponential}(1).$$

This parameterization ensures $c_1 < c_2$ while allowing the data to determine threshold locations. The exponential prior on Δ weakly favors moderate separation between rank categories.

Normalizations and identification. Several normalizations ensure model identification:

1. **Curvature:** We fix $\rho = 1.5$, corresponding to an elasticity of transformation $1/(\rho - 1) = 2$. This is within the range typical for CET production functions and could not be separately identified from the heterogeneity parameters without strong functional form assumptions or additional moments.
2. **Supply intercept:** We set $\ell_2 = 0$ (social and emotional skills have equal baseline production costs, $\kappa_S = \kappa_E$), normalizing the supply tilt to Academic versus non-Academic only. This identification restriction is without loss of generality given our three-category setup.
3. **Production scale:** We normalize $g_A = 1$ when computing skill mixes, pinning down one point on the production frontier. Combined with the budget B_i , this determines the absolute scale of skill production.

These normalizations reduce the parameter space without loss of economic content, as the model primitives of interest—variance in benefits versus costs—remain identified through the joint pattern of ratings and rankings across categories.

E.3.8 The hierarchical parameters estimated in Stan

Block	Symbol in code	Economic meaning
Preference intercepts	$\gamma_{\beta1,0}, \gamma_{\beta2,0}$	Baseline academic vs non-academic, social vs emotional tilts
Preference effects	$\gamma_{\beta1}, \gamma_{\beta2}$	How demographics shift preference parameters
Supply intercept	$\gamma_{\ell1,0}$	Baseline log-ratio $\log(\kappa_A/\kappa_{SE})$
Supply effects	$\gamma_{\ell1}$	How demographics and teachers shift production costs
Budget intercept	$\gamma_{B,0}$	Baseline effective resources
Budget effects	γ_B	How income/siblings shift resources
Residual std. devs.	$\sigma_{\beta1}, \sigma_{\beta2}, \sigma_{\ell1}, \sigma_B$	Unexplained heterogeneity (conditional on covariates)
Curvature	$\rho = 1.5$	Elasticity of transformation (fixed)
Rating noise	σ_{rating}	Perception / measurement error
Rank cut-points	$c_1, \Delta = c_2 - c_1$	Thresholds in ordered probit

The key inferential targets are the *total variances* in preferences and costs:

$$\text{Var}[\text{logit}(\beta_{1i})] = \text{Var}(\mathbf{X}_{\beta1,i}^\top \boldsymbol{\gamma}_{\beta1}) + \sigma_{\beta1}^2, \quad \text{Var}[\ell_{1i}] = \text{Var}(\mathbf{X}_{\ell1,i}^\top \boldsymbol{\gamma}_{\ell1}) + \sigma_{\ell1}^2.$$

Comparing these variances (or equivalently, the variances of $\log T_i$ and $\log \lambda_i$ after rescaling by $1/\rho$) reveals whether observed specialization is primarily driven by benefit or cost heterogeneity. The sign of the empirical preference-level slope corresponds structurally to whether cost or benefit variance dominates in this decomposition.

E.3.9 Estimation details

The model is estimated using Stan's Hamiltonian Monte Carlo with the No-U-Turn Sampler (NUTS). We run 4 chains with 2,000 warmup iterations and 3,000 post-warmup draws per chain, yielding 12,000 total posterior samples. We set `adapt_delta = 0.95` and `max_treedepth = 12` to improve sampling efficiency in the presence of complex posterior geometry induced by the ratings-rankings likelihood and demographic covariates. Convergence is assessed via $\hat{R} < 1.01$ and effective sample sizes (ESS) > 400 for all parameters of interest. The full Stan code is reproduced below.

```
// ----- 3-category CET model -----

data {
    int<lower=1> N;
    array[N, 3] real<lower=0, upper=100> rating;
    array[N, 3] int<lower=1, upper=3> rank;

    // Covariate dimensions (set to 0 for no covariates)
    int<lower=0> K_beta1; // Number of covariates for beta1
    int<lower=0> K_beta2; // Number of covariates for beta2
    int<lower=0> K_lkA; // Number of covariates for log(kappa_A)
    int<lower=0> K_lkS; // Number of covariates for log(kappa_S)
    int<lower=0> K_B; // Number of covariates for budget

    // Covariate matrices (can be empty if K=0)
    matrix[N, K_beta1] X_beta1;
    matrix[N, K_beta2] X_beta2;
    matrix[N, K_lkA] X_lkA;
    matrix[N, K_lkS] X_lkS;
    matrix[N, K_B] X_B;

    // Control flag for identification
    int<lower=0, upper=1> estimate_lkappa_SE; // 0 = assume kappa_S = kappa_E, 1 =
        estimate separately
}

parameters {
    // Preference parameters (demand)
    real gamma_beta1_0;
    vector[K_beta1] gamma_beta1;
    real<lower=0> sigma_logit_beta1;
    vector[N] z_beta1;

    real gamma_beta2_0;
    vector[K_beta2] gamma_beta2;
    real<lower=0> sigma_logit_beta2;
    vector[N] z_beta2;

    // Supply parameters - log(kappa) for each category
}
```

```

// Academic - always estimated
real gamma_lkA_0;
vector[K_lkA] gamma_lkA;
real<lower=0> sigma_lkA;
vector[N] z_lkA;

// Social - parameters exist but only used if estimate_lkappa_SE = 1
real gamma_lkS_0;
vector[K_lkS] gamma_lkS;
real<lower=0> sigma_lkS;
vector[N] z_lkS;

// Emotional: NOT ESTIMATED - normalized to 1 (log = 0)
// No parameters needed

// Budget parameters
real gamma_B_0;
vector[K_B] gamma_B;
real<lower=0> sigma_logB;
vector[N] z_logB;

// Rating noise
real<lower=0> sigma_rating;

// Ordered-probit cut-points
real cut1;
real<lower=0> cut_diff;
}

transformed parameters {
    real rho = 1.5;
    real inv_rho = 1.0 / rho;

    // Individual-level preference parameters
    vector[N] logit_beta1;
    vector[N] logit_beta2;

    // Individual-level log(kappa) parameters
    vector[N] lkappa_A;
    vector[N] lkappa_S;
    vector[N] lkappa_E; // This will be set to 0 for normalization

    // Budget
    vector[N] logB;
    vector[N] B;

    // === Compute preference parameters ===
    if (K_beta1 > 0) {

```

```

logit_beta1 = gamma_beta1_0 + X_beta1 * gamma_beta1 + sigma_logit_beta1 *
    z_beta1;
} else {
    logit_beta1 = gamma_beta1_0 + sigma_logit_beta1 * z_beta1;
}

if (K_beta2 > 0) {
    logit_beta2 = gamma_beta2_0 + X_beta2 * gamma_beta2 + sigma_logit_beta2 *
        z_beta2;
} else {
    logit_beta2 = gamma_beta2_0 + sigma_logit_beta2 * z_beta2;
}

// === Compute supply parameters (log kappa ratios) ===
if (K_lkA > 0) {
    lkappa_A = gamma_lkA_0 + X_lkA * gamma_lkA + sigma_lkA * z_lkA;
} else {
    lkappa_A = gamma_lkA_0 + sigma_lkA * z_lkA;
}

// NORMALIZATION: Always set kappa_E = 1 (lkappa_E = 0)
lkappa_E = rep_vector(0.0, N);

// For baseline: set kappa_S = kappa_E = 1
if (estimate_lkappa_SE == 1) {
    // Estimate kappa_S separately (but kappa_E is still normalized to 1)
    if (K_lkS > 0) {
        lkappa_S = gamma_lkS_0 + X_lkS * gamma_lkS + sigma_lkS * z_lkS;
    } else {
        lkappa_S = gamma_lkS_0 + sigma_lkS * z_lkS;
    }
} else {
    // Baseline: kappa_S = kappa_E = 1
    lkappa_S = rep_vector(0.0, N);
}

// === Compute budget ===
if (K_B > 0) {
    logB = gamma_B_0 + X_B * gamma_B + sigma_logB * z_logB;
} else {
    logB = gamma_B_0 + sigma_logB * z_logB;
}
B = exp(logB);

// === Compute skill mixes (hybrid: vectorize what's easy, loop the rest) ===

// Step 1: Compute log(s_SE) - VECTORIZED
vector[N] log_s_SE = inv_rho * logit_beta2;

```

```

// Steps 2-4: Compute log(kappa_N), log(s_A), and log(g_*) in single loop
vector[N] log_kappa_N;
vector[N] log_s_A;
vector[N] log_g_A = rep_vector(0.0, N);
vector[N] log_g_S;
vector[N] log_g_E;

for (i in 1:N) {
    // Step 2: Compute log(kappa_N)
    real term1 = rho * (log_s_SE[i] - lkappa_S[i]);
    real term2 = -rho * lkappa_E[i];
    log_kappa_N[i] = log1p_exp(log_s_SE[i]) - inv_rho * log_sum_exp(term1, term2);

    // Step 3: Compute log(s_A)
    log_s_A[i] = inv_rho * logit_beta1[i] + lkappa_A[i] - log_kappa_N[i];

    // Step 4: Compute log(g_E) and log(g_S)
    log_g_E[i] = -log_s_A[i] - log1p_exp(log_s_SE[i]);
    log_g_S[i] = log_s_SE[i] + log_g_E[i];
}

// Step 5: Exponentiate - VECTORIZED
vector[N] g_A = exp(log_g_A);
vector[N] g_S = exp(log_g_S);
vector[N] g_E = exp(log_g_E);

// Cutpoints
vector[2] cut;
cut[1] = cut1;
cut[2] = cut1 + cut_diff;
}

model {
    // === PRIORS ===

    // Priors on preference intercepts
    gamma_beta1_0 ~ normal(0, 0.5);
    gamma_beta2_0 ~ normal(0, 0.5);

    // Priors on supply intercepts
    // gamma_lkA_0: log(kappa_A / kappa_E) - always estimated
    gamma_lkA_0 ~ normal(0, 0.5);

    // gamma_lkS_0: log(kappa_S / kappa_E) - only used if estimate_lkappa_SE = 1
    // But we need to give it a prior regardless since it's a parameter
    if (estimate_lkappa_SE == 1) {
        gamma_lkS_0 ~ normal(0, 0.5);
    } else {
        // Weak prior when not used
    }
}

```

```

    gamma_lkS_0 ~ normal(0, 10);
}

// Prior on budget intercept - this absorbs the scale
gamma_B_0 ~ normal(log(75), 0.5);

// Priors on covariate effects
if (K_beta1 > 0) gamma_beta1 ~ normal(0, 0.5);
if (K_beta2 > 0) gamma_beta2 ~ normal(0, 0.5);
if (K_lkA > 0) gamma_lkA ~ normal(0, 0.5);
if (estimate_lkappa_SE == 1) {
    if (K_lkS > 0) gamma_lkS ~ normal(0, 0.5);
} else {
    if (K_lkS > 0) gamma_lkS ~ normal(0, 10);
}
if (K_B > 0) gamma_B ~ normal(0, 0.3);

// Priors on heterogeneity
sigma_logit_beta1 ~ exponential(2);
sigma_logit_beta2 ~ exponential(2);
sigma_lkA ~ exponential(2);
if (estimate_lkappa_SE == 1) {
    sigma_lkS ~ exponential(2);
} else {
    sigma_lkS ~ exponential(0.1); // Tight prior when not used
}
sigma_logB ~ exponential(3);

sigma_rating ~ normal(10, 5);
cut1 ~ normal(0, 2);
cut_diff ~ exponential(1);

// Standard normal priors on z's
z_beta1 ~ std_normal();
z_beta2 ~ std_normal();
z_lkA ~ std_normal();

// z_lkS gets prior even in baseline (but won't affect results since lkappa_S =
// 0)
if (estimate_lkappa_SE == 1) {
    z_lkS ~ std_normal();
} else {
    z_lkS ~ normal(0, 0.01); // Very tight when not used
}

z_logB ~ std_normal();

// === LIKELIHOOD ===
for (i in 1:N) {

```

```

// Ratings: r_ik ~ N(B_i * g_k, sigma_rating^2)
rating[i,1] ~ normal(B[i] * g_A[i], sigma_rating);
rating[i,2] ~ normal(B[i] * g_S[i], sigma_rating);
rating[i,3] ~ normal(B[i] * g_E[i], sigma_rating);

// Rankings: ordered probit on latent utilities
vector[3] util;
util[1] = logit_beta1[i] - log_g_A[i];
util[2] = logit_beta2[i] + log1m_inv_logit(logit_beta2[i]) - log_g_S[i];
util[3] = log1m_inv_logit(logit_beta2[i]) - log_g_E[i];

for (k in 1:3) {
    real eta = util[k];
    vector[3] prob;
    prob[1] = 1 - Phi(cut[2] - eta);
    prob[2] = Phi(cut[2] - eta) - Phi(cut[1] - eta);
    prob[3] = Phi(cut[1] - eta);
    rank[i,k] ~ categorical(prob);
}
}

generated quantities {
    // Compute implied population means
    real mu_logit_beta1_implied;
    real mu_logit_beta2_implied;
    real mu_lkA_implied;
    real mu_lkS_implied;
    real mu_logB_implied;

    if (K_beta1 > 0) {
        mu_logit_beta1_implied = gamma_beta1_0 + mean(X_beta1 * gamma_beta1);
    } else {
        mu_logit_beta1_implied = gamma_beta1_0;
    }

    if (K_beta2 > 0) {
        mu_logit_beta2_implied = gamma_beta2_0 + mean(X_beta2 * gamma_beta2);
    } else {
        mu_logit_beta2_implied = gamma_beta2_0;
    }

    if (K_lkA > 0) {
        mu_lkA_implied = gamma_lkA_0 + mean(X_lkA * gamma_lkA);
    } else {
        mu_lkA_implied = gamma_lkA_0;
    }

    if (estimate_lkappa_SE == 1) {

```

```

if (K_lkS > 0) {
    mu_lkS_implied = gamma_lkS_0 + mean(X_lkS * gamma_lkS);
} else {
    mu_lkS_implied = gamma_lkS_0;
}
} else {
    mu_lkS_implied = 0.0; // In baseline, kappa_S = kappa_E = 1
}

if (K_B > 0) {
    mu_logB_implied = gamma_B_0 + mean(X_B * gamma_B);
} else {
    mu_logB_implied = gamma_B_0;
}
}

```