Biased Parental Beliefs: Experimental Evidence from Norway*

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Abstract

Parents' beliefs about their children's abilities shape parental behavior and decision-making. But do parents process information about their children's abilities objectively or in a biased way? I study this question in a large-scale lab-in-the-field experiment with Norwegian elementary school students and their parents ($N = 743$ parent–child pairs) to examine how parents update beliefs when receiving noisy signals about their child's performance in a cognitive (mathematics) or a non-cognitive (prosociality) skill. In mathematics, parents update symmetrically, placing about one third of the Bayesian weight on both positive and negative signals. In prosociality, by contrast, parents apply around 60% of the Bayesian weight to positive information but very little weigh to negative information. The asymmetry is particularly pronounced when signals are framed as reflecting parents' own traits: in this case, parents react roughly 200% more strongly to good than to bad news. Following negative prosocial signals, parents engage in defensive processing: they downplay their child's effort and the relevance of the signals. Survey evidence indicates that these domain differences stem from two factors: parents are better informed about their child's performance in mathematics, and they view prosociality as more central to their child's broader life success. Biased belief updating thus emerges when information is sparse and outcomes are self-relevant, with important implications for how feedback is designed and delivered in educational contexts.

JEL Classification: C93, D83, D91, I21, I24.

Keywords: Belief updating, motivated reasoning, human capital, field experiment.

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1 Introduction

Parents routinely encounter noisy information about their children's performance, through exam results, teacher feedback, and everyday observations. The beliefs parents form based on these guide their behavior and decision-making and the opportunities available to their children (Dizon-Ross, 2019; Giannola, 2024). Yet little is known about whether parents process performance information objectively or in systematically biased ways. Parents are psychologically motivated to maintain favorable views of their children: children's success reflects positively on parents' own competence and decision-making, while acknowledging poor performance may threaten parents' self-image. This motivation creates potential for biased belief updating, where parents weigh information about their child's performance differently depending on whether it is positive or negative. If parents systematically overweight positive signals or downplay negative ones, they may fail to provide compensating support when it is most needed, misallocating time, attention, or resources in ways that reinforce disadvantages. Thus, understanding how parents form and update beliefs is central to models of human capital investment and to the design of feedback provision in education.

This paper investigates whether parents update beliefs about their children's performance objectively or systematically distort information in self-serving ways. I compare belief updating across two fundamental dimensions of human capital: cognitive skills (mathematics) and non-cognitive skills (prosociality). This comparison is motivated by extensive research demonstrating that these represent distinct, complementary dimensions with implications for long-term educational and labor market outcomes, including evolving returns (Heckman et al., 2006; Deming, 2017; Edin et al., 2022; Woessmann, 2025; Deming and Silliman, 2024). This paper provides the first causal evidence on biased belief updating among parents, documenting both general deviations from Bayesian updating and domain-specific asymmetries. I also identify how ego-relevance shapes belief updating, shedding light on the underlying motives that drive parents' concern for their children's performance across domains.

Assessing whether parents update beliefs about their children in a biased way comes with two main challenges. First, identifying and benchmarking biases in belief updating requires controlled settings with repeated probabilistic belief elicitations – data that are seldom available in observational studies. Second, the information parents receive and their motives for processing it are typically endogenous in observational settings, making causal inference difficult. These challenges highlight the need for an experimental design that links children's performance with parents' repeated belief elicitations. I address these challenges through a large-scale lab-in-the-field experiment in Norwegian elementary schools – an ideal setting for studying how parents process information about their child's performance. The sample includes children aged 11–12 (7^{th} grade) and one of their parents ($N = 743$ parent–child pairs).[1] Moreover, the experimental

[1] Parent participation was randomly assigned within households when both parents provided consent.

data is linked to rich Norwegian administrative data that allows to explore heterogeneity across socioeconomic background and family characteristics such as birth order and assess whether experimentally elicited beliefs predict long-run parental investments and child outcomes.[2]

The experimental design is composed of two incentivized experiments, one with children and one with parents, linked at the level of the child. First, children complete tasks in both domains, generating real performance data on which the performance signals are based. Mathematics performance is measured by the number of correct answers on a curriculum-aligned quiz, while prosocial performance is measured by the aggregate amount given to another child in a series of donation games. Parents then report incentivized beliefs about their child's relative performance in one of these domains. Afterwards, parents receive a noisy but unambiguous performance signal based on their child's actual performance and report an updated belief. Parents complete two independent rounds of this task, each based on a separate and independent signal, allowing me to observe sequential belief updating in response to new information.

Guided by a simple conceptual framework, I vary the ego-relevance of performance signals via an information treatment that alters the personal relevance parents attach to their child's performance signals. Parents are randomly assigned to one of three information conditions. In the *Child–Relevance* condition, parents read a passage linking children's performance to later-life outcomes such as education, health, and employment. This renders the signals indirectly ego-relevant to parents through their identification with the child and the child's future prospects. In the *Parent–Relevance* condition, parents read about intergenerational skill transmission, suggesting that children's performance reflects parents' own characteristics. This makes signals directly self-relevant to parents. A control group receives no additional information. These conditions test whether ego-relevance operates through concern for the child's future well-being (*Child–Relevance*) or through parents' self-image as reflected in their child's abilities (*Parent–Relevance*). All parents receive performance signals generated by the same process; only the motivational context varies. This design isolates the causal effect of ego-relevance on belief updating.

I document three main findings. First, I find clear evidence of motivated updating in the *prosocial* domain. Parents exhibit strikingly asymmetric belief updating: they respond about twice as strongly to positive as to negative signals. A favorable signal raises beliefs by roughly 7–9 percentage points, whereas an unfavorable signal lowers them by only 1–2 points. Structural estimates confirm this asymmetry—parents apply roughly half of the Bayesian weight to positive information ($\beta_P \delta \approx 0.5$) but assign virtually no weight to negative information. The asymmetry is particularly pronounced when signals are framed as reflecting parents own traits: in this case, parents react about 200% more strongly to good than to bad news ($\beta_P / |\beta_N| \approx 2.2$). In *mathematics*, by contrast, parents update conservatively but symmetrically, giving roughly equal weight to positive and negative news and adjusting their beliefs by about one third of the Bayesian magnitude,

[2] Linkage to administrative data has been approved and is currently in progress; analyses based on these data will be incorporated in subsequent versions of the paper.

consistent with a more objective, accuracy-oriented response.

Second, across both domains, parents exhibit base-rate neglect, underweighting their prior beliefs relative to the Bayesian benchmark ($\delta < 1$). The degree of underweighting is bigger in prosociality ($\delta = 0.68$) than in mathematics ($\delta = 0.88$), indicating that parents rely less on their priors when interpreting prosocial performance and more when evaluating mathematical performance. For reference, the estimate for mathematics ($\delta = 0.88$) lies close to the upper end of the range typically found in comparable belief-updating studies involving IQ or cognitive ability, where δ values range between 0.84 to 0.92 (e.g., Coutts, 2019; Möbius et al., 2022; Drobner, 2022). In contrast, the estimate for prosociality ($\delta = 0.68$) is considerably lower. The only comparable individual-level study in a social or prosocial context, Jiao et al. (2024), reports even smaller coefficients ($\delta = 0.43$-0.56), suggesting that belief updating in this domain tends to be particularly conservative. These cross-study comparisons should, however, be interpreted with caution, as existing studies focus on individuals updating about their *own* performance, whereas my design examines updating about one's *child's* performance.

Third, the asymmetry in prosocial updating carries through to downstream outcomes. Parents who receive negative prosocial signals downplay their child's effort and the importance of the signals for future life outcomes, yet at the same time report higher aspirations for their child's tertiary education and display a greater willingness to invest in educational goods, as measured by a stylized parental investment measure. This pattern is consistent with defensive optimism: when confronted with threatening information in a self-relevant domain, parents protect a positive narrative by reinterpreting bad news and compensating through increased investment. In mathematics, by contrast, negative signals lower both perceived effort and investment intentions, consistent with a more objective, accuracy-oriented adjustment process.

Why does biased belief updating emerge in prosociality but not in mathematics? Two complementary factors may help explain this pattern. First, parents appear substantially better informed about their child's mathematical performance, even in the absence of formal grades. I find a stronger correspondence between children's actual performance and parents' beliefs in mathematics than in prosociality. Exposure to homework, teacher feedback, and peer comparisons provides relatively objective signals that limit the scope for belief distortion. In contrast, parents receive far fewer and less standardized signals about prosocial behavior, creating informational ambiguity that leaves more room for selective interpretation. Second, survey evidence suggests that parents view prosociality as more central to their child's broader life success, whereas mathematics is seen as relevant mainly for academic achievement.[3] Together, these patterns are consistent with the idea that motivated reasoning is more likely to arise when information is ambiguous and when the domain is psychologically self-relevant—either directly, by reflecting the parent's own traits and values, or indirectly, through the parent's identification with the child's future success.

[3]The survey evidence was collected independently from the experimental data collection and is thus unaffected by treatment assignment.

The paper advances and contributes to existing research in three ways. First, it contributes to the research on motivated reasoning and belief updating in ego-relevant domains such as intelligence, physical attractiveness, generosity, and financial decision-making (e.g., Bénabou and Tirole, 2002; Eil and Rao, 2011; Möbius et al., 2022; Coutts, 2019; Barron, 2021; Jiao et al., 2024). I retain the canonical design of sequential, incentivized belief elicitations but examine a distinct setting in which the signals concern the child's performance rather than one's own. This allows me to identify belief updating in an interdependent context where another person's outcomes directly affect one's self-image. In doing so, the paper advances the motivated-reasoning literature by showing how ego-relevance can emerge either directly, when a child's performance reflects on the parent's own traits, or indirectly, through parents' identification with their childs successes and failures. While the focus is on the parent–child relationship, the mechanism generalizes to other interpersonal settings—such as advisor–advisee, mentor–mentee, or spousal relationships—where one party's outcomes shape the other's self-image. Finally, the paper contributes to a small and emerging literature on interdependent beliefs (Bauer et al., 2023; Dickinson, 2024; Dickinson and Villeval, 2025). Whereas that literature has focused primarily on political and in-group/out-group contexts, I hold the signal source constant while experimentally varying its motivational relevance.

Second, the paper advances the human capital literature by explicitly linking parental belief formation to the distinction between cognitive and non-cognitive skills, two complementary dimensions that jointly shape long-term educational and labor market outcomes. While non-cognitive skills have become increasingly important in modern labor markets (see Deming and Silliman, 2024; Woessmann, 2025; Heckman et al., 2006; Almlund et al., 2011; Deming and Kahn, 2018; Edin et al., 2022; Izadi and Tuhkuri, 2025), the parental beliefs literature (Boneva and Rauh, 2018; Attanasio et al., 2022a; Bhalotra et al., 2025; Kiessling, 2021) has largely treated children's abilities as one-dimensional, leaving domain-specific beliefs understudied. This paper moves beyond that limitation by experimentally eliciting parents' beliefs about their own child's performance in distinct domains, rather than relying on hypothetical scenarios. In doing so, it provides the first causal evidence on how parents interpret information differently across skill domains.

Third, it provides systematic evidence on how individuals update beliefs when exposed to sequential and noisy information about a personally relevant outcome, moving beyond prior work that focuses on one-shot, perfectly informative settings (e.g., Gan, 2021; Dizon-Ross, 2019; Bergman, 2021). Prior studies typically present parents with precise, definitive feedback—such as their child's exact test score or rank—which eliminates uncertainty about the true state of the child and precludes observing how parents process and weigh information, the very process through which bias may operate. In contrast, my design allows me to quantify both the extent and direction of bias in belief updating relative to a Bayesian benchmark, capturing how parents process information over time. Building on related work showing that parents anchor to local reference groups (Kinsler and Pavan, 2021; Eble and Hu, 2022), I causally identify the mechanisms through which such cognitive biases emerge and how their magnitude differs across domains.

Lastly, the paper advances our understanding of parent–child interactions by contributing to a growing body of lab-in-the-field studies that combine experimental control with realistic settings (Müller, 2024; Tungodden and Willén, 2023; Bergman, 2021; Sund, 2023; Carlana and Corno, 2024; Houser et al., 2016; Brouwer et al., 2022). Most closely related are two Norwegian studies (Tungodden and Willén, 2023; Sund, 2023) that examine parental decision-making on behalf of children—such as choosing competitive environments or granting unfair advantages - and implement these decisions to assess their impact on children's behavior. This paper extends that literature by focusing on the antecedent stage of parental decision-making: how parents form and update beliefs about their child's performance. While the Norwegian setting provides particularly clean conditions for studying belief formation[4], these mechanisms likely operate broadly, as parents everywhere must interpret ambiguous signals about their children's abilities and decide how to act on them.

The remainder of the paper proceeds as follows. Section 2 introduces the experimental design in detail, and Section **??** develops the conceptual framework. Section 4 outlines the implementation and institutional background. Section 5 presents the main findings, followed by Section 6, which discusses why biased belief updating emerges for prosociality but not for mathematics. Section 7 concludes.

2 Experimental Design

The experiment consists of two sequential stages: the *children stage*, measuring the child's performance in mathematics and prosocial behavior, and the *parent stage*, capturing how parents update beliefs about their child's performance. After outlining the children and parent stage, I describe the two dimensions of exogenous treatment variation on the parents' stage.

2.1 Children Stage

Children participate in the experiment at their school, during school hours. Before they log-in to the study, children are informed that participation in the study is voluntary and that they can withdraw their consent at any point in time. Students are also informed that by taking part in the study, they will earn a prize. More specifically, they are informed that they can earn tokens that will be translated into a prize after they study is completed. Students are told that participation alone earns them 50 tokens, and that they will get the opportunity to earn additional tokens throughout the study.[5] To access the study, the child has to enter a unique participation code, allowing me to link the study of the child to that of the parent. As the children are 11–12 years

[4] Norwegian schools do not introduce formal grades until 8$^{\text{th}}$ grade (age 13–14), meaning parents in my sample have limited exposure to standardized performance feedback. This information-sparse environment makes the experimentally provided signals particularly salient and reduces the risk that they are diluted by other sources of information.

[5] The average prize value is 100 NOK ($\approx$ 9 USD).

of age, the study interphase and use of language is adapted to accommodate for the age group. The children are guided through the survey by Spiffy, an animated character. In addition, the text is frequently combined with illustrations. Importantly, they are made aware that they at no point will receive information about their actual absolute or relative performance. This last bit of information is used in a comprehension question which children will have to answer correctly in order to proceed. Having done so, they proceed to the main modules of the experiment. In this, children complete two incentivized tasks measuring performance for mathematics and prosocial behavior. These measures are later used to truthfully generate the performance signals that are shown to parents.

Mathematics. The first task that children complete is a mathematics quiz aligned with the national curriculum.[6] The quiz contains 15 multiple-choice questions, each with four answer options and one correct answer. Children have four minutes to answer as many questions as they wish and can skip questions without penalty. To incentivize effort, each correct answer earns tokens if the quiz is randomly selected for payment.[7]

Prosociality. After completing the mathematics quiz, children take part in a series of dictator games to measure their prosociality. Following Woessmann (2025), I classify it as an economically meaningful skill dimension similar to cognitive skills because these prosocial preferences are malleable (Kosse et al., 2020), can be learned and accumulated (Almlund et al., 2011), and have documented labor market returns (Falk et al., 2018). To measure these prosocial preferences[8], I use a set of four dictator games from Bonan et al. (2023), which has been validated with primary school children in El Salvador. This set of games was chosen because it yields a distribution of prosocial behavior, allowing for a differentiated top-bottom split.[9] In each game, children (as the dictator") allocate 10 tokens between themselves and another child (the recipient") described as being in need and supported by the Norwegian Red Cross.[10] The games vary in the initial endowments and whether the child can alter the other child's initial endowment in addition to allocating the ten tokens. I measure prosociality as the total tokens allocated to the other child across the

[6] The mathematics quiz always precedes the prosociality task as the order was determined by Barron et al. (2025).

[7] To determine a child's placement in the top or bottom half of the performance distribution, domain-specific cutoffs were established using data from two schools surveyed prior to the main experiment. In the mathematics domain, children were categorized as being in the top half if they scored above 3 correct questions. For children whose scores fell exactly at the cutoff, placement in the top or bottom half was assigned randomly. These cutoffs were applied uniformly across all participants during the main data collection.

[8] The dictator game is a widely used experimental paradigm which provides a revealed-preference measure of altruism and fairness concerns. In its standard form, one participant, the "dictator," is given an endowment and unilaterally decides how much of it to keep and how much to allocate to a passive recipient, who has no influence over the outcome. The amount transferred to the recipient is interpreted as a measure of generosity or altruism (see review in Sutter et al., 2019).

[9] To determine a child's placement in the top or bottom half of the performance distribution, domain-specific cutoffs were established using data from two schools surveyed prior to the main experiment. In the prosocial domain, the top half included those who donated more than 19 out of 40 tokens across four dictator games. For children whose scores fell exactly at the cutoff, placement in the top or bottom half was assigned randomly.

[10] The Norwegian Red Cross supports financially disadvantaged families in Norway through programs such as *Ferie for alle* (in English: Holidays for All).

four games, providing a continuous measure of prosocial behavior. Children know that one game is randomly selected for payment, with tokens given to the other child converted to donations to the Norwegian Red Cross and tokens kept added to the child's total. For an overview of the set of dictator games, please see Appendix B.2.

2.2 Parent Stage

On the parents' side, the survey starts with a confirmation of their consent to participate and an explanation of the incentives. Besides knowing that the study is related to the study that their child has participated in at school, parents are incentivized to partake in the study through lottery tickets. At the beginning of the study, parents are informed that the lottery will have three prizes of 10,000 NOK each, in the form of vouchers for a large electronics retail store in Norway. Parents are informed that by completing the survey, they will earn three lottery tickets, and that they have the opportunity to earn ten additional tickets throughout the survey.[11]

Next, parents are provided with information about the study that their child has participated in in school. More specifically, they are informed that the child has participated in a task, and that their performance in the task will be compared to the performance of students from other schools that completed the same task earlier (hereafter referred to as the reference group).[12] To fixate ideas, they are provided with more information about the task the child completed.

Parents are informed that their child and the other children are ranked based on their performance in the task, from the best to the worst performer. Based on this ranking, students are divided into two groups: a top half, consisting of those scoring above the median, and a bottom half, consisting of those scoring below the median. In case of a tie, parents know that the rank will be randomly determined. The ranking and median cut-off are computed once using the reference group of children surveyed earlier, and this fixed threshold is then applied uniformly to all participants in the study. To ensure understanding, parents must correctly answer a comprehension question before proceeding. Finally, parents are informed that their child will not learn their true performance – neither relative nor absolute – at any point during the study.

Belief elicitation. Across all treatment conditions, parents are asked at several points in time about the likelihood of their child's performance placing in the top half of the reference group. Parents state their belief in a probabilistic manner (from slider from 0 to 100% without anchoring) about a binary state (i.e. top half).

Parental beliefs are elicited in an incentive-compatible procedure through a variation of the Becker-DeGroot-Marschak mechanism (Becker et al., 1964).[13] While payment details are accessible

[11] Appendix C.1 and C.2 provide transcripts of the actual instructions used.

[12] To make it easily comprehensible to parents, we inform parents that they should think about it as roughly 30 students.

[13] In each round, the computer first draws a random number ("Draw 1") uniformly between 1 and 100. If this number

via a clickable "Payment Details" button, they are not shown explicitly by default. Danz et al. (2022) demonstrate that simply informing participants about the incentive compatibility of the belief elicitation mechanism, without disclosing quantitative details, can improve the accuracy of reported beliefs. Participants are truthfully informed that beliefs will be elicited at multiple times, but that only one randomly selected belief will be selected to determine the number of bonus lottery tickets they receive.

Signal-generating process. After parents have stated their prior belief, parents are presented with an unbiased signal about their child's relative performance.

Each signal is binary and unbiased yet noisy. More specifically, each signal is correct (i.e., indicates the true state of the child) two out of three times. This implies that when the child actually places in the top half, the parent observes with probability 2/3 the signal *"Your child places in the top half"* and with probability 1/3 the opposite ("Your child does not place in the top half."). Conversely, when the child is actually in the bottom half, the parents observes with probability 2/3 *"Your child does not place in the top half"* and with probability 1/3 the opposite ("Your child places in the top half.").

Following Coutts (2019), Drobner and Goerg (2024) and Liu and Wang (2025), the signal generating process to generate the noisy but unbiased signals is communicated to parents in an intuiitive manner using three cartoon "messengers". In the study at hand, the messengers take the form of trolls, drawing on characters from Norwegian folklore.[14] While two of the messengers always tell the truth (i.e., indicate the true state of the child) with clear eyes, the third troll always lies (i.e., indicates the false state of the child) and has red eyes. From this set of trolls, one troll is randomly selected and reports a signal, so called message, to parents.

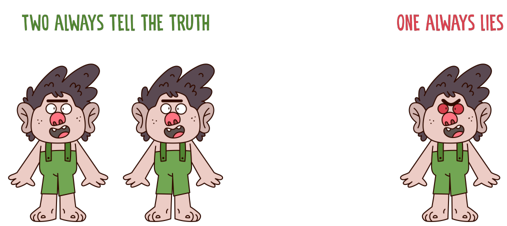


Figure 1: Signal generating process

Signals indicating top-half placement are termed **top** or **good/positive** signals; those indicating bottom-half placement are refered to as **bottom** or **bad/negative** signals (Figure 2).

When delivering the signals, parents cannot infer whether the truthful or lying messenger has sent

is lower than the participant's stated probability, the participant receives the bonus if the statement is true and does not receive it if the statement is false. If Draw 1 is higher than the stated probability, a second random number ("Draw 2") is drawn, also uniformly between 1 and 100. The participant receives the bonus if Draw 2 is lower than Draw 1, and does not receive it otherwise.

[14] Trolls feature prominently in Norwegian cultural heritage, appearing in folklore, fairy tales, and tourism materials.

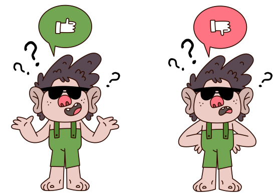


Figure 2: Noisy but unbiased signal: Positive (left) and negative (right) signal

the signal as the messenger's eyes remain covered. The signals in this experiment are thus simple, clearly structured, stochastic, and the signal generating process is uniform across all parents. This setup allows for a transparent test of belief updating behavior, both in terms of asymmetries in response to positive versus negative signals and deviations from Bayesian updating, as the experiment elicits all components necessary to compute normative posterior beliefs.

Rounds of belief updating. In total, parents receive two signals and update their beliefs twice. The first round includes elicitation of the prior, observing the first signal and stating the posterior. The second round includes observing a second signal and stating a posterior. The posterior from round 1, becomes the prior of round 2. Signals across rounds are independent and generated by the same signal generating process. Before observing each signal, the signal generating process is repeated to parents to emphasize that the signals are independent. Observing multiple rounds of belief updating allows to study belief dynamics over time as well as increase power while ensuring uncertainty about the true state of the child (i.e., whether the child places in the top or bottom half) to the parent. The latter is a feature that Drobner (2022) identifies as essential for observing biased belief updating. The four possible signal sequences that a parent can observe are therefore: *Good–Good*, *Good–Bad*, *Bad–Good*, and *Bad–Bad*.

Prior → Signal 1 → Posterior 1 → Signal 2 → Posterior 2

Figure 3: Full sequence of elicited beliefs and signals

Other outcomes. In addition to eliciting beliefs, I include three survey questions to assess whether parents engage in ex-post rationalization after receiving signals. Specifically, I ask parents: (i) how important they perceive their child's performance to be for the child's future success, (ii) how much effort they believe the child exerted, and (iii) to what extent they view the child's performance as reflective of their own abilities. All responses are recorded on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).

Finally, a subset of parents is also asked about their aspirations for their child's future academic trajectory in secondary and tertiary education. I also ask parents how much of the voucher amount they would invest in an educational good if they win the lottery. I treat this as a stylized measure of parental educational investment. Parents are informed that their choice is binding in the event that they win.

Survey measures. Lastly, there is a survey module in which parents answer demographic and background questions (number of children, educational attainment, degree in STEM etc.). I also ask parents to explain their thought process how they reacted to the signals and updated their beliefs in an open ended question.

2.3 Treatment Variation

The experiment features a 2×3 design with two between-subject treatment variations: (i) the *domain* in which parents receive signals, and (ii) the *motivational context* in which those signals are interpreted. Together, the domain and motivational context treatments allow me to test whether biased belief updating arises from *what* the signal is about and *why* it matters to the parent.

Domain assignment. Parents are first randomly assigned to one of two domains: *mathematics* or *prosociality*. This determines whether they receive signals about their child's relative performance on a cognitive task (number of correctly answered questions in an incentivized mathematics quiz) or on a non-cognitive task (aggregate giving in a set of incentivized dictator games).

Motivational context. Within each domain, parents are further randomized into one of three motivational contexts: *Control (No Information)*, *Child–Relevance*, or *Parent–Relevance*. These contexts are introduced *after* parents state their prior beliefs but *before* observing the first performance signal, allowing the motivational context to influence how signals are interpreted without affecting baseline beliefs (Drobner and Goerg, 2024).

- In the ***Control*** condition, parents receive no additional information before observing the signals. This serves as a neutral benchmark.
- In the ***Child–Relevance*** condition, parents read a short passage summarizing scientific evidence that links children's performance on similar tasks to later-life outcomes such as education, health, and employment. This motivational context is designed to induce *indirect ego-relevance* to the parent: the child's performance matters for the child's future, which is important to the parent but not directly about the parent.
- In the ***Parent–Relevance*** condition, parents read a short passage summarizing scientific evidence on the intergenerational transmission of skills, suggesting that children's performance reflects their parents' characteristics. This motivational context induces *direct ego-relevance*, making the signals personally self-relevant to the parent.

All passages include references to scientific studies and are accompanied by a clickable "References" button in the survey interface. Screenshots of the respective screens are shown in Figures 30 and 31.

Before reading the information passage, parents are asked how strongly they believe the stated relationship to hold in general. This provides a baseline measure of perceived relevance. To ensure engagement and comprehension, participants are informed that they can earn two additional lottery tickets by correctly answering a short comprehension question about the passage at the end of the survey.

Together, these treatment dimensions allow for testing whether belief updating differs: (i) across domains (mathematics vs. prosociality), and (ii) across motivational contexts that vary in ego-relevance (none vs. indirect vs. direct).

An overview of the full experimental procedure is provided in Figure 4.

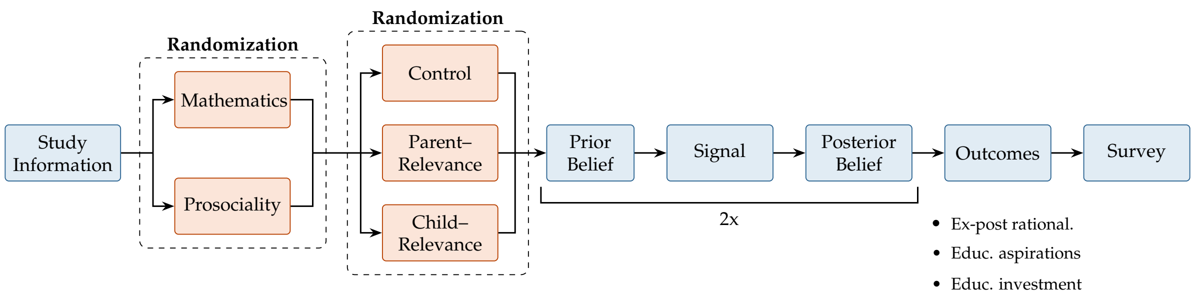


Figure 4: Experimental flow

The experimental design achieves high internal validity by tightly controlling the information environment. Parents receive binary performance signals whose precision is common knowledge, allowing for a clean test of belief updating under uncertainty. This setup mirrors real-world situations, such as when a child performs poorly on a test, where parents must interpret uncertain information and infer what it implies about their child's performance. At the same time, the design simplifies everyday information environments in two important ways, making it more stylized and limiting external generalizability. First, signals are noisy but clearly defined and uniformly presented (top-half vs. bottom-half), whereas real-world information is often ambiguous, context-dependent, and varies across individuals. Second, performance is expressed in relative rather than absolute or continuous terms. While these abstractions make the task more stylized and less naturalistic, they enable precise measurement of belief formation and facilitate direct comparison to a Bayesian benchmark.

3 Conceptual Framework

This section outlines a conceptual framework that formalizes how parents form beliefs about their child's performance under biased information processing and how such beliefs shape subsequent investment decisions.

Following Drobner and Goerg (2024) and Dickinson and Villeval (2025), I model the utility of parents' holding a belief $\hat{\gamma}$ about their child's relative performance as consisting of three components: (i) a direct utility from holding the belief itself, (ii) a payoff associated with holding accurate beliefs about the child's performance, and (iii) a cognitive cost of belief distortion. In each round, parents form a belief about whether their child ranks in the top half of a reference group after observing a noisy but unbiased signal s, which can take two values: a good signal ("Your child is in the top half") or a bad signal ("Your child is not in the top half"). They are fully informed about the signal-generating process and its informativeness p_{st}, allowing them to compute a Bayesian posterior:

$$\gamma_{st} = \frac{p_{st}\gamma_{t-1}}{p_{st}\gamma_{t-1} + (1-p_{st})(1-\gamma_{t-1})}.$$

However, parents may interpret the same signal as more or less informative – behaving as if p_{st} were $\hat{p}_{st}$. This misperception of signal precision ($p_{st} \to \hat{p}_{st}$) provides a micro-foundation for biased belief formation: it distorts the odds ratio underlying Bayesian updating, leading to systematically optimistic posteriors when favorable information is overweighted relative to unfavorable information.

To capture this process in a tractable form, I express it as a reduced-form utility specification in which the reported belief $\hat{\gamma}$ may deviate from the Bayesian benchmark γ due to ego-relevant motives and cognitive costs of distortion:

$$U_{Belief} = \alpha\hat{\gamma} + \frac{1}{2}(1 + 2\gamma\hat{\gamma} - \hat{\gamma}^2)M - \beta(\hat{\gamma} - \gamma)^2.$$

The first term, $\alpha\hat{\gamma}$, captures *direct belief utility*: parents derive psychological utility from holding a favorable belief about their child's relative performance. The parameter $\alpha > 0$ reflects how much the belief about the child's relative performance matters to the parent (i.e., how ego-relevant it is).

The second term, $\frac{1}{2}(1 + 2\gamma\hat{\gamma} - \hat{\gamma}^2)M$, represents the payoff from holding accurate beliefs about the child's relative performance where M is the incentive for accurate beliefs. It is maximized when $\gamma = \hat{\gamma}$, meaning that the belief that parents report $\hat{\gamma}$ coincides with the belief that is formed based on Bayes' rule γ. The third term, $\beta(\hat{\gamma} - \gamma)^2$, represents the *cognitive cost* of distorting beliefs away from the objective belief γ. This term, which is subtracted from utility, can be interpreted as the mental effort required to sustain self-serving interpretations of evidence.

Maximizing U_{Belief} with respect to the reported belief $\hat{\gamma}$ yields the optimal belief distortion:

$$\hat{\gamma}^* = \gamma + \frac{\alpha}{M + 2\beta}. \tag{1}$$

Equation (1) provides a reduced-form representation of biased belief formation in which ego-relevance induces an additive shift in reported beliefs. One micro-foundation for this reduced form is a model in which parents misperceive the precision of the signal ($p_{st} \rightarrow \hat{p}_{st}$), thereby updating as if the signal were more informative when it is favorable and less informative when it is unfavorable. This likelihood-distortion mechanism produces the same qualitative pattern of belief distortions, but Equation (1) abstracts from these micro-foundations into a tractable, utility-based framework that highlights how ego-relevance, accuracy incentives, and cognitive costs jointly shape reported beliefs.

To capture the observed asymmetry in belief updating, I allow the ego-relevance parameter α to vary with the valence of the signal, such that $\alpha = \alpha^{+} > 0$ following positive signals and $\alpha = \alpha^{-} < \alpha^{+}$ following negative signals. Intuitively, more ego-relevant and thus yields greater direct belief utility, whereas negative information is psychologically less acceptable and therefore associated with a lower marginal return to favorable belief distortion. This simple extension implies that even when accuracy incentives and cognitive costs are constant, belief distortions become signal-dependent, leading parents to respond more strongly to good than to bad news – producing asymmetric updating as predicted in Hypothesis H1.

Together, these mechanisms link the theoretical framework directly to the experimentally induced variations in ego-relevance described below.

3.1 Hypotheses

The framework implies that parents optimally balance the psychological benefits of holding favorable beliefs with the monetary and cognitive costs for holding inaccurate beliefs. As shown in Equation (1), the deviation of the reported belief from the Bayesian benchmark depends on the ratio $\frac{\alpha}{M+2\beta}$. This implies that higher ego-relevance (α) increases optimistic bias, whereas stronger accuracy incentives (M) and higher cognitive costs of distortion (β) reduce it.

In the experimental context, the incentive parameter M is constant across conditions, while ego-relevance α is exogenously manipulated through two exogenous variations in a between manner. First, the *domain assignment* varies whether parents receive signals about their child's performance in prosociality or mathematics, capturing differences in the self-relevance of domains to parents. Secondly within a domain, I manipulate the relevance of the signals through information conditions: the *Parent–Relevance* information condition induces direct ego-relevance to the parent while the *Child–Relevance* condition induces indirect ego-relevance to the parent. Lastly, the *Control* condition serves as a neutral baseline.

This framework gives rise to the following empirically testable predictions.

H1 (Optimistic updating). Parents update beliefs about their child's relative performance more optimistically than predicted by Bayesian updating ($\hat{\gamma}^{*} > \gamma$), overweighting positive relative to negative signals.

H2 (Domain difference). Optimism is stronger in the *prosociality* domain than in the *mathematics* domain, reflecting higher perceived self-relevance of their child's prosocial performance to parents than for their performance in mathematics ($\alpha_{\text{Prosociality}} > \alpha_{\text{Mathematics}}$).

H3 (Relevance channel). Optimism increases with the ego-relevance of the information condition to the parent, with the strongest bias in the *Parent–Relevance* condition, followed by *Child–Relevance*, and lowest in the Control condition ($\alpha_{\text{Parent–Relevance}} > \alpha_{\text{Child–Relevance}} > \alpha_{\text{Control}}$).

3.2 The Role of Biased Beliefs in Parental Decision-Making

Below, I sketch a stylized one-period model to highlight the implications of biased beliefs for parental investment behavior. Following the tradition of altruistic parental models (e.g., Becker and Tomes, 1986; Cunha and Heckman, 2007; Attanasio et al., 2022b), I assume that parents derive utility from their own consumption and from their child's human capital development. In this one-period setting, parents choose consumption C_i and parental investment X_i to maximize:

$$\max_{C_i, X_i} \quad U_i(C_i) + V_i(H_i') \tag{2}$$

subject to the budget constraint:

$$Y_i = C_i + pX_i, \tag{3}$$

and the production function:

$$H_i' = f(\hat{H}_i, X_i, Z_i, \varepsilon_i). \tag{4}$$

Here, Y_i denotes household income and p the unit cost of investment. The child's post-investment human capital is denoted by H_i', and it is produced via a technology $f(\cdot)$ that depends on the parent's belief about the child's initial ability $\hat{H}_i$, the level of investment X_i, observable background factors Z_i, and an unobservable shock ε_i.

In this formulation, I assume that the production function $f(\cdot)$ is objective and known. That is, parents correctly perceive the mapping from inputs to outputs, and bias arises only through their belief about the child's initial ability. Specifically, parents make decisions based on a perceived ability $\hat{H}_i$ that may deviate from the true ability H_i due to motivated reasoning/biased processing of information.

Substituting the budget constraint into the objective function yields a reduced-form optimization problem in a single choice variable:

$$\max_{X_i} \quad U_i(Y_i - pX_i) + V_i\left(f(\hat{H}_i, X_i, Z_i, \varepsilon_i)\right). \tag{5}$$

Assuming interior solutions and differentiability, the first-order condition characterizing the optimal level of investment X_i^* is given by:

$$p \cdot U_i'(Y_i - pX_i) = V_i'\left(f(\hat{H}_i, X_i, Z_i, \varepsilon_i)\right) \cdot \frac{\partial f}{\partial X_i}(\hat{H}_i, X_i, Z_i). \tag{6}$$

The left-hand side represents the marginal utility cost of investing (i.e., the marginal loss from reduced consumption), while the right-hand side captures the perceived marginal benefit of investment via its contribution to the child's human capital. Crucially, this marginal benefit is evaluated using the parent's belief about the child's ability, $\hat{H}_i$, rather than the true H_i.

The behavioral implications of biased beliefs hinge on the curvature of the production function. If ability and investment are *complements*, that is, if the cross-partial derivative $\frac{\partial^2 f}{\partial H \partial X} > 0$, then higher perceived ability increases the marginal return to investment. In this case, an upward bias in beliefs leads parents to overinvest relative to what would be optimal under correct beliefs. Although such overinvestment may be inefficient, it still results in higher skill production and may carry limited welfare loss.

In contrast, if ability and investment are *substitutes*, such that $\frac{\partial^2 f}{\partial H \partial X} < 0$, then higher perceived ability reduces the marginal benefit of investment. In this case, biased beliefs lead to underinvestment in children whose actual ability is lower than perceived. This scenario is particularly concerning, as it implies that children who would benefit most from additional support may receive less of it due to motivated reasoning/biased processing of information.

The welfare implications of biased beliefs depend critically on the underlying technology of skill formation, particularly the degree to which ability and investment are technological complements or substitutes. Figure 5 illustrates these mechanisms in a stylized framework.

4 Implementation and Background

This study combines data collected through a lab-in-the-field experiment with high-quality administrative data on both parents and their children. The data is linked at the level of the individual.

4.1 Recruitment Procedure

I recruit parent–child pairs from schools across Norway. Schools were contacted via email with an invitation to participate in the study, which included an overview of the research and a request to administer a one-hour survey to their seventh-grade students during class time.

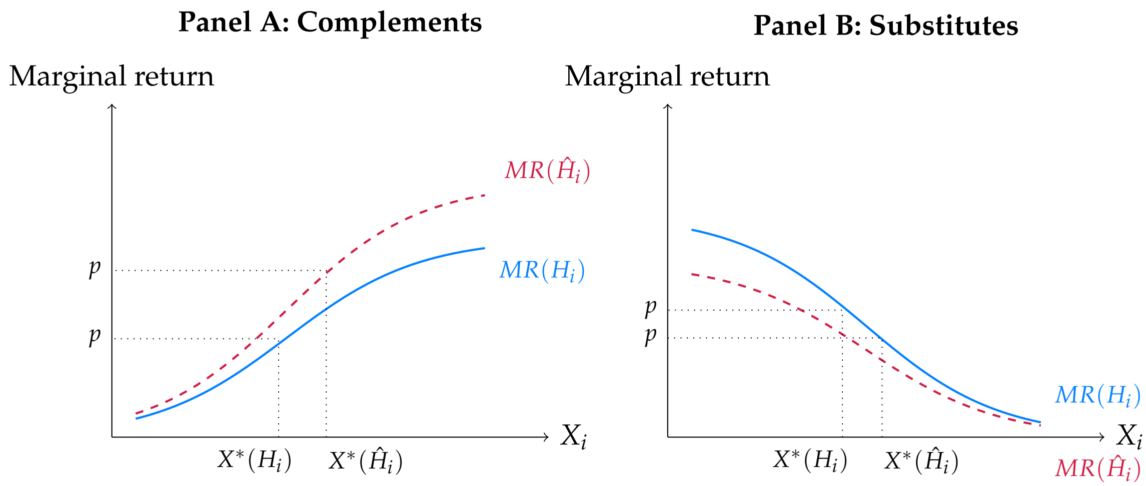


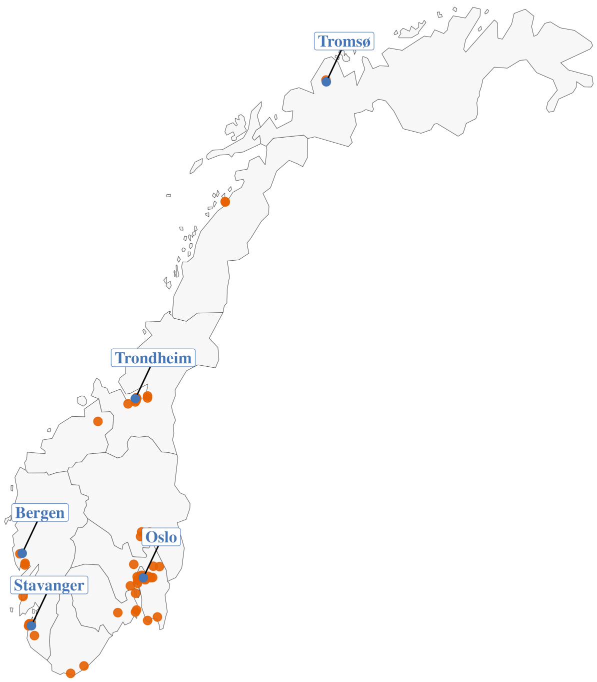
Figure 5: Effect of biased beliefs on optimal investment under different production technologies. In Panel A (complements), an upward bias in perceived ability increases the marginal return to investment and leads to overinvestment. In Panel B (substitutes), the same bias decreases the perceived need for investment, leading to underinvestment.

As evident in Figure 6 covers schools across all Norwegian counties, closely mirroring the national population distribution. Representation is slightly higher in central regions such as Trøndelag and Buskerud and somewhat lower in western and northern counties.[15] Representation is slightly higher in central regions such as Trøndelag and Buskerud and somewhat lower in Western and Northern counties. The invitation clarified that participating children would receive a prize based on their survey responses and that their parents would subsequently be invited to complete a related follow-up survey.[16] The stated purpose of the study was to explore children's learning environments.

Within each participating school, all seventh-grade classes were invited. Class teachers or grade-level coordinators distributed the invitation to parents via email, which included a link and QR code to an online consent form. Parents provided consent for both their own and their child's participation before the child takes part. Both children and parents were free to withdraw from the study at any point in their respective surveys. Further details on the recruitment process are provided in Appendix B.3.

[15]Only schools with more than 50 students in grade seven were invited to participate to ensure adequate sample sizes per school, as not all parents were expected to provide consent. This selection criterion may also help explain the slight overrepresentation of schools in more central counties and the underrepresentation of those in rural regions.

[16]To ensure the prizes were appealing to children, I partnered with the museum store of the VilVite Science Centre, a children's science museum in Bergen (VilVite Science Centre). Prizes were shipped to schools after data collection, and each child's prize was based on the number of tokens earned in the survey. Further details are provided in Appendix B.5.



County	Schools (%)	Pop. (%)	Ratio
Eastern Norway	50	51	0.98
Innlandet	6	6.8	0.88
Østfold	4	5.6	0.71
Buskerud	6	4.9	1.22
Vestfold of Telemark	4	7.7	0.52
Oslo	12	12.9	0.93
Akershus	18	13.1	1.37
Western Norway	24	25.6	0.94
Vestland	8	11.7	0.68
Møre og Romsdal	2	4.9	0.41
Rogaland	14	9.0	1.56
Southern Norway	4	5.8	0.69
Agder	4	5.8	0.69
Northern Norway	6	8.8	0.68
Nordland	4	4.4	0.91
Troms og Finnmark	2	4.4	0.45
Trøndelag	16	8.7	1.84
Trøndelag	16	8.7	1.84
Average ratio			0.94

Note: The average ratio (0.94) reflects the unweighted mean of county-level ratios between school and population shares. Population shares are based on Statistics Norway (2025a). Orange markers indicate the location of sampled schools.

Figure 6: Distribution of Sampled Schools and Population Shares Across Norwegian Counties

4.2 Data Collection

Data collection took place between October 2024 and May 2025. Children completed the survey during class, using tablets or desktop computers under teacher supervision. The survey, programmed in oTree (Chen et al., 2016), typically lasted 30–45 minutes (one school hour) and was usually conducted after lunch (between 12:00 and 13:00).[17]

After a child completed the survey, one parent, randomly selected if contact information was available for both, received a personalized survey link via text message later that same afternoon. Parents could complete the survey on a smartphone, tablet, or desktop computer. If the selected parent did not respond, a reminder message was sent that evening. If there was still no response by the following day, the second parent (if applicable) was invited using the same message sequence the following day: an afternoon invitation followed by an evening reminder if necessary. This sequential invitation strategy was designed to maximize completed child–parent survey pairs.

One potential concern is that parents may have spoken with their child about the survey before

[17]The child data collection was conducted concurrently with Barron et al. (2025).

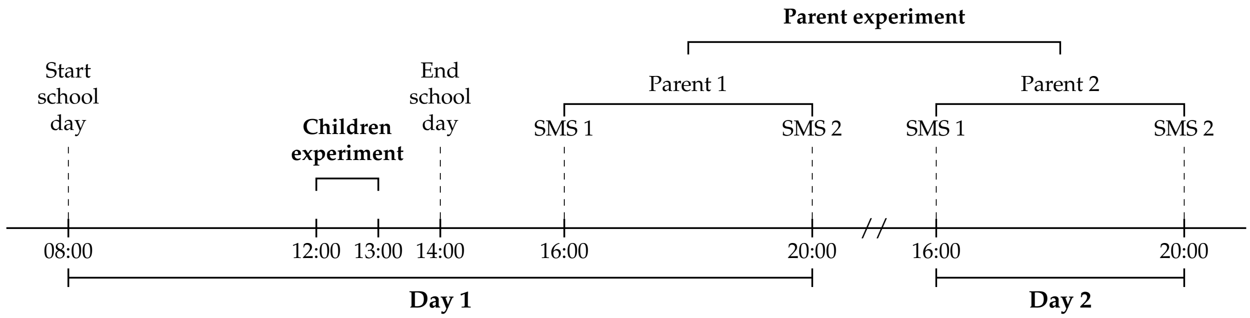


Figure 7: Timeline of the children and parent experiment

completing their own survey. While this possibility cannot be entirely ruled out, its implications are likely limited for two reasons. First, children were not informed about either their relative or absolute performance during the survey, and the parent survey concerns the child's relative performance in comparison to a reference group drawn from other schools. Thus, children were unable to share meaningful information about their own performance. Second, parents were explicitly instructed not to discuss the survey with their child while completing it. Given that many schools scheduled survey sessions toward the end of the school day, some parent–child interaction before survey completion is difficult to avoid and, to some extent, anticipated.

4.2.1 Sample

The sample comprises $N = 743$ child–parent pairs, each of whom completed their respective survey.

Children – Experimental data. The child sample includes $N = 369$ boys (49.66%) and $N = 374$ girls (50.34%). In the mathematics quiz, children answered an average of 4.2 questions correctly; boys averaged 4.47 and girls 3.94 correct answers. This gender gap is statistically significant (Wilcoxon rank sum test, p-value < 0.001) and aligns with primary-level mathematics patterns documented in Kaarstein et al. (2024). In prosociality, the pattern reverses: girls donate an average of 16.12 tokens (out of 40) across all dictator games, compared to 13.03 tokens for boys (Wilcoxon rank sum test, p-value < 0.01). On average, children give 14.6 tokens (36.53%) to the other child. There are no systematic differences across domains or information conditions in child-level variables (see Tables 6–8). 18.71% of children give nothing to (or even takes tokens from) the other child across all four games, with a higher proportion of boys (60.43%) than girls (39.57%) showing such a behavior.

Parents – Experimental data. The parent sample consists of $N = 511$ mothers (69.15%) and $N = 228$ fathers (30.85%), indicating differences in participation rates despite the initial randomization of invitations to parents.[18] Most parents hold a university degree (74.52%), compared to

[18]Four parents preferred not to report their gender. It is beyond the scope of this study to determine whether this reflects differing willingness to engage with the survey or differences in availability at the time the invitation was

25.48% with upper secondary education or lower. This suggests positive selection relative to the Norwegian population.[19] This selection may reflect the timing of the invitation (during the day), the online format, and the recruitment strategy, which targeted larger schools that tend to be located in more urban areas. 26.8% of parents report holding a STEM degree. Single-child families make up 17.4% of the sample, while the majority of families has two children 68.2%. 14.4% of families have more than two children. As with the child-level variables, there are no systematic differences across domains or information conditions in parent-level variables (see Tables 6–8).

Administrative data. In the future, I will link registry data from Statistics Norway to the experimental data.[20] For parents, this will include demographic characteristics, education, labor market participation, and income. For children, it will include performance in national tests from fifth grade and family composition (number of siblings, gender, and birth year). This will enable analyses such as whether parental belief updating varies by birth order of the child or number of children.[21]

4.3 Institutional Background

The study is situated in primary schools throughout Norway. The primary education system in Norway consists of ten years of compulsory school, starting the year a child turns six. These ten years of mandatory education are split by primary school (6–12 years of age) and lower secondary school (13–16 years of age).[22] For all levels of schooling, the public education system offers free education to all children, and more than 95 % of children attend public schools for their primary and lower secondary education. Annual per-student spending in primary education is 17,779 USD, well above the OECD average, and class sizes and student–teacher ratios are smaller than the OECD average.[23] After mandatory schooling, students may attend optional upper secondary education (grades 11–13), choosing between an academic track that leads to higher education or vocational training that leads to trade certification. The upper secondary education take-up rate is 97.8% (Norwegian Directorate for Education and Training, 2022). Final-year grades in grade 10 determine admission to the upper secondary education via a centralized, merit-based system

received.

[19]In 2024, 23.1% of Norwegians aged 16+ had not completed upper secondary education, 35.6% had completed it, 3.3% had tertiary vocational education, and 37.9% had higher education (Statistics Norway, 2025b).

[20]At the current point in time, I have not gained access to the registry data. All analysis is thus solely based on the data gathered through the lab-in-the-field experiment.

[21]Initial linkage will cover available registry data for current seventh graders, with additional variables, such as lower secondary grades and high school track, linked as they become available.

[22]While some schools offer grades 1–10, most children switch schools after grade 7.

[23]Norway invests substantially in its education system. At the primary level, annual per-student spending is approximately $17,800, which is considerably higher than the OECD average of around $11,900. Norwegian schools also maintain relatively low student–teacher ratios, with about 10 students per teacher in primary school and 8 in lower secondary, compared to OECD averages of 14 and 13, respectively. Primary schools in Norway also tend to be smaller: the median school enrolls around 23 students per grade level, while the OECD median is 27. However, there is wide variation across schools. In the largest 5 percent of Norwegian primary schools, grade-level cohorts consist of 72 or more students (compared to 91 or more in the OECD), whereas the smallest 5 percent of schools have just three or fewer students per grade level (compared to five or fewer in the OECD).

(Dalla-Zuanna et al., 2025).

Whereas the curriculum is set by the central government, the public primary schools are run by the municipalities. The students part-taking in our study are in grade seven (11–12 years of age), which means they are attending the last year of their primary education. It is of particular relevance to this study that lower secondary schools do not track students by ability, and only from grade eight onward students receive grades in mandatory subjects twice per year. Before grade eight, students are only tested for their basic reading (Norwegian), mathematics, and English skills through a national test in grade five. The national tests are intended to give information about the basic knowledge of the students and is used to assess and evaluate the quality of education provided by the schools. The national tests are conducted in grade five, eight, and nine. Although there are no grades for children in primary school, it is likely that parents are to some extent informed about their child's academic achievement through for example teacher-parent meetings arranged by the schools and their child's score on the national tests in grade five.

The fact that Norway is ranked second both on the Human Development Index and the United Nation's Gender Inequality Index (United Nations Development Programme, 2024), does not mean it is without gender differences. Based on the average national test scores for grade five in language (Norwegian) and mathematics, we observe a clear gender difference. Whereas girls tend to do better on reading in the national language test (girls have an average test score of 50, compared to the average test score of boys being 48), boys tend to outperform girls in mathematics (boys have an average test score of 52, compared to the average test score of girls being 47) in the school year 2024–2025 (Norwegian Directorate for Education and Training, 2025). In tertiary education, 68% of women obtain a degree compared to 47% of men. Gender segregation in fields of study remains pronounced: only 12% of women in tertiary education pursue STEM fields, while 7% of men choose education-related fields. Despite women's academic success, labor market outcomes remain unequal; for example, women with tertiary qualifications earn, on average, 85% of men's wages. Among those without upper secondary education, the employment rate is 61% for women and 73% for men (OECD, 2024).

5 Results

This section presents the empirical results, tracing how parents form, update, and act on beliefs about their child's abilities. I first document the accuracy of parents' initial beliefs across domains and verify that the experimental manipulations successfully altered perceived ego-relevance. I then examine how parents update their beliefs in response to sequential performance signals. I do so first descriptively, then using a structural model to differentiate how parents respond to positive and negative signals and to quantify deviations from Bayesian updating. Finally, I connect these updating patterns to downstream outcomes, showing how domain-specific biases in information processing extend to post-hoc rationalization, educational aspirations, and investment behavior.

5.1 Belief Accuracy and Aggregate Patterns

Before analyzing belief updating structurally, it is important to first document the accuracy of parents' initial beliefs and how these priors differ across domains. In a Bayesian framework with a binary state (child in top vs. bottom half), the normative prior for an uninformed parent is 50%, since half of children in the reference group fall above and half below the cutoff. A rational parent without private information should thus start from this neutral prior and only adjust beliefs once new performance signals are observed. Figure 8 shows that parents' average prior beliefs are moderately optimistic in both domains: on average, they assign a probability well above 50 percent to their child being in the top half of the distribution (red dashed line). There is, however, no meaningful difference in the mean level of optimism across domains.

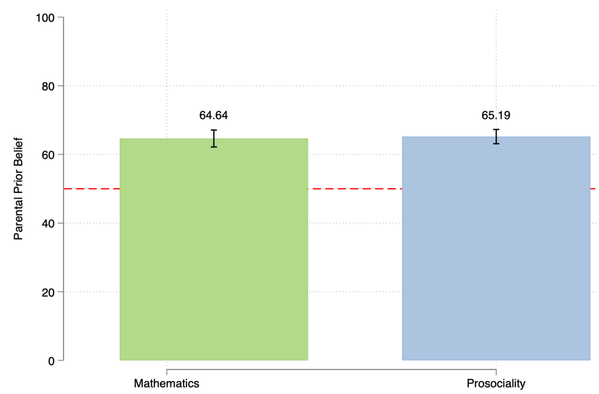


Figure 8: Average Parental Prior Beliefs by Domain

To unpack this optimism, Figures 9a and 9b classify parents based on whether their prior correctly identifies the child's relative standing, top or bottom half of the distribution. Specifically, I distinguish between three belief types: (i) *overestimators*, whose stated belief exceeds 50% when their child is actually in the bottom half; (ii) *underestimators*, whose belief falls below 50% when the child is in the top half; and (iii) *accurate classifiers*, who correctly locate the child in the appropriate half.

In *prosociality*, nearly half of parents overestimate their child's position, while only about 10% underestimate it. Roughly one third correctly identify whether their child belongs to the top or bottom half. In contrast, priors in *mathematics* are less skewed and more evenly distributed across accuracy categories: a majority of parents correctly classify their child, and the shares of over- and underestimation are roughly symmetric. These patterns indicate that parental beliefs in prosociality are not only more optimistic on average but also less precise, consistent with a domain where objective performance is harder to gauge.

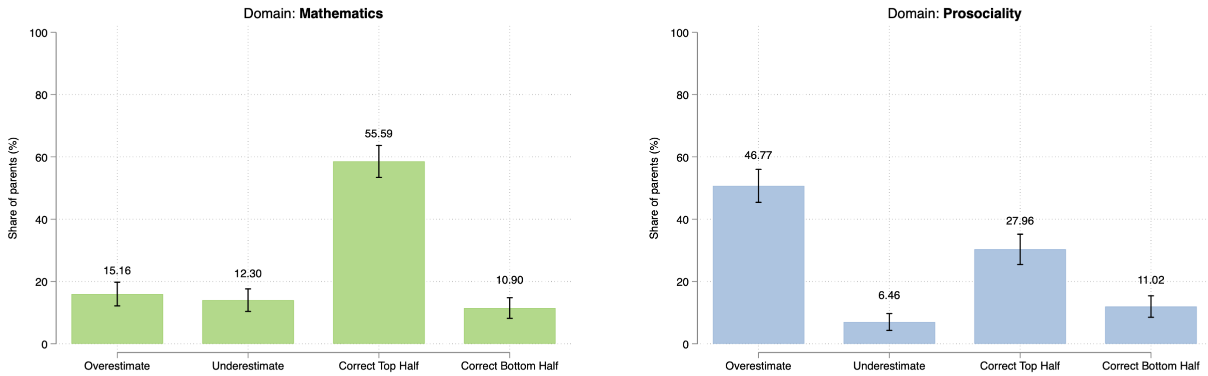


Figure 9: Classification of Prior Beliefs by Domain

5.2 Descriptive Belief Updating

Each parent received two independent signals about their child's relative performance, indicating whether the child belonged to the top or bottom half of the reference group (see Section 2 for details). These sequential signals could therefore form three possible combinations: two positive, two negative, or mixed (one positive and one negative, in either order). Importantly, identical signal sequences can correspond to different true rankings of the child.[24]

Signal patterns and belief dynamics. Figure 10 plots the evolution of mean parental beliefs across the two signal rounds, pooling across domains and information treatments. Parents update beliefs in the expected direction-increasing them after positive signals and decreasing them after negative ones—despite having no prior exposure to experimental belief-elicitation tasks and participating in a natural, real-world setting. The magnitude of belief changes declines after the second signal for positive and mixed signals, suggesting that updates taper as parents consolidate their beliefs. Mixed-signal sequences yield the smallest average change, consistent with the opposing nature of the information they convey.

When disaggregating by domain as evident in Figure 23a and Figure 23b, distinct dynamics emerge. In the *prosociality* domain, positive signals induce strong upward revisions, while negative signals lead to modest downward adjustments. In contrast, in *mathematics*, negative signals trigger sharper downward revisions, and positive signals produce comparatively smaller gains. Mixed signals in both domains result in limited net updating. Notably, priors are more tightly clustered in prosociality, whereas mathematics exhibits greater dispersion in initial beliefs. These contrasts point to differences both in prior uncertainty and in responsiveness to good versus bad signals.

Direction and accuracy of updating. Consistent with these visual patterns, mean changes in

[24]For instance, two positive signals are more likely if the child truly belongs to the top half (probability 2/3 per signal) but can also occur by chance for a child in the bottom half (probability 1/3 per signal).

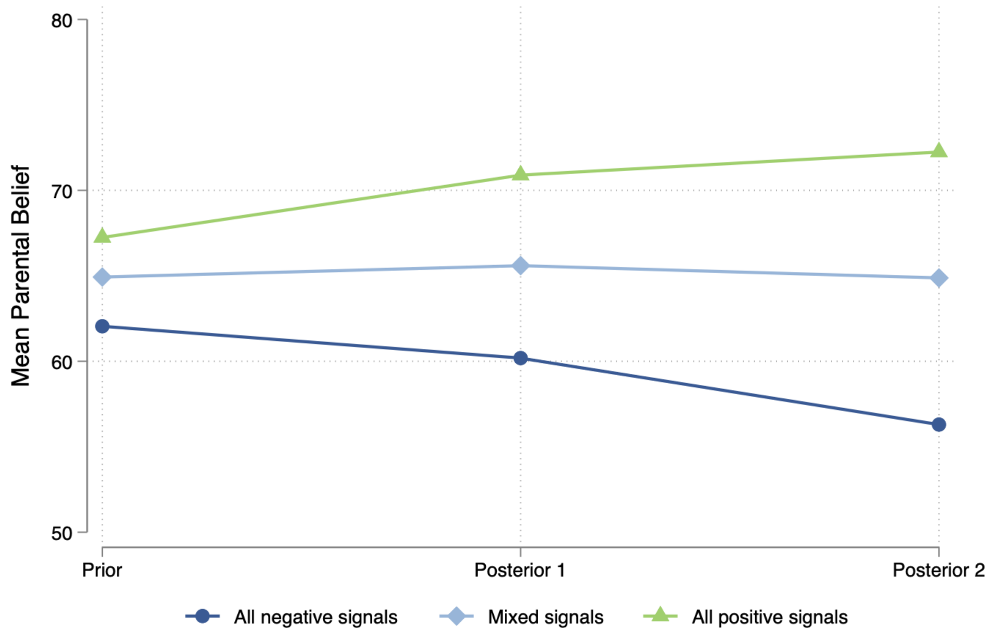


Figure 10: Belief Dynamics (Domains Pooled)

beliefs confirm clear asymmetries across domains. Across all parents, a positive signal increases beliefs by about 4.1 pp after the first round and 3.0 pp after the second, while a negative signal lowers beliefs by roughly 2.7 pp and 5.1 pp, respectively. In *prosociality*, parents raise their beliefs by 5.7 pp (round 1) and 3.1 pp (round 2) after positive signals and lower them by 1.8 pp (round 1) and 4.7 pp (round 2) after negative ones. In *mathematics*, the corresponding changes are smaller but more symmetric – 3.0 pp (round 1) and 3.0 pp (round 2) for positive signals, and -4.0 pp (round 1) and -5.6 pp (round 2) for negative signals. Together, these patterns demonstrate that parents update in the expected direction across all conditions; however, the magnitude and asymmetry of updating differ across domains, suggesting distinct belief formation processes.

Regression evidence. Table 10 presents OLS regressions of belief changes on signal valence, round, and domain indicators. As evident in Columns (1), parents on average lower their beliefs by about 3.9 pp after a negative signal but raise them by about 3.6 pp after a positive one, implying a differential response of roughly 7.5 pp between the two. Columns (2) and (3) add domain and round interactions: while updates are somewhat larger in prosociality and smaller in the second round, these differences are not statistically significant. The fully interacted specification in Column (4) yields the same qualitative pattern: parents react substantially to good news, modestly to bad news, and consistently across rounds and domains. These regressions provide a first quantitative characterization of belief formation, showing that parents treat signals as informative and adjust beliefs in the expected direction; however, the size of updates depends. The descriptive and regression evidence together reveal systematic differences in the sensitivity and dispersion of belief changes across domains: parents are more responsive and optimistic in prosociality, but more calibrated and symmetric in mathematics.

While the preceding regressions quantify the average magnitude of belief revisions, they do not reveal whether parents consistently adjust their beliefs in the direction implied by the information they receive. To examine the directional accuracy of belief updating, I classify each change as (i) *correct* if beliefs move in the same direction as the signal, (ii) *no update* if beliefs remain unchanged, and (iii) *wrong* if beliefs move counter to the signal.[25] Across domains, the majority of parents revise beliefs in the correct direction at least once, but relatively few do so consistently across both signals. In mathematics, about 68% of parents update correctly in at least one round and 29% in both, while roughly 40% make at least one wrong update and 7% do so twice. Around 38% show at least one case of no adjustment and 17% never update in either round. In prosociality, correct updating is similarly common, 70% at least once and 27% in both rounds, but wrong updates are more frequent (48% at least once, 9% twice), and about one third of parents show no change at least once. These patterns show that parents generally react sensibly to new information, yet updating is far from uniformly Bayesian. Some parents fail to adjust when receiving information, while others revise in the wrong direction. The prevalence of wrong updates is higher in prosociality—consistent with greater optimism or selective inattention to unfavorable signals—whereas mathematics exhibits more zero updates, consistent with greater caution.

Domain-specific responsiveness. To test whether these initial differences translate into distinct updating patterns, Tables 1 and 9 report domain-specific regressions of posterior beliefs on prior beliefs and signal combinations. In both domains, prior beliefs are strongly predictive of posteriors, with coefficients between 0.6 and 0.8, indicating substantial persistence. However, clear domain contrasts emerge in responsiveness to information.

In *prosociality*, parents exhibit marked upward revisions in the *ego-relevance* treatments relative to the Control group: posterior beliefs are about 6.6 pp higher after two positive signals and 4.8 pp higher under mixed signals. This pattern suggests that when performance feedback is personally meaningful, parents place greater weight on favorable information while partially discounting unfavorable signals. In *mathematics*, by contrast, ego-relevance has little effect on how parents respond to good news, while two negative signals lower posterior beliefs by about 3 pp on average—consistent with greater sensitivity to poor performance. Taken together, these results indicate a systematic asymmetry: parents are more optimistic and noise-tolerant in prosociality, whereas they are more calibrated and attentive to negative performance in mathematics.

Taken together, the descriptive results show that parents treat the experimental signals as informative and update beliefs in the expected direction, but the magnitude and asymmetry of these updates differ sharply across domains. To formally test whether parents apply systematically different weights to positive versus negative signals, I next estimate a structural belief-updating

[25] An update is coded as correct if $\text{sign}(\Delta\text{belief}) = \text{sign}(\text{signal})$, wrong if the signs differ, and zero if $\Delta\text{belief} = 0$. "Any" refers to the pattern occurring in at least one round, and "both" indicates that it occurs in both rounds.

Table 1: Prosociality: Aggregate Belief Updating Patterns

	(1) Full Sample	(2) Two Good Signals	(3) Mixed Signals	(4) Two Bad Signals
Info vs. No Info	3.48*	6.57**	4.76*	0.43
	(1.779)	(3.147)	(2.548)	(3.466)
Prior	0.61***	0.55***	0.76***	0.50***
	(0.059)	(0.117)	(0.063)	(0.120)
Child's Share Score	0.13**	0.11	0.05	0.02
	(0.057)	(0.093)	(0.091)	(0.112)
Boy	3.46*	3.39	2.04	4.92
	(1.803)	(3.091)	(2.364)	(3.744)
Mother	0.43	-1.21	5.64*	-3.76
	(1.933)	(3.034)	(2.960)	(3.826)
Constant	19.48***	27.98***	7.30	27.41***
	(4.702)	(6.888)	(6.637)	(8.993)
Observations	361	82	160	119
R^2	0.371	0.448	0.534	0.242

Notes: Analysis uses OLS regressions with robust standard errors in parentheses. Stars reflect significance in a t-test of the null hypothesis that coefficients are equal to 0. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

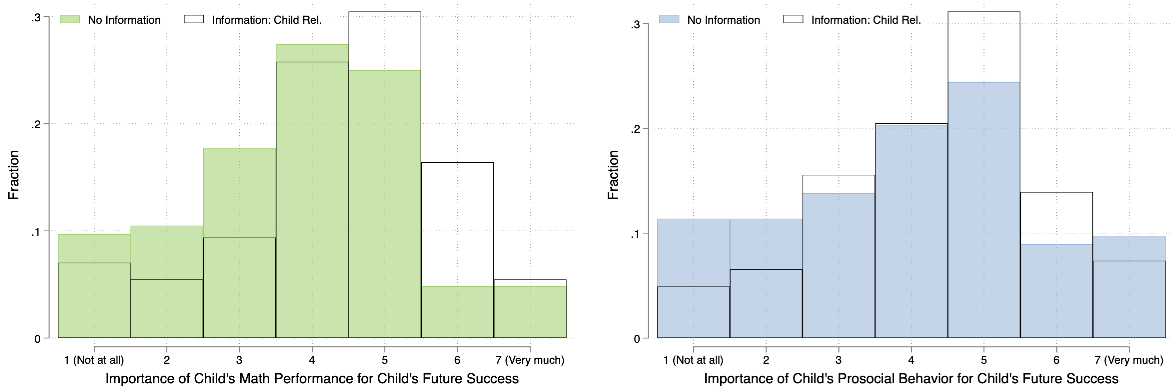
model separately for mathematics and prosociality. Before turning to this analysis, I first verify that the experimental treatments successfully altered perceived ego-relevance, the psychological foundation for subsequent belief updating.

5.3 Validation of the Ego-Relevance Manipulation

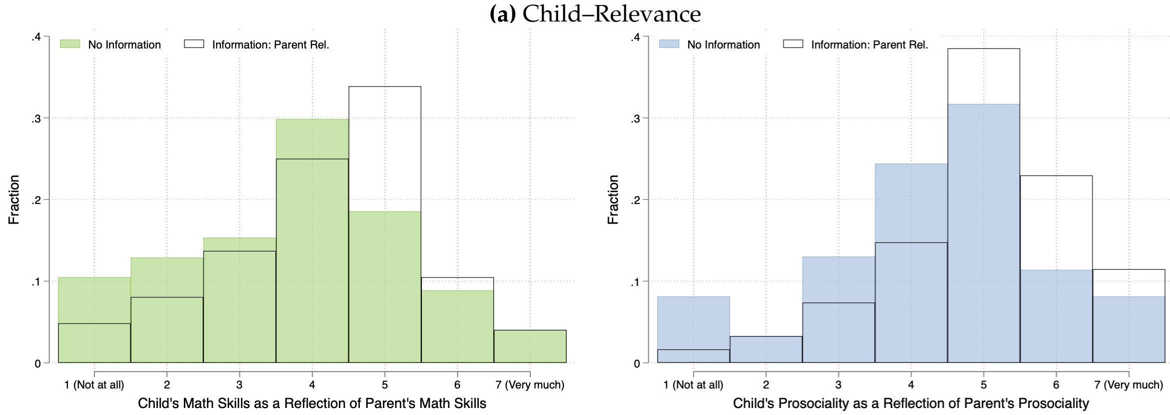
A key design feature of the experiment is the exogenous manipulation of the *ego-relevance* of performance signals. Before analyzing belief updating, it is important to verify that these manipulations worked as intended. Two dimensions of ego-relevance were varied: the *Parent–Relevance* condition emphasized the link between the child's performance and the parent's own abilities (direct ego-relevance), whereas the *Child–Relevance* condition highlighted the implications of performance for the child's future success (indirect ego-relevance). Parents in the *Control* group received no information.

Ego-relevance was measured immediately after the belief updating task using 7-point Likert-scale items. Direct ego-relevance was elicited with the question: *"To what extent do you think your child's performance on the [math quiz / sharing game] reflects your own [mathematical ability / willingness to share]?"* Indirect ego-relevance was measured by asking: *"How important do you think your child's performance on the [math quiz / sharing game] is for their future success?"*

Figure 11 summarizes the resulting distributions by information condition and domain. The manipulations were effective. Parents in the *Parent–Relevance* condition reported significantly higher perceived intergenerational transmission of skills than those in the control condition (Wilcoxon rank-sum test: mathematics $p = 0.011$, prosociality $p < 0.01$). Similarly, those in the *Child–Relevance* condition rated the importance of their child's performance for life outcomes significantly higher (mathematics $p < 0.01$, prosociality $p = 0.093$). These results confirm that the experimental treatments successfully increased perceived ego-relevance along both dimensions.



(a) Child–Relevance



(b) Parent–Relevance

Figure 11: Manipulation Checks by Domain and Information Condition

Having confirmed that the treatments shifted perceived ego-relevance as intended, I next estimate a structural model of belief updating that quantifies how parents weight positive and negative information relative to the Bayesian benchmark.

5.4 Structural Belief Updating

The descriptive results documented above reveal systematic domain differences in how parents respond to information: they are more optimistic and responsive to positive signals in prosociality, but more symmetric and accuracy-oriented in mathematics. To formally quantify these differences and benchmark them against rational (Bayesian) updating—and to assess how parents weight positive versus negative information, I estimate a structural model of belief updating following

Möbius et al. (2022). This framework, widely used to study belief formation under uncertainty (e.g., Eil and Rao, 2011; Benoît and Dubra, 2011; Serra-Garcia and Szech, 2021), is particularly well suited to this setting because parents' beliefs and the experimental signals are expressed as probabilities over a binary outcome (whether the child ranks in the top or bottom half)

$$\begin{aligned}\text{logit}(\hat{\mu}_{i,t}) \;=\; \delta \cdot \text{logit}(\hat{\mu}_{i,t-1}) \;+\; \beta_P \cdot \mathbb{I}\{s_{i,t} = P\} \cdot \lambda_{P,t} \;+\; \beta_N \cdot \mathbb{I}\{s_{i,t} = N\} \cdot \lambda_{N,t} \\ +\; \theta \cdot \mathbb{I}\{\text{TopHalf}_i\} \;+\; \varepsilon_{i,t}\end{aligned} \tag{7}$$

By experimental design, each signal reveals the truth two out of three times, implying known log-likelihood ratios of $\lambda_P = \log(2)$ and $\lambda_N = -\log(2)$. Under Bayesian updating, posteriors in log-odds should move exactly by these amounts, such that $\delta = \beta_P = \beta_N = 1$. Deviations from these coefficients characterize distinct forms of non-Bayesian updating: $\delta < 1$ indicates underweighting of prior beliefs (base-rate neglect) and $\delta > 1$ indicates overweighting of prior beliefs (confirmation bias), $\beta_P, \beta_N < 1$ reflect conservative updating, and $\beta_P \neq \beta_N$ captures asymmetric weighting of good versus bad news. θ picks up any residual correlation between the child's actual top-half status and the parent's posterior that is not captured by the prior or the public signals, and the Bayesian benchmark is $\theta = 0$ because the true state is unobserved by a rational updater.

Empirical results. The model is estimated separately for each domain and within domains by information condition, clustering standard errors at the parent level. Figure 12 summarizes the estimated signal weights β_P and β_N by domain, while Table 2 report full results.

Across both domains, parents update beliefs conservatively relative to the Bayesian benchmark. The persistence of priors is substantial but below unity ($\delta < 1$), indicating that they place less weight on prior beliefs than a fully Bayesian updater would. This base-rate neglect is stronger in prosociality ($\delta = 0.68$, $p < 0.01$) than in mathematics ($\delta = 0.88$, $p < 0.01$), implying that parents rely more on their initial assessments when judging cognitive performance and less when interpreting prosocial performance.

In *prosociality*, parents underweight both types of signals relative to the Bayesian benchmark ($\beta_P, \beta_N < 1$) but place markedly greater weight on positive information (see Figure 23b and Table 3). The asymmetry is statistically significant in both information conditions (*Child–Relevance*: $\beta_P - \beta_N = 0.63$, $p = 0.002$; *Parent–Relevance*: $\beta_P - \beta_N = 1.15$, $p = 0.001$), but absent in the control condition. Quantitatively, using the relevance-pooled specification ($\delta = 0.68$), parents respond to favorable signals with about half of the Bayesian weight ($\beta_P \delta \approx 0.52$), implying belief revisions of roughly +7–9 pp rather than the +15–18 pp predicted by Bayes, after accounting for the attenuated prior slope ($\delta < 1$). In contrast, unfavorable signals carry almost no weight ($\beta_N = -0.13$, $\beta_N \delta \approx -0.09$), translating into changes of only –1–2 pp instead of –15 pp. The resulting ratio of positive-to-negative signal weights ($\beta_P / |\beta_N| \approx 6$ overall, ≈ 2 in the *Parent–Relevance* condition) indicates that parents give substantially more attention to good news than to bad news when interpreting socio-emotional performance. Notably, the negative coefficient on β_N in the *Parent–*

Relevance condition (-0.36, $p < 0.01$) suggests a *backlash* effect—parents actually increase rather than decrease their beliefs after receiving unfavorable feedback when the information is directly self-relevant. Round-level estimates confirm that these asymmetries are driven primarily by first-round reactions.

In *mathematics*, by contrast, parents update their beliefs in a more balanced and accuracy-oriented manner. They respond to both positive and negative signals with similar magnitude and direction, showing little evidence of motivated asymmetry. Structurally, the estimated coefficients are $\beta_P = 0.36$ and $\beta_N = 0.31$, with no statistically significant difference between them ($|\beta_P - \beta_N| < 0.06$, all $p > 0.65$; see Figure 23a and Table 4). The relative difference between positive and negative signal weights is only about 10% and remains insignificant across rounds and information conditions. Quantitatively, with $\delta = 0.87$, both positive and negative signals receive roughly 30% of the Bayesian weight ($\beta\delta \approx 0.30$), implying belief revisions of about +4–5 pp and –4–5 pp rather than the ±15 pp predicted by Bayes. Parents thus update conservatively but symmetrically—incorporating new information at about one third of the Bayesian magnitude, consistent with broad conservatism rather than motivated asymmetry.

Robustness. To account for extreme priors at 0 or 100% (for which the logit transformation is undefined), I replicate the analysis replacing boundary values with values of 0.01 and 0.99. The resulting estimates remain virtually unchanged: parents in both domains underweight signals relative to the Bayesian benchmark, and the asymmetric weighting of positive over negative information in prosociality remains robust (Tables 15–16). The results are robust to alternative specifications that exclude outliers and to models allowing for round-specific effects. Detailed round-by-round estimates are reported in Table 11 and Table 12 (prosociality) and in Table 13 and Table 14 (mathematics).

In *prosociality*, parents place virtually all their updating weight on positive signals ($\beta_P = 0.6$) and none on negative ones ($\beta_N \approx 0$) (Column 3 in Table 2). In *mathematics*, by contrast, parents update symmetrically in response to good and bad signals but at roughly one third of the Bayesian strength (Column 2 in Table 2). Despite these deviations, the structural model accounts for a large share of variation in posterior beliefs ($R^2 \approx 0.7$–0.8), indicating that parents follow a coherent yet systematically biased updating rule. The evidence suggests that these asymmetries stem not from random noise or misunderstanding but from motivational forces: in prosociality, parents selectively downplay negative feedback that threatens the child's (and their own) image, particularly when signals are ego-relevant. In mathematics, by contrast, updating appears more rational and balanced, consistent with an environment where performance is observable and less tied to parental identity. Belief formation thus depends not only on the informational content of signals but also on their psychological meaning to the receiver.

Together, these findings provide clear evidence of selective optimism in the prosocial domain and conservative, symmetric updating in mathematics. The next section examines whether these cognitive asymmetries extend to how parents evaluate and act upon feedback.

Table 2: Belief Updating – Domains

	(1) Full sample	(2) Mathematics	(3) Prosociality
Prior (δ)	0.827***	0.874***	0.741***
	(0.026)	(0.033)	(0.043)
Pos. signal (β_P)	0.481***	0.356***	0.595***
	(0.058)	(0.078)	(0.085)
Neg. signal (β_N)	0.136***	0.305***	-0.027***
	(0.044)	(0.067)	(0.072)
Child in top half	-0.006	0.024	0.016
	(0.035)	(0.056)	(0.049)
$\beta_P - \beta_N$	0.345	0.052	0.621
P-value $\beta_P - \beta_N$	0.000	0.655	0.000
P-value Chow-Test (relative to 2)			0.003
Observations	1361	671	690
R^2	0.766	0.816	0.708

Notes: Analysis uses OLS regressions with robust standard errors clustered at the individual level and no constant. The analysis excludes observations with boundary beliefs of 0 or 1. Stars indicate two-sided tests vs 1 for δ, β_P, β_N; the 'Child in top half' coefficient is tested vs 0. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

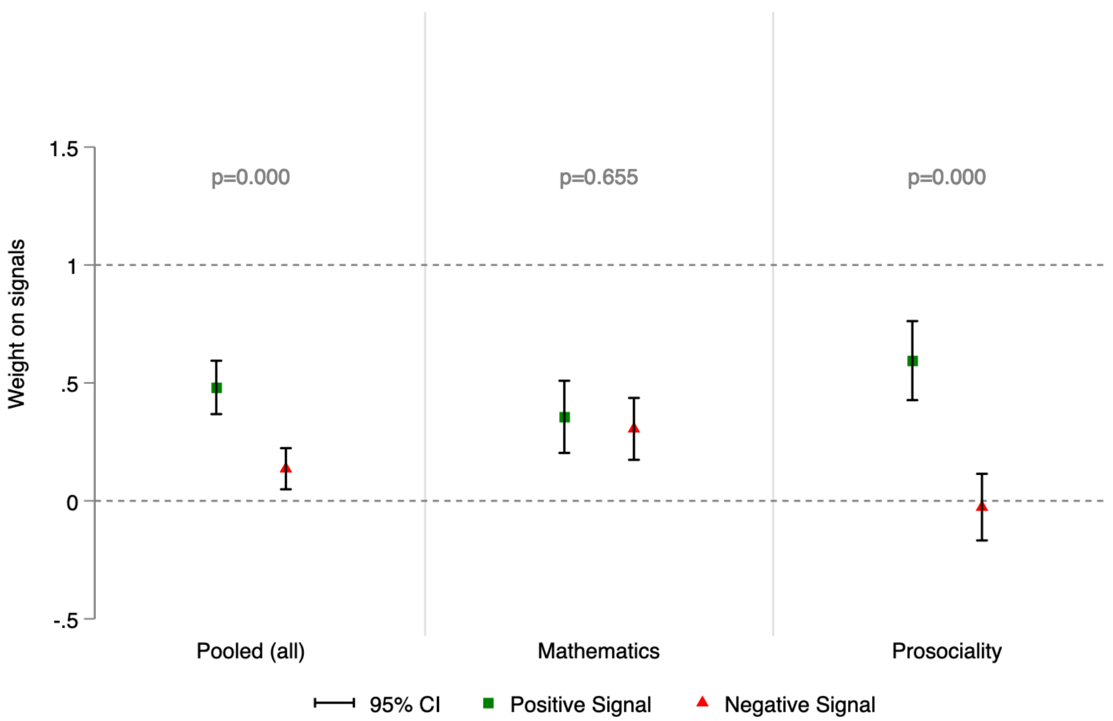


Figure 12: Estimates of β_P and β_N by Domain

Table 3: Belief Updating – Prosociality

	(1) Full sample	(2) Control	(3) Rel. (pooled)	(4) Child – Rel.	(5) Parent – Rel.
Prior (δ)	0.741***	0.861***	0.678***	0.753***	0.602***
	(0.043)	(0.049)	(0.058)	(0.055)	(0.100)
Pos. signal (β_P)	0.595***	0.242***	0.761**	0.738*	0.787
	(0.085)	(0.122)	(0.113)	(0.141)	(0.178)
Neg. signal (β_N)	-0.027***	0.158***	-0.130***	0.113***	-0.358***
	(0.072)	(0.072)	(0.104)	(0.098)	(0.179)
Child in top half	0.016	0.113	-0.024	-0.053	0.022
	(0.049)	(0.077)	(0.065)	(0.078)	(0.107)
$\beta_P - \beta_N$	0.621	0.085	0.891	0.625	1.146
P-value $\beta_P - \beta_N$	0.000	0.585	0.000	0.002	0.001
P-value Chow-Test (relative to 2)			0.007	0.116	0.011
Observations	690	234	456	233	223
R^2	0.708	0.777	0.687	0.746	0.647

Notes: Analysis uses OLS regressions with robust standard errors clustered at the individual level and no constant. Analysis excludes observations with boundary beliefs 0 or 1. Stars indicate two-sided tests vs 1 for δ, β_P, β_N; the 'Child in top half' coefficient is tested vs 0. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

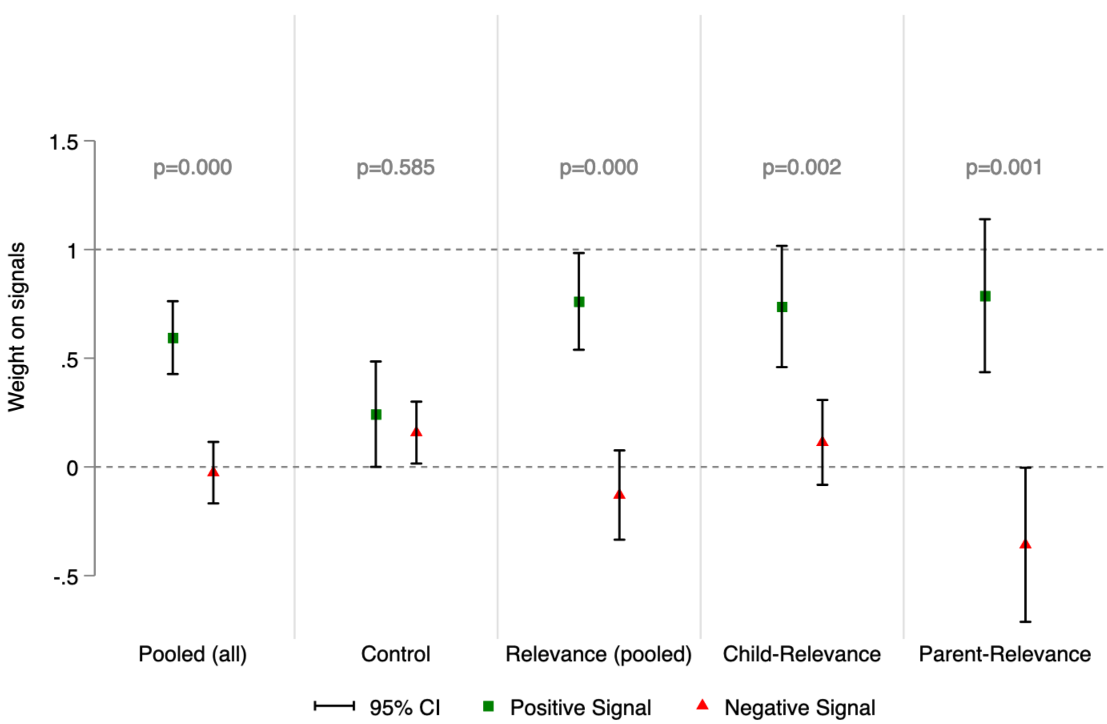


Figure 13: Prosociality: Estimates of β_P and β_N by Information Condition

Table 4: Belief Updating – Mathematics

	(1) Full sample	(2) Control	(3) Rel. (pooled)	(4) Child – Rel.	(5) Parent – Rel.
Prior (δ)	0.874***	0.865***	0.876***	0.845**	0.901*
	(0.033)	(0.049)	(0.039)	(0.061)	(0.054)
Pos. signal (β_P)	0.356***	0.310***	0.393***	0.402***	0.396***
	(0.078)	(0.093)	(0.115)	(0.178)	(0.145)
Neg. signal (β_N)	0.305***	0.207***	0.351***	0.341***	0.327***
	(0.067)	(0.074)	(0.094)	(0.157)	(0.117)
Child in top half	0.024	0.027	0.012	0.004	0.004
	(0.056)	(0.057)	(0.082)	(0.140)	(0.078)
$\beta_P - \beta_N$	0.051	0.103	0.042	0.060	0.070
P-value $\beta_P - \beta_N$	0.655	0.404	0.806	0.837	0.681
P-value Chow-Test (relative to 2)			0.884	0.914	0.911
Observations	671	227	444	218	226
R^2	0.816	0.814	0.818	0.785	0.842

Notes: Analysis uses OLS regressions with robust standard errors clustered at the individual level and no constant. Analysis excludes observations with boundary beliefs 0 or 1. Stars indicate two-sided tests vs 1 for δ, β_P, β_N; the 'Child in top half' coefficient is tested vs 0. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

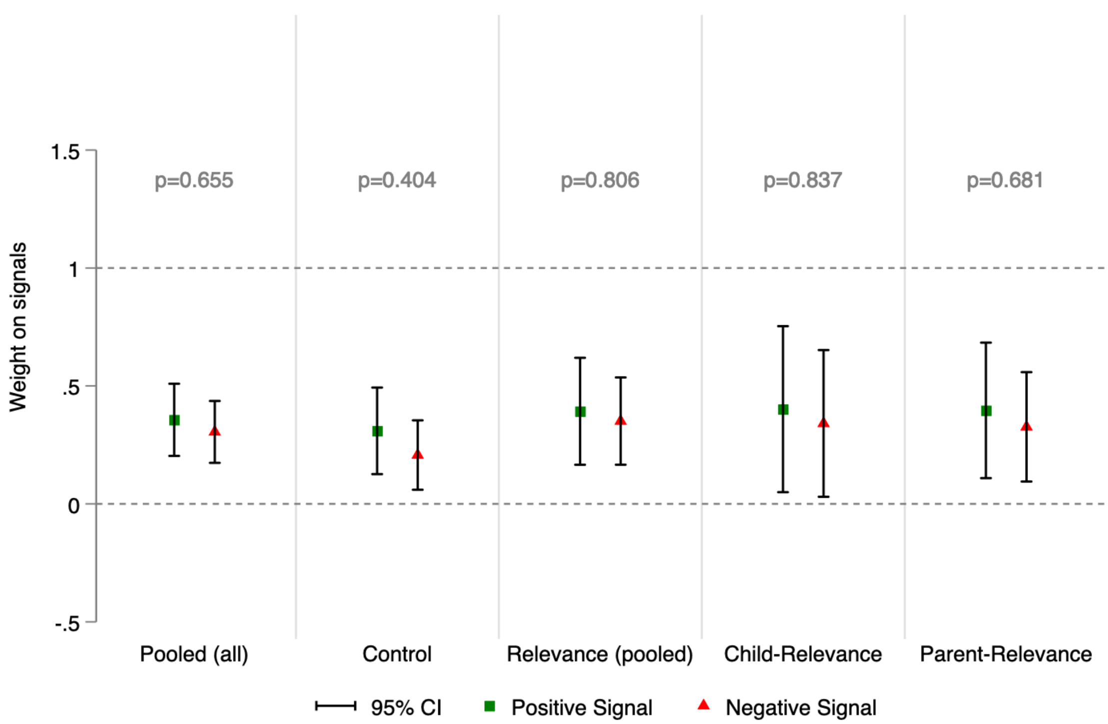


Figure 14: Mathematics: Estimates of β_P and β_N by Information Condition

5.5 Heterogeneity in Belief Updating

Gender of the child.

Gender of the parent.

Number of children.

5.6 Downstream Responses: Rationalization, Educational Aspirations and Investment

The structural belief updating results show that parents in the prosociality domain asymmetrically weight positive and negative signals, placing significantly more weight on positive news and, in the *Parent–Relevance* condition, even increasing beliefs after negative signals. No such asymmetry appears in mathematics, where updating is less conservative and symmetric. I now examine how these belief patterns translate into subsequent parental evaluations and aspirations, focusing first on cognitive responses, such as ex-post rationalization, and then on behavioral outcomes related to educational goals and investment intentions.

5.6.1 Ex-Post Rationalization

If the domain-specific asymmetries in belief updating reflect motivational forces, they should also shape how parents *interpret* information ex-post, not just how they numerically update. One likely channel is *ex-post rationalization*: when faced with negative signals, parents may defensively reinterpret or downplay the information to preserve a favorable image of their child—and, by extension, themselves. To examine this mechanism, I test whether receiving more negative signals predicts lower post-task evaluations of (i) the child's effort, (ii) the perceived similarity between the child's ability and the parent's own ability (direct ego-relevance), and (iii) the perceived importance of the child's performance for later life outcomes (indirect ego-relevance). Each outcome is measured on a seven-point Likert scale. For each domain, I estimate the following ordered logit specification:

$$\text{Rating}_i = \beta_0 + \beta_1\,\text{Prior}_i + \beta_2\,\#\text{NegativeSignals}_i + \beta_3\,\text{Information}_i + \gamma' X_i + \epsilon_i, \tag{8}$$

where Prior_i is the parent's baseline belief, $\#\text{NegativeSignals}_i$ counts the number of negative signals observed (0–2), Information_i indicates assignment to any information condition (1) versus control (0), and X_i includes controls for the child's actual performance.

The results closely mirror the structural patterns. In *prosociality*, each additional negative signal significantly lowers ratings of the child's effort (-0.35, $p < 0.01$), the perceived similarity between parent and child skills (-0.30, $p < 0.05$), and the perceived importance of the signals for later life outcomes (-0.29, $p < 0.05$). These magnitudes correspond to approximately a half-point decline on the 7-point Likert scale per additional negative signal, with an effect size of 0.25–0.30 standard deviations.

In *mathematics*, the coefficients are smaller (-0.17, -0.09, -0.05) and statistically insignificant, although the signs are directionally consistent. The lack of significance aligns with the symmetric updating pattern observed in the structural analysis: when information is perceived as more objective and less identity-relevant, parents appear less motivated to reinterpret unfavorable news.

Taken together, these results suggest that the motivational asymmetry observed in prosociality extends beyond numerical updating to encompass how parents cognitively rationalize signals. Parents not only discount negative signals in belief formation but also reinterpret them ex-post to preserve a positive narrative about their child.

Table 5: Outcome – Ex-Post Rationalization for the Domain of Prosociality

	(1) Child's Effort	(2) Importance for Parent's Own Skills	(3) Importance for Child's Later Life Outcomes
Neg. Signals	-0.35***	-0.30**	-0.29**
	(0.136)	(0.134)	(0.137)
Prior	0.05***	0.04***	0.02***
	(0.005)	(0.005)	(0.005)
Child's Share Score	0.01	0.00	-0.01
	(0.007)	(0.007)	(0.007)
Info vs. No Info	0.24	0.66***	0.35*
	(0.203)	(0.199)	(0.201)
Observations	367	367	367
Pseudo R^2	0.087	0.066	0.019

Notes: Subjects' stated belief that the child exerted effort as well as stated belief about the strength of inter-generational transmission and relevance for the child's later life outcomes on a seven-point Likert scale. The analysis uses Ordered Logistic Regressions with standard errors in parentheses. Stars reflect significance in a t-test of the null hypothesis that coefficients are equal to 0. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.6.2 Educational Aspirations and Investment Behavior

For a subset of parents ($N = 278$), I additionally collected data on three outcomes related to their child's education: (i) aspirations for the child's upper secondary track, (ii) aspirations for tertiary education, and (iii) the share of a 1,000 NOK voucher that parents were willing to spend on educational goods.[26] These measures provide an exploratory test of whether domain-specific differences in belief updating and information processing translate into stated educational goals and investment behavior. The smaller sample size warrants caution in interpreting these results. Given the smaller sample size, I pool the information conditions within each domain.[27] For each

[26]Parents were informed that the stated choice would be binding if they won the lottery.

[27]This aggregation increases power but precludes distinguishing between direct and indirect ego-relevance.

outcome, I estimate the following specification separately by domain:

$$\text{Outcome}_i = \beta_0 + \beta_1\,\text{Prior}_i + \beta_2\,\#\text{NegativeSignals}_i + \beta_3\,\text{Information}_i + \gamma' X_i + \epsilon_i, \tag{9}$$

where Prior_i denotes the parent's initial belief, $\#\text{NegativeSignals}_i$ counts the number of negative signals observed (0–2), Information_i is an indicator for treatment assignment, and X_i includes the child's actual performance. Educational aspirations, defined as binary indicators for academic-track upper secondary school and tertiary education, are estimated using Probit models, while the share of the voucher allocated to educational goods is estimated using OLS.

Educational aspirations. In *prosociality*, parents who received more negative signals report higher aspirations for tertiary education (Table 18, $\beta = 0.40$, $p < 0.05$), whereas aspirations for the upper secondary track are unaffected. This pattern aligns with the earlier evidence of asymmetric updating: when confronted with unfavorable signals for prosociality, parents may reassert a positive long-term narrative, interpreting setbacks as temporary and emphasizing the child's future potential. Because tertiary education is temporally distant and abstract, it provides a psychologically convenient domain for defensive optimism, unlike the more immediate and constrained secondary-track decision.

In *mathematics*, aspirations show no statistically significant response to negative signals (Table 19). The coefficients are small and only weakly positive for tertiary education ($\beta = 0.42$, $p < 0.10$), consistent with more symmetric and rational updating in this domain. Variation in aspirations is also limited in this small and relatively educated sample, where academic-track and tertiary goals are the modal expectation.

Parental investment. Patterns in investment behavior provide further support for domain-specific motivational responses. In *prosociality*, parents who received more negative signals allocated a larger share of the voucher to educational goods ($\beta = 0.20$, $p < 0.10$; Table 20), suggesting a compensatory response, an effort to counteract perceived weaknesses in a malleable, non-cognitive domain. In *mathematics*, the relationship reverses in sign ($\beta = -0.21$, $p = 0.13$; Table 21), consistent with a complementary investment pattern where resources are directed toward areas of perceived strength rather than remediation.

Taken together, these exploratory results indicate that the motivational asymmetries shaping belief updating also influence parents' broader aspirations and investment decisions. In prosociality, defensive optimism manifests as higher long-term aspirations and compensatory spending following negative signals; in mathematics, parents appear more calibrated and reinforce existing competencies. These behavioral outcomes thus provide external validation of the structural belief-updating results.

Together, these findings reveal that domain-specific motivational asymmetries are not confined to belief formation. They extend to how parents interpret and act on signals, influencing cognitive rationalization and tangible educational intentions. This broader consistency supports the interpretation of belief updating as a psychologically motivated rather than purely informational process. However, the evidence on downstream behavior remains suggestive: further research is needed to establish how parental beliefs translate into actual investment decisions and long-term child outcomes.

These investment patterns can be reconciled with the conceptual framework outlined in Section 3 in two complementary ways. First, if ability and investment are *technological substitutes*, even a small downward revision of perceived ability increases the marginal return to investment, prompting compensatory behavior despite muted belief updating. This interpretation is consistent with the prosociality domain, where non-cognitive skills may be viewed as malleable and improvable through effort and support. Second, the results may also reflect *psychological* channels beyond the belief mechanism in the framework: parents confronted with negative socio-emotional feedback may experience a motivational drive to reaffirm their child's potential and self-image, leading to increased stated investment independent of posterior beliefs. Both mechanisms imply that defensive processing in prosociality operates not only through belief formation but also through motivational responses that shape behavioral intentions.

6 Discussion

Parents update beliefs cautiously in both domains. However, they asymmetrically weight positive and negative signals only in the prosocial domain. The asymmetry is concentrated in the *Child–Relevance* and *Parent–Relevance* arms. In this section, I explore potential mechanisms underlying this domain-specific pattern. Several lines of evidence point to distinct but complementary explanations, which I will now discuss.

Information environments and scope for bias. Parents differ in their knowledge of their child's performance across domains. In mathematics, parental beliefs track children's true performance more closely, as indicated by the positive relationship shown in Figure 15a. Although formal grades are only introduced in eighth grade, this pattern suggests that parents have access to relatively accurate information about their child's mathematical performance, even before formal assessments. Plausible sources of this knowledge include help with homework, informal teacher feedback, and parent–child conversations. These channels seem to allow parents to form beliefs that align more closely with actual performance.

In contrast, this correspondence is much weaker in the prosocial domain: parents' beliefs about their child's generosity are only weakly correlated with observed behavior (Figure 15b). This likely reflects the limited and less standardized nature of behavioral feedback.[28] Moreover, egalitar-

[28]Assessments of student conduct are only introduced from grade 8 onward and primarily concern adherence to school rules rather than social behavior. The assessment includes three broad categories: (1) Good: generally good conduct, (2) Fairly good: clear deviations from normal conduct, and (3) Poor: reserved for extraordinary cases. All students start from the best category (Norwegian Directorate for Education and Training, 2024).

ian norms prominent in Norwegian society likely discourage overt social comparisons[29], further reducing the visibility of individual differences. While parents may observe their children's everyday social interactions, children's behavior often differs between private and public settings, complicating inference further.

These differential information environments likely shape the extent to which biased belief updating can occur. In mathematics, parents are less likely to process information in a biased manner because their existing knowledge constrains the scope for distortion. In contrast, in the prosocial domain, parents encounter far fewer and less standardized signals about their child's behavior. This informational ambiguity allows for greater interpretive flexibility of the signals, creating room for the biased processing of signals and the maintenance of overly optimistic beliefs.

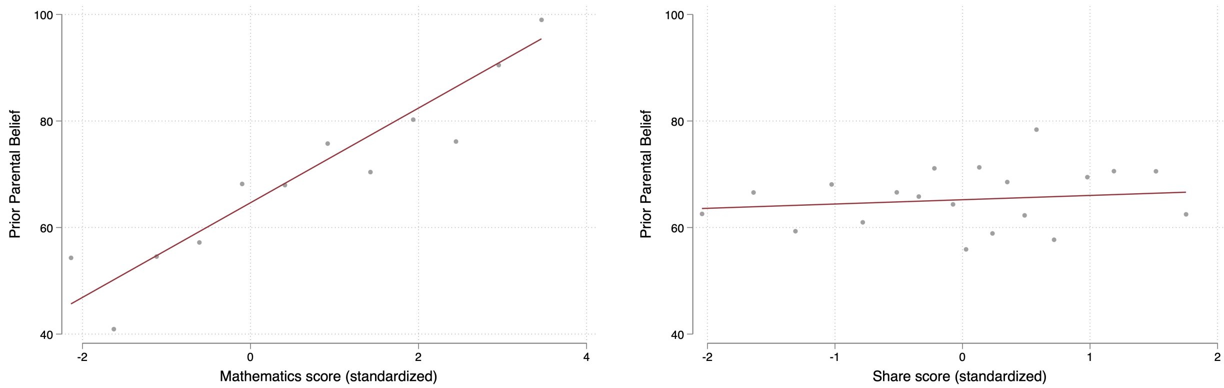
This interpretation aligns with findings from the belief-updating literature, which suggest that biased information processing requires a degree of unresolved uncertainty; specifically, motivated distortions can no longer be maintained once the true state of the world becomes clear (e.g., Drobner, 2022). In mathematics, where parents' informational environment is relatively precise, biased processing is less feasible. In prosociality, by contrast, ambiguity shields parents from disconfirming evidence, enabling them to sustain favorable beliefs even in the face of negative signals.

One limitation of this study is the absence of a measure capturing parents' confidence in their prior beliefs. Parents may hold their prior beliefs with greater confidence in mathematics than in prosociality, which would contribute to the observed rigidity of beliefs in the cognitive relative to the non-cognitive domain. It is also possible that parents would have responded differently if the signals in the cognitive domain had been based on a standardized measure of intelligence, such as Raven's Progressive Matrices, a tool frequently used in belief updating studies. However, implementing such a measure was not feasible due to time constraints and concerns that parents would perceive it as overly sensitive or stigmatizing, potentially compromising the study's feasibility.

Domain-specific meanings. Beyond differences in information availability, the asymmetric updating pattern may also reflect how parents value and interpret the two skill domains. Mathematics and prosociality represent distinct skill domains that differ in their perceived relevance for various aspects of children's outcomes. These differences may influence how parents process new information about their child's performance

Survey data indicate that parents view prosocial (non-cognitive) skills as more consequential for a wide range of long-term life outcomes, while mathematical (cognitive) skills are seen as primarily relevant for academic success. Parents associate mathematics almost exclusively with doing well in school (Mean = 5.38; p-value < 0.001), while they attribute substantially higher importance to prosocial skills for success in employment (Mean = 6.27; p-value < 0.001), forming

[29]This reflects the cultural norm often referred to as the "Law of Jante," originating from Sandemose's 1933 novel "A Fugitive Crosses His Tracks". The concept captures a social ideal of modesty and equality in Norwegian society, emphasizing humility and discouraging individuals from standing out or boasting about personal success (Sandemose, 1933).



(a) Mathematics

(b) Prosociality

Figure 15: Relationship between Children's Performance and Parental Beliefs

a stable life partnership (Mean = 7.49; p-value < 0.001), and being a valued member of society (Mean = 6.93; p-value < 0.001). The differences are large and highly significant (all p-value < 0.01), suggesting that parents draw a clear boundary between what each skill is "for": mathematics is viewed as instrumental for educational attainment, while prosociality is regarded as foundational for broader life success. Survey evidence further shows that parents perceive prosocial skills not only as more relevant for long-term life outcomes of the child but also as more likely to be passed from parent to child (Figure 24).

The role of gender stereotypes. Gendered perceptions further complicate how parents interpret performance signals across domains, but their connection to asymmetric updating is more nuanced. Both mothers and fathers rate girls as directionally (though not significantly) more prosocial than boys, showing no significant gender differences in perceived interest (p-value = 0.694), social returns (p-value = 0.371), or performance (p-value = 0.110). Prosociality thus appears as a "girl domain," but one viewed as normatively neutral and non-threatening. Mathematics, by contrast, remains a "boy domain" associated with stronger and more consequential stereotypes, with both mothers and fathers perceiving boys as more interested in and better at mathematics (all gender differences highly significant, p-value < 0.01). Mothers are even more likely than fathers to believe boys outperform girls in math-related interest, performance, and social returns (p-value < 0.001 across all dimensions).

These gendered associations may contribute to the observed patterns in two ways. First, the weaker and less controversial nature of gender stereotypes in prosociality may reduce parents' defensiveness when receiving signals; yet the domain's broader perceived importance for life success still motivates optimistic belief maintenance. Second, the stronger stereotypes in mathematics may lead parents to attribute their child's performance more to innate ability or external factors (schools, teachers), thereby reducing the emotional stakes of negative signals and limiting biased updating.

Taken together, these patterns suggest that biased belief updating requires both informational ambiguity and psychological motivation, working in tandem. In prosociality, sparse and interpretable signals create room for biased processing, while perceived importance for life success create motivation to maintain optimistic beliefs. In mathematics, frequent objective feedback constrains distortion, while external responsibility (schools) reduces ego-threat. The gender stereotype evidence, while suggestive, appears secondary; it may interact with these core mechanisms by varying the emotional stakes of feedback, but does not on its own explain the domain-specific asymmetry. Consequently, biased belief updating emerges most strongly where signals touch upon both personal meaning and uncertainty, conditions characteristic of the prosocial domain.

Supplementary survey. To test these mechanisms more directly and systematically, I conduct a supplementary survey based on an online sample recruited through Norstat, a leading European panel provider. The survey samples parents of children under the age of 18 residing in Norway and consists of four main parts. Parents are randomly assigned to answer questions about either their child's prosocial or mathematical performance. First, after demographic questions and an attention check, parents report first- and second-order beliefs about their child's relative standing in the assigned domain and their confidence in those beliefs. Second, parents are shown the task used in the main experiment and asked to evaluate how well it captures the relevant performance. The survey also measures perceptions of responsibility for skill development, specifically, whether parents or schools are primarily responsible. This distinction is important: mathematics could be viewed as primarily the remit of schools and teachers, which may limit its ego-relevance for parents, whereas prosociality is often seen as a core parental responsibility. Consequently, signals about prosociality may feel more self-relevant and emotionally charged, making it more susceptible to biased processing. Third, parents indicate how strongly they believe improvements in the assigned skill affect their child's future pecuniary and non-pecuniary success and well-being, and how they would adjust time and effort if their child were performing well or poorly, allowing inference on whether they view investments as substitutes or complements. Finally, the survey elicits whether parents view "more of a skill" as inherently better (perceived monotonicity), how malleable they consider the skill to be, and how central the domain is to their self-image as a parent. These measures systematically test whether domain differences in perceived responsibility, malleability, value, and self-relevance can account for the asymmetric belief updating observed in the main experiment.

7 Conclusion

This study provides experimental evidence on how parents update beliefs about their child's relative performance when signals are noisy and ego-relevant to the parent. Using a lab-in-the-field study with Norwegian seventh-graders and their parents, I compare belief updating across mathematics and prosociality while manipulating the ego-relevance of performance signals. The pattern of updating is domain-specific: in mathematics, weighing of signals is symmetric and unaffected by informational context; in prosociality, parents place substantially greater weight on positive signals than on negative ones, with the gap largest when direct ego-relevance is made salient by highlighting intergenerational skill transmission between children and parents. Across both domains, parents update conservatively relative to the Bayesian benchmark, which captures full incorporation of information. The prosocial domain also reveals distinctive behavioral responses. Parents who observe more negative signals are more likely to downplay their child's effort, the relevance of the signal, and parent–child similarity, yet simultaneously report higher educational aspirations and a greater willingness to invest in their child's education. These patterns are consistent with defensive processing in response to ego-threatening information and identity-affirming behavior.

Suggestive survey evidence sheds light on why asymmetric updating emerges in prosociality but not for mathematics. Two complementary mechanisms explain this pattern. First, parents receive more frequent and objective feedback about mathematical performance through homework and teacher communication. This existing knowledge base constrains the scope for biased interpretation, as belief distortions would conflict with the relatively precise information parents already possess about their child's performance. In contrast, prosocial behavior is observed less systematically, creating ambiguity that permits selective processing of signals. Second, parents view prosociality as foundational for their child's broader life success, making signals in this domain more self-relevant and emotionally charged than mathematics, which parents tend to see as primarily the school's domain. Together, these factors create conditions under which biased updating is both possible (due to ambiguity) and psychologically compelling (due to self-relevance).

The findings contribute to three areas of the literature. First, they extend research on biased belief updating by demonstrating it applies not only to beliefs about one's own performance, but also to beliefs about others whose outcomes are tied to one's identity. Whereas prior work has primarily focused on self-assessment, where individuals directly evaluate their own performance, this study shows that similar asymmetries emerge when parents evaluate their children's performance. Crucially, this asymmetry depends on both informational conditions and psychological stakes: it emerges where ambiguity permits interpretive flexibility and where self-relevance creates motivation to protect positive beliefs.

Second, the findings enrich the literature on parental beliefs and investments by documenting the cognitive and psychological processes through which parents interpret performance signals about their children. While prior work has primarily examined how providing parents with accurate information affects educational investments, this study reveals mechanisms that limit such interventions' effectiveness. Parents do not simply incorporate new information but actively reinterpret it in ways that protect their self-image and maintain optimistic views in ego-relevant domains. The defensive processing observed here, where negative signals trigger both discounting and increased investment intentions, suggests a more complex relationship between beliefs and behavior than previously recognized.

Third, the study introduces a framework for understanding belief updating about others' performance that distinguishes between direct and indirect ego-relevance. Direct ego-relevance arises when one's own identity or competence is explicitly implicated by another's performance (as in the *Parent–Relevance* condition), while indirect ego-relevance stems from relational proximity without explicit self-evaluation (as in the *Child–Relevance* condition). This framework extends beyond the parent-child context to other settings where individuals evaluate the performance of others with whom they share identity, responsibility, or group membership, including coworkers, teammates, advisor/advisees, political allies, or other in-group members. Understanding how ego-relevance shapes belief formation in these contexts has implications for teamwork, organizational dynamics, political polarization, and social cohesion more broadly.

Lastly, these findings have implications for the intergenerational transmission of inequality. If parents systematically interpret signals about prosocial skills in self-enhancing ways, this may influence how they guide, praise, and invest in their children's social development. Given that prosocial skills are increasingly recognized as critical for labor market success and well-being, biased beliefs in this domain could have meaningful consequences for children's long-term outcomes. An open question is whether children exposed to such patterns also come to hold biased beliefs about their own abilities, thereby transmitting biased belief updating across generations. Understanding whether and how parental belief distortions shape children's self-perceptions and motivation represents a crucial direction for future research.

This study has limitations that suggest avenues for future work. First, the analysis focuses on a specific context (Norwegian seventh-graders and their parents) and it remains an open question whether similar patterns would emerge in different cultural settings, age groups, or educational systems. Second, while the experimental design isolates the belief updating process by holding the information environment fixed, real-world belief formation often involves active information search. In such settings, selective exposure and information avoidance may both play important roles: parents not only update beliefs based on the information they receive, but also *choose* which information to seek out, or to avoid altogether, depending on its emotional or identity relevance. Future research should explore how parents navigate this two-stage process of selecting and interpreting information about their children, and how these behaviors jointly shape the development of beliefs, aspirations, and investments. Finally, examining the longer-term consequences of biased parental beliefs, both for parental behavior and for children's own skill development and self-concept, would provide valuable insight into the mechanisms through which cognitive biases contribute to the reproduction of advantage and disadvantage across generations.

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A Additional Empirical Analyses

A.1 Descriptives

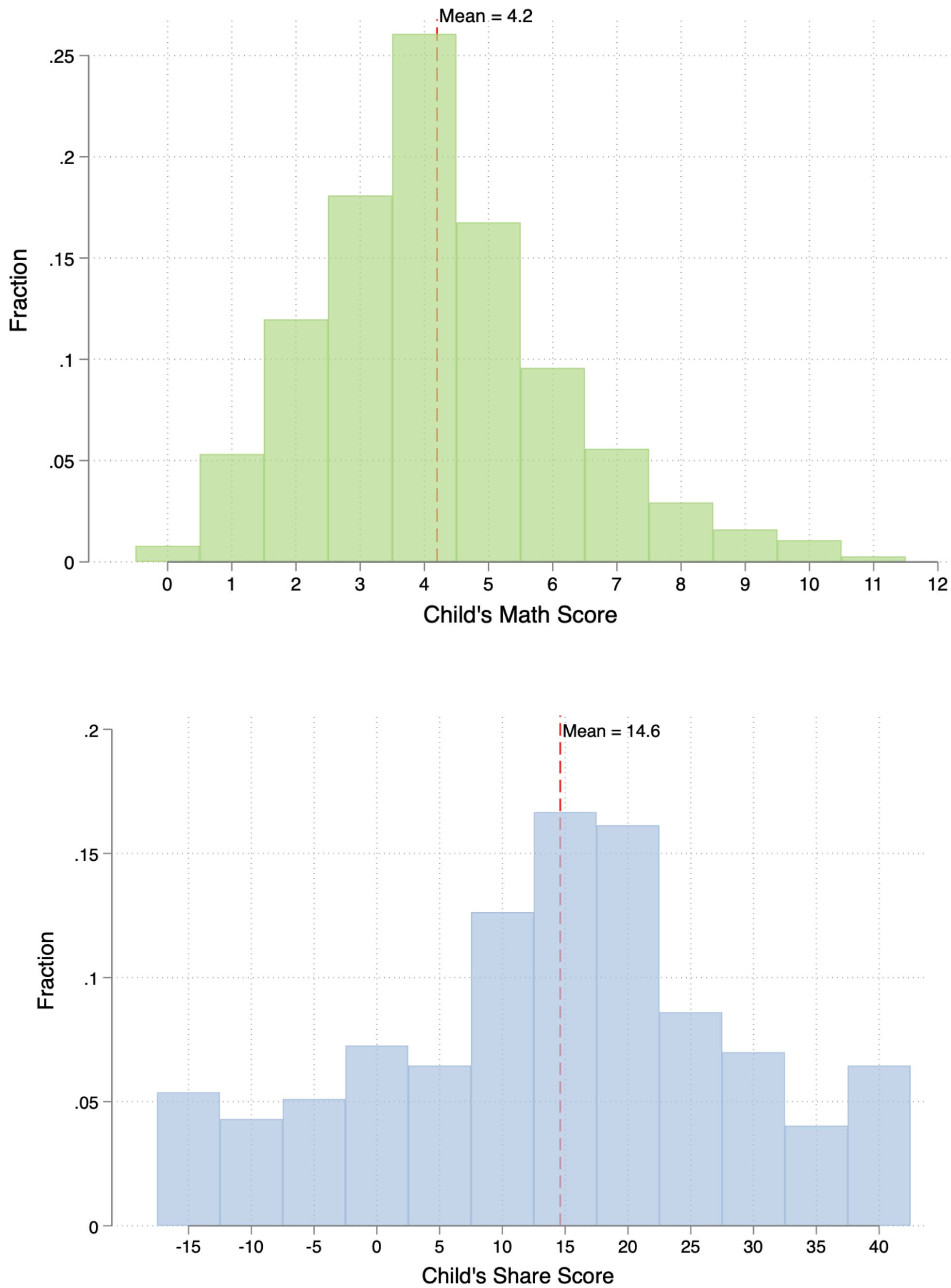
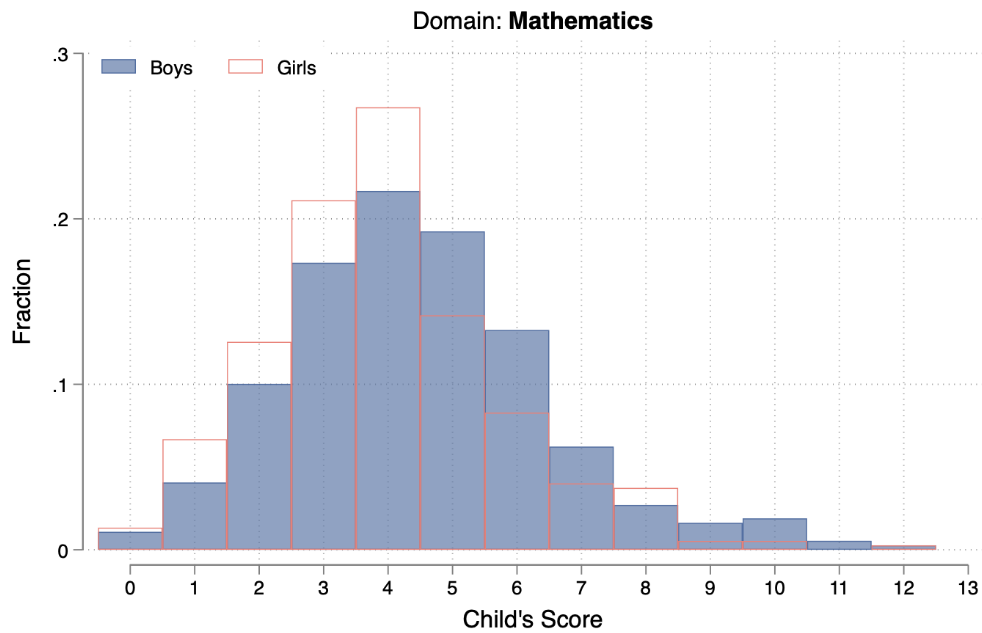


Figure 16: Distribution of Scores



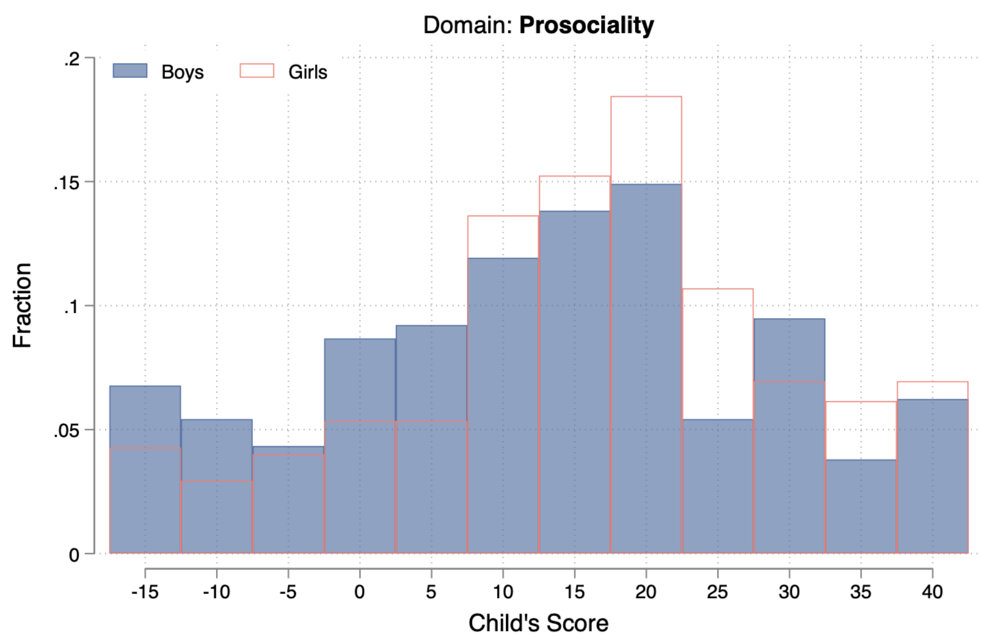


Figure 17: Distribution of Scores, Differentiated for Boys and Girls

A.2 Balances Tables

Table 6: Balance Table – Domains

	(1) **Full Sample**	(2) **Domain: Mathematics**	(3) **Domain: Prosociality**	(4) **Difference p-value (2 vs. 3)**
Children				
Score in math quiz	4.20	4.19	4.20	1.000
	(1.97)	(1.92)	(2.02)	
Score sharing game	14.61	15.15	14.05	0.359
	(14.50)	(14.65)	(14.34)	
Indicator child is male	0.50	0.49	0.50	0.769
	(0.50)	(0.50)	(0.50)	
Parents				
Prior belief	64.91	64.64	65.19	0.267
	(22.56)	(24.43)	(20.53)	
Indicator mother	0.69	0.70	0.68	0.633
	(0.46)	(0.46)	(0.47)	
Indicator university education	0.75	0.72	0.77	0.176
	(0.44)	(0.45)	(0.42)	
Observations	748	376	372	

Notes: For comparisons of child and parent gender or education level (all dummy variables), p-values are based on Fisher's exact test; for all other comparisons, a Kolmogorov–Smirnov test was used. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Balance Table – Prosociality

	(1) **Full Sample**	(2) **Control**	(3) **Child – Rel.**	(4) **Parent – Rel.**	(5) **Difference p-value (2 vs. 3)**	(6) **Difference p-value (2 vs. 4)**
Children						
Score in math quiz	4.20	3.95	4.35	4.31	0.587	0.282
	(2.02)	(1.96)	(2.10)	(1.98)		
Score in sharing game	14.05	13.49	13.90	14.77	0.992	0.892
	(14.34)	(14.18)	(14.54)	(14.39)		
Indicator child is male	0.50	0.48	0.50	0.52	0.800	0.610
	(0.50)	(0.50)	(0.50)	(0.50)		
Parents						
Prior belief	65.19	65.50	64.10	65.96	0.972	0.981
	(20.53)	(20.64)	(19.90)	(21.16)		
Indicator mother	0.68	0.66	0.72	0.67	0.337	0.892
	(0.47)	(0.48)	(0.45)	(0.47)		
Indicator university education	0.77	0.75	0.76	0.79	0.882	0.446
	(0.42)	(0.43)	(0.43)	(0.41)		
Observations	372	125	123	124		

Notes: For comparisons of child and parent gender or education level (all dummy variables), p-values are based on Fisher's exact test; for all other comparisons, a Kolmogorov–Smirnov test was used. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Balance Table – Mathematics

	(1) **Full Sample**	(2) **Control**	(3) **Child – Rel.**	(4) **Parent – Rel.**	(5) **Difference p-value (2 vs. 3)**	(6) **Difference p-value (2 vs. 4)**
Children						
Score in math quiz	4.19	4.20	4.31	4.06	0.580	0.959
	(1.92)	(1.92)	(1.81)	(2.02)		
Score in sharing game	15.15	15.26	15.60	14.59	0.994	0.607
	(14.65)	(14.85)	(14.94)	(14.23)		
Indicator child is male	0.49	0.55	0.43	0.49	0.078	0.446
	(0.50)	(0.50)	(0.50)	(0.50)		
Parents						
Prior belief	64.64	63.28	67.60	62.94	0.163	0.714
	(24.43)	(21.81)	(25.32)	(25.84)		
Indicator mother	0.70	0.72	0.65	0.73	0.221	0.887
	(0.46)	(0.45)	(0.48)	(0.44)		
Indicator university education	0.72	0.71	0.76	0.475	0.882	0.889
	(0.45)	(0.45)	(0.43)	(0.46)		
Observations	376	124	128	124		

Notes: For comparisons of child and parent gender or education level (all dummy variables), p-values are based on Fisher's exact test; for all other comparisons, a Kolmogorov–Smirnov test was used. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

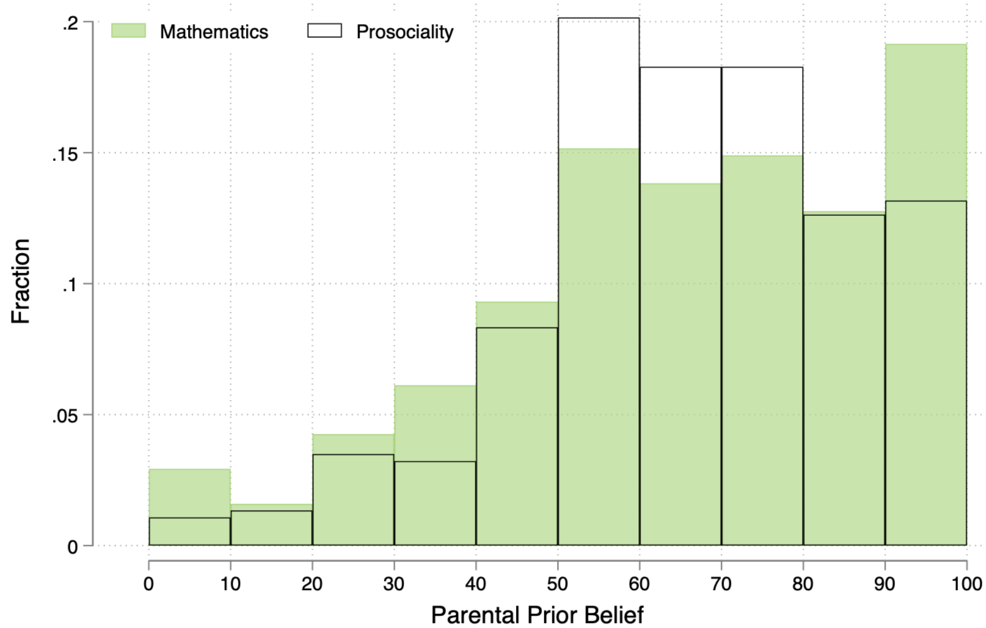


Figure 18: Distribution of Prior Beliefs, Separated by Domains

A.3 Belief Descriptives

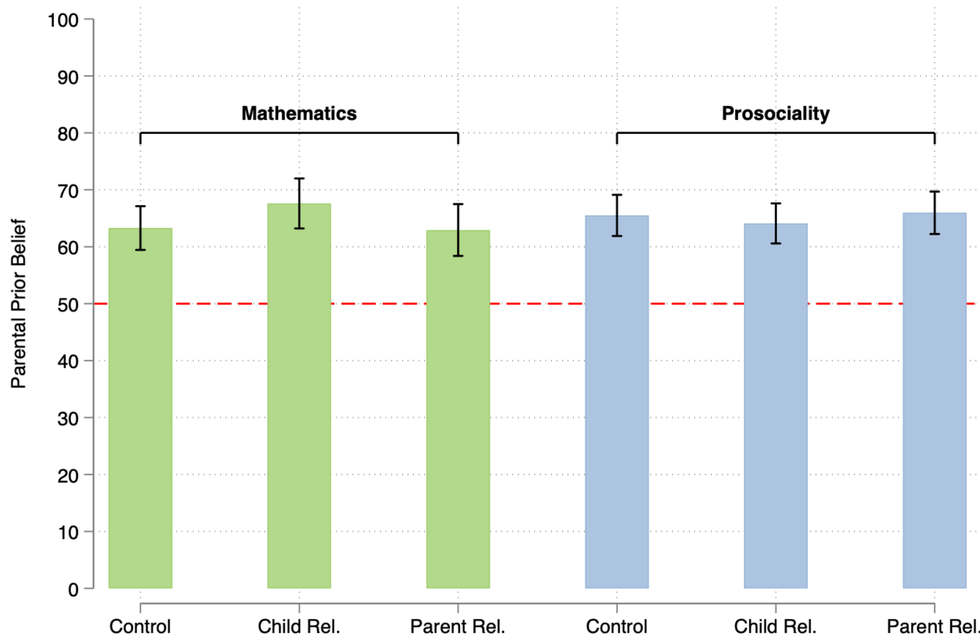


Figure 19: Prior Beliefs Across Domains and Information Conditions

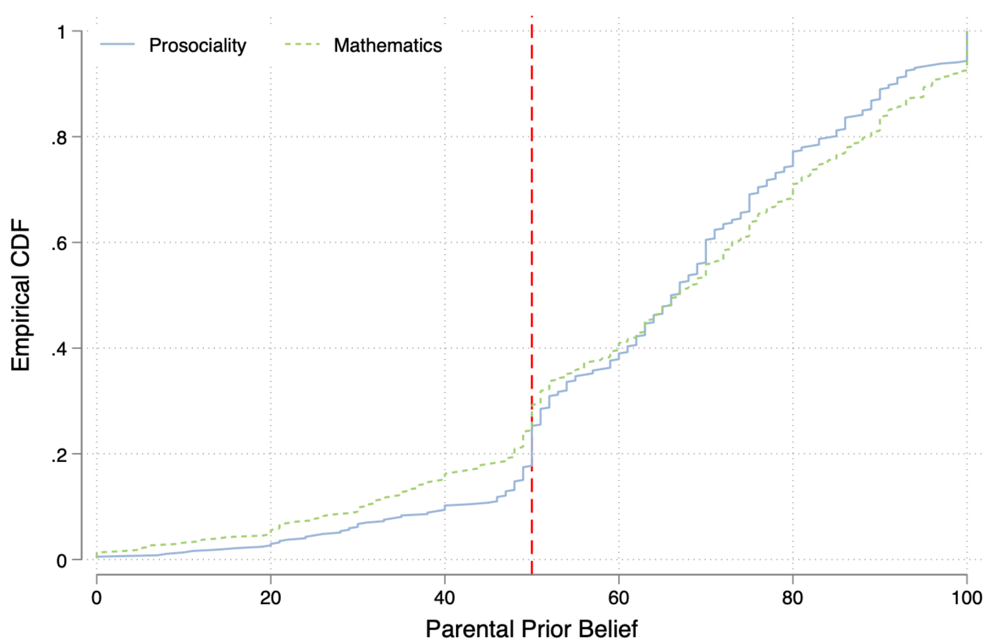


Figure 20: Cumulative Distribution Functions of Initial Beliefs

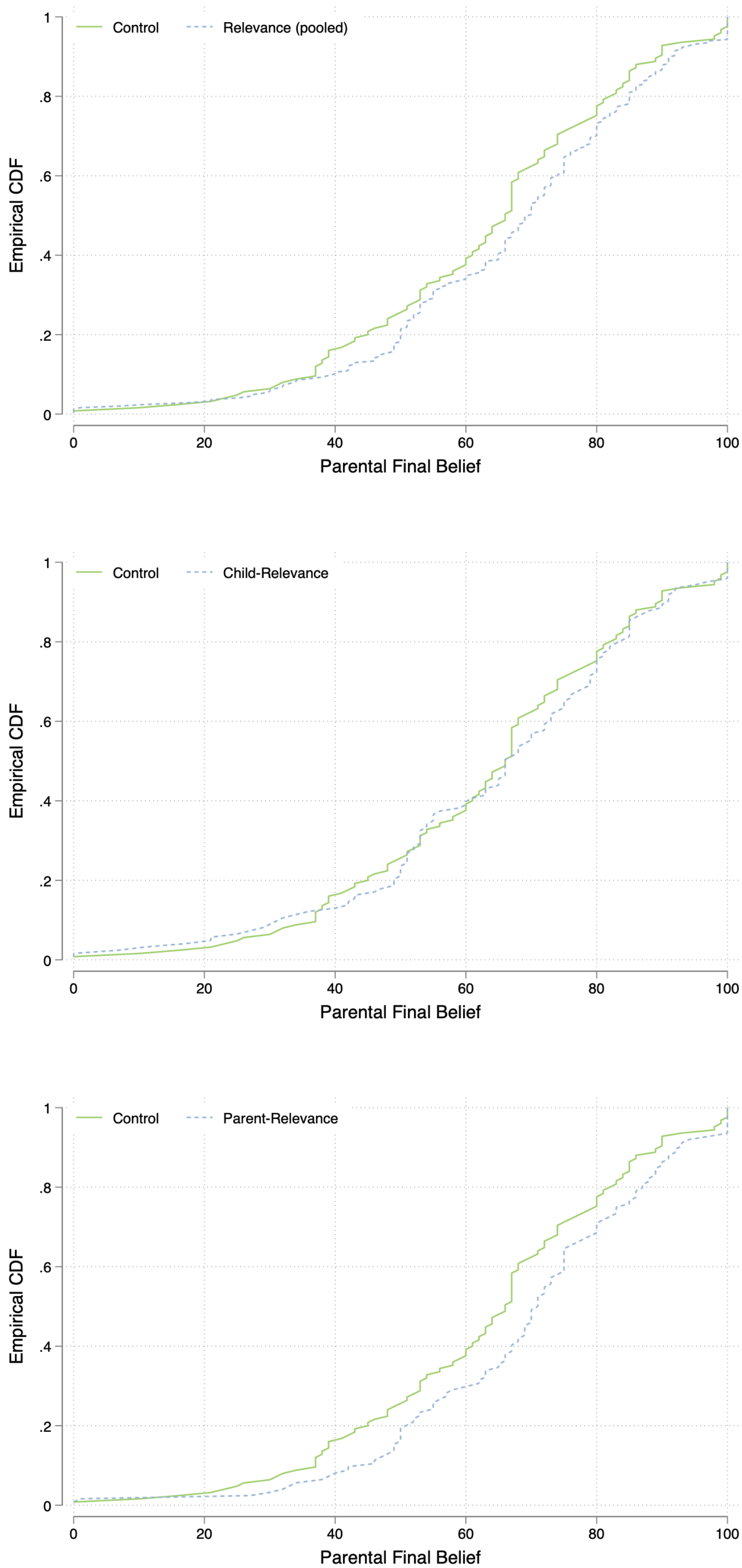


Figure 21: Cumulative Distribution Functions of Final Beliefs for the Domain Prosociality

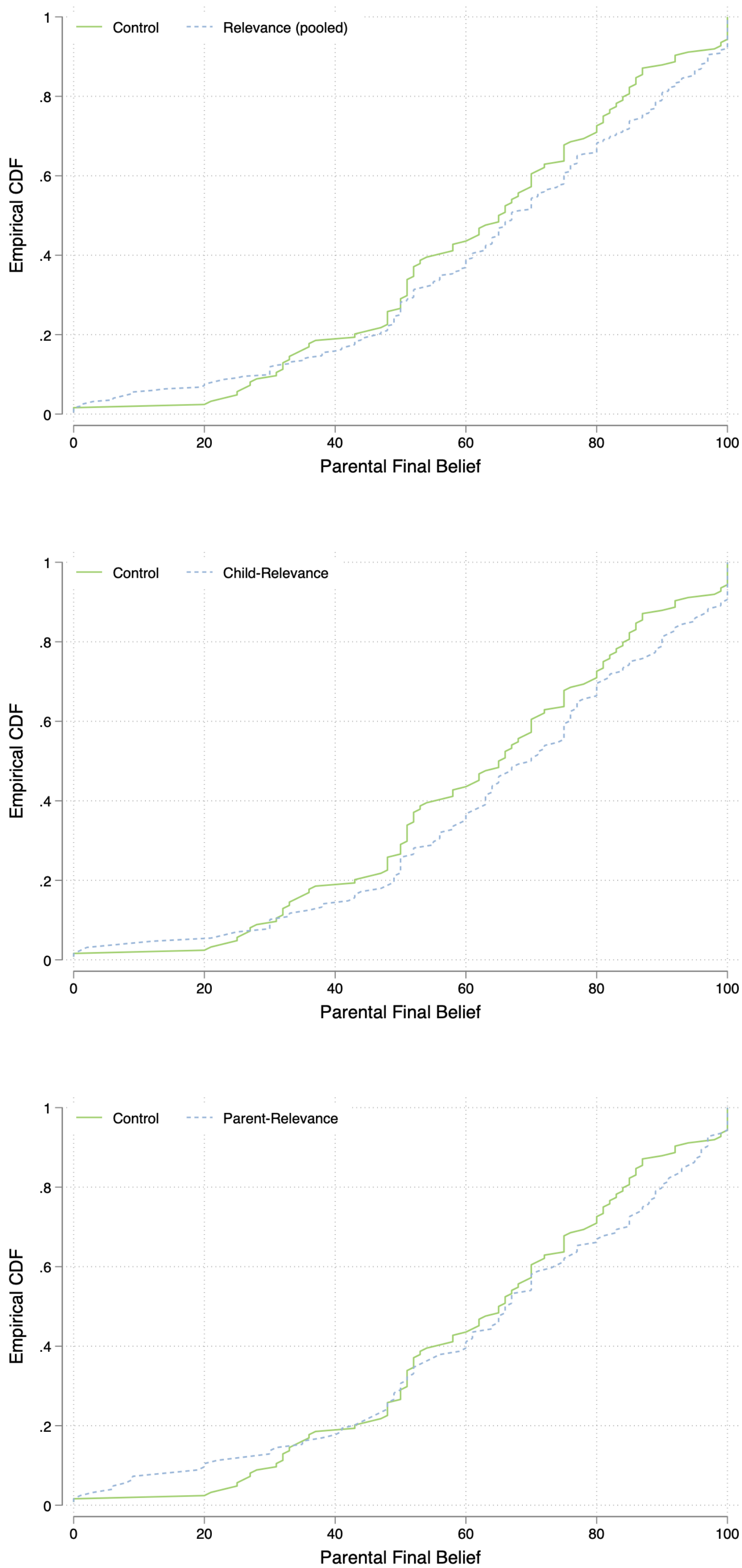


Figure 22: Cumulative Distribution Functions of Final Beliefs for the Domain Mathematics

Table 9: Mathematics: Aggregate Belief Updating Patterns

	(1) Full Sample	(2) Two Good Signals	(3) Mixed Signals	(4) Two Bad Signals
Info vs. No Info	0.43	-0.13	1.16	-2.85
	(1.371)	(1.685)	(2.148)	(4.351)
Prior	0.83***	0.78***	0.84***	0.82***
	(0.038)	(0.050)	(0.060)	(0.117)
Child's Math Score	0.95**	0.33	-0.10	0.59
	(0.409)	(0.545)	(0.465)	(1.518)
Boy	-0.41	-1.95	-1.60	4.20
	(1.469)	(1.674)	(2.323)	(4.889)
Mother	1.01	0.25	0.73	-3.68
	(1.882)	(2.049)	(2.814)	(6.363)
Constant	5.67*	17.87***	9.77**	2.74
	(2.945)	(4.946)	(4.401)	(9.193)
Observations	373	139	173	61
R^2	0.690	0.797	0.655	0.609

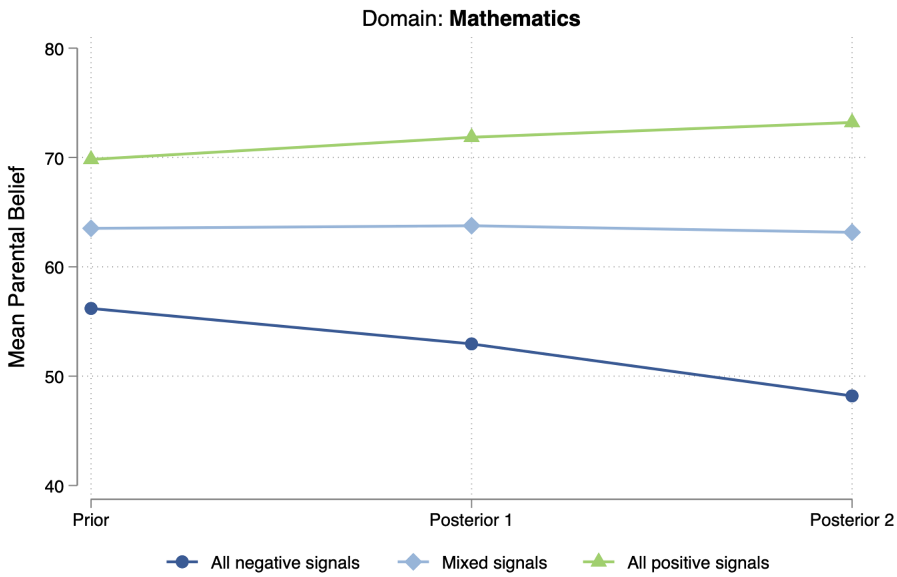
Notes: Analysis uses OLS regressions with robust standard errors in parentheses. Stars reflect significance in a t-test of the null hypothesis that coefficients are equal to 0. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A.4 Belief Dynamics

Table 10: Belief Updating by Signal, Round, and Domain

	(1) Signal	(2) Signal × Domain	(3) Signal × Round	(4) Full
Positive Signal	7.46***	7.79***	6.76***	6.95***
	(0.732)	(0.984)	(0.990)	(1.187)
Prosociality		1.58		2.22
		(1.066)		(1.480)
Pos. Signal × Prosociality		-0.21		0.47
		(1.484)		(1.995)
Round 2			-2.44**	-1.60
			(1.093)	(1.473)
Pos. Signal × Round 2			1.36	1.61
			(1.308)	(1.635)
Prosociality × Round 2				-1.38
				(2.139)
Pos. Signal × Prosociality × Round 2				-1.24
				(2.643)
Constant	-3.90***	-4.81***	-2.67***	-3.98***
	(0.536)	(0.773)	(0.769)	(0.981)
Observations	1496	1496	1496	1496
R^2	0.0728	0.0756	0.0773	0.0814

Notes: OLS regressions with robust standard errors in parentheses, clustered at the parent level. Stars indicate significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Reference categories: Negative signal, Mathematics domain, and Round 1.



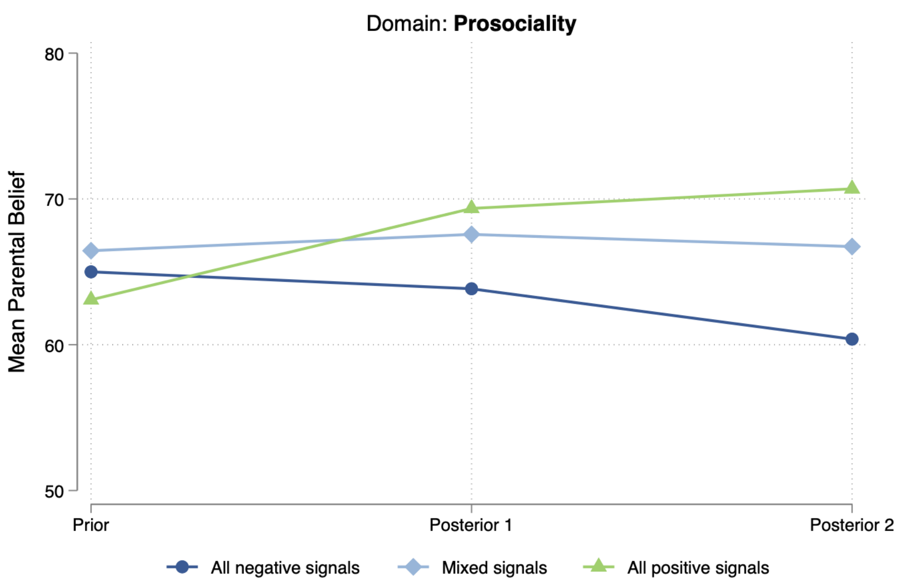


Figure 23: Belief Dynamics

A.5 Belief Updating

Table 11: Belief Updating – Prosociality Round 1

	(1) Full sample	(2) Control	(3) Rel. (pooled)	(4) Child – Rel.	(5) Parent – Rel.
Prior (δ)	0.663***	0.818***	0.593***	0.715***	0.460***
	(0.062)	(0.054)	(0.083)	(0.073)	(0.145)
Pos. signal (β_P)	0.829	0.212***	1.071	1.010	1.174
	(0.115)	(0.101)	(0.149)	(0.168)	(0.272)
Neg. signal (β_N)	-0.238***	0.112***	-0.407***	-0.087***	-0.679***
	(0.100)	(0.107)	(0.133)	(0.120)	(0.212)
Child in top half	-0.086	0.062	-0.128	-0.178	-0.088
	(0.075)	(0.077)	(0.101)	(0.119)	(0.166)
$\beta_P - \beta_N$	1.067	0.099	1.478	1.096	1.853
P-value $\beta_P - \beta_N$	0.000	0.568	0.000	0.000	0.000
P-value Chow-Test (relative to 2)			0.006	0.113	0.014
Observations	343	115	228	118	110
R^2	0.691	0.822	0.668	0.770	0.595

Notes: Analysis uses OLS regressions with robust standard errors clustered at the individual level and no constant. Analysis excludes observations with boundary beliefs 0 or 1. Stars indicate two-sided tests vs 1 for δ, β_P, β_N; the 'Child in top half' coefficient is tested vs 0. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Belief Updating – Prosociality Round 2

	(1) Full sample	(2) Control	(3) Rel. (pooled)	(4) Child – Rel.	(5) Parent – Rel.
Prior (δ)	0.831***	0.899	0.797***	0.821**	0.769**
	(0.050)	(0.085)	(0.062)	(0.071)	(0.103)
Pos. signal (β_P)	0.329***	0.274***	0.370***	0.372***	0.362***
	(0.119)	(0.232)	(0.139)	(0.179)	(0.219)
Neg. signal (β_N)	0.203***	0.196***	0.203***	0.335***	0.057***
	(0.093)	(0.139)	(0.126)	(0.129)	(0.226)
Child in top half	0.116	0.160	0.088	0.085	0.114
	(0.077)	(0.140)	(0.091)	(0.129)	(0.125)
$\beta_P - \beta_N$	0.126	0.078	0.168	0.037	0.305
P-value $\beta_P - \beta_N$	0.492	0.810	0.469	0.887	0.449
P-value Chow-Test (relative to 2)			0.411	0.673	0.275
Observations	347	119	228	115	113
R^2	0.739	0.751	0.737	0.742	0.737

Notes: Analysis uses OLS regressions with robust standard errors clustered at the individual level and no constant. Analysis excludes observations with boundary beliefs 0 or 1. Stars indicate two-sided tests vs 1 for δ, β_P, β_N; the 'Child in top half' coefficient is tested vs 0. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Belief Updating – Mathematics Round 1

	(1) Full sample	(2) Control	(3) Rel. (pooled)	(4) Child – Rel.	(5) Parent – Rel.
Prior (δ)	0.866***	0.833**	0.876**	0.781**	0.976
	(0.046)	(0.082)	(0.053)	(0.086)	(0.053)
Pos. signal (β_P)	0.380***	0.361***	0.388***	0.253***	0.526**
	(0.111)	(0.146)	(0.157)	(0.249)	(0.197)
Neg. signal (β_N)	0.234***	0.039***	0.333***	0.448**	0.137***
	(0.105)	(0.115)	(0.151)	(0.246)	(0.152)
Child in top half	0.017	-0.067	0.052	0.149	-0.093
	(0.092)	(0.096)	(0.130)	(0.190)	(0.152)
$\beta_P - \beta_N$	0.146	0.322	0.056	-0.195	0.388
P-value $\beta_P - \beta_N$	0.445	0.142	0.842	0.673	0.206
P-value Chow-Test (relative to 2)			0.685	0.807	0.545
Observations	343	115	228	118	110
R^2	0.691	0.822	0.668	0.770	0.595

Notes: Analysis uses OLS regressions with robust standard errors clustered at the individual level and no constant. Analysis excludes observations with boundary beliefs 0 or 1. Stars indicate two-sided tests vs 1 for δ, β_P, β_N; the 'Child in top half' coefficient is tested vs 0. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Belief Updating – Mathematics Round 2

	(1) Full sample	(2) Control	(3) Rel. (pooled)	(4) Child – Rel.	(5) Parent – Rel.
Prior (δ)	0.880**	0.900*	0.878*	0.914	0.844
	(0.054)	(0.060)	(0.064)	(0.073)	(0.103)
Pos. signal (β_P)	0.332***	0.249***	0.389***	0.587	0.271***
	(0.124)	(0.149)	(0.181)	(0.273)	(0.228)
Neg. signal (β_N)	0.368***	0.371***	0.363***	0.229***	0.503**
	(0.087)	(0.132)	(0.113)	(0.167)	(0.198)
Child in top half	0.031	0.118	-0.025	-0.164	0.086
	(0.079)	(0.115)	(0.111)	(0.198)	(0.118)
$\beta_P - \beta_N$	-0.036	-0.122	0.026	0.358	-0.232
P-value $\beta_P - \beta_N$	0.830	0.608	0.911	0.330	0.425
P-value Chow-Test (relative to 2)			0.805	0.987	0.645
Observations	336	113	223	110	113
R^2	0.818	0.827	0.816	0.799	0.833

Notes: Analysis uses OLS regressions with robust standard errors clustered at the individual level and no constant. Analysis excludes observations with boundary beliefs 0 or 1. Stars indicate two-sided tests vs 1 for δ, β_P, β_N; the 'Child in top half' coefficient is tested vs 0. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Belief Updating – Prosociality: Boundaries Replaced

	(1) Full sample	(2) Control	(3) Rel. (pooled)	(4) Child – Rel.	(5) Parent – Rel.
Prior (δ)	0.730***	0.784***	0.701***	0.671***	0.724***
	(0.047)	(0.066)	(0.062)	(0.101)	(0.075)
Pos. signal (β_P)	0.676***	0.194***	0.883	0.970	0.759
	(0.111)	(0.196)	(0.131)	(0.179)	(0.188)
Neg. signal (β_N)	-0.071***	-0.015***	-0.100***	0.186***	-0.348***
	(0.084)	(0.143)	(0.106)	(0.120)	(0.162)
Child in top half	-0.009	0.127	-0.052	0.008	-0.087
	(0.071)	(0.101)	(0.094)	(0.138)	(0.134)
$\beta_P - \beta_N$	0.747	0.209	0.983	0.784	1.107
P-value $\beta_P - \beta_N$	0.000	0.483	0.000	0.001	0.000
P-value Chow-Test (relative to 2)			0.109	0.171	0.200
Observations	744	250	494	246	248
R^2	0.665	0.732	0.645	0.571	0.718

Notes: Analysis uses OLS regressions with robust standard errors clustered at the individual level and no constant. Analysis excludes observations with boundary beliefs 0 or 1. Stars indicate two-sided tests vs 1 for δ, β_P, β_N; the 'Child in top half' coefficient is tested vs 0. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Belief Updating – Mathematics: Boundaries Replaced

	(1) Full sample	(2) Control	(3) Rel. (pooled)	(4) Child – Rel.	(5) Parent – Rel.
Prior (δ)	0.890***	0.952*	0.873***	0.851***	0.897***
	(0.026)	(0.027)	(0.032)	(0.050)	(0.039)
Pos. signal (β_P)	0.462***	0.338***	0.528***	0.696	0.428***
	(0.094)	(0.098)	(0.141)	(0.272)	(0.152)
Neg. signal (β_N)	0.281***	0.251***	0.279***	0.184(***)	0.308***
	(0.080)	(0.080)	(0.113)	(0.216)	(0.108)
Child in top half	-0.031	-0.039	-0.047	-0.159	0.021
	(0.063)	(0.072)	(0.092)	(0.173)	(0.084)
$\beta_P - \beta_N$	0.1817	0.0868	0.2491	0.512	0.120
P-value $\beta_P - \beta_N$	0.171	0.473	0.219	0.235	0.460
P-value Chow-Test (relative to 2)			0.891	0.911	0.636
Observations	752	248	504	256	248
R^2	0.834	0.898	0.814	0.787	0.846

Notes: Analysis uses OLS regressions with robust standard errors clustered at the individual level and no constant. Analysis excludes observations with boundary beliefs 0 or 1. Stars indicate two-sided tests vs 1 for δ, β_P, β_N; the 'Child in top half' coefficient is tested vs 0. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A.6 Further Outcomes

Table 17: Outcome – Ex-Post Rationalization for the Domain of Mathematics

	(1) Child's Effort	(2) Importance for Parent's Own Skills	(3) Importance for Child's Later Life Outcomes
Neg. signals	-0.17	-0.09	-0.05
	(0.137)	(0.138)	(0.140)
Prior	0.03***	0.02***	0.02***
	(0.004)	(0.004)	(0.004)
Child's Math score	-0.01	0.00	0.01
	(0.054)	(0.053)	(0.053)
Info vs. No Info	0.26	0.48**	0.26
	(0.195)	(0.195)	(0.193)
Observations	376	376	376
Pseudo R^2	0.039	0.019	0.017

Notes: Subjects' stated belief that the child exerted effort as well as stated belief about the strength of inter-generational transmission and relevance for the child's later life outcomes on a seven-point Likert scale. The analysis uses Ordered Logistic Regressions with standard errors in parentheses. Stars reflect significance in a t-test of the null hypothesis that coefficients are equal to 0. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Outcome – Educational Aspirations for the Domain of Prosociality

	(1) Academic Highschool	(2) University Degree
Neg. Signals	0.06	0.40**
	(0.175)	(0.200)
Prior	0.01*	0.01*
	(0.006)	(0.007)
Child's Share Score	-0.01	0.00
	(0.009)	(0.010)
Info vs. No Info	0.11	0.26
	(0.260)	(0.289)
Constant	-0.18	-0.58
	(0.506)	(0.566)
Observations	117	120
Pseudo R^2	0.031	0.073

Notes: The analysis uses Probit regressions with standard errors in parentheses. The dependent variables are indicator variables that take the value one if parents state that they expect their child to attend academic highschool or obtain a university degree. Stars reflect significance in a t-test of the null hypothesis that coefficients are equal to 0. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Outcome – Educational Aspirations for the Domain of Mathematics

	(1) Academic Highschool	(2) University Degree
Neg. signals	0.20	0.42*
	(0.212)	(0.254)
Prior	0.02***	0.02***
	(0.006)	(0.006)
Child's Math Score	0.09	0.09
	(0.083)	(0.093)
Info vs. No Info	0.41	-0.16
	(0.294)	(0.373)
Constant	-1.73***	-0.64
	(0.568)	(0.585)
Observations	109	109
Pseudo R^2	0.1843	0.1683

Notes: The analysis uses Probit regressions with standard errors in parentheses. The dependent variables are indicator variables that take the value one if parents state that they expect their child to attend academic highschool or obtain a university degree. Stars reflect significance in a t-test of the null hypothesis that coefficients are equal to 0. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 20: Outcome – Parental Investment for the Domain of Prosociality

	(1) Educ. Investment (stand.)
Neg. Signals	0.20*
	(0.113)
Prior	0.01
	(0.004)
Child's Share Score	-0.00
	(0.006)
Info vs. No Info	0.20
	(0.179)
Constant	-0.59*
	(0.345)
Observations	140
R^2	0.047

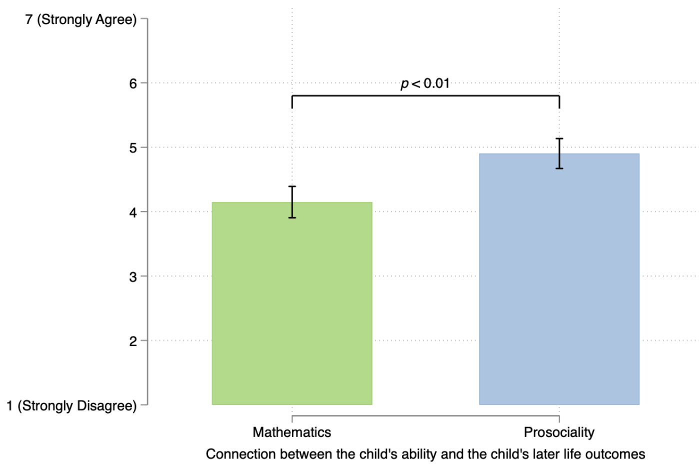
Notes: The analysis uses OLS regression with robust standard errors in parentheses. The dependent variable (educational investment) is standardized. Stars reflect significance in a t-test of the null hypothesis that coefficients are equal to 0. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Outcome – Parental Investment for the Domain of Mathematics

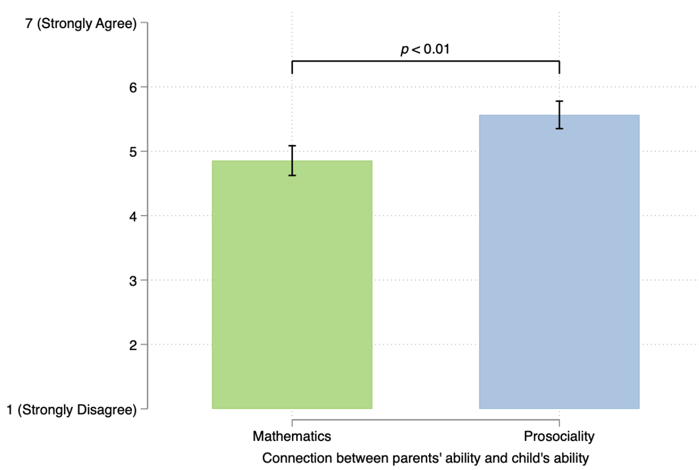
	(1) Educ. Investment (stand.)
Neg. Signals	-0.21
	(0.133)
Prior	0.00
	(0.004)
Child's Math Score	-0.11**
	(0.045)
Info vs. No Info	0.28
	(0.184)
Constant	0.29
	(0.305)
Observations	138
R^2	0.056

Notes: The analysis uses OLS regression with robust standard errors in parentheses. The dependent variable (educational investment) is standardized. Stars reflect significance in a t-test of the null hypothesis that coefficients are equal to 0. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A.7 Perception of Skill Domains



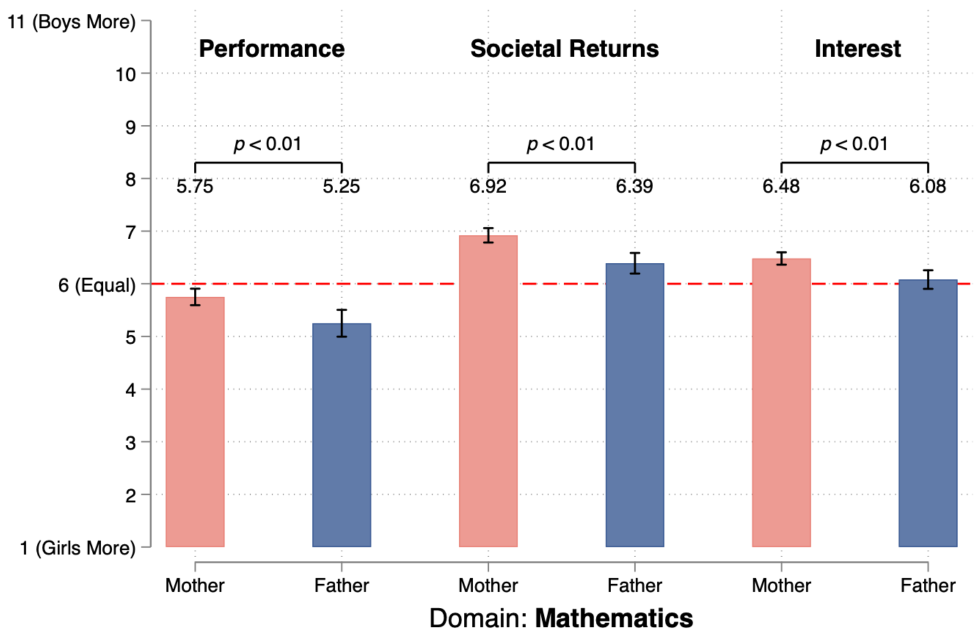
(a) Relevance of Skills



(b) Transmission of Skills

Note: These measures reflect baseline responses, recorded before any informational treatment was administered.

Figure 24: Parental Perception of the Relevance and Intergenerational Transmission of Skills



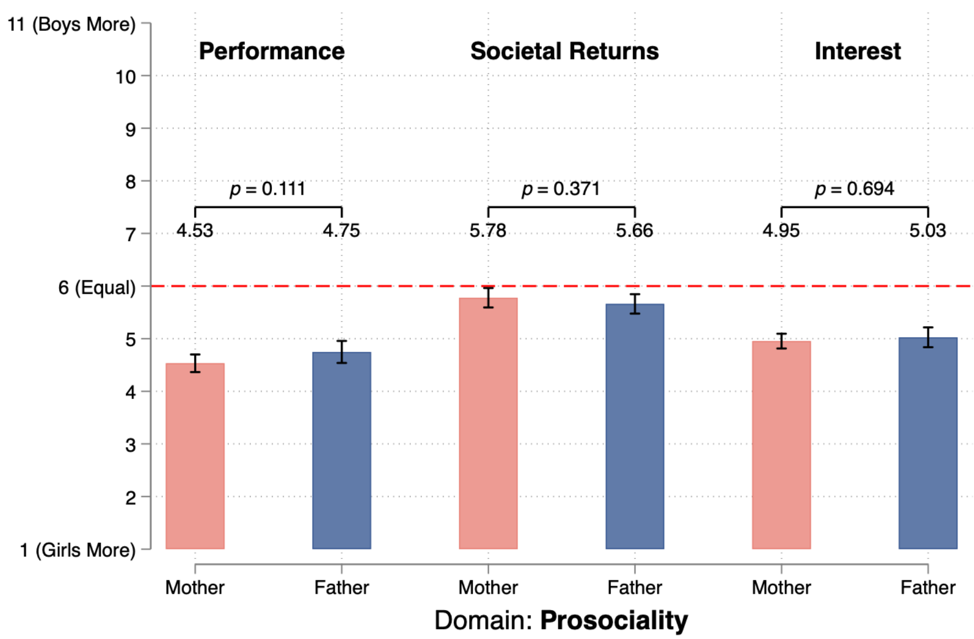


Figure 25: Parental Perceptions of Gendered Skill Domains: Performance, Societal Returns, and Interest

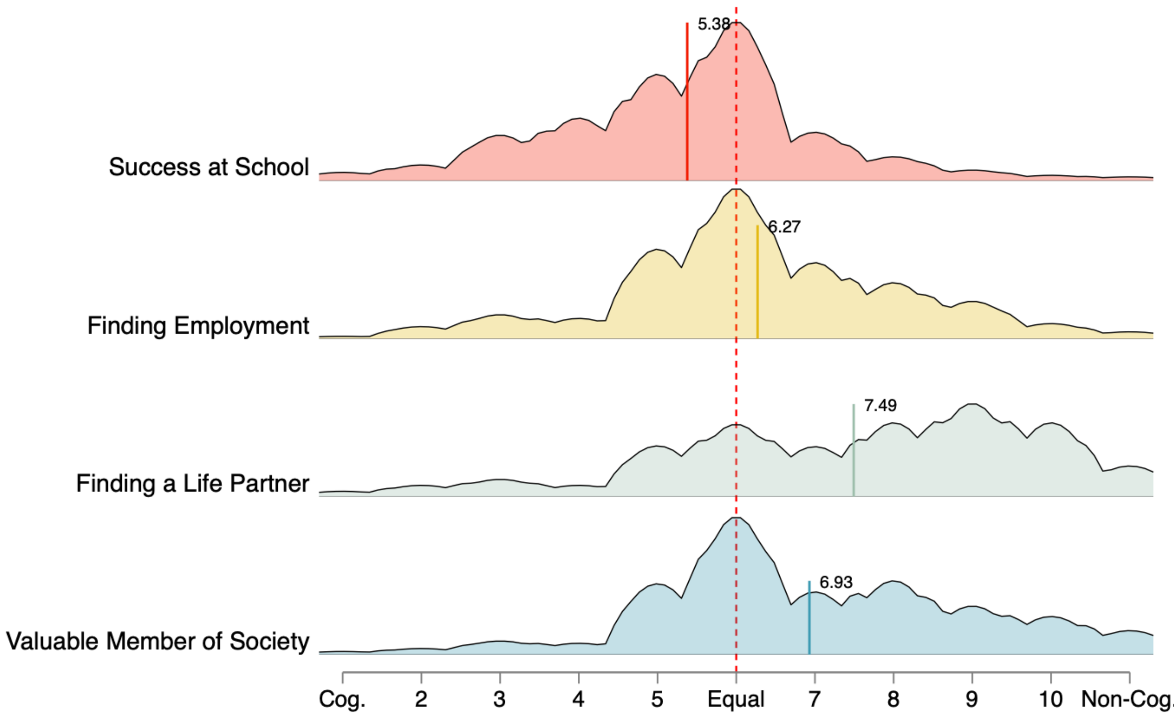


Figure 26: Perceived Relative Importance of Skills for Outcomes

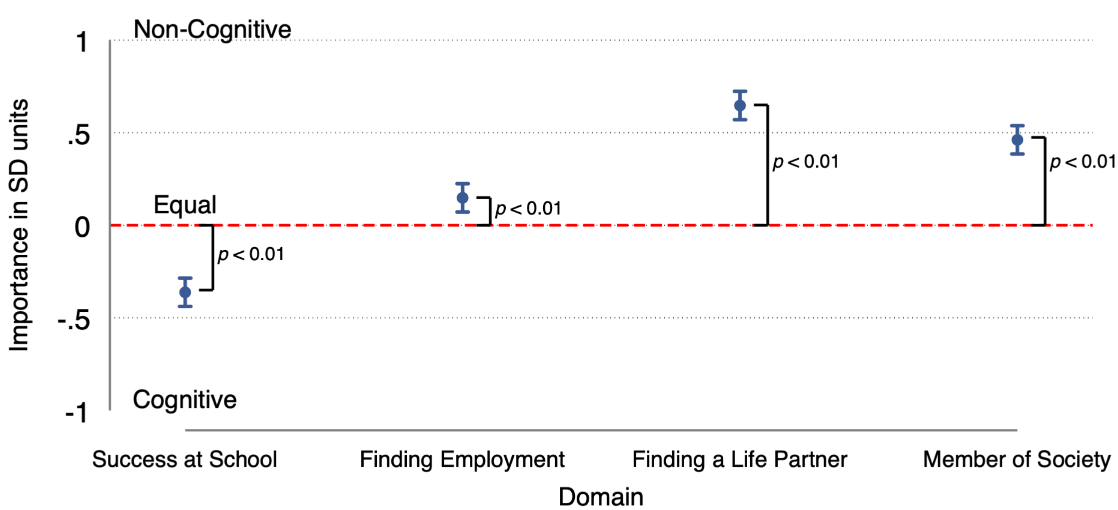


Figure 27: Are Skills Equally Important for Outcomes?

A.8 Heterogeneity

A.8.1 Child's Gender

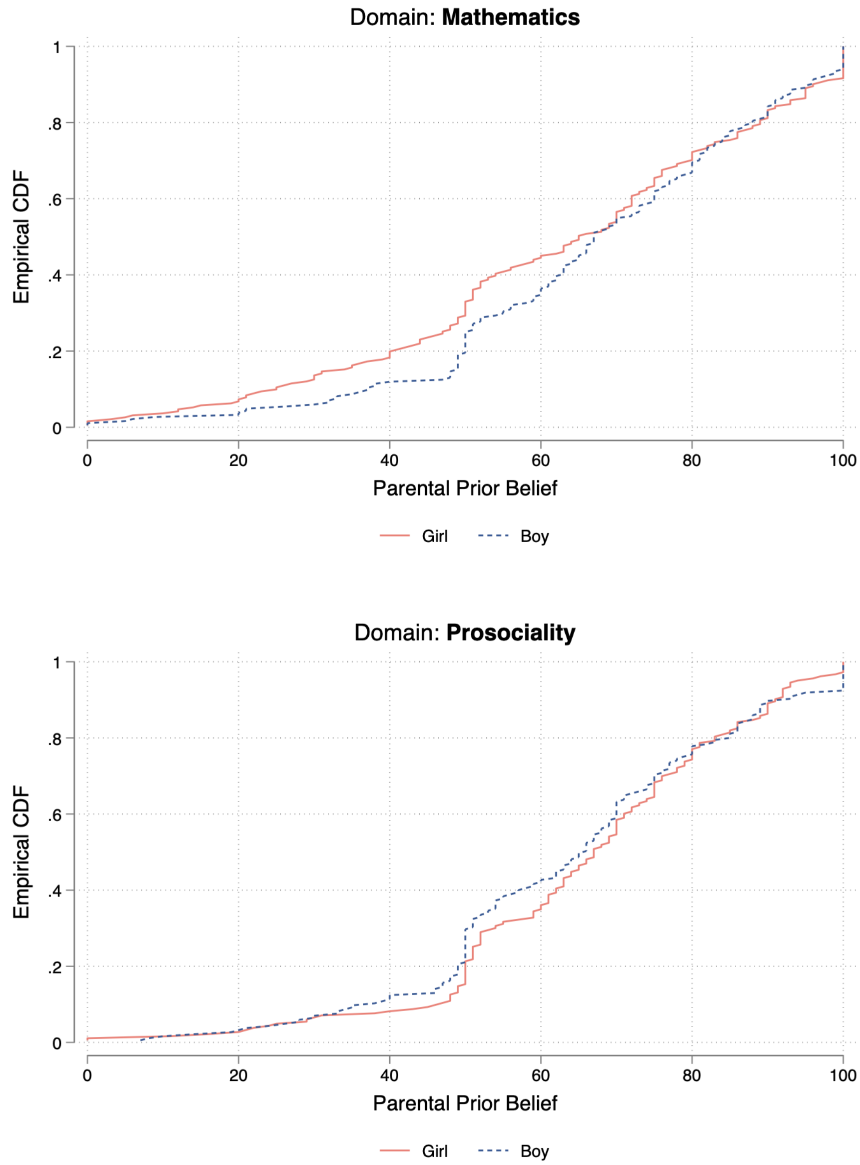


Figure 28: Parental Prior Beliefs, Separated by Girl/Boy

A.8.2 Parents' Gender

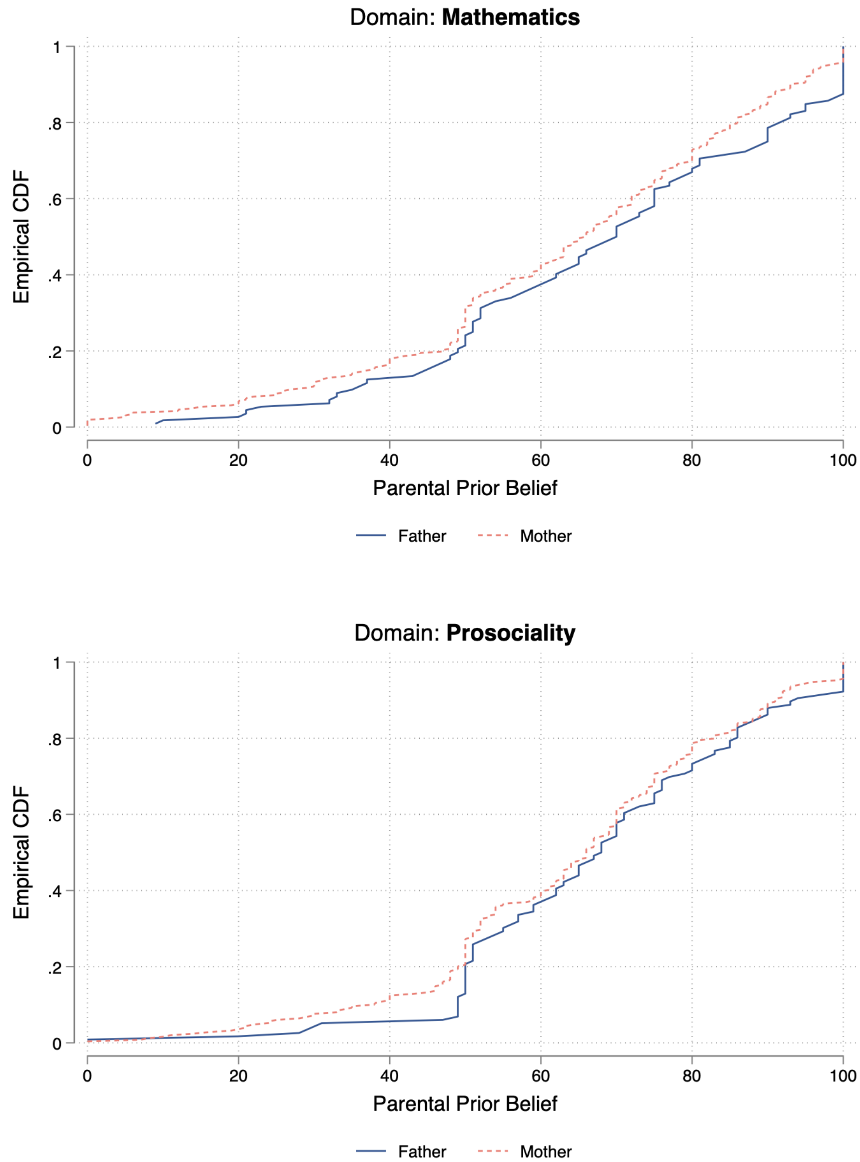


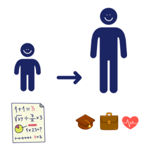
Figure 29: Parental Prior Beliefs, Separated by Mother/Father

B Supplementary Material

B.1 Screens of the Information Conditions

Please take time to read the information below carefully: **0:30**

Research has shown that children who **do well in school, for example in mathematics quizzes, often do well later in life**.



Research has documented that children with good test results pursue **longer education** later in life (Auceio & James, 2021), have **jobs with higher income** (Chamberlain, 2013; Chetty et al., 2014), and have **better health outcomes** (Heckman et al., 2006).

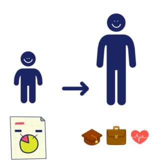
[+] References

[In the online survey, participants could click to expand this section]

- Aucejo, E., & James, J. (2021). The path to college education: The role of math and verbal skills. *Journal of Political Economy*, *129*(10), 2905–2946.
- Chamberlain, G. E. (2013). Predictive effects of teachers and schools on test scores, college attendance, and earnings. *Proceedings of the National Academy of Sciences*, *110*(43), 17176–17182.
- Chetty, R., Friedman, J. N., & Rockoff, J. E. (2014). Measuring the impacts of teachers II: Teacher value-added and student outcomes in adulthood. *American Economic Review*, *104*(9), 2633–2679.
- Heckman, J., Stixrud, J., & Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics*, *24*(3), 411–482.

Please take time to read the information below carefully: **0:30**

Research has shown that **children who share more with others often do well later in life**.



Research has documented that children with good test results later in life have **longer education** (Caprara et al., 2000)**, jobs with higher income** (Kosse & Tincani, 2020), and **better health** (Becker et al., 2012).

[+] References

[In the online survey, participants could click to expand this section]

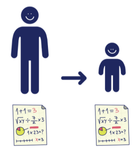
- Caprara, G. V., Barbaranelli, C., Pastorelli, C., Bandura, A., & Zimbardo, P. G. (2000). Prosocial foundations of children's academic achievement. Psychological Science, 11(4), 302-306.
- Kosse, F., & Tincani, M. M. (2020). Prosociality predicts labor market success around the world. Nature Communications, 11, Article 5298.
- Becker, A., Deckers, T., Dohmen, T., Falk, A., & Kosse, F. (2012). The relationship between economic preferences and psychological personality measures. Annual Review of Economics, 4, 453-478.

Figure 30: Information treatment – Relevance of skills. Mathematics domain (top) and Prosociality domain (bottom).

Please take the time to read the information below carefully: **0:30**

Research has shown that there is a **connection between parents' math skills and children's math skills** (Brown & Taylor, 2011; Hanushek et al., 2021; de Coulon et al., 2011).

Parents who have good math skills also tend to have children with good math skills.



This is captured in the saying: **"The apple doesn't fall far from the tree!"**

[+] References

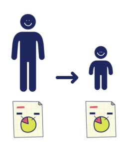
[In the online survey, participants could click to expand this section.]

- Brown, S., McIntosh, S., & Taylor, K. (2011). Following in your parents' footsteps? Empirical analysis of matched parent-offspring test scores. *Oxford Bulletin of Economics and Statistics*, *73*(1), 40–58.
- Hanushek, E. A., Jacobs, B., Schwerdt, G., van der Velden, R., Vermeulen, S., & Wiederhold, S. (2021). The intergenerational transmission of cognitive skills: An investigation of the causal impact of families on student outcomes. NBER Working Paper No. 29450.
- de Coulon, A., Meschi, E., & Vignoles, A. (2011). Parents' skills and children's cognitive and non-cognitive outcomes. *Education Economics*, *19*(5), 451–474.

Please take the time to read the information below carefully: **0:30**

Research has shown that there is a **connection between willingness to give to others in parents and children** (Eisenberg et al., 2006; Kosse et al., 2020).

Parents who have greater willingness to share, have children who also have greater willingness to share.



This is captured in the saying: **"The apple doesn't fall far from the tree!"**

[+] References

[In the online survey, participants could click to expand this section.]

- Eisenberg, N., Fabes, R. A., & Spinrad, T. L. (2006). Development. In N. Eisenberg (Ed.), Handbook of child psychology: Vol. 3. Social, emotional, and personality development (6th ed., pp. 646–718). John Wiley & Sons.
- Kosse, F., Deckers, T., Pinger, P., Schildberg-Hörisch, H., & Falk, A. (2020). The formation of pro-sociality: Causal evidence on the role of social environment. Journal of Political Economy, 128(2), 434–467.

Figure 31: Information treatment – Transmission of skills. Mathematics domain (top) and Prosociality domain (bottom).

B.2 Description of the Dictator Games

This study adapts a series of dictator games from Bonan et al. (2023), originally designed to study prosocial behavior among primary school students in El Salvador. The games were selected to elicit meaningful variation in children's prosocial choices, facilitating the construction of noisy performance signals.

Each child plays four dictator games in the role of allocator/dictator. The recipient is described as another child in need, supported by the Norwegian Red Cross through programs such as *Holiday for All* (*Ferie for alle*). In each game, the child allocates ten tokens between themselves and the recipient. Illustrations accompany every game, showing both children and their initial endowments. The first game is always presented first, while the remaining three are shown in randomized order. The games differ in their initial endowments and in whether the dictator has the option to take from the recipient.

The four games are as follows:

- **Child (5) – Other Child (5):** Baseline game; both start with 5 tokens. The child allocates 10 additional tokens.
- **Child (5) – Other Child (5):** Both start with 5 tokens. The child allocates 10 additional tokens and may also take any number of the other child's tokens.
- **Child (2) – Other Child (5):** The child starts with 2 tokens, the other with 5. The child allocates 10 additional tokens and may take from the other child.
- **Child (8) – Other Child (5):** The child starts with 8 tokens, the other with 5. The child allocates 10 additional tokens and may take from the other child.

This implies that in Game 1, the child can allocate between 0 and 10 tokens to the recipient, keeping the remainder. In Games 2-4, the child can allocate between 0 and 15 tokens to themselves, as taking from the recipient is allowed.

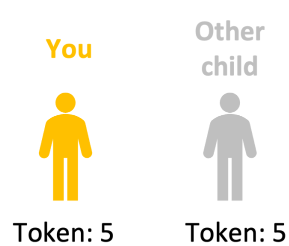


Figure 32: Supporting Illustration of the Dictator Game

B.3 Recruitment Procedure

This document outlines the procedure to recruit parents and children for the study through schools.

Step 1: Construction of the school database

I constructed a dataset of all schools in Norway with at least fifty students in seventh grade, the study's target group. This threshold ensured a sufficiently large number of potential participants per school, given the expected participation rate. The initial list of schools was derived from the national school database provided by the Norwegian Directorate for Education and Training (Utdanningsdirektoratet). For each school, I recorded the school's name, the name and email address of the principal, and the names and email addresses of the grade leaders and, where applicable, the class teachers. This information was extracted manually from each school's official website.

Step 2: Stratified random sampling of schools

To create a random yet regionally balanced sample of schools, I implemented a stratified random sampling procedure based on county-level population shares. In each sampling round, I drew a set of $N = 30$ schools, which I subsequently contacted for participation. The distribution across counties in the first round was as follows: Agder (2), Innlandet (2), Møre og Romsdal (1), Nordland (1), Oslo (4), Rogaland (3), Troms og Finnmark (1), Trøndelag (3), Vestfold og Telemark (2), Vestland (4), and Viken (7). This distribution approximated each county's population share. Within each county, the predetermined number of schools was randomly selected using a fixed random seed to ensure reproducibility. Each new round constituted a fresh random draw excluding schools that had already been contacted. I repeated this procedure until the pool of eligible schools was exhausted, maintaining the intended stratification across counties while preserving randomization within each stratum.

Step 3: Recruitment of schools

For each selected school, we sent an email from the project's dedicated email address associated with the Norwegian School of Economics to the principal and seventh-grade leader(s). Where applicable, we also included the teachers responsible for the seventh-grade classes. Following a school's expression of interest, we coordinated with teachers to schedule data collection. The survey was scheduled for the end of the school day to align with the experimental design requirements (Barron et al., 2025). Schools typically administered the study between 12:00 and 13:00. If schools did not respond to the initial email, we sent a follow-up message a few days later before marking them as unresponsive. Schools that declined to participate were not contacted again.

Step 4: Recruitment of participants (parents and children)

Two weeks before the scheduled survey at each participating school, we distributed invitation letters via email containing a QR code for study registration to parents via grade leaders and class teachers. The consent form requested parental consent for (i) their child's participation, (ii) their own participation in two surveys, and (iii) data linkage to administrative records. Parents also had the option to provide partial consent, for example, agreeing to their child's participation but declining data linkage. Both parents and children had to read and provide informed consent at the beginning of their respective surveys. Either the parent or the child could withdraw consent at any point during participation. Prior to the study, we informed schools about sign-up progress and encouraged teachers to resend invitations when sign-up rates were low. We also responded to individual questions from both teachers and parents.

Addendum

In March 2025, we extended the recruitment procedure to include schools with smaller seventh-grade cohorts, specifically those with between forty and fifty students. This decision was driven by the limited number of schools with at least fifty seventh-grade students. Some schools declined participation due to constraints such as time, limited resources, or involvement in other studies, while others did not respond to recruitment emails or follow-ups. It was unclear whether non-response reflected a lack of interest or email delivery issues.

B.4 Information on Schools

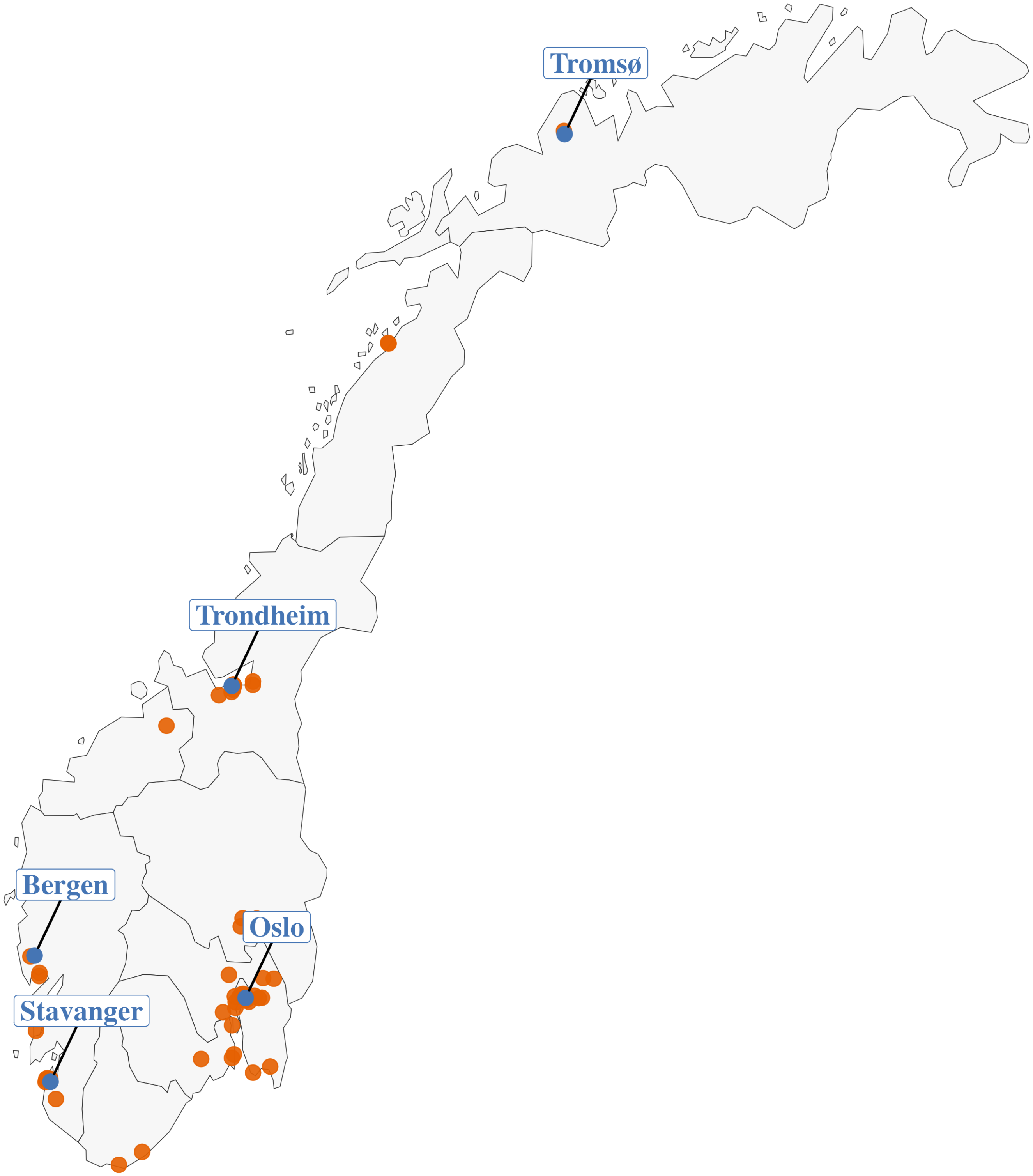


Figure 33: Locations of Participating Schools

Table 22: Participation by School

School Name	Children Participated	Parents Participated
Årnes	N=23	N=19
Arnestad	N=30	N=22
Bekkestua	N=48	N=35
Børsa	N=19	N=12
Ekeberg	N=15	N=14
Fjellhamar	N=19	N=15
Fosslia	N=30	N=18
Fredheim	N=34	N=24
Gjerpen	N=16	N=13
Goa	N=29	N=22
Grødem	N=15	N=10
Hånes	N=39	N=28
Harestad	N=41	N=29
Hjortsberg	N=27	N=19
Hvaler	N=21	N=8
Ime	N=17	N=17
Korta	N=11	N=11
Kuventræ	N=19	N=16
Kvåle	N=22	N=16
Kvernevik	N=22	N=11
Labakken	N=12	N=8
Lade	N=19	N=17
Lånke	N=16	N=12
Lunde	N=25	N=13
Mellom-Nes	N=16	N=10
Mortesnes	N=5	N=5
Olsvik	N=19	N=15
Øren	N=20	N=16
Prestrud	N=46	N=30
Riddersand	N=16	N=11
Rønvik	N=20	N=11
Rustad	N=11	N=9
Rykinn	N=21	N=15
Sagene	N=12	N=7
Saltvern	N=40	N=26
Sandeåsen	N=9	N=9
Skeie	N=10	N=7
Skogmo	N=9	N=8
Smestad	N=13	N=9
Solås	N=22	N=15
Steindal	N=10	N=7
Strindheim	N=16	N=14
Surnadal	N=15	N=10
Sveio	N=17	N=13
Svendstuen	N=17	N=9
Tømmerås	N=11	N=6
Tonstad	N=15	N=11
Utleira	N=38	N=31
Vålerenga	N=24	N=16
Vang	N=11	N=6
Voksen	N=22	N=13
Total	N=1054	N=748

Table 23: Experimental and National Test Scores at Schools

		Experimental Scores		National Tests 5th grade		
School	**County**	**Mathematics**	**Prosociality**	**Mathematics**	**Reading**	**English**
Årnes	Viken	3.95	13.58	48	50	49
Arnestad	Viken	4.64	22.50	48	51	50
Bekkestua	Viken	4.66	15.54	55	52	51
Børsa	Trøndelag	4.33	15.17	53	55	54
Ekeberg	Oslo	3.93	22.64	55	56	53
Fjellhamar	Viken	3.27	14.40	51	50	52
Fosslia	Trøndelag	3.83	15.89	NA	51	NA
Fredheim	Innlandet	4.54	15.58	NA	53	53
Gjerpen	Telemark	3.00	10.00	47	47	44
Goa	Rogaland	5.36	10.41	51	49	49
Grødem	Rogaland	5.10	4.70	54	53	52
Hånes	Agder	3.93	11.21	NA	NA	NA
Harestad	Rogaland	4.28	12.52	51	47	47
Hjortsberg	Viken	4.53	19.00	48	49	49
Hvaler	Viken	4.38	17.75	47	44	45
Ime	Agder	5.41	15.88	50	49	49
Korta	Innlandet	4.09	15.36	48	50	49
Kuventræ	Vestland	4.94	11.56	51	48	48
Kvåle	Vestland	4.19	15.19	NA	NA	NA
Kvernevik	Rogaland	3.55	16.09	48	48	55
Labakken	Vestfold	4.50	15.13	46	48	47
Lade	Trøndelag	3.65	13.76	46	48	47
Lånke	Trøndelag	3.83	19.00	49	NA	NA
Lunde	Vestfold og Telemark	4.15	10.92	49	50	52
Mellom-Nes	Viken	3.90	15.00	54	52	49
Mortesnes	Troms og Finnmark	5.40	9.40	51	51	48
Olsvik	Vestland	3.80	9.53	48	48	49
Øren*	Viken	4.31	10.50	54	52	50
Prestrud	Innlandet	4.20	14.67	51	52	50
Riddersand	Viken	4.36	13.55	47	48	49
Rønvik	Nordland	4.82	4.55	50	47	NA
Rustad	Oslo	4.44	10.22	49	50	52
Rykinn	Viken	4.40	14.73	NA	49	NA
Sagene	Oslo	2.57	25.57	48	50	48
Saltvern*	Nordland	3.65	18.15	51	52	51
Sandeåsen	Vestfold	4.22	26.22	51	55	51
Skeie	Rogaland	3.29	18.29	51	51	52
Skogmo	Viken	3.88	17.13	53	52	50
Smestad	Oslo	4.11	15.78	55	54	53
Solås*	Rogaland	4.73	14.87	46	48	50
Steindal	Trøndelag	4.00	15.29	50	50	47
Strindheim	Trøndelag	3.71	11.29	51	49	48
Surnadal	Møre og Romsdal	3.20	16.40	46	46	46
Sveio	Vestland	4.08	11.00	46	50	49
Svendstuen	Oslo	4.78	5.67	55	51	49
Tømmerås	Viken	2.67	6.50	47	45	44
Tonstad	Trøndelag	4.55	23.45	48	50	49
Utleira	Trøndelag	3.65	11.13	49	47	47
Vålerenga	Oslo	5.13	13.69	53	55	53
Vang	Viken	4.83	20.67	49	53	51
Voksen	Oslo	3.62	24.15	57	58	53
Norway		4.20	14.61	50	50	50

Note: National exam scores are from 2022–23 and classified into three mastery levels (Reading: level 1 ($\leq$ 42), level 2 (43–55), level 3 ($\geq$ 56); Math: level 1 ($\leq$ 43), level 2 (44–56), level 3 ($\geq$ 57); English: level 1 ($\leq$ 42), level 2 (43–57), level 3 ($\geq$ 58)). Experimental scores use different scales (Math: 0–15; Prosociality: -15–40). Missing values are NA; where 2022–23 data are absent, 2023–24 data are used.*

B.5 Incentives

Children Students were informed in the invitation letter that their choices and tokens earned during the experiment would determine their final prize. Because this study was conducted concurrently with Barron et al. (2025), which used the same experimental sessions, total token earnings comprised several components, including tasks unrelated to the present study. Each student began with an initial endowment of 50 tokens for participation before completing quizzes in mathematics and Norwegian, presented in random order. For each domain, students answered 15 questions and provided estimates of their prior and posterior beliefs. For payment, one element per domain, either the prior belief, posterior belief, or quiz performance, was randomly selected. Correct belief estimates earned 10 tokens, and correct quiz answers earned 5 tokens each. Students also played four dictator games, from which one was randomly chosen for implementation. The number of tokens the student kept in the selected game counted toward their prize, while tokens donated were aggregated and converted to Norwegian kroner at a fixed rate before being transferred to the Norwegian Red Cross.

To provide tangible and age-appropriate incentives, the store at the VilVite Science Centre in Bergen (VilVite Science Centre), a local science museum, was selected as a partner. After each school's participation, labeled prize packages were shipped to the school, marked with each student's participation number and class, and distributed by teachers to students after the study's completion. Each shipment included thank-you letters for participating students and their parents, stickers featuring the experiment's mascot, and a separate thank-you letter for the teachers who facilitated the data collection.

Children's prizes were tiered according to their total token earnings, as follows:

- **Prize 1 – Low:** Color-changing fidget ball (69 NOK; ≈6.12 USD) for students earning 75 tokens or fewer.
- **Prize 2 – Medium:** Magic Scratch Notes (99 NOK; ≈8.78 USD) for students earning 76–92 tokens.
- **Prize 3 – High:** 4×4×4 Rubik's cube (139 NOK; ≈12.32 USD) for students earning more than 92 tokens.

Parents Parents received lottery tickets as compensation for their participation. During the survey, they answered three incentivized belief questions: one prior belief and two posterior beliefs after observing signals. One of these questions was randomly selected to determine bonus lottery tickets using the crossover method, giving parents the opportunity to earn 10 additional tickets. The total number of tickets determined each parent's chance of winning. The lottery included three prizes of 10,000 NOK (≈900 USD), each awarded as a voucher for a major Norwegian electronics retailer. After data collection concluded at all schools, the lottery was conducted and winners were notified.

Figure 34: Overview of the Children's Prizes

Figure 35: Sticker Featuring the Experiment's Mascot

B.6 Structural Belief Updating Model

Setup and Assumptions

I consider a binary state space: the true state is either *Child in Top Half* or *Child Not in Top Half*. At each time t, an individual observes a binary signal that can indicate either *Child in Top Half* or *Child Not in Top Half*.

Symmetric Signal Assumption: I assume that the signal is equally accurate in both directions. Specifically, let $p_{\textit{Top Half},t}$ denote the probability that the signal correctly indicates *Child in Top Half* when the true state is *Child in Top Half* (the true positive rate). Similarly, let $p_{\textit{Not Top Half},t}$ denote the probability that the signal correctly indicates *Child Not in Top Half* when the true state is *Child Not in Top Half* (the true negative rate). I assume:

$$p_{\textit{Not Top Half},t} = p_{\textit{Top Half},t}.$$

Under this assumption, the false positive rate equals $1 - p_{\textit{Top Half},t}$, and the false negative rate also equals $1 - p_{\textit{Top Half},t}$.

Notation: For brevity, I write $\mu_t \equiv \mu_{\textit{Top Half},t}$ and $p_t \equiv p_{\textit{Top Half},t}$ throughout.

Bayesian Updating Formula

Under the symmetric signal assumption, when the signal indicates *Child in Top Half* at time t, the objective Bayesian posterior can be expressed as:

$$\mu_t = \frac{p_t \, \mu_{t-1}}{p_t \, \mu_{t-1} + (1 - p_t)\,(1 - \mu_{t-1})}.$$

Here, μ_t denotes the posterior belief that the true state is *Child in Top Half* after observing the signal *Child in Top Half* at time t. The numerator reflects the probability of observing the signal *Child in Top Half* given that the true state is *Child in Top Half*, weighted by the prior belief μ_{t-1} of the child being in the top half. The denominator represents the total probability of observing the signal *Child in Top Half*, considering both cases: (i) when the true state is *Child in Top Half*, and (ii) when the true state is *Child Not in Top Half*. Note that the term $(1 - p_t)$ appearing in the denominator is the false positive rate (under symmetry), which equals $1 - p_t$ due to the symmetric signal assumption.

Odds and Logit: The odds of an event with probability p are defined as $\frac{p}{1-p}$. The logit function, which is the logarithm of the odds, is given by:

$$\text{logit}(p) = \log\left(\frac{p}{1-p}\right).$$

Step 1: Express posterior in terms of odds

Consider the Bayesian updating formula for the posterior belief μ_t:

$$\mu_t = \frac{p_t\,\mu_{t-1}}{p_t\,\mu_{t-1} + (1-p_t)\,(1-\mu_{t-1})}.$$

This expression can be rewritten in terms of odds. Begin by expressing the posterior odds as:

$$\frac{\mu_t}{1-\mu_t} = \frac{\dfrac{p_t\,\mu_{t-1}}{p_t\,\mu_{t-1} + (1-p_t)\,(1-\mu_{t-1})}}{1 - \dfrac{p_t\,\mu_{t-1}}{p_t\,\mu_{t-1} + (1-p_t)\,(1-\mu_{t-1})}}.$$

Simplifying the denominator yields:

$$1 - \frac{p_t\,\mu_{t-1}}{p_t\,\mu_{t-1} + (1-p_t)(1-\mu_{t-1})} = \frac{(1-p_t)(1-\mu_{t-1})}{p_t\,\mu_{t-1} + (1-p_t)(1-\mu_{t-1})}.$$

Substituting back and simplifying gives:

$$\frac{\mu_t}{1-\mu_t} = \frac{p_t\,\mu_{t-1}}{(1-p_t)\,(1-\mu_{t-1})}.$$

This shows that the posterior odds are determined by the prior odds scaled by the likelihood ratio:

$$\frac{\mu_t}{1-\mu_t} = \frac{\mu_{t-1}}{1-\mu_{t-1}} \cdot \frac{p_t}{1-p_t}.$$

Step 2: Logit transformation

Taking the logarithm of both sides yields:

$$\log\left(\frac{\mu_t}{1-\mu_t}\right) = \log\left(\frac{p_t\,\mu_{t-1}}{(1-p_t)\,(1-\mu_{t-1})}\right).$$

Using the logarithmic rules $\log(ab) = \log(a) + \log(b)$ and $\log(a/b) = \log(a) - \log(b)$, I can decompose the terms:

$$\log\left(\frac{p_t\,\mu_{t-1}}{(1-p_t)(1-\mu_{t-1})}\right) = \log(p_t) + \log(\mu_{t-1}) - \log(1-p_t) - \log(1-\mu_{t-1}).$$

Grouping terms gives:

$$\log\left(\frac{\mu_t}{1-\mu_t}\right) = \log\left(\frac{\mu_{t-1}}{1-\mu_{t-1}}\right) + \log\left(\frac{p_t}{1-p_t}\right).$$

Equivalently,

$$\text{logit}\left(\mu_t\right) = \text{logit}\left(\mu_{t-1}\right) + \log\left(\frac{p_t}{1-p_t}\right).$$

Step 3: Incorporate signal specificity

To account for whether the observed signal indicates *Child in Top Half* or *Child Not in Top Half*, I include indicator functions that select the appropriate direction of updating. Let s_t denote the observed signal at time t. The updating rule can be written compactly as:

$$\text{logit}\left(\mu_t\right) = \text{logit}\left(\mu_{t-1}\right) + \left[\mathbb{1}\left(s_t = \textit{Top Half}\right) - \mathbb{1}\left(s_t = \textit{Not Top Half}\right)\right]\log\left(\frac{p_t}{1-p_t}\right).$$

This formulation captures that positive signals (*Top Half*) increase the log-odds of the child being in the top half by $\log\left(\frac{p_t}{1-p_t}\right)$, while negative signals (*Not Top Half*) decrease it by the same magnitude.

B Experimental Instructions

C.1 Experimental Instructions – Mathematics

Welcome!

Thank you for participating in this survey! The survey will take approximately five to seven minutes and is related to the survey your child participated in at school earlier.

This survey is separate from the previous survey you may have participated in at an earlier point in time. It is not necessary to have completed the previous survey to participate in this part. This is the last survey we will ask you to answer.

Please complete this part of the survey alone and do not talk with your child about this part of the survey or about your child's part of the survey (which was answered earlier) while you are answering. This is important for our research. You can of course talk about the survey with your child afterwards.

Below you find the consent declaration regarding your participation in the survey. It contains the same information that you previously approved.

> **[+] Consent Declaration**
>
> *[In the online survey, participants could click to expand this section]*
>
> Participation in this survey is voluntary, and you can end or withdraw your participation at any time. If you agree to participate, we ask you to complete the survey. The survey will be linked to de-identified data from the Income and Education Register of Statistics Norway. De-identified data means that all personally identifiable information has been replaced with a key code that points to a list of personally identifiable information.
>
> As with all research, there is a possibility that your confidentiality may be breached, but we take precautions to minimize this risk. The list of personally identifiable information will be stored on a server with two-factor authentication in an encrypted file. No researchers will have access to personally identifiable information, and if the results of the survey are published or presented, no personally identifiable information will be provided.

If you have questions about the research project, you can contact us by phone [Phone Number] (preferably via text message) or email at [Email Address].

Press the button below to provide consent and begin the survey.

Lottery Information

As a thank you for completing this survey, you will be entered into a lottery to win one of three gift cards, each worth 10,000 NOK!

- By completing the survey, you will automatically receive 3 lottery tickets.
- The gift card is for an electronics store (Elkjøp).

But you can earn more entries into the lottery! How?

- We will ask you questions about your child and ask you to make guesses.
- For each question, you can 10 bonus lottery tickets.
- The best way to earn to earn bonus lottery tickets is by providing your best guess.
- One question will be randomly selected to determine your bonus lottery tickets.

> **[+] Bonus Lottery Ticket Details**
>
> *[In the online survey, participants could click to expand this section]*
>
> **Step 1: Estimate the probability (A)**
>
> Estimate the probability that your child is in the top half of performers. Provide a probability (A) between 0 (0% chance) and 1 (100% chance).
>
> **Step 2: Random number draw (B)**
>
> A random number (B) between 0 and 1 will be drawn after you submit your probability estimate. This could be, for example, 0.32 or 0.72.
>
> **Step 3: How the number of bonus lottery tickets is determined**
>
> The number of bonus lottery tickets depends on A, B, and whether your child actually places in the top half.
>
> - **Case 1 - If B is greater than A**: You receive bonus lottery tickets with probability equal to A.
> - **Case 2 - If B is less than or equal to A**: You receive bonus lottery tickets only if your child actually ranks in the top half.

So you should give your best guess on each question about where your child places as if it were the question that counts - because it might be!

These questions are subjective and there are no right or wrong answers. These questions help us understand your thought process better.

We will now explain how the messages work.

Mathematics Quiz

Your child participated in a **mathematics quiz** as part of the research survey during class today.

How does the mathematics quiz work:

i. The quiz consisted of questions adapted to the seventh grade math curriculum.
ii. Your child received 5 points for each correctly answered question.

During the survey you will receive several messages about how your child's performance compares to other seventh graders in the **mathematics quiz**.

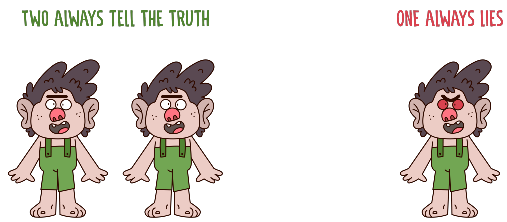
These students (approximately 30 students) are from other schools that participated in the survey earlier and completed the same tasks as your child.

All students are ranked from first place (most questions answered correctly) to last place (fewest questions answered correctly). Half of the students are in the top half and the other half are not.

How Messages Work

The messages you will see will be either positive ("Your child is in the **top half**.") or negative ("Your child is **not in the top half**.").

There are three trolls, all of whom know your child's performance. This means the trolls know whether your child places in the top half.



One of the three trolls will be randomly selected, with each having an equal chance of being chosen.

The troll that was chosen will tell you whether your child places in the top half or not, but you don't know whether the troll is telling the truth or lying since the troll is wearing sunglasses.

<u>During this survey you will never find out your child's actual performance in the mathematics quiz!</u>

Comprehension Check

That was a lot of information! Please answer the question below correctly to confirm that you have understood everything.

Based on the troll's message, will you know for certain whether your child places in the top half?

- ○ Yes

- No

Prior Belief Elicitation

Before seeing any messages...

What do you think is the probability that **your child** places **in the top half** in the **mathematics quiz** among all students who participated?

You will earn the most bonus lottery tickets by reporting your most accurate guess.

Please click on the slider to indicate your answer.

0%: Certain child in bottom half ———————— **100%: Certain child in top half**

Masking

[Screen shown to parents in Information – Transmission condition]

On a scale from 1 (strongly disagree) to 7 (strongly agree)...

Do you generally believe there is a connection between **parents' and children's mathematical abilities**?

[Drop-down menu from 1 to 7]

Information 1/2

[Screen shown to parents in Information–Transmission condition]

Before you receive messages about your child's performance in the mathematics quiz, we would like to show you a brief **summary of research findings on the connection between parents' and children's mathematical abilities**.

If you answer a question about this research correctly at the end of the survey, you will receive **2 bonus lottery tickets**.

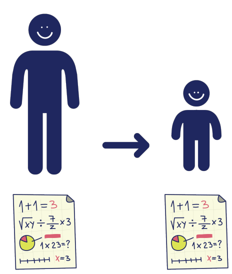
Information 2/2

[Screen shown to parents in Information–Transmission condition]

Please take the time to read the information below carefully: **0:30**

Research has shown that there is a **connection between parents' math skills and children's math skills** (Brown & Taylor, 2011; Hanushek et al., 2021; de Coulon et al., 2011).

Parents who have good math skills also tend to have children with good math skills.



This is captured in the saying: **"The apple doesn't fall far from the tree!"**

[+] References

[In the online survey, participants could click to expand this section.]

- Brown, S., McIntosh, S., & Taylor, K. (2011). Following in your parents' footsteps? Empirical analysis of matched parent-offspring test scores. *Oxford Bulletin of Economics and Statistics*, *73*(1), 40–58.
- Hanushek, E. A., Jacobs, B., Schwerdt, G., van der Velden, R., Vermeulen, S., & Wiederhold, S. (2021). The intergenerational transmission of cognitive skills: An investigation of the causal impact of families on student outcomes. NBER Working Paper No. 29450.
- de Coulon, A., Meschi, E., & Vignoles, A. (2011). Parents' skills and children's cognitive and non-cognitive outcomes. *Education Economics*, *19*(5), 451–474.

Masking

[Screen shown to parents in Information – Relevance condition]

On a scale from 1 (strongly disagree) to 7 (strongly agree)...

Do you generally believe there is a connection between **children's mathematical abilities** and **how children perform later in life**?

[Drop-down menu from 1 to 7]

Information 1/2

[Screen shown to parents in Information–Relevance condition]

Before you receive messages about your child's performance in the **mathematics quiz**, we would like to show you a brief **summary of research findings on the connection between children's math skills and how they perform later in life**.

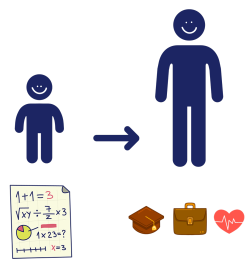
If you answer a question about this research correctly at the end of the survey, you will receive **2 bonus lottery tickets**.

Information 2/2

[Screen shown to parents in Information – Relevance condition]

Please take time to read the information below carefully: **0:30**

Research has shown that children who **do well in school, for example in mathematics quizzes, often do well later in life**.



Research has documented that children with good test results pursue **longer education** later in life (Auceio & James, 2021), have **jobs with higher income** (Chamberlain, 2013; Chetty et al., 2014), and have **better health outcomes** (Heckman et al., 2006).

[+] References

[In the online survey, participants could click to expand this section]

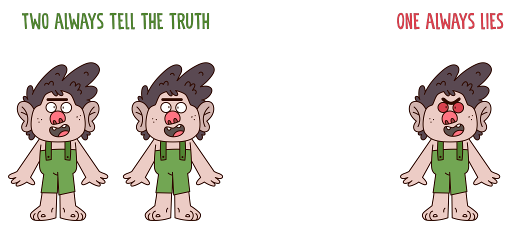
- Aucejo, E., & James, J. (2021). The path to college education: The role of math and verbal skills. *Journal of Political Economy*, *129*(10), 2905–2946.
- Chamberlain, G. E. (2013). Predictive effects of teachers and schools on test scores, college attendance, and earnings. *Proceedings of the National Academy of Sciences*, *110*(43), 17176–17182.
- Chetty, R., Friedman, J. N., & Rockoff, J. E. (2014). Measuring the impacts of teachers II: Teacher value-added and student outcomes in adulthood. *American Economic Review*, *104*(9), 2633–2679.
- Heckman, J., Stixrud, J., & Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics*, *24*(3), 411–482.

Message 1

You will now see the **first message** about the **mathematics quiz**.

How Messages Work

- We will ask you some questions about your child and ask you to make some guesses.
- For each question you can earn 10 bonus lottery tickets.
- The best way to earn more lottery tickets is by providing your best guess.
- One question will be randomly selected to determine your bonus lottery tickets.



Mathematics Quiz: Message 1

The chosen troll says: *"Your child places in the* ***top half*** *of the* ***mathematics quiz****."*

Posterior Belief Elicitation 1

After receiving this first message...

What do you think is the probability that **your child** places **in the top half** in the **mathematics quiz** among all students who participated?

You will earn the most bonus lottery tickets by reporting your most accurate guess.

Please click on the slider to indicate your answer.

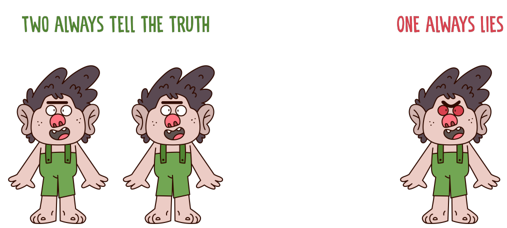
0%: Certain child in bottom half ______________________ **100%: Certain child in top half**

Click the Next button to see the **second message** about the **mathematics quiz**.

Message 2

How Messages Work

- We will ask you some questions about your child and ask you to make some guesses.
- For each question you can earn 10 bonus lottery tickets.
- The best way to earn more lottery tickets is by providing your best guess.
- One question will be randomly selected to determine your bonus lottery tickets.



Mathematics Quiz: Message 2

The chosen troll says: *"Your child does* ***not place in the top half*** *of the* ***mathematics quiz****."*

Posterior Belief Elicitation 2

After receiving this second message...

What do you think is the probability that **your child** places **in the top half** in the **mathematics quiz** among all students who participated?

You will earn the most bonus lottery tickets by reporting your most accurate guess.

Please click on the slider to indicate your answer.

0%: Certain child in bottom half	______________	**100%: Certain child in top half**

Transition

Now we have some final questions for you!

Ex-Post Rationalization

[Questions are displayed in randomized order.]

Please answer the following questions on a scale from 1 (strongly disagree) to 7 (strongly agree)...

1. How important do you think **your child's performance on the mathematics quiz** is for their future success?

[Drop-down menu from 1 to 7]

2. How hard do you think **your child tried to achieve the best possible score on the mathematics quiz**?

[Drop-down menu from 1 to 7]

3. To what extent do you think **your child's performance on the mathematics quiz** reflects **your own abilities in math**?

[Drop-down menu from 1 to 7]

Educational Aspirations

1. What type of education do you hope your child will pursue at the secondary school level?

- ○ Academic high school
- ○ Vocational high school
- ○ Prefer not to answer

2. What is the highest level of education you hope your child will achieve?

- ○ Secondary school
- ○ Vocational or professional training
- ○ Bachelor's degree
- ○ Master's degree
- ○ Doctoral degree
- ○ Prefer not to answer

Investment Decision

Imagine that you have won the lottery (for participating in this survey) and received a gift card worth 10,000 NOK from Elkjøp.

We would like to offer you the opportunity to specify how much of the gift card value you would like to allocate toward purchasing educational materials for your child.

Please specify the amount below. We will use this amount to help you select and purchase appropriate educational resources for your child (textbooks, educational technology, learning-focused activities, books, and other materials).

Note! This is a binding commitment if you win the lottery.

Amount (in NOK) I would like to invest in educational materials for my child. Please enter an amount between 0 NOK and 10,000 NOK.

[Number field]

Demographics

Finally, we have some demographic questions for you.

1. Your gender:

- ○ Male
- ○ Female
- ○ Other

2. What is the highest level of education you have completed?

- ○ Elementary school
- ○ Some secondary school
- ○ Secondary school diploma
- ○ Vocational certificate/professional training
- ○ Some university education
- ○ Bachelor's degree
- ○ Master's degree
- ○ Doctoral degree
- ○ Prefer not to answer

3. Is your degree in a STEM field?

- ○ Yes
- ○ No
- ○ Not applicable
- ○ Prefer not to answer

4. Do you have any other children besides the child you're answering about in this survey?

- ○ No
- ○ Yes, younger children
- ○ Yes, older children

- ○ Yes, both older and younger children
- ○ Yes, children of the same age
- ○ Yes, children of the same age and younger
- ○ Yes, children of the same age and older
- ○ Yes, children of the same age, older, and younger
- ○ Prefer not to answer

Research Comprehension Check

[Screen shown to parents in Information–Transmission conditions and Information–Relevance]

Earlier in the survey you read a short section that highlighted some research findings.

If you answer the question below correctly, you will receive **2 bonus lottery tickets**.

[If parents in Information – Transmission:]
Which researchers studied the connection between parents' skills and children's skills?

[If parents in Information – Relevance:]
Which researchers studied the connection between children's test performance and their outcomes as adults?

- ○ Hanushek and colleagues
- ○ Chetty and colleagues

Trust in Information

[Screen shown to parents in Information–Transmission and Information–Relevance conditions]

[If parents in Information – Transmission:]
Earlier we showed you information about the connection between parents' skills and their children's skills.

[If parents in Information – Relevance:]
Earlier we showed you information about the connection between children's test performance and their adult outcomes.

How reliable do you consider this information to be?

- ○ Very reliable
- ○ Somewhat reliable
- ○ Neither reliable nor unreliable
- ○ Somewhat unreliable
- ○ Very unreliable

Final Reflection

Please write a message describing how you would explain to your child how you thought about the three guesses.

[Open text response]

Your answer will help us understand your reasoning.

Thank You

Thank you for participating in this survey!

The lottery tickets you have earned have been recorded. If you are selected as a winner, we will contact you no later than the end of May 2025.

Have a wonderful day!

C.2 Experimental Instructions – Prosociality

Welcome!

Thank you for participating in this survey! The survey will take approximately five to seven minutes and is related to the survey your child participated in at school earlier.

This survey is separate from the previous survey you may have participated in at an earlier point in time. It is not necessary to have completed the previous survey to participate in this part. This is the last survey we will ask you to answer.

Please complete this part of the survey alone and do not talk with your child about this part of the survey or about your child's part of the survey (which was answered earlier) while you are answering. This is important for our research. You can of course talk about the survey with your child afterwards.

Below you find the consent declaration regarding your participation in the survey. It contains the same information that you previously approved.

> **[+] Consent Declaration**
>
> *[In the online survey, participants could click to expand this section]*
>
> Participation in this survey is voluntary, and you can end or withdraw your participation at any time. If you agree to participate, we ask you to complete the survey. The survey will be linked to de-identified data from the Income and Education Register of Statistics Norway. De-identified data means that all personally identifiable information has been replaced with a key code that points to a list of personally identifiable information.
>
> As with all research, there is a possibility that your confidentiality may be breached, but we take precautions to minimize this risk. The list of personally identifiable information will be stored on a server with two-factor authentication in an encrypted file. No researchers will have access to personally identifiable information, and if the results of the survey are published or presented, no personally identifiable information will be provided.

If you have questions about the research project, you can contact us by phone [Phone Number] (preferably via text message) or email at [Email Address].

Press the button below to provide consent and begin the survey.

Lottery Information

As a thank you for completing this survey, you will be entered into a lottery to win one of three gift cards, each worth 10,000 NOK!

- By completing the survey, you will automatically receive 3 lottery tickets.
- The gift card is for an electronics store (Elkjøp).

But you can earn more entries into the lottery! How?

- We will ask you questions about your child and ask you to make guesses.
- For each question, you can 10 bonus lottery tickets.
- The best way to earn to earn bonus lottery tickets is by providing your best guess.
- One question will be randomly selected to determine your bonus lottery tickets.

[+] Bonus Lottery Ticket Details

[In the online survey, participants could click to expand this section]

Step 1: Estimate the probability (A)

Estimate the probability that your child is in the top half of performers. Provide a probability (A) between 0 (0% chance) and 1 (100% chance).

Step 2: Random number draw (B)

A random number (B) between 0 and 1 will be drawn after you submit your probability estimate. This could be, for example, 0.32 or 0.72.

Step 3: How the number of bonus lottery tickets is determined

The number of bonus lottery tickets depends on A, B, and whether your child actually places in the top half.

- **Case 1 - If B is greater than A**: You receive bonus lottery tickets with probability equal to A.
- **Case 2 - If B is less than or equal to A**: You receive bonus lottery tickets only if your child actually ranks in the top half.

So you should give your best guess on each question about where your child places as if it were the question that counts - because it might be!

These questions are subjective and there are no right or wrong answers. These questions help us understand your thought process better.

We will now explain how the messages work.

Sharing Game

Your child participated in a **sharing game** as part of the research survey during class today.

How does the sharing game work:

i. Your child was asked to distribute 10 points between themselves and another child who is supported by the Red Cross. There were four such games.
ii. A sharing game was randomly selected. In this game, the points your child kept count as prize money for them, while points given to the other child will be converted to money and donated to the Red Cross.

- -

During the survey you will receive several messages about how your child's performance compares to other seventh graders in the **sharing game**.

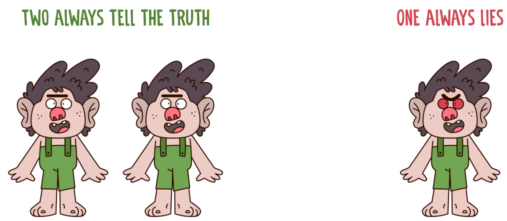
These students (approximately 30 students) are from other schools that participated in the survey earlier and completed the same tasks as your child.

All students are ranked from first place (most questions answered correctly) to last place (fewest questions answered correctly). Half of the students are in the top half and the other half are not.

How Messages Work

The messages you will see will be either positive ("Your child is in the **top half**.") or negative ("Your child is **not in the top half**.").

There are three trolls, all of whom know your child's performance. This means the trolls know whether your child places in the top half.



One of the three trolls will be randomly selected, with each having an equal chance of being chosen.

The troll that was chosen will tell you whether your child places in the top half or not, but you don't know whether the troll is telling the truth or lying since the troll is wearing sunglasses.

During this survey you will never find out your child's actual performance in the sharing game!

Comprehension Check

That was a lot of information! Please answer the question below correctly to confirm that you have understood everything.

Based on the troll's message, will you know for certain whether your child places in the top half?

- ○ Yes

◦ No

Prior Belief Elicitation

Before seeing any messages...

What do you think is the probability that **your child** places **in the top half** in the **sharing game** among all students who participated?

You will earn the most bonus lottery tickets by reporting your most accurate guess.

Please click on the slider to indicate your answer.

0%: Certain child in bottom half	________________	**100%: Certain child in top half**

Masking

[Screen shown to parents in Information – Transmission condition]

On a scale from 1 (strongly disagree) to 7 (strongly agree)...

Do you generally believe that there is a connection between **parents' willingness to share and a child's willingness to share**?

[Drop-down menu from 1 to 7]

Information 1/2

[Screen shown to parents in Information–Transmission condition]

Before you receive messages about your child's performance in the sharing game, we would like to show you a brief **summary of research findings on the connection between parents and children's willingness to share**.

If you answer a question about this research correctly at the end of the survey, you will receive **2 bonus lottery tickets**.

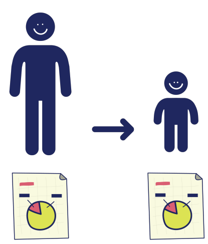
Information 2/2

[Screen shown to parents in Information–Transmission condition]

Please take the time to read the information below carefully: **0:30**

Research has shown that there is a **connection between willingness to give to others in parents and children** (Eisenberg et al., 2006; Kosse et al., 2020).

Parents who have greater willingness to share, have children who also have greater willingness to share.



This is captured in the saying: **"The apple doesn't fall far from the tree!"**

> **[+] References**
>
> *[In the online survey, participants could click to expand this section.]*
>
>
> - Eisenberg, N., Fabes, R. A., & Spinrad, T. L. (2006). Development. In N. Eisenberg (Ed.), Handbook of child psychology: Vol. 3. Social, emotional, and personality development (6th ed., pp. 646–718). John Wiley & Sons.
> - Kosse, F., Deckers, T., Pinger, P., Schildberg-Hörisch, H., & Falk, A. (2020). The formation of pro-sociality: Causal evidence on the role of social environment. Journal of Political Economy, 128(2), 434–467.
>

Masking

[Screen shown to parents in Information – Relevance condition]

On a scale from 1 (strongly disagree) to 7 (strongly agree)...

Do you generally believe that there is a connection between a **child's willingness to share** and how the child **performs later in life**?

[Drop-down menu from 1 to 7]

Information 1/2

[Screen shown to parents in Information–Relevance condition]

Before you receive messages about your child's performance in the **sharing game**, we would like to show you a brief **summary of research findings on the connection between children's willingness to share and how they perform later in life**.

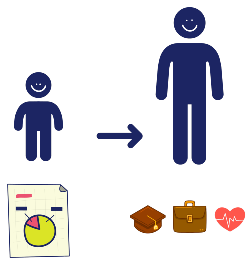
If you answer a question about this research correctly at the end of the survey, you will receive **2 bonus lottery tickets**.

Information 2/2

[Screen shown to parents in Information – Relevance condition]

Please take time to read the information below carefully: **0:30**

Research has shown that **children who share more with others often do well later in life**.



Research has documented that children with good test results later in life have **longer education** (Caprara et al., 2000), **jobs with higher income** (Kosse & Tincani, 2020), and **better health** (Becker et al., 2012).

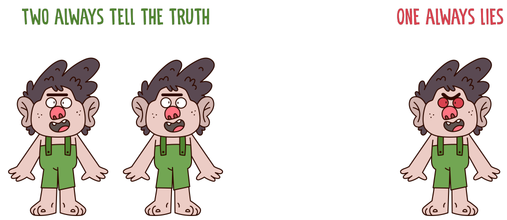
> **[+] References**
>
> *[In the online survey, participants could click to expand this section]*
>
> - Caprara, G. V., Barbaranelli, C., Pastorelli, C., Bandura, A., & Zimbardo, P. G. (2000). Prosocial foundations of children's academic achievement. Psychological Science, 11(4), 302-306.
> - Kosse, F., & Tincani, M. M. (2020). Prosociality predicts labor market success around the world. Nature Communications, 11, Article 5298.
> - Becker, A., Deckers, T., Dohmen, T., Falk, A., & Kosse, F. (2012). The relationship between economic preferences and psychological personality measures. Annual Review of Economics, 4, 453-478.

Message 1

You will now see the **first message** about the **sharing game**.

How Messages Work

- We will ask you some questions about your child and ask you to make some guesses.
- For each question you can earn 10 bonus lottery tickets.
- The best way to earn more lottery tickets is by providing your best guess.
- One question will be randomly selected to determine your bonus lottery tickets.



Sharing game: Message 1

The chosen troll says: *"Your child places in the* ***top half*** *of the* ***sharing game****."*

Posterior Belief Elicitation 1

After receiving this first message...

What do you think is the probability that **your child** places **in the top half** in the **sharing game** among all students who participated?

You will earn the most bonus lottery tickets by reporting your most accurate guess.

Please click on the slider to indicate your answer.

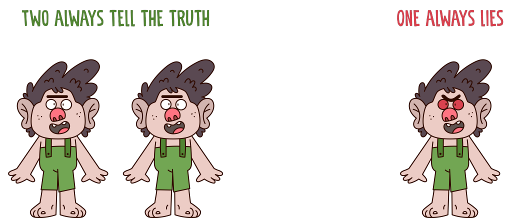
0%: Certain child in bottom half ______________________ **100%: Certain child in top half**

Click the Next button to see the **second message** about the **sharing game**.

Message 2

How Messages Work

- We will ask you some questions about your child and ask you to make some guesses.
- For each question you can earn 10 bonus lottery tickets.
- The best way to earn more lottery tickets is by providing your best guess.
- One question will be randomly selected to determine your bonus lottery tickets.



Sharing game: Message 2

The chosen troll says: *"Your child does **not place in the top half** of the **sharing game**."*

Posterior Belief Elicitation 2

After receiving this second message...

What do you think is the probability that **your child** places **in the top half** in the **sharing game** among all students who participated?

You will earn the most bonus lottery tickets by reporting your most accurate guess.

Please click on the slider to indicate your answer.

0%: Certain child in bottom half ____________________ **100%: Certain child in top half**

Transition

Now we have some final questions for you!

Ex-Post Rationalization

[Questions are displayed in randomized order.]

Please answer the following questions on a scale from 1 (strongly disagree) to 7 (strongly agree)...

1. How important do you think **your child's choices in the sharing game** is for their future success?

[Drop-down menu from 1 to 7]

2. How well-considered were **the decisions your child made in the sharing game**?

[Drop-down menu from 1 to 7]

3. To what extent do you think **your child's choices in the sharing game** reflect **your own willingness to share**?

[Drop-down menu from 1 to 7]

Educational Aspirations

1. What type of education do you hope your child will pursue at the secondary school level?

- ○ Academic high school

- ○ Vocational high school
- ○ Prefer not to answer

2. What is the highest level of education you hope your child will achieve?

- ○ Secondary school
- ○ Vocational or professional training
- ○ Bachelor's degree
- ○ Master's degree
- ○ Doctoral degree
- ○ Prefer not to answer

Investment Decision

Imagine that you have won the lottery (for participating in this survey) and received a gift card worth 10,000 NOK from Elkjøp.

We would like to offer you the opportunity to specify how much of the gift card value you would like to allocate toward purchasing educational materials for your child.

Please specify the amount below. We will use this amount to help you select and purchase appropriate educational resources for your child (textbooks, educational technology, learning-focused activities, books, and other materials).

Note! This is a binding commitment if you win the lottery.

Amount (in NOK) I would like to invest in educational materials for my child. Please enter an amount between 0 NOK and 10,000 NOK.

[Number field]

Demographics

Finally, we have some demographic questions for you.

1. Your gender:

- ○ Male
- ○ Female
- ○ Other

2. What is the highest level of education you have completed?

- ○ Elementary school
- ○ Some secondary school
- ○ Secondary school diploma
- ○ Vocational certificate/professional training
- ○ Some university education
- ○ Bachelor's degree
- ○ Master's degree
- ○ Doctoral degree
- ○ Prefer not to answer

3. Is your degree in a STEM field?

- ○ Yes
- ○ No
- ○ Not applicable
- ○ Prefer not to answer

4. Do you have any other children besides the child you're answering about in this survey?

- ○ No
- ○ Yes, younger children
- ○ Yes, older children
- ○ Yes, both older and younger children
- ○ Yes, children of the same age
- ○ Yes, children of the same age and younger
- ○ Yes, children of the same age and older
- ○ Yes, children of the same age, older, and younger
- ○ Prefer not to answer

Research Comprehension Check

[Screen shown to parents in Information–Transmission conditions and Information–Relevance]

Earlier in the survey you read a short section that highlighted some research findings.

If you answer the question below correctly, you will receive **2 bonus lottery tickets**.

[If parents in Information – Transmission:]
Which researchers studied the connection between parents' willingness to share and their children's willingness to share?

[If parents in Information – Relevance:]
Which researchers studied the connection between children's willingness to share and their outcomes as adults?

- ○ Eisenberg and colleagues
- ○ Becker and colleagues

Trust in Information

[Screen shown to parents in Information–Transmission and Information–Relevance conditions]

[If parents in Information – Transmission:]
Earlier we showed you information about the connection between parents' willingness to share and their children's willingness to share.

[If parents in Information – Relevance:]
Earlier we showed you information about the connection between children's willingness to share and their outcomes as adults.

How reliable do you consider this information to be?

- ○ Very reliable
- ○ Somewhat reliable
- ○ Neither reliable nor unreliable
- ○ Somewhat unreliable
- ○ Very unreliable

Final Reflection

Please write a message describing how you would explain to your child how you thought about the three guesses.

[Open text response]

Your answer will help us understand your reasoning.

Thank You

Thank you for participating in this survey!

The lottery tickets you have earned have been recorded. If you are selected as a winner, we will contact you no later than the end of May 2025.

Have a wonderful day!