Strategic Interactions and Peer Learning in Contests *

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Many educational systems rely on rank-based rewards to allocate college seats or grades. While rewarding relative performance can boost effort, it may also discourage cooperation, as students strategically limit knowledge sharing to protect their standing, potentially reducing total learning. This paper studies how competition shapes individual effort, peer interactions, and skill production, using a structural model and a tightly linked experiment. The model, in which heterogeneous agents make effort choices, formalizes how competition shapes interactions. The experiment varies competition intensity and peer matching to generate rich behavioral data for structural estimation, collected through a custom-designed learning platform. Results show that moderate competition increases both individual and peer learning, while intense competition shifts effort away from cooperation. Under intense competition, students with similar ability levels interact less than they normally would, crowding out peer learning. LLM-based interaction analysis confirms that cooperative language declines as competition intensifies. Structural model quantifies production and preference components. Peer learning entails lower disutility compared to individual learning. Barriers to participation are higher for lower-ability students, while peer learning helps reduce them. Counterfactual policies suggest that moderate rank-based incentives combined with piece-rate rewards improve learning behavior. When barriers to individual learning participation are reduced, equity improves, while efficiency gains are stronger when collaboration barriers are lowered.

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1 Introduction

Many education systems rely on rank-based rewards, where students are evaluated relative to one another through standardized tests or classroom exams. At the college admissions level, rankings may be national, as in Turkey, China, or South Korea, or school-based, as in the U.S. Texas Top Ten Percent Rule.[1] These policies guarantee admission to students who graduate among the top performers in their high school. At the classroom level, grading may also be rank-based, such as curve grading, rather than absolute thresholds. Some systems combine absolute and relative performance, weighting both in admissions or grades.[2] Rank-based incentives also extend beyond education to workplaces, sales teams, and sports. Across these contexts, the contest structure determines the reference group, whether individuals compete with classmates or with a much larger population.

Competition can encourage students to put in more effort and learn more, especially when they are close in ability to their peers and the marginal return to effort is higher (Tincani, 2024). At the same time, competition in rank based systems that create strong within school rivalry can shift focus away from learning and toward simply winning. The literature also points out that competition can weaken prosocial behavior and create negative peer spillovers. (S. Chen and Hu, 2024, Kosse et al., 2023). In this way, competition has both positive and negative effects on learning outcomes. While the literature has made progress in understanding peer effects and competition separately, we know less about the mechanisms through which competition influences behavior and outcomes, including the joint production of academic and social skills through peer learning. Part of this gap is due to limited interaction level data (there are many network data sets but much less on actual exchanges to my knowledge) and the lack of models that bring these tensions together.

This paper combines a novel experiment with a model to study strategic interactions under competition, where students may reduce cooperation in order to maintain their rank. Competition can boost individual effort, but it can also crowd out peer learning and lower overall learning. I ask two sets of research questions. First, how do reward structures influence students' learning behavior? Can we quantify strategic responses to rank based incentives? And how do these responses affect learning and skill production? Second, how can the negative spillovers of competition on peer learning be reduced while preserving its benefits? And is there an efficient way to compose peer groups so that pre-college skill production is maximized in a contest environment?

I connect the theoretical and empirical contest literature to advance our understanding of the learning process of high school students, focusing on two types of study modes: individual and peer learning, within a competitive environment. I use the concept of peer learning to encompass all forms of peer interactions, including studying with friends, tutoring, and group work. The concept of competition, on the other hand, refers to the rank-based contests that expose students to within school/classroom rivalry. I incorporate peer learning into an empirical contest model by embedding it within an education production function that enters the utility, allowing me to capture behavioral dynamics that are missing in the standard contest frameworks.

In particular, I emphasize three features of this setting that are critical to understanding student behavior and learning outcomes in contest environment. First, learning is not done in isolation,

[1] Other examples include the University of California's Eligibility in Local Context (ELC) program and Chile's PACE system.

[2] For example, in Turkey the college entrance exam score is combined with a weight on the student's high school GPA.

schools, as the primary learning environment, are characterized by social interactions among students. Second, students make day-to-day study decisions depending on their previous knowledge and relative standing in the contest. Third, as different from teamwork studies in the labor market or in personnel economics, the prize in college admission contests is not shared among the group members. This creates a unique tension where students may be reluctant to share their knowledge with others, as it may reduce their relative standing in this high stakes college contest. This makes collaborative effort decisions more complex and requires a more structured analysis to study the better group compositions.

Studying students' learning decisions in the type of environment described above is difficult using observational data, such as academic outcomes, due to several methodological challenges. One is the well known reflection problem (Manski, 1993), along with endogenous group formation, which may depend on unobservable characteristics. In addition, the structure of competition itself makes it hard to isolate the causal effects of both competition and peer learning on learning outcomes. More importantly, I am not aware of any observational panel data that captures the necessary mapping between day to day learning decisions, including individual effort and peer interactions, and skill production.

To overcome these challenges, I execute a structurally motivated large-scaled field experiment involving 10 high schools, 1200+ students. The experiment provides exogenous variation in peer composition and competition. The setting of a field experiment allows me to observe how individual and peer learning study efforts respond to competition. Structural econometric methods allow me to directly quantify labor (study) supply elasticity and study time productivity, as well as the effect of competition on the two. Furthermore, by running the experiment across a diverse set of students and schools, I can explore how the effects of competition and peer learning differ by initial ability (proxied by a baseline exam score), school quality, and socioeconomic status, which eases conducting counterfactual policies aimed at reducing learning inequality.

In the first part of the paper, I present a theoretical framework that formalizes the mechanisms through which competition and peer learning shape study choices and skill production. I derive comparative statics to illustrate how changes in the external environment affect student behavior. This framework guides the experimental design by identifying which variables to manipulate, such as competition intensity and peer assignment, and what data to collect, including effort, peer interaction, and measures of academic and social skill development, in order to identify the model parameters. In the model, students differ in both observable and unobservable characteristics that influence learning outcomes. These include ability, which enters the production function, and effort cost, which affects disutility. Outcomes depend on both individually supplied effort and peer learning effort, where the latter captures gains from interaction. Student preferences reflect intrinsic utility from skill gains and extrinsic utility from winning a prize, such as better grades or college admission. The external environment governs the intensity of competition, defined by the number of competitors and the number of prizes.

The theoretical results yield three main insights. First, as competition intensity increases, equilibrium peer interaction declines. Reduced peer interaction is substituted by higher individual effort. Second, there is selective collaboration. For any given competitive environment, there exists a threshold in peer ability gap below which students choose not to collaborate and instead increase their individual effort. Third, total learning, or overall skill production, declines under intense competition.

In the second part of the paper, I describe the experimental design, the data collection process, and the main experimental findings. The experiment consists of several stages: a baseline survey to collect key demographic variables and student networks, as well as to document the competitive environment at baseline; a baseline exam to proxy ability levels; a ten day website training period; and an endline exam followed by an endline survey. The randomization has two main components. First, each student is assigned to work either individually (*Individual* mode) or in pairs (*Pair* mode) using the learning platform, which allows for interactions for those working in pairs. Second, they are assigned to one of three reward arms: no competition (*Control*), moderate competition (*Moderate*), or intense competition (*Intense*). Students in *Pair* mode are always assigned to the same reward arm. Note that study mode only shapes the learning environment; all students take the final exam individually, and prizes depend solely on their own performance. Students are informed about their baseline scores and corresponding ranks if in the competition arm. After receiving this information, students begin the training period on the learning website populated with practice questions. The platform records their real time effort decisions and peer interactions, including chat messages.

The baseline survey documents three patterns that both inform the setting and motivate the need for an experiment. First, students sort into friendship and study networks based on academic and personality traits. The choice of study partners is shaped by the level of competition in the environment: in more competitive settings, students tend to choose peers with higher ranks and GPA but lower levels of cooperativeness. Second, on average, students report higher productivity when studying individually but higher motivation when studying with peers. This suggests that peer interactions should enter both the effort supply and the outcome production functions.

The experiment results can be summarized as follows. First, moderate competition stimulates both peer and self learning. Under moderate competition, students in the *Pair* mode show a 17% higher rate of website activity at the intensive margin compared to those in the *Individual* mode. In contrast, intense competition shifts effort away from peer learning toward self learning, with the web engagement rate around 30% higher for the *Individual* mode than the *Pair* mode. In the moderate competition arm, however, the behavior of students close to the margin of winning a prize resembles that observed under intense competition. Second, among students in the *Pair* mode, chat frequency is lowest in the *Intense* arm and highest in the *Moderate* arm. Moreover, LLM-based (large language model) chat labeling suggestively shows that cooperative language is most prevalent in the *Control* arm. Third, effort is also shaped by peer match type. In the *Control* arm, individuals matched with peers of similar ability tend to exert more effort and engage in more frequent interactions. This dynamic particularly benefits low and medium ability students, who exhibit greater learning gains compared to high ability students. Under competition, however, individuals with similar ability levels interact less, and the effects on learning are less clear relative to the *Control* group.

Competition also affects outcomes. On the academic side, based on the final exam, I find that competition generally improves learning for those in the *Individual* study mode. Interestingly, being in the *Pair* mode alone does not necessarily lead to better academic outcomes, although the effect is suggestively positive. A more detailed analysis shows that lower ability students benefit more from peer interaction. However, the combination of intense competition and peer learning appears to have a negative effect on learning outcomes. The average score in the *Intense-Pair* group is about 0.3 standard deviations lower than in the *Intense-Individual* group. This result suggests that encouraging team based learning in a highly competitive setting may not always be effective.

On the social behavior side, based on the final survey, I find that students in the competition arms display lower levels of cooperative and prosocial behavior compared to those in the *Control* arm.

In the third part of the paper, I present the empirical model, the identification and estimation strategy, and the structural estimation results. The empirical model follows the theoretical framework laid out in Section 2, while allowing for student heterogeneity in both preferences and the cost side. The cost function includes fixed costs for individual effort and peer interaction. In the first stage, I estimate the production function outside the structural model using a control function approach that uses variation across experimental arms. In the second stage, I estimate the structural parameters using a simulated method of moments (SMM) approach. The estimation results provides three main insights. First, peer interactions generate positive learning gains, especially for lower ability students matched with higher ability peers. Second, there is significant multidimensional heterogeneity in preferences and costs. Third, peer learning on average comes with lower disutility costs compared to self learning. Based on the estimates, the fixed cost of individual study is lower for higher ability students, while the fixed cost of peer learning is lower for lower ability students. That is, lower ability students are more likely to enter the learning process with support from a peer. Finally, I estimate a social skill production function. The results suggest that peer interaction improves social skill formation, while competition reduces it.

Finally, I conduct counterfactual policy simulations along three dimensions: classroom composition through peer assignment, competition intensity, and cost reduction policies aimed at increasing participation at the extensive margin. The counterfactuals are grounded in the structural estimates and the equilibrium concept outlined in the empirical section. The main objective is to evaluate average student skill levels, combining both academic and social skills, under each policy scenario and compare them to the baseline outcomes observed in the experiment.

First, I vary competition intensity by changing the weight on rank-based rewards relative to piece-rate rewards. The results show that, at the extensive margin, collaboration decreases while individual effort participation increases with competition intensity. At the intensive margin, individual effort rises with competition, while peer effort follows a non-monotonic pattern, peaking at moderate weights. Second, I target the barriers to learning by reducing the fixed costs of individual and peer learning. The results suggest that equity improves when the fixed costs of individual learning are reduced, while efficiency gains are stronger when the fixed costs of peer learning are lowered.

Related Literature. This project contributes to four main strands of literature. The first strand relates to the research on competition, cooperation, and social interactions. A significant portion of this literature utilizes experimental or lab data to examine how competition affects peer behaviors. For instance, studies by Bornstein et al. (2002) and Bigoni et al. (2015) analyze these dynamics.[3] More recent studies employ field data to assess how competition influences prosocial and cooperative behaviors among students. For example, Kosse et al. (2023) investigates how exposure to competitive environments shapes students' prosocial behaviors over the short and long term. Further research explores additional aspects of peer effects within competitive settings. S. Chen and Hu (2024) examines peer effects arising from competitive dynamics due to dorm assignments, while Tincani (2024) studies heterogeneous peer effects influenced by within-classroom rank, leveraging data from the Chilean earthquake. Calsamiglia and Loviglio (2019) provides evidence on negative

[3] Additional studies in this area include, but are not limited to, Bratti et al. (2011), Grosch et al. (2022), Lien et al. (2021), and Reuben and Tyran (2010).

peer effects driven by grading systems. This paper diverges slightly from the existing literature by focusing on how competition affects study time, specifically in contexts with peer matching. To the best of my knowledge, this is the first study to examine the effects of competition on study time allocation, conditional on peer matching.

Additionally, by investigating peer interactions, this paper contributes to literature on social interactions within classroom settings (Bhargava, 2025; Calvó-Armengol et al., 2009; Conley et al., 2024; De Giorgi & Pellizzari, 2014; Fruehwirth, 2013). While much of this literature assumes that students conform to their peers, this study introduces the added dimension of competition-induced strategic interactions. My results, in addition, validate the results of Boucher et al. (2024) in that linear-in-means peer effects are not sufficient to explain the observed behaviors in competitive settings and may lead to policy misinterpretations.

The second strand of relevant literature focuses on teamwork and productivity. Closely related to this study are recent works examining human capital and teamwork. Herkenhoff et al. (2024), Bartel et al. (2014), and Y. Chen (2021) explore the role of human capital in team production, with the first study specifically modeling human capital formation in a team context. Another body of research examines the impact of incentives on effort and productivity. For instance, Drago and Garvey (1998) and Bandiera et al. (2013) document how incentives influence workers' willingness to assist each other, partner selection, and team productivity. Sheremeta (2018) surveys literature on group contests, highlighting how incentive mechanisms foster within-group cooperation. Recent studies by Deming (2017) and Weidmann and Deming (2021) underscore the growing significance of social skills in the workplace. This paper aligns most closely with the learning model developed by Herkenhoff et al. (2024), adapting it to the educational context of contest-driven environments.

The third strand connects to literature on contests, specifically work modeling college admissions as contest games. Early contributions by Olszewski and Siegel (2016) and Bodoh-Creed and Hickman (2018) present college admissions as large contest games. Bodoh-Creed and Hickman (2019) explores how prize allocation functions in college admissions under different affirmative action scenarios using a continuum model. C. Cotton et al. (2022) provides a theoretical examination of affirmative action's effect on pre-college human capital, with a structural version estimating contest model parameters in the U.S. K. Krishna et al. (2022) demonstrates potential Pareto improvements in the college admission process within a continuum contest model, while Ozer and Krishna (2024) examines percent plans' impact on high school students' efforts, extending the framework of C. Cotton et al. (2022). Additional studies employ experimental or quasi-random methods to assess how affirmative action influences student effort in competitive environments (Akhtari et al., 2024; Calsamiglia et al., 2013; Franke, 2012). This study advances the literature by modeling peer learning within a contest framework, presenting the first theoretical and empirical analysis of how competition affects peer-driven human capital formation.

The final strand of literature pertains to education policy and skill assessment. Jacob and Rothstein (2016) offers a comprehensive analysis of test scores and addresses what traditional assessment systems overlook, such as non-cognitive skills. Additionally, Ozer et al. (2024) discusses how various test conditions—including time pressure, question difficulty, and negative marking—impact student sorting. This paper extends this literature by showing that policy adjustments in contest environments can indirectly influence student sorting, particularly by non-academic characteristics like social skills.

The remainder of this paper is organized as follows. In Section 2, I provide a theoretical model of the students' effort allocation as a response to the contest setting. Section 3 describes the experimental design and the data collection process as well as the main experimental results. In Section 4, I describe the empirical model, the strategy to identify the model parameters and present results from the structural estimation. In Section 5, I provide counterfactual policy simulations. Finally, I conclude in Section 6.

2 A Theory of Peer Learning in Contests

In this section, I provide a theoretical framework of learning, effort, and competition using contest models. Accordingly, human capital production depends on exam preparation effort choices. To develop competency in a subject, students must engage in active learning. In my setting, students need to improve their skills to do well in the final exam that will determine their score and prize. The purpose of the theoretical model is to provide an intuitive framework and comparative statics analysis that will guide the experimental design. The core model primitives include student types, which shape learning and mapping between study efforts and contest prizes.

2.1 Illustrative Example

To see how the strategic interaction works, consider the following simple example. Imagine a society with two students: Alice, a high type (H), and a low type (L), where type refers to ability and known by both students. Suppose each student makes two decisions: whether to exert individual effort e, and whether to interact with their peer p. Their human capital production functions are given by:

$$S_H = H \cdot e + \phi_{HL} \cdot \mathbb{1}\{p_H = p_L = 1\}, \quad S_L = L \cdot e + \phi_{LH} \cdot \mathbb{1}\{p_L = p_H = 1\}.$$

At the same time, exerting effort is costly, with cost c_e for positive effort, and c_p representing the interaction/coordination cost. For this simple example, let the numerical values be as follows: both effort and interaction costs are $c_e = 0.75$ and $c_p = 0.75$ for both students. Let the spillover term be $\phi_{HL} = 1$, and let ϕ_{LH} take value 2 with probability L/H and 1 with probability $1 - L/H$. Intuitively, the gain for the high type is limited, while the gain for the low type may be higher, especially when the ability gap is smaller.

Rank-Based Contest— Assume students compete for a prize and make strategic choices of effort and interaction levels in a Nash equilibrium. The prize is awarded to the student with the highest score and is worth $P = 1$. Students also intrinsically value score. Let expected payoff be written as $EU(e, p) = P_{\mathbf{1}\{\text{win}\}} + S - c_e e - c_p p$.

(i) Distant Peers: Let $H = 2$, $L = 0.8$. With probability 0.4, the low type gains 2 units from interaction, and with probability 0.6, gains 1. Then:

$$EU_H(1,1) = 2.5 > EU_H(1,0) = 2.25 > EU_H(0,1) = 0.55 > EU_H(0,0) = 0$$
$$EU_L(1,1) = 1.4 > EU_L(0,1) = 1.35 > EU_L(1,0) = 0.05 > EU_L(0,0) = 0$$

Both students choosing $e^* = 1$ and $p^* = 1$ is the unique Nash equilibrium. The intuition is that if interaction does not pose a threat to the high type's chances of winning, then both students will choose to interact. A similar logic applies to contests with more than two students or multiple prizes: even when peers are close in ability, multiple prizes can encourage interaction because the high type's chances of winning are less threatened.

(ii) Close Peers: Now let $H = 2$, $L = 1.5$. With probability 0.75, the low type gains 2 units from interaction; with probability 0.25, he gains 1. Then:

$$EU_H(1,0) = 2.25 > EU_H(1,1) = 1.75 > EU_H(0,1) = 0.5 > EU_H(0,0) = 0$$
$$EU_L(1,1) = 2.5 > EU_L(0,1) = 1.75 > EU_L(1,0) = 0.75 > EU_L(0,0) = 0$$

While the low type still benefits from interaction, the high type does not. Since interaction occurs only when both students choose to interact, and the high type opts out, interaction does not happen. The optimal choice for both students is $e^* = 1$, $p^* = 0$ and this strategy profile is the unique equilibrium. The intuition is that when interaction poses a threat to the high type's winning prospects, she will opt out, which shuts down the opportunity for interaction and any gains from interaction.

2.2 Model: Environment

2.2.1 Students The environment consists of N students, each characterized by their type tuple a_i, θ_i, which represents known ability and private cost type. The distribution of θ, denoted by F_θ, is defined on the support $\left[\underline{\theta}, \bar{\theta}\right]$ and is common knowledge within the reference group.[4] The type a_i captures factors that directly influence the score production function. θ_i enters the cost side.[5]

2.2.2 Student Interaction Students interact within a reference group (e.g., a classroom environment). Each student may be assigned (at most) one peer to study with. The peer's type is denoted by a_j. The interaction, interpreted as collaborative study effort that facilitates knowledge sharing, between a student pair influences score production in the final test. Peer assignment is determined by an exogenous assignment rule $\mathcal{A}(i,j) : \{1,\ldots,N\} \times \{1,\ldots,N\} \setminus \{(i,i)\} \to \{0,1\}$, which, for simplicity, is assumed to be binary rather than probabilistic assignment: $\mathcal{A}(i,j) = 1$ if students i and j are assigned to each other, and 0 otherwise. For every i, there is one unique partner. Students know who they are paired with before making effort choices.

2.2.3 Score Production Function Students produce scores according to a production function, which takes own and peer's type and efforts as inputs. The score production function is postulated by:

$$S_i = f(e; a_i) + \sum_{j=1}^{N} \mathcal{A}(i,j) \cdot g(p_{ij}; a_i, a_j) \tag{1}$$

where S_i represents the final score of student i, and e_i denotes the individual effort exerted by student i. The parameter a_i reflects the student's ability, which determines the productivity

[4] In the empirical model presented in Section 4, students are characterized by multidimensional heterogeneity, which influence the preferences. However, for the purposes of the theoretical framework, I focus on a single private dimension relevant to the predictions guiding the experimental design.

[5] Private θ makes rival effort random from one's own perspective, delivering a differentiable winning probability function hence a clean comparative statics.

of their effort. The exogenous assignment function $\mathcal{A}(i, j)$ specifies the pairing of students. The spillover function $g(\cdot)$ captures the learning benefits derived from interaction between students i and j. The effective learning from interaction is represented as $p_{ij} = h(p_i, p_j)$, where $h(\cdot)$ can take various forms, such as minimum, average, or multiplicative (cross-complementarity) operations.[6] Intuitively, the spillover component is realized only when both students actively engage in interaction, and its magnitude depends on the intensity of their interaction, p_i and p_j.[7] The following assumption provides the functional properties of the sub-functions.

Assumption 1. *$f(\cdot)$, $g(\cdot)$, and $h(\cdot)$ satisfy the following properties.*

(i) $f_e(e_i, a_i) > 0$ *and* $\limsup_{e_i \to \infty} f_e(e_i, a_i) < \infty$ *and* $f_a > 0$

(ii) $g(0; a_i, a_j) = 0$; $g_p(p; a_i, a_j) > 0$; $\frac{\partial g_p}{\partial (a_j - a_i)} \geq 0$, *and* $\limsup_{p \to \infty} g_p(p; a_i, a_j) < \infty$.

(iii) $h_{p_i} \geq 0$ *and* $h_{p_j} \geq 0$; $h(p_i, p_j) = h(p_j, p_i)$; $h(p_i, 0) = h(p_i, 0) = 0$; $0 \leq h_{p_i}(p_i, p_j) \leq 1$.

The assumption (i) states that the marginal productivity of individual effort is positive and bounded. Combined with strictly convex costs, this ensures a finite, interior optimum. Assumption (ii) requires that the spillover function is non-negative and exhibits increasing returns to scale in peer interaction. Additionally, the marginal gain from interaction is weakly higher when the partner has greater ability, so the lower-ability student benefits more from interaction. The last assumption (iii) is related to the effective interaction function. I assume symmetry, non-negativity and bounded marginal effects, and null-baseline. These conditions ensure that interaction is mutual and cannot be forced unilaterally.

2.2.4 Cost of Effort and Interaction Supplying individual effort and interacting with peers is costly for students. The cost of effort is given by $c_i(e_i, p_i|\theta_i) = \theta_i c(e_i + \xi p_i)$ where $c(\cdot)$ is the common labor-supply cost function for effort. Costs are twice differentiable and convex in effort, $c'(e) > 0$ and $c''(e) > 0$. The second component of the cost function is cost of interaction or working with a peer. ξ is the weighting of peer learning in the cost function. Note that the cost of effort scales with the unobservable type θ_i. The higher the θ the costlier for students to engage in any type of learning effort, whether it is self-learning or peer-learning.

2.2.5 Contest and Prizes The contest governs the external environment in which students play a game. Students form expectations about their winning probabilities for rewards based on the contest scheme. Based on the expectations, students decide on their effort level. For each student i, prizes govern the external incentives. I define a flexible prize function that nests both rank-based (tournament) and score-based reward schemes. Formally, I define the prize function as:

$$R_i = (1 - \lambda)\rho S_i + \lambda \mathbf{1}_{\left(S_i \geq S_{(N,k)}\right)} V \tag{2}$$

where S_i is the final score of student i, ρ is the score-to-money conversion rate in the piece-rate part, V is the prize value, and $S_{(N,k)}$ is the k-th order statistic of the scores among N students. That is, among N students, only the top-k students will receive the prize. The parameter λ governs the weight of the rank-based prize allocation. The prize value V is fixed and common across all students. Note that others' effort choices affect the prize function in the rank-based contest since

[6] For instance, h could represent the minimum of the inputs to reflect bottleneck effects.

[7] This approach differs from traditional peer social interaction models (Brock & Durlauf, 2001; Manski, 1993) by explicitly modeling spillover as a function of effective interaction or meeting.

the indicator function depends on an order statistic of the scores. Combining all the terms, let the external contest scheme can be compiled in a mechanism $\mathcal{M} = (\lambda, \rho, k, V)$. The mechanism $\mathcal{M}$ specifies how scores are converted into prizes. Changing λ corresponds to switching from a piece-rate scheme to tournament or any mixture in between.[8,9]

2.2.6 Net Utility Students have preferences over prize and score and they incur disutility from the cost of effort. Students maximize the net utility, which is the expected utility from the prize and score minus the cost of effort, given by:

$$\pi_i = \mathbb{E}[u(S_i, R_i)] - c_i(e_i, p_i|\theta_i) \tag{3}$$

where $u(S_i, P_i)$ is the utility obtained from the prize.[10] Note that others' effort choices affect the expected utility through the prize function in the rank-based case as provided by Equation (2). Moreover, even without rank-based tournament incentives, the peer interaction term in the score production function introduces a channel where the effort choices of others influence an individual's expected utility.

2.2.7 Skill Production At the end of the study period, student i's final skill stock, κ_i, is determined by interim effort and interaction choices, as well as their initial skill level, κ_{0i}:

$$\kappa_i = \mathcal{F}(e_i, p_i \mid \kappa_{0i}) \tag{4}$$

The object κ_i is a comprehensive measure of skill accumulation, distinct from the contest score S_i that determines utility and rewards. From the student's perspective, only (S_i, R_i) matter for payoffs, so the production function $\mathcal{F}$ plays no role in their decision problem and does not affect equilibrium behavior. However, κ_i is the relevant outcome for the planner, as it captures the human capital gains resulting from the contest environment. While estimation of $\mathcal{F}$ is deferred to Section 4, it is introduced here to complete the timeline of events and to fix notation for the subsequent welfare discussion.

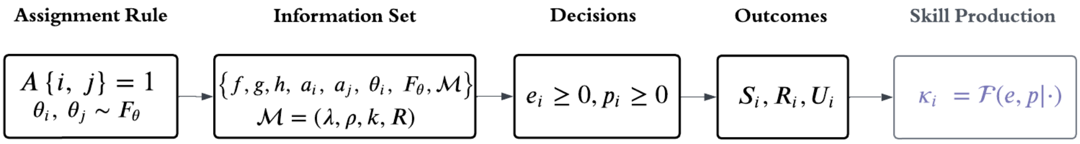
2.2.8 Summary: Timing of Events Figure 1 displays the timing of the main events in the model to provide a concrete reference point.

[8] Throughout the analysis, I treat $\mathcal{M}$ as exogenous design parameters and studying how changes in its' component affect equilibrium choices. The experiment essentially varies $\mathcal{M}$ to test the predictions identify the model.

[9] The prize rule can be viewed as a direct mechanism à la Myerson (1981). When $\lambda = 1$ and $k = 1$, the mechanism collapses to the classic rank-order scheme analyzed by Lazear and Rosen (1981). At $\lambda = 0$, the mechanism becomes a simple piece-rate reward, echoing the linear contracts in Holmstrom and Milgrom (1991). The contribution here is to let the designer choose λ and embed it in a setting with peer interaction. The mechanism not only affects individual effort but also the collaboration decision. This interaction channel is absent from the standard contest-design papers of Moldovanu and Sela (2001) and V. Krishna and Morgan (1997).

[10] The theoretical predictions regarding strategic interactions remain valid under the assumption that only monetary prizes affect utility. However, in the empirical specifications, I model the utility function as $u(P_i, S_i)$ because experimental evidence suggests that students also value the learning process. To maintain consistency across the study and enable meaningful counterfactual analysis, I incorporate an intrinsic-score component. I let the data tell if students care about score itself beyond money rewards.

Figure 1: Model Timeline



Nature draws the cost types, students are exogenously assigned to peers according to the rule $\mathcal{A}(i, j)$. Given the common knowledge as well as private information, each student simultaneously picks both individual effort and peer learning effort $e_i, p_i \geq 0$. Scores and prizes are then realized, delivering contemporaneous utility U_i. After all pay-offs are settled, a final, non-strategic stage converts actions into skill gains, κ_i as depicted in the gray box.

2.3 Equilibrium

I now formalize the Bayesian Nash equilibrium (BNE) of the game in which abilities are publicly observed, cost parameters $\theta_i \sim F$ are i.i.d and privately observed, each student chooses a pair of actions $(e_i, p_i) \in \mathbb{R}^2_+$, scores are deterministic once actions are fixed. When combined with the equilibrium strategies of other students in the reference group, a student can forecast the form of prize mapping in the equilibrium. A BNE is a set of decision rules $\{e_i^*, p_i^*\}_{i=1}^N$ such that, for every student i and for every realization of the private types,

$$(e_i^*, p_i^*) = \underset{e_i, p_i}{\text{arg max}}\ \mathbb{E}[u(S_i, R_i)] - c_i\,(e_i, p_i|\theta_i)$$

where the prize R_i depends on win probabilities which are taken over the unknown cost types of rivals.[11,12] A detailed discussion on the existence and uniqueness of the equilibrium, including the necessary conditions and proofs, is provided in Appendix A.1 for completeness.

2.3.1 Benchmark: Equilibrium with $N = 2$. Suppose that there are only two students, i and j, in the environment. In the explicit form, the net expected utility can be denoted as

$$\pi_i\,(e_i, p_i) = \mathbb{E}\left[u\left(S_i\,(e_i, p_i, p_j)\,, (1-\lambda)\rho S_i\,(e_i, p_i, p_j) + \lambda V \mathbf{1}\left\{S_i\,(e_i, p_i, p_j) \geq S_j\,(e_j, p_j)\right\}\right)\right] - \theta_i c\,(e_i + \xi p_i) \quad (5)$$

The only uncertainty for student i is the rival's private cost draw. Denote $G_j(s) = Pr\left[S_j \leq s | a_j, e_j, p_j\right]$.[13] and $\varphi_j = G_j'$. To better understand the role of strategic interactions, consider the following two special cases.

[11] Each rival's equilibrium score is a deterministic function of their own ability and cost type, combined with the peer effect from their assigned partner. Since the assignment rule is realized independently of individual types, any given rival remains an i.i.d. draw from the joint distribution of ability and cost type, irrespective of their pairing. The marginal score CDF remains invariant across all assignment patterns. Therefore, integrating over the assignment graph does not change the comparative statics predictions.

[12] An alternative approach to modeling uncertainty could involve introducing a stochastic component to the final score in Equation (1). While this would still yield similar first-order conditions for expected payoffs, modeling uncertainty through θ has two advantages. First, it ensures a smooth and differentiable winning probability function, which simplifies comparative statics. Second, it aligns the theoretical framework with the structural estimation process, where the F_θ distribution is identified and used for counterfactual analysis.

[13] This distribution is in fact an integral over the equilibrium strategies of the other student over their private cost types, $\theta_j \sim F_\theta$. Formally, with decision rules $(e^*(\theta), p^*(\theta))$, $G(s) = \int_\Theta \mathbf{1}(S(e^*(\vartheta), p^*(\vartheta); a_j, a_i) \leq s) dF_\theta(\vartheta)$.

(i) Case 1: $\lambda = 0$— In this case, prize is only based on the individual's own score. The net expected payoff is given by $\pi_i(e_i, p_i) = \mathbb{E}[u(S_i, \rho S_i)] - \theta_i c(e_i + \xi p_i)$. Strategic interaction is absent but their effect on the scores via function $h(\cdot)$. Suppose everyone is a grade-maximizer. A student will simply want to maximize her score as a function of her effort choice given the peer's effort choice. The first-order conditions for the maximization problem is given by:

$$\mathbb{E}[(u_S + \rho u_R) f_e] = \theta_i c'(e_i + \xi p_i) \quad \text{and} \quad \mathbb{E}_{\theta_j}[(u_S + \rho u_R) g_p \cdot h_{p_i}] = \theta_i \xi c'(e_i + \xi p_i) \tag{6}$$

From this first-order condition we can see that the effort choice of student i is independent of strategic effort choice due to competitive channel. In this special case, the equilibrium behavior will be $p_i^*, p_j^* > 0$ if and only if both $\theta_i, \theta_j < \theta^*$. That is, as long as their private costs can afford, they will choose to interact with each other. Mathematical derivations are provided in Appendix A.1.2.

(ii) Case 2: $\lambda = 1$— In this case, the prize is only based on the rank. The net expected payoff is given by $\pi_i(e_i, p_i) = \mathbb{E}[u(S_i, R_i)] - \theta_i c(e_i + \xi p_i)$.

The first-order conditions for the maximization problem is given by:

$$\mathbb{E}[(u_S + V u_R \varphi_j(S_i)) f_e] = \theta_i c'(e_i + \xi p_i) \tag{7}$$

$$\mathbb{E}[\underbrace{(u_S + V u_R \varphi_j(S_i)) g_p \cdot h_{p_i}}_{\text{own gain}} - \underbrace{V u_R \varphi_j(S_i) g_p \cdot h_{p_i}(p_j, p_i)}_{\text{rival gain}}] = \theta_i \xi c'(e_i + \xi p_i) \tag{8}$$

The expression in parentheses in Equation (8) comes from Leibniz rule.[14] Before moving on the comparative statics analysis, few words are in order. In the non-competitive setting (Equation (6)), the marginal benefit of each action depends on the assigned peer only via the $h(\cdot)$ function, still leading to an individualistic optimization over an expected payoff. However, under-rank based competition (Equations (7) and (8)), the incentives become strategic. Now, the FOC for p_i includes a new term capturing the impact of p_i on the peer's score S_j, thus affecting one's own probability of winning (weakly) negatively. This introduces a competitive externality: increasing p_i may improve one's own score but also can raise the rival's performance, offsetting the benefit. In this competitive setting, the equilibrium will be such that $p_i^*, p_j^* > 0$ if and only if $\theta_i, \theta_j < \theta^{**} < \theta^*$. That is, the threshold for interaction is more stringent than in the non-competitive case. Since p^* will be reduced, the equilibrium e^* should increase for Equation (7) to hold. Mathematical derivations are provided in Appendix A.1.3. A formal proposition providing the comparative statics in λ is as follows.

Proposition 1. *(Competition and p^*) As the competition weight λ increases, the equilibrium peer learning effort p^* decreases, i.e., $\frac{\partial p^*}{\partial \lambda} < 0$. The threshold to engage in peer learning becomes more stringent, i.e., $\theta(\lambda_2) < \theta(\lambda_1)$ for $0 \leq \lambda_1 < \lambda_2 \leq 1$, resulting in fewer students choosing to interact. Reduced peer learning leads to higher individual effort, i.e., $\frac{\partial e^*}{\partial \lambda} > 0$ due to substitution effects.*

Above results hold for a given pair of students with known abilities, a_i and a_j. Note however that the p choice depends on the distribution of ability gaps since the gain from interaction differs by ability difference as laid out by Assumption *1 (ii)*. For the smaller ability gaps, the density function $\varphi_j(S_i)$ will be large since the scores will be close to each other. Hence the rival gain term in Equation (8) will be large and the resulting p_i^* will be small. For larger ability gaps, the density function $\varphi_j(S_i)$ will be small since the scores will be far apart. Hence the positive peer interaction

[14] Decision p_i also shifts the rival PDF. The exact derivation is provided in Appendix A.1.3.

might occur if the score benefit outweighs the cost of interaction like in the non-competitive case. A formal proposition is as follows.

Proposition 2. *(Selective Collaboration: Competition and Ability Gap) Let $d = a_i - a_j \geq 0$ denote the ability gap between student i and j. For any positive prize spread $\lambda \in (0, 1]$, there exists a unique ability gap $\bar{d}(\theta_i, \lambda)$ such that $p_i^* = p_j^* = 0$ for $d \leq \bar{d}(\theta_i, \lambda)$ or $\theta_i \geq \theta^{**}(d; \lambda)$.*

Intuitively, competition eliminates peer help when the students are nearly tied since the rival gain term dominates the own gain term. As the leader's advantage grows, the penalty wanes, interaction become attractive until the cost of interaction outweighs the benefits. Full derivations are provided in Appendix A.1.4.

2.3.2 General Case: $N \geq 2, k \geq 1$.

Equilibrium here is analogous to the $N = 2$ case. Given the equilibrium strategies of the other $N-1$ students and the type distribution of costs θ, each student forms an expectation over the probability of winning a prize. Because each student's final score S_i is deterministic conditional on actions and abilities, and cost types are independently drawn, the score distribution of a random rival is summarized by the CDF $G(s) := \Pr[S_j \leq s]$, as before. Denote by $P^w_{(N,k)}$ the probability that student i's score exceeds enough rivals to finish in the top k out of N; its exact form is in Appendix A.1.5. Under the policy $\lambda = 0$ effort choices remain individualistic. Each student maximizes her own payoff given the prize probabilities implied by $G(\cdot)$, so the basic first–order conditions coincide with the two–person benchmark. To build intuition before the formal analysis, think about a student's position in the type (or score) distribution. Close to the prize margin (the kth highest score), a one–point improvement in S_i produces a large jump in $P^w_{(N,k)}$; locally this is almost the same as increasing the effective prize spread λ in the two–person case. If the $N-1$ peers that matter for the margin are themselves clustered near that cutoff, the strategic externality is strong and behaviour closely resembles the two–player contest between similarly able students. By contrast, well inside the winning set (or far outside it) the marginal probability of entering or dropping out is negligible, so the marginal prize value is near zero and effort falls back toward the piece–rate (nonstrategic) level. Interaction decisions therefore mirror the $\lambda = 0$ case: strategic helping matters most near the margin and becomes irrelevant once the margin is either safely cleared or hopelessly out of reach. Let $\delta_i = \lambda R P^{w\prime}_{(N,k)}(S_i)$ denote the marginal tournament return to own score.

Proposition 3. *(Behavior w.r.t Winning Margin)*

(i) Fix the constest parameters $\mathcal{M}$. The equilibrium individual effort $e_i^*(\theta_i)$ is strictly increasing in δ_i. Consequently, a student whose expected rank lies near the prize cutoff (i.e. with the largest δ_i) supplies the highest effort within the reference group.

(ii) The equilibrium peer effort is strictly decreasing in the tournament slope: $\frac{\partial e_j^*}{\partial \delta_i} < 0$. There exists a critical value $\bar{\delta}_i = (1 + (1-\lambda)\rho)\frac{\partial S_i / \partial p_i}{-B(d)}$ such that $p_i^* = 0$ whenever $\delta_i < \bar{\delta}_i$.

Proof can be found in Appendix A.1.6.

2.4 Social Welfare

One of the primary goals of this study is to provide policy insights on peer assignment strategies, such as tracking, by shifting the focus in the peer effects literature from a *desire to conform* approach to a *desire to compete* approach (as discussed by Tincani, 2024). In this setting, students respond to contest incentives, but their final skill levels, κ_i, which are important for long-term outcomes, are not priced into their private pay-offs. The planner, in contrast, internalizes the broader consequences of peer interaction and skill accumulation. To quantify the potential misalignment between private and social objectives, I define a welfare score for any contest environment. Welfare depends on the equilibrium choices of effort and peer help, as well as the institutional design, specifically, the contest mechanism $\mathcal{M}$ and the assignment rule $\mathcal{A}$. Formally, I define:

$$\mathbf{W}(\mathcal{A}, \mathcal{M}) = \sum_i \kappa_i(\mathcal{A}, \mathcal{M}) \tag{9}$$

This reflects an output-maximizing or skill-maximizing planner who values total skill accumulation and treats effort costs as privately borne. I assume the planner has direct control over matching, i.e., they can assign students to study pairs, and can also choose the parameters of the contest mechanism. The assignment rule $\mathcal{A}$ governs the nature of peer spillovers, while the contest mechanism $\mathcal{M}$ determines the external incentives shaping effort and peer behavior. The main purpose of introducing this welfare object is to evaluate the implications of alternative contest environments for total human capital. While I do not solve for the globally optimal policy, this framework allows meaningful welfare comparisons across policies, including different matching and incentive designs. These comparisons are carried out in Section 5.

2.5 Discussion on the Model Restrictions

Peer Assignment. The model employs an assignment rule, $\mathcal{A}(i, j)$, to emphasize that peer allocation is exogenous, differing from standard matching functions where pairings result from equilibrium choices. This approach is motivated by the focus on exogenous group assignment or classroom composition policies. Additionally, the model assumes that a study group consists of two individuals. While this simplification may not fully reflect reality, as students often have multiple study peers in practice, it remains analytically tractable. By collapsing multiple study peers into a single representative peer, the model effectively captures how exposure to different peer groups influences human capital production.[15]

Prize Constraints. Because the focus of this paper is on strategic behavior rather than on optimal prize distribution, I assume the designer sets prizes arbitrarily and faces no binding budget constraint, so the budget does not distort the designer's incentive choices.

Information and Beliefs. The theoretical model assumes that abilities influencing score production are publicly observable. While real-world abilities are often measured with noise, educational settings frequently provide signals, such as published test scores or class rankings. To maintain focus on the core mechanisms of prizes and peer interactions shaping behavior, the model abstracts away from another heterogeneity dimension. This simplification sharpens the theoretical predictions and aligns with the experimental design.[16]

3 A Field Experiment to Quantify Effort Dynamics

Following the advice by Manski (1993) that *"Given that identification based on observed behavior alone is so tenuous, experimental and subjective data will have to play an important role in future efforts to*

[15] This simplification is also utilized by Herkenhoff et al. (2024).

[16] In addition to these restrictions, this model assumes the absence of teacher effort adjustments in response to different prize or assignment mechanisms, thereby considering a partial equilibrium framework.

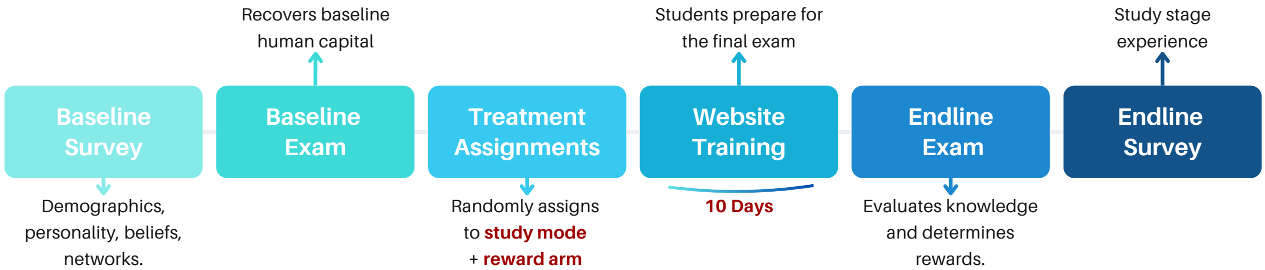
learn about social effects.”, I designed a survey and a novel field experiment to quantify the effort dynamics of students in a competitive environment. Note that, one looking at the observational data only might not be able to tell whether the low level of peer interaction or learning is due to students’ social preferences or due to the strategic behavior of students. This fact motivated my field-experimental design, carefully developed to decompose learning into individual and group study components as well as the strategic behavior of students due to competition. My research design forms part of a new literature that employs field experiments for a purpose of identifying the structural parameters of a model instead of testing the predictions of a model. (e.g. Agte et al., 2024, Attanasio et al., 2012, C. Cotton et al., 2020, Hedblom et al., 2019, Todd and Wolpin, 2006).

The experiment was not only designed to test the impact of competition, but also to create a data-generating process with the right observables and variation needed to identify the model components and break down the mechanisms of learning in contests. The goal for this process is to reflect students’ everyday academic environment and the kinds of choices they normally face. To recover students’ baseline human capital, I need data on their initial academic performance. I also need choice data, specifically, daily study logs that track how much time students spend studying alone versus with a peer. Effort is measured using detailed activity data: how long students spend on each problem, and how many quizzes or problems they complete. On top of this, I collect background information such as demographics, parental education and income, and school quality, in order to analyze heterogeneity in responses and to control for differences.

3.1 Experimental Design

In this section, I provide a detailed description of the experimental design which involves a sequence of stages, that is carefully designed to identify the main model components. Figure 2 presents a visual representation of the experiment timeline, starting with the baseline survey and exam, followed by the training stage, and concluding with the final exam and survey.

Figure 2: Experiment Timeline



3.1.1 Study Sample and Recruitment. The field experiment included 1405 10th grade students across demographically and academically distinct 10 high schools in a metropolitan city of Turkey during Fall 2024.[17,18] In the September of 2024, my implementation team and I contacted our

[17] The experiment was conducted in Malatya Province, which is located in the Eastern Turkiye.

[18] Students at this grade level are typically 15–16 years old. The choice of grade was carefully considered. I wanted to focus on high schoolers since the stakes are much higher for them due to college preparation. I didn’t want to include 9th graders, since their academic involvement is often perceived to be weaker at that stage, and I also avoided 11th and 12th graders because college exam preparation starts early in Türkiye, and those students are generally less available for a project like this that requires some time flexibility.

sample schools and briefed them about the relevance of the study and the importance of their participation. To have a representative sample in terms of academic background, schools were recruited based on a stratified sampling method. I grouped schools into three strata based on their 2024 high school entrance exam cutoff score. Four schools were selected from each stratum.[19] However, by the time the study began, two schools (one from the low stratum and one from middle stratum) decided to withdraw from the study. The sample included 10 schools and 51 classrooms.

I collaborated closely with school administrators, who served as the primary point of contact with students until the experimental sessions began. Administrators were generally supportive and welcomed the study as an opportunity to improve student outcomes. The research team handled the distribution of all study materials, including consent forms, baseline and post-exams as well as online surveys.[20] They also provided technical support for the learning website throughout the study. Participation was voluntary, and approximately 5% of the targeted sample opted out.[21]

Before implementation of the first stage: baseline survey, all the school administrators went through an information sessions carried by the research team. The information aimed to capture dos and don'ts during the baseline and final surveys + classroom tests.[22] In order to ensure that administrators and teachers do not change their behavior due to the specific nature of the study, they were not informed about the exact incentive types or the rationale behind the randomization design. School admins were informed that findings from the study would be shared with them and a training session would be conducted to provide suggestions on how to improve the learning outcomes of their students with the right peer pairings and incentives.

3.1.2 Baseline Survey. I conducted a baseline survey, designed in-house, to collect information on students' demographic characteristics, parental education, and income.[23] The survey also included questions about academic performance, friends' network, and study choices with peers. Additionally, I collected information on students' personality traits using the Big Five Inventory (BFI-10) and the Cooperative/Competitive Strategy Scale (Tang, 1999).[24] Section O.A.2.2 provides a chart on the survey flow and the details regarding the measures I use can be found in Table OA.1. In addition, I include a detailed discussion of processing the survey variables for final use in Section O.B.1.

The survey was conducted online but within classrooms. In our sample schools, the policy of the school administration allows students to carry their phones to school, provided they store them in a locked box during school hours. I leveraged this policy to conduct the online surveys

[19] Additional details regarding school selection procedure can be found in Online Appendix O.A.1.

[20] Lack of either parental or student consent was sufficient for opting out. Before the study, parents received an assent form detailing the study, including the research team's contact information and data security measures. The form also provided an option for parents to opt their children out by contacting the research team via email or phone. On the first day of the study, students were informed about the study, given the option to opt out, and provided with contact information to withdraw at any stage.

[21] These students declined participation from the outset and never engaged with the study. Hence, they did not complete the baseline survey or receive any treatment assignment.

[22] These include exam rules and teachers' role in the classroom as a proctor both for baseline/final exam and baseline survey.

[23] Additional demographic questions covers study conditions at home such as access to Internet or having a private room.

[24] During the pilot and testing stage, I first ran a broader set of questions, then narrowed down based on the survey responses, qualitative interviews with the pilot sample, and the feedback from educators.

in a low-cost manner but still in a controlled classroom environment. For students lacking an internet-enabled device, battery, or data, the implementation team provided devices, chargers, or mobile Wi-Fi when needed. See Figure OA.5 for an example of classroom survey implementation. Students are not allowed to talk to each other during the survey, and teachers were instructed to monitor the classroom to ensure that students do not share their answers. The implementation team still collected information about implementation-related variables like presence of proctor, or student noise level. See Table OA.6 for the summary of implementation-related variables.

During our survey visit, we informed students about the general purpose of the study and the importance of their participation. We also informed them about the baseline exam, final exam, and exam preparation, specifically the website by drawing the timeline on the white board. The information provided in this visit is not specific to any treatment arm. Section O.A.3.1 provides more details on this in-classroom survey implementation and the speech delivered to students.[25]

The baseline survey is approximately 20 to 30 minutes long. Students are incentivized with guaranteed ₺100 for their successful completion of the survey. Figure OA.3 displays the distribution of time spent on the survey. Section O.A.2.3 provides a summary of survey quality checks.

3.1.3 Study Material. The study material for this project was selected with four key considerations in mind. First, the material needed to lead to quick improvements, allowing me to study learning over a short period. Second, it had to be suitable for both individual and peer learning, promoting discussion and knowledge sharing.[26] Third, the material needed to be easily accessible on an online platform across various devices. Fourth, to avoid interference with other ongoing school activities, the chosen topics should not overlap with the 10th grade Fall curriculum. However, the material should still be relevant for their future academic pursuits, particularly college exam preparation.[27] In collaboration with high school Mathematics teachers, I selected three topics from the 9th grade Mathematics curriculum: Logic, Sets, and Equations and Inequalities.[28] To prevent students from rushing to study these topics before the baseline exam, they were not informed about the specific topics in advance.

3.1.4 Baseline In-Classroom Test. Following the baseline survey, I conducted a baseline in-classroom test across all sample schools on the same day.[29] The test, designed by educational professionals, aimed to measure baseline knowledge or ex-ante knowledge stock according to the model. It was structured to be completed within a 40-minute classroom hour and included 25 multiple-choice questions on selected topics, with negative markings imposed.[30] Table A2 pro-

[25] The timing of the entire study is designed such that the baseline survey coincides with the end of the mid-term exams while the final exam is one-week ahead of the end of the semester exams. It's reasonable to wonder whether the survey questions might somehow shape the treatment effects. Even though they're not directly related, they could still give some subtle hints about what's coming. However, there is a minimum 10-day gap between the survey and the treatment arm information disclosure, which should help break potential links.

[26] Math subjects that emphasize formulaic or memory-based learning, such as trigonometry, may be less suitable for peer learning.

[27] Choosing relevant study material for their academic future was crucial to maintain a minimum required level of engagement.

[28] I collaborated with a high school outside the study sample, where math teachers voluntarily contributed to designing study and exam materials throughout the experiment.

[29] The exams were distributed to the schools on the Monday following the survey completion week, to be conducted on Tuesday. Schools followed the proposed class hour to prevent any across-school information sharing. The research team collected the question booklets to mitigate any information sharing concerns.

[30] In this study sample, the regular multiple-choice exams students take mostly include negative marking. To align with their actual test experience, I designed the exam format to be similar.

vides details about the exam specifications, including question types, difficulty, and topic. The questions vary across several dimensions, including topic, difficulty, and whether they require memory-based recall or analytical thinking.[31] The exam was conducted in a proctored environment. More details about exam implementation can be found in Section O.A.3.2.

3.1.5 Randomization Design. Figure 3 illustrates the experimental design. I implement a two-tier randomization. The first tier randomizes the study mode. A student is randomly assigned to either study alone (*Individual* mode) or with a peer (*Pair* mode). Those in the *Individual* mode study on their own using the website.[32] Those in the *Pair* mode are randomly and anonymously matched with a peer to study together using the website. The match stays fixed throughout the study, and both students always face the same conditions. The second tier randomizes the reward structure. A student is randomly assigned to one of three arms: *Control*, *Moderate* competition, or *Intense* competition. The *Control* arm follows a piece-rate structure where students are paid 20 ৳ per correct answer on a 25-question final exam. The *Moderate* competition arm is a rank-based contest with 10 students competing for 3 equal prizes (500 ৳ each). The *Intense* competition arm is also rank-based, but with 2 students competing for a single prize of 500 ৳.[33] Members of a pair are always assigned to the same reward arm. The *Intense* arm was specifically designed to improve statistical power for identifying behavioral responses at the margin of winning. The *Moderate* arm didn't guarantee a clear ex-ante separation at the margin, given the planned sample sizes. The label "Intense" comes from the fact that it's a zero-sum setup, only one of the two students can win, while in the Moderate arm, three students can win and both members of a pair can potentially win together.

In both competition arms, smaller reference groups are created within ability strata based on baseline scores. Students are grouped into three strata: Low, Medium, and High. This makes sure that students are neither too close nor too far apart in ability, so that the competitive environment is meaningful. Members of a pair are always placed in the same stratum and grouped into the same competition pool. For example, in the Moderate competition arm, a group of 10 competitors can include both Individual- and Pair-mode students, but team members are always placed in the same pool.[34] The *Control* and *Intense* arms were each designed to include 399 students, while the *Moderate* arm includes around 465 students. This is because the expected attrition rate is higher in the *Moderate* arm due to its competition structure and the lower probability of winning a prize. For the study mode, the randomization ensures that the number of students in the *Pair* mode is twice that of the *Individual* mode. This is to make sure I have enough students in the *Pair* mode to observe behavior, taking into account the higher expected attrition from coordination and scheduling costs.[35] The effective sample used in the experimental and structural analysis is however smaller due to the exclusion of a group of students who were exposed to an unintended

[31] See Appendix B.2 for details about how these question specifications are defined.

[32] The website has two versions with different user interfaces, one for *Individual* mode and one for *Pair* mode.

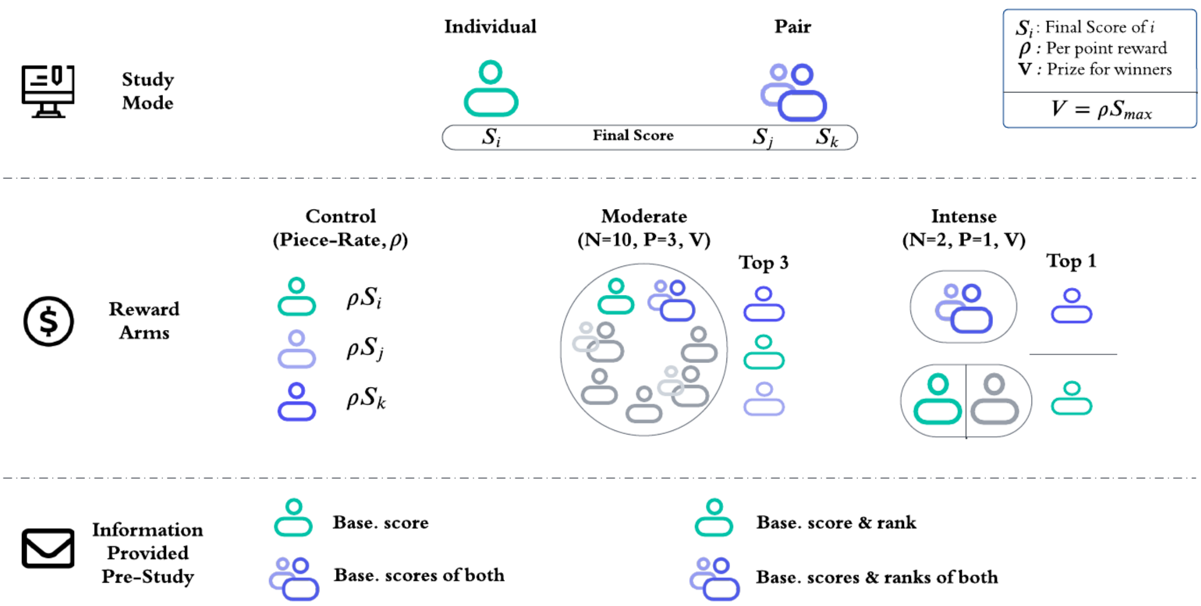
[33] Prize values (20 and 500 ৳) were chosen so that average payments are similar across arms. This helps ensure that observed differences come from strategic differences in the setup, not from the prize values themselves.

[34] When forming groups of 10 students within each stratum, the total number wasn't always divisible by 10. As a result, 2–3 groups in each stratum ended up with 11 students.

[35] Among the sample, 41 students (around 3%) from two schools reside in school dormitories where phones must be turned in after 7 PM. Because of the extra coordination required in the *Pair* mode, these students were placed in the *Individual* mode. One concern here is whether dormitory students are systematically different from their peers. Baseline exam results show that this is not the case: in one school, the average score for dormitory students was 14.31 compared to 14.15 for others, and the difference is not statistically significant based on a two-sided t-test. I also run robustness checks to account for any remaining concerns.

fieldwork complication. Appendix D.5.3 gives more detail on this issue and how I excluded them from the analysis.

Figure 3: Experiment Design



3.1.6 Information Given to Students. Each student received a detailed individualized information text message that included their assigned reward structure and study mode. The message also contained login credentials for the study website, along with details about the final exam date and format, the reward scheme, their baseline exam performance, and a user guide for the website.[36] Students in the *Control* arm were informed only about their own scores and, if in the *Pair* mode, the score of their matched peer. Students in the competition arms (*Moderate* and *Intense*) received information about both their score and rank within their reference group, as well as the score and rank of their assigned team member if in the *Pair* mode. The text templates are provided in Online Appendix O.A.4.

3.1.7 Preparation Stage. In this stage, students are asked to use a custom-designed study website to prepare for the final exam which determines the prize they will get. The website consists of quizzes, broadly covering the chosen study material. During the preparation stage, the research team sent messages every day to students to remind them of the web use and the importance of their participation as well as prize structure.[37] Online Appendix O.A.5 provides the template for the daily reminder messages. While 10 days may not be sufficient for quick progress, the prepara-

[36] During the intervention, the website was not open for sign-ups, only students we registered could sign in. This was mainly due to the exogenous assignment of study peers. However, for privacy reasons, students were required to change their login credentials after their first login.

[37] Specifically, for students in the rank-based arms and *Pair* mode, I reminded them that their teammate is in the same competition pool. During the first four days, reminders were sent daily to ensure that everyone was on the same page. For the remainder of the preparation period, reminders were sent every two days to avoid overwhelming students.

tion duration is kept at 10 days to ensure students do not suffer from implementation fatigue.[38]

3.1.8 Website Structure. The website was accessible through a login credential assigned to each student, provided in the initial information text. The web server automatically recorded site activity without affecting the user experience. The website consists of quizzes that broadly cover the chosen study material. Each quiz is randomly ordered and includes eight questions of varying difficulty. Questions were drawn from various sources, with input from high school math teachers. To measure difficulty levels, I collaborated with tutors to assign difficulty ratings to 200 randomly selected questions from the full question pool. Table A2 summarizes the tutor-assigned characteristics of the quiz questions, with a comparison of baseline and final exam characteristics.

In total, 80 quizzes were available in the quiz pool, and every day, students were assigned four random quizzes on their dashboard. This random assignment was intended to prevent students from cross communicating with classmates to answer the same questions. Students in the *Pair* mode received the same four quizzes as their partner. Each quiz was unlocked sequentially, meaning a student had to complete one before accessing the next. This ensured that both *Pair* members worked on the same quizzes, allowing them to review identical questions even if one completed fewer quizzes than the other. The Algorithm 1 shows how the review session was designed for the *Pair* mode and the Algorithm 2 shows the *Individual* study mode design. Figure A2 provides a screenshot of the quiz page. As shown in the screenshot, after completing each quiz, students were asked to self-report their effort as an additional measure.

For students in the *Individual* study mode, quizzes were completed independently by selecting answers to multiple-choice questions. The website also included a text editor below each question, where students could write out their detailed steps. Answer reviews were made available daily at 7:00 PM. Figure A5 and Figure A6 shows an example of the result and instructional page. The *Pair* study mode provided basic tools for interaction. Students in this mode were paired with one study partner, and a chat box was always available for scheduling study sessions and discussing questions. Each student was expected to complete their assigned quizzes independently before 7:00 PM. After this time, they could review their answers, discuss the questions with their partner, and submit a final answer. Figure A4 provides an example of the review page.[39]

On the first day of the preparation stage, students were asked to log in at the same time to coordinate their daily study schedule and avoid scheduling conflicts. Given the higher coordination cost in *Pair* mode compared to *Individual* mode, all students *Pair* mode were informed that they would receive a ₺200 bonus if they logged in and completed quizzes with their study partner for at least three days.[40] If a student was matched with a partner who did not show up for two consecutive days, they were reassigned to another student from the same reward arm whose

[38] The choice of the number of days is also based on two papers using similar approach: C. S. Cotton et al. (2022) and C. Cotton et al. (2020).

[39] One concern regarding the timing of the review session for team mode or the answer display for *Individual* mode was that some students might have after-school extracurricular activities. The research team received accommodation requests from a few students who could not attend at 7:00 pm. In response, students were informed that they could schedule their session anytime between 7:00 and 10:00 pm and were advised to inform their teammates. Despite this flexibility, a few students dropped out of the study for this reason. However, the majority of students were able to adjust their schedules accordingly. Yet, the research team, on the fourth day of preparation, jointly decided to update the review session time to 8:00 pm for the team mode and answer display time to 8:00 pm for the *Individual* mode. Students were informed about this change via text message.

[40] This *Pair* bonus was introduced on the third day of the preparation stage, allowing me to distinguish treatment effects from bonus effects. As confirmed by our final survey, students in the *Pair* mode faced communication and scheduling challenges, particularly in the *Intense* competition arm.

partner also did not show up.[41] The website automatically recorded time spent on the platform, the number of quizzes solved, and chat box usage intensity.[42]

The website was designed to be mobile-friendly, considering that phone usage is more common than computer usage among the target population. Website activity data indicates that 42% of students accessed the platform via mobile phones, 30% used computers, and the remaining used tablets. One concern was internet access. The baseline survey showed that 87% of students had home Wi-Fi, while the rest relied on mobile data, except for 16 students who had no stable internet access. However, usage data suggests that students without home internet access participated at similar rates (40% usage) compared to those with home Wi-Fi, suggesting that they may have found alternative access methods.[43] As with any online study, there was the potential for technical challenges. To minimize disruptions, the research team provided a technical support callback number for students who needed assistance. Most support requests were related to password resets and missing study partners. Table OA.3 summarizes the reasons for technical support requests. Password resets were resolved immediately, while missing study partners were reassigned by matching the student with another available peer for the following day.[44]

The other concern that could bias the results was exam preparation through other channels. Specifically, those in the group study mode might have studied individually using other resources (YouTube courses or other Ed-Tech like Khan Academy) due to the scheduling or coordination costs. To control for this, each day when students log on the website, they are asked to provide a time use on activities for the day.[45] Table A12 displays the summary of time use on the other activities besides the website. The results show that students used other resources as well. While not too restrictive, I emphasized in the information text that the website content is the most relevant to the final exam content. Robustness checks are also conducted to account for this potential bias.

3.1.9 In-Classroom Final Test. Finally, I conducted the final exam. The final exam was similar to the baseline exam in terms of the content and difficulty. More details about the final exam specifications can be found in Table A2. A week after the final exam, students received their prizes in a sealed envelope.

3.1.10 Final Survey. I conducted a final survey to gather information on students' experiences with the website and the impact of external incentives on their study choices. The final survey was administered after the final exam and prize distribution. Due to time constraints imposed by final semester exams, the survey was conducted entirely online. To encourage participation, students were incentivized with a random lottery of ₺300 for completing the survey.[46] The final survey took approximately 5-10 minutes to complete. Figure OA.4 shows the distribution of time spent

[41] The main analyses focus exclusively on the first matches since the second matches are assigned only after the fourth day; however, robustness checks accounting for match changes are also conducted.

[42] Since the chat box could raise ethical concerns, such as inappropriate language or privacy violations, a detection tool was implemented to flag and report any such cases to the admin. This policy was clearly stated in the information text, and the final admin report indicated that a few violations occurred, with some students asking the name/school/gender of their study partner.

[43] Additionally, no students contacted the research team requesting devices or internet access.

[44] Reassignments followed the same randomization procedure, and students were informed via personalized text messages, which also included their new partner's baseline score only.

[45] Once logged on the website a pop-up survey appears on the screen. To proceed other activities, the survey was required to be filled. Figure A1 displays this pop-up survey.

[46] The incentive was to reward randomly selected 25 students with ₺300.

on the survey. In total, 364 students completed the final survey. The attrition could be attributed to several factors. First, the final survey was conducted entirely online, without in-person visits from the research team. Second, implementation fatigue may have played a role. Third, selective attrition might have occurred, as some students who did not receive any rewards from the final exam could have been discouraged from participating.[47]

3.2 Balance and Sample Characteristics

Table A3 presents the background characteristics of the study sample, categorized by strata. The sample consists of $1,405$ students, with approximately 56% being female.[48] About 72% of the students have a personal room, 87% have Wi-Fi at home, and 72% own a personal laptop or tablet. The average 9$^{\text{th}}$ grade Literature score is around 85 (out of 100), and the Math score is approximately 80. On average, students have 1-2 siblings. Regarding socioeconomic status, the average household income is around ₺$35,000$ per month. Additional details can be found in Appendix B.4. Table A4 displays the balance of covariates across treatment arms. I conduct a two-level balance check: first across the reward arms, and then across the study modes within each reward arm. Out of the 72 comparisons (12 covariates, 3 within and 3 across comparisons) made, I observe imbalance at the 10% significance level in only 8 cases. To account for these minor imbalances, specifically coming from gender and academic imbalances, I use regression analysis in the following sections, which allows me to control for these covariates.

3.3 Baseline Survey Facts

I begin the empirical analysis by documenting two key facts from the baseline survey. These serve two purposes. First, they provide a descriptive overview of the sample before any treatment is introduced. Second, they help motivate both the experimental design and the structural model.

Fact 1. ***(Network Choice and Competition)***:

(i) Students sort into friendship and study networks based on academic and personality traits.

(ii) The choice of study partner is influenced by how competitive the environment is.

(iii) Students in highly competitive schools are less likely to include close competitors in their networks.

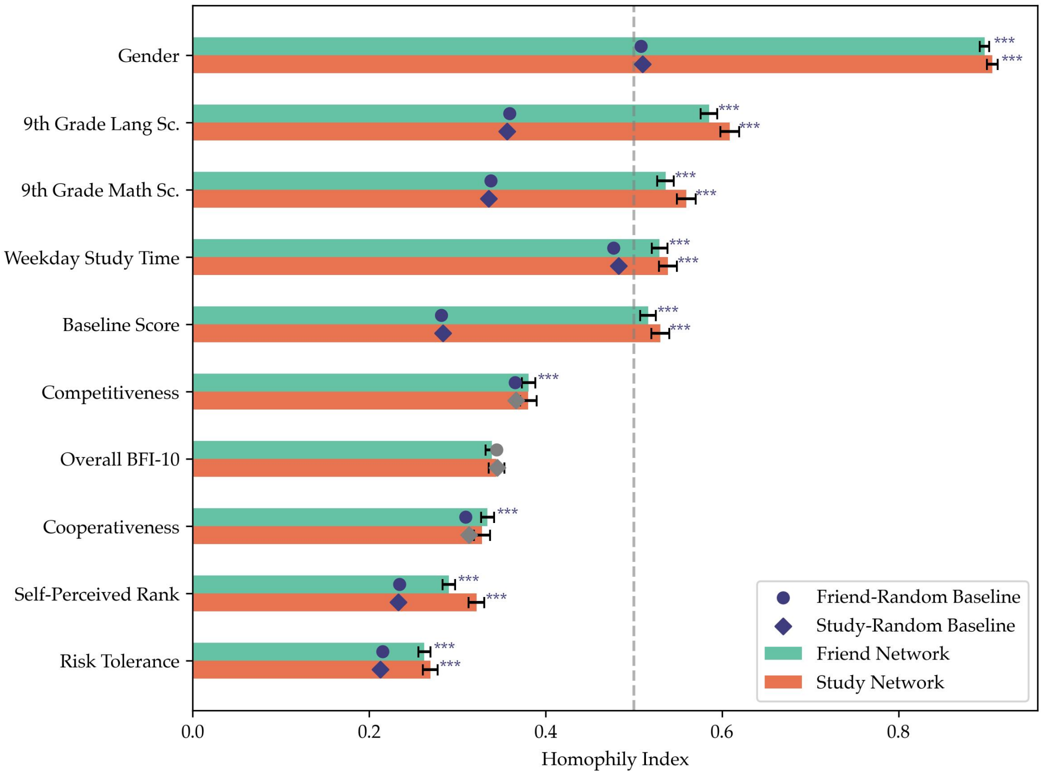
Each fact is supported by a distinct set of analyses. Before going into the discussion, I briefly describe how each was carried out. To document (i), I construct a homophily index for different set of covariates, including gender, personality traits, competitiveness, cooperativeness, and academic performance. Details regarding the construction of the homophily index can be found in Section C.1.1. The homophily measures are presented in Figure 4. Students exhibit strong homophily across both friendship and study networks. Homophily is particularly pronounced for gender, substantially exceeding the baseline of 0.5. Academic performance variables also demonstrate robust homophily, with values approaching 0.65. Characteristics such as competitiveness, risk tolerance, and rank show moderate but significant homophily. Interestingly, the Big Five per-

[47] The fraction of students who completed the final survey varies by study mode within each arm. In the *Control* and *Moderate* arms, differences between *Individual* and *Pair* study modes are small ($p_\Delta = 0.34$ and $p_\Delta = 0.52$, respectively). In the *Intense* competition arm, the fraction is higher in the *Individual* mode (0.32) than in the *Pair* mode (0.24), with a difference that is suggestive but not statistically significant at conventional levels ($p_\Delta = 0.108$).

[48] This number refers to students who completed the baseline survey. The number of students who took the baseline exam and were therefore assigned to treatment arms is $1,263$. The full survey sample is used when documenting baseline survey facts.

sonality traits exhibit weaker patterns of homophily, suggesting either limited sorting along these dimensions or the possibility that these survey metrics may not adequately capture soft skills.[49]

Figure 4: Homophily in Friendship and Study Networks



Notes: This figure shows the homophily levels in friendship and study networks. Each bar couple represents the average homophily level in friendship and study networks for a given covariate. The black bars shows the 95% confidence intervals. The circle and diamond markers indicate the expected homophily under random assignment (based on permutation tests with 500 samples). Asterisks denote significance compared to the random baseline.

Sub-fact (ii) is documented as follows. In the survey, students were asked to name a classmate they would prefer to study with under two different hypothetical scenarios: one where prizes are rank-based, and another where rewards depend on individual performance or a fixed threshold. Table 1 reports the pairwise differences in the characteristics of chosen friends across these two setups.[50] When the rewards are rank-based, the selected study partner tends to have stronger academic performance such as a higher class rank or GPA. In terms of personality, students are more likely to choose peers who are more competitive and less cooperative, with less pronounced differences in other non-cognitive traits. These differences are statistically significant at the 5% level. This result also connects to the theoretical predictions on selective collaboration: under competition, the lower ranked student may want to choose a stronger partner, but the higher ranked student may not want to collaborate with someone weaker leading to no collaboration in equilibrium.

[49] Note that the homophily index is computed using observed nominations only. Some peers are missing from the analysis either because the student skipped the nomination question or because the nominated peer could not be matched to any student in my sample. Across study and friend networks, approximately 220 peers are missing. Consequently, the estimates reflect similarity among recoverable ties only. If observed ties exhibit stronger homophily, this may upwardly bias the index.

[50] Numbers are reported in Z-scores.

Table 1: Friend Choice In Hypothetical Contest: Characteristics

Characteristic	N	Rank-Based Choice	Threshold-Based Choice	Difference	p_Δ
Panel A: Academic Characteristics					
Rank	1139	0.634	0.407	0.227	0.000
GPA	1139	0.251	0.177	0.074	0.000
Study Time	1097	0.139	0.048	0.091	0.004
Panel B: Personality Traits					
Competitiveness	1114	0.134	0.061	0.073	0.044
Cooperativeness	1114	-0.126	-0.063	-0.063	0.092
Mental Health	1114	0.143	0.042	0.101	0.002
Openness	1114	0.029	-0.006	0.035	0.465
Conscientiousness	1114	0.228	0.069	0.159	0.000
Extraversion	1114	0.025	-0.004	0.030	0.446
Agreeableness	1114	0.036	0.045	-0.009	0.921
Neuroticism	1114	0.152	0.082	0.069	0.018

Notes: This table reports the average characteristics of the peers selected by students under two hypothetical reward scenarios. All variables are standardized.

Sub-fact (iii) is explored by examining students' nominations of nearby competitors within their friendship and study networks. Regression details and results are provided in Appendix C.1.2. The findings show that students at both the top and bottom of the rank distribution are less likely to include nearby competitors in their networks. Additionally, students in highly competitive schools are less likely to form connections with close competitors. These patterns may stem from two possible mechanisms: first, competition might create tension among close competitors, leading to avoidance; second, lower-ranked students might see limited learning benefits from nearby competitors, prompting similar behavior. The experimental design helps disentangle these mechanisms. Further heterogeneity analyses are presented in Appendix C.1.2.

Fact 2. *(**Study Motivation and Productivity**):*

(i) On average, students report higher productivity when studying individually, and higher motivation when studying with peers.

(ii) Higher academic rank and competitiveness are positively associated with self-reported motivation and productivity when studying alone, and negatively associated with these outcomes when studying with peers.

Sub-fact (i) is documented in Figure A9, which compares self-reported study motivation and productivity across different study modes. Sub-fact (ii) comes from regression analysis, with details and regression table results presented in Appendix C.2. A one-unit increase in self rank is associated with a 0.192 $(SE = 0.028)$ increase in motivation and a 0.211 $(SE = 0.038)$ increase in productivity when studying alone. The competitiveness index shows a similar pattern, with positive associations in the individual mode and negative ones in the peer mode. Specifically, competitiveness is associated with a 0.190 $(SE = 0.022)$ increase in motivation and a 0.162 $(SE = 0.030)$ increase in productivity when studying alone, but a -0.108 $(SE = 0.031)$ and -0.099 $(SE = 0.028)$ change in motivation and productivity, respectively, when studying with peers. In addition, students from low-competition schools report significantly lower outcomes when studying alone: -0.243 $(SE = 0.077)$ for motivation and -0.318 $(SE = 0.071)$ for productivity. These patterns suggest that peer learning affects both the production side and the cost (motivation) side of effort, which aligns with the model setup. The experiment design also creates exogenous variation to causally identify these effects. Students' beliefs about the return to effort provide additional support for the patterns in study productivity. Figure A10 shows the average expected score and rank as a function of study hours, differentiated by the ability level of the study partner. Students generally expect better outcomes both in scores and ranks when studying more hours, regardless of study mode. However, the perceived return is highest when paired with higher-ability peers, followed by equal-ability peers and studying alone (which are fairly similar), and lowest when paired with lower-ability peers. This pattern suggests that students' beliefs about peer learning opportunities are consistent with the belief formation reasoning assumed in the model.

The survey findings serve two purposes. First, they provide suggestive evidence that students respond to perceived competitiveness and external reward structures. Second, they highlight the need for exogenous variation in both peer composition and reward structures to identify the causal effects of competition on study behavior. This is crucial because, as suggested by the survey, students tend to form friendships based on both academic and noncognitive characteristics, and their friendship choices are influenced by the reward structure. Consequently, unobserved factors may correlate with both friendship choices and study behavior, potentially confounding the analysis.

3.4 Experiment Analysis

Building on the experimental findings, I focus on two primary dimensions. First, I analyze the treatment effects on behavior, specifically website engagement and peer interactions. Second, I evaluate the impact of the treatment arms on skill development, including academic learning gains and social skill outcomes.

3.4.1 Effort and Interaction Behaviors. I begin with a simple intent-to-treat (ITT) analysis to examine the impact of treatment arms on website activity.

Website Activity Across Arms & Study Modes—Table 2 reports students' login behavior across reward arms and study modes. The outcome is the number of days students logged into the website during the study period. The first row presents unconditional login frequency (including zeros). In both the *Control* and *Moderate* arms, login frequency is higher in the *Pair* mode compared to the *Individual* mode, 1.245 vs. 1.041 in *Control*, and 1.352 vs. 1.038 in *Moderate*. The difference is more pronounced in the *Moderate* arm ($p = 0.196$), suggesting that moderate competition does not necessarily crowd out peer learning. In contrast, in the *Intense* arm, the pattern reverses: students in the *Pair* mode logged in less often than those in the *Individual* mode, 1.270 vs. 1.667. While this difference is not statistically significant ($p = 0.378$), it is suggestive of a potential crowding-out effect of intense competition on peer collaboration. Importantly, these differences are largely driven by the extensive margin. The third row shows that the fraction of students who ever logged in ranges from roughly 0.38 to 0.49 across all arms and study modes. For example, in the *Intense* arm, 49.3% of students in the *Individual* mode logged in at least once, compared to only 42.9% in the *Pair* mode. When we condition on logging in (second row), the intensive margin patterns largely mirror the unconditional results. For instance, mean login days among those who ever logged in is highest in the *Intense-Individual* group (3.378), followed by *Moderate-Pair* group (3.085). This suggests that high-stakes competition may increase individual effort but does not enhance peer effort in a comparable way. Overall, these results support Proposition 1 in the theory section: as competition intensifies, peer interaction diminishes, reducing the share of pairs with positive p

at the extensive margin. These findings are robust to the introduction of the pair bonus, as shown in Table A13. Even before the bonus was introduced, login activity in the *Pair* mode exceeded that in *Individual* mode in the *Control* and *Moderate* arms, but not in the *Intense* arm.

Table 2: Web Engagement by Reward Arm and Study Mode

	Control			Moderate			Intense		
	Ind	Pair	p_Δ	Ind	Pair	p_Δ	Ind	Pair	p_Δ
Mean Days Logged In	1.041	1.245	0.932	1.038	1.352	0.196	1.667	1.270	0.378
	(0.187)	(0.160)		(0.191)	(0.157)		(0.312)	(0.161)	
Mean Days (If Logged In)	2.372	3.137	0.051	2.619	3.085	0.029	3.378	2.957	0.973
	(0.329)	(0.286)		(0.366)	(0.232)		(0.493)	(0.262)	
Fraction Ever Logged In	0.439	0.397		0.396	0.438		0.493	0.429	
N	98	184		106	162		75	163	

Notes: This table reports login behavior across study mode and reward arms. "Mean Days Logged In" refers to the average number of days students logged into the platform, including zeros. "Mean Days-If Logged In" is conditional on students who logged in at least once. "Fraction Ever Logged In" indicates the share of students who logged in at least once. The p_Δ column shows the p-value from a Mann-Whitney U test comparing the means between Individual and Pair modes within each reward arm. Standard errors are in parentheses.

To account for zeros and to control for other characteristics, I run a regression analysis using negative binomial models. Table 3 presents the regression results. I estimate two models: OLS, and Negative Binomial (NB) to analyze website log-in behavior.[51] The Model 4 includes classroom fixed effects to absorb any unobserved heterogeneity at the classroom level such as differences in teacher quality or classroom dynamics. This is particularly relevant in my context, since some classrooms may have systematically lower participation or engagement with the project.

According to the Negative Binomial results, in the *Control* group, the log-in frequency in the *Pair* mode is higher compared to the *Individual* mode across all three models, although this difference is not statistically significant. In the *Moderate* arm, however, the log-in frequency is significantly higher in the *Pair* mode relative to the *Individual* mode at the 5% level (see Columns 3 and 4). In the *Intense* arm, the log-in frequency is lower in the *Pair* mode compared to the *Individual* mode, particularly evident in Column 2. In terms of student heterogeneity, as we move from Panel A to Panel C, the coefficient on *Female* decreases while remaining positive (e.g., from 0.576 in Column 2 of Panel A to 0.120 in Column 2 of Panel C). With a log link function, this corresponds to a change in expected log-in frequency from approximately $\exp(0.576) \approx 1.78$ (or 78% higher) to $\exp(0.120) \approx 1.13$ (or 13% higher). This pattern suggests that while female students are more engaged with the platform overall, their engagement declines as competitive intensity increases. Finally, the baseline score is positively associated with log-in frequency across all arms and specifications, with consistent coefficient magnitudes around 0.08. This implies roughly an 8% increase in log-in frequency per unit increase in baseline score, under the log link function.

From the above analysis across arms, we see that when members of a *Pair* are close to the margin of winning a prize, their engagement strategies shift. A closer look at the *Moderate* competition

[51] Given that nearly half the population did not log in, the data contains many zeros. To test whether these zeros are structural, I run a Zero-Inflated Negative Binomial (ZINB) model, which allows for an excess zero-inflation process. However, the inflation constant is not significantly different from zero. The NB model provides a better fit, while OLS is included for comparison, showing a poorer fit due to the discrete and right-skewed nature of the outcome. A full table including ZINB model is given in Table OA.7.

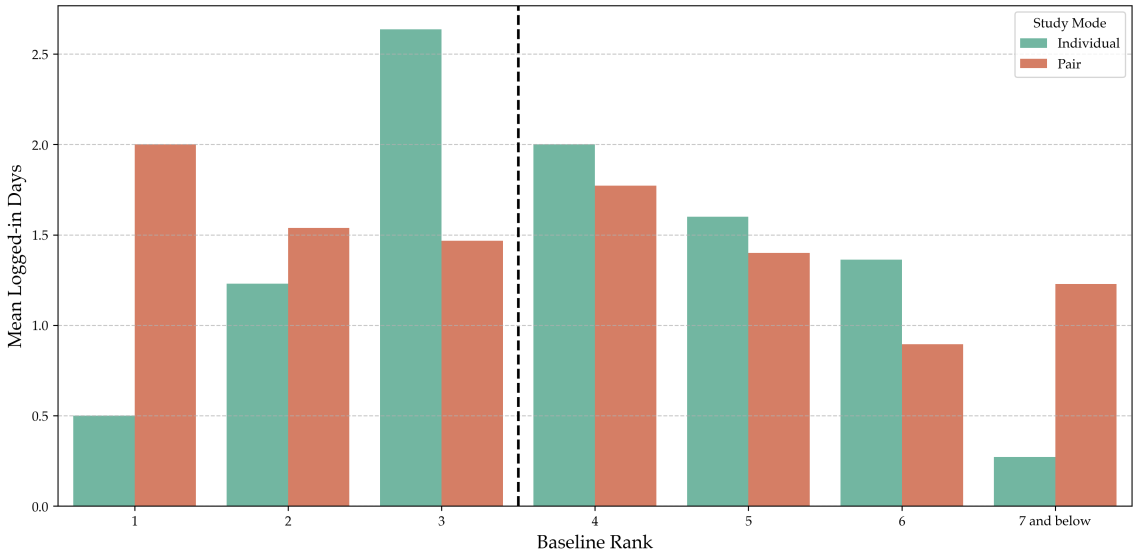
Table 3: Website Activity: Regression Results

	OLS				Negative Binomial			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel A: Control								
Constant	1.041***	0.818***	0.118	-0.390	0.040	-0.154	-0.858***	-1.422*
	(0.210)	(0.239)	(0.285)	(0.941)	(0.141)	(0.166)	(0.217)	(0.805)
Pair	0.204	0.148	0.167	0.248	0.179	0.099	0.144	0.225
	(0.260)	(0.260)	(0.252)	(0.274)	(0.173)	(0.174)	(0.179)	(0.211)
Female		0.474*	0.645***	0.567**		0.415**	0.576***	0.408**
		(0.249)	(0.245)	(0.261)		(0.167)	(0.174)	(0.202)
Base Score			0.097***	0.116***			0.081***	0.086***
			(0.023)	(0.042)			(0.015)	(0.030)
N	282	282	282	282	282	282	282	282
Classroom FE	No	No	No	Yes	No	No	No	Yes
Log-Likelihood	-605.016	-603.192	-594.372	-560.762	-422.403	-419.383	-405.817	-357.287
Panel B: Moderate								
Constant	1.038***	0.986***	0.215	0.781	0.037	-0.010	-0.780***	-0.264
	(0.194)	(0.253)	(0.293)	(0.734)	(0.136)	(0.176)	(0.230)	(0.520)
Pair	0.314	0.324	0.334	0.412	0.264	0.274	0.354**	0.538**
	(0.249)	(0.252)	(0.242)	(0.269)	(0.171)	(0.172)	(0.178)	(0.222)
Female		0.080	0.171	0.286		0.070	0.156	0.101
		(0.249)	(0.241)	(0.271)		(0.168)	(0.174)	(0.213)
Base Score			0.101***	0.109***			0.081***	0.084***
			(0.021)	(0.040)			(0.015)	(0.031)
N	268	268	268	268	268	268	268	268
Classroom FE	No	No	No	Yes	No	No	No	Yes
Log-Likelihood	-564.631	-564.579	-553.723	-522.931	-409.492	-409.405	-394.577	-340.639
Panel C: Intense								
Constant	1.667***	1.633***	0.708*	1.491*	0.511***	0.478***	-0.209	0.276
	(0.264)	(0.318)	(0.370)	(0.901)	(0.146)	(0.178)	(0.229)	(0.571)
Pair	-0.397	-0.396	-0.187	-0.260	-0.272	-0.276	-0.135	-0.138
	(0.319)	(0.320)	(0.311)	(0.329)	(0.180)	(0.180)	(0.186)	(0.232)
Female		0.057	0.066	0.057		0.062	0.120	0.223
		(0.301)	(0.289)	(0.296)		(0.173)	(0.177)	(0.214)
Base Score			0.121***	0.068			0.073***	0.045
			(0.027)	(0.052)			(0.016)	(0.037)
N	238	238	238	238	238	238	238	238
Classroom FE	No	No	No	Yes	No	No	No	Yes
Log-Likelihood	-533.434	-533.416	-523.709	-480.564	-386.155	-386.091	-374.220	-320.215

Notes: This table reports regression results for student login behavior across reward arms. The dependent variable is the number of days a student logged into the website. Columns (1)–(4) use OLS; columns (1)–(3) exclude classroom fixed effects, while column (4) includes them. Columns (1)–(4) under NB use negative binomial regressions with the same structure. "Pair" is an indicator for pair-mode assignment. "Base Score" refers to the student's baseline academic performance. Standard errors are in parentheses.

arm reveals a similar pattern and can be directly related to Proposition 3 in the theoretical model. As a reminder, in the *Moderate* arm, 10 students compete for 3 equal prizes. Figure 5 plots the mean number of days logged in against students' baseline exam rank. Two key patterns are observed. First, effort levels are highest near the prize cutoff. Second, there is a shift in the form of effort: *individual* study increases sharply near the margin, while *peer* learning is higher both above and below the cutoff, i.e. far from the margin. This suggests that students allocate effort differently depending on their relative position in the rank distribution. Even though the sample size per rank group is smaller in the *Moderate* arm, we observe the same strategic response as in the *Intense* arm for those near the margin.[52] Taken together, these patterns suggest that the degree to which students respond to competition depends on how close they are to the threshold for winning a prize.

Figure 5: Mean Days Logged-in by Baseline Rank



Notes: This figure shows the average logged-in days against rank from baseline exam. The vertical dashed line indicates the margin of winning a prize. The difference in the mean logged-in days between *Individual* and *Pair* modes is statistically significant at the 10% level for above (1-2), around (3-5) and below the margin (6-10), using permutation test with 10000 samples.

While log-in data provides insights into students' engagement, it does not capture the intensity of their study efforts. To address this, I analyze the time spent on the website as a measure of effort following C. S. Cotton et al. (2022). First, I calculate the total time spent on the website by each student. Time measurement is at the page level and I got time measures on different activities. A difficulty in measuring time spent on the website is that students can leave the website open without actively engaging with it.[53] To address this, I chose a truncation point after which a hole occurs in the support of the time spent distribution. Appendix D.1 provides the details on how I calculate website time spent.

For regression analysis, I run the following specification for each reward arm separately: $\log(\text{TimeSpent}_i) = \alpha + \beta_1 Pair_i + \beta_2 \text{BaselineScore}_i + \beta_3 X + \varepsilon_i$ The results on the time spent on the website are presented in Table A8. The patterns follow similar trends as the log-in frequency.

[52] The patterns are robust to *Pair* bonus. See Figure A12.
[53] Automatic session timeout was set to two hours.

Peer Interactions: Chat Frequency— The previous subsection compared study modes within each arm. The focus now shifts to comparing the *Pair* mode across arms. The website used in the experiment has a chat feature for collaboration, which allows students to communicate with their study peer over the study material. Table 4 reports a descriptive analysis of chat messages across treatment arms. The results suggest that the chat activity is highest in the *Moderate* arm, with the *Intense* arm showing the lowest activity. The differences are tested using Mann Whitney U tests, which show that the differences in unconditional chat messages across Control and Moderate as well as Moderate and Intense are significant at the 10% level. At the extensive margin, I observe that the fraction of students who ever texted their matched peer is highest in the *Moderate* arm (0.347) and lowest in the *Intense* arm (0.279). Notably, pairwise comparisons between the *Moderate* arm and both the Control and Intense arms reveal significant differences at the 10% level.

A similar pattern can be observed when we take a closer look at the *Moderate* arm. Figure 6 provides a breakdown of the fraction of students who ever sent a message in this arm, by their baseline exam rank. The interaction rate shows a decrease as we approach the margin, followed by an increase at the extremes - with approximately 60% of top-ranked students and over 30% of bottom-ranked students attempted to chat.

Table 4: Descriptive Statistics: Chat Interaction (*Pair* Mode Only)

	Values			p_Δ		
	Control	Moderate	Intense	C vs. M	C vs. I	M vs. I
Chat Messages	4.818	6.535	3.735	0.108	0.975	0.096
	(1.325)	(1.740)	(0.845)			
Chat Messages - Conditional	41.931	47.850	29.968	0.752	0.807	0.737
	(10.168)	(11.728)	(5.448)			
Fraction Ever Messaged	0.281	0.347	0.279	0.092	1.000	0.090

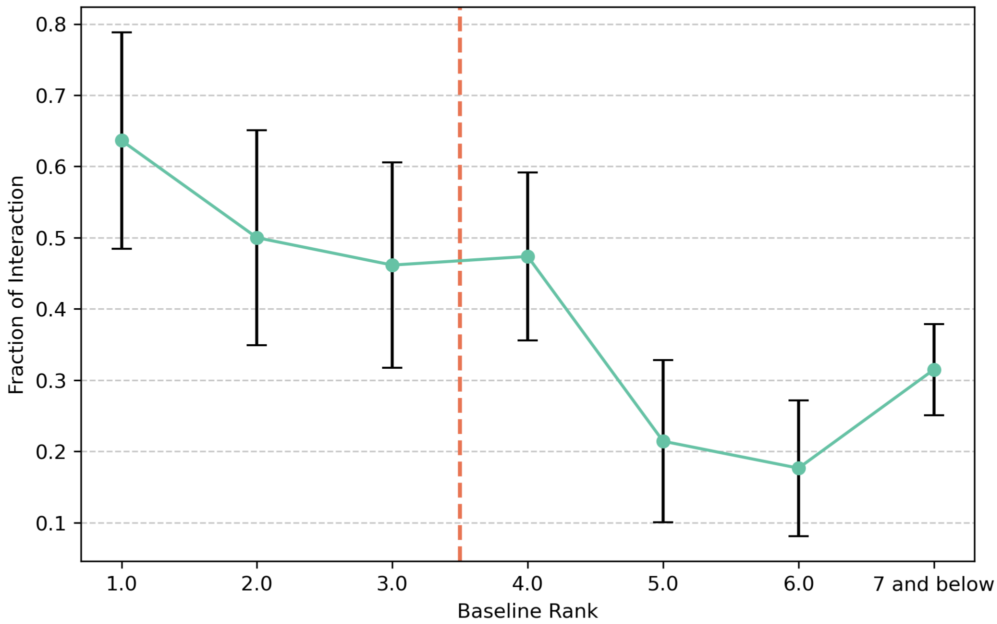
Notes: This table reports chat interaction statistics among students in the *Pair* mode, across the three reward arms. “Chat Messages” refers to the average number of messages sent per student, including zeros. “Chat Messages – Conditional” restricts to those who sent at least one message. “Fraction Ever Messaged” show the share of students who sent at least one message. Standard errors are in parentheses. The final three columns report p-values from Mann–Whitney U tests comparing the means between reward arms.

It’s important to note that these metrics do not suggest that participants in the Intense arm avoided using the website. Rather, they logged in but spent less time engaging in real-time chat. Table A9 shows the distribution of students across different web engagement categories The Intense arm had the highest proportion (0.15) of students who Logged in but did not chat, while the Moderate arm showed the highest proportion (0.35) among those who were both logged in and attempted to chat. This indicates that students in the Intense arm engaged with the website but less through peer study. This observation aligns with Proposition 1.[54]

Peer Interactions: LLM Chat Labeling— Besides the frequency of chat messages, I also analyze the content of the chat data to understand the nature of interactions between students. The chat

[54] Students who received a reply from their partner had an average of 2.11 login days, compared to 0.61 login days for those who did not receive a reply.

Figure 6: Fraction of Interaction by Baseline Rank



Notes: This figure shows the fraction of interaction against rank from baseline exam. The vertical dashed line indicates the margin of winning a prize. The black bars show the 95% confidence intervals.

data is fully anonymous, as all interactions and peer matching remain anonymous. To classify textual data, I employ large language model (LLM) classification, fine-tuned specifically for this task. The implementation leverages Together AI's serverless API for inference.[55] I use a few-shot learning approach with LLM to classify chat messages into pre-defined categories.[56] Additional details on training/validation of the prompt and the output processing can be found in Appendix D.4. Table 5 shows the summary of chat data across treatment arms. There are four labels: Cooperative Language, Task Related Content, Anonymity Risk, and Prize Related content.[57] The numbers suggest that cooperative language is highest in the Control arm when competition doesn't exist.[58] These patterns are also validated in the final survey such that students were asked to report their assigned peer's characteristics. Table 8 shows the summary of peer characteristics reported by students in the final survey. The results suggest that cooperative and prosocial behaviors are lowest in the Intense competition arm.

Peer Type and Web Engagement— To explore whether website engagement behavior is influenced by peer ability type, I conduct the following analysis. Among students assigned to the *Pair* mode, I, first, categorize peers based on their baseline exam scores into two groups: peers

[55] Note that the data is already designed to be anonymous. However, to further ensure privacy, no data is permitted to be used by either DeepSeek/Meta or Together AI, the former due to the open-source nature of the models, and Together AI, due to the API agreement.

[56] I provide the LLM with a structured prompt, engineered for this task, that includes a few examples of the categories and their definitions to guide its classification decisions. Each message is classified into binary categories. The full prompt can be found in the Appendix D.4.

[57] Task Related label includes both math-related discussions as well as technical content such as discussions on what quiz to discuss or how to submit the answers.

[58] However, the differences between arms across categories do not reach statistical significance at conventional levels based on Mann–Whitney U tests.

Table 5: LLM Chat Analysis

	Control		Moderate		Intense	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Coop. Language	0.183	0.285	0.129	0.217	0.138	0.227
Task Related	0.426	0.333	0.381	0.336	0.438	0.337
Anonymity Risk	0.051	0.142	0.057	0.146	0.080	0.190
Prize Related	0.001	0.006	0.004	0.033	0.004	0.017
Total Messages	1260		1863		814	
N	77 (0.28)		106 (0.34)		74 (0.27)	

Notes: This table reports means and standard deviations of LLM-assigned labels per user. "Total Messages" is the aggregate across all users in an arm. "N" is the number of users who sent messages, with proportions relative to all users in parentheses.

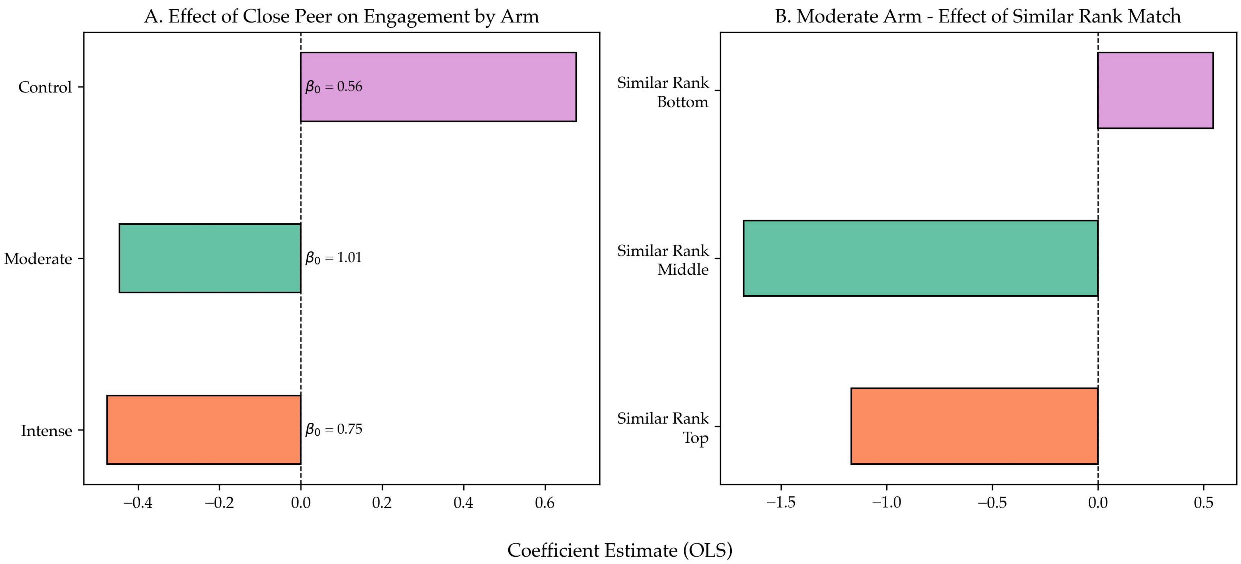
whose baseline score difference is at most 1 point (close peers) and those whose score difference is greater than 1 point (distant peers). Panel A of Figure 7 presents the β_1 value from the regression $y_i = \beta_0 + \beta_1 \times$ Similar Peer $+ \beta_3$Base. Score $+ \varepsilon_i$, where y_i is the web log-in frequency for student i and Similar Peer is a dummy variable equal to 1 if student i has a peer with a baseline score within 1 point of their score. The regression is run separately for each arm.[59] Results suggest that in the absence of competition, having a close peer is associated 0.677 more logged-in days in the Control arm. The higher the competition, the less likely a student is to log in when they have a close peer, -0.446 in the Moderate arm and -0.476 in the Intense arm. Panel B, on the other hand shows the interaction coefficients from the regression $y_i = \beta_0 + \beta_1 \times$Similar Rank$+\beta_2\times$RankGroup$+\beta_3\times$Similar Rank$\times$RankGroup$+\beta_4$Base. Score$+\varepsilon_i$, where Similar Rank is a dummy variable equal to 1 if student i and her pair are in the same rank group in the *Moderate* arm. Accordingly, in the Moderate arm, students around the margin of winning a prize are less likely to log in (< -1.5) when they have a peer with the similar rank.[60]

In addition, Table 6 shows chat patterns by initiator and responder roles.[61] I break the results down by whether the student scored lower or higher than their teammate. Students with higher scores are more likely to initiate and respond to chats. Those with lower scores are less likely to start the conversation but more likely to respond when their partner does. Across the performance categories, initiation and response rates are generally highest in the *Moderate* arm, except for one case where the response rate for *Control* is highest when the lower-ranked student initiates.

Quiz Attempts and Other Activities— During the 10-day period, a total of $1,467$ quizzes and $8,529$ questions were individually attempted, and 128 quizzes / 826 questions were attempted by *Pair*s. Additionally, the guide/training pages were visited 514 times, and quiz results were viewed 510 times. On average, students reported an effort level of 4.39 (on a scale of 1 to 10) in response to the question displayed after each quiz attempt, as given in Figure A3.

[59] Table A10 provides the full regression results.
[60] These results should be interpreted as suggestive due to low precision of the estimates. Full results are available in Table A11. More discussion can be found in Appendix D.3.
[61] The website chat data records the date/time for each message sent, from which I can tell the order of the messages.

Figure 7: Peer Similarity and Website Activity



Notes: Panel A presents OLS coefficients from regressions of website log-in on peer similarity defined by score similarity across reward arms. Panel B displays OLS coefficients from regression of website log in on peer similarity defined by rank similarity for the Moderate arm only.

Table 6: Chat Behavior by Relative Performance and Reward Arm

Lower Performer	**Treatment Arm**	**Initiated (%)**	**Responded (%)**	**N**
	Control	26.2	21.1	145
No	Intense	25.7	13.9	140
	Moderate	30.7	30.0	163
	Control	18.6	41.7	129
Yes	Intense	17.4	39.1	132
	Moderate	23.8	30.6	151

Notes: “Initiated (%)” is the fraction of all participants who initiated a message. “Responded (%)” is the fraction of initiators who received a response.

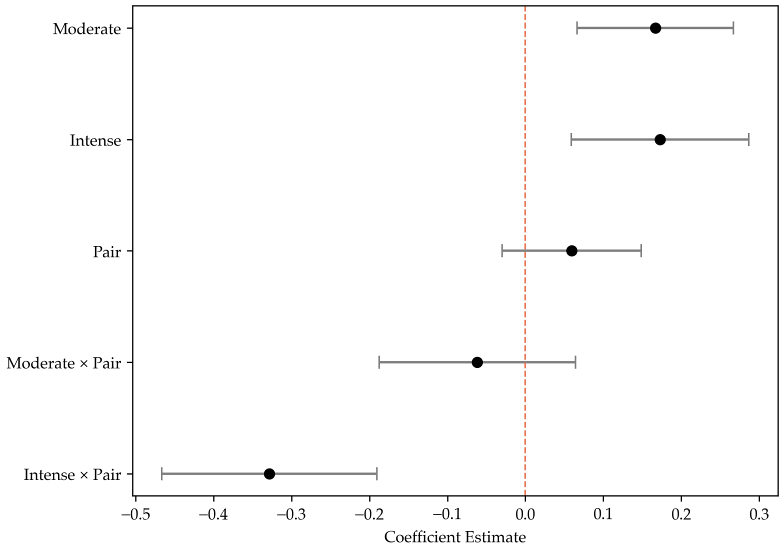
3.4.2 Learning Outcomes. Table A15 displays descriptive statistics of pre- and post-in-classroom exam results for the entire population, as well as broken down by effort investment status. The mean baseline score is 6.53, with investors (subjects who log in to the website at least once) having a higher mean score of 8.49. The mean final exam score is 7.34, with investors achieving a higher mean score of 9.43. Table A16 shows the correlation between baseline and final exam scores by arm and study mode. In both the Control and Moderate arms, the correlation is similar for both *Individual* and *Pair* study modes. However, in the Intense arm, the correlation is higher for the *Individual* mode compared to the *Pair* mode. This suggests that competition and peer learning affect student evaluation and sorting.

Figure 8 presents the regression results for the final exam score. I estimate the following specification: $Y_i = \beta_0 + \beta_1\text{Moderate} + \beta_2\text{Intense} + \beta_3\text{Pair} + \beta_4\text{ModeratePair} + \beta_5\text{IntensePair} + X_i + \epsilon_i$.[62] Prior to the analysis, baseline and final exam scores were standardized to have a mean of zero and a standard deviation of one. The omitted category is the *Control-Individual* group. The results reveal several key patterns in learning outcomes across treatment arms and study modes. First, both reward arms have a positive effect on performance. In the fully saturated specification, baseline achievement is a strong predictor of final score and accounts for a large share of the R^2. Students in the *Moderate* arm, when assigned to the *Individual* study mode, score about 0.17 standard deviations higher than those in the *Control* arm. A similar effect size is observed for the *Intense* arm, with a gain of approximately 0.18 standard deviations. The *Pair* mode alone does not have a significant effect. However, this masks important heterogeneity, which I explore later by student ability group. Most notably, when the *Intense* treatment is implemented in the *Pair* mode, student performance decreases substantially. The final exam score in this group is about 0.33 standard deviations lower than in the *Intense-Individual* group, and roughly equal to the *Control* mean. In other words, intense competition appears to backfire when students are paired, eliminating the gains observed under individual study. Gender differences in test scores are small and imprecisely estimated. The full regression table is provided in Table A18. In summary, the *Moderate* reward arm leads to modest learning gains. The *Intense* reward arm improves learning only under individual study mode, and reduces performance when implemented in pair-based study. While these results are specifically focusing on final outcome by aggregating all exam items, I also conduct a more detailed analysis at the item level to account for potential differences in exam difficulty and explain heterogeneity by question types. Specifically, Table A19 presents results from a linear probability model using item-level response data. The outcomes are binary indicators for whether a question was attempted or not, and whether it was answered correctly or not. Results are reported separately for two question types: memory-based and analytical questions. As before, competition shapes outcomes across both domains. The *Moderate* treatment increases *analytical correctness* by 6.4 percentage points, though it has no significant effect on the likelihood of attempting questions. It also does not significantly affect memory-related outcomes. The *Intense* treatment has stronger effects, raising *attempt rates* by 11.4 pp for analytical and 5.4 pp for memory questions. However, while it improves *analytical correctness* by 3.9 pp, it has a *negative effect on memory correctness*, reducing it by 5.3 pp. Studying in *Pairs*, in isolation, has a modest positive effect, improving *analytical correctness* by 4.2 pp, with no significant effects on other outcomes. The interaction terms reveal

[62] As shown in Table A17, there are small differences in final exam participation across treatment arms, which could bias the outcome regressions. I estimate a probit selection model for exam participation and include the associated inverse Mills ratio in the outcome regression. The likelihood ratio test for the selection equation is not significant ($p = .20$), and the coefficient on the Mills ratio is also not statistically significant. I therefore proceed with OLS estimates for an intent-to-treat interpretation.

more nuanced effects: the *Intense* $\times$ *Pair* combination has large *negative impacts*, particularly on *analytical attempt* (-9.8 pp) and *analytical correctness* (-8.9 pp), as well as *memory attempt* (-5.8 pp). These findings suggest that intense competition can backfire in team settings. All specifications include controls for prior exam attempt and correctness in the same domain, along with classroom and question fixed effects.

Figure 8: Final Exam Regression Coefficients



Notes: This figure displays coefficient estimates from the regression of standardized final exam score on treatment arm and study mode indicators, controlling for baseline exam score and gender. The omitted category is *Control - Individual*. The markers show point estimates, and the horizontal lines represent 95% confidence intervals. Baseline and final exam scores are standardized to have a mean of zero and a standard deviation of one.

Who Learns More? Under Which Conditions? Beyond the basic regression analysis, I also investigate which peer matching produce higher scores by focusing exclusively on the *Pair* study mode. Table 7 examines whether being assigned to a peer with a similar baseline score affects final exam performance. In the *Control* arm, the coefficient on *Similar Peer* is positive (0.057), suggesting a small gain of about 0.06 standard deviations, though not statistically significant. In the *Moderate* arm, the effect is close to zero (-0.036), while in the *Intense* arm, it turns negative (-0.188), possibly indicating that similarity under high competition may crowd out learning. The interaction term (*Similar* $\times$ *Baseline*) is positive in the *Moderate* arm (0.250) but negative in the *Intense* arm (-0.305), implying that higher baseline score students benefit more from similar peers under moderate incentives, but may be negatively affected in more competitive environments.

3.4.3 Social Skills. Competition and peer interactions are not only inputs to academic skills production but may also shape the development of social skills. As shown earlier, at the intensive margin (among those who actually interacted with their peers), the use of cooperative language is suggestively lower in the competition arms than in the Control arm. If one believes that students with lower cooperativeness are also less likely to engage with peers, the true gap might be even wider. In addition, students were asked to evaluate their assigned peer's social behavior in the final survey. Table 8 summarizes these peer-perceived ratings across treatment arms. Suggestively, peer-rated social behavior is lowest in the *Intense* arm: for example, the average cooperativeness rating is 3.35 compared to 4.07 in the *Control* arm. The pattern is similar for prosociality (3.47 vs.

Table 7: Effect of Close Peer Assignment on Final Score

	Control	Moderate	Intense
Similar Peer	0.057	-0.036	-0.188
	(0.127)	(0.142)	(0.173)
Base. Score	0.677***	0.792***	0.638***
	(0.051)	(0.065)	(0.071)
Similar x Base. Score	0.196	0.250	-0.305
	(0.193)	(0.173)	(0.253)
Constant	0.014	0.158**	-0.127*
	(0.056)	(0.072)	(0.076)
N	159	121	144

Notes: Dependent variable is final score (standardized). Close Peer is an indicator for whether the absolute score gap to a peer is at most 1 points.

3.89), and promptness is also lowest in the Intense arm. Interestingly, the *Moderate* arm has slightly higher ratings than Control in some domains (e.g., promptness at 3.65 vs. 3.29), but lower in others. These patterns suggest that more intense competition may crowd out prosocial behavior, at least in peer-perceived terms.[63] Regression results that pool all characteristics and run on treatment are shown in Table A20.

Table 8: Assigned Peer's Characteristics

	Cooperativeness	Prosociality	Promptness	Friendliness	N
Control	4.071	3.893	3.286	4.643	44
Moderate	3.742	3.806	3.645	4.774	49
Intense	3.353	3.471	2.941	4.588	27

Notes: This table summarizes students' reported perceptions of their assigned peers' characteristics across treatment arms. Pairwise comparisons between arms were conducted using Mann-Whitney tests, with no statistically significant differences observed. All characteristics were rated on a Likert scale ranging from 1 to 10, where 1 represents "Very Low" and 10 represents "Very High".

3.4.4 External Validity. Although the experiment was conducted in Turkish Grade 10 classrooms, similar high-stakes contest environments exist in many education systems around the world such as China's Gaokao, India's JEE, and selective college admissions in the United States. The core mechanism, where rank-based incentives increase the marginal return to individual effort while crowding out peer interactions, is likely to be relevant in any setting with relative grading. That said, the magnitude of the estimated effects may differ across contexts, as cultural norms, institutional features, and social expectations around competition and collaboration vary. These contextual differences may limit the direct generalizability of the results. To explore this further,

[63] Note that the final survey response rate is around 30%, and slightly lower in the *Intense* arm. To assess robustness to selective survey attrition, I compute Lee (2009) bounds on treatment effects, which account for differential response rates across arms. The method assumes monotonic selection which is competition weakly decreases the probability of response and that nonresponse comes from the lower tail of the outcome distribution. Bounds are constructed by trimming the control group to match the lower response rate in treatment arms. Under these assumptions, the treatment effect of the *Intense* arm relative to *Control* on peer-rated cooperativeness lies in $[-6.62, 1.38]$; for *Moderate* vs. *Control*, the bounds are $[-6.18, 2.82]$. Similar ranges are found for prosociality and friendliness. These intervals are tighter than Manski (worst-case) bounds and suggest the main conclusions are qualitatively robust to selection under monotonicity.

the post-estimation counterfactual analysis incorporates the method proposed by Gechter (2024) to bound the skill production function in both the U.S. and Chinese settings, providing a structured way to assess external validity. Regarding time horizon related external validity, the experiment I conducted covers ten days of exam preparation. However, high school students typically prepare for the exam for a longer period, ranging from 1 to 4 years until college. Accordingly, the estimates should be interpreted as *local in time*. Absent long run panel data I cannot pin down which force dominates. A full dynamic simulation, extending the structural model with discounting and habit formation, is left for future work.

3.5 Discussion of Experimental Findings

Before proceeding to the model estimation, it is useful to clarify how the experimental findings will inform the modeling process. Based on the above analysis, I outline the key findings that will be incorporated into the model estimation in the following section.

Experimental Finding 1. *Study efforts overall respond to the reward structure: higher competition leads to increased effort levels. The allocation of effort is shaped by the reward structure. Intense competition is associated with reduced peer interaction and lower levels of peer learning.*

Experimental Finding 2. *The effect of competition on study behavior varies with peer composition. In particular, closer peer matches experience reduced peer interaction under intense competition.*

Experimental Finding 3. *Skill production is influenced by both the reward structure and study mode. Learning gains are lowest under intense competition when students study in pairs. Social skills are also negatively affected by intense competition.*

4 Empirical Model Identification and Estimation

This section provides an empirical counterpart to the theoretical framework outlined in Section 2, aiming to estimate the core model primitives and parameters to inform policy counterfactuals. The empirical model incorporates three key extensions: first, it accounts for multidimensional student heterogeneity, including preferences for scores, prizes, and cost types. This addition serves two purposes: to better explain the experimental data patterns and to enable more targeted counterfactual analyses. Second, it adopts a parametric approximation to the solution concept for computational tractability. Lastly, it introduces fixed effort costs to capture extensive margin decisions, along with ability-type-specific cost heterogeneity. The following subsections detail the empirical specifications, identification strategy, and estimation results.

4.1 Empirical Specifications

I specify production, utility and cost functions and the contest structure before I move on the model estimation. In addition, I define an approximated solution concept for estimation efficiency.

Production Function — I parametrize the score production function as a log-linear form:

$$\ln S_i = \beta_0 + \underbrace{\beta_1 \ln a_i}_{\text{Own Ability}} + \underbrace{\beta_2 \cdot \tilde{e}_i}_{\text{Individual Effort}} + \underbrace{\beta_3 \cdot (\tilde{e}_i)^2}_{\text{Dim. Returns}} + \sum_{j=1}^{N} \underbrace{\mathcal{A}(i,j) \cdot \tilde{p}_i \cdot (\beta_4 + \beta_5 d_{ji} + \beta_6 \ln a_i \cdot d_{ji})}_{\text{Peer Spillovers}} + \varepsilon_i \quad (10)$$

where $\mathcal{A}(i,j)$ is the binary exogenous assignment mechanism, $d_{ji} = \max\{\ln a_j - \ln a_i, 0\}$ represents the ability gap between student j and i, and $\tilde{p}_i$ denotes the effective peer interaction effort.[64] Effective peer interaction effort is defined as the minimum interaction level between paired peers. Specifically, if i attempts peer interaction ($p_i > 0$) but their paired peer does not interact ($p_j = 0$), then the effective peer interaction effort is zero, $\tilde{p}_i = 0$.[65] To handle the mass at zero, effort inputs are transformed using the inverse hyperbolic sine function: $\tilde{e}_i = \text{asinh}(e_i)$ and $\tilde{p}_i = \text{asinh}(\min\{p_i, p_j\})$.

Preferences — I assume a quasi-linear utility function as follows:

$$u(S_i, P_i) = \underbrace{\eta_i \log(S_i)}_{\text{Intrinsic value}} + \underbrace{\nu_i P_i}_{\text{Extrinsic value}} \tag{11}$$

The first part of the utility captures intrinsic value of achievement and the second part captures the extrinsic value of the prize. The reason to include the prize linearly is that classroom prizes are typically small relative to lifetime wealth and I assume that students behave locally risk neutral in dollars. The difference in utility between *Reward Arm*s equals a dollar amount, which makes the interpretation easier. Students can trade off score and money at the margin, via the η/ν ratio, to be decided by the data. The taste parameters allow for differential value put on scores and prizes by different students. The intrinsic value of scores, η_i, and its distribution is calibrated using the baseline survey as described below. The extrinsic value of the prize, ν_i, is to be estimated within the model and I assume it varies with family income type (*Low income*, *High income*) and ability type (*Low ability*, *High ability*).[66] The choice of ability and income type-specific money taste serves two key purposes. First, it improves the model fit and estimation precision. Second, it enables the design and evaluation of group-targeted counterfactual policies.

Cost Function — I specify the cost of efforts $j \in \{e, p\}$ for individual i as follows:

$$C_i(e_i, p_i) = \underbrace{\frac{\theta_i}{\gamma}(e_i + \xi p_i)^{\gamma}}_{\text{Convex cost of total input}} + \underbrace{\Gamma_{eg}\mathbf{1}_{\{e_i>0\}}}_{\text{Fixed cost of individual effort}} + \underbrace{\Gamma_{pg}\mathbf{1}_{\{p_i>0\}}}_{\text{Fixed cost of peer interaction}} \tag{12}$$

where γ is the curvature parameter governing the common cost schedule. The terms Γ_{eg} and Γ_{pg} represent fixed (start-up) costs associated with initiating individual effort and peer interaction effort, respectively, for students of ability type g. Intuitively, at the extensive margin, a student chooses to exert effort or engage in peer interaction if and only if the expected net benefit exceeds the relevant fixed cost. The parameter ξ captures the relative cost weight of peer interaction effort: when $\xi > 1$, peer learning is more costly than individual learning, and vice versa when $\xi < 1$. The term θ_i represents an individual-specific cost parameter that captures unobserved heterogeneity in the disutility of effort. Cost types are assumed to be drawn from a log-normal distribution, such that $\ln \theta_i \mid g_i = g \sim \mathcal{N}(\mu_{\theta g}, \sigma^2_{\theta g})$, where $g \in L, H$ denotes the student's ability type.

[64] For those who are in the *Individual* study mode in the experiment, $\mathcal{A}(i,j) = 0$ for all $j \in \{1, \ldots, N\}$.

[65] Similarly, even if both p_i and p_j are positive, if no actual interaction occurs, the effective peer interaction effort remains zero.

[66] Ability types are defined based on the median of baseline scores.

Reward Structures — I will use all the experimental reward structures as exogenous variables. Specifically, Column 4 in Table A23 shows the utilities in each arm. Let $r \in \{C, M, I\}$ index the three experimental arms:[67] In the *Control* arm, each point of score pays a constant rate $b =$ ৳$20, S_i \leq 25$. The monetary payoff is therefore, $P_i^C = bS_i$. In the *Moderate* competition arm, $G = 10$ and $K = 3$. The top–3 performers receive the fixed prize $B =$ ৳500. The monetary payoff is given by $P_i^M = B\, \mathbf{1}_{\{S_i \geq S_{(10,3)}\}}$. In the *Intense* competition arm, $G = 2$ and $K = 1$. The top–1 performer receives the fixed prize $B =$ ৳500. The monetary payoff is given by $P_i^I = B\, \mathbf{1}_{\{S_i \geq S_{(2,1)}\}}$.[68]

Approximated Solution Concept — In the Theory Section 2, I presented comparative statics results based on the Bayesian Nash Equilibrium. Note that when I move theory to structural estimation, each agent's best response depends on the joint distribution of other players, which requires integrating over multidimensional heterogeneity as well as student peer matches inside every simulated moment evaluation, possibly making the computation intractable. Following Tincani et al. (2023) which uses an approximation to the true equilibrium in a similar context, I posit a parametric approximation to the probability of winning in contest, $P_i^w(S_i \geq S_{(N,k)})$, such that the suggested form is in line with the theoretical results. It is only through this probability that others' (e_{-i}^*, p_{-i}^*) choices affect the payoff of student i. I denote the parametric approximation as $\tilde{P}_i^w(e_i, p_i; \boldsymbol{\delta})$, where the parameter $\boldsymbol{\delta}$ captures the strategy profile of other students. Let the utility with this approximation be denoted as $\tilde{U}_i(e_i, p_i; \boldsymbol{\delta})$. Expected utility can be expressed as $\mathbb{E}\tilde{U}_i = \eta_i S_i(e_i, p_i) + \nu \tilde{P}_i^w(e_i, p_i; \boldsymbol{\delta})B$.

Definition 1. *An approximation to the pure strategy Bayesian Nash Equilibrium is a $\boldsymbol{\delta}^*$ such that:*

(i) given $\boldsymbol{\delta}^*$, each student i chooses an effort decision tuple (e_i^*, p_i^*) that maximizes her expected utility:

$$(e_i^*, p_i^*) = \arg\max_{e_i, p_i} \mathbb{E}\tilde{U}_i(e_i, p_i; \boldsymbol{\delta}^*) - C_i(e_i, p_i) \tag{13}$$

(ii) Given the profile of decision rules $\{(e_i^*, p_i^*)\}_{i=1}^N$, the approximated probability is close to the true probability: $P_i^w \approx \tilde{P}_i^w\ \forall i$.

Appendix E.1.1 discusses the existence and uniqueness of the approximated equilibrium and shows how its properties align with theoretical results. The approximated probability of winning, $\tilde{P}_i^w(e_i, p_i; \boldsymbol{\delta})$, can be expressed as follows:

$$\tilde{P}_i^w(e_i, p_i; \boldsymbol{\delta}) = \Phi(\delta_0 + \delta_1\, G(e_i, p_i) + \delta_2\, \text{Info}_i), \tag{14}$$

where $G(e_i, p_i)$ is the deterministic part of the score which depends on the effort inputs. Info_i captures the baseline rank (and if available, the peer score gap) that the student observes before making any decision. The probit form is the result of own score noise and the cutoff score noise, approximated by normal distributions. Since the information across arms and study modes differs, the coefficients $\boldsymbol{\delta}$ are arm-specific. Derivation of the probability and the arm-specific $\boldsymbol{\delta}$ values are provided in Appendix E.1.1. For compactness, Column (7) in Table A23 shows the solution characterizations for each arm and study mode.

[67] The letters stand for *Control*, *Moderate*, and *Intense* reward arms.

[68] In the model, the monetary unit is US dollars. The exchange rate during the experiment period was approximately $\$1 \approx$ ৳34.

4.2 Measurements

4.2.1 Measurement of Ability. Ability enters score production function. I proxy ability using the baseline exam scores, conducted before the treatments were assigned. In the robustness checks, I provide an alternative ability measure using item response data following the specific IRT model used in Akyol et al. (2022) and Ozer et al. (2024) which takes care of negative markings.[69] Appendix E.3.2 provides a detailed description of the measurement model.

4.2.2 Measurement of Effort. The Equation (10) requires accurate measurement of individual effort, e_i, and peer interactions, p_i. In the *Individual* mode, all recorded website activity can be directly attributed to individual effort, e_i. However, it becomes more complex in the *Pair* mode. While a student might log in to the website, they might not be actively studying with their peer, rather working alone, especially if their peer is not online. Using the detailed web data, I separate the effort of *Pair* mode students into two components: the individual effort, e_i, and the interactive peer effort, p_i. I count the number of times a student engages in learning activities alone and the number of times they attempt interact with their peer. Appendix E.3.1 provides a detailed description of this procedure and provides distribution of the effort measures. Once p_i and p_j is defined, I can compute the effective peer interaction effort, $\tilde{p}_i$.

4.3 Identification Strategy

The aim of the structural estimation is to identify the parameters of the score production function, $\boldsymbol{\beta}$ as well as the parameters of the preferences and cost functions, which provide $\{\eta_i, \nu_i, \theta_i\}$. In addition, other common parameters, $\{\xi, \gamma, \Gamma_{eg}, \Gamma_{pg}\}$, need to be identified. With observational data, identifying such a model would be challenging. For example, it would be hard to disentangle whether an increase in effort is driven by a taste for performance, η_i, or simply by a lower effort cost, θ_i. A rich survey data and experimental variation, through changes in the reward structure, peer assignment (if applicable), and heterogeneity across the sample, provides the necessary identifying variation to separate these effects. I discuss the identification of each parameter in detail below. To reduce computational burden, I separate the estimation of the production function from the estimation of preferences. Stage 1 recovers the mapping from inputs to final output; Stage 2 uses those estimates to infer how preferences determine the observed input choices.[70] An overview of the identification and estimation strategy is provided in Figure 9. Stage 1 is followed by Stage 2, which consists of two sub-steps. After estimating the main model, I separately estimate the skill production function. This is then followed by counterfactual policy simulations.

4.3.1 Stage 1: Production Function Parameters. Identifying Equation (10) poses two main challenges: endogeneity and selection. The two-level randomization strategy adopted in my experimental design addresses these by creating exogenous variation in peer composition and effort incentives, allowing for unbiased estimation of the production function parameters. Specifically, peer formation is exogenous and thus the link between the unobserved characteristics of students i and j, η_i, ν_i, θ_i and η_j, ν_j, θ_j is automatically broken. Second, changing the reward structure plays

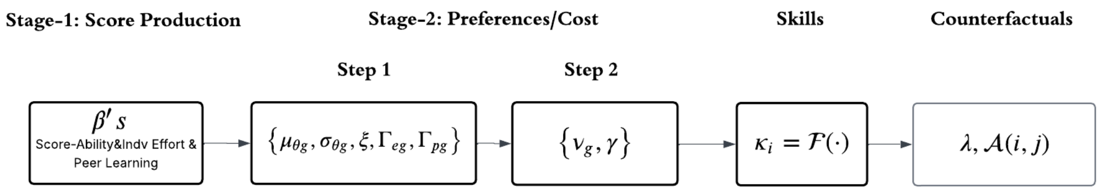
[69] The reason to use IRT measure in robustness is that the raw sum of the items has binomial noise with variance that depends on the ability itself. Using all items jointly to estimate a latent trait prevents attenuation bias and strengthens the identification.

[70] This two-stage structure, technology first, preferences (or supply) second, follows studies such as C. Cotton et al. (2020) and Arcidiacono and Miller (2011).

a role like an instrument, i.e. moving effort inputs up or down, while keeping the unobserved heterogeneity constant.[71] Together, these orthogonal shocks provide me a fully saturated design that separately pins down own-effort returns, (β_2, β_3), and peer spillovers, $(\beta_4, \beta_5, \beta_6)$. Table 9 Panel A shows the identifying variation and the data used. Given the endogeneity of effort and peer interaction, I employ a control function approach for the parameter estimation.[72] I estimate Equation (10) controlling for the residuals of the first-stage regressions of effort and peer interaction on the ability proxy, a_i, and the reward structures.[73]

To interpret the parameters meaningfully, I rely on four assumptions: (i) *ε_i is conditionally independent of unobserved types η_i, ν_i, θ_i , given the ability proxy a_i*, (ii) *ε_i is iid across students*, (iii) $\mathbb{E}\left[\varepsilon_i | a_i\right] = 0 \ \forall a_i$., (iv) *Reward structures affect the final scores only through e_i and p_i.* Intuitively, private types affect only the decision to exert effort, not the score production function shocks. Conditional on choosing to exert effort, I assume that students operate at their production possibility frontier. Second, production shocks are independent across students and may be related to exam and exam day conditions.[74] Third, once ability is controlled for, any remaining variation in the score production function is due to the unobserved shocks, ε_i. Finally, assumption (iv) formalizes the exclusion restriction that experimental reward structures do not directly (e.g. motivationally or psychologically) affect the score production function, but only through the effort choices, which itself is a reflection of motivational changes.

Figure 9: Identification and Estimation Overview



4.3.2 Stage 2: Preferences and Cost Parameters—

The parameters of the preferences and cost functions include $\{\eta_i, \nu_{LL}, \nu_{LH}, \nu_{HL}, \nu_{HH}\}$ for preferences, and $\{\mu_{\theta L}, \mu_{\theta H}, \sigma_{\theta L}, \sigma_{\theta H}, \gamma, \xi, \Gamma_{eL}, \Gamma_{eH}, \Gamma_{pL}, \Gamma_{pH}\}$ for cost functions. Identification of these parameters echoes the results established in (D'Haultfœuille & Février, 2015; D'Haultfoeuille et al., 2021; Guerre et al., 2009; Torgovitsky, 2015), as well as the empirical setup in C. Cotton et al. (2020).

Mainly, the variation in contract (prize) arms, by keeping the unobserved heterogeneity distribution constant, moves the marginal benefit / cost tradeoff. Before discussing the moments, it might be useful to build some intuition with a simple notation. Let $\boldsymbol{X}_i = \{a_i, r_i, \varepsilon_i\}$ denote the student's observable type, the arm, and the shock to the score. Effort, e_i is a function of these, together with the latent types $\boldsymbol{t}_i = \{\eta_i, \nu_i, \theta_i\}$ as well as the common cost parameters, $\{\gamma, \xi, \Gamma_{eg}, \Gamma_{pg}\}$.

[71] There is a simulateneity bias, otherwise: lower ability students might spend more effort on studying and still has low score output.

[72] The control function method offers a flexible strategy for correcting endogeneity in structural models with nonlinear and interaction effects involving endogenous regressors; see Wooldridge (2015).

[73] Note also that there is slight selective attrition in final exam participation, as shown in Table A17. The control function approach accounts for this layer of endogeneity as well.

[74] I can weaken this assumption by allowing clustered errors at the arm and peer group level. The results would still hold.

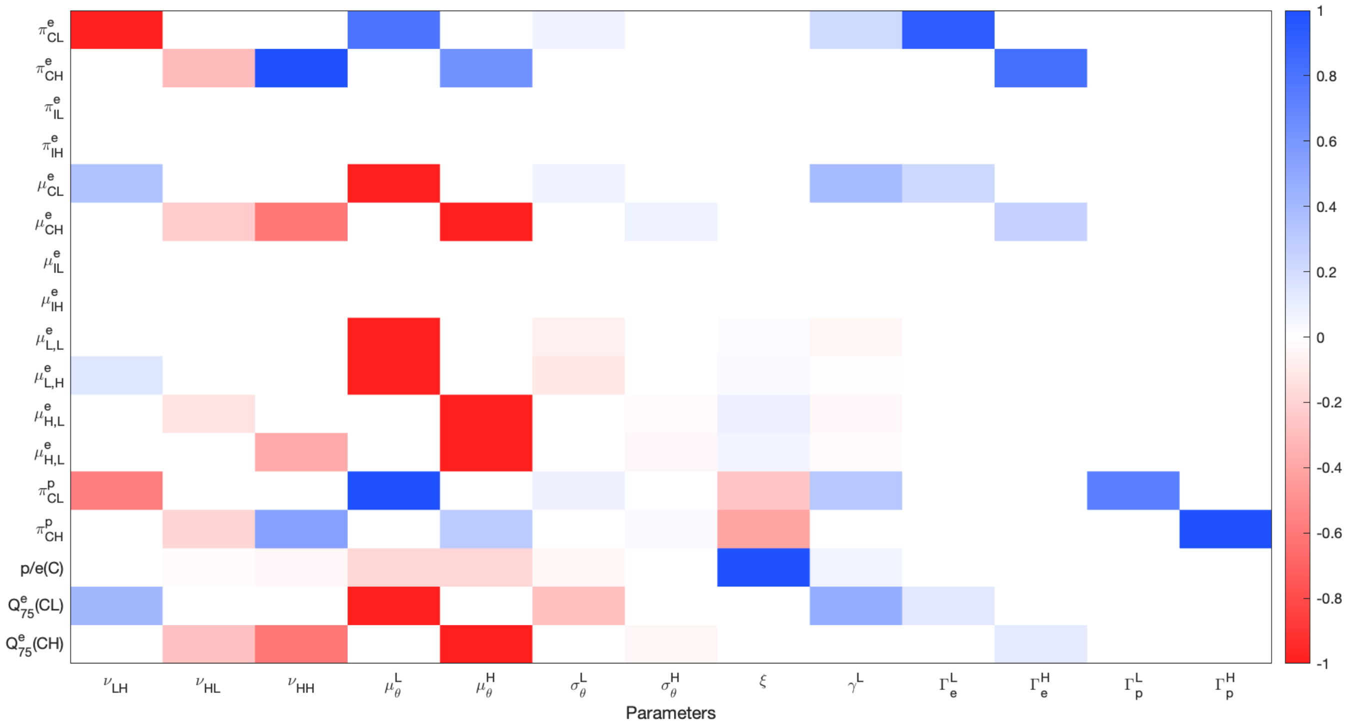
Conditional on observables and reward structure, effort is assumed to be monotonic in a single type index $\boldsymbol{t}$. The quantile shifts help me specifically pin down common cost schedule γ and ν parameters. While across-arm comparisons allow me to identify the common cost schedule and prize taste, cross-sectional variation allows identification other parameters as discussed below.

In Step 1, I focus on estimating a subset of parameters using only variation from the *Control* arm, since solving the full model is computationally intensive. As shown in Table 9, I identify the distribution of θ/ν, the relative cost parameter ξ, and the fixed cost terms Γ_{eg} and Γ_{pg} from this arm. Starting with the θ/ν ratio, observe that in the *Control-Individual* setting, the first-order condition is given by Equation (30). Once η_i is calibrated, the only unknown is the composite parameter $\tilde{\theta}_i = \theta_i/\nu_i$. Using the empirical mean and standard deviation of effort in the control arm, I estimate the distributional parameters $\mu_{\tilde{\theta}}$ and σ_{θ}. To separately identify ν_i and μ_{θ}, I leverage the *Intense Competition* arm, where variation across rivals allows disentangling of θ and ν. In addition, cross-sectional variation in effort provides identification of the curvature parameter γ, since it enters as a slope coefficient after taking the logarithm of the first-order condition. A more detailed identification argument is provided in Appendix E.2. The parameter ξ, which governs the relative disutility of peer effort, is identified using the ratio of peer interaction effort to individual effort among students with $e > 0$ and $p > 0$ in the *Control-Pair* condition. Finally, the fixed cost parameters Γ_{eg} and Γ_{pg} are identified from the observed extensive-margin behavior—specifically, the share of students with $e = 0$ and $p = 0$ in the *Control-Pair* arm, separately by ability group $g \in \{L, H\}$. Additional identification details and intuition are provided in Appendix E.2.

I also include a sensitivity map in Figure 10, which illustrates how the selected moments respond to changes in the parameters.[75] Each cell reports the local derivative of a moment with respect to a parameter, normalized (moment-wise) for comparability across scales. Red cells indicate a negative relationship, while blue cells indicate a positive relationship. The figure show that certain parameters such as $\mu_{\theta L}$ and $\mu_{\theta H}$ are informed by multiple moments, while others like Γ_{pL} and Γ_{pH} are primarily identified by a single moment. Overall map illustrates that identification is not concentrated by a few moments, but rather spread across the selected moments. Note that some color patterns might initially seem counterintuitive. This is because both the extensive and intensive margins are at play. For instance, while the share of individuals exerting zero effort increases, the average effort among those who do exert effort also rises due to selection effects.

[75] Each parameter is varied over a grid while holding all other parameters fixed at their estimated values reported in Table 9.

Figure 10: Identification: Sensitivity Map



Notes: This figure presents the sensitivity of moments targeted to the estimated parameters. The $y-$ axis represents the moments, while the $x-$ axis represents the parameters. The color intensity indicates the sensitivity level, red for negative relationship and blue for positive relationship.

4.4 Estimation Strategy and Results

4.4.1 Score Production Function First, I apply a set of variable transformations. Final and baseline exam scores (the latter as ability proxy) are adjusted by adding the minimum of the two plus 1 before taking the logarithms, due to the negative scores resulting from negative markings. Effort and peer interaction measures are transformed using the inverse hyperbolic sine (asinh) transformation for easier interpretation.[76] The asinh transformation is defined at zero and approximates the natural logarithm for $e \geq 1$, thus preserving the semi-elasticity interpretation.[77] I estimate a control function model for active users which is corrected after selection into being active. Rather than using the full sample with transformed zeros, I estimate a two part model following Mullahy and Norton (2024) since the mass at zero compromises the estimation of the production function otherwise. First, a probit model links the web log-in decision to the baseline ability, and all reward arms and study modes, yielding the inverse Mills ratio, $\hat{\lambda}$. Second, I regress the asinh-transformed effort and peer interaction measures on the same instruments plus $\hat{\lambda}$, and I obtain the residuals $\hat{v}_e, \hat{v}_p$. Instruments are strong (first stage $F-$statistics are above 20 for both effort and peer inter-

[76] Recent papers such as Azoulay et al. (2019), Beerli et al. (2021), and Berkouwer and Dean (2022) have used this transformation for similar purposes.

[77] Note that J. Chen and Roth (2024) suggests alternative ways to handle zeros for correct percentage change interpretation, such as separating the extensive and intensive margin estimations, which I partly follow in my estimation approach. Also, I fix the scale parameter of the asinh transformation to 1 and provide robustness checks with alternative scale parameters following J. Chen and Roth (2024).

action).[78] Third, I estimate Equation (10) using the residuals as additional regressors.[79]

Panel A of Table 9 shows the estimation results. The intercept value β_0 represents the baseline score level, which is estimated to be 0.358. The baseline score, which is used as ability proxy strongly predicts the current score, with an elasticity of 0.790. The individual effort effect, β_2, is estimated to be 0.279, indicating that a 1% increase in the individual learning effort leads to a 0.279% increase in the score. Individual effort also exhibits diminishing returns, as suggested by the negative coefficient of the squared term, $\beta_3 = -0.049$. The baseline peer effects are estimated to be 0.155. The gain from peer interactions for the lower types, captured by β_4, is estimated to be 0.584, indicating that a 1% increase in the peer's ability leads to a 0.584% increase in the score of the student. However, the heterogeneity of the peer spillover effect, β_5, is estimated to be negative at -0.290. That is lower ability students benefit more from their peers' ability than higher ability students. Note that the standard errors are obtained using delta method (using Murphy-Topel adjustment) to account for the multi-stage propagation of the sampling variability. The lower significance of some parameters is likely due to the limited sample of students exhibiting positive interactive effort.[80] Appendix E.3.4 provides additional robustness checks for the production function estimation, including alternative estimation procedures, as well as alternative measures.

For the estimation of heteroskedastic score production shock CDFs, $F_\varepsilon(\varepsilon \mid a_i)$, I first compute the fitted residuals, $\hat{\varepsilon}_i = \ln S_i - \widehat{\ln S_i}$, where $\widehat{\ln S_i}$ is the predicted score from the model.[81] I then partition the sample into 2 groups based on the observable characteristic a_i, such that each group $\mathcal{I}^a_j$, for $j = \{1, 2\}$, contains individuals with $a_i \in I^a_j$. Within each group, I define the support of the residuals as $\{\hat{\varepsilon}_i\}_{i|a_i \in I^a_j}$.[82] I then smooth the empirical CDFs of the fitted residuals using Kernel density function with a bandwith of 0.2. Figure A14 shows the smoothed distribution of the residuals for each group. These distributions will be used in the second stage of the estimation which uses Simulated Method of Moments (SMM).

4.4.2 Internal Calibration To discipline the score taste distribution, I directly calibrate the individual specific η_i parameters using the baseline survey data.[83] The goal is to anchor the relative importance of grades in utility terms that can be compared with monetary incentives. This procedure helps me fix η and reserve the prize and cost related parameters for structural estimation. The calibration is carried out in three steps. First, I extract the latent motivation for grades or academic performance. I use survey items related to self-reported attitudes. Each student gets a latent motivation score, $\eta_i^{\text{raw}} \in \mathbb{R}_+$, which is standardized to have mean zero and unit variance.

[78] The individual effort instruments include arm dummies, study mode dummies, and their interactions, as well as baseline ability. The peer interaction instruments include arm dummies only since the *Individual* mode does not have peer interaction. The residual values for the *Individual* mode subjects are set to zero.

[79] In constructing the production function estimation sample, I exclude individuals whose final scores are unusually low compared to their baseline scores. Specifically, I remove observations (≈ 22) where the gap is more than two standard deviations below the mean gap. As robustness, I also estimate the model without the exclusion, which yields similar results with more noise on the peer interactions coefficients.

[80] A post-hoc power calculation, using the observed standard error, suggests that detecting the estimated effects at the 10% significance level with 80% power would require a sample size of approximately 1,300–1,500. However, the estimation sample includes only 325 active students, of whom roughly 148 exhibit strictly positive peer effort ($p_i > 0$). Moreover, when the gap-related terms are included directly in the regression without conditioning on $p_i > 0$, they become statistically significant.

[81] Note that White's general test provides $LM = 15.21$, with p-value < 0.001, rejecting the null hypothesis of homoskedasticity.

[82] The sub-intervals are equal length. The choice of three groups reflects the experimental stratification.

[83] One other option is to calibrate distribution parameters and treat η_i as a latent variable drawn from this distribution. However, given the other latent variables in the model, another randomness is not desirable.

Table 9: Parameter Description, Identification, and Estimates

Parameter	Description	Data	Identifying Variation	Estimate	SE
Panel A: Score Production Function					
β_0	Baseline Score Level	All	Intercept	0.358	0.156
β_1	Ability Elasticity	All	Variation in Baseline Scores	0.790	0.083
β_2	Individual Effort Effect	All	Exog. Effort Change	0.279	0.162
β_3	Effort Curvature	All	Exog. Effort Change	-0.049	0.016
β_4	Peer Spillover	Pair	Peer Interaction	0.155	0.149
β_5	Incremental Spillover	Pair	Random peer assignment	0.584	0.321
β_6	Spillover Heterogeneity	Pair	Interaction of Gap and Ability	-0.290	0.169
Panel B: Preferences					
$\nu_{L,L}$	Prize Taste (Low a, Low Y)	All - Individual	Effort When Stakes are Small	1.804	
$\nu_{L,H}$	Prize Taste (Low a, High Y)	All - Individual	Dispersion of Effort	2.306	
$\nu_{H,L}$	Prize Taste (High a, Low Y)	All - Individual	Effort Jump with Prize	1.660	
$\nu_{H,H}$	Prize Taste (High a, High Y)	All - Individual	Het. in Effort Response	0.744	
Panel C: Cost					
γ	Cost Curvature	All Arms - Individual	Tails & cross-arm gaps	1.951	
ξ	Rel. weight on peer effort	Control - Pair	p/e ratio	0.424	
Γ_{eL}	Fixed studying cost	Control - Individual	Share $e_i = 0$	2.534	
Γ_{eH}	Fixed studying cost	Control - Individual	Share $e_i = 0$	0.156	
Γ_{pL}	Fixed peer effort cost	Control - Pair	Share $p_i = 0$	5.217	
Γ_{pH}	Fixed peer effort cost	Control - Pair	Share $p_i = 0$	2.298	
$\mu_{\theta L}$	Mean Cost of Effort	Control-Individual	Mean Effort Level	1.247	
$\mu_{\theta H}$	Mean Cost of Effort	Control-Individual	Mean Effort Level	1.260	
$\sigma_{\theta L}$	Dispersion of Effort	Control-Individual	Effort Dispersion	0.647	
$\sigma_{\theta H}$	Dispersion of Effort	Control-Individual	Effort Dispersion	0.922	

Notes: This table reports model parameters with their descriptions, data sources, and sources of identifying variation. Standard errors are reported in parentheses next to point estimates. Estimates correspond to the baseline production and cost specification. Production function standard errors are obtained using the delta method. Cost and preference parameters' standard errors are obtained using a non-parametric bootstrap with 400 resamples.

Appendix E.3.5 provides additional details on the calibration procedure.[84] Second, I map latent traits to utility units. To get the conversion parameter, I focus on *Control* arm Low ability-Low Income students and I impose a normalization that their marginal utility of money is the numéraire, i.e., $\mathbb{E}[\nu_i|g = L, y = L] = 1$. By also setting the marginal utility from extrinsic and intrinsic rewards equal for average score student, I get the utility scale. Specifically, $\mathbb{E}[\eta_i/S_i|g = L] = b$. Writing $\eta_i = \kappa_\eta \eta_i^{\text{raw}}$ yields the conversion parameter $\kappa_\eta = 1.164$. I apply the scale to the latent motivation scores, η_i^{raw}, to obtain the utility-based score tastes, $\eta_i = \kappa_\eta \eta_i^{\text{raw}}$. Mean η for Low ability students is 2.41 while it is 2.49 for High ability students. This suggests that at the mean scores the low type-low income student values the next point at $2.41/4.34 \approx$ USD, while the cash reward is worth USD 0.566. Extrinsic cash is therefore worth the same as intrinsic score for this group. With η-parameters now fixed on a money-interpretable scale, the next structural estimation process will focus on the remaining ν-related parameters and effort cost parameters.

4.4.3 Estimation via Simulated Method of Moments The model parameters including the prize taste parameters, cost function, and fixed costs of exerting individual and peer effort are jointly estimated using a Simulated Method of Moments (SMM) approach.[85] The estimation leverages counterfactual variation across experimental arms, following the strategy suggested by C. Cotton et al. (2020). A short description of the estimation procedure is as follows. For an initial guess of the parameters, $\mathbf{\Theta}^0$,[86]

(i) Draw θ_i and ε_i from their respective distributions, $\mathcal{N}(\mu_g^\theta, \sigma_g^\theta)$ and F_ε for $g \in \{L, H\}$ Q times, where Q is the number of simulations. Store $\{\theta_i, \varepsilon_i\}_{q=1}^{Q}$.

(ii) Given parameter values and data, $D = \{a_i, a_j, \text{arm}_i, \text{studymode}_i\}$, first simulate the scores, approximated winning probabilities, $\tilde{P}_i^w(e_i, p_i; \boldsymbol{\delta})$, and prizes. Then, find the optimal effort choices, (e_i^*, p_i^*), for each student i by solving the FOC characterizations as laid out in Table A23.[87]

(iii) Construct the model moments counterparts of the empirical moments, $\mathbf{m}^{\text{model}}(\mathbf{\Theta}) = \frac{1}{Q}\sum_{q=1}^{Q} \mathbf{m}^{\text{model}}(\mathbf{\Theta}; \eta_i^q, \nu_i^q, \theta_i^q)$. Then search for the parameter values that minimize the loss function, which is the distance between the empirical moments, $\mathbf{m}^{\text{data}}$, and the model moments, $\mathbf{m}^{\text{model}}(\mathbf{\Theta})$:

$$\mathbf{\Theta}^* = \arg\min_{\mathbf{\Theta}} \mathcal{L}(\mathbf{\Theta}) = \left(\mathbf{m}^{\text{data}} - \mathbf{m}^{\text{model}}(\mathbf{\Theta})\right) \boldsymbol{W} \left(\mathbf{m}^{\text{data}} - \mathbf{m}^{\text{model}}(\mathbf{\Theta})\right) \tag{15}$$

where $\boldsymbol{W}$ is a positive definite weighting matrix. I search for the best-fitting parameters using a grid search (a finer Halton sequence) over the parameter space followed by a local optimization routine. During the optimization process, I employ an augmented loss function defined in Equation 39. It penalizes large deviations from the guardrail conditions, provided

[84] One concern with the survey calibration is that the respondents' understanding of the questions may differ. Robustness checks address this by using alternative survey questions.

[85] If the experimental variation had been limited to piece-rate contracts only, I could have relied on a more standard GMM approach with linear moment conditions, leveraging shifts in marginal returns to effort. However, the introduction of competition arms complicates this structure: marginal incentives now depend on endogenous win probabilities, and activation decisions involve fixed costs and private heterogeneity. Simulated Method of Moments (SMM) offers a flexible framework to directly model these features, capturing both the strategic effort choices under information frictions and the variation in participation probabilities, while allowing me to target rich empirical moments observed in the data.

[86] The full list of parameters is $\mathbf{\Theta}^0 = \left\{\nu_{LH}^0, \nu_{HL}^0, \nu_{HH}^0, \mu_{\theta,L}^0, \mu_{\theta,H}^0, \sigma_{\theta,L}^0, \sigma_{\theta,H}^0, \gamma^0, \xi^0, \Gamma_{eL}^0, \Gamma_{pL}^0, \Gamma_{eH}^0, \Gamma_{pH}^0\right\}$.

[87] Model solution code can be found in the GitHub repository.

by 90% confidence intervals. Appendix E.3.6 provides further details on the estimation procedure, including technical aspects of global and local optimization, and $\sqrt{N}-$consistency and asymptotic normality of the estimator.

4.4.4 SMM Estimates.

Structural estimates of the model as well as bootstrapped standard errors are given in Table 9.

Preferences— Panel B presents the estimates of the prize taste parameters. The estimated mean prize taste for the Low ability-Low income group, ν_{LL}, is 1.804. The estimated mean prize taste for the Low ability-High income group, ν_{LH}, is 2.306, indicating that this group values the monetary prize more than the Low ability-Low income group. The estimated mean prize taste for the High ability-Low income group, ν_{HL}, is 1.660, suggesting that this group values the monetary prize approximately 8% less than the Low ability-Low income group. The estimated mean prize taste for the High ability-High income group, ν_{HH}, is 0.744.

Cost Parameters— Panel C provides the estimates of the cost parameters. The curvature of the cost function, γ, is estimated to be 1.951 indicating a moderately convex cost function. The relative weight on peer effort, ξ, is estimated to be 0.424, suggesting that the disutility from peer effort is less than half that of individual effort. The estimated fixed cost of studying alone is $\Gamma_e^L = 2.534$ for low-ability students and $\Gamma_e^H = 0.156$ for high-ability students, while the fixed cost of peer effort is $\Gamma_p^L = 2.298$ for the low-ability group and $\Gamma_p^H = 1.260$ for the high-ability group. These suggest that high-ability students face a lower fixed cost of individual effort compared to low-ability students. However, for low ability students, the fixed cost of peer effort is lower compared to their individual cost of effort. Standard errors are obtained through a block-bootstrap procedure for which the details are given in Appendix E.3.7.

4.5 Model Fit and Validation

Model Fit: I begin by evaluating the model fit by comparing the empirical moments with the model-generated moments, as shown in Table 10. In Step 1, which leverages variation from the *Control* arm, the model accurately replicates both the extensive and intensive margin patterns of effort and peer interaction. It also captures the heterogeneity across ability types, though it slightly underpredicts effort in the upper tail. Step 2 focuses on the *Intense* competition arms. The results indicate that the estimated parameters provide a consistent explanation for both the extensive and intensive margins of behavior across experimental arms, proving a strong overall fit.

Validation: Next, I assess the model's out-of-sample validity by examining untargeted moments. In particular, the *Moderate* arm is reserved as a validation sample, while the *Control* and *Intense* arms are used for model estimation/training. Table A25 reports the corresponding validation moments.

4.6 Revisiting Skill Production

In the Theory section, the model timeline shown in Table 1 makes it clear that skill production takes place at the end of the period, after effort choices are made. The theory part was kept general in terms of how skill production is modeled. In the empirical part, however, I focus on two specific types of skills: academic skills and social skills. Earlier, I estimated the score production function, which at this point can be interpreted as the academic skill production function. That is,

Table 10: Model Fit

Moment	Description	Data	Model
Panel A: Step 1			
$\Pr(e{=}0)^L$	Share Zero Effort (Low)	0.709	0.711
$\Pr(e{=}0)^H$	Share Zero Effort (High)	0.372	0.392
$\mu_e^L(C)$	Mean Effort - Control (Low)	0.339	0.342
$\mu_e^H(C)$	Mean Effort - Control (High)	0.735	0.766
$\Pr(p{=}0)^L$	Share Zero Interaction (Low)	0.683	0.684
$\Pr(p{=}0)^H$	Share Zero Interaction (High)	0.506	0.507
$\mathbb{E}[\log(p/e)]$	Interaction, Indv. Log Ratio	0.122	0.093
$P_{75}(e)^L$	Effort P75 - Control (Low)	0.429	0.426
$P_{75}(e)^H$	Effort P75 - Control (High)	1.000	0.975
Panel B: Step 2			
$\mu_e^L(I, LInc)$	Mean Effort - Intense (Low, LInc)	0.521	0.521
$\mu_e^L(I, HInc)$	Mean Effort - Intense (Low, HInc)	0.610	0.610
$\mu_e^H(I, LInc)$	Mean Effort - Intense (High, LInc)	0.907	0.907
$\mu_e^H(I, HInc)$	Mean Effort - Intense (High, HInc)	0.687	0.687

Notes: This table compares the data moments with their model-implied counterparts. Panel A reports the moments used in Step 1, primarily from the Control arms, while Panel B shows the Step 2 moments from the Intense competition arms.

I denote academic skill production as $\kappa^A = \mathcal{F}^A(e, p|\cdot)$, as given in Equation (10). In this section, I extend the analysis to include social skills as well. I denote this as $\kappa^H = \mathcal{F}^H(p|\cdot)$ and estimate the corresponding social skill production function in the context of this study.[88] I model the social skill production function as a Cobb Douglas function, where baseline social skills and peer interactions are the key inputs. Total factor productivity (TFP) is allowed to vary across individuals i:

$$\kappa_i^H = TFP_i^H \times \text{BS}_i^{\beta_B^H} \times p_i^{\beta_p^H} \times \varepsilon_i^H \tag{16}$$

Here, κ_i^H is the final social skill level, TFP_i^H is the individual's total factor productivity, BS_i is the baseline social skill level, p_i is the peer interaction input, and ε_i^H is the error term.[89] I model TFP_i^H as a function of observed exogenous characteristics, denoted by W_i^H, which include the environment's competitiveness, λ, and other variables such as gender and ability:[90]

$$\log(TFP_i^H) = \mathbf{W}_i^H \alpha_0^H \tag{17}$$

[88] This approach also speaks to concerns in the prior literature that use factor models to estimate production functions (Cunha & Heckman, 2008; Del Boca et al., 2019), where measurement error can correlate with unobserved heterogeneity. To my knowledge, this is the first paper to estimate a skill production function where both individual and peer effort inputs are endogenously chosen in a contest environment by pre-estimating the structural model and using real-time experimental variation to control investment.

[89] I do not include individual effort e_i in the social skill production function. This is because e_i primarily reflects self-study, which does not directly contribute to social skill formation. In the data, especially in *Pair* mode, e_i may behave substitutively with p_i, making it redundant to include both.

[90] In the final estimation, I include only the environment's competitiveness, λ, as a determinant of TFP. Other variables like gender and ability are already used in the selection equations, and their effects in the outcome equation are not clear.

Substituting Equation (17) into Equation (16) and taking logarithms, I obtain:

$$\log(\kappa_i^H) = \lambda_i \alpha_0^H + \beta_B^H \log(\text{BS}_i) + \beta_p^H \log(p_i) + \log(\varepsilon_i^H) \tag{18}$$

Before moving on to the estimation, a few words are in order. In the initial estimation steps, I only included peer interaction inputs, which are determined endogenously by competitiveness in the equilibrium. But with that setup, the coefficient on peer interaction came out negative. That is, while the level of peer interaction (not the e/p ratio) was higher in more competitive environments, the cooperativeness levels, as also shown in Section 3.4.3, were actually lower in those same settings. Although it may seem counterintuitive that more peer interaction leads to lower social skills, this suggests that it is not just the quantity of interaction that matters, but also the quality. This is why it becomes important to include competitiveness directly as a determinant of the effectiveness of peer interaction, to better capture that quality aspect.[91]

Estimating Equation (18) comes with a few challenges. First, while baseline social skills are directly observed from the baseline survey, final social skills are only observed for students who participated in the endline survey.[92,93] Peer rated social skills are available only for students in *Pair* mode, and only for the subset who completed the endline survey. For representativeness, I compute inverse probability weights of the form $w_i = 1/\hat{\pi}_i$, where $\hat{\pi}_i$ is the predicted probability that student i participated in the endline survey. I estimate $\hat{\pi}_i$ using a logit model with baseline observables and reward arm dummies as predictors. Within each arm, I treat the 1 to 5 Likert scale ratings for Cooperativeness, Friendliness, and Prosociality as draws from a five category multinomial. Let c_{aj} denote the number of students in arm a who received a rating of j for a given trait. Starting from a flat prior, I form the posterior $Dirichlet(c_{a1}+1, \ldots, c_{a5}+1)$ and draw $M = 20$ sets of arm specific category probabilities. Every missing peer rating is then imputed as an independent draw from the corresponding multinomial. The three items are then averaged to form the final social skill measure. Full details and math are provided in Appendix E.6.1. Table 11 presents the estimation results for the social skill production function. Estimation follows the same two step procedure used before in the score production function. In the first step, I estimate the selection equation for website participation using a probit model. In the second step, I estimate the outcome regression including the IMR. Standard errors are computed using the Murphy-Topel correction. The results show that competition intensity is negatively associated with social skill production. The estimated coefficient is -0.193 with a standard error of 0.102.[94,95] The coefficient β_p^H on peer interaction is positive and significant, suggesting that interaction is beneficial for social skill formation. However, competition appears to crowd out the quality of these interactions enough that the net effect may turn negative. Baseline skills also have a positive but imprecise effect.

[91] Future work could explore these channels more directly, for example by holding the quantity of peer interaction constant while varying the prize spreads to isolate competitiveness effects.

[92] Baseline skills, measured using the Cooperativeness Index, are missing only for a small number of students who did not complete the baseline survey in full. I impute these missing values using KNN imputation with predictors such as baseline ability and gender.

[93] The baseline measures of academic and social skills across the sample are reported in Table A26, broken down by background characteristics. These measures show variation in initial skills across students, especially in academic scores.

[94] The competition coefficient remains directionally stable even when Dirichlet weights are not restricted to be within arm.

[95] Reward arms are used as a proxy for competition intensity. This variable takes values between 0 and 1.

Table 11: Social Skills Production Estimation

Parameter	Description	Estimate	SE
α_0^H	Competition intensity	-0.193	0.102
β_B^H	Baseline Skills	0.350	0.339
β_p^H	Peer Interactions	0.079	0.043

Notes: This table reports the estimates from the social skills production function in Equation 18. Estimates and standard errors are the Rubin-averages across $M = 20$ imputations.

5 Counterfactual Policy Simulations

One of the main goals of this research is to inform policies on how classroom environments and incentive mechanisms can be designed to improve students' skill development. The following subsections present counterfactual policy simulations based on the estimated model. I first describe the policy objectives and the outcomes of interest, and then present four counterfactual exercises: (i) classroom composition and skill production, (ii) competition intensity and skill production, (iii) costs and participation at the extensive margin with an emphasis on inequality, and (iv) skill evaluation and sorting in the long run, that is, whether these policies help us better distinguish students based on their underlying skills.

5.1 Policy Objectives

The estimated model from the previous sections which include the estimation of the full contest model and the human capital production function can be used to analyze counterfactual policies in equilibrium. To compare across different policies, I choose a carefully selected outcomes. I conceptualize policy impacts as operating along two distinct structural margins: the *extensive margin* and the *intensive margin*. The extensive margin captures changes in participation in supplying effort, while the intensive margin reflects the intensity of skill production among those who choose to exert effort. The extensive margin, in effect, captures an equity criteria as normative while the intensive margin captures efficiency in that it defines the cost-effectiveness of the policy in improving student performance. Both the extensive and intensive margin comparisons are made relative to a baseline scenario that mirrors the experimental setup. The first two sets of counterfactuals focus on the intensive margin, while the third set focuses on the extensive margin. The final set of counterfactuals examines how these policies influence skill evaluation and sorting in the long run.

While the standard approach in welfare economics is to evaluate policy counterfactuals using revealed preference theory, I take a different route here for both conceptual and practical reasons. First, in settings like education where the agents are students (or sometimes parents or teachers), individuals may face frictions such as limited information, myopia, or limited attention.[96] These factors can distort observed choices and make them a poor reflection of underlying preferences. So instead of relying on revealed preferences for welfare analysis, I take a more outcome based approach. I focus on extensive and intensive margins as the main behavioral channels to evaluate the effects of policies.

[96] For instance, younger people tend to discount the future more (e.g. Bishai, 2004).

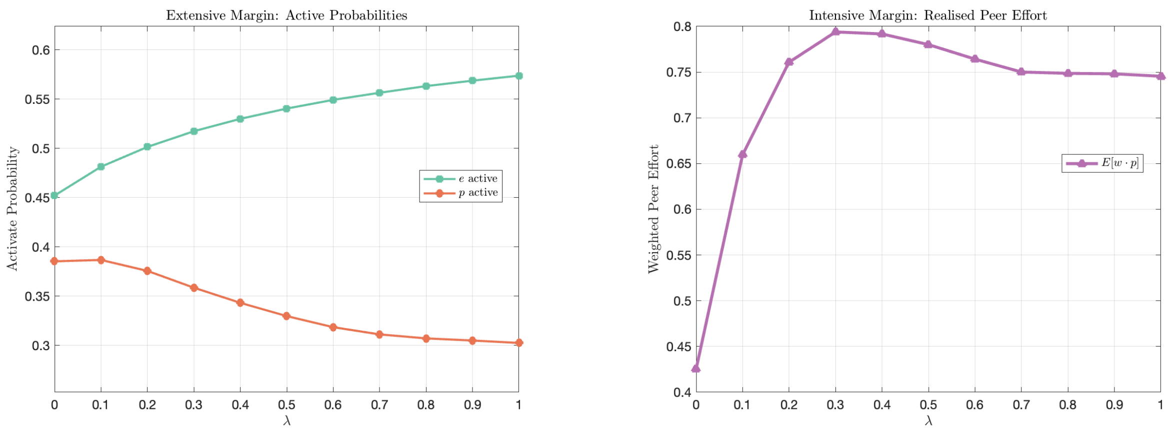
5.2 Competition Intensity

To quantify the effect of competition intensity on both extensive and intensive margin behavior, I simulate an environment with two agents ($N = 2$) and vary the competition parameter λ in

$$R_i = (1 - \lambda)\rho S_i + \lambda \cdot \mathbf{1}_{\{S_i \geq S_{[k]}\}} \cdot V,$$

as defined in the theory section. The parameters V and ρ are fixed at their experimental values. While the experiment implements only the two extreme cases—$\lambda = 0$ (purely individual rewards) and $\lambda = 1$ (pure tournament rewards)—this exercise allows me to trace the full spectrum of competition intensity in a cost-effective manner.[97] Figure 11 summarizes the results. On the extensive margin (left panel), the probability of being active increases monotonically with λ: from about 0.45 at $\lambda = 0$ to 0.58 at $\lambda = 1$, reflecting stronger incentives to participate as competition intensifies. In contrast, the probability of exerting peerab effort declines. from roughly 0.38 to 0.30 suggesting reduced engagement in helping peers under stronger competitive pressure. On the intensive margin (right panel), average peer effort displays a non-monotonic pattern. It rises sharply from 0.40 at $\lambda = 0$ to a peak of about 0.80 around $\lambda \approx 0.3$–0.4, and then gradually declines toward 0.70 as λ approaches one. This hump-shaped pattern indicates that moderate levels of competition stimulate peer interactions and learning, but excessive competition discourages cooperation, as individuals begin to view peers as direct rivals rather than collaborators. Overall, these patterns show that increasing competition enhances individual participation and effort but can crowd out cooperative behavior once rivalry becomes too strong.

Figure 11: Extensive and Intensive Margin Behavior by Competition Intensity



Notes: This figure presents the extensive and intensive margin behavior as a function of competition intensity, λ. The left panel shows the extensive margin participation rates for individual and peer effort, while the right panel displays the average peer effort levels among participants.

5.3 Classroom Composition

The design of the experiment allows me to have clear measures of peer effects depending on the group composition. Taking these effects, I can study the alternative groupings that maximize the overall skill production with also some weight on participation rates.

[insert the heatmap]

[97] Ideally, an experiment would include several intermediate treatment arms varying λ, but this would require a much larger sample and higher costs. Structural estimation enables this counterfactual exercise at minimal expense.

5.4 Participation at the Extensive Margin

The objective of this counterfactual exercise is to examine the equity and efficiency aspects of reducing barriers to participation for both types of effort. Theoretically, this corresponds to lowering Γ_{eg} and Γ_{pg}, which represent the fixed costs of engaging in individual and peer effort, respectively. Intuitively, these might correspond to examples like access to technology or resources, providing clear feedback that lowers the mental start-up cost, and easing structured group activities and coordination tools. I conduct the exercise by reducing these fixed costs by 25% and simulating the resulting participation rates. First, I reduce the fixed costs only for individual effort, and then only for peer effort. Table 12 presents the results. The first two rows report changes in individual effort participation rates, while the last two rows show the corresponding changes for peer effort. When individual effort fixed costs are reduced, participation among the low-ability group increases by 6.84 percentage points, compared to only 0.46 percentage points for the high-ability group, who are already highly active. This indicates that lowering the fixed costs of individual effort can help close the participation gap between low- and high-ability students. When peer effort fixed costs are reduced, participation increases by 6.61 percentage points for the low-ability group and by 3.92 percentage points for the high-ability group. Beyond its equity effects, this pattern suggests that reducing the fixed costs of peer effort can also be an efficient way to boost overall participation, given the larger total increase observed.

Table 12: Participation Change with Reduced Fixed Costs

Group	**Baseline**	**Counterfactual**	**Δ (ppts)**
Low Ab. Active e	0.2888	0.3572	6.84
High Ab. Active e	0.6165	0.6211	0.46
Low Ab. Active p	0.2921	0.3582	6.61
High Ab. Active p	0.4617	0.5009	3.92

Notes: This table presents the changes in participation rates at the extensive margin when fixed costs of effort and peer effort are reduced by 25%. The baseline scenario reflects the original estimated model with the experimental data, while the counterfactual scenario incorporates the reduced fixed costs. The Δ column shows the percentage point changes in participation rates for different ability groups.

6 Conclusion

Over the last decade, research in economics on child and adolescent development has shown that the return to investing in human capital is often greater than the return to investing in physical capital. This calls for a shift from a scarcity mindset in education to a more complete view that promotes learning and development for all students throughout the life cycle. Countries or regions may design systems that select a limited number of students for prestigious colleges, but if this creates an unhealthy competition that limits actual learning, then the education system is not serving its core purpose.

This study advances the peer learning and competition literatures by combining a structurally motivated field experiment with insights and solutions that guide education policy. The main takeaway is that pushing for more peer learning without understanding how students behave may not work. A low level of peer interaction does not only reflect students' preferences but also their strategic choices in a given environment. Closing learning gaps between high and low ability students requires more than encouraging collaboration. What matters is getting the right group composition and the right incentives. If designed well, peer learning can work even under competitive settings.

The findings also point to important differences across students. The combination of detailed survey data, a carefully designed and implemented large-scale experiment, and structural modeling allows me to study differences in learning costs and motivation. I find that while students do not vary much in how much they value learning, they do differ in how costly it is for them to engage. This means that effective policy needs to reduce the barriers to learning for those who find it harder to participate. Creating the right environment can help bring these students into the learning process in ways that would not happen on their own.

The results also suggest that competition shapes how students behave in ways that go beyond the classroom. When students are conditioned to view learning as a race, they may become less able to see collaboration as a source of value. This mindset can carry over into later stages of life. Although I do not model long term skill accumulation, simulations show how competition and peer learning affect the early stages of learning. Future work should study these dynamics over time using more granular data that follows students through school and into the labor market.

Finally, this study treats many parts of the education system as given, including teacher effort, school quality, family support, and the value of rewards. However, these are likely to respond to incentives. A dynamic framework would help us understand how schools, teachers, and parents adjust their behavior in response to competitive pressure. In some cases, this may mean that schools focus only on the most competitive students, and therefore limiting the skill development of other students. More research is needed to understand how these parts of the system interact and how to design policies that support broader learning goals.

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Appendices

A Theory

This appendix section provides additional theoretical results, including equilibrium existence and uniqueness, derivations of first-order conditions, and proofs of propositions stated in the main text.

A.1 Equilibrium

A.1.1 Existence and Uniqueness. The equilibrium defined in Section 2.3 exists and is unique. By Assumption $1(i)$, the marginal benefits from own effort and interaction are bounded, implying that $V_i \leq K(e_i + p_i)$ for some constant $K > 0$. Since the marginal cost grows unbounded in both dimensions, the objective is coercive, and any maximizer lies within a compact rectangle $[0, \bar{e}] \times [0, \bar{p}]$, where $\bar{e}$ and $\bar{p}$ depend only on K and the support of θ. This strategy set is non-empty, compact, and convex. The prize component of the utility is weakly concave due to the piecewise-linear structure of the score function. Subtracting a strictly convex cost ensures that the objective remains strictly quasi-concave in own actions. This guarantees that each player's best response is single-valued, unique, and upper hemi-continuous in opponents' strategies. Existence of a Bayesian Nash equilibrium follows from Glicksberg's fixed-point theorem (1952). Uniqueness is also guaranteed. The own-action second derivatives of the net utility π_i are strictly negative, while all cross-partials are weakly negative and bounded. In particular, the interaction channel satisfies $h_p \leq 1$, so externalities remain mild. These properties make the game diagonally strictly concave in the sense of Rosen (1965), and the best-response map is a contraction. Note that the interaction function h may exhibit kinks. For example, $h(p_i, p_j) = \min\{p_i, p_j\}$ is not differentiable along the diagonal. Nevertheless, uniqueness continues to hold: on either side of the kink the game is smooth and strictly concave in own actions. The payoff is continuous at the kink, and the best response remains single-valued and continuous. In addition, I assume Single-Crossing rule holds $\frac{\partial^2 U_i}{\partial x_i \partial \theta_i} < 0$ for $x_i \in \{e_i, p_i\}$. This ensures that higher-cost types choose lower actions, and the equilibrium is monotone in types. While this is not a necessary condition for uniqueness, it facilitates comparative statics and estimation.

A.1.2 $N = 2,\ \lambda = 0$ **FOCs.** Let $M_0 = \mathbb{E}[u_S + \rho\, u_R]$ The interior first-order condition for player i can be written as $M_0\, S_p(p_i, p_j) = \theta_i\, c'(p_i)$, where $S_p(p_i, p_j)$ denotes the marginal effect of p_i on the (expected) social payoff term S, and $c'(\cdot)$ is the marginal cost of effort. Solve for θ_i to obtain the threshold implied by the interior condition: $\bar{\theta}_i(p_i, p_j) = \frac{M_0\, S_p(p_i,p_j)}{c'(p_i)}$. Interpretation: for a given pair (p_i, p_j), player i has an interior solution (i.e. $p_i > 0$) only when her private parameter satisfies $\theta_i > \bar{\theta}_i(p_i, p_j)$. Assume $a_i > a_j$ and, as in the text, that the interaction mechanically benefits the lower-ability student relatively more, so that $S_p(p_i, p_j) \ < \ S_p(p_j, p_i)$. With $M > 0$ and $c'(\cdot) > 0$ this implies $\bar{\theta}_i(p_i, p_j) \ < \ \bar{\theta}_j(p_j, p_i)$. Under the assumptions above and given $h(0, p_j) = 0$, there exists a common cutoff θ^* such that in equilibrium $p_i^* > 0$ and $p_j^* > 0 \iff \theta_i, \theta_j > \theta^*$. Each player's interior solution requires $\theta_i = \bar{\theta}_i(p_i, p_j)$. The comparison $\bar{\theta}_i < \bar{\theta}_j$ (for $a_i > a_j$) implies that the larger threshold $\bar{\theta}_i$ is the binding cutoff: if $\theta_i \leq \bar{\theta}_i$ then player j optimally sets $p_i = 0$. By $h(0, p_j) = 0$ this removes any interaction benefit to j coming from i's activity, so j will not have an incentive to choose $p_j > 0$ unless $\theta_j > \bar{\theta}_i$ as well. Therefore both players choose positive effort only when both private parameters exceed the same binding value $\theta^* = \bar{\theta}_j$. Conversely, if $\theta_i, \theta_j > \theta^*$ then the interior FOCs can be satisfied with $p_i, p_j > 0$.

A.1.3 $N = 2, \lambda = 1$ **FOCs.** *Leibniz Rule:* We first need the derivation $\frac{d}{dp_i} G_j(S_i; p_i)$. Since p_i is an argument for both the upper limit S_i and the CDF, we can apply the Leibniz rule.

$$\frac{d}{dp_i} G_{-i}\left(S_i; p_i\right) = \underbrace{\left.\frac{\partial G_{-i}}{\partial s}\right|_{s=S_i}}_{=\varphi_{-i}(S_i;p_i)} \frac{\partial S_i}{\partial p_i} + \underbrace{\left.\frac{\partial G_{-i}}{\partial p_i}\right|_{s=S_i}}_{\text{Leibniz rule}} \tag{19}$$

Write the CDF in the integral form:

$$G_{-i}\left(s; p_i\right) = \int_{-\infty}^{s} \varphi_{-i}(s; p_i) ds \Rightarrow \frac{\partial G_{-i}}{\partial p_i} = \int_{-\infty}^{s} \frac{\partial \varphi_{-i}}{\partial p_i}(u; p_i) du \tag{20}$$

A dp_i increase raises j's score by $\frac{\partial S_j}{\partial p_i} dp_i$, shifting the entire density to the right:

$$\frac{\partial \varphi_{-i}}{\partial p_i}\left(u; p_i\right) = -\varphi_{-i}\left(u; p_i\right) \frac{\partial S_{-i}}{\partial p_i}, \tag{21}$$

Evaluating at $u = S_i$ gives:

$$\frac{\partial G_{-i}}{\partial p_i}\left(S_i; p_i\right) = -\varphi_{-i}\left(S_i; p_i\right) \frac{\partial S_{-i}}{\partial p_i}. \tag{22}$$

Threshold Rule: Let $M_1 = u_S$ and $M_R = V u_R \varphi_j(S_i), G_i = \mathbb{E}\left[g_p h_{p_i}(0, p_j)\right], G_j = \mathbb{E}\left[g_p h_{p_j}(p_j, 0)\right]$. The threshold in this case for player i is $\theta_i^{**} = \frac{M_1 G_i - M_R G_j}{\xi c'(0)}$ and her behavior is binding given i has higher ability as in the previous case. To compare the two cases' threshold, we need one additional assumption on the scale parity.

Assumption 2. *At $p = 0$, the marginal benefit of a score point is no higher in the tournament than in the piece-rate: $M_1 \leq M_0$.*

Intuitively, this assumption keeps the benefits comparable across the two cases. When we subtract the two thresholds, we have $\theta^* - \theta^{**} = \frac{M_R G_j}{\xi c'(0)} > 0 \quad$ since $M_R > 0$ and $G_j > 0$. In conclusion, pure tournament incentives shrink the set of types that find peer interaction worthwhile.

A.1.4 Proof of Proposition 2 Let $d \equiv a_i - a_j \geq 0$ and write $H(d) = \varphi(d)[G_j(d) - G_i(d)]$, with $\varphi(d) = f_{S_i - S_j}(0)$. Assume $G_i'(d) < 0$ and $H'(d) < 0$ for $d > 0$ (the leader's own marginal learning gain falls in the gap, while the competition penalty wanes as ties become rarer). With prize–spread $\lambda \in (0,1]$ the leader's marginal benefit from an infinitesimal increase in p_i at $(p_i, p_j) = (0,0)$ is $\mathrm{MB}_i(d;\lambda) = u_S\, G_i(d) + (1-\lambda)\rho\, u_R\, G_i(d) - \lambda V u_R\, H(d)$. Differentiating gives

$$\frac{\partial \mathrm{MB}_i}{\partial d} = [u_S + (1-\lambda)\rho u_R] G_i'(d) - \lambda V u_R H'(d) > 0,$$

so MB_i is increasing in the ability gap under the stated signs. Let $C \equiv \theta_i \xi c'(0)$ denote the marginal cost of the first unit of help; since $\mathrm{MB}_i(0;\lambda) < C$ and $\lim_{d\to d_{\max}} \mathrm{MB}_i(d;\lambda) = 0^+$, continuity and the monotonicity above yield a unique $\bar{d}(\theta_i,\lambda)$ solving $\mathrm{MB}_i(\bar{d};\lambda) = C$. By best–response logic together with the cross–complementarity of $h(\cdot)$, this cutoff determines the equilibrium interaction rule in Proposition 2: for gaps below $\bar{d}$ the prize–probability loss dominates the leader's learning gain and helping is not worthwhile; as the gap widens the tie density $\varphi(d)$ collapses and the penalty shrinks faster than the (slowly falling) own–learning gain, so the net marginal benefit rises and crosses cost at $\bar{d}$, allowing positive help; for very large gaps the raw learning term $G_i(d)$ becomes negligible and marginal cost again dominates, restoring $p_i^* = p_j^* = 0$.

A.1.5 $P^w_{(N,k)}$ Expression $P^w_{(N,k)}(s) = \sum_{m=0}^{k-1} \binom{N-1}{m} [1-G(s)]^m G(s)^{N-1-m}$ with the derivative given by $P^{w\prime}_{(N,k)}(s) = (N-1)\varphi(s) \sum_{m=0}^{k-2} \binom{N-2}{m} [1-G(s)]^m G(s)^{N-2-m}$.

A.1.6 Proof of Proposition 3 The individual effort e FOC can be written as

$$(\kappa + \delta_i) \frac{\partial S_i}{\partial e_i} - \theta_i c'(e_i) = 0, \qquad \text{where } \kappa = 1 + (1-\lambda)\rho$$

Define $F(e;\theta_i,\delta_i) = (\kappa+\delta_i)\frac{\partial S_i}{\partial e} - \theta_i c'(e)$. By regularity conditions ($c'' > 0, \partial^2 S_i/\partial e^2 < 0$), we have

$$\frac{\partial F}{\partial e} = (\kappa+\delta_i)\frac{\partial^2 S_i}{\partial e^2} - \theta_i c''(e) < 0$$

Using implicit function theorem, differentiate $F(e^*, \theta_i, \delta_i)$ with respect to δ_i:

$$\frac{\partial F}{\partial e}\frac{\partial e_i^*}{\partial \delta_i} + \frac{\partial F}{\partial \delta_i} = 0 \quad \Longrightarrow \quad \frac{\partial e_i^*}{\partial \delta_i} = -\frac{\partial F/\partial \delta_i}{\partial F/\partial e} = -\frac{\frac{\partial S_i}{\partial e}}{\partial F/\partial e}$$

Since $\partial F/\partial e < 0$ and $\partial S_i/\partial e > 0$, we have $\partial e_i^*/\partial \delta_i > 0$.
(ii) Let $A(p) = \frac{\partial S_i}{\partial p_i}(p), \quad \Delta(p) = A(p) - \frac{\partial S_j}{\partial p_i}(p), \quad \kappa = 1 + (1-\lambda)\rho, \quad \delta = \lambda R \pi'_{P,N}(S_i)$ The peer-effort FOC can be written as $F(p;\theta_i,\delta) = (\kappa+\delta)A(p) + \delta\Delta(p) - \theta_i c'(p) = 0$ F is continuously differentiable and

$$\frac{\partial F}{\partial p} = (\kappa+\delta)\frac{\partial A}{\partial p} + \delta\frac{\partial \Delta}{\partial p} - \theta_i c''(p) < 0$$

The implicit function theorem yields

$$\frac{\partial p^*}{\partial \delta} = -\frac{F_\delta}{F_p} = -\frac{A(p^*) + B(p^*)}{F_p}.$$

$A(p^*) > 0$ and for leaders $B(p^*) < 0$. Hence $\frac{\partial p^*}{\partial \delta} < 0$. For laggards algebra reverses and peer effort incentives stay positive or even rise near the cutoff. Evaluate F at $p = 0$. By $c'(0) = 0$,

$$F(0;\theta_i,\delta) = (\kappa+\delta)A(0) + \delta B(0) = \kappa A(0) + \delta(A(0) + B(0))$$

For leaders $A(0) + B(0) < A(0)$. There is a unique critical value $\bar{\delta} = \kappa \frac{A(0)}{-\Delta(0)} > 0$ such that $F\left(0; \theta_i, \bar{\delta}\right) = 0$...

B Experiment Design Details

This appendix provides additional experiment analysis details, including baseline and final survey analyses, measurement of important variables, website details, experiment results robustness checks, and additional results.

B.1 Implementation

B.1.1 Full Prize Structure. Table A1 presents the full prize structure of the experiment. The table includes all stages of the experiment, who is eligible for the reward, the amount of the reward, and the conditions that need to be met to receive the reward.

Table A1: Full Prize Structure

Stage	Who	Reward	Conditions
Baseline Survey	All participants	৳100	Complete baseline survey
Final Exam – Control	*Individual* / *Pair*	৳20 p.p.	Solve≥3 quiz on≥3 different days
Final Exam – Moderate	Top 3 of 10 (Indiv. / *Pair*)	৳500	Solve≥3 quiz on≥3 different days
Final Exam – Intense	Top 1 of 2 (Indiv. / *Pair*)	৳500	Solve≥3 quiz on≥3 different days
Pair Bonus	All *Pair* Mode participants	৳200	Review≥3 quiz with peer on≥3 different days
Endline Survey	Random 25 students	৳300	Complete endline survey

Notes: The condition was initially set at 7 quizzes, but was later relaxed due to: (i) technical challenges with the website, and (ii) the upcoming exam period, to avoid discouraging participation with a high login-day requirement.

B.2 Exam Characteristics

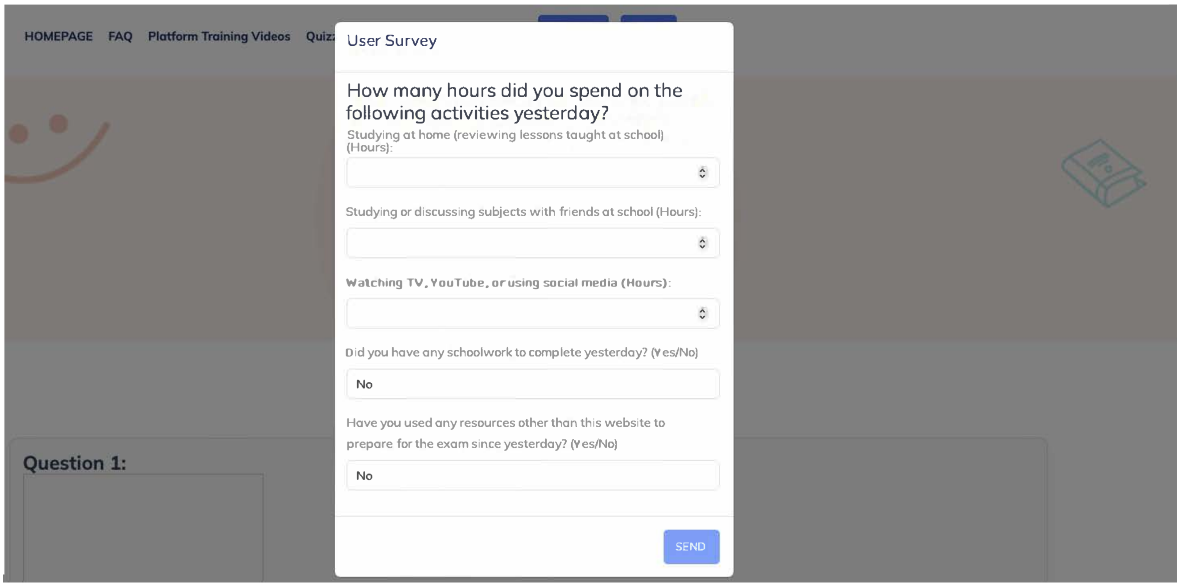
To evaluate the exam characteristics, I collaborated with three college students who also work as private math tutors. These tutors are more familiar with current exam structures than regular teachers who might be less familiar with recent testing formats. To prevent ordering bias (such as fatigue effects), each tutor received exam and website questions in a randomized order. I then aggregated their evaluations to determine the average characteristics of both exams. Both the baseline and endline exams were designed to be of similar difficulty. Table A2 presents the specifications of the exams together with a random selection of questions used in the online learning platform.

B.3 Study Environment: Website

B.3.1 Website Screenshots. Figures A2, A1, A3, A4, A5, and A6 show the screenshots of the website used in the experiment.

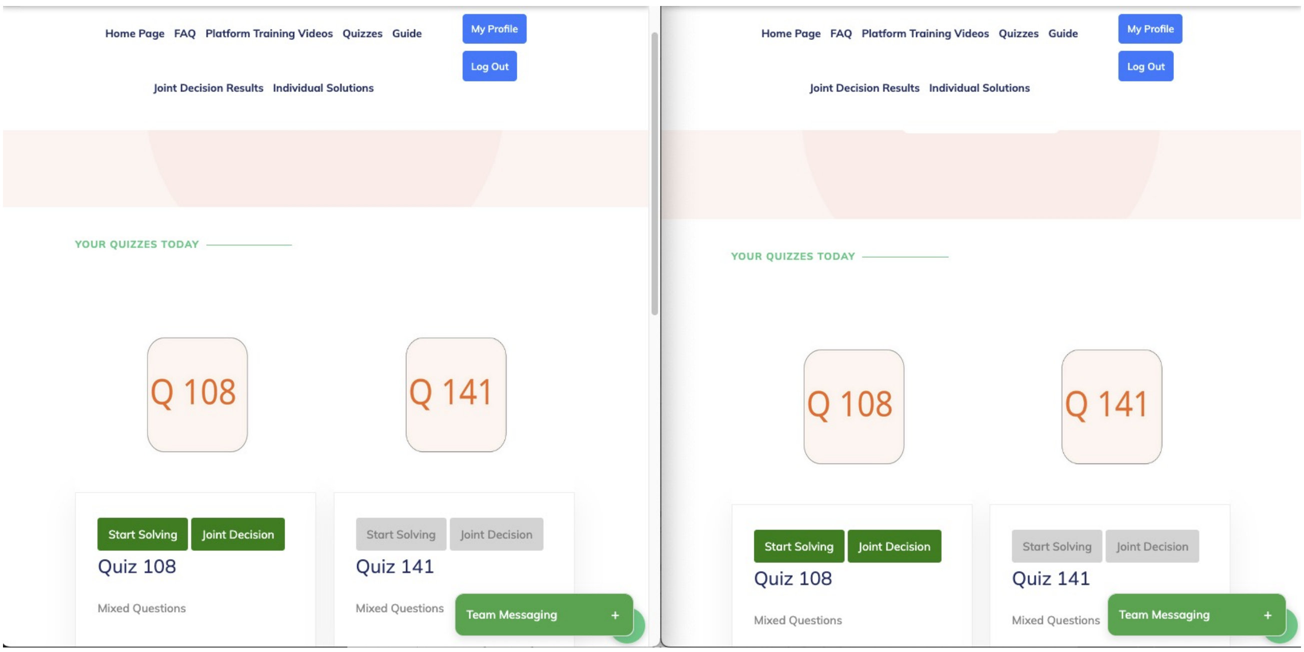
B.3.2 Study Modes: Descriptive Algorithm. The Algorithm 1 describes the conditions under which a student can access the quiz for *Pair* Mode. The quiz is available for solving until 7.00

Figure A1: Website: Daily Pop-up Survey



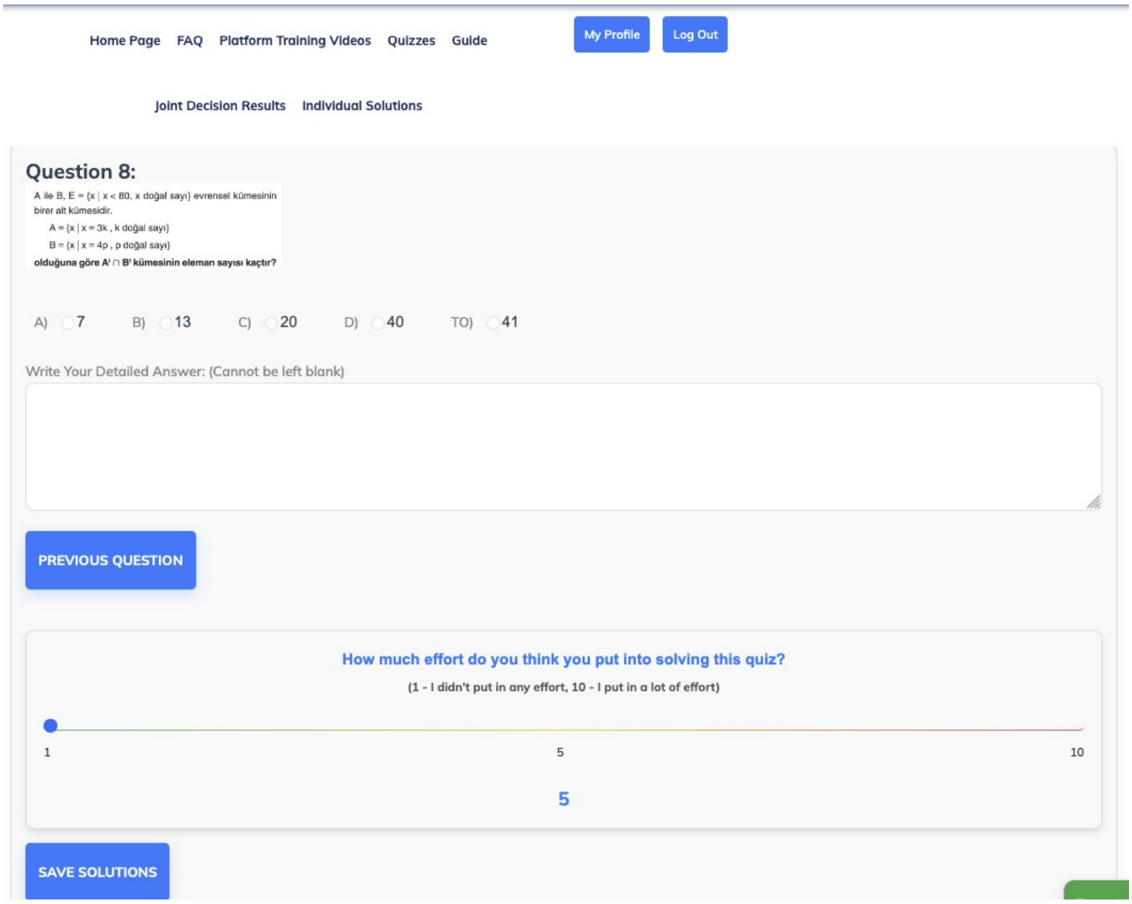
Notes: This figure shows a (translated) screenshot of the daily pop-up survey that appears on the study website used throughout the experiment.

Figure A2: Website: Quiz Page



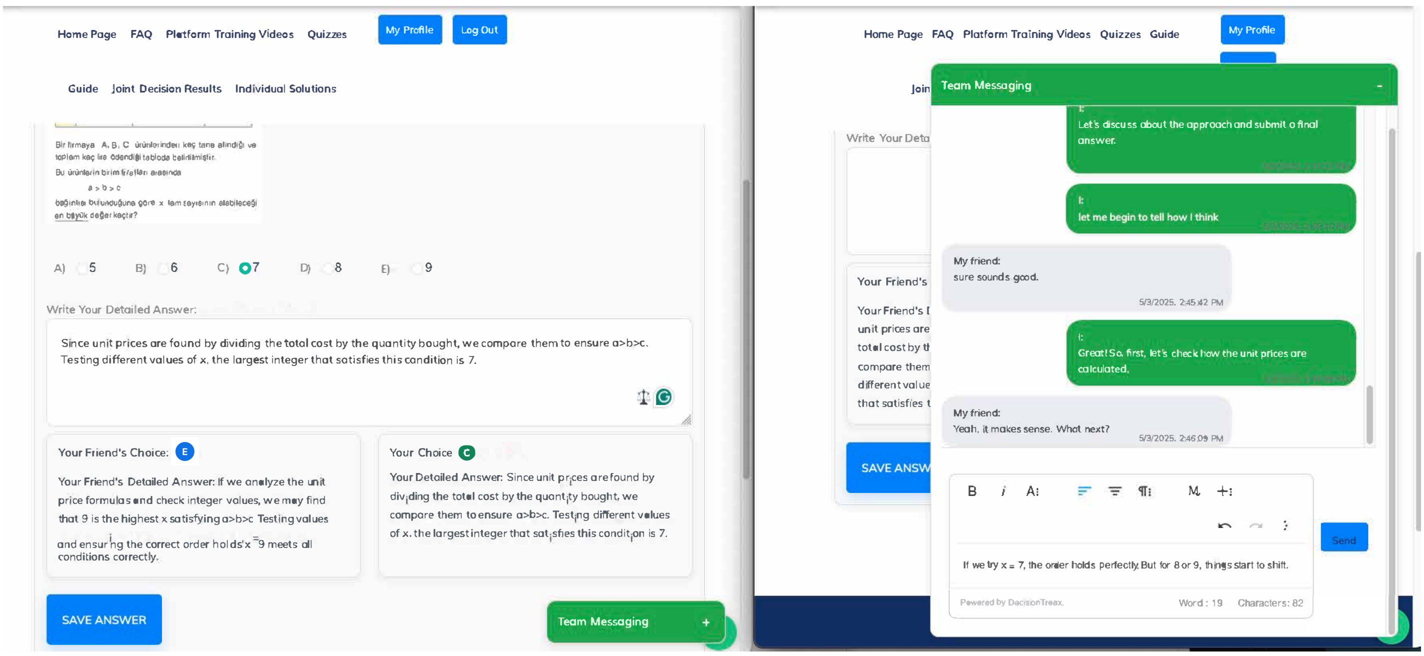
Notes: This figure shows a (auto-translated) screenshot of the quiz page on the study website for the team study mode.

Figure A3: Website: A Quiz Example



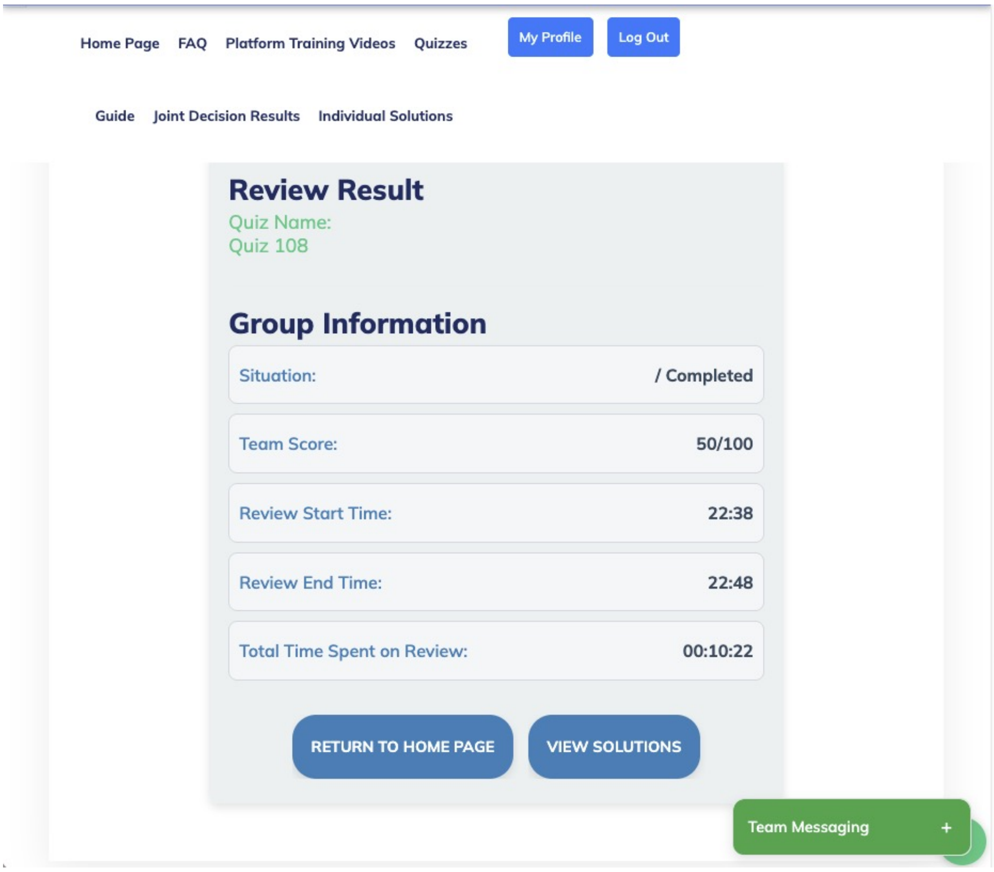
Notes: This figure shows a (auto-translated) screenshot of a quiz's last page whcih includes a single question effort survey.

Figure A4: Website: Review Session



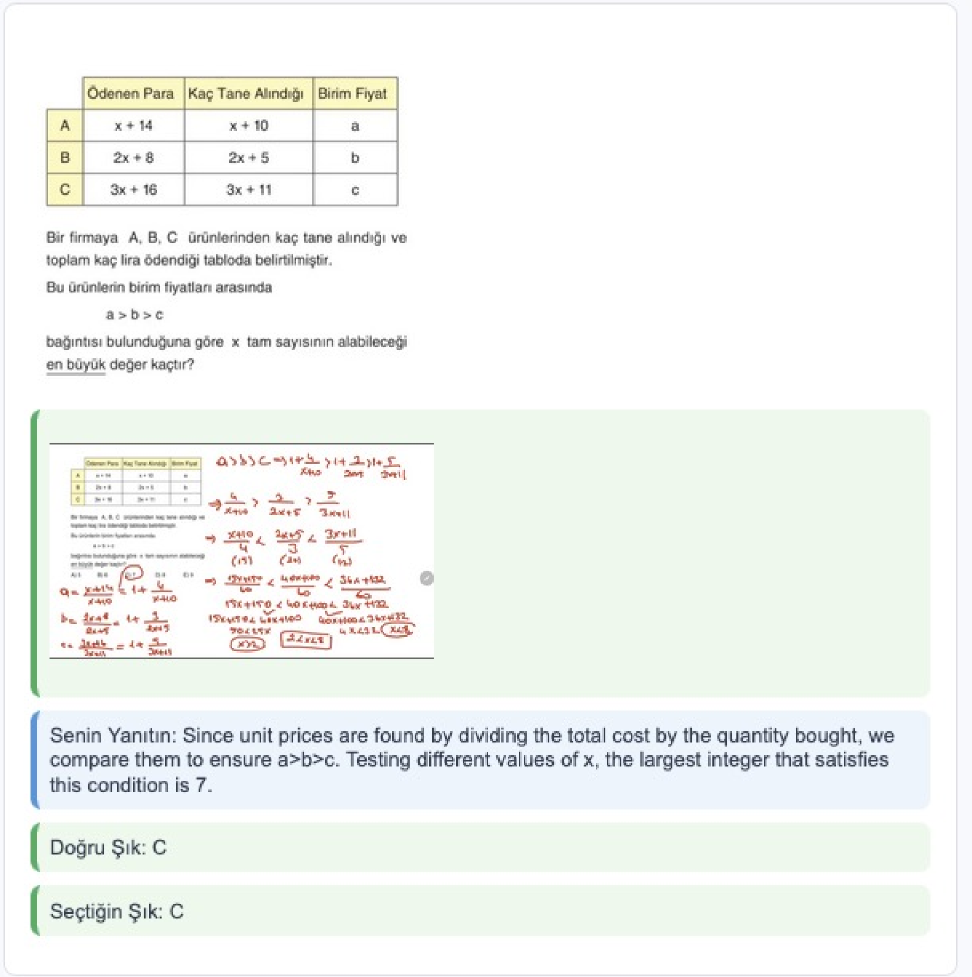
Notes: This figure shows a (auto-translated) screenshot of a review session.

Figure A5: Website: Results Page



Notes: This figure shows a (auto-translated) screenshot of the results page.

Figure A6: Website: Instructional Page



Notes: This figure shows a (translated) screenshot of the instructional page.

Table A2: Exams Specifications

	N	Logic	Sets	Equations	Difficulty	Memory	Analytic
Baseline Exam	25	0.28	0.28	0.44	2.72	0.48	0.52
Final Exam	25	0.32	0.28	0.40	3.28	0.44	0.56
Web Quiz	200	0.15	0.33	0.51	2.88	0.54	0.46

Notes: This table summarizes the exam characteristics for the baseline and the final exam. Except Difficulty, the other variables are the proportion of questions in each category. The difficulty level is measured on a scale from 1 to 5, where 1 indicates "Very Easy" and 5 indicates "Very Hard".

PM, and after that, it can be reviewed until 10.00 PM with the team member.[98] The Algorithm 2 describes the conditions under which a student can access the quiz for *Individual* Mode.

Algorithm 1 Quiz Access Control: *Pair* Mode

Require: User is logged in
Ensure: Quiz solving and answer review conditions are met

```
Start
if User is not logged in then
    Redirect to login page
else
    if Current time < 19:00 then
        Quiz can be solved
    else
        if Quiz has already been solved then
            if 19:00 ≤ Current time < 22:00 then
                Quiz answer display is available
            else
                Process complete
            end if
        else
            Quiz can be solved
        end if
    end if
end if
End
```

B.4 Sample Characteristics and Balance

Table A3 presents the summary statistics of the sample. In addition to the analysis presented in the main text, I also include summary statistics of the parental background variables. On average, 39% of mothers and 46% of fathers have completed higher education, with slightly higher rates among students from high-income strata. A significant majority of fathers (87%) participate in the labor force, compared to 32% of mothers. Notably, mothers' participation in the labor force is

[98] Note that we updated the 7.00 PM to 8.00 PM to leave students more time for their own quiz engagement time before review.

Algorithm 2 Quiz Access Control: *Individual* Mode

Require: User is logged in
Ensure: Quiz solving and review conditions are met

```
Start
if User is not logged in then
    Redirect to login page
else
    if Current time < 19:00 then
        Quiz can be solved
    else
        if Quiz has already been solved then
            if 19:00 ≤ Current time < 22:00 then
                Quiz answers display is available
            else
                Process complete
            end if
        else
            Quiz can be solved
        end if
    end if
end if
End
```

higher among students from high-income strata. The panel highlights socioeconomic differences in both student and parental backgrounds, which are important to consider when interpreting the results of the structural model, particularly regarding cost heterogeneity. Table A4 presents the balance of covariates by treatment status at baseline.

Table A3: Sample Characteristics

Panel A: Student Variables				
Variable	**All**	**Low**	**Medium**	**High**
Female	0.56	0.59	0.56	0.54
	(0.01)	(0.02)	(0.02)	(0.02)
Household Income	5.50	5.37	5.34	5.82
	(0.05)	(0.09)	(0.09)	(0.10)
Num. Younger Sib.	0.89	0.90	0.89	0.87
	(0.02)	(0.04)	(0.04)	(0.04)
Num. Older Sib.	0.81	0.76	0.86	0.78
	(0.02)	(0.04)	(0.05)	(0.05)
Has personal room	0.72	0.70	0.73	0.74
	(0.01)	(0.02)	(0.02)	(0.02)
Has Wi-Fi at home	0.87	0.86	0.86	0.89
	(0.01)	(0.02)	(0.02)	(0.02)
Has Personal Laptop/Tablet	0.72	0.71	0.70	0.76
	(0.01)	(0.02)	(0.02)	(0.02)
9th Grade Lit. score	85.85	81.61	84.63	91.47
	(0.34)	(0.69)	(0.60)	(0.47)
9th Grade Math score	79.23	70.98	78.34	88.28
	(0.50)	(1.00)	(0.84)	(0.67)
Panel B: Parental Background				
Mom Educ.				
$\leq$ Primary Sch.	0.25	0.25	0.24	0.24
Secondary	0.37	0.42	0.41	0.30
Higher Education	0.38	0.33	0.35	0.46
Mom Col. Major				
Arts and Humanities	0.06	0.10	0.04	0.05
Business / Finance	0.12	0.11	0.13	0.12
Engineering	0.05	0.05	0.06	0.04
Health	0.25	0.29	0.31	0.20
Literature, Language	0.37	0.35	0.33	0.41
Science and Math	0.07	0.05	0.03	0.11
Social Sciences	0.08	0.06	0.10	0.06
Mom Empl. Status				
In Labor Market	0.32	0.28	0.27	0.39
Not in Labor Market	0.68	0.72	0.73	0.61
Dad Educ.				
$\leq$ Primary Sch.	0.14	0.14	0.14	0.13
Secondary	0.41	0.47	0.42	0.31
Higher Education	0.46	0.38	0.43	0.56
Dad Col. Major				
Arts and Humanities	0.03	0.03	0.02	0.04
Business / Finance	0.20	0.20	0.19	0.21
Engineering	0.18	0.17	0.21	0.15
Health	0.11	0.10	0.15	0.08
Literature, Language	0.26	0.27	0.24	0.27
Science and Math	0.08	0.08	0.07	0.10
Social Sciences	0.14	0.15	0.11	0.15
Dad Empl. Status				
In Labor Market	0.87	0.86	0.87	0.87
Not in Labor Market	0.13	0.14	0.13	0.13

Notes: This table reports summary statistics on student variables and parental background. Household income categories are as follows: 1 = ₺1-5000, 2 = ₺5.000-10.000, 3 = ₺10.000-20.000, 4 = ₺20.000-30.000, 5 = ₺30.000-40.000, 6 = ₺40.000-50.000, 7 = ₺50.000-75.000, 8 = ₺75.000-100.000, 9 = ₺>100.000. A value of 0 indicates no reported household income.

Table A4: Baseline Covariates

	Control			Intense			Moderate			p_{Δ}		
Covariate	$\mu_{C,I}$	$\mu_{C,P}$	$p_{\Delta I,P}$	$\mu_{I,I}$	$\mu_{I,P}$	$p_{\Delta I,P}$	$\mu_{M,I}$	$\mu_{M,T}$	$p_{\Delta I,P}$	$p_{\Delta C,I}$	$p_{\Delta C,M}$	$p_{\Delta I,M}$
Panel A: Student Background												
Gender	0.469	0.587	0.061	0.587	0.577	0.885	0.651	0.531	0.050	0.441	0.447	0.973
Household Income	5.582	5.386	0.437	5.880	5.325	0.039	5.396	5.333	0.797	0.792	0.574	0.413
Has Personal Laptop/Tablet	0.786	0.772	0.788	0.680	0.724	0.498	0.698	0.753	0.329	0.083	0.218	0.595
Has Wi-Fi at Home	0.898	0.902	0.911	0.813	0.865	0.328	0.896	0.901	0.895	0.073	0.955	0.086
Has a Private Room	0.755	0.690	0.243	0.627	0.699	0.278	0.745	0.741	0.934	0.371	0.434	0.102
9th Grade Lit. Score	83.153	84.628	0.383	88.147	84.566	0.022	84.067	86.528	0.150	0.157	0.206	0.894
9th Grade Math Score	76.112	76.350	0.923	80.267	78.019	0.380	77.087	79.665	0.299	0.149	0.154	0.960
N	98	183		75	159		104	161				
Panel B: Personal Characteristics												
Risk Tolerance	0.545	0.627	0.184	0.707	0.576	0.047	0.613	0.642	0.631	0.659	0.432	0.751
Altruism	-0.094	-0.114	0.872	0.075	-0.026	0.453	0.197	0.047	0.242	0.208	0.014	0.270
Patience	0.396	0.430	0.430	0.436	0.377	0.221	0.374	0.408	0.391	0.448	0.409	0.980
Competitiveness	0.607	0.632	0.326	0.599	0.607	0.768	0.599	0.619	0.421	0.281	0.464	0.710
Cooperativeness	0.625	0.604	0.328	0.607	0.600	0.770	0.630	0.606	0.263	0.564	0.790	0.403
N	93	175		73	154		102	154				

Notes: This table reports the balance of covariates by treatment status at baseline. $p_{\Delta I,T}$ refers to the p-value of the difference in means between the Individual and Team modes. $p_{\Delta C,T1}$ refers to the p-value of the difference in means between the Control and Intense modes at baseline. $p_{\Delta C,T2}$ refers to the p-value of the difference in means between the Control and Moderate modes at baseline. $p_{\Delta T1,T2}$ refers to the p-value of the difference in means between the Intense and Moderate modes at baseline.

C Baseline Results: Survey

C.1 Fact 1: Network Choice and Competition

C.1.1 Homophily Index. In order to document *Fact 1 (i)*, I construct a homophily index for each covariate, including gender, personality traits, competitiveness, cooperativeness, and academic performance. The survey asks students to nominate up to five friends and three study partners within their class. For each student, the homophily index is calculated as the fraction of their reported friends (or study partners) who exhibit similar characteristics. To ensure comparability, all covariates are standardized to have a mean of 0 and a standard deviation of 1 before computing the homophily index. The homophily index for an individual i for a covariate v is defined as follows:

$$H_i^v = \frac{1}{N_i} \sum_{j \in \mathcal{N}_i} \mathbf{1}(|v_i - v_j| < \tau) \tag{23}$$

where N_i is the number of friends (or study partners) of student i, $\mathcal{N}_i$ is the set of friends (or study partners) of student i, and τ is a threshold that determines the level of similarity required for two individuals to be considered similar. In this case, I set $\tau = 0.5$. The homophily index is bounded between 0 and 1 and captures the share of peers who are similar to the individual on a given trait. Under random assignment of friends, the expected homophily depends on the distribution of that trait in the population. For binary traits such as gender, the expected homophily under random assignment converges to the probability that two randomly drawn individuals share the same category. For example, 0.5 if the population is gender-balanced. For continuous traits (like GPA or risk tolerance), I define similarity using a threshold (e.g., within 0.5 standard deviations). The expected homophily under random matching can be lower, just because two random people are less likely to be that close. So in practice, the baseline I'm comparing to the "random" homophily isn't fixed at 0.5 for every variable. It depends on how the data are distributed. That's why I estimate the expected value of homophily under random assignment using permutation tests.

C.1.2 Nearby Competitors. This section provides additional results regarding the choice of friendship and reported nearby competitors and adds some robustness checks.

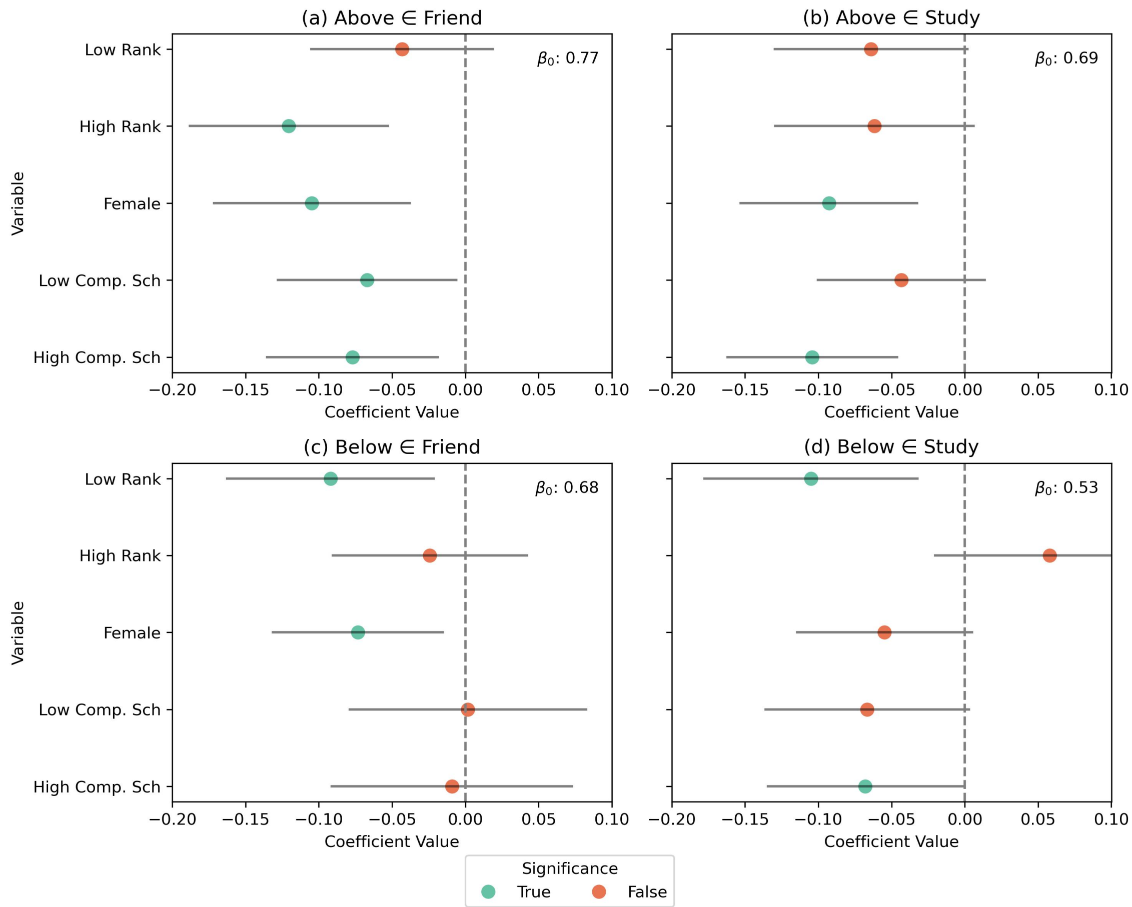
To document Fact 1 (ii), I run the following regression.

$$\mathcal{N}_{d,i}^w = \beta_0 + \beta_1 \text{LowerRank}_i + \beta_2 \text{HigherRank}_i + \beta_4 \mathbf{1}\{s_i \in HC\} + \mathbf{1}\{s_i \in LC\} + X_i + \varepsilon_i \tag{24}$$

where $\mathcal{N}_{d,i}^w$ is a dummy variable equal to 1 if student i's reported classmate in position $w \in \{\text{above}, \text{below}\}$ appears in the $d \in \{\text{friendship}, \text{study}\}$ network. LowerRank is a dummy for students who report being in a lower rank range, and HigherRank for those in a higher rank range. Reported rank takes values from 1 to 6, where 1 corresponds to the lowest bin (ranked 25th or below in class) and 6 to the highest (ranked 1st–5th).[99] X_i is a vector of demographic controls, including gender and household income. LC and HC are indicators for whether student i's school falls into the low- or high-competition groups, based on high school entrance cutoff scores. The omitted category is medium-competition schools. Standard errors are clustered at the school-by-classroom level. I run a separate regression for each combination of w and d. Results from the regression is presented in Figure A7.

[99] The number of students in each rank category is $(16, 58, 213, 345, 402, 337)$. To construct the rank dummies, I grouped the first three categories into "Lower", the fourth and fifth into "Middle", and kept the last as "Higher".

Figure A7: Nearby Classmates vs Network Inclusion



Notes: This figure shows the coefficients of the regression in Equation 24. The bar lines indicate the 95% confidence intervals. Green color represent significant coefficients and the orange color represent insignificant coefficients.

Results indicate that across all models the intercepts, β_0 range from 0.53 to 0.77, indicating a high baseline probability of nominating peers, before accounting for other factors. Across all models except for the Below $\in$ Study, higher ranked students and lower ranked students are less likely to include nearby competitors in their networks. For the higher ranked ones, the highest effect is observed with -0.14 for Above $\in$ Friend.[100] Female students on average less likely to include nearby ones in the network with the effect around -0.10. In addition, compared to moderately competitive schools, students in low and high competitive schools are less likely to include nearby competitors in their networks, with the effect around -0.05. [101][102]

Familarity Bias— One concern regarding reported nearby competitors is that students may be biased toward nominating their friends, either due to familiarity or a kind of halo effect. Fig-

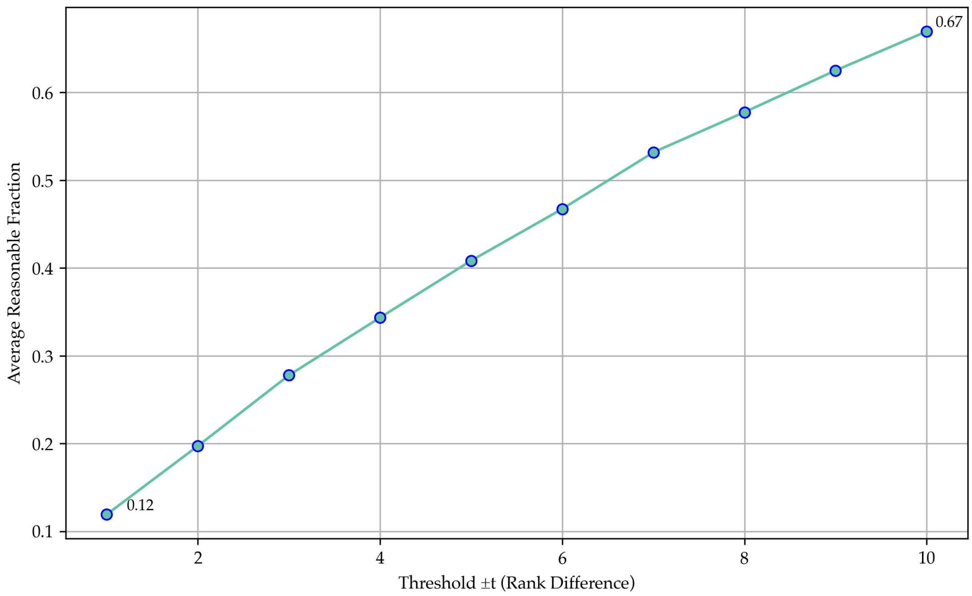
[100] One concern regarding nearby competitors at the top of the distribution is that some students may not perceive anyone as a competitor above them. In line with this expectation, the survey shows that 23 students reported having no one ranked above them. When I exclude these observations and re-run the regressions, the overall patterns remain consistent with the main results, aside from some level shifts. For instance, in the regression for Above $\in$ Friend, the coefficient on High Rank increases slightly from -0.14 in the main regression to -0.12 in the filtered sample.

[101] Second concern with this analysis is a potential familiarity bias. That is, students might report the people they know as nearby competitors. As a robustness check, besides the self reported ranks, I used the actual ranks based on baseline scores.

[102] Additional results regarding the Fact 1 can be found on Online Appendix O.B.2.

ure A8 examines the accuracy of these nominations. Using an academic index (the average of 9th grade Literature and Mathematics scores), I ranked students and evaluated how close the reported above/below peers are in the actual ranking. The x-axis shows the allowable margin of error in rank difference. Accuracy gradually increases with looser thresholds, but only after allowing for a difference of six ranks or more do a majority of the nominations qualify as "reasonable" (i.e., within the specified band). Given an average classroom size of 32–35 students, this indicates that students do not have particularly precise knowledge of their peers' academic standing. While these results suggest some degree of familiarity bias or limited information, my analysis focuses on students' *perceived* nearby competitors regardless of whether they are objectively accurate.[103]

Figure A8: Proximity of Reported Peer Rankings to Actual Rank



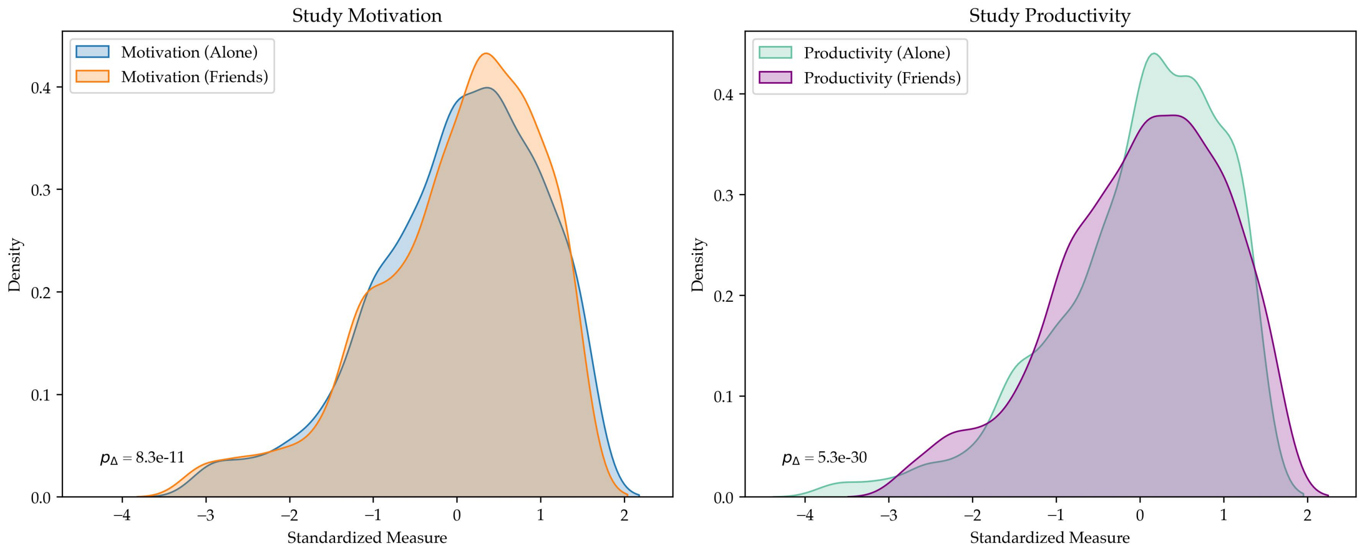
Notes: This figure shows the accuracy of reported nearby competitors.

C.2 Fact 2: Study Motivation and Productivity.

Figure A9 shows the distribution of students' responses to the survey questions regarding their motivation and productivity.

[103] To account for missing or unmatched peer IDs, the vertical axis in Figure A8 is scaled by the highest achievable match rate, calculated at threshold $t = 35$, which approximates the full class size. This normalization ensures that values reflect the share of accurate nominations relative to what is possible in the data.

Figure A9: Self Reported Study Motivation and Productivity



Notes: This figure shows the distribution of students' responses to the survey questions regarding their motivation and productivity. The null hypotheses of distributional equality are rejected by the Kolmogorov-Smirnov test. The $p-$values are reported in the figure.

To document sub-fact (ii), I run the following regression:

$$Y_i^w = \alpha + \beta_1 \text{SelfRank}_i + \beta_3 CompI_i + \beta_4 \mathbf{1}\{s_i \in HC\} + \mathbf{1}\{s_i \in LC\} + X_i + \varepsilon_i \tag{25}$$

where Y_i^w is the outcome variable of interest, which can be either self-reported motivation or productivity.

Table A5: Study Motivation and Productivity

	Motivation (Alone)	Motivation (Friends)	Productivity (Alone)	Productivity (Friends)
Constant	-0.029	0.115	-0.013	0.132*
	(0.049)	(0.073)	(0.053)	(0.071)
Self Rank	0.192***	0.026	0.211***	-0.021
	(0.028)	(0.034)	(0.038)	(0.025)
Female	0.208***	-0.187***	0.209***	-0.187***
	(0.057)	(0.039)	(0.058)	(0.035)
HH Income	-0.026	0.013	0.024	-0.014
	(0.018)	(0.024)	(0.030)	(0.028)
Competitiveness Index	0.190***	-0.108***	0.162***	-0.099***
	(0.022)	(0.031)	(0.032)	(0.025)
High Competition	-0.001	0.067	-0.068	0.121
	(0.085)	(0.127)	(0.071)	(0.125)
Low Competition	-0.243***	0.018	-0.318***	0.015
	(0.077)	(0.123)	(0.071)	(0.129)
R-squared	0.108	0.020	0.114	0.020
R-squared Adj.	0.105	0.016	0.110	0.016
N	1331	1331	1331	1331

Notes: This table reports OLS estimates from regressions of self-reported study motivation and productivity on student characteristics. Each column corresponds to a different outcome and study context. All outcomes are standardized. Standard errors are in parentheses.

Table A6: Friend Characteristics and Study Motivation and Productivity

	Motivation (Alone)	Motivation (Friends)	Productivity (Alone)	Productivity (Friends)
Constant	-0.103**	0.121**	-0.114*	0.124**
	(0.046)	(0.051)	(0.060)	(0.054)
Friend Competitiveness	-0.021	-0.064	-0.009	-0.040
	(0.061)	(0.044)	(0.089)	(0.034)
Friend Academic	-0.074	0.101**	-0.136*	0.122***
	(0.046)	(0.039)	(0.069)	(0.038)
Friend Mental Health	0.079**	-0.037	0.129**	-0.069
	(0.036)	(0.043)	(0.056)	(0.045)
R-squared	0.047	0.015	0.064	0.017
R-squared Adj.	0.043	0.010	0.060	0.012
Controls	Y	Y	Y	Y
N	1341	1341	1341	1341

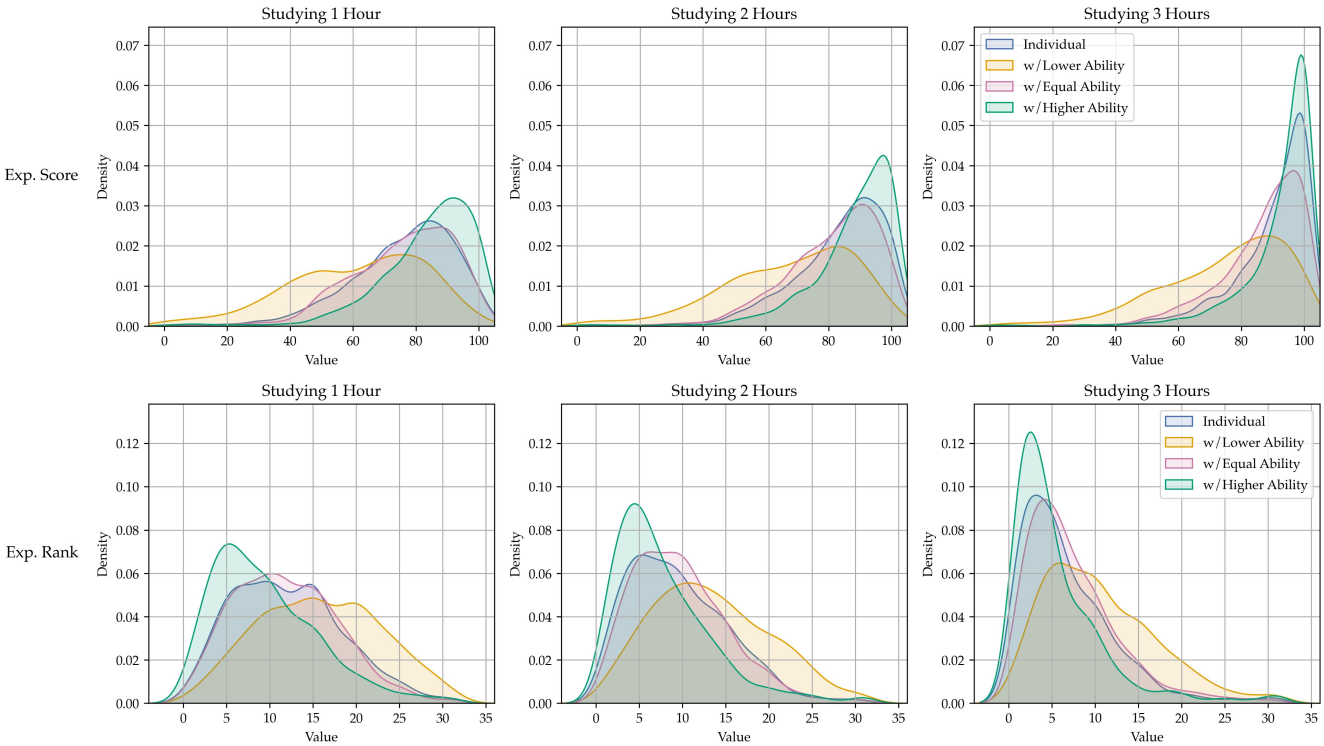
Notes: This table reports the results of the regression of self-reported motivation and productivity on friend characteristics. The competitiveness index is the mean of the competitiveness index of the friends. The academic index is the mean of 9^{th} grade Literature and Mathematics scores of the friends. The mental health index is the mean of the mental health index of the friends. The controls include self characteristics such as gender, household income, and academic performance. The standard errors are clustered at the school level.

C.3 Fact 3: Return to Effort.

Figure A10 shows the distribution of students' responses to the survey questions regarding their return to effort across self studying and studying with friends of varying abilities. [104]

[104] These questions were inspired by Tincani et al. (2023). The relevant survey questions' prompt are given in Table OA.1.

Figure A10: Self-Reported Return to Effort



Notes: This figure shows the distribution of students' responses to the survey questions regarding their return to effort. The first row shows the expected score in a threshold-based system, and the second row shows the expected rank in a rank-based system.

D Experiment Analysis

D.1 Effort Measures

Throughout the experimental and structural analysis, I use the following measures of effort obtained from the website data.

Log-In Frequency. The main analysis in the body of the text uses the number of days a student logged into the website as one proxy for effort. This measure is straightforward: it is derived from the database as a binary variable that indicates whether a student logged in on a given day.

Time Spent on the Website. Ideally, I'd love to get the total daily time spent on the website by each student using their actual log in and log out times, since time on the website can be reasonably interpreted as effort since the platform contains nothing other than academic quizzes and review sessions. But this requires having timestamps for both log in and log out. The issue is that, as shown in the Human-Computer Interaction literature, manual logout behavior is weak (e.g., Suoranta et al., 2014).[105] Anticipating this, the system is designed to automatically log out students after 120 minutes of inactivity, which means students need to log in again to continue giving me a way to detect session breaks.

The platform records all activities separately in the database (Azure SQL Database). The main logs include login history, quiz and question attempts (for both *Individual* and *Pair* modes), result

[105] Potential reasons might be the lack of perceived risks as opposed to other fields such as online banking.

view behavior after completing a quiz, and whether a student viewed the guide pages.

The procedure I follow is assigning learning activities to individual web sessions. To define a user-level learning session, I use the login logs. I first chronologically ordered the login timestamps for each user. I compute the time gaps between consecutive logins and isolated meaningful gaps from system driven forced logouts (e.g. 120 minutes). I, then focused on short gaps under 30 minutes, which are more likely to reflect within-session activity. I fit a Gaussian Mixture Model on the log of time gaps. I defined the threshold for session continuity as the 95th percentile of the shorter gap cluster.[106] A new session was flagged if a user's login gap exceeded this threshold. Next, I clean activity-level data and assign each activity to a session. First, students can view the guide page for training. Guide view events are recorded with their log in timestamps. For each event, I identified the closest session by computing the time difference between the event date and the session start date. I then aggregated the total guide view time by summing durations of all matched events. To measure time spent on the individual quiz attempts (both Individual and Pair modes), I first processed the timestamp metadata associated with each quiz attempt. I computed an initial estimate of quiz duration. To address missing or unreliable duration data, I implemented a complementary text-effort based imputation. For each quiz attempt, I used the answer text total character count across all questions in a quiz. I then calculated a median seconds per character rate from completed quizzes and applied this rate to impute durations for quizzes with missing values. Additionally, I incorporated data from quiz result views. I then matched each quiz attempt to the closest session based on the timestamp. The same procedure was applied to the review sessions in the *Pair* mode. For chat-based interaction time, I segmented chat sessions based on inactivity: if the time gap between messages exceeded 20 minutes, a new session was initiated. I then define sessions as interactive if messages were exchanged within the session. I then attributed the full duration to both participants. If non-interactive session, I attributed the time to the student who initiated the session.

Note that the duration data is not perfect due to the nature of the website and how students interact with it. To address this, I used a two-step imputation strategy for quiz durations. First, for quiz attempts with durations exceeding 60 minutes which are likely to be outliers or technical artifacts, I replaced the duration with the maximum observed duration for that quiz, excluding the outliers. Second, for quiz attempts that are missing duration data entirely (e.g., due to absent end timestamps and no recorded text input), I imputed duration using the 25th percentile of observed durations for the corresponding quiz. This provides a conservative estimate for students who likely opened the quiz but did not meaningfully engage.

Table A7 presents the summary statistics of these activities. On the intensive margin, the mean days logged is 2.69 days, with a median quiz score of 46% and average quiz effort of 6.03. Mean active chat duration for a chat session is 8.89 minutes.

D.1.1 Additional Web Time-Spent Results. Regression results with website time spent as the dependent variable are presented in Table A8.

D.2 Peer Interactions

Table A9 presents the summary statistics of chat interactions by type across three different categories: *Never Logged In*, *Logged In but Never Interacted*, and *Interacted*.

[106] If the model failed to separate the two clusters, I use the 90th percentile of the short gap distribution.

Table A7: Summary Statistics of Web-Based Effort Measures

Variable	Mean	Std Dev	Median	N
Login Count	2.69	2.82	2.00	1746
Avg Quiz Score	45.87	25.76	46.75	609
Avg Quiz Effort	6.03	2.65	6.33	609
Quiz Duration	15.30	27.75	0.00	1746
Active Chat Duration	8.89	21.65	0.00	606
Guide Duration	29.29	79.41	0.92	70
Result View Effort	0.43	2.93	0.00	695

Notes: This table summarizes the daily web-based effort measures across users.

D.3 Peer Distance Measure

To analyze effort conditional on peer type and distance from the peer, I first compute the absolute difference between a student's baseline score and their peer's score. Within each stratum, I then examine the distribution of these distances. Figure A11 shows the distribution of score and score gap. Note that I created three strata based on the baseline score: Low (L), Medium (M), and High (H), by ensuring that each stratum has approximately equal numbers of students. Thus, the density of the scores in each stratum might be different. The left panel shows the distribution of baseline scores. The dispersion of the scores is highest in the High stratum, followed by the Low and Medium strata.[107] The right panel shows the score gap distribution, and as expected, there are observations with large gaps in the High stratum. Thus, creating distant versus close peer groups requires a more careful approach to account for the distributional differences across strata. When the closeness threshold is defined as ± 1 point, the majority of peers fall into the *Distant* group across all strata. However, when the threshold is widened to ± 4 points, the majority of peers shift into the *Close* group, and in the *Medium* stratum, no peers remain in the *Distant* group. Ensuring equal number of students in each close versus distant peer group requires defining different thresholds for each stratum, which is not meaningful given that it naturally assumes differential perception of closeness. The main results use a threshold of ± 1 , defining close peers, reflecting a strict notion of similarity. Results are qualitatively robust to using a wider threshold of up to ± 2, however for higher thresholds > 2, the sign and magnitude of the coefficients change except the *Intense* arm.

D.4 Fine-Tuning Chat Data Analysis

To optimize the classification prompt, I first fine-tuned it using a training set of 100 randomly selected messages, iterating based on classification accuracy and misclassification patterns. The final prompt was validated on a separate test set, achieving 92% accuracy.[108] For classification, I employed an ensemble approach using Llama 3.1, Qwen, and DeepSeek.[109] Each model labeled the dataset independently based on the optimized prompt, and final labels were assigned using a majority vote rule, ensuring robustness and reducing model-specific biases.

[107] Negative score values are possible due to negative markings.
[108] Training is done using DeepSeek R1 Distill Llama 70B.
[109] Specifically, the models used are DeepSeek R1 Distill Llama 70B, Meta Llama 3.1 70B Instruct Turbo, and Qwen 2.5 Coder 32B Instruct. The model choices depend on cost-effectiveness (the size of the models conditional on the per token pricing). Temperature is set to 0.0 in all models to reduce hallucinations or random variation in JSON structure.

Table A8: Website Time Spent: Regression Results

	OLS			GLM		
	(1)	(2)	(3)	(1)	(2)	(3)
Panel A: Control						
Constant	1.161***	1.072***	0.136	0.150	0.074	-1.026***
	(0.209)	(0.240)	(0.278)	(0.170)	(0.197)	(0.284)
Pair	0.098	0.075	0.100	0.081	0.060	0.222
	(0.259)	(0.260)	(0.246)	(0.211)	(0.214)	(0.252)
Female		0.191	0.420*		0.157	0.450*
		(0.249)	(0.239)		(0.204)	(0.244)
Base Score			0.129***			0.110***
			(0.022)			(0.023)
N	282	282	282	282	282	282
Log-Likelihood	-604.029	-603.733	-587.633	40.624	42.331	73.301
Panel B: Moderate						
Constant	1.106***	1.096***	0.127	0.101	0.084	-0.872***
	(0.208)	(0.271)	(0.309)	(0.152)	(0.198)	(0.280)
Pair	0.498*	0.500*	0.513**	0.372*	0.376*	0.513**
	(0.267)	(0.270)	(0.256)	(0.195)	(0.197)	(0.231)
Female		0.016	0.131		0.024	0.098
		(0.267)	(0.254)		(0.195)	(0.230)
Base Score			0.127***			0.099***
			(0.023)			(0.021)
N	268	268	268	268	268	268
Log-Likelihood	-583.322	-583.320	-568.184	-40.504	-40.049	0.842
Panel C: Intense						
Constant	1.785***	1.712***	0.681**	0.579***	0.512**	-0.372
	(0.245)	(0.295)	(0.336)	(0.177)	(0.214)	(0.293)
Pair	-0.539*	-0.538*	-0.305	-0.360*	-0.374*	-0.171
	(0.296)	(0.296)	(0.283)	(0.214)	(0.215)	(0.247)
Female		0.123	0.133		0.130	0.204
		(0.279)	(0.263)		(0.202)	(0.230)
Base Score			0.135***			0.091***
			(0.025)			(0.022)
N	238	238	238	238	238	238
Log-Likelihood	-515.377	-515.279	-500.980	-41.828	-40.005	-5.747

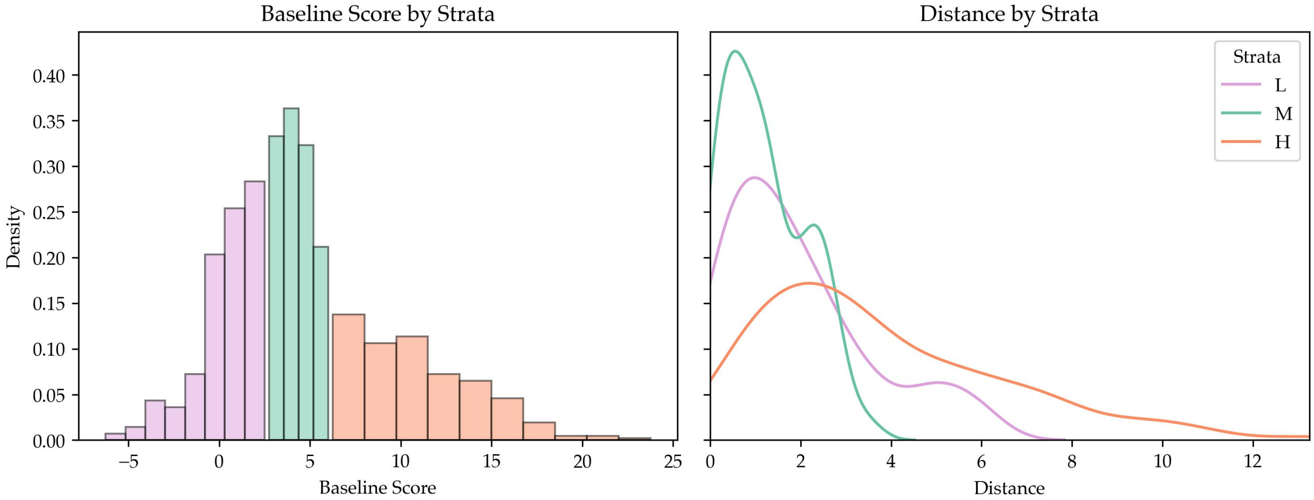
Notes: This table shows the regression results for total time spent on the study website across different reward arms. Columns (1)–(3) report OLS estimates with different controls, while columns (1)–(3) under GLM provide robustness using a generalized linear model. The "Pair" is a dummy variable indicating whether the user is in the Pair study mode. Standard errors are in parentheses.

Table A9: Interaction Types by Reward Arm

Interaction Type	**Control**	**Moderate**	**Intense**
Never Logged In	0.599	0.535	0.570
Login Only	0.120	0.118	0.151
Login + Chat	0.281	0.347	0.279

Notes: This table reports the share of students in each interaction category—"Never Logged In", "Login Only", and "Login + Chat" within each reward arm, limited to those in the *Pair* mode.

Figure A11: Distribution of Peer Distance by Strata



Notes: This figure plots the distribution of peer distance for each stratum. The x-axis shows the absolute difference between a student's baseline score and their peer's score. The $y-$axis shows the density.

Table A10: Effect of Close Peer Assignment on Web Engagement

	Control	Moderate	Intense
Close Peer	0.677*	-0.446	-0.476
	(0.379)	(0.408)	(0.331)
Base Score	0.088***	0.082**	0.100***
	(0.031)	(0.033)	(0.029)
Constant	0.562**	1.011***	0.749***
	(0.266)	(0.332)	(0.252)
N	184	140	178

Notes: This table shows OLS regression results by experimental arm. The dependent variable is number of logged-in days. The variable *Close Peer* is an indicator for whether the absolute score gap to a peer is at most 1 point.

Table A11: Effect of Peer Rank Similarity on Web Engagement (Moderate Arm)

	Log-In		**Interaction**	
	(1)	(2)	(3)	(4)
Similar Rank	0.902	0.544	0.127	0.030
	(0.954)	(0.968)	(0.220)	(0.222)
Middle	1.128*	0.646	0.185	0.055
	(0.677)	(0.725)	(0.156)	(0.166)
Top	1.163*	0.493	0.276**	0.095
	(0.592)	(0.699)	(0.136)	(0.160)
SR × Middle	-2.494*	-1.677	-0.433	-0.213
	(1.484)	(1.543)	(0.342)	(0.354)
SR × Top	-1.860	-1.168	-0.120	0.067
	(1.315)	(1.362)	(0.303)	(0.312)
Baseline Score		0.070*		0.019**
		(0.039)		(0.009)
Constant	0.598	0.595	0.173	0.173
	(0.689)	(0.683)	(0.159)	(0.157)
N	140	140	140	140

Notes: Each column represents an OLS regression using Moderate arm data. The dependent variable is the number of days logged in. Baseline score is included where specified.

D.4.1 LLM Prompting The following is the final prompt used for both Llama 3.1, Qwen, and DeepSeek models:

```
You are a highly accurate classification model. Classify the following Turkish
message into binary categories (1 if present, 0 if not). Always return 1 if the
category is clearly present. Otherwise, return 0. Do not return "null". A message
can belong to none, one, or multiple categories. If message content is missing, you
can skip it.
Categories: - CoopLanguage (1/0): The message uses cooperative or encouraging
language, such as expressing willingness to work together, motivating peers, or
offering support. Examples: suggesting group effort, cheering others on, asking to
collaborate.
- TaskRelated (1/0): The message talks about quiz content, math tasks, technical
issues, or coordination related to work or platform usage. Includes problem-solving,
scheduling, and system navigation.
- AnonymityRisk (1/0): The message shares or requests personal or identifying
details, including names, school names, phone numbers, gender, or social media
handles. - IncentiveMention (1/0): The message mentions rewards, payments, or
financial incentives related to the task or quiz.
CoopLanguage: - "Quiz çözelim mi?" - "Ben 7 gibi gireceğim." - "Beraber yapalım mı?"
- "Ben yardımcı olurum." - "Birlikte çözelim!" - "Hadi başarırız!"
TaskRelated: - "Ben A şıkkını buldum." - "Sistemde sorun var." - "Nereden
başlıyoruz?" - "Bence 4 tane seçebiliriz." - "8'de başlayalım mı?" - "Kaç soru/quiz
çözelim sence?"
AnonymityRisk: - "Benim adım Ali." - "Sen hangi okuldasın?" - "Kimsin?" - "ismin ne?"
- "Kız mısın, erkek mi?" - "Instagram hesabın var mi?" - "Kimle eşleştim?"
IncentiveMention: - "Kazanan ne kadar alacak?" - "Ödül ne zaman yatacak?"
Message: "message"
ONLY return a JSON object with integers 0 or 1. Do NOT include explanations or extra
text.
Example output: "CoopLanguage": 1, "TaskRelated": 0, "AnonymityRisk": 0,
"IncentiveMention": 0
```

D.5 Experiment Robustness Checks

D.5.1 Other Activities During Preparation Stage. To control for other activities students engaged in during the preparation stage, which might impact overall learning, I collected information through the website using a pop-up survey, as displayed in Figure A1.[110] Table A12 summarizes the results. Across the ten days of preparation (excluding the first day, which was only intended for students to log in and watch training videos), a total of 195 unique students provided survey responses, ranging from a low of around 30 users (in the later stages) to a high of 96 users (on Day 3, when *Individual* study mode students were also included). Note that these numbers may not reflect overall engagement, since the pop-up survey was shown only if a student started solving a quiz; it was not displayed otherwise. As a result, students who logged in but did not solve a quiz on a given day are not captured in these numbers. The response rates follow the similar pattern as the overall engagement rates with the Intense arm Pair mode having the lowest response (0.11) and Intense arm *Individual* mode (.20) having the highest response rates. Due to the low number of responses, I conduct Mann-Whitney U tests to compare the distributions of responses across treatment arms. Focusing only on the days after the third day (when *Individual* study mode students were also included), the results suggest that there are no statistically significant differences across arms for most variables. The only exception is the "If Had Homeworks" variable, where the difference between the Control and Moderate arms is statistically significant at the 10% level, with $p-$ value of 0.08. However, according to the regression results, the magnitude

[110] Due to a software issue, the pop-up survey was not displayed for students in the *Individual* study mode during the first two days of exam preparation.

of the *Pair* coefficient remains larger in the Moderate arm.[111]

Table A12: Other Activities During Preparation Stage

Variable	**Control**	**Intense**	**Moderate**
If Had Homework	0.86	0.87	0.77
	(0.04)	(0.04)	(0.04)
Study Time	2.09	1.91	2.1
	(0.15)	(0.13)	(0.11)
Used Other Sources	0.67	0.59	0.61
	(0.06)	(0.06)	(0.05)
If Homeworks Affected	0.02	0.25	0.18
	(0.09)	(0.1)	(0.08)

Notes: This table reports the summary of other academic activities students engaged in during the preparation stage. *If Homeworks Affected* is a Likert scale variable where 1 indicates "Strongly Positively Affected" and 5 indicates "Strongly Negatively Affected".

D.5.2 Dorm Students. As stated in the main body, students who resided in dormitories were assigned to the *Individual* study mode due to strict phone policy requirements from the dormitory administration. One concern here is whether dorm students are systematically different from the rest of the sample. Looking at background characteristics, the fraction of female students among dorm residents is 0.58, compared to 0.54 in the High stratum from Table A3. Household income is slightly lower, around 5.71 compared to 5.82 in the High category. The mean Literature and Math scores are 93.63 and 91.07, respectively, compared to 91.47 and 88.28. While the differences in baseline scores are not statistically significant (within respective schools), dorm students seem to have slightly higher academic performance. To check robustness, I re-ran the analysis on effort and scores controlling for these students. When the full model for website log-in days is estimated (NB – Column 4 in Table 3), the coefficient values on Pair are slightly higher, and the significance levels remain unchanged.

D.5.3 Grading Issue. Due to an error in the answer key for one of the baseline exam booklets, a subset of students received incorrect information about their scores and ranks. Since booklet distribution within classrooms was random, and seating within a desk is unlikely to correlate with ability, the error can be treated as random. Endline survey suggests that awareness of this issue is not common. Students also had no direct way of verifying their results, as booklets were collected immediately and correct answers were not shared.[112] To be conservative, I exclude any student whose known and actual score differ by more than one question. I also exclude students whose known and actual rank differ by more than one in the *Intense* arm, and more than three in

[111] While not statistically significant, possibly due to the small sample size (small finall survey response rate) of around 50 students per arm.

[112] There were four distinct versions of the baseline exam to prevent cheating. Exams were graded using an optical reader based on a single answer key per version. One version had multiple answer key errors; the others had at most one. Around 311 students received the problematic version, though not all were directly affected, it depends on which questions were attempted. The issue was only discovered after the final exam. In the endline survey, students were later informed of the error and the IRB was also informed.

the *Moderate* arm. All balance checks reflect this restricted sample. Importantly, the main results remain robust both qualitatively and quantitatively even when this restriction is not imposed. See GitHub for a comparison.

D.5.4 Potential SUTVA Violations. Violations in my set-up might arise due to two reasons. One is related to the main treatment assignment: for example, if students in different reward arms are aware of differential incentives, they might feel this is unfair and put in less effort than they would have if they didn't know others' assignments. The second concern is more specific to the grading issue. Students in the same classroom might discuss their scores and behave differently. These are both potential violations of the stable unit treatment value assumption (SUTVA), since one student's outcome could be influenced by others' treatment. To address this, I re-ran the analysis with clustered standard errors at the classroom level. Figure A14 shows the results where all standard errors are clustered at the classroom level. Accordingly, compared to the table in the main body, the significance of the results stayed the same for the Control and Moderate arms, while it decreased for the Intense arm. Importantly, the magnitude and direction of the estimates remain stable across specifications, reinforcing the robustness of the results.

D.5.5 Pair Bonus. The pair bonus was introduced on the third day of the website training due to high coordination costs in the Pair mode, which led to low engagement early on. Since the main results in the body of the paper may partly reflect the effect of this bonus, I re-ran the analysis focusing only on the first two days of the experiment, before the pair bonus was introduced. The main descriptive results are shown in Table A13. The patterns are qualitatively similar to the main results. I also estimated a regression similar to the one in Table 3, restricting the log in data to the first two days. The results are again qualitatively consistent: in the full model (NB – Column 4), the Pair coefficients are 0.187, 0.232, and –0.061 for the Control, Moderate, and Intense arms, respectively, while not statistically significant at conventional levels possibly due to smaller log-in rates in the first two days.

Table A13: Website Activity: Before Pair Bonus

	Control		**Moderate**		**Intense**	
	Ind	Pair	Ind	Pair	Ind	Pair
Mean Days Logged in	0.561	0.560	0.530	0.602	0.693	0.577
	(0.715)	(0.785)	(0.714)	(0.813)	(0.816)	(0.790)
Mean Days-If Logged In	1.310	1.493	1.326	1.537	1.486	1.492
	(0.462)	(0.500)	(0.469)	(0.499)	(0.500)	(0.500)
Fraction Ever Logged In	0.429	0.375	0.400	0.392	0.467	0.387
N	98	184	115	171	75	163

Notes: This table summarizes website login behavior before the introduction of the pair bonus, across study modes and reward arms. "Mean Days Logged In" is calculated over the full sample, while "Mean Days–If Logged In" conditions on students who logged in at least once (with standard errors in parentheses). "Fraction Ever Logged In" reports the share of students with at least one login.

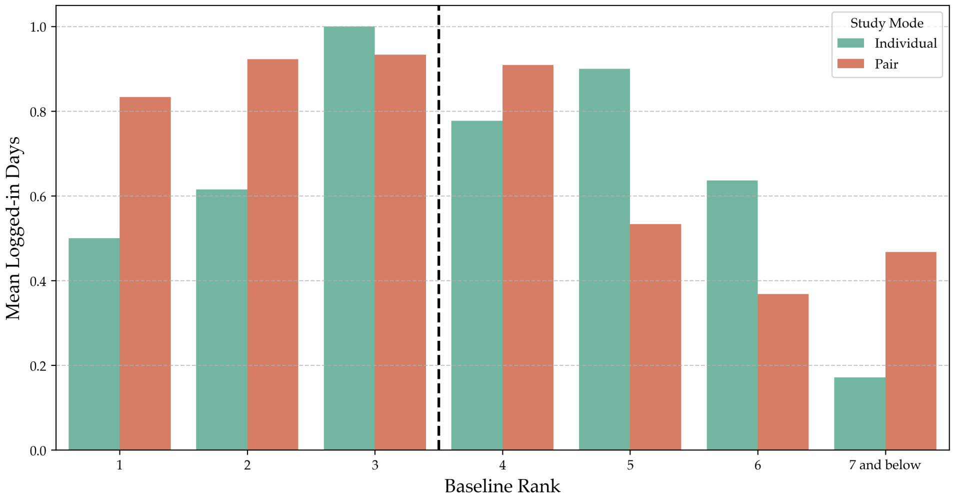
D.5.6 Information Effect. While the main difference across the arms is the reward structure and the study mode, there are also natural differences in the amount of information available to students, based on what they see in the text messages they received. For example, in the Individual

Table A14: Website Activity: Regression Results (Clustered at Classroom Level)

	OLS				Negative Binomial			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel A: Control								
Constant	1.041***	0.818***	0.118	-0.390	0.040	-0.154	-0.858***	-1.422***
	(0.196)	(0.194)	(0.155)	(0.363)	(0.188)	(0.200)	(0.238)	(0.323)
Pair	0.204	0.148	0.167	0.248	0.179	0.099	0.144	0.225
	(0.204)	(0.204)	(0.189)	(0.195)	(0.182)	(0.184)	(0.181)	(0.236)
Female		0.474*	0.645***	0.567*		0.415**	0.576***	0.408
		(0.243)	(0.233)	(0.293)		(0.198)	(0.197)	(0.265)
Base Score			0.097***	0.116**			0.081***	0.086**
			(0.022)	(0.055)			(0.018)	(0.036)
N	282	282	282	282	282	282	282	282
Classroom FE	No	No	No	Yes	No	No	No	Yes
Log-Likelihood	-605.016	-603.192	-594.372	-560.762	-422.403	-419.383	-405.817	-357.287
Panel B: Moderate								
Constant	1.038***	0.986***	0.215	0.781***	0.037	-0.010	-0.780***	-0.264
	(0.206)	(0.245)	(0.254)	(0.299)	(0.198)	(0.229)	(0.275)	(0.330)
Pair	0.314	0.324	0.334	0.412	0.264	0.274	0.354*	0.538*
	(0.254)	(0.254)	(0.228)	(0.275)	(0.224)	(0.223)	(0.201)	(0.306)
Female		0.080	0.171	0.286		0.070	0.156	0.101
		(0.269)	(0.264)	(0.311)		(0.221)	(0.212)	(0.286)
Base Score			0.101***	0.109**			0.081***	0.084*
			(0.026)	(0.055)			(0.021)	(0.045)
N	268	268	268	268	268	268	268	268
Classroom FE	No	No	No	Yes	No	No	No	Yes
Log-Likelihood	-564.631	-564.579	-553.723	-522.931	-409.492	-409.405	-394.577	-340.639
Panel C: Intense								
Constant	1.667***	1.633***	0.708**	1.491***	0.511**	0.478*	-0.209	0.276*
	(0.391)	(0.460)	(0.341)	(0.354)	(0.235)	(0.280)	(0.294)	(0.142)
Pair	-0.397	-0.396	-0.187	-0.260	-0.272	-0.276	-0.135	-0.138
	(0.375)	(0.377)	(0.318)	(0.370)	(0.235)	(0.234)	(0.217)	(0.294)
Female		0.057	0.066	0.057		0.062	0.120	0.223
		(0.283)	(0.279)	(0.352)		(0.206)	(0.223)	(0.302)
Base Score			0.121***	0.068			0.073***	0.045
			(0.044)	(0.046)			(0.021)	(0.035)
N	238	238	238	238	238	238	238	238
Classroom FE	No	No	No	Yes	No	No	No	Yes
Log-Likelihood	-533.434	-533.416	-523.709	-480.564	-386.155	-386.091	-374.220	-320.215

Notes: This table reports regression results with standard errors clustered at the classroom level (defined as unique combinations of classroom and school). Columns (4) include classroom fixed effects.

Figure A12: Mean Days Logged-in by Baseline Rank



Notes: This figure shows the average days logged-in (for first two days) against rank from baseline exam. The vertical dashed line indicates the margin of winning a prize.

mode, students only see their own scores and ranks (if they are in the *Moderate* or *Intense* arm), while in the Pair mode, they can also see their teammate's scores and ranks.[113] I address in the structural analysis by explicitly modeling the information differences.

D.6 Exams Analysis

Tables A15 and A16 present the summary statistics and correlation of the exam scores, respectively.

Table A15: Baseline and Final Exam Summary Statistics

	Mean	Median	SE	N
Panel A: Baseline Exam				
All	6.532	5.500	0.192	788
Investors	8.495	8.000	0.318	336
Non-Investors	5.072	4.250	0.213	452
Panel B: Final Exam				
All	7.342	6.250	0.248	664
Investors	9.473	8.750	0.401	280
Non-Investors	5.788	4.500	0.289	384

Notes: This table provides summary statistics for the baseline and final exams. SE stands for Standard Error.

D.7 Final Survey Results

Additional results from the final survey are presented in this section. The final survey was conducted to gather information about students' perceptions of their assigned peers, their study

[113] The information angle was not explicitly part of the experimental design, since doing so would have complicated things especially in the *Moderate* arm, where each group has 10 students and showing everyone's baseline performance would be too much.

Table A16: Baseline and Final Exams - Correlation by Arms

	Control	Moderate	Intense
Individual	0.705	0.787	0.843
N	98	106	75
Team	0.748	0.801	0.621
N	184	162	163

Notes: This table shows the correlation between baseline and final exams by arms. The first row shows the correlation, and the second row shows the count of students.

Table A17: Final Exam Participation

	Control			Moderate			Intense			p_Δ		
	$\mu_{C,I}$	$\mu_{C,T}$	$p_{\Delta I,T}$	$\mu_{M,I}$	$\mu_{M,T}$	$p_{\Delta I,T}$	$\mu_{In,I}$	$\mu_{In,T}$	$p_{\Delta I,T}$	$p_{\Delta C,M}$	$p_{\Delta C,In}$	$p_{\Delta M,In}$
Fraction	0.856	0.852	0.911	0.822	0.860	0.252	0.780	0.824	0.297	0.582	0.043	0.113
N	140	310		173	366		127	272				

Notes: This table reports the final exam participation across reward and study mode arms.

habits, and their overall experience during the experiment. Around 30% percentage of students completed the final survey with differences across reward arms and study modes.[114]

D.7.1 Social Behavior. Table A20 presents the regression results regarding the students' perceptions of their peers' social skills. Accordingly, competition reduces the social skills of the peers and more so for the Intense arm. The results are consistent across the three measures of social skills.

E Structural Analysis

E.1 Model Specifications

E.1.1 Approximated Equilibrium In Definition 1, I introduce the approximated equilibrium for the game, which replaces the discontinuous win indicator with a smoothed probit winning probability. This transformation ensures that each player's objective function is continuous and strictly concave in their own actions, and depends only on their individual information set. The approximation preserves key qualitative properties of the Bayesian Nash Equilibrium (BNE), including monotonicity: higher-cost types exert less effort. Additionally, the approximation maintains the ordinal ranking of students' utilities, preserving the comparative statics and welfare implications of the original game.

Next, I derive the approximated probabilities for each arm. Firstly, I can write the score production process as $S_i = S_i^0 + G_i(e_i, p_i) + \epsilon_i$, derived as follows. Let the baseline score be given by

$$S_i^0 = \exp(\beta_0 + \beta_1 \ln a_i + \varepsilon_i^0),$$

[114] The response rate for the *Control-Individual* is 0.24, *Control-Pair* 0.28, *Moderate-Individual* 0.27, *Moderate-Pair* 0.24, *Intense-Individual* 0.31, and *Intense-Pair* 0.23. The fractions are also in line with the main treatment effects.

Table A18: Final Exam Regression Results

	(1)	(2)	(3)
Constant	0.008	-0.068	-0.089
	(0.055)	(0.072)	(0.077)
Base. Score	0.728***	0.723***	0.726***
	(0.025)	(0.025)	(0.025)
Pair	-0.050	0.064	0.059
	(0.054)	(0.089)	(0.089)
Moderate	0.124**	0.174*	0.167*
	(0.061)	(0.100)	(0.100)
Intense	-0.052	0.177	0.173
	(0.064)	(0.113)	(0.114)
Moderate × Pair		-0.072	-0.062
		(0.125)	(0.126)
Intense × Pair		-0.335**	-0.328**
		(0.138)	(0.138)
Female			0.044
			(0.052)
R-squared	0.566	0.571	0.571
R-squared Adj.	0.564	0.567	0.566
Observations	664	664	664

Notes: This table presents the regression results for the final exam scores. The dependent variable is the standardized final exam score. The independent variables include the baseline score, treatment arms, study mode, and interaction terms. Standard errors are clustered at the individual level.

Table A19: Final Exam Regression Results: Attempt and Correct Outcomes

	Analytical		**Memory**	
	Attempt	Correct	Attempt	Correct
Moderate	0.017	0.064***	-0.006	0.016
	(0.016)	(0.016)	(0.018)	(0.018)
Intense	0.114***	0.039**	0.054***	-0.053***
	(0.017)	(0.017)	(0.019)	(0.019)
Pair	-0.005	0.042***	-0.016	0.003
	(0.014)	(0.014)	(0.016)	(0.016)
Moderate x Pair	0.003	-0.038*	0.023	0.009
	(0.020)	(0.020)	(0.023)	(0.022)
Intense x Pair	-0.098***	-0.089***	-0.058**	-0.000
	(0.021)	(0.021)	(0.024)	(0.024)
Baseline Analytical Attempt	0.324***			
	(0.018)			
Baseline Analytical Correct		0.262***		
		(0.028)		
Baseline Memory Attempt			0.258***	
			(0.022)	
Baseline Memory Correct				0.323***
				(0.029)
R-squared	0.181	0.225	0.175	0.247
Classroom FE	Yes	Yes	Yes	Yes
Question FE	Yes	Yes	Yes	Yes
N	11,032	11,032	8,668	8,668

Notes: This table reports OLS estimates using only final exam responses. Regressions control for prior baseline attempt/correctness in the same domain. All models include classroom and question fixed effects. Standard errors in parentheses.

Table A20: Treatment Effects on Peer-Rated Traits

	(1)	(2)	(3)	(4)
Friendliness	1.121**	1.121**	1.108**	1.108***
	(0.440)	(0.437)	(0.447)	(0.376)
Prosociality	0.047	0.047	-0.010	-0.010
	(0.440)	(0.437)	(0.447)	(0.376)
Moderate		-0.664*	-0.710*	-1.786***
		(0.399)	(0.408)	(0.442)
Intense		-1.108**	-1.125**	-2.124***
		(0.496)	(0.507)	(0.613)
Base. Competitiveness			-2.511**	-3.931***
			(0.971)	(1.172)
Classroom FE	No	No	No	Yes
Observations	321	321	306	306

Notes: Outcome is peer-perceived trait rating (standardized and pooled across cooperativeness, prosociality, and friendliness). All regressions include trait fixed effects. Column (4) adds classroom fixed effects..

and ε_i^0 is a baseline shock. The production can be written as

$$\ln S_i - \ln S_i^0 = \Delta_i(e_i, p_i) = \beta_2 \ln e_i + \beta_3 (\ln e_i)^2 + \ln p_i \left(\beta_4 + \beta_5 d_{ji} + \beta_6 \ln a_i \cdot d_{ji}\right) + \tilde{\varepsilon}_i,$$

where $\tilde{\varepsilon}_i = \varepsilon_i - \varepsilon_i^0$. This implies the exact decomposition $S_i = S_i^0 \exp[g(e_i, p_i)] \exp[\tilde{\varepsilon}_i]$, where $g(e_i, p_i)$ collects the deterministic terms in $\Delta_i(e_i, p_i)$. Using a first-order Taylor approximation, we have $\exp[g(e_i, p_i)] \approx 1 + g(e_i, p_i), \quad \exp[\tilde{\varepsilon}_i] \approx 1 + \tilde{\varepsilon}_i$, which is valid for small g and $\tilde{\varepsilon}$ (as both are in logs). Substituting yields the linearised form:

$$S_i = S_i^0 + G(e_i, p_i) + \epsilon_i,$$

where $G(e_i, p_i) = S_i^0 g(e_i, p_i)$ and $\epsilon_i = S_i^0 \tilde{\varepsilon}_i$.

I begin with defining the approximated probability, $\tilde{P}_i^w(II)$ for Intense arm, *Individual* mode.

Intense-Individual — As provided in column 3 of Table A23, student knows own baseline score S_i^0 and the corresponding rank r_i^0. In this case, student does not know the peer's baseline score, improvement, or noise.

Student i wins if

$$S_i^0 + G_i(e_i) + \epsilon_i \geq S_j^0 + G_j(e_j) + \epsilon_j,$$

which can be rearranged as:

$$G_i(e_i) \geq \Delta_{ij}^0 + (G_j - \mu_G) + \mu_G + (\epsilon_j - \epsilon_i),$$

where $\Delta_{ij}^0 = S_j^0 - S_i^0$ is the baseline score gap, $\mu_G = \mathbb{E}[G_j]$ (prior mean of the peer's improvement), and $\omega \equiv G_j - \mu_G + (\epsilon_j - \epsilon_i) \sim \mathcal{N}(0, \sigma_G^2 + 2\sigma_\epsilon^2)$, where σ_G^2 is the variance of the peer's improvement and σ_ϵ^2 is the variance of the noise. Let the total standard deviation be denoted as $\tau_I := \sqrt{\sigma_G^2 + 2\sigma_\epsilon^2}$.

In this treatment arm, only the rank r_i^0 is observed, so the rank difference $\Delta_i^{\text{rank}} := r_i^0 - r_j^0$ is known. Since the cutoff is the median in this 2-player game, the percentile of student i is $1 - \frac{r_i^0 - 0.5}{2}$, corresponding to a z-score of either $+0.674$ or -0.674. If baseline scores are normally distributed, a one-rank difference corresponds to a score gap of approximately $\sigma_{S_0} \Delta_i^{\text{rank}}$. So I approximate the expected leader-laggard gap as: $\Delta_{ij}^0 \approx \sigma_{S_0}\Delta_i^{\text{rank}}$. Then the winning rule becomes:

$$G_i(e_i) \geq \sigma_{S_0}\Delta_i^{\text{rank}} + \mu_G + \omega,$$

and the winning probability is given by:

$$\tilde{P}_i^{w,II} = \Pr\left(\frac{\omega}{\tau_I} \leq \frac{G_i(e_i)}{\tau_I} - \frac{\sigma_{S_0}}{\tau_I}\Delta_i^{\text{rank}} - \frac{\mu_G}{\tau_I}\right),$$

which can be written in Probit form:

$$\Phi\left(\delta_0^I + \delta_1^I G_i(e_i) + \delta_2^I \Delta_i^{\text{rank}}\right), \tag{26}$$

where $\delta_0^I = -\frac{\mu_G}{\tau_I}, \quad \delta_1^I = \frac{1}{\tau_I}, \quad \delta_2^I = -\frac{\sigma_{S_0}}{\tau_I}$.

Intense-Pair — In this version, students observe both S_i^0 and S_j^0, so the baseline gap Δ_{ij}^0 is directly known. The winning rule becomes:

$$G_i(e_i, p_i) \geq \Delta_{ij}^0 + \mu_G + \omega,$$

with the same noise structure as above. Hence,

$$\tilde{P}_i^{w,IP} = \Phi\left(\delta_0^I + \delta_1^I G_i(e_i, p_i) + \delta_2^I \Delta_{ij}^0\right), \tag{27}$$

where $\delta_2^I = -\frac{1}{\tau_I}$, and the rest are as defined above.

Moderate-Individual — In this arm, the student observes her own baseline score S_i^0 and rank r_i^0, but not the cutoff score. She does, however, know that the top 3 out of 10 will win, i.e., the cutoff percentile is 0.7. The corresponding standard-normal quantile is $z_{0.7} \approx 0.524$.

The student's own percentile is $1 - \frac{r_i^0 - 0.5}{2}$, and the corresponding z-score is:

$$z_i^{\text{rank}} = \Phi^{-1}\left(1 - \frac{r_i^0 - 0.5}{2}\right).$$

Define the standardized rank gap to the cutoff as:

$$\Delta_i^{\text{rank}} = z_i^{\text{rank}} - z_{0.7}.$$

As before, convert this to score units: $\Delta_{ij}^0 \approx \sigma_{S_0}\Delta_i^{\text{rank}}$. Let's start from the primitive winning rule:

$$S_i^0 + G_i + \epsilon_i \geq S_{(3)}$$

Write the cutoff score as $S_{(3)} = \mu_C + (S_{(3)} - \mu_C)$. The winning rule becomes:

$$G_i \geq \mu_C - S_i^0 + \underbrace{(S_{(3)} - \mu_C) - \epsilon_i}_{\omega}.$$

Now, the cutoff (C) score $S_{(3)}$ is random, with distribution given by order statistics: $S_{(3)} \sim \mathcal{N}(\mu_C, \tau_C^2)$, where

$$\tau_C^2 = 0.3(\sigma_{S_0}^2 + \sigma_G^2) + 2\sigma_\epsilon^2.$$

The winning rule becomes:

$$G_i(e_i, p_i) \geq \sigma_{S_0} \Delta_i^{\text{rank}} + \mu_C + \omega, \quad \omega \sim \mathcal{N}(0, \tau_C^2),$$

so the winning probability is:

$$\tilde{P}_i^{w,MI} = \Phi\left(\delta_0^M + \delta_1^M G_i(e_i, p_i) + \delta_2^M \Delta_i^{\text{rank}}\right), \tag{28}$$

where

$$\delta_0^M = -\frac{\mu_C}{\tau_C}, \quad \delta_1^M = \frac{1}{\tau_C}, \quad \delta_2^M = -\frac{\sigma_{S_0}}{\tau_C}.$$

Moderate-Pair — In this version, students observe S_i^0, S_j^0, and both ranks. While the cutoff is still unobserved, the peer's baseline score provides additional information.[115] I incorporate this by adjusting the perceived score gap. Specifically, define:

$$\widetilde{\Delta}_i^{\text{rank}} = \Delta_i^{\text{rank}} + \rho_M \cdot \frac{\Delta_{ij}^0}{\sigma_{S_0}},$$

where ρ_M captures how informative the peer score is about the cutoff location. Then, the winning probability follows the same structure as before:

$$\tilde{P}_i^{w,MP} = \Phi\left(\delta_0^M + \delta_1^M G_i(e_i, p_i) + \delta_2^M \widetilde{\Delta}_i^{\text{rank}}\right), \tag{29}$$

with the same δ coefficients as in the Moderate-Individual arm. The intuition is that if the peer has a higher score, the expected cutoff is likely higher than what rank alone would suggest, and vice versa.

To summarize, the winning probability in all four arms can be written in the unified Probit form:

$$\tilde{P}_i^{w,k} = \Phi\left(\delta_0^k + \delta_1^k G_i(e_i, p_i) + \delta_2^k \Delta_i^*\right),$$

where $\Delta_i^* = \Delta_i^{\text{rank}}$ for II, IP, and MI, and $\Delta_i^* = \widetilde{\Delta}_i^{\text{rank}}$ in MP. Table A21 summarizes the coefficients used in the approximated winning probabilities for each arm.

Table A21: Arm-Specific Approximated Winning Probabilities

Arm (k)	δ_0^k	δ_1^k	δ_2^k
II	$-\frac{\mu_\Delta}{\tau_I}$	$\frac{1}{\tau_I}$	$-\frac{\sigma_\Delta}{\tau_I}$
IP	$-\frac{\mu_\Delta}{\tau_I}$	$\frac{1}{\tau_I}$	$-\frac{1}{\tau_I}$
MI	$-\frac{\mu_M}{\sigma_\Delta \tau_M}$	$\frac{1}{\sigma_\Delta \tau_M}$	$-\frac{1}{\tau_M}$
MP	$-\frac{\mu_M}{\sigma_\Delta \tau_M}$	$\frac{1}{\sigma_\Delta \tau_M}$	$-\frac{1}{\tau_M}$

Notes: This table summarizes the coefficients used in the approximated winning probabilities for each arm. The μ_Δ and σ_Δ are the mean and standard deviation of the baseline score gap, while τ_I and τ_M are the total standard deviations for Intense and Moderate arms, respectively.

E.1.2 Experiment Driven Choices Table A23 presents the arm-specific model components and the solutions for each arm.

[115] For example, if student's partner ranked 4th with score S_j^0, this suggests the cutoff is likely above S_j^0.

Table A22: Information sets & Beliefs

Symbol	Known to i	Unknown to i	Prior for the unknown
a_i, a_j	yes	–	–
a_k, a_ℓ	–	yes	i.i.d. from pdf $h_A(\cdot)$
θ_i	yes	–	–
$\theta_j, \theta_k, \theta_\ell$	–	yes	i.i.d. from CDF $G(\theta)$

Table A23: Arm-Specific Variation and Solutions

Reward Arm	Study Mode	Info	Score, S	Utility, U	Cost, C	$\tilde{P}^w$	Solution, e and p
Control	*Individual*	S_i^0	S_1	$\eta_i \log S_i + \nu_i b S_i$	C_1	–	Eq. (30a) and (30b)
	Pair	S_i^0, S_j^0	$S_1 + S_2$	$\eta_i \log S_i + \nu_i b S_i$	$C_1 + C_2$	–	Eq. (30a), (30b), (31a), (31b)
Moderate	*Individual*	S_i^0, r_i^0	S_1	$\eta_i \log S_i + \nu_i \tilde{P}_i^w B$	C_1	Eq. (28)	Eq. (34a) and (34b)
	Pair	$S_i^0, S_j^0, r_i^0, r_j^0$	$S_1 + S_2$	$\eta_i \log S_i + \nu_i \tilde{P}_i^w B$	$C_1 + C_2$	Eq. (29)	Eq. (35a), (35b), (35c)
Intense	*Individual*	S_i^0, r_i^0	S_1	$\eta_i \log S_i + \nu_i \tilde{P}_i^w B$	C_1	Eq. (26)	Eq. (32a) and (32b)
	Pair	$S_i^0, S_j^0, r_i^0, r_j^0$	$S_1 + S_2$	$\eta_i \log S_i + \nu_i \tilde{P}_i^w B$	$C_1 + C_2$	Eq. (27)	Eq. (33a), (33b), (33c)

Notes: $S_1 = \beta_0 + \beta_1 \ln a + \beta_2 \tilde{e} + \beta_3 \tilde{e}^2$ and $S_2 = \tilde{p}\,(\beta_4 + \beta_5 d + \beta_6 \ln a \cdot d)$. The values of b and B are ৳20 and ৳500, respectively. $\tilde{P}^w$ is the approximated winning probability. $C_1 = \frac{\theta}{\gamma}\,(e_i^\gamma) + \Gamma_e \mathbf{1}_{\{e_i>0\}}$ and $C_1 + C_2 = \frac{\theta}{\gamma}\,(e + \xi p)^\gamma + \Gamma_{eg}\mathbf{1}_{\{e>0\}} + \Gamma_{pg}\mathbf{1}_{\{p>0\}}$.

The optimality conditions by arm/mode are given by the following equations:

- **Control-Individual:** $\max_e \eta_i \ln S_i + \nu_i b S_i - C_1$

$$(\eta_i + \nu_i b S_i)\,\frac{\beta_2 + 2\beta_3 \text{asinh}(e_i^{int})}{\sqrt{1 + (e_i^{int})^2}} = \theta_i\,\left(e_i^{int}\right)^{\gamma-1} \tag{30a}$$

$$e_i^* = \begin{cases} e_i^{int} & \text{if } \Pi(e_i^{int}) > \Gamma_e \\ 0 & \text{otherwise} \end{cases} \tag{30b}$$

  where $\Pi(e^{int})$ is $U_i - \theta_i \frac{e_i^{int\gamma}}{\gamma} - U_{0i}$. The second term on LHS is the marginal effect of effort on score, multiplied by the marginal utility of score. U_{0i} is the outside option utility for individual i, which is the utility without any kind of participation. Intuitively, there exists a subset of students who opt not to exert effort yet still take the final exam, in which case their utility is derived entirely from the score determined purely by their baseline ability.

- **Control-Pair:** $\max_{e,p} \eta_i \ln S_i + \nu_i b S_i - C_1 - C_2$. In addition to the conditions above, the following first-order condition holds:

$$(\eta_i + \nu_i b S_i)\,\frac{\beta_4 + \beta_5 d_{ji} + \beta_6 \ln a_i d_{ji}}{\sqrt{1 + (p_i^{int})^2}} = \theta_i \xi\,\left(e_i^{int} + \xi p_i^{int}\right)^{\gamma-1} \tag{31a}$$

$$p_i^* = \begin{cases} p_i^{int} & \text{if } \Pi(p_i^{int}) > \Gamma_p \\ 0 & \text{otherwise} \end{cases} \tag{31b}$$

  where $\Pi(p^{int})$ is $U_i - \theta_i \frac{(e_i^{int} + \xi p^{int})^\gamma}{\gamma} - U_{0i}$. U_{0i} is the outside option utility for individual i, which is the utility without any kind of participation.

- **Intense-Individual:** $\max_e \eta_i \ln S_i + \nu_i \tilde{P}_i^{II} B - C_1$

$$\left(\eta_i + \nu_i B\phi(z_i^{II})\frac{1}{\sqrt{2}\sigma_\epsilon}\right) G_e = \theta_i e_i^{\gamma-1} \tag{32a}$$

$$e_i^* = \begin{cases} e_i^{int} & \text{if } \Pi(e_i^{int}) > \Gamma_e \\ 0 & \text{otherwise} \end{cases} \tag{32b}$$

where G_e denotes the marginal effect of effort on score, corresponding to the second term on the left-hand side of (30a). For compactness, I omit the full expression above, which takes the form $\frac{\beta_2+2\beta_3,\text{asinh}(e_i^{int})}{\sqrt{1+(e_i^{int})^2}}$.

- **Intense-Pair:** $\max_{e,p} \eta_i \ln S_i + \nu_i \tilde{P}_i^{IP} B - C_1 - C_2$

$$\left(\eta_i + \nu_i B\phi(z_i^{IP})\frac{1}{\sqrt{2}\sigma_\epsilon}\right) G_e = \theta_i (e_i^{int} + \xi p_i^{int})^{\gamma-1} \tag{33a}$$

$$\left(\eta_i + \nu_i B\phi(z_i^{IP})\frac{1}{\sqrt{2}\sigma_\epsilon}\right) G_p = \theta_i \xi \left(e_i^{int} + \xi p_i^{int}\right)^{\gamma-1} \tag{33b}$$

$$j_i^* = \begin{cases} j_i^{int} & \text{if } \Pi(j_i^{int}) > \Gamma_j \\ 0 & \text{otherwise} \end{cases} \quad for \quad j \in \{e, p\} \tag{33c}$$

where G_e and G_p denote the marginal effects of effort and peer effort on score, respectively. For compactness, I omit the full expressions. G_p takes the form $\frac{\beta_4+\beta_5 d_{ji}+\beta_6 \ln a_i d_{ji}}{\sqrt{1+(p_i^{int})^2}}$.

- **Moderate-Individual:** $\max_e \eta_i \ln S_i + \nu_i \tilde{P}_i^{MI} B - C_1$

$$\left(\eta_i + \nu_i B\phi(z_i^{MI})\frac{1}{\sqrt{2}\sigma_\epsilon}\right) G_e = \theta_i e_i^{\gamma-1} \tag{34a}$$

$$e_i^* = \begin{cases} e_i^{int} & \text{if } \Pi(e_i^{int}) > \Gamma_e \\ 0 & \text{otherwise} \end{cases} \tag{34b}$$

- **Moderate-Pair:** $\max_{e,p} \eta_i \ln S_i + \nu_i \tilde{P}_i^{MP} B - C_1 - C_2$

$$\left(\eta_i + \nu_i B\phi(z_i^{MP})\frac{1}{\sqrt{2}\sigma_\epsilon}\right) G_e = \theta_i (e_i^{int} + \xi p_i^{int})^{\gamma-1} \tag{35a}$$

$$\left(\eta_i + \nu_i B\phi(z_i^{MP})\frac{1}{\sqrt{2}\sigma_\epsilon}\right) G_p = \theta_i \xi \left(e_i^{int} + \xi p_i^{int}\right)^{\gamma-1} \tag{35b}$$

$$j_i^* = \begin{cases} j_i^{int} & \text{if } \Pi(j_i^{int}) > \Gamma_j \\ 0 & \text{otherwise} \end{cases} \quad for \quad j \in \{e, p\} \tag{35c}$$

E.1.3 Solution Algorithms The Control arm solutions are relatively straightforward, involving a fixed-point problem in a one-dimensional space. In contrast, the Contest arms require solving for fixed points in two dimensions due to the strategic interdependence of players' effort choices.[116]

[116] Interdependent effort decisions are modeled conditional on participation. This separation is standard in structural models with private types and noisy signals.

Specifically, I solve for a fixed point over rival expectations using an iterative loop. The full procedure is detailed in Algorithm 3.

Algorithm 3 Solver for Contest-Arm Study Effort

Require: student parameters $\{\eta_{id}, \nu_{id}, \theta_{id}, \gamma_{id}\}$, latent abilities $\ln A_{id}$, prize B_{arm}, production parameters $\beta_{0:3}$, shock s.d. σ_ε, rival index matrix $J \in \{1, \ldots, N\}^{N \times K}$

Pre-compute ability term: $A_{id} \leftarrow \beta_0 + \beta_1 \ln A_{id}$ ▷ $N \times Nd$
Initial effort: $e_{id}^{(0)} \leftarrow \max\{[(\eta_{id} + \nu_{id} B_{\text{arm}}/4)/\theta_{id}]^{1/(\gamma_{id}-1)},\ e_{\min}\}$

repeat[Outer fixed-point loop] ▷ typically 3–5 iterations
  Build rival gains once: $G_{idk} \leftarrow G(e^{(t)}_{J(i,k),d})$ for $k = 1{:}K$
  for `newt` $= 1$ to 3 **do** ▷ vectorised Newton–Kantorovich
    $e \leftarrow \max\{\exp(\ln e),\ e_{\min}\}$, $G \leftarrow G(e)$, $G' \leftarrow g'(e)$
    $Z_{idk} \leftarrow \dfrac{A_{id} - A_{idk} + G_{id} - G_{idk}}{\sqrt{2}\sigma_\varepsilon}$
    $\bar{\phi}_{id} \leftarrow \frac{1}{K} \sum_k \phi(Z_{idk})$
    $\text{MB}_{id} \leftarrow [\eta_{id} + \nu_{id} B_{\text{arm}} \bar{\phi}_{id}/(\sqrt{2}\sigma_\varepsilon)]\, G'_{id}$
    $\text{MC}_{id} \leftarrow \theta_{id} e_{id}^{\gamma_{id}-1}$
    $F_{id} \leftarrow \text{MB}_{id} - \text{MC}_{id}$ ▷ residual
    $F'_{id} \leftarrow \text{MB}_{id}/e_{id} - \theta_{id}(\gamma_{id} - 1) e_{id}^{\gamma_{id}-1}$
    $\Delta \ln e_{id} \leftarrow \text{clip}(F_{id}/F'_{id}, -3, 3)$
    $\ln e_{id} \leftarrow \text{clip}(\ln e_{id} - \Delta \ln e_{id},\ \ln e_{\min},\ \ln 50)$
  end for
  Damped update: $e_{id}^{(t+1)} \leftarrow \zeta e_{id}^{(t)} + (1 - \zeta)\exp(\ln e_{id})$ with $\zeta = 0.7$
until $\max_{i,d} |e_{id}^{(t+1)} - e_{id}^{(t)}| < 10^{-6}$

One-shot best response polish: two further Newton passes without damping; relax
2pt $e^*_{id} \leftarrow 0.5\, e_{id}^{\text{BR}} + 0.5\, e_{id}^{(t+1)}$
return equilibrium efforts e^*_{id} and derived objects (P^{win}_{id}, S_{id}, activation weight, etc.)

The above algorithm shows solution only for effort e for *Intense* arm as an example. The solution for both e and p requires a similar approach, but with a two-dimensional Newton step.

E.2 Identification Intuition

In this section, I walk through the mathematical details that show how the model parameters are identified. I start with how the first-step estimation pins down the distribution of θ_i/ν_i and the curvature parameter γ. Divide both sides of Equation (30a) by ν_i:

$$\frac{\eta_i + \nu_i \cdot r \cdot S_i}{\nu_i} \cdot G'(e_i) = \frac{\theta_i}{\nu_i} \cdot e_i^{\gamma_i - 1} \tag{36}$$

Since η_i/ν_i is calibrated from the baseline survey, the only unknown in this equation is the ratio θ_i/ν_i, given a value for γ_i. So for a fixed γ_i, this gives a one-to-one mapping between θ_i/ν_i and effort. Using SMM estimation, I recover the distribution. Define the observable marginal-benefit index as:

$$M_i = \left(\frac{\eta_i}{\nu_i} + rS_i\right) G'(e_i) = M_i(e_i, \text{data})$$

Then the FOC becomes: $e_i^{\gamma-1} = \frac{M_i}{\theta_i/\nu_i}$. Taking logs gives:

$$\ln e_i = \frac{1}{\gamma - 1} \left(\ln M_i - \ln\left(\theta_i/\nu_i\right)\right) \tag{37}$$

This gives a linear relationship between $\ln e_i$ and $\ln M_i$, with slope $1/(\gamma-1)$ and an individual fixed effect $-\ln(\theta_i/\nu_i)/(\gamma-1)$. So I can identify γ from the slope, and then use the level (or fixed effect) to recover the distribution of θ_i/ν_i. Rewriting:$\frac{\theta_i}{\nu_i} = M_i \cdot e_i^{1-\gamma}$ This gives the full distribution of θ_i/ν_i, summarized by $(\mu_{\theta/\nu}, \sigma_\theta)$, since the group-specific ν's are held fixed.

Identifying Levels of θ_i and ν_i— To separately identify the levels of θ_i and ν_i, I use variation from the *Contest arms*, where the FOC includes strategic interaction terms:

$$\eta_i G'(e_i) + \nu_i B\bar{\varphi}_i \cdot \frac{G'(e_i)}{\sqrt{2}\sigma_\varepsilon} = \left(\frac{\theta_i}{\nu_i}\right) \nu_i \cdot e_i^{\hat{\gamma}-1}$$

Substitute $K_i \equiv \theta_i/\nu_i$ from Step 1:

$$\eta_i G'(e_i) + \nu_i B\bar{\varphi}_i \cdot \frac{G'(e_i)}{\sqrt{2}\sigma_\varepsilon} = K_i \cdot \nu_i \cdot e_i^{\hat{\gamma}-1}$$

Solving for ν_i:

$$\nu_i = \frac{\eta_i G'(e_i)}{K_i e_i^{\hat{\gamma}-1} - \frac{B\bar{\varphi}_i G'(e_i)}{\sqrt{2}\sigma_\varepsilon}} \quad (\text{denominator} \neq 0)$$

Then back out: $\theta_i = K_i \cdot \nu_i$ So now both parameters are identified, and I can update μ_θ accordingly.

Identification of ξ (Relative Disutility of Peer Effort)— Now, let's identify ξ, which governs how costly peer effort is relative to individual effort. When both e and p are strictly positive, the joint FOCs are:

$$(\eta_i + \nu_i r S_i) \cdot G'(e_i) = \theta_i (e_i + \xi p_i)^{\gamma-1}$$
$$(\eta_i + \nu_i r S_i) \cdot G'(p_i) = \theta_i \xi (e_i + \xi p_i)^{\gamma-1}$$

Taking the ratio: $\frac{G'(e_i)}{G'(p_i)} = \frac{1}{\xi}$ So ξ is directly identified from the ratio of marginal utilities.

Identification of Fixed Cost Parameters Γ_e and Γ_p— Finally, for the fixed cost parameters that govern the extensive margin, define the utility gains from participation:

$$\Delta U_i^E = U_i(e_i, p_i) - U_i(0, p_i), \quad \Delta U_i^P = U_i(e_i, p_i) - U_i(e_i, 0)$$

Assume a logistic participation rule:

$$w_i^E = \frac{1}{1 + \exp(-0.5(\Delta U_i^E - \Gamma_e))}, \quad w_i^P = \frac{1}{1 + \exp(-0.5(\Delta U_i^P - \Gamma_p))}$$

Since ΔU_i^E and ΔU_i^P are known once $(\gamma, \nu_i, \theta_i, \xi)$ are estimated, I match model-implied activation rates to observed ones: $\Pr(e_i > 0) = \frac{1}{N}\sum_i w_i^E(\Gamma_e), \quad \Pr(p_i > 0) = \frac{1}{N}\sum_i w_i^P(\Gamma_p)$. This gives me the fixed cost parameters Γ_e and Γ_p.

E.3 Empirical Model Estimation

In this section, I present the details and robustness of the structural estimation procedure of the main model estimation which consists of score production function estimation and preference/cost estimations.

E.3.1 Score Production Function. First, I present the measurement details of the score production function as well as alternative specifications.

E.3.2 Ability Measurement Model. The human capital formation model in Section 2 requires proxies for ability, traits that are inherently latent. One might consider using baseline exam scores, but they're likely to reflect more than just ability: test-taking conditions like question difficulty or negative marking matter, and measuring learning by simply subtracting baseline from final scores would be, at best, naive. Instead, I estimate ability and learning using a student decision-making model in multiple-choice exams, following the framework in Akyol et al. (2022) and Ozer et al. (2024). Below I sketch the core of the model preliminaries; for the full set-up please refer to Akyol et al. (2022). The setting is a multiple-choice test with Q questions (25 in my case). For each question, the student decides whether to answer (A) or skip (NA), knowing that wrong answers are penalized. If answering, they choose one of five options, only one of which is correct. A correct answer gives 1 point, an incorrect one costs 0.25, and skipping gives 0.

When approaching a question, the student receives a 5-dimensional signal vector (Z^k) for $k \in \{1, 2, 3, 4, 5\}$, one signal per option. The higher the signal, the more likely the option is correct. Each signal Z^k follows a Pareto distribution F^k with support $[m_k, \infty)$ and shape parameter β^k.[117] To prevent signals from being perfectly informative, I assume all m_k are the same. Following the literature, signals for all incorrect options come from the same distribution: that is, $\beta^k = \alpha$ for incorrect choices, while the correct option has shape parameter β^c. Using Bayes' rule, the probability of correctly identifying the answer, denoted π^c, is given by:

$$\pi^c = \mathbb{P}(c|\mathbf{Z}) = \frac{Z_c^{\alpha-\beta^c}}{\sum_k Z_k^{\alpha-\beta^c}} \tag{38}$$

What matters here is the gap between α and β^c. If they're close, the student is effectively guessing. I normalize $\beta^c = 1$ and treat α as a proxy for ability. The student answers the question if

$$\pi^c > \frac{U(0) - U(-0.25)}{U(1) - U(-0.25)} = \bar{\tau}$$

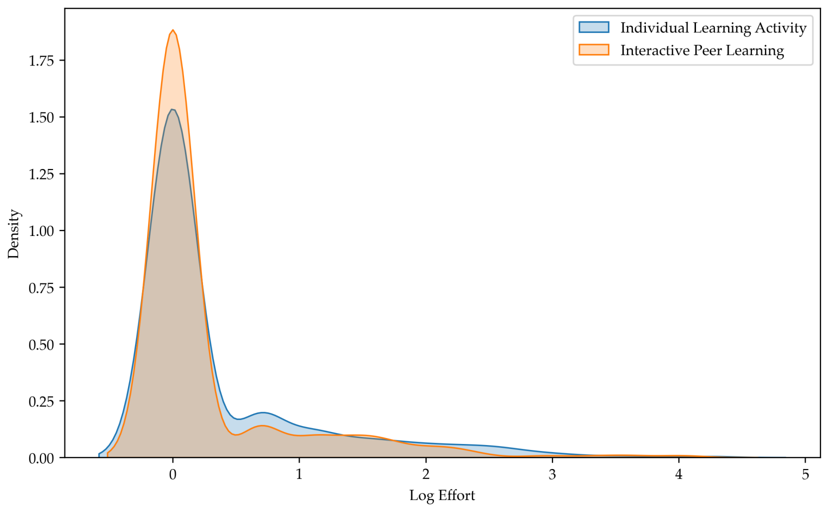
where $\bar{\tau}$ reflects the student's confidence or risk aversion—it's the threshold for whether they feel confident enough to answer. This setup lets me separately identify both ability (through α)

[117] That is, the density of Z^k is $\frac{\beta^k m_k^{\beta^k}}{Z^{k\beta^k+1}}$.

and confidence/risk preferences (through $\bar{\tau}$).[118] With this framework, I find that the variance of the ability distribution is 61.8% smaller than the variance in raw test scores. However, the rank correlation stays high at 0.752 between the two measures.

E.3.3 Effort Measurements As explained in Section D.1, a student can engage with a range of activities on the website, all designed for learning purposes. For each activity, I record the number of times a student engages with it, for example, quiz attempt counts, guide view counts, or active peer interaction counts (separated from inactive peer interaction attempts). An alternative, smoother measure could be the minutes spent on different activities. However, due to a substantial amount of idle time recorded in the database, the count-based measures are considered more accurate.[119] As individual effort, I take the number of quizzes solved. I also add the number of web activity sessions (which might include other web-based learning activities).[120] For peer learning, I first focused only on live interactions, specifically live chat sessions and live quiz-solving sessions. But the number of such observations is really low (around 55), so I expand the definition to include web activity as well, but only for individuals who had at least one live interaction with their peer. The idea is to avoid overmeasuring peer effort for those in the *Pair* mode who log in but don't actually try to interact (and I do see that happening more in the *Intense* arm, for example). Figure A13 shows how these effort measures are distributed across students.

Figure A13: Effort Measurement



Notes: This figure presents the distribution of effort measures across students.

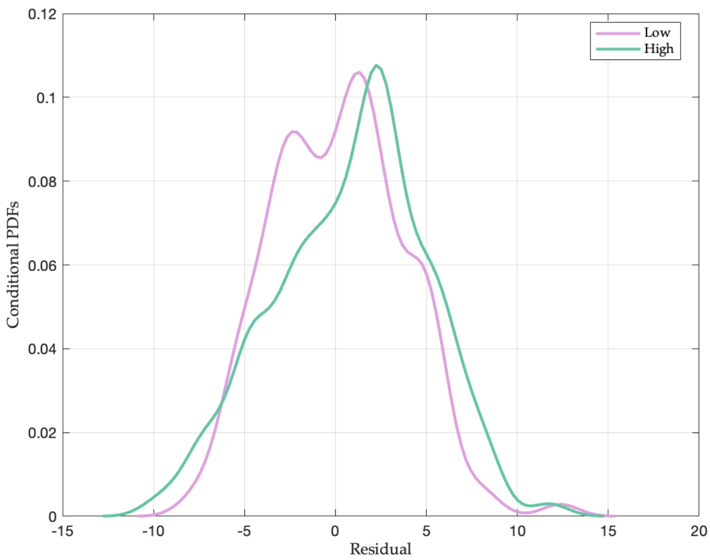
E.3.4 Production Function Estimation Robustness. I employ a rich set of robustness checks to ensure the reliability of the score production function estimates. These checks include a sequential estimation procedure, where I first estimate the solo effort coefficients and then the peer effort coefficients, to reduce variability coming from systematic differences across study modes. I also consider not dropping observations with unusually low final scores compared to baseline scores, to check whether the results are sensitive to that filtering step. I further drop students with

[118] For the full estimation algorithm, see Ozer et al. (2024), Appendix B.1.

[119] Note that I cleaned some activities that were repeatedly recorded within a short time window, which likely reflects that multiple tabs were open for the same activity.

[120] There are some cases where students have a web session but no recorded quiz-related activities. I still count these as effort to separate them from those who didn't invest at all. I address this in the robustness checks.

Figure A14: Heteroskedastic Score Shocks



Notes: This figure presents the smoothed PDFs of the residuals for each group. The bandwidth is set to 0.2.

very low baseline ability to see whether the peer-related coefficients still have the expected signs. Lastly, I use an alternative ability measure based on IRT scores; with this measure, the sign of β_5 remains the same, but it is not statistically different from zero. Table A24 presents the results of these robustness checks. Across all robustness checks, the magnitude and direction of the coefficients remain consistent (with the exception of β_5 in the IRT-based ability measure). The estimates for β_2 range between 0.3 and 0.5, while β_4 consistently falls between 0.2 and 0.3. The main estimation table reports standard errors using the Murphy-Topel sandwich estimator. For robustness, I also compute bootstrapped standard errors with 500 replications. The resulting SE values for coefficients β_0 through β_6 are 0.193, 0.086, 0.176, 0.016, 0.210, 0.0405, and 0.0169, respectively.

Table A24: Robustness Checks for Production Function Estimation

Check Name	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\beta}_5$	**Takeaway**
Baseline	0.790	0.279	-0.048	0.155	0.584	Reference
Sequential Estim.	0.792	0.190	-0.051	0.337	0.304	Slight shifts
Do Not Ignore Outliers	0.680	0.368	-0.033	0.284	0.192	Stable
IRT Ability	0.600	0.553	-0.058	0.399	-0.348	One Sign Flip
Drop Very Low Ability	0.813	0.262	-0.045	0.144	0.093	Lower β_5
Standardized Vars	0.701	0.504	-0.388	0.204	0.198	Stable

E.3.5 Internal Calibration Details The taste parameters $\{\mu_{\eta g}, \sigma_{\eta g}\}$ for $g \in \{L, H\}$ are calibrated using responses to the survey question *"How motivating do you find grades and test scores?"*, measured on a 1–10 scale. With a single ordinal item, I apply a strictly monotone transformation: specifically, I compute normal scores $s_i = \Phi^{-1}(r_i)$, where r_i is the Blom-adjusted midrank of respondent i's score in the *pooled sample*. I then map s_i to the preference parameter η_i via a *global affine transformation*, choosing parameters a and b so that the 5th and 95th percentiles of s_i correspond exactly to $\eta_{\min}$ and $\eta_{\max}$, respectively. Formally,$\eta_i = a + b\, s_i$, with a and b determined by the percentile-matching conditions. Finally, I report the mean and standard deviation of η separately for the low- and high-ability groups. As a robustness check, I also estimated an IRT-style graded response model using two items — the above question and *"Things I learn will help me later in life"*. The results are qualitatively similar, with $\mu_{\eta L} = 2.42$ and $\mu_{\eta H} = 2.43$.

E.3.6 SMM Detailed Estimation Procedure. Parameter estimation algorithm follows the standard Simulated Method of Moments (SMM) approach. I first evaluate the loss function $\mathcal{L}(\boldsymbol{\Theta})$ on a grid of $20,000$ points for the parameter vector $\boldsymbol{\Theta}$. To ensure a well-distributed and low-discrepancy sequence over the parameter space, I use a Halton sequence. The local optimization procedure is then performed from the best 20 points of the grid search using interior-point algorithm. For each of these points, perform both local and global optimization using quasi-Newton and non-uniform Pattern search methods (NUPS) with different mesh sizes applied adaptively to ensure convergence to the global optimum. The parameter set with the lowest loss function value is selected as the estimated parameter vector $\hat{\boldsymbol{\Theta}}$. To stabilize estimation and prevent the solver from exploring implausible regions, I augment the SMM objective with a penalty term that activates when model-generated moments lie outside the empirical 90% confidence intervals. Formally, the augmented loss function is defined as:

$$
\begin{aligned}
\mathcal{L}_\omega(\boldsymbol{\Theta}) &= \left(\mathbf{m}^{\text{data}} - \mathbf{m}^{\text{model}}(\boldsymbol{\Theta})\right)' W \left(\mathbf{m}^{\text{data}} - \mathbf{m}^{\text{model}}(\boldsymbol{\Theta})\right) \\
&+ \omega_0 \sum_{k=1}^{K} \left[\left(\hat{m}_k^{\text{model}}(\boldsymbol{\Theta}) - \hat{m}_{k,\text{upper}}^{\text{data}}\right)^2 \mathbb{1}\left\{\hat{m}_k^{\text{model}} > \hat{m}_{k,\text{upper}}^{\text{data}}\right\} + \left(\hat{m}_{k,\text{lower}}^{\text{data}} - \hat{m}_k^{\text{model}}(\boldsymbol{\Theta})\right)^2 \mathbb{1}\left\{\hat{m}_k^{\text{model}} < \hat{m}_{k,\text{lower}}^{\text{data}}\right\} \right] \qquad (39)
\end{aligned}
$$

where ω_0 governs the strength of guardrail and set to 5, fine tuned over multiple optimization iterations. $\hat{m}_{k,\text{lower}}^{\text{data}}$ and $\hat{m}_{k,\text{upper}}^{\text{data}}$ corresponds to the empirical 90% confidence intervals.[121] These guardrail conditions are included to reduce the number of iterations, needed for convergence. Standard asymptotic theory for the SMM estimator applies given the standard regularity conditions (i.i.d sampling, smooth and identifying moment conditions, etc.). (see Davidson and MacKinnon (2003) for details). The guardrail conditions do not affect the asymptotic properties since they it enters the loss function with a fixed weight and is $O_p(1)$. The estimation procedure, is conducted in MATLAB2025 on Mac M2 with 16GB RAM and 8 CPU cores. The estimation procedure is parallelized both at the grid search and local optimization stages.

E.3.7 Standard Errors. The main model standard errors are computed using the bootstrap method. For a balanced bootstrap data, I follow a block bootstrap procedure which balance on gender, baseline scores, reward arms, and study modes. I create `2x3x3x2` bin blocks for the bootstrap sample where the first dimension is gender, the second dimension is three bins of baseline scores, the third dimension is the reward arm, and the last dimension is study mode. In total, there are 36 blocks and each has N_k observations, where N_k is the number of observations in the k-th block. I draw a bootstrap sample by randomly selecting N_k observations from each block with replacement. The full bootstrap sample is then constructed by appending each block's sample. I repeat this process $B = 500$ times. For each bootstrap sample, I re-compute the empirical moments and the model parameters. Bootstrap runs take the parameter estimates out of the main estimation loop as the initial values. The standard errors are then calculated as the standard deviation of the bootstrap estimates across the B samples. The bootstrap procedure is implemented in Penn State's High

[121] The confidence intervals are constructed using bootstrapped standard errors of the empirical moments, based on the same 500 bootstrap samples described in Section E.3.7.

Performance Computing Cluster (HPC) with the resources of 60 cores and 8 GB per core.

E.4 Model Fit and Validation

Table A25 presents the out of sample validation results. Control and Intense arms are used for estimation, while the Moderate arm is reserved for validation. The model successfully captures the main patterns in the Moderate arm, including extensive margin participation rates and average effort levels across ability groups.

Table A25: Model Validation

Moment	Description	Data	Model
Panel A: Moderate Arm			
$\Pr(e{=}0)^L$	Share Zero Effort (Low)	0.673	0.745
$\Pr(e{=}0)^H$	Share Zero Effort (High)	0.537	0.454
$\mu_e^L(M)$	Mean Effort - Moderate (Low)	0.504	0.447
$\mu_e^H(M)$	Mean Effort - Moderate (High)	0.771	0.790

Notes: This table compares the data moments with their model-implied counterparts for untargeted moments.

E.5 Structural Estimation Robustness Checks

Structural estimation robustness checks are conducted along three dimensions. First, I re-estimate the model using alternative functional forms. Specifically, I consider a log-linear production function and a linear utility function. Second, I re-estimate the model using alternative effort measures. Specifically, I use a more inclusive measure of individual effort that captures all web activities (not just quizzes) and a more restrictive measure of peer effort that includes only live interactions (excluding web activities). Third, as a stress test, I set competition-arm prizes to zero and re-estimate the model to show that the policy conclusions are locally and globally robust. [insert table] Across all robustness checks, the main qualitative results hold.

E.6 Skill Production

Table A26 presents the initial academic and social skill levels across different groups.

E.6.1 Imputation. Let $y_{ik} \in \{1, \ldots, 5\}$ denote the recoded rating on item $k \in \{C, H, P\}$ for student i and let $a(i) \in \{$ Control, Moderate, Intense $\}$ be the contest arm.

$$
\begin{aligned}
w_i &= 1/\hat{\pi}_i, \quad \hat{\pi}_i = \Pr(\text{ partner responds } \mid X_i)\,; \\
c_{aj} &= \sum_{i:a(i)=a,\, y_{i1}\ \text{obs.}} w_i \mathbf{1}\{y_{i1} = j\}\,, \quad j = 1, \ldots, 5; \\
\boldsymbol{\alpha}^{(a)} &= \mathbf{c}_a + (1,1,1,1,1); \quad \mathbf{p}^{(a)} \mid \text{data} \sim \text{Dirichlet}\left(\boldsymbol{\alpha}^{(a)}\right).
\end{aligned}
$$

For $m = 1, \ldots, M$: 1. draw $\mathbf{P}^{(a)}_{(m)}$ from the arm-specific Dirichlet; 2. for every student i with missing item 1 in arm a draw $\tilde{y}_{i1,(m)} \sim$ Categorical $\left(\mathbf{p}^{(a)}_{(m)}\right)$; 3. repeat steps 1-2 for items 2 and 5. Aggregate index $\kappa^H_{i,(m)} = \frac{1}{3}\sum_{k\in\{C,H,P\}} \tilde{y}_{ik,(m)}, \quad \kappa^H_{i,(m)} \in [1, 5]$.

Table A26: Baseline Skills by Subsample

	All	Female	Low Competitive	Medium Competitive	High Competitive
Panel A: Cognitive Scores					
Baseline Exam	6.64	6.23	2.37	6.27	11.43
	(5.29)	(4.93)	(2.61)	(3.56)	(4.68)
9-th Grade Lit. Score	85.90	86.89	75.87	86.86	95.21
	(12.80)	(11.94)	(13.26)	(9.97)	(4.55)
9-th Grade Math Score	79.23	78.80	62.71	82.83	92.73
	(18.73)	(18.35)	(17.65)	(14.31)	(7.21)
N	1263	709	444	391	428
Panel B: Noncognitive Scores					
BFI-Overall	3.45	3.46	3.43	3.49	3.44
	(0.40)	(0.39)	(0.41)	(0.40)	(0.40)
Competitiveness	0.61	0.60	0.62	0.59	0.60
	(0.19)	(0.19)	(0.20)	(0.20)	(0.18)
Cooperativeness	0.62	0.61	0.63	0.62	0.61
	(0.17)	(0.16)	(0.17)	(0.18)	(0.16)
Prosociality	0.27	0.29	0.28	0.28	0.25
	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)
N	1263	709	444	391	428

Notes: This table presents means and standard deviations (in parentheses) of key outcome variables across subsamples.

F Policy Analysis

F.1 Classroom Design: Direct Assignment

Online Appendix to "Strategic Interactions and Peer Learning in Contests"

O.A Experiment

O.A.1 School Recruitment

For school selection, I focused on Science and Anatolian High Schools, excluding Vocational High Schools. The selection was further limited to schools in the central districts of Malatya, as these schools are more comparable to each other, while those in rural areas were not considered. Within this targeted group, there are two subgroups: schools that admit students based on the high school entrance exam and those that admit students based on neighborhood assignment and middle school GPA. The first group is generally more competitive, while the second group still includes strong schools due to their location-based selection criteria. To ensure a representative sample, I selected schools based on stratification, categorizing them into High, Medium, and Low strata based on entrance cutoffs and choosing four schools from each stratum. The High Stratum included all four available schools with a cutoff ≥ 450. The Medium Stratum included four exam schools with cutoffs between $375 - 420$, along with one non-exam school with the highest cutoff in its category, considered a mid-tier school in the local context. One of the selected exam schools later declined participation after initially granting permission. The Low Stratum consisted of schools with a cutoff above 75, excluding those with very low scores to maintain a minimum engagement level.[122] This selection method ensured a diverse yet comparable sample of schools.[123]

O.A.2 Surveys

O.A.2.1 Details on Survey Variables. The surveys I conducted aimed to capture a comprehensive set of variables related to students' academic experiences, including competitiveness and peer learning dynamics. Figure OA.1 shows the baseline survey flow. The survey covers modules on demographic characteristics, academic performance, peer learning dynamics, beliefs about effort and peer learning, risk and social preferences, and noncognitive skills, including competitiveness. The follow-up survey concentrated on participants' experiences during the preparation period, particularly their use of the website. Both surveys featured a mix of response formats, such as Likert scales, slider questions, multiple-choice questions, and open-ended questions. Slider questions were predominantly used for quantification purposes. Some survey questions measuring the variables of interest were drawn from a wide range of studies in economics, psychology, and education, as detailed in Table OA.1.

O.A.2.2 Survey Flow Figure OA.1 and OA.2 illustrate the flow of the baseline and endline surveys, respectively. In the baseline survey, there are seven modules, each with a specific focus described inside the relevant box. The end survey consists of three modules, with the first module

[122] When reaching out to other potential schools in the Low stratum, the research team found that the 10^{th} grade enrollment was much smaller than expected due to student retention patterns, which was one reason for excluding these schools.

[123] Five schools (2 H, 1 M, 2 L strata schools) in my sample also participated in a survey conducted approximately eight months earlier for a separate study Ozer and Li (2025). Although the two studies are entirely independent, and the previous one did not involve any treatment, this overlap might introduce a familiarity effect. However, when I re-estimate the main results while controlling for this variable, the findings (from Table 3) remain robust.

Table OA.1: Survey Variables and References

Variable	Components: Questions/Prompts	References
Panel A: Preferences		
Risk Tolerance	*Which option would you choose? X for sure OR a fair coin flip in which you get 200 if heads, 0 if tails.* (10 questions with varying X.)	Boyle et al. (2012)
Patience	*Which one would you choose? 150 now OR X in two months?* (10 questions with varying X.)	??
Altruism	*Imagine we gave you 1000 TL, but another student did not get. How much share?*	??
Panel B: Mental Wellbeing and Noncognitive Skills		
Wellbeing Assessment	Question from Hedonia and Eudaimonia sub-scales.	Symonds et al. (2022)
Noncognitive skills	e.g. *I see myself as someone who is outgoing.*	(BFI-10) - Rammstedt and John (2007)
Competitiveness	e.g. *To succeed, one must compete against others.*	Tang (1999)
Panel C: School Experience		
Interaction with teachers	*How often do you interact with your teachers?*	Endo and Harpel (1982)
Classroom Comfort	*How comfortable are you asking questions in the classroom?*	Ryan and Pintrich (1997)
Panel D: Parental Input		
Parental Relationship		THEOP
Panel E: Return to Effort and Study Choice		
Return to Effort	*What score/rank do you expect to achieve by studying X hours alone? What score/rank do you expect to achieve by studying X hours with a peer of Y ability?*	Adapted from Tincani et al. (2023).
Study Choice	*Who would you study with if the reward scheme is threshold-based/rank-based? What percentage to allocate individual and to peer study under threshold-based/rank-based system?*	

being about website experience, second module about whether the incentives were effective, and the last module is about the time use over the experiment period.

O.A.2.3 Survey Response Quality. This section focuses on the quality of survey responses, distinct from data quality, which requires separate tests for differences between survey responses and revealed preferences. To assess survey response quality, I use two measures. First, I analyze the duration of survey responses. Figures OA.3 and OA.4 display the time distribution for the baseline and endline surveys, respectively. Responses with minimal time spent are considered incomplete and are excluded from the analysis. However, responses with excessively long durations are included, as students may have left the survey open for extended periods without submitting. Second, I evaluate attention levels using an attention check question in the baseline survey: *"This is an attention check question. Please select both Strongly Agree and Strongly Disagree."* Results show that 89% of students passed the attention check by selecting both options, 6% selected one of the options, and 5% chose other options. Additional analyses excluding students who failed the attention check indicate that the main results remain robust. In addition, at the end of the survey, I asked students to report the effort they put into the survey. Only 3% reported putting in no effort, while 30% reported putting in a lot of effort, and 46% reported putting in some effort.

Figure OA.1: Baseline Survey Flow

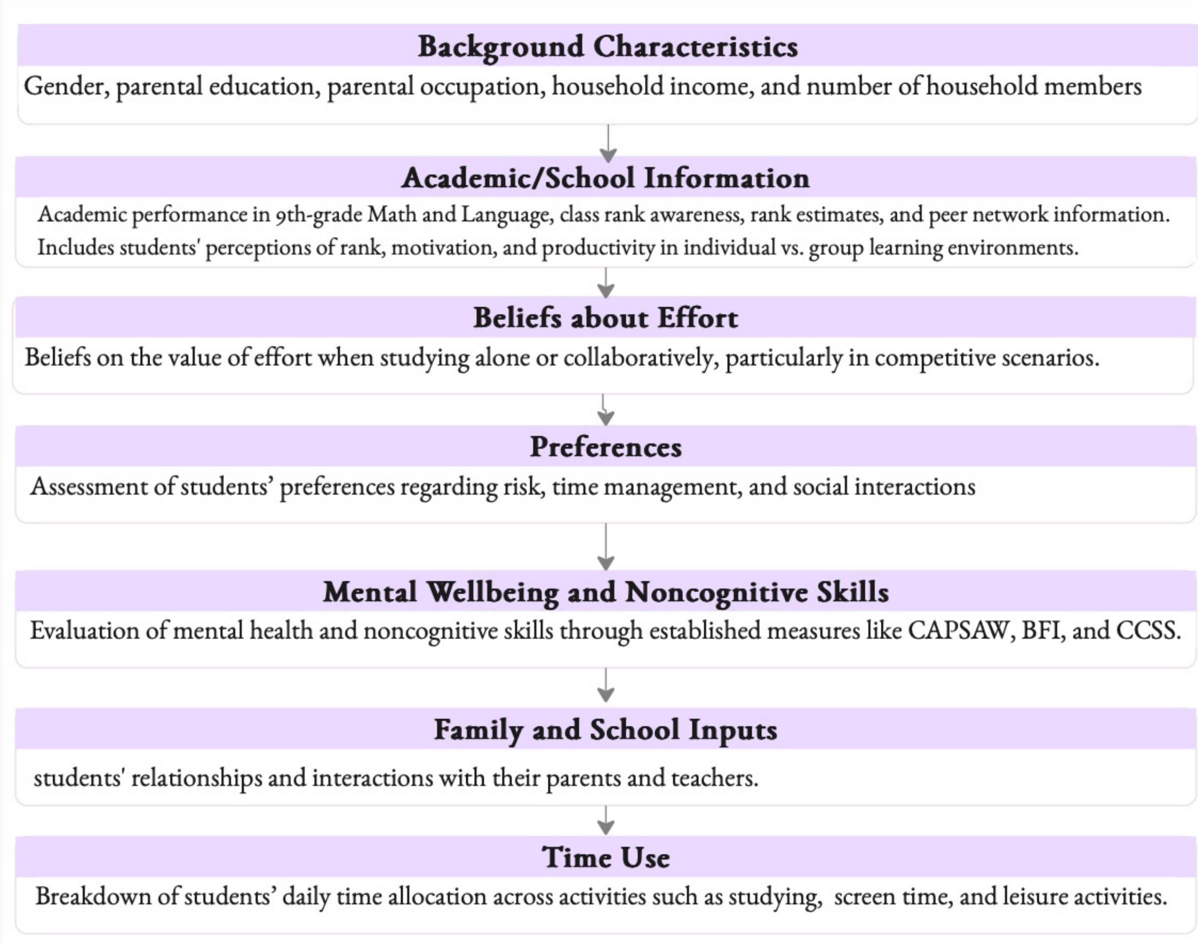
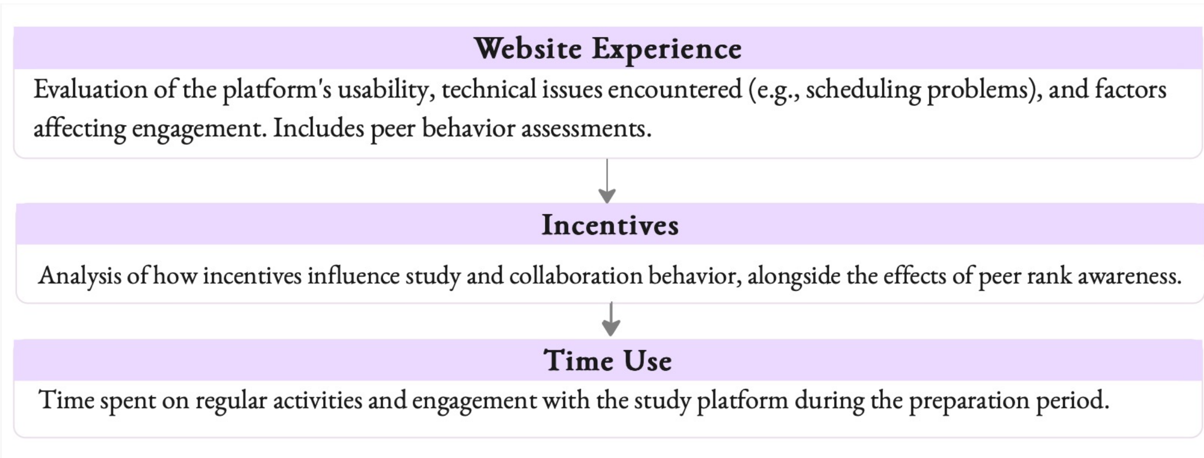


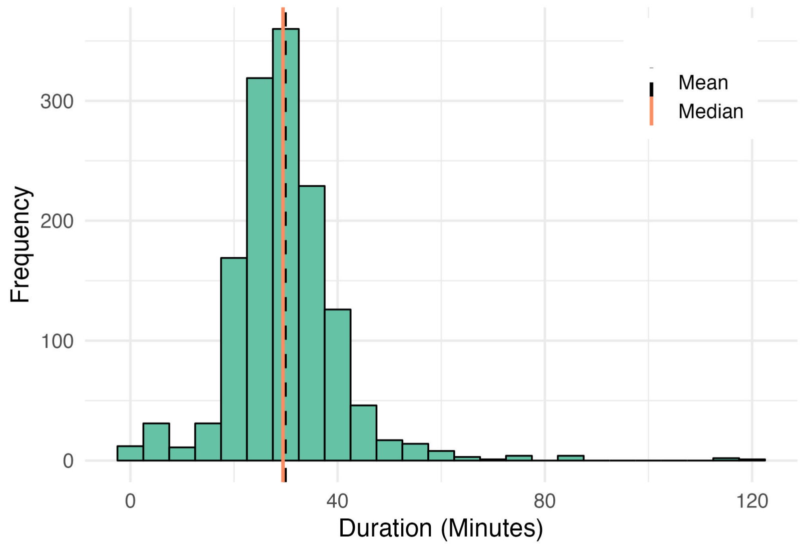
Figure OA.2: Endline Survey Flow



O.A.3 School Visits

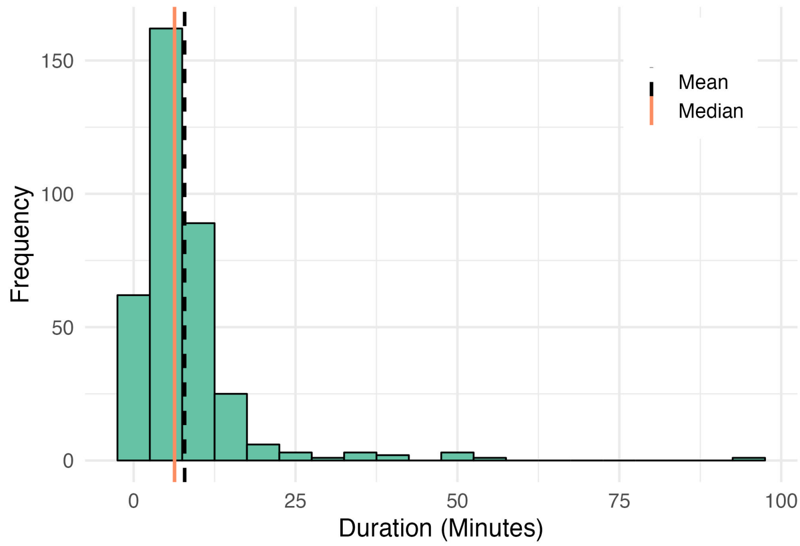
O.A.3.1 First Visit: Survey and General Information.

Figure OA.3: Baseline Survey Duration



Notes: This figure illustrates the distribution of time spent by students on the baseline survey. The median time is indicated by an orange line, while the mean time is represented by a dashed black line. Responses exceeding 120 minutes are capped at 120 minutes.

Figure OA.4: Endline Survey Duration



Notes: This figure illustrates the distribution of time spent by students on the endline survey. The median time is indicated by an orange line, while the mean time is represented by a dashed black line. Responses exceeding 120 minutes are capped at 120 minutes.

"Hi, **[Introduction of the implementers]**. In this study, we aim to understand students' study habits and their impact on learning. Today, you will complete a carefully designed survey on your phones, for which the QR code will be distributed shortly. It is very important for this study's success that you answer honestly and carefully. The survey software will check the quality of your answers using advanced statistical tools. By providing high-quality responses (e.g., avoiding straightlining), you will be eligible for a guaranteed prize of ৳100, to be distributed at the end of the study. Note that your participation is voluntary. The data we collect will be anonymized and kept confidential. Next week, you will take a baseline Math exam to assess your initial knowledge. After a 10-day preparation period, you will take a final exam, with the opportunity to earn up to ₺500 based on your performance. To prepare for the final exam, you will have access to a website where you can practice with a study partner, whom we will assign. Details about the exams and website access will be sent via text messages. You will start the baseline survey soon. We will provide Wi-Fi access for the next hour. Is there anyone who needs a device or charger, etc.? **[Enumerator counts and distributes the extra devices]**." [124]

Figure OA.5 illustrates students participating in the in-classroom survey using their phones.

Figure OA.5: Students Taking In-Classroom Surveys

Notes: This photograph shows an example of students participating in the in-classroom survey using their phones.

O.A.3.2 Visits to Conduct Baseline and Final Exams. The implementation team visited the schools twice for each exam. The first visit was to distribute the exams and reiterate the procedures to be followed by the schools. During this visit, the importance of proctoring to prevent any cheating was emphasized to the school administrators. The exam booklets were sealed in envelopes when handed over to the school administrators. The second visit was to collect the completed exams. Due to the infeasibility of monitoring every school/classroom, the implementers were not present in the schools during the exams.

O.A.4 Incentives: Information Texts

Below are the templates for the text messages sent to students on the first day of the preparation stage.[125]

1. **Individual Mode**

   "Hello [student name],

[124] There are three cases where we allowed students to take the survey at home on the same day. First, if the student was absent on the day of the survey. Second, if the number of students needing a device exceeded the number of available devices. Third, if a student reported a preference to take the survey at home due to discomfort using another device. In these cases, students were allowed to complete the survey by 8:00 PM on the same day.

[125] The information about payments is also reiterated the following day to ensure students have a clear understanding of the payment scheme. Otherwise, their attention might shift to other parts of the message.

You will be able to log into the website today at 7:00 PM. Please make sure to log in on time. The platform can be accessed at focusandstudyhub.net using the following credentials: Username: [username], Password: [passsword].

After logging in, please update your password using your own email password and save it somewhere secure to avoid forgetting it. If you experience any login issues, feel free to contact us at 5xxxxxxxxx.

The final exam will take place on December 19 and will last for one class period, consisting of 25 multiple-choice questions with negative marking.

If Control:

> You can earn up to ৳500 based on performance, with each correct net answer worth ৳20. For example, a net score of 10 earns ৳200, while a net score of 15.25 results in ৳305. Keep in mind that your final score matters, not your ranking. Your score from the first exam was [score], and the practice tests on the website will help you prepare for the final exam, which will include similar questions.

Else If Moderate or Intense:

> Your ranking in the exam will be determined within a group of [N] participants, including yourself. If you place in the top [P] within this group, you will receive a ৳500 reward. This means that in the second exam, your ranking within the group will matter more than your score. Your score from the first exam is [score], and your ranking among the [N] participants is [rank]. The practice tests on the website will help you better prepare for the final exam, which will include questions similar to those on the platform.

The platform is designed for individual study, where you can complete quizzes within the day, and view their results at 7:00 PM each evening. To better understand how the platform works, please watch the instructional video available at this [link]. Today's session is intended for you to explore the system with actual quiz-solving beginning after 10:00 PM. If you need any technical assistance, you can join the Zoom support session between 7:00 and 10:00 PM at this link. For any questions, feel free to reach out us at 5xxxxxxxxx. "

2. Pair Mode

"Hello [student name],

You will be able to log into the website today at 7:00 PM. Please make sure to log in on time. The platform can be accessed at focusandstudyhub.net using the following credentials: Username: [username], Password: [passsword].

After logging in, please update your password using your own email password and save it somewhere secure to avoid forgetting it. If you experience any login issues, feel free to contact us at 5xxxxxxxxx.

The final exam will take place on December 19 and will last for one class period, consisting of 25 multiple-choice questions with negative marking.

If Control:

> You can earn up to ৳500 based on performance, with each correct net answer worth ৳20. For example, a net score of 10 earns ৳200, while a net score of 15.25 results in ৳305. Keep in mind that your final score matters, not your ranking. During the preparation process for the final exam, you will have a team partner on the website. Your score from the first exam is [score], and your teammate's score is [peer score]. The practice tests on the website will help you better prepare for the final exam, which will include questions similar to those on the platform.

Else If Moderate or Intense:

> Your ranking in the exam will be determined within a group of [N] participants, including you and your team partner. If you place in the top [P] within this group, you will receive a ৳500 reward, meaning that your ranking is more important than your score.
>
> During the preparation process, you will have a team partner on the website. Your score from the first exam is [score], with a ranking of [rank], while your teammate's score is [peer score], with a ranking of [peer rank]. The practice tests on the website will help you better prepare for the final exam, which will include questions similar to those on the platform.[126]

You can complete the assigned quizzes individually on the Quiz Page before 7:00 PM each day. The same day at 7:00 PM, you and your teammate should be online together to discuss and make joint decisions for the quizzes.

Communication is key! If you are delayed, inform your teammate via Chat before 7:00 PM (e.g., "Can we start at 7:10?"). During your joint session, maintaining effective communication with your teammate is essential. Before

[126] In the Intense arm, rank information is not explicitly provided, as the scores themselves reflect the relative ranking between the two participants.

submitting a final answer, each team member must discuss and reach a consensus on their assigned questions.

To understand how to use the platform effectively, please watch the Group Training Video available at this [link]. The Chat feature should only be used for communication related to the quizzes. Sharing personal information or using it for purposes unrelated to the study is strictly prohibited. Any misuse or violation of these rules will result in removal from the project. All communication must be respectful and aligned with the study's objectives. If you need any technical assistance, you can join the Zoom support session between 7:00 and 10:00 PM at this link. For any questions, feel free to reach out us at 5xxxxxxxxx. "

O.A.5 Preparation Stage Reminder Texts

One concern with the messages above was that students might not read them carefully, especially since the payment scheme could be easily overlooked given the length of the message (more concerning for the *Pair* mode). Given the clarification questions we received from students and the need to ensure website engagement during the 10-day study period, we sent reminder texts around 5 PM on a given day.[127] The reminders mainly aimed to emphasize the prize structure related to the final exam, particularly for the Moderate and Intense arm *Pair* modes, by emphasizing that their teammate is in the same competition pool as they were. This was important to ensure that students understood the competition setup and stayed engaged. The (translated) reminder text template is as follows:

"Hello. Thank you for your interest! You can visit focusandstudyhub.net/quizzes to complete your daily quizzes and prepare for the final exam. Your reward from the final exam depends on [reward arm specific payment scheme]. Note that to be eligible for a prize, you need to log in the website and complete quizzes. Thank you for cooperation."

As a sanity check on whether students understood the prize structure even starting from the first day, I looked at website activity patterns for each day of preparation in the *Moderate* and *Intense* arms, where rank-based rewards were in place. Table OA.2 shows the ratio of the fraction of students logging in from the team mode to those in the individual mode. The ratio is above 1 for the *Moderate* arm on all days except the first day, and stays relatively stable. For the Intense arm, the ratio is below 1 throughout, except on Day 6, and falls below 0.5 toward the end. Day 3 is when the *Pair* bonus was introduced, which likely explains the increase in the ratios for both arms on and after that day. These patterns suggest that students likely understood the competition structure even from the beginning.

Table OA.2: Fraction of *Pair* to *Individual* Logins by Day and Arm

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
Moderate	0.938	1.241	1.754	1.469	1.591	1.683	1.058	1.030	1.069	1.346
Intense	0.795	0.889	0.983	0.836	0.646	1.189	0.646	0.700	0.267	0.374

Notes: This table shows the ratio of the fraction of students logging in from the *Pair* mode to those in the *Individual* mode, for each competition arm and training day.

O.A.6 Callbacks Summary

Table OA.3 summarizes the reasons for students inquiries during the experiment.

[127] For the first four days, reminder messages were sent daily to make sure everyone was clear about the prize structure and website technical details. After that, they were sent once every two days for the rest of the period. The timing of the reminder messages was chosen based on students' typical schedules, as most in the study sample finished school around 3:45 PM and be back home before 5.00 PM.

Table OA.3: Student Inquiries

Panel A: Early Period		Panel B: Mid Period		Panel C: Late Period	
Reason	Fraction	Reason	Fraction	Reason	Fraction
Web Login	0.355	Web Login	0.154	Web Login	0.043
Inactive Pair	0.210	Inactive Pair	0.374	Inactive Pair	0.304
Quizzes	0.113	Quizzes	0.165	Quizzes	0.174
General Info	0.121	General Info	0.088	General Info	0.130
Other	0.202	Other	0.220	Other	0.348
Total Texts/Calls	124	Total Texts/Calls	91	Total Texts/Calls	23

Notes: This table summarizes the reasons for student inquiries during the experiment. Early period is the first 2 days, Mid Period is the next 4 days, and Late Period is the last 3 days of the experiment. *Other* category includes other technical issues and general questions such as "When will be the final exam?" or "When will we get our results/prizes?".

O.B Baseline Survey Analysis

O.B.1 Processing Survey Variables.

i. **Friend Variables.** Students are asked to report the names of their friends for either network questions or study choice questions. While anonymizing the data, I matched the friends' names with the students' names using a string similarity algorithm based on the Jaro-Winkler distance.[128]

ii. **Competitiveness and Cooperativeness Variables.** For measuring competitiveness and cooperativeness traits, I used the CCSS scale. For competitiveness, I included the following items: *"It is important to me to do better than others," "Success is only achieved through individual effort," and "To succeed, one must compete against others."* For cooperativeness, I used: *"Joint effort is the best way to achieve success," "Success is best achieved through cooperation rather than through competition," and "I enjoy working with others to achieve joint success."* All items were evaluated on a 1-5 Likert scale, where 1 represents "Always" and 5 represents "Never." I reversed the scale coding so that higher values indicate stronger competitiveness or cooperativeness traits. I calculated the mean response across the respective items to create separate competitiveness and cooperativeness indices.

iii. **Risk and Time Preference Variables.** To measure risk preferences, I presented students with a series of binary choices between a lottery (a fair coin flip offering 200 if heads, 0 if tails) and varying certain amounts of money. For each participant, I count the number of instances where they selected the lottery over the certain amount, using this frequency as an index of risk tolerance. Similarly, for time preferences, students chose between receiving 150 units of currency immediately or a larger amount after a two-month delay, with the future amount systematically varied across questions. I use the frequency of choices favoring the delayed payment as a measure of patience.

iv. **Noncognitive Skills Variables.** To measure noncognitive skills, I use the BFI-10 scale, which includes measures for Openness, Conscientiousness, Extraversion, Agreeableness, and Neu-

[128] If the distance between two strings is less than 0.25, then I match, otherwise skip given that not all reported friends exist in the data.

roticism. Questions use a Likert scale with 1 representing "Strongly Agree" and 5 representing "Strongly Disagree." I reverse the scale coding[129] so that higher values indicate stronger presence of each trait. Then, I calculate the mean response across the respective items to create separate indices for each noncognitive skill.

v. **Mental Health Variables.** I use questions from the CAPSAW scale to measure mental health, which includes items such as *"Are you happy in general?"*, *"Do you think people care about you?"*, *"Do you feel safe in general?"*, *"Can you do the things you want to do in your life?"*, *"If you have a problem, can you find a way to deal with it?"*, *and "Do you think you are helpful to other people?"*. Responses are recorded on a 1-5 Likert scale where 1 represents "Always" and 5 represents "Never". I reverse the scale coding so that higher values indicate stronger mental health. I then calculate the mean response across all items to create a composite index for mental health assessment.

The codes where I process the raw survey data are available in the GitHub repository.

O.B.2 Additional Survey Results

In this section, additional results regarding the survey reported nearby competitors is provided.

O.B.2.1 Gender Differences in Nearby Competitors. Table OA.4 summarizes the gender fraction reported for the nearby competitors.

Table OA.4: Gender Differences in Nearby Competitors

Self Gender	Above \ Below	Male	Female
Male	Male	0.718	0.118
	Female	0.088	0.075
Female	Male	0.075	0.164
	Female	0.156	0.606

Notes: This table summarizes the fraction of students ranked above or below, categorized by both the gender of the student being ranked and the gender of the reporter.

O.B.2.2 Feelings about Friends' Impact on Academics and Competition. Table OA.5 summarizes students' feelings about how their friends impact their academic performance and competition.

O.B.3 Robustness of the Survey Results

In this section, I conduct robustness checks for the facts presented in the main text based on the initial survey.

[129] Reverse coding is done except for negatively phrased items: *"I see myself as someone who tends to be lazy," "I see myself as someone who tends to find fault with others,"* and *"I see myself as someone who is relaxed, handles stress well."*

Table OA.5: Feelings about Friends: Academic Effect and Competition

	Positive Influence	Feels Competing
Constant	0.144**	0.271***
	(0.072)	(0.055)
Rank	0.055*	0.195***
	(0.029)	(0.029)
$Rank^2$	-0.085***	0.022
	(0.023)	(0.021)
Female	0.037	-0.432***
	(0.071)	(0.057)
High Comp. Sch	-0.071	0.078
	(0.077)	(0.079)
Low Comp. Sch	-0.158**	-0.218**
	(0.078)	(0.092)
R-squared	0.024	0.102
R-squared Adj.	0.020	0.099
N	1359	1359

Notes: This table summarizes the feelings about friends' impact on academic performance and competition.

O.B.3.1 Implementation-Induced Variation. During the implementation, I collected various variables to analyze the robustness of the results ex-post. Table OA.6 summarizes these implementation stage variables. For instance, the majority of the school administrators were very co-operative throughout the implementation stages (Average of 1.57 on a scale 0-2.).[130] Similarly, teachers on average were supportive, with only 18% of classrooms lacking proctors during the baseline survey. We were told by the school admin that proctors were always present during in-classroom exams. Wi-Fi access was available in 68% of the cases.[131] Students were on average not noisy. Lastly, the recall confidence variable indicates that implementers on average are confident about the implementation stage variables (2.59 on a scale of 1-3).

I conduct robustness checks for regression-based survey facts by controlling for these implementation stage variables. Regarding Fact 1, the estimated coefficients on the main independent variables – *Low Rank, High Rank, Female, High Competitive and Low Competitive School*— are highly robust to the inclusing of these controls except the coefficient on *High Competitive School* in *Below-Friend* becomes larger in absolute value.

O.B.3.2 Attentive Students Only. I examine the robustness of the facts reported based on the survey to students' attentiveness and effort in responding to the survey. Following Chinoy et al. (2023), I implement four stringent criteria to identify the most attentive students. For this analysis, I drop students who did not pass these criteria. I label a student as inattentive if they meet any of the following criteria: (i) those who report putting less than 3 on a scale of $1-5$ regarding the effort they put into the survey, (ii) those who frequently select extreme values (1 or 5) in the survey questions, (iii) those who select the middle option consistently, and (v) those with response

[130] Cooperativeness, as assigned by two implementers, is defined as the willingness of school administrators to provide necessary information and support during the implementation.

[131] The lack of Wi-Fi access might be due to some classrooms being apart the majority of the classrooms or that despite hotspot presence, the location of the classrooms was not suitable for healthy Internet access. In those cases, students are suggested to use their own data, with additional support from implementers' personal hotspot share.

Table OA.6: Implementation Stage Variables

Variable	**Mean**	**SD**
Administrative Cooperation	1.57	0.64
Teacher Support	2.36	0.66
Proctor Presence	0.82	0.39
Wi-Fi Access	0.68	0.47
Student Noise Level	1.72	0.78
Weather Condition	42.65	1.61
Number of Students	33.06	1.39
Recall Confidence	2.59	0.54

Notes: This table summarizes various variables collected during the implementation stage of the experiment. Cooperation is categorized as follows: 1 = Not Cooperative, 2 = Somewhat Cooperative, 3 = Very Cooperative. Teacher support is categorized as follows: 1 = Not Supportive, 2 = Somewhat Supportive, 3 = Very Supportive. Student noise level is categorized as follows: 1 = Not Noisy, 2 = Somewhat Noisy, 3 = Very Noisy. Recall Confidence is categorized as follows: 1 = Not Confident, 2 = Somewhat Confident, 3 = Very Confident.

times at the extreme ends of the distribution (i.e., less than 5 minutes or more than 60 minutes). In total, 14% of the students are flagged as inattentive based on these criteria, and they are dropped from the analysis for the robustness check.[132] Regarding Fact 1, when I re-estimate the main regression results using only attentive students, all the coefficients' signs and significance remains the same with marginal differences in the magnitudes. Regarding Fact 2 about homophily in the friendship and study choice networks, the results are robust except the homophily in Weekday Study time category significantly lowers from around 0.5 to 0.2. The patterns regarding Fact 3 about motivation and productivity stay at the similar levels. Regarding Fact 5, the significance levels of the differences do not get lower except Cooperativeness, which now has an updated p-value of 0.137. However, the direction of the effect remains the same.

O.C Additional Experiment Results

O.C.1 Activity Regressions

[132] Among inattentive students, 38% are flagged for extreme answer selection, 32% for extreme response time, 18% for low self-reported effort, and 12% for consistently selecting the midpoint. Regarding predictors of inattentiveness, being female is associated with a 3.75 percentage point lower likelihood of being flagged as inattentive (driven primarily by the extreme answer selection criterion), while other factors such as grades do not show statistically significant relationship.

Table OA.7: Website Log-in: Regression Results

	OLS			ZINB			NB		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Panel A: Control									
Constant	1.041***	0.818***	0.118	0.321	0.184	-0.867***	0.040	-0.154	-0.858***
	(0.210)	(0.239)	(0.285)	(0.294)	(0.272)	(0.274)	(0.141)	(0.166)	(0.217)
Pair	0.204	0.148	0.167	0.225	0.144	0.136	0.179	0.099	0.144
	(0.260)	(0.260)	(0.252)	(0.228)	(0.227)	(0.234)	(0.173)	(0.174)	(0.179)
Female		0.474*	0.645***		0.427**	0.575**		0.415**	0.576***
		(0.249)	(0.245)		(0.214)	(0.228)		(0.167)	(0.174)
Base Score			0.097***			0.083***			0.081***
			(0.023)			(0.021)			(0.015)
N	282	282	282	282	282	282	282	282	282
Log-Likelihood	-605.016	-603.192	-594.372	-404.426	-402.520	-395.177	-422.403	-419.383	-405.817
Panel B: Moderate									
Constant	1.038***	0.986***	0.215	0.608***	0.566**	-0.479	0.037	-0.010	-0.780***
	(0.194)	(0.253)	(0.293)	(0.194)	(0.236)	(0.496)	(0.136)	(0.176)	(0.230)
Pair	0.314	0.324	0.334	0.254	0.264	0.363*	0.264	0.274	0.354**
	(0.249)	(0.252)	(0.242)	(0.194)	(0.196)	(0.213)	(0.171)	(0.172)	(0.178)
Female		0.080	0.171		0.063	0.143		0.070	0.156
		(0.249)	(0.241)		(0.191)	(0.209)		(0.168)	(0.174)
Base Score			0.101***			0.072***			0.081***
			(0.021)			(0.023)			(0.015)
N	268	268	268	268	268	268	268	268	268
Log-Likelihood	-564.631	-564.579	-553.723	-392.865	-392.812	-386.644	-409.492	-409.405	-394.577
Panel C: Intense									
Constant	1.667***	1.633***	0.708*	0.816***	0.798**	-0.166	0.511***	0.478***	-0.209
	(0.264)	(0.318)	(0.370)	(0.270)	(0.310)	(0.365)	(0.146)	(0.178)	(0.229)
Pair	-0.397	-0.396	-0.187	-0.254	-0.258	-0.142	-0.272	-0.276	-0.135
	(0.319)	(0.320)	(0.311)	(0.229)	(0.232)	(0.238)	(0.180)	(0.180)	(0.186)
Female		0.057	0.066		0.027	0.130		0.062	0.120
		(0.301)	(0.289)		(0.225)	(0.227)		(0.173)	(0.177)
Base Score			0.121***			0.071***			0.073***
			(0.027)			(0.021)			(0.016)
N	238	238	238	238	238	238	238	238	238
Log-Likelihood	-533.434	-533.416	-523.709	-371.685	-371.677	-365.468	-386.155	-386.091	-374.220

Notes: This table reports regression results for website log-in behavior across reward arms. Each panel corresponds to a separate reward arm (Control, Moderate, Intense). Columns (1)–(3) report results from OLS, zero-inflated negative binomial (ZINB), and negative binomial (NB) models, respectively. The dependent variable is the number of days a student logged into the platform. "Pair" is an indicator for being assigned to the pair study mode. "Base Score" refers to the student's baseline academic performance. Standard errors are in parentheses.