ABSTRACT

Title of Dissertation: ESSAYS ON
EDUCATION INVESTMENT DECISIONS

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This dissertation focuses on the economics of education in developing countries with a partic-ular focus on parental educational investment decisions in China. In Chapter 1, I explore how parents' belief affect their investments in children's education using a randomized field experiment with parents of high school students in China. I document two types of information frictions that result in systematic biases in parents' beliefs about children's ability: overconfidence in future performance and underestimating college admission requirements. I then introduce two interventions to correct parents' belief biases. In the first intervention, I use machine-learning techniques to generate predictions on children's future academic performance and distribute them to randomly selected parents. In the second intervention, I give randomly selected parents a report that lists the feasible colleges corresponding to their children's current academic performance. I find that both interventions lead to dramatic reductions in belief biases. In addition, parents report higher levels of monetary investments in children's education, which significantly improved children's academic performance. I also find significant non-linearity in the impacts of ability

belief on parental educational investments around their aspirations.

In Chapter 2, I investigate the impacts of peer effects on parental educational investment decisions. Using a randomized experiment with 3379 parents of high-school students in China, I identify two channels of social influence in parents' decisions on children's educational investments: parents adjust their decisions based on other parents' behaviors because they learn from other parents' decisions (”social learning”) or because their children are facing competition from peers (”competition externality”). I find that both channels have statistically significant effects on parents' investment decisions and increase their willingness to buy an educational service by over 20%. Although the average effects of the two channels are not statistically different, the main channels of peer effects are heterogeneous by parents' educational background: parents with higher education, higher income, and those who only have one child are more likely to learn from peers' decisions whereas those with lower education, lower-income, and more than one child are mainly incentivized by the competition externality.

Chapter 3 provides a theoretical explanation for the empirical findings documented in Chapter 1. I introduce the reference-dependent utility theory into the parental education investment decisions by cooperating parents' aspirations into their utility and assuming parents' utility function is discontinuous at the thresholds of achieving aspirations. The modification generates an interesting non-monotonic correlation between ability and optimal educational investments around the aspirations. When children haven't achieved their aspirations, parental educational investment is substitutive to children's ability - the lower the ability, the higher the investment. In contrast, when the aspirations are already reached, parents' investment becomes complementary to children's ability - the higher the ability, the higher the investment. This model can rationalize the remedial investments behaviors.

ESSAYS ON EDUCATION INVESTMENT DECISIONS

by

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Dedication

I dedicate this dissertation to my parents for their endless love and support.

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I would like to express my appreciation to all the people who helped me to make this thesis possible.

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Chapter 1: How Parents' Beliefs About Their Children's Academic Ability Affect Educational Investments

1.1 Introduction

Education is an important determinant of income (Ashenfelter and Rouse (1998); Bonjour et al. (2003); Miller et al. (1995); Stephens and Yang (2014)) , employment (Oreopoulos and Petronijevic (2013); Stiglitz (1975)), health (Oreopoulos (2006)), and social status. Parental investment in their children's education is one of the primary factors influencing educational success. However, parents might lack the information needed to build accurate beliefs about their children's abilities and thus fail to optimize educational investment. A small literature has begun to explore interventions to solve information frictions coming from limited access to performance records (Barrera-Osorio et al. (2020)) and the inability to make use of performance information because of illiteracy (Dizon-Ross (2019)). But we still know little about whether educated parents who have access to academic records are biased in their beliefs about their children's ability, or about policies that can help improve their decisions on educational investment.

I investigate the belief biases[1] among educated parents who have access to academic records and the potential solutions using surveys and a randomized field experiment with parents of high

[1] In this paper, parents' beliefs about children's academic ability is defined by their answers to the question "What would be your child's in-school ranking if they perform normally?" and belief bias is measured by the difference between that and the true ranking.

school students in China. I firstly use a survey to document two types of information frictions among these parents: parents are too optimistic about the academic performance improvements their children can achieve in the future, and they underestimate the difficulties of college admission. I then introduce two novel interventions to eliminate the two sources of friction, respectively. The first intervention aims at overconfidence in future improvements. I use a well-trained machine-learning algorithm to generate predictions of students' College Entrance Exam (CEE) in-school ranking[2] and provide them to randomly selected parents. The second intervention targets parents' misunderstanding of the difficulties of college admission. I provide information on the matching between children's current in-school ranking[3] and the tier of feasible colleges. I conduct follow-up surveys after two, four, and six months to measure the intervention impacts. Combining the surveys with rich administrative data from the school, I find that the intervention leads to dramatic reductions in belief biases. More importantly, parents report higher levels of monetary investments in children's education, which significantly improved children's academic performance.

I start with a theoretical framework in which I specify two factors that affect parents' investments in children's education: a signal on children's ability and parents' aspirations for their children's performance. The theoretical model predicts that the effects of ability signal and aspiration depend on the likelihood of children reaching their parents' aspirations (e.g. getting into parents' ideal colleges). If the signal indicates children need additional help to get into the ideal colleges, parents are incentivized economically or psychologically to help their children improve their academic performance in order to get into the ideal colleges. When the ability

[2]CEE in-school ranking refers to the ranking of children's CEE score among the CEE scores of all other students from the same school. The lower the CEE in-school ranking, the higher the CEE score, the better the performance.

[3]Current in-school ranking refers to the average ranking of children's exam performance among all other students from the same school. The smaller the current in-school ranking, the better the performance.

signal becomes more negative, which indicates children's ability is lower, parents increase investments in children as the amount of help needed for children to get into the ideal colleges becomes larger. By contrast, if the signal indicates that the children are very likely to get into the ideal colleges without additional help, parents invest more when the ability signal becomes more positive.

I then estimate the impact of providing information about children's ability on parental educati-onal investment and children's performance, using a field experiment with 748 parents of high school students in China. In the first treatment, I randomly selected 249 parents and provided them with a prediction of their children's CEE in-school ranking generated by a machine-learning algorithm. This intervention targets the biases caused by information mismatch in the time dimension. Specifically, parents' utility depends on children's performance in the future, whereas they can only observe children's performance in the past and current periods. The machine-learning prediction can correct parents' misprediction of children's future performance. The algorithm is trained by LASSO using historical data on alumni who graduated in the past ten years and has proven to be effective in predicting students' future performance. The Predicted R^2 in the test sample[4] is over 95%. In the second treatment, which is orthogonal to the first, I gave 249 randomly selected parents a report that lists the tier of colleges corresponding to their children's current in-school ranking. This intervention aims at removing the information friction related to the scale of information, in that parents only know their children's relative ranking among local peers, but college admission depends on their ranking in a much broader peer group[5].

[4]Predicted R^2 is a statistical measure that represents the proportion of the variance for a dependent variable in new observations that's explained by a regression model. It indicates how well a regression model predicts responses for new observations.

[5]Existing literature shows that parents' beliefs about their children's ability relative to the overall cohort may be distorted by children's ability among local peers (Kinsler and Pavan (2021)), resulting in underestimation of the difficulties of getting into ideal colleges. Building the link between in-school ranks and colleges can adjust the bias

Reduced form results show that both interventions lead parents to update their beliefs on children's abilities shortly after the intervention. Specifically, the first treatment (machine-learning intervention) reduced parents' belief inaccuracies by almost 50%. Since parents were overall too optimistic in the baseline, on average, the treatment generates negative shocks about children's true ability. As a result, parents increased their monetary investment in education by 4.8%, which increased their children's in-school ranking by 2.9%. The second intervention (matching between in-school ranking and colleges) also made parents adjust their aspirations; parents' belief about the CEE in-school ranking needed for the ideal tier of colleges became 5.6% smaller (they realized it is more difficult to get into ideal colleges), and the treated parents significantly downgraded their ideal tier of colleges. Consequently, parents' spending on children's education increased by 3.1%, leading to a 2% improvement in children's in-school ranking. While my interventions significantly influenced the monetary investment in education, there was no impact on parents' spending on children's daily needs or on time investments in children.

I then test the causal impact of parents' beliefs about children's ability on educational investment and the consequent effects on children's performance using IV estimations, in which ability beliefs or educational investment are instrumented by randomized treatments. Results show that the causal effects of parents' ability beliefs and aspirations on their monetary investments are non-linear around their aspirations. Parents who previously believed it would be challenging for their children to achieve their aspirations increased educational investment if they received negative information shocks on their children's ability. In contrast, parents who believed their children would easily get into the ideal colleges increased spending if they received positive shocks on their children's abilities. This finding helps us understand when and why parental

in parents' aspirations.

investments and students' abilities become substitutes or complements.

This paper builds on and contributes to three main strands of literature. First, it sheds light on the literature studying parental educational decisions. Existing research has provided suggestive evidence on how parental investments in education are affected by their beliefs about children's efforts (Bergman (2021),Bursztyn and Coffman (2012)) or return to education (Jensen (2010); List et al. (2021); Loyalka et al. (2013); Nguyen (2008)). But there is very little evidence of the causal effects of parents' belief in children's ability on their general investment decisions because it is challenging to find exogenous changes in beliefs about children's ability[6]. This paper adds to the literature by generating exogenous shocks to parental beliefs on children's ability and using those shocks to identify causal effects of parental beliefs on educational investments[7]. Moreover, the novel panel dataset on parents' general investments in children's education allows me to evaluate the persistency of the treatment impacts over time.

Second, this research contributes to the branch of studies on information friction. While there is literature showing information frictions in parental educational decision-making due to limited access to performance information (Barrera-Osorio et al. (2020); Bergman (2021); Bursztyn and Coffman (2012)), illiteracy of parents (Dizon-Ross (2019)), or lack of information on return to education or school quality (Hastings and Weinstein (2008); Jensen (2010); Nguyen

[6]Some research has explored the influences of information about individual factors, such as effort, on their investment decisions (Bergman (2021); Bursztyn and Coffman (2012)), yet very few of them manage to estimate the causal effects of parents' belief in children's ability on their general investment decisions because of the difficulty to find exogenous changes in parental beliefs about children's ability.

[7]There is a rich literature on the decision-making based on subjective beliefs and the formation of such beliefs (Billot et al. (2005); Camerer and Weber (1992); de Finetti (1970); Dickey (1980); Gilboa (2009); Gilboa and Schmeidler (1993); Gilboa et al. (2008); Grimm and Mengel (2018); Kadane and Larkey (1982,?); Savage (1954)). Empirical work has shown several factors that could affect parents' belief about children's ability, such as education (Biroli et al. (2020)), income (Boneva and Rauh (2018); Cunha et al. (2020)), and socioeconomic status (List et al., 2021). Instead of exploring various types of factors influencing parents' beliefs, this paper focuses on the impacts of parental beliefs on their decision-making, behavior, and children's academic outcomes. For simplicity, I assume parents' beliefs about children's ability follow the Bayesian belief updates and new information may initiate updates in the mean and variance of the believed ability distribution.

(2008)), this paper is among the first to document under-explored information frictions driven by misperceptions of available performance and college admission information among well-educated parents in China. More importantly, I provide novel and cost-efficient ways to solve these frictions and prove that the tools used are effective in increasing educational investment and improving student performance.

This paper also enriches the modeling of educational investment decisions (Becker (1962); Becker and Tomes (1976); Glomm (1997); Raut and Tran (2005)). There is rich empirical evidence of the impacts of parents' aspirations on children's educational attainments (Galab et al. (2013); Spera et al. (2008)) and parental educational investments (Bernard et al. (2019)). However, the importance of aspiration has not yet been demonstrated in theoretical frameworks. My paper, using a novel data set, advances this literature by incorporating aspiration, a widely used concept in general economics and strategic management decisions (Genicot and Ray (2020); Shinkle (2011)), in the parental investment decision model and testing the model predictions on the effects of aspirations on parents' educational investment behaviors. The introduction of aspirations causes an interesting non-monotonic between ability belief and investments around aspirations, which illustrates when and why parental investments and students' ability become substitutes or complements.

The paper proceeds as follows. Section 1.2 describes the background and context. Section 1.3 explains the theoretical framework. Section 1.4 provides details on the experimental design. Section 1.5 describes the data and summary statistics. Section 1.6 presents the empirical strategies and results, and Section 1.7 concludes.

1.2 Background

Educational investment is an important type of household expenditure in both developing and developed countries. In the United States, households spend 1,539 USD[8] on children's education each year. The expenditure on children's education is also pronounced in some developing countries. For example, the household annual education spending in the Bahamas and Chile can be as high as 2,388 and 2,194 USD (Acerenza and Gandelman (2020)). According to CNN Money's survey in 2017, the average total spending on education per child[9] in China is around 42,892 USD, which is the 6th-highest spending among all countries and regions. Although the amount of spending on education in China is slightly lower than that in the US (58,464 USD), it accounts for a much higher share of household expenditures considering the big gap in the annual wage between China and the US[10]. Moreover, parental investment in children's education has snowballed in the past few years; the average growth rate of China's after-school training market was over 30% from 2017 to 2019[11]. The dramatic increase in parental investment has also attracted attention from policy-makers[12].

My experiment was conducted with parents of 12th-grade students in China. One important advantage of studying educational investment in China is that most of the students in my sample

[8]Mean spending in 2014 PPP adjusted dollars.

[9]CNN surveyed for the average total spending per child, not annual spending.

[10]The mean annual disposable income in 2017 for China is 23,488 RMB (around 3,476 USD) and this number for the US is 44,110 USD(OECD (2022)).

[11]According to the White Paper published by Oliver Wyman in collaboration with China's National Institute of Education Sciences and the Tomorrow Advancing Life Group ("TAL Group"), the market size of China's K-12 (kindergarten-to-12th-grade) after-school training has been snowballing at an average annual rate of over 30% from 2017 to 2019. The total market size was over 800 billion Yuan (around 123 billion USD) in 2019.

[12]The General Office of the Communist Party of China Central Committee released a document on June 26, 2021, in which it lists reducing the educational costs for children as one of six primary goals. The General Office of the Communist Party of China Central Committee and the General Office of the State Council jointly issued a guideline on July 24, 2021, which pledges to adopt a strict approval and supervision system for off-campus tutoring programs in order to reduce parents' educational burden significantly within three years.

are the only children in their families[13]. This setting dramatically simplifies the parental investment decision-making because parents are not facing tradeoffs or equality issues between children (Almond and Mazumder (2012); Becker and Tomes (1976); Bharadwaj et al. (2018)).

The school involved in this research is a public school. Although high school education is not compulsory, the tuition fee for public schools is fixed at a relatively low rate, 900 Yuan (138.5 USD) per year. However, there are a lot of additional expenditures on curriculum-related tutoring or remedial classes, because college admission is high-stakes in this society[14], and academic performance plays a crucial role in college admission. Data from my baseline survey shows that, besides the school fees, parents spent an average of 1,319 Yuan (202.9 USD) per child each month, which is roughly 20%[15] of monthly household income.

Because of the clear classification of tiers of colleges and the significant gaps between the values awarded to degrees for different tiers, most parents in China have preferences on the tiers of colleges that they'd like their children to get in (refer to as "ideal tier of colleges" for convenience). How parents choose their ideal tier of colleges is very complicated and maybe endogenous to a wide range of factors[16], such as parents' educational background, income, experience in the past, and other parents around them. Despite the intricacy of the decision

[13]China had the "one-child" policy from 1982 to 2015. In this period, most families were only allowed to have one child.

[14]College admission is high stakes because universities in China have very clear tiers. The most standard and widely accepted classification includes five tiers, the "985" universities, the "211" universities, the "1st tier" universities, the "2nd tier" universities, and specialized colleges. The tiers of college can significantly affect individuals' social status and their outcomes in the labor market and marriage market.

[15]The ratio I found in my sample is higher than Yuan and Zhang's finding: the share of education expense in household disposable income was around 9.9% in 2002. There are several reasons which can explain the difference. First, household spending on education has been increasing rapidly. Second, as the participants in my sample are parents of 12th-grade students, their expenditure on children's education is expected to be higher than other parents. Third, the self-reported income level may be subject to under-reporting issues, as parents may not want to reveal their real income level.

[16]How parents choose the ideal tier of colleges is a very important and interesting research question that has not been well-explored in existing literature yet, but it is beyond the scope of this paper because of data limitations. This paper instead focuses on how the ideal tier of college and aspirations affect parents' educational investment decisions.

itself, parents' ideal tier of colleges is quite stable, and their aspirations for children's academic performance depend on both the ideal tier they choose and the difficulty of getting into these colleges.

Since the current college admission system in China relies solely on students' academic performance on the CEE[17], this exam is of great concern to parents of high school students. With this exam in mind, parents make educational investment decisions based on their predictions of children's college admission. Parental prediction of children's college admission can be disentangled into two steps. They firstly predict children's CEE in-school ranking and then match the CEE in-school ranking to college tiers. However, I found that there are information frictions in both steps that could bias parents' predictions. First, there are substantial errors in parents' predictions about children's future performance. In the baseline survey, I tested parents' short-term prediction accuracy by asking them to predict their children's in-school ranking in the next month. I then compared it with children's actual performance in that month and found that a majority of parents (almost 80%) have prediction errors larger than 10%. Parents' long-term prediction can be even less accurate because it involves more across-time variations. Second, parents have difficulty matching in-school ranking to the tier of colleges. Although parents have access to children's performance, the information only reveals children's in-school or in-class ranking. However, college admission depends purely on the in-province ranking on the CEE. The standard cohort size in a school is around 1,000 peers, whereas the cohort size in a province is over 400,000 peers. Mismatch[18] between the two rankings could cause misunderstandings of

[17] All 12th-grade students across the country take the CEE simultaneously during July 6-8. Students from the same province use the same examination paper. Their answers are graded anonymously by the same group of evaluators, and CEE scores rank all 12th-grade students from the same province. The province's education bureau governs the admission based on in-province rankings.

[18] In the baseline, parents' belief about the rank needed for a tier 1 (top ten) college is 42, whereas the actual rank needed for a tier 1 college is 35.

the difficulty of getting into ideal colleges and therefore result in unreasonable aspirations.

1.3 Theoretical Framework

1.3.1 Setting

Parents have a certain amount of endowments I and they need to allocate them to two potential investments: consumption C and education investment in a child E. Assume the child's ability is t. With given ability t and parental education investment E, the child's school performance (e.g. score in CEE exam) is $R = R(t, E)$. Parents' utility function is as below.

$$u \equiv U(C) + V(t, E)$$

It has two components, the utility from consumption $U(C)$ and the utility from the child's academic performance $V(t, E)$. Parents need to optimize the allocation of the endowments based on a signal $\hat{t} = t + \Delta t$ observed.

Therefore, the parent's objective function is

$$u(E) \equiv U(I - E) + V(t, E)$$

Based on real parental educational investment decisions, I made the following reasonable assumptions.

Assumption 1 $\quad U' > 0, U'' < 0$

The utility from consumption is increasing and concave.

Assumption 2 $V(t, E)) = R(t, E) + k \cdot 1\{R(t, E) \geq A\}$

where A is parents' aspiration, which represents the lowest academic performance needed to reach the ideal tier of colleges parents want their child to get into. Parents will get an additional bonus k when their children successfully reach their aspirations. $1\{R(t, E) \geq A\}$ is defined as below:

$$1\{R(t, E) \geq A\} = \begin{cases} 1, \text{ if } R(t, E) \geq A \\ 0, \text{ Otherwise} \end{cases}$$

The utility of the child's education contains two parts: 1. a "skill" function (e.g. test scores) which is continuous and differentiable in t and E; and 2. a bonus for reaching the aspiration.

Assumption 3 $\frac{\partial R}{\partial t} > 0, \frac{\partial R}{\partial E} > 0, \frac{\partial^2 R}{\partial t^2} < 0, \frac{\partial^2 R}{\partial E^2} < 0, \frac{\partial^2 R}{\partial E \partial t} > 0$

The "skill" function is assumed to be increasing and concave in both ability and education investment. Moreover, individuals with higher abilities will have higher marginal benefits at any given education investment level.

Assumption 4 $\frac{\partial A}{\partial t} = 0$

I assume the aspiration is decided exogenously and it may change for factors such as changes in the public's valuation of schools or variations in the admission competition.

Assumption 5 To simplify the setting, I assume parents receive full information about the kid's ability[19], $\hat{t} = t$.

[19] Release Assumption 5 does not change the key findings fundamentally. The detailed discussion on the decisions with an imperfect signal can be found in Chapter 3.

For convenience, I use E^* to denote the global maximum for

$$u_1(E) \equiv U(I - E) + R(t, E)$$

E^{**} denotes the unique solution to $R(t, E) = A$.

$$R(t, E^{**}) = A \tag{1.1}$$

As the objective function u is upper semicontinuous and all the necessary and sufficient conditions for a global maximum are satisfied[20] (Rockafellar and Wets (1998)), the global optimum exists and it can only occur at four points: E^*, E^{**}, 0, and I. As the two corner solutions are not common in the setting of this research, this paper will focus on the situations when the global maximum occurs at E^* or E^{**}[21].

1.3.2 Properties of E^*

As E^* is defined as the global maximum for $u_1 = U(C) + R(t, E)$. The following equation is valid at the E^* point.

$$\frac{\partial U(I - E^*)}{\partial C} = \frac{\partial R(t, E^*)}{\partial E} \tag{1.2}$$

By taking partial derivatives of both sides with respect to t, I can know that E^* is increasing in ability t.

[20]The detailed proofs can be found in Appendix A.

[21]The corner solutions can be ruled out by an additional assumption as simple as assume $\frac{\partial U(E|E=0)}{\partial E} = \infty$ and $\frac{\partial U(E|E=I)}{\partial E} = -\infty$.

$$\frac{\partial E^*}{\partial t} = -\frac{\partial^2 R(t,E^*)}{\partial E \partial t} \cdot (\frac{\partial^2 U}{\partial C^2} + \frac{\partial^2 R(t,E^*)}{\partial E^2})^{-1} > 0 \tag{1.3}$$

1.3.3 Properties of E^{**}

As E^{**} is defined as the amount of educational investment needed to reach aspiration A, we find that E^{**} is decreasing in ability t by taking partial derivatives of both sides of Equation (1.1) with respect to t,

$$\frac{\partial E^{**}}{\partial t} = -\frac{\partial R(t,E^{**})}{\partial t} \cdot (\frac{\partial R(t,E^{**})}{\partial E})^{-1} < 0 \tag{1.4}$$

1.3.4 Marginal Change in Ability Signal

Let's assume a child with ability level t_1 and educational investment E^* will just be able to reach the aspiration. In another word, the two functions $E^*(t)$ and $E^{**}(t)$ interact with each other at $t = t_1$.

As E^* is increasing in t (Equation 1.3) whereas E^{**} is decreasing in t (Equation 1.4), E^* is smaller than E^{**} for all ability levels that is lower than t_1, and E^* is greater than E^{**} when ability is higher than t_1.

The interaction point t_1 split ability levels into two regions, and the optimal strategy is different in the two regions.

When $t < t_1$: The equilibrium depends on the magnitudes of the utility at E^* and E^{**}. Let's assume the two utilities are equal at t_0[22]. For ability levels lower than t_0, the optimal investment

[22] In the extreme case where the bonus is large enough, parents always prefer E^{**} regardless of how low the ability is.

level is E^* which is increasing in ability, whereas for ability levels in between t_0 and t_1, the optimal investment shift to E^{**} which is decreasing in ability.

When $t \geq t_1$: As E^* is not smaller than E^{**}, a child will always reach the aspiration at the E^* point so the equilibrium always stays at E^*, and the optimal investment level is increasing in ability.

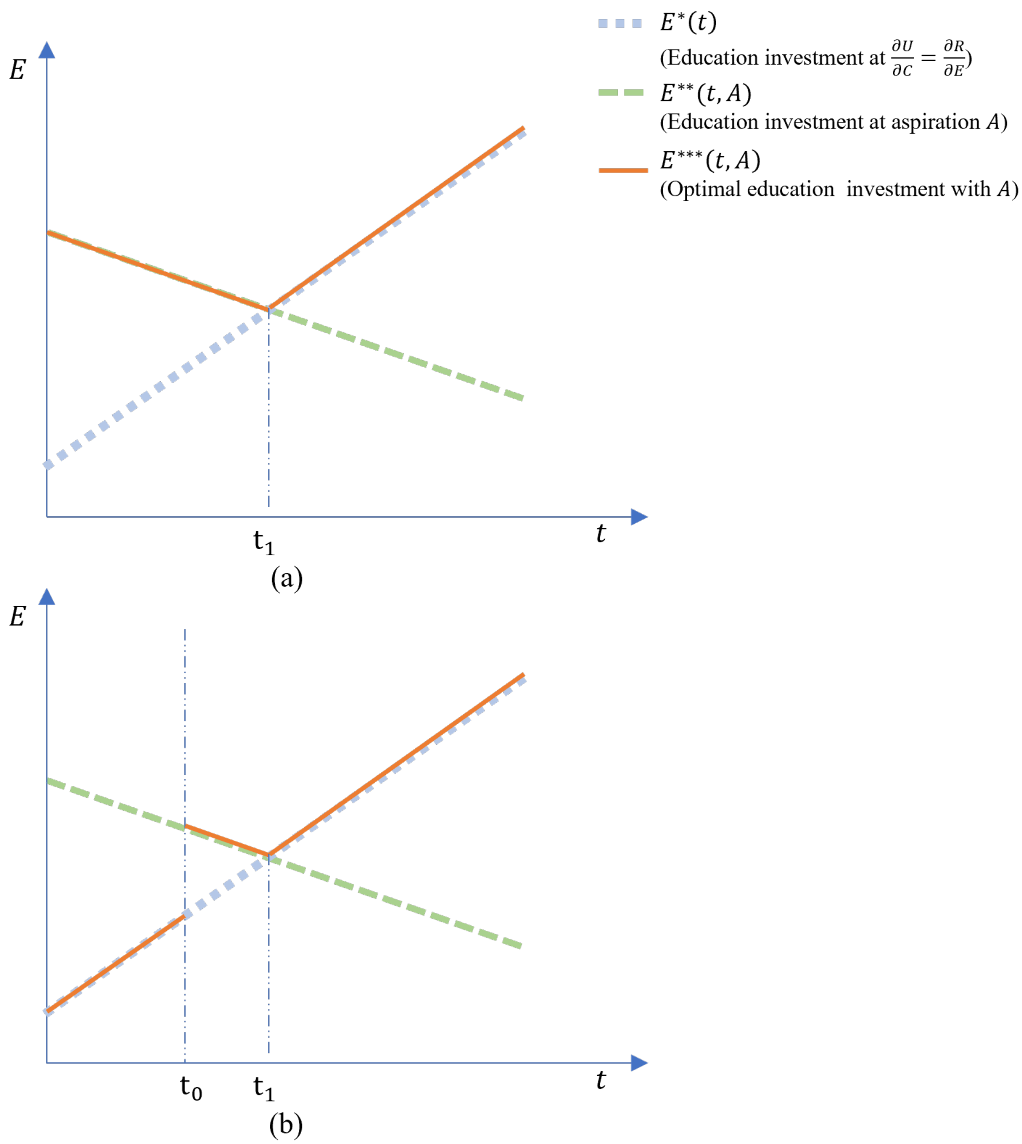


Figure 1.1: How Optimal Strategy Change in Ability

As shown in Figure 1.1, when children can reach the aspiration with E^*, parents' optimal investment level stays at the E^* point and it's increasing in ability. However, when children fail to reach the aspiration with E^*, parents will be incentivized by the bonus to increase their investments in children to help them reach the goal. To optimize their utility, parents will stop investing once the children's performances reach their aspirations, so the lower the ability, the higher the investment. When the children's ability is so low that the bonus will not be sufficient to cover the additional costs for reaching the aspiration, parents' optimal investment level will go back to E^* and the correlation returns to positive again.

1.3.5 Marginal Change in Aspiration

Now I discuss how a marginal exogenous change in aspiration affects parents' optimal educational investment level. As I am focusing on a trivial change in the aspiration that's driven by some exogenous factors, I assume such a minor change in aspiration does not change the amount of bonus (k) for reaching aspiration. This assumption is reasonable and realistic. In real life, the test scores needed to get into a certain college depend on factors such as some unpredictable random variations in the competitiveness of admission across application seasons. These factors do affect the lowest test score needed for admission (aspiration) but it does not change the reward for reaching the aspiration as the ideal college itself and how it's valued by the society stay unchanged.

A marginal change in aspiration can result in a move in both the interaction point for E^* and E^{**} (from t_1 to $t_1^{'}$) and the interaction point for utilities at the two levels (from t_0 to $t_0^{'}$)). A small increase in aspiration will move both interaction points to a slightly higher level as shown

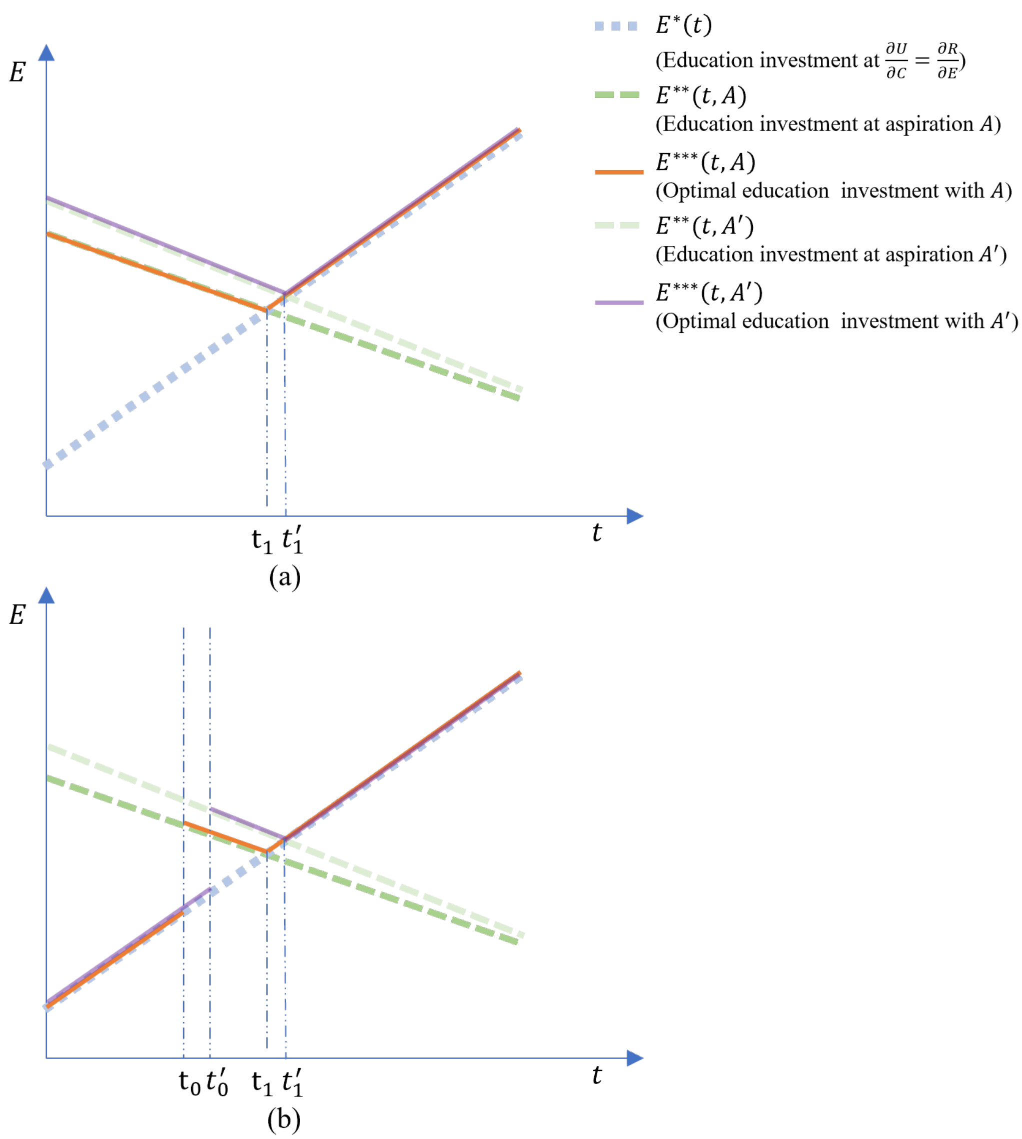


Figure 1.2: How Optimal Strategy Change in Aspiration

in Figure 1.2. For ability lower than t_0 or not smaller than $t_1^{'}$, the equilibrium stays the same. If the ability is within $[t_0^{'}, t_1^{'})$, a marginal increase in aspiration drives up the optimal educational investment level slightly, whereas it results in a significant decrease in the optimal educational investment for ability within $[t_0, t_0^{'})$ (negligible when the change in aspiration is small enough) because the equilibrium shift from E^{**} to E^{*}.

In other words, when children's ability is too low (bonus is not enough to cover the additional costs for reaching the aspiration) or too high (can reach aspiration at E^*), parents' optimal investment stays at the E^* and marginal changes in aspiration do not affect their investment level. When parents are investing at the E^{**} level to help children reach their aspirations, a marginal increase in aspiration will increase parents' investment level.

To conclude, the model predicts the causal effects of ability and aspiration on parental educational investment are nonlinear around the threshold or reaching aspiration. When the ability is low, parents will always prefer the E^* point. Their investment is positively correlated with ability whereas aspiration has no impact. When ability increases to levels at which the additional cost of reaching aspiration A is lower than the bonus, parents shift their investment from E^* to E^{**}, and their optimal education investments is decreasing in ability and increasing in aspiration. The reason is that education investment in a smarter child is more efficient and then the amount of investment needed to reach the aspiration becomes lower. A more challenging aspiration increases the amount of help needed to reach the aspiration at any ability level. Moreover, when the ability is high enough so that children's academic performance at the E^* point is sufficient to reach the aspiration, parents' investment will go back to the E^* point, the correlation between optimal education investment and ability is back to positive again, and the impacts of a marginal change in aspiration on investment are gone.

1.4 Experimental Design

I used a field experiment to validate the interesting nonlinearity feature found in the theoretical part. The experiment was implemented in a high school in Guizhou, China. The sample is limited to parents of 12th-grade students in the science track[23]. I chose to work with the 12th grade because the performance data in the second half of the 11th grade has the best predictive power for students' performance on the College Entrance Exam, so the predictions generated for students in the 12th grade are more accurate and reliable than predictions for students in 10th or 11th grade. Moreover, parents' aspirations for children become clearer when students are advanced to the 12th grade. In total, 748 parents with children enrolling in the 12th-grade science track were selected in the baseline[24]. The experiment includes two orthogonal interventions, delivering two types of information shocks to randomly selected parents. The information shocks were designed to remove the two information frictions that existed in parents' beliefs about children's performance on the college entrance exam: the misprediction of children's CEE in-school ranking and the mismatch between the in-school ranking and college tiers. Eliminating the biases in parents' beliefs can generate exogenous changes in parents' beliefs about children's ability and aspirations, which allows me to investigate the causal effects of ability belief and aspiration on investment.

[23]During my study period, there were two tracks in high school: the science track and the liberal arts track. Students had to pick one track at the end of the 10th grade. Students choosing different tracks focus on different curriculums in the 11th and 12th grades, so their scores are not comparable. Students in different tracks are ranked and admitted independently in the college entrance exam. Students in the liberal arts track are not included in the sample because the school has a much smaller cohort size (around 250 students), resulting in relatively large variations in the predictive power and rank-to-college matching accuracy.

[24]The 12th-grade science track has 17 classes and around 785 students. All 17 classes participated in the experiment, and the response rate for the baseline survey was 95%.

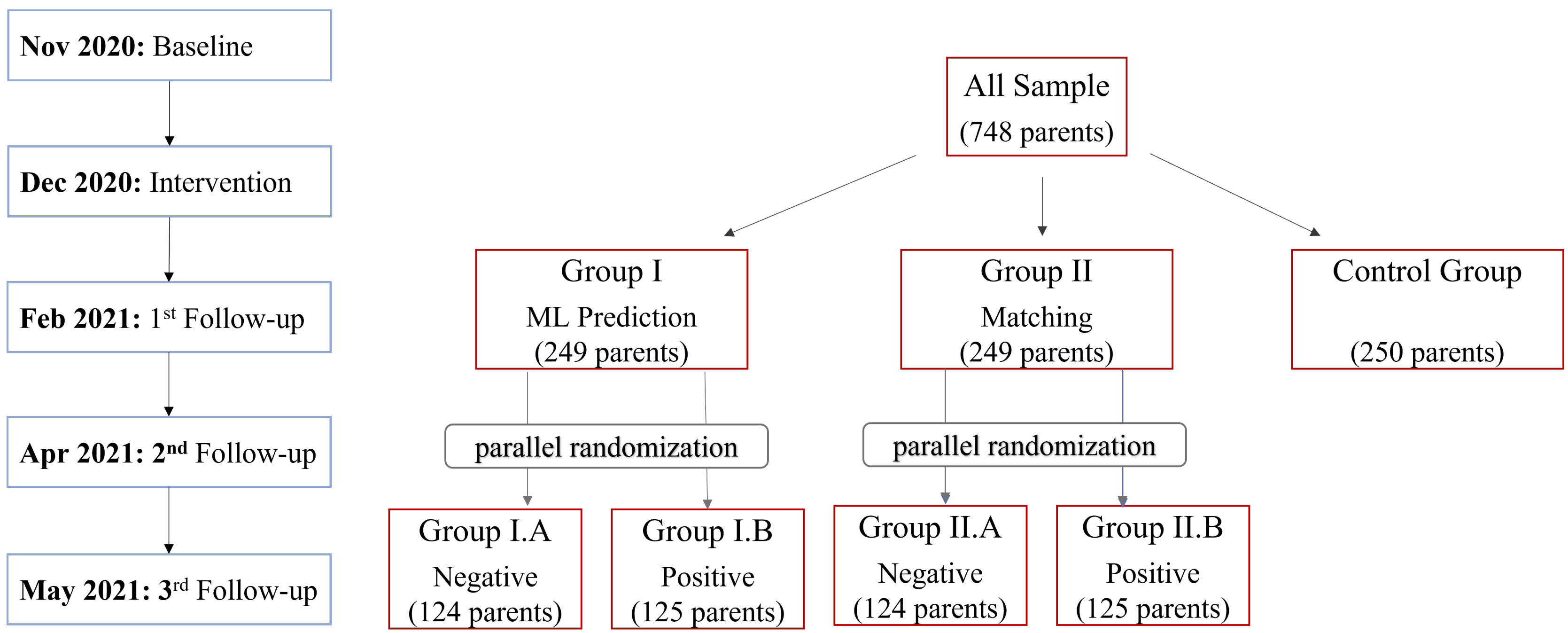


Figure 1.3: Experimental Design

Figure 1.3 summarizes the timeline and interventions of the experiment. In November 2020, I collected the baseline survey for all participants. I then randomized parents into treatment and control groups and prepared the tailored intervention reports for participants. In December 2020, I sent the intervention reports to parents. I collected three rounds of follow-up surveys around two months, four months, and six months after the intervention, respectively.

Within each class, parents were randomized into three groups: treatment group I, treatment group II, and the control group. Parents in treatment group I were assigned to receive machine-learning predictions of their children's CEE in-school ranking, whereas those in treatment group II were assigned to receive a rank-to-college matching report. Under both treatment groups, parents were further randomized into two subgroups A and B, where those in groups I.B and II.B received a more positive framing than parents in treatment groups I.A and II.A. As an incentive to participate in the whole experiment, parents in all groups received detailed performance analysis reports regularly[25], which provides a summary of a student's general performance in all curriculums, a detailed analysis for each module in each subject, and a list of weak knowledge points for each subject. More details about each of the two interventions are explained below.

1.4.1 Intervention 1 - Machine Learning Prediction

In the first intervention, I provided information to randomly selected parents (Group I in Figure 1.3) about a prediction of children's CEE performance generated by a well-trained machine-learning algorithm. The algorithm was established using rich administrative data on monthly performance data of students who graduated from the school from 2011 to 2020. The

[25] I updated the reports every two months, right before collecting each follow-up survey. When the reports were updated, I sent parents a reminder to check the updates. Parents had to finish the follow-up surveys to view the latest reports.

data includes not only each student's score and in-school ranking in monthly exams but also their CEE scores and the CEE in-school and CEE in-province ranking. Using this data, I trained a machine-learning algorithm to predict students' CEE performance based on their performance in the 10th and 11th grades. Specifically, I used LASSO regression because it performs variable selection which can identify good predictors of future performance. I used 5-fold cross-validation to select the optimal shrinkage parameter and bootstrapped the training progress 1000 times to generate the 95% confidence intervals for the predictions. For each round of the training, the sample was randomly split into five folds. The algorithm used each fold as the validation set for the estimations fit on the remaining four folds to find the optimal shrinkage parameter. A prediction was generated using the selected shrinkage parameter. Then I bootstrapped this training progress 1000 times to get a distribution of the machine-learning predictions and the confidence interval for the prediction.

In addition, I randomly varied the framing of the machine-learning prediction to make it more positive (treatment Group I.B) or more negative (treatment Group I.A). Specifically, instead of telling parents the exact prediction of the CEE in-school ranking of their children, I distributed information on the range of rankings. For each student, I presented a visual representation of five bins and marked where the student's machine-learning prediction was located. The bin covering the predicted ranking was compared with four other bins with worse (or better) rankings to make the information appear more positive (or negative). Moreover, when I constructed the bins, instead of using machine-learning prediction directly, I extended the prediction intervals slightly[26] by adding some smaller (or larger) rankings to make the information more positive

[26] The bin width is set to be 50% wider than the 95% confidence interval of machine-learning predictions. For example, if the machine-learning prediction width is 20, I added the ten ranks just below or above the prediction as the selected bin.

(or more negative). Lastly, I also changed the shading color of the bins. The shading color of the chosen bin was blue for the positive framing group and red for the negative framing group. I present an example in Figure 1.4. The exact ranking predicted for the student shown in Figure 1.4 is 201 to 220. In a positive framing, the graph shows that the prediction is located in the bin with the best rankings among all five bins listed and the range of the bin is from 191 to 220. In a negative framing, the graph indicates that the prediction is in the bin with the worst rankings among all bins shown and the range of the bin is from 201 to 230.

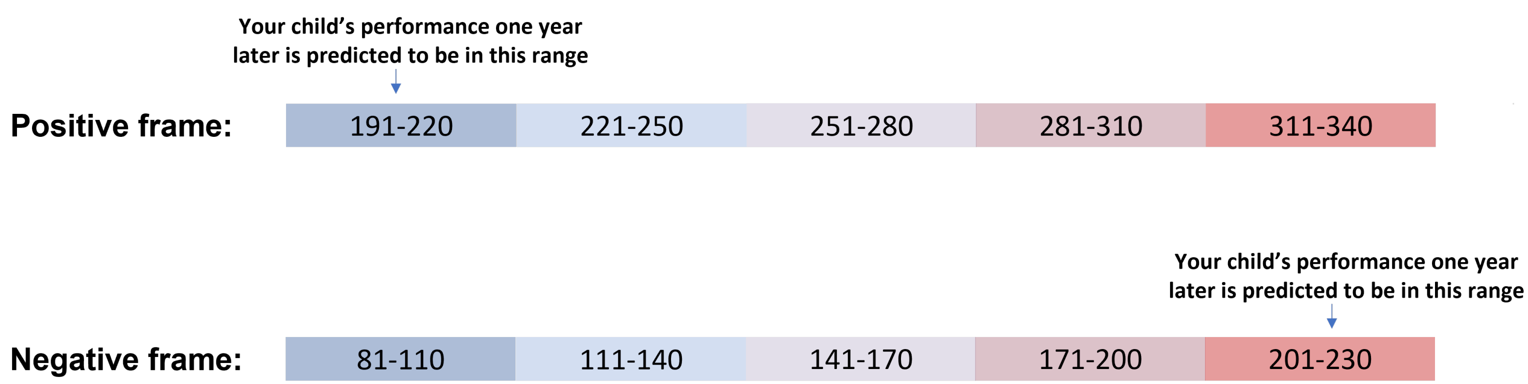


Figure 1.4: Machine Learning Prediction Example

Figure B.1 in Appendix B shows a sample of the machine-learning report. The report started with a brief introduction of the machine-learning methodology. Then it explained the algorithm and data that were used to generate the prediction. Importantly, to convince parents that the algorithm can provide accurate and reliable predictions, the report compared the accuracy of parents' predictions about their children's performance on the CEE to the algorithm's predictions using pilot data. The report emphasized that only 21% of parents have prediction errors[27] less than 10%, but the ratio for machine-learning predictions is as high as 89%. Lastly, the report visualizes where the prediction is located among five bins.

1.4.2 Intervention 2 - Rank-to-College Matching

In the second intervention, treated parents (Group II in Figure 1.3) were provided with a rank-to-college matching report to help them understand the matching between CEE in-school ranking and tier of colleges. The report included two main pieces of information. First, I showed parents the CEE scores of students who graduated from the same high school in the previous two years (cohorts 2017 and 2018), whose CEE in-school rankings were similar to their children's current in-school ranking. Second, I listed the best three colleges[28] that these students could have been admitted to in 2017 and 2018.

Similar to intervention 1, I randomly varied the framing of the report to make it more positive (treatment Group II.A) or more negative (treatment Group II.B). In Group II.A, I showed

[27] Prediction errors are defined as the ratio of the difference between predicted and the real in-school ranking to the real in-school ranking in the CEE period. The CEE period is defined as the last two months of the 12th grade (May - June). Here I used students' average in-school ranking during the CEE period to represent their actual performance during the CEE period. This evaluator is more reliable than the CEE grade itself because the CEE grade only represents performance on one exam, which is subject to more unexpected variations.

[28] The best three college admissions are decided based on a student's CEE score and a list of the minimum admission scores for each college (publicly available) in the same year.

the CEE scores and the matched best colleges of previous graduates with better performance than a treated student; in Group II.B, I used information about previous graduates with worse performance than a treated student. Because the average standard deviation of students' current in-school rankings is around 10%, I set the variation to be 10% of the children's actual current in-school rankings. For example, suppose a child's actual current in-school ranking was 200. Parents in Group II.A received information about a previous graduate whose CEE in-school ranking was 180, to make the information more positive; parents in Group II.B received relatively more negative information in the form of a previous graduate whose CEE in-school ranking was 220.

The intervention reports were sent to parents electronically through WeChat, the most popular instant messaging and social media app in China, in December 2020. Samples of the intervention reports are available in Appendix I. To properly deliver the individualized reports to parents online, I built a private website for reports distribution. The headteachers were asked to share the website link with parents through WeChat; after parents logged into the website, they were authorized to check the reports about their children. Each report had a unique QR code that could be used to retrieve the report online at any time. I also collected the browsing history record to check whether parents had read the report and asked the headteachers to send reminders to parents if needed. The intervention was delivered successfully; over 98% of parents read the report online. I also asked parents about the intervention reports in the first follow-up survey, and 95% of parents confirmed they had received and read the report.

One concern is whether there are any spillover effects across groups. I have taken several measures to avoid the potential spillovers in both the design and the implementation of the experiment. First of all, all the intervention information is individualized, and the information was delivered to parents privately through a well-designed website. In the intervention report, I made it clear that this information is not beneficial to other parents because each student has a unique trend over time and it's not possible to know one student's future performance based on other students' predictions. Moreover, based on my communication with parents before the intervention, this information was sensitive and most of them would not be willing to share it with others. This is confirmed in my follow-up surveys, in which I asked whether they shared the information with others (or heard about the information from others) and a majority of them answered no.

1.5 Data and Summary Statistics

The analysis combines data from two main sources, including administrative data from the school and survey data that I collected from parents.

1.5.1 Survey data

I conducted four rounds of surveys with parents, including a baseline survey before the intervention in November 2020 and three follow-up surveys collected two months, four months, and six months after the intervention, respectively. All four surveys were distributed to parents through WeChat[29]. In the surveys, I collected information from both treatment and control groups about the information on family demographics, parents' beliefs about their children's abilities, aspirations (measured by the expectation of the tier of college that a child could be admitted

[29]All surveys were implemented online and sent out to parents through headteachers via WeChat. Parents had up to two days to finish the surveys. I counted the completion rates every four hours and asked headteachers to send out reminders when necessary. One concern is whether the surveys were answered by decision-makers in each household. In my experiment, each class had set up a group chat for parents, and, usually, each family had one representative in the group chat. Headteachers used this tool as the primary way to communicate with parents. The survey links were also shared through the group chat and answered by each family representative. Because many important reminders and information were announced in the group chat, it is reasonable to assume each family will let the person in charge of children's studying be the representative.

to, and the CEE in-school rankings needed for the ideal tier of colleges), and different types of investments in children.

Table 1.1 shows summary statistics for key variables collected in the survey prior to the intervention. The first set of variables shows some demographic characteristics of the families in our sample. The average level of household income[30] is around the third level, which means that the annual household income is between 50,000 - 100,000 RMB (around 7,700 - 15,400 USD). The average number of children in a family is around 1.49. More than half of the parents have finished high school, and around 35% of parents have received college or higher education.

In Panel B, Table 1.1, I report statistics on parents' beliefs about children's ability and their aspirations[31]. Parental ability belief was measured by asking parents about their belief in children's current in-school ranking[32] (referred to as "rank belief"). Comparing it with children's actual current in-school ranking, the difference measures inaccuracies in parental belief. The data shows that parents are too optimistic about their children's performance at the baseline; while the average actual current in-school ranking is around 370, the average parental ability belief is around 328, indicating a bias of more than 10%.

One explanation of parents' prediction bias is that there are natural variations in children's performance from time to time. To test this I compare students' performance on the n^{th} exam with their performance on other exams close to it (the $n-2^{th}$, $n-1^{th}$, $n+1^{th}$, and $n+2^{th}$ exam) using the performance data before the intervention (Sep 2020 to Dec 2020). The average performance on the four neighbor exams can be a proxy for students' actual ability during the period of taking

[30]Because parents had shown concerns over the open question on their income in the pilot, in the main experiment, the survey asked parents to select their annual household income levels. In the question, I listed six levels: below 30k, 30k to 50k, 50k to 100k, 100k to 200k, 200k to 500k, and over 500k RMB.

[31]Online Appendix F.1 shows the survey questions used to measure parental ability beliefs and aspirations.

[32]A smaller ranking indicates better performance.

Table 1.1: Pre-Intervention Summary Statistics

	ML	Matching	Control	Total
A. Demographics				
IncomeLevel[A]	3.012	3.072	2.900	2.995
	(1.195)	(1.327)	(1.375)	(1.302)
ChildNum	1.494	1.478	1.500	1.491
	(0.918)	(0.791)	(0.859)	(0.860)
FatherEdu[B]	2.702	2.924	2.876	2.834
	(1.065)	(1.043)	(1.092)	(1.070)
MotheEdu[B]	2.641	2.719	2.692	2.684
	(1.111)	(1.082)	(1.107)	(1.099)
B. Performance, Belief, and Aspiration				
SchoolRank[C]	370.1	368.1	371.1	369.8
	(207.0)	(206.1)	(213.5)	(208.6)
RankBelief	330.8	323.8	328.7	327.8
	(195.1)	(196.0)	(198.9)	(196.5)
RankBelief-SchoolRank	-39.32	-44.32	-42.37	-42.01
	(57.24)	(58.74)	(59.68)	(58.52)
IdealTier[D]	4.089	4.048	4.084	4.074
	(1.747)	(1.724)	(1.767)	(1.744)
GoalRank[E]	205.7	202.4	198.9	202.4
	(154.5)	(147.0)	(147.2)	(149.4)
C. Parental Investment				
Edu. Monetary Inv.[F]	2687.7	2619.2	2608.4	2638.4
	(2832.6)	(2754.0)	(2228.8)	(2617.3)
Oth. Monetary Inv.[F]	1439.9	1396.0	1300.6	1378.6
	(1404.6)	(1364.8)	(1111.2)	(1299.2)
Edu. Time Inv.[G]	26.68	26.37	25.10	26.05
	(25.43)	(24.79)	(22.61)	(24.28)
Oth. Time Inv.[G]	14.67	14.06	13.00	13.91
	(15.43)	(13.93)	(11.69)	(13.76)
Sample Size				
Sample Size	249	249	250	748

Notes: Data sources are baseline survey and baseline performance records data. Each observation is a parent.

[A] $IncomeLevel$ is the level of household annual income and it has six levels, Level 1-6 represent below 30k, 30k to 50k, 50k to 100k, 100k to 200k, 200k to 500k, and over 500k RMB, respectively.

[B] Parents' education backgrounds are estimated by the highest degree earned. There are 5 levels, Level 1-5 represent less or equal to primary school, secondary school, high school, college, and graduate, respectively.

[C] $SchoolRank$ is the average ranking of children's exam performance among all other students from the same school. The smaller the $SchoolRank$, the better the performance.

[D] $IdealTier$ is the tier of colleges that parents want their children to get into. Colleges are classified into 7 tiers based on the ranking of their average entry scores among all colleges in China. Tier 1-7 represent top 10, 11th-30th, 31st-50th, 51st-100th, 101st-200th, 201st-300th, 301st-500th colleges, respectively.

[E] $GoalRank$ is parents' belief about the in-school ranking needed to get into the ideal tier of colleges.

[F] Total RMB spent in the past two months.

[G] Average hours spent per week in the past two months.

the n^{th} exam, so that the gap can be a proxy of how vibrant the exam performance is. I find that the magnitude of parents' biases (average absolute bias is 51.75) is 26% greater than the variation of performance on one exam (the average absolute gap is 41.22). More importantly, parents' bias is significantly skewed to the left - most parents' beliefs of their children's abilities are better than children's average performance (average bias gap is -42.01). Whereas the performance vibrations across exams are quite balanced - the average gap is very close to 0 (0.07). To sum up, the magnitude of biases in parents' beliefs about children's abilities is substantial and the majority of parents are too optimistic and overestimating their children's abilities.

In addition, I used two questions to measure parental aspirations: the ideal tier[33] of college that they want their children to get into and their belief about the CEE in-school ranking needed to get into the ideal tier (referred to as "goal rank"). Because both "rank belief" and "goal rank" are measured with in-school ranking, we can identify parents' prior beliefs about whether their children have achieved their aspirations by comparing those two variables. Specifically, if the rank belief is smaller than or equal to the goal rank, parents think their children have achieved their aspirations and are likely to get into the ideal colleges. Statistics reported in Table 1.1, Panel B show that, on average, parents think their children have not achieved their aspirations; the goal rank (205.7) is much smaller than the rank belief (330.8), meaning that most children need to make substantial improvements in their academic performance during the last year of high school to get into parents' ideal colleges.

I also asked a set of questions to measure parents' monetary and time investments in children in the past two months. There are three categories of parental monetary investments:

[33] Colleges are classified into 7 tiers based on the ranking of their average entry scores among all colleges in China. Tiers 1 to 7 are representing top 10, 11^{th}-30^{th}, 31^{st}-50^{th}, 51^{st}-100^{th}, 101^{st}-200^{th}, 201^{st}-300^{th}, 301^{st}-500^{th} colleges.

school fees[34] (tuition collected by the school and unofficial fees collected by the class), investments in additional practice books and remedial tutoring, and other non-educational expenses such as allowance and transportation fees. According to Panel C in Table 1.1, the educational monetary investment spent within two months was around 20% of household income over that period. The time investments listed in Panel C are the number of hours spent on children's educational or non-educational activities each week. Educational time investments include time spent on monitoring children's studying, sending them to school or picking them up after school, and communicating with teachers. The average educational time investment is around 26 hours per week[35]. Other time investments account for the time spent with children on entertainment activities such as watching movies or shopping together. The investments related to education, including both monetary and time investments, are almost twice the amount spent on non-educati-onal issues.

Since I have five randomization groups, I use the following regression to check the balance across groups in the baseline for the key variables:

$$\begin{aligned} Y_{ib} = \alpha &+ \beta_1 ML_i \cdot Negative_i \\ &+ \beta_2 ML_i \cdot Positive_i \\ &+ \beta_3 Matching_i \cdot Negative_i \\ &+ \beta_4 Matching_i \cdot Positive_i + \epsilon_i \end{aligned} \tag{1.5}$$

where i denotes the parents and b represents the baseline data. Y_{ib} are the key variables I'd like to check for sample balance in the baseline stage.

The results shown in Table 1.2 indicate that, prior to my intervention, there was no signific-

[34] In the survey, I did not ask questions about school fees for three reasons. First, school fees are fixed at the class level, so parents have no flexibility to adjust this part of their investments; second, it is common but illegal for a class to collect unofficial fees, so parents and teachers are concerned when they are asked about those fees; third, my randomization is within classes, so differences in class-level fees should be canceled out when comparing across different randomization groups.

[35] Most parents send their children to school and pick them up after school every day, which takes around 14-21 hours per week.

ant difference across groups on any of the key variables, suggesting that my randomization was valid.

1.5.2 Administrative Data on Student Performance

I got access to students' performance data for all school-level exams since they started high school[36] and the CEE scores for both past cohorts (graduated in 2011-2020) and the current cohort (graduating in 2021). Data on graduated cohorts were used to establish the machine-learning algorithm and to generate reports in both interventions.

I created two performance indicators using the administrative data: in-school ranking and in-province ranking. First, for each school-level exam, I generated in-school rankings by sorting scores from high to low. Because students took school-level exams frequently, I have enough records to generate performance information for each survey round. More specifically, I use the average ranking of all exams taken after the previous survey round and before the next survey round to represent the children's academic performance in that period. The baseline performance is measured by the average ranking of all exams taken within the two months before the baseline. Second, two province-level exams provide me with students' in-province rankings. The first one is a mock CEE[37] exam hosted by the education bureau three months before the intervention, and the second one is the CEE taken six months after the intervention. The results of both exams provide a detailed list of the cumulative number of students for each score at the province level, which allows me to generate in-province rankings for students in my sample.

[36] In the 10th and 11th grades, students take around three school-level exams each semester. When advanced to the 12th grade, students take two to three school-level exams every month.

[37] This exam is organized to help schools, teachers, and students know their relative rankings among the cohort, which is beneficial to plan for the review process in the 12th grade.

Table 1.2: Sample Balance Check

A. Demographics

VARIABLES	IncomeLevel[A]	ChildNum	FatherEdu[B]	MotherEdu[B]
	(1)	(2)	(3)	(4)
ML X Negative	0.0194	-0.0172	-0.1583	-0.0791
	(0.143)	(0.094)	(0.117)	(0.121)
ML X Positive	0.2040	0.0184	-0.1800	-0.0280
	(0.143)	(0.094)	(0.117)	(0.121)
Matching X Negative	0.1403	0.0204	0.0514	0.0177
	(0.143)	(0.094)	(0.117)	(0.121)
Matching X Positive	0.2040	0.0216	0.0440	0.0360
	(0.143)	(0.094)	(0.117)	(0.121)
Observations	748	748	748	748
R-squared	0.005	0.010	0.008	0.001

B. Performance, Belief, and Aspiration

VARIABLES	ln(RankBelief)	$ln(\|RankBelief - SchoolRank\|)$	ln(SchoolRank)[C]	IdealTier[D]	ln(GoalRank)[E]
	(5)	(6)	(7)	(8)	(9)
ML X Negative	0.0310	0.0231	0.0189	-0.0195	0.0513
	(0.103)	(0.132)	(0.100)	(0.192)	(0.113)
ML X Positive	-0.0075	0.0095	-0.0021	0.0040	0.0193
	(0.103)	(0.132)	(0.100)	(0.192)	(0.113)
Matching X Negative	-0.0141	0.0270	0.0020	-0.0517	-0.0006
	(0.103)	(0.132)	(0.100)	(0.192)	(0.113)
Matching X Positive	-0.0196	-0.0250	-0.0035	-0.0200	0.0260
	(0.103)	(0.132)	(0.100)	(0.192)	(0.112)
Observations	748	748	748	748	738
R-squared	0.000	0.001	0.000	0.000	0.000

C. Parental Investment

VARIABLES	ln(Edu. Monetary Inv.)[F]	ln(Oth. Monetary Inv.)[F]	ln(Edu. Time Inv.)[G]	ln(Oth. Time Inv.)[G]
	(10)	(11)	(12)	(13)
ML X Negative	0.0428	0.0365	0.0359	0.0490
	(0.117)	(0.088)	(0.117)	(0.104)
ML X Positive	0.0021	0.0399	-0.0175	0.0273
	(0.117)	(0.088)	(0.117)	(0.104)
Matching X Negative	0.0045	0.0101	-0.0132	0.0140
	(0.117)	(0.088)	(0.117)	(0.104)
Matching X Positive	0.0654	0.0496	0.0795	0.0544
	(0.117)	(0.088)	(0.117)	(0.104)
Observations	748	748	748	748
R-squared	0.001	0.001	0.001	0.001

Notes: *** , ** , * denotes significance at the 1%, 5% and 10% levels respectively. Robust standard errors in parenthesis. Data sources are baseline survey and baseline performance records data. Each observation is a parent.

[A] $IncomeLevel$ is the level of household annual income and it has six levels, Level 1-6 represent below 30k, 30k to 50k, 50k to 100k, 100k to 200k, 200k to 500k, and over 500k RMB, respectively.

[B] Parents' education backgrounds are estimated by the highest degree earned. There are 5 levels, Level 1-5 represent less or equal to primary school, secondary school, high school, college, and graduate, respectively.

[C] $SchoolRank$ is the average ranking of children's exam performance among all other students from the same school. The smaller the $SchoolRank$, the better the performance.

[D] $IdealTier$ is the tier of colleges that parents want their children to get into. Colleges are classified into 7 tiers based on the ranking of their average entry scores among all colleges in China. Tier 1-7 represent top 10, 11th-30th, 31st-50th, 51st-100th, 101st-200th, 201st-300th, 301st-500th colleges, respectively.

[E] $GoalRank$ is parents' belief about the in-school ranking needed to get into the ideal tier of colleges.

[F] Total RMB spent in the past two months.

[G] Average hours spent per week in the past two months.

1.6 Estimation Strategy

I employ two types of empirical estimation strategies. First, I exploit the randomized experiment to compare outcomes between treatment and control groups (reduced form estimation). Second, I use an instrumental variable method to estimate the causal impact of parental belief about children's ability on educational investment, and the causal effect of educational investment on student performance, using the randomized treatments as the instrumental variables.

1.6.1 Reduced Form

The main empirical specification is

$$\begin{aligned} Y_{it} = \alpha + \gamma_i + \lambda Post_{it} &+ \beta_1 Post \cdot ML_i \cdot Negative_i \\ &+ \beta_2 Post \cdot ML_i \cdot Positive_i \\ &+ \beta_3 Post \cdot Matching_i \cdot Negative_i \\ &+ \beta_4 Post \cdot Matching_i \cdot Positive_i + \epsilon_{it} \end{aligned} \tag{1.6}$$

Here, i denotes the parents or children, t denotes the period[38], and Y_{it} is an outcome variable, and it can be parents' belief about their children's current in-school ranking, parents' belief accuracy, parents' aspirations on children (ideal tier and goal rank), or children's academic performance (in-school or in-province rankings). ML_i is an indicator for the machine-learning treatment and $Matching_i$ indicates the rank-to-college matching treatment. $Negative_i$ and $Positive_i$ are dummies indicating the framing styles. $Negative_i$ is equal to 1 if the information received is constructed in less favorable ways, whereas $Positive_i$ is set to 1 if the report is framed in the more positive way. I pool the three periods after the intervention and generate an indicator Post to distinguish post periods from the baseline period. γ_i represents the individual fixed effect

[38] t is set to 0, 1, 2, and 3 for the baseline, 1st follow-up, 2nd follow-up, and 3rd follow-up surveys, respectively.

and the standard errors are clustered at the individual level. In the specification, four treatment groups are represented separately using interaction terms. The parameters of interest are β_1, β_2, β_3, and β_4, which measure the differential change in the outcome variable in each treatment group relative to that in the control group.

Other than the overall treatment effects, I also explore how treatment effects vary across time. This is vital in the educational investment setting because some educational investments cannot be made immediately[39] and it usually takes time for most educational investments to show impacts. To show the trend of the treatment effects across time, I use the full panel of four rounds of survey data and estimate the following equation:

$$\begin{aligned} Y_{it} = \alpha + \gamma_i + \sum_{t=1}^{3}(\theta_t Round_t &+ \mu_{1t} Round_t \cdot ML_i \cdot Negative_i \\ &+ \mu_{2t} Round_t \cdot ML_i \cdot Positive_i \\ &+ \mu_{3t} Round_t \cdot Matching_i \cdot Negative_i \\ &+ \mu_{4t} Round_t \cdot Matching_i \cdot Positive_i) + \epsilon_{it} \end{aligned} \tag{1.7}$$

Here, I include $Round_t$ as indicators of the three rounds of the follow-up surveys. μ_{1t}-μ_{42t} are the parameters of interest; they represent the treatment effects among each treatment group in each round. The three post periods allow me to test whether the treatment effects are lagged and whether the effects are persistent.

1.6.2 Instrumental Variable

If the treatments have significant impacts on parents' beliefs about children's ability, I can use treatment dummies as instrumental variables to estimate the causal impact of parental beliefs

[39]For example, some remedial classes do not admit students after they get started. If parents do not enroll in a course when it starts, they may need to wait for the next round of courses.

on educational investment and the consequent impact on children's academic performance.

I first test the impact of parental ability beliefs on educational investment. As shown in Section 1.3, the theoretical model predicts the signs of the effects to be heterogeneous across parents' beliefs about the likelihood of children achieving their aspirations. If parents think children's ability is not high enough to reach their aspirations, they invest more when their belief about their children's current in-school ranking increases or their goal rank decreases. This is because, when parents think children haven't achieved their parents' aspirations, they are incentivized economically or psychol-ogically to do more to help their children get into the ideal tier of colleges. When parents realize that their children's ability is lower (rank belief becomes larger) or the difficulty of ideal colleges' admission is higher (goal rank becomes smaller) than their prior beliefs, the amount of help needed for children to reach the ideal tier of colleges also becomes greater. By contrast, if parents think children are very likely to get into the ideal tier of colleges, they invest more when their belief about their children's ability becomes higher - that is, when their belief about their children's current in-school ranking becomes smaller (smaller ranking means better performance). I use the following estimations to test the causal impact of parental ability beliefs on educational investment and the heterogeneity of the impact.

I define two dummies: $Reach_i$ and $NoReach_i$, to indicate whether or not, in the baseline period, parents thought their children were likely to achieve the parents' aspiration. $Reach_i$ is 1 if the baseline rank belief did not reach the goal rank (the ranking needed for their ideal tier of colleges), and zero otherwise. I interact the two dummies with parental ability belief and aspiration and get four interaction terms (R_{it})[40]. I then instrument them with instrumental

[40] R_{it} includes $Reach_i$ X $RankBelief$, $NoReach_i$ X $RankBelief$, $Reach_i$ X $GoalRank$, and $NoReach_i$ X $GoalRank$

variables Z_{it} in the first stage.

$$R_{it} = \alpha + \gamma_i + \sum_{t=1}^{3} (\theta_t Round_t + \theta_t Round_t \cdot Reach_i + \mu_{zt} \cdot Z_{it} + X_{it}^{'} \beta + \epsilon_{it}) \tag{1.8}$$

The instrumental variables Z_{it} include interaction terms of treatment dummies with round dummies and reach dummies. I also include a vector of control variables, X_{it}.

Because treatment effects on investment and performance are likely to be delayed, I use the lagged predicted value for parental ability belief and aspiration in the second-stage equation.

$$Y_{it} = \lambda + \eta_i + \tau_1 Round_t + \tau_2 Round_t \cdot Reach_i + \sigma_R \hat{R}_{it-1} + X_{it}^{'} \beta + \epsilon_{it} \tag{1.9}$$

where $t = \{0, 1, 2, 3\}$.

I then test the causal effects of parental investments on children's performance. I use the same equation for the identification except that the instrumental variables used here become interaction terms of treatment dummies with round dummies, and investments are the variables being instrumented. Data from the first round of the follow-up survey are also excluded because of the potential delay in treatment effects on performance.

1.7 Results

I firstly report the reduced form estimation results, demonstrating the impact of different treatments on parental belief inaccuracies, educational investments, and children's performance. I then show the IV estimation results to discuss the causal effects of ability belief and aspiration on investments and the causal impact of investment on performance.

1.7.1 Results on Ability Belief

I start with estimating the treatment effects on parental belief about children's ability using the estimation Equation (1.6). As shown in column 1 in Table 1.3, the rank belief of the two groups receiving machine-learning predictions significantly increased by 6.2%. Since parents are on average overly optimistic about their children's performance, this indicates that the treatment helped correct parents' belief biases: the changes in rank beliefs driven by the machine-learning treatment correspond to a 48.9% reduction in belief inaccuracies (column 3, Table 1.3). In columns 2 and 4, I test whether the treatment effect varies with whether the prediction information was framed more positively or more negatively. Interestingly, the treatment effect is significantly larger when the information was framed in a more negative way. Specifically, the belief inaccuracy decreased by 57.1% among the machine-learning treatment group with more negative framing, while it only decreased by 40.8% among the group with more positive framing. The negative framing treatment generates larger impacts because, as most parents were optimistic about their children's ability in the baseline, the machine-learning predictions were likely to be worse than their own beliefs and the intervention provided a negative shock to most parents. Compared to the positive framing, the negative framing moves the information even farther away from the optimistic parents' prior beliefs and causes a bigger shock.

In contrast, the rank-to-college matching intervention had no significant effect on ability beliefs. This is reasonable since the rank-to-college report provided no additional information on students' abilities. The belief accuracy, however, was reduced significantly. This effect is mainly driven by improvement in performance but not by the update in ability beliefs. As I will show later, the second intervention resulted in improvement in children's performance, so it reduced the absolute gap between the actual performance and the ability belief of optimistic parents.

Table 1.3: Effects on Parental Ability Belief (Pooled)

VARIABLES	$ln(RankBelief)$		$ln(\|RankBelief - SchoolRank\|)$	
	(1)	(2)	(3)	(4)
Post	0.001	0.001	0.380***	0.380***
	(0.009)	(0.009)	(0.055)	(0.055)
Post X ML	0.062***		-0.489***	
	(0.013)		(0.078)	
Post X Matching	0.013		-0.198**	
	(0.013)		(0.078)	
Post ML X Negative		0.083***		-0.571***
		(0.016)		(0.095)
Post X ML X Positive		0.040**		-0.408***
		(0.016)		(0.095)
Post X Matching X Negative		0.017		-0.266***
		(0.016)		(0.096)
Post X Matching X Positive		0.010		-0.131
		(0.017)		(0.096)
Observations	2,742	2,742	2,748	2,748
R-squared	0.023	0.025	0.030	0.031
Control Group Mean	5.49		3.77	
Individual Fixed Effect	Y			
Num of Participants	748			

Notes: *** , ** , * denotes significance at the 1%, 5% and 10% levels respectively. Robust standard errors in parenthesis. Data sources are baseline & followup survey data and performance records data. Each observation is a survey response, so each parent has 2-4 observations. $Post$ dummy is 1 if the observation is post-intervention. The coefficients of the interaction terms between $Post$ and the four treatment dummies are representing the differential changes for each treatment group compared to the control one.

1.7.2 Results on Aspiration

In Table 1.4, I look at the impact of the two interventions on parental aspiration. I use two indicators for aspiration. The first one is named as ”ideal tier”, representing the ideal tier of college parents want their children to get into. The ”ideal tier” is a categorized variable with seven categories (1-7). The smaller the number, the better the college. The second indicator is "goal rank", which refers to parents' belief about the in-school ranking needed for the ideal tier. The results show that parents receiving rank-to-college matching information did adjust their aspirations. Specifically, parents' goal ranks decreased significantly by 5.6%, and their ideal tier of colleges increased by 0.11. The two results suggest that matching information makes parents realize the difficulty of getting into the ideal tier of colleges and makes them aim at colleges below their previous goals. However, the effects are statistically significant only in the group receiving less favorable matching information. Considering that most parents are too optimistic in the baseline, the results are reasonable, as the negative framing reports have greater treatment intensity on optimistic parents.

Although theoretically, the machine-learning treatment may result in updates in aspirations through changing parental ability beliefs, I do not find significant empirical evidence of aspirations changes among parents receiving machine-learning predictions. One possible reason is that the magnitude of the belief change in the machine-learning treatment is not large enough to initiate significant adjustments in ideal tiers of colleges.

1.7.3 Results on Investment

Here, I check how treatments affect four types of parental investments in children: educational monetary investment, other monetary investment, educational time investment, and other time investment. The results are presented in Table 1.5. Both interventions significantly increased educational monetary investment. The magnitudes of the effects for machine-learning prediction and matching reports are 4.8% and 3.1%, respectively, and the difference between the two

Table 1.4: Effects on Parental Aspiration (Pooled)

VARIABLES	$ln(GoalRank)$[A]		$IdealTier$[B]	
	(1)	(2)	(3)	(4)
Post	0.130***	0.130***	0.264***	0.264***
	(0.021)	(0.021)	(0.033)	(0.033)
Post X ML	-0.042		-0.020	
	(0.030)		(0.046)	
Post X Matching	-0.056*		0.111**	
	(0.030)		(0.047)	
Post ML X Negative		-0.033		-0.004
		(0.036)		(0.058)
Post X ML X Positive		-0.052		-0.035
		(0.036)		(0.058)
Post X Matching X Negative		-0.072**		0.193***
		(0.036)		(0.058)
Post X Matching X Positive		-0.040		0.029
		(0.036)		(0.058)
Observations	2,771	2,771	2,712	2,712
R-squared	0.033	0.033	0.107	0.111
Control Group Mean	5.05		4.34	
Individual Fixed Effect	Y			
Num of Participants	748			

Notes: *** , ** , * denotes significance at the 1%, 5% and 10% levels respectively. Robust standard errors in parenthesis. Data sources are baseline & followup survey data. Each observation is a survey response, so each parent has 2-4 observations. $Post$ dummy is 1 if the observation is post-intervention. The coefficients of the interaction terms between $Post$ and the four treatment dummies are representing the differential changes for each treatment group compared to the control one.

[A] $GoalRank$ is parents' belief about the in-school ranking needed to get into the ideal tier of colleges.

[B] $IdealTier$ is the tier of colleges that parents want their children to get into. Colleges are classified into 7 tiers based on the ranking of their average entry scores among all colleges in China. Tier 1 to 7 are representing top 10, 11th-30th, 31st-50th, 51st-100th, 101st-200th, 201st-300th, 301st-500th colleges.

treatment effects is insignificant. The effects are significant only for the treatment groups where the information was framed more negatively.

In contrast, no effects have been identified on the other three types of investments. Observing no effects for educational time investment is reasonable in this setting because the 12th-grade students already have a busy schedule, so parents can hardly increase their educational time investment even if they want to. This is not inconsistent with the findings on increases in educational investment, because parents can switch children to more expensive tutoring programs without changing the total time spent on such programs.

1.7.4 Results on Performance

Students' academic performance is estimated using both in-school rankings and in-province rankings. The advantage of the in-school ranking measure is that it is available in all periods, allowing me to check the trend of effects over time. However, one concern about in-school ranking is that it is a relative ranking among 12th-grade students in the science track from this school, and almost all of their parents are participating in this experiment (half as control and half as treated), so the treatment effects may be overestimated. The in-province ranking can overcome this issue because it is measured among a much bigger peer group where the externality of the relative ranking becomes ignorable. Another advantage of using the in-province ranking is that it is the key determinant of college admissions, which is the outcome that we eventually care about.

Results are presented in Table 1.6. Compared to the control group, the performances of children in both treatment groups significantly have been significantly improved. The effects on in-school ranking decreased by 2.9% and 2% in the machine-learning and matching treatment

Table 1.5: Effects on Parental Investments (Pooled)

VARIABLES	$ln(Edu.MonetaryInv.)^{A}$		$ln(Oth.MonetaryInv.)^{B}$		$ln(Edu.TimeInv.)^{C}$		$ln(Oth.TimeInv.)^{D}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	0.131***	0.131***	0.027**	0.027**	0.209***	0.209***	0.070***	0.070***
	(0.012)	(0.012)	(0.011)	(0.011)	(0.016)	(0.016)	(0.013)	(0.013)
Post X ML	0.048***		-0.003		0.011		0.011	
	(0.017)		(0.016)		(0.023)		(0.018)	
Post X Matching	0.031*		0.009		0.005		0.003	
	(0.017)		(0.016)		(0.023)		(0.018)	
Post ML X Negative		0.062***		-0.006		0.014		0.007
		(0.021)		(0.020)		(0.028)		(0.022)
Post X ML X Positive		0.033		0.001		0.008		0.015
		(0.021)		(0.020)		(0.028)		(0.022)
Post X Matching X Negative		0.042**		0.014		-0.001		0.004
		(0.021)		(0.020)		(0.028)		(0.022)
Post X Matching X Positive		0.019		0.004		0.011		0.003
		(0.021)		(0.020)		(0.028)		(0.022)
Observations	2,808	2,808	2,808	2,808	2,808	2,808	2,808	2,808
R-squared	0.205	0.207	0.010	0.010	0.201	0.201	0.049	0.049
Control Group Mean	7.56		7.00		3.12		2.43	
Individual Fixed Effect	Y							
Num of Participants	748							

Notes: *** , ** , * denotes significance at the 1%, 5% and 10% levels respectively. Robust standard errors in parenthesis. Data sources are baseline & followup survey data. Each observation is a survey response, so each parent has 2-4 observations. $Post$ dummy is 1 if the observation is post-intervention. The coefficients of the interaction terms between $Post$ and the four treatment dummies are representing the differential changes for each treatment group compared to the control one.

[A] Total RMB spent in the past two months on issues related to children's education.

[B] Total RMB spent in the past two months on issues not related to children's education.

[C] Average hours spent per week in the past two months on issues related to children's education.

[D] Average hours spent per week in the past two months on issues not related to children's education.

groups, respectively, and the in-province ranking improved by 6.5% and 4.8% in the two treatment groups, respectively. Consistent with the impact on other outcomes, the impact on performance is especially salient among the treatment groups receiving negatively framed information.

1.7.5 Dynamic Effects

To track how parents adjust their beliefs and behaviors across time, I explore the dynamics of the treatment effects by estimating Equation (1.7). The results are reported in Table 1.7 and Figure 1.5. Columns 1 - 4 show that parents update their ability beliefs and aspirations shortly after receiving intervention information, and the changes persist over time. However, the educatio-nal monetary investment adjustments (column 5) are lagged by one survey round, which is about two months. Specifically, there are no significant treatment effects on any of the groups in the first period. Parental educational monetary investment in children starts to experience a significant increase in the second period and persists to the last period. This finding confirms the prediction that parental educational investment may be lagged because educational investments may not be adjusted immediately. Like the pooled results, no significant effects are identified for all three other types of investments (columns 6 - 8). Similar to the investments, the differential changes in children's performance (column 9) [41] become significant from the second round and stay to the end of the study period.

1.7.6 IV Estimation Results

As shown in the reduced form results, the randomized treatments cause significant changes in parental beliefs, aspirations, and investments, which allows me to use the randomized treatment

[41] Here, I only check the in-school rank since the in-province rank only has one post period.

Table 1.6: Effects on Students' Performance (Pooled)

VARIABLES	$ln(SchoolRank)^{\text{A}}$			$ln(ProvRank)^{\text{B}}$	
	(1)	(2)		(3)	(4)
Post		0.029***			-0.017
		(0.006)			(0.017)
Post X ML	-0.029***			-0.065***	
	(0.009)			(0.024)	
Post X Matching	-0.020**			-0.048**	
	(0.009)			(0.024)	
Post ML X Negative		-0.034***			-0.069**
		(0.011)			(0.029)
Post X ML X Positive		-0.024**			-0.060**
		(0.011)			(0.029)
Post X Matching X Negative		-0.027**			-0.063**
		(0.011)			(0.029)
Post X Matching X Positive		-0.012			-0.032
		(0.011)			(0.029)
Observations	2,842	2,842		1,490	1,490
R-squared	0.013	0.013		0.044	0.044
Num of Participants	748	748	745	745	
Control Group Mean	5.65			10.08	
Individual Fixed Effect			Y		

Notes: *** , ** , * denotes significance at the 1%, 5% and 10% levels respectively. Robust standard errors in parenthesis. Data sources are performance records data pre and post-intervention. As in-school rank is collected with each round of followup survey, each parent has 2-4 observations in the $SchoolRank$. $ProvRank$ only has one observation after the intervention so each parent has 2 observations. $Post$ dummy is 1 if the observation is post-intervention. The coefficients of the interaction terms between $Post$ and the four treatment dummies are representing the differential changes for each treatment group compared to the control one.

[A] $SchoolRank$ is the average ranking of children's academic performance on school's monthly exams among all other students from the same school. The smaller the $SchoolRank$, the better the performance.

[B] $ProvRank$ is the ranking of children's performance on province-level exams among all other students from the same province. The smaller the $ProvRank$, the better the performance.

Table 1.7: Dynamic Effects Across Time

VARIABLES	$ln(RankBelief)$	$ln(\lvert RankBelief - Rank \rvert)$	$GoalRank$[A]	$IdealTier$[B]	$ln(Edu.MonetaryInv.)$[C]	$ln(Oth.MonetaryInv.)$[D]	$ln(Edu.TimeInv.)$[E]	$ln(Oth.TimeInv.)$[F]	$ln(SchoolRank)$[G]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post1	-0.006	0.346***	0.124***	0.234***	0.125***	0.031**	0.181***	0.057***	0.013*
	(0.011)	(0.067)	(0.026)	(0.040)	(0.014)	(0.014)	(0.020)	(0.015)	(0.008)
Post2	-0.001	0.431***	0.150***	0.250***	0.127***	0.024*	0.224***	0.068***	0.032***
	(0.012)	(0.069)	(0.026)	(0.041)	(0.015)	(0.014)	(0.020)	(0.016)	(0.008)
Post3	0.011	0.374***	0.128***	0.296***	0.155***	0.030**	0.233***	0.088***	0.036***
	(0.012)	(0.067)	(0.026)	(0.040)	(0.014)	(0.014)	(0.020)	(0.015)	(0.020)
Post1 X ML	0.088***	-0.548***	-0.058	-0.019	0.014	-0.015	0.025	0.011	-0.017
	(0.016)	(0.094)	(0.036)	(0.056)	(0.020)	(0.020)	(0.028)	(0.022)	(0.011)
Post2 X ML	0.044***	-0.446	-0.054	-0.031	0.072***	0.006	0.011	0.016	-0.039***
	(0.017)	(0.097)	(0.037)	(0.058)	(0.021)	(0.020)	(0.029)	(0.022)	(0.011)
Post3 X ML	0.054***	-0.471***	-0.014	-0.007	0.058***	0	-0.004	0.006	-0.028**
	(0.016)	(0.096)	(0.037)	(0.057)	(0.020)	(0.020)	(0.028)	(0.022)	(0.011)
Post1 X Matching	0.011	-0.131	-0.076**	0.121**	0.022	0.001	0.002	-0.003	-0.007
	(0.016)	(0.095)	(0.037)	(0.057)	(0.020)	(0.020)	(0.029)	(0.022)	(0.011)
Post2 X Matching	0.012	-0.258***	-0.064*	0.115**	0.037*	0.005	0.023	0.006	-0.023**
	(0.017)	(0.098)	(0.037)	(0.059)	(0.020)	(0.020)	(0.029)	(0.022)	(0.011)
Post3 X Matching	0.021	-0.246**	-0.027	0.097*	0.034*	0.019	-0.011	0.006	-0.020*
	(0.016)	(0.096)	(0.036)	(0.057)	(0.020)	(0.020)	(0.028)	(0.022)	(0.011)
Observations	2,775	2,781	2,815	2,781	2,842	2,842	2,842	2,842	
R-squared	0.034	0.035	0.037	0.11	0.225	0.012	0.208	0.019	
Individual Fixed Effect					Y				
Num of Participants					748				

Notes: *** , ** , * denotes significance at the 1%, 5% and 10% levels respectively. Robust standard errors in parenthesis. Data sources are baseline & followup survey data and performance records data. Each observation is a survey response, so each parent has 2-4 observations. $Post1$-$Post3$ are time dummies representing the three rounds of follow-ups. The coefficients of the interaction terms between time dummies and the two treatment dummies are representing the treatment effects for each treatment group at each period.

[A] $GoalRank$ is parents' belief about the in-school ranking needed to get into the ideal tier of colleges.

[B] $IdealTier$ is the tier of colleges that parents want their children to get into. Colleges are classified into 7 tiers based on the ranking of their average entry scores among all colleges in China. Tier 1-7 represent top 10, 11th-30th, 31st-50th, 51st-100th, 101st-200th, 201st-300th, 301st-500th colleges, respectively.

[C] Total RMB spent in the past two months on issues related to children's education.

[D] Total RMB spent in the past two months on issues not related to children's education.

[E] Average hours spent per week in the past two months on issues related to children's education.

[F] Average hours spent per week in the past two months on issues not related to children's education.

[G] $SchoolRank$ is the average ranking of children's academic performance on school's monthly exams among all other students from the same school. The smaller the $SchoolRank$, the better the performance.

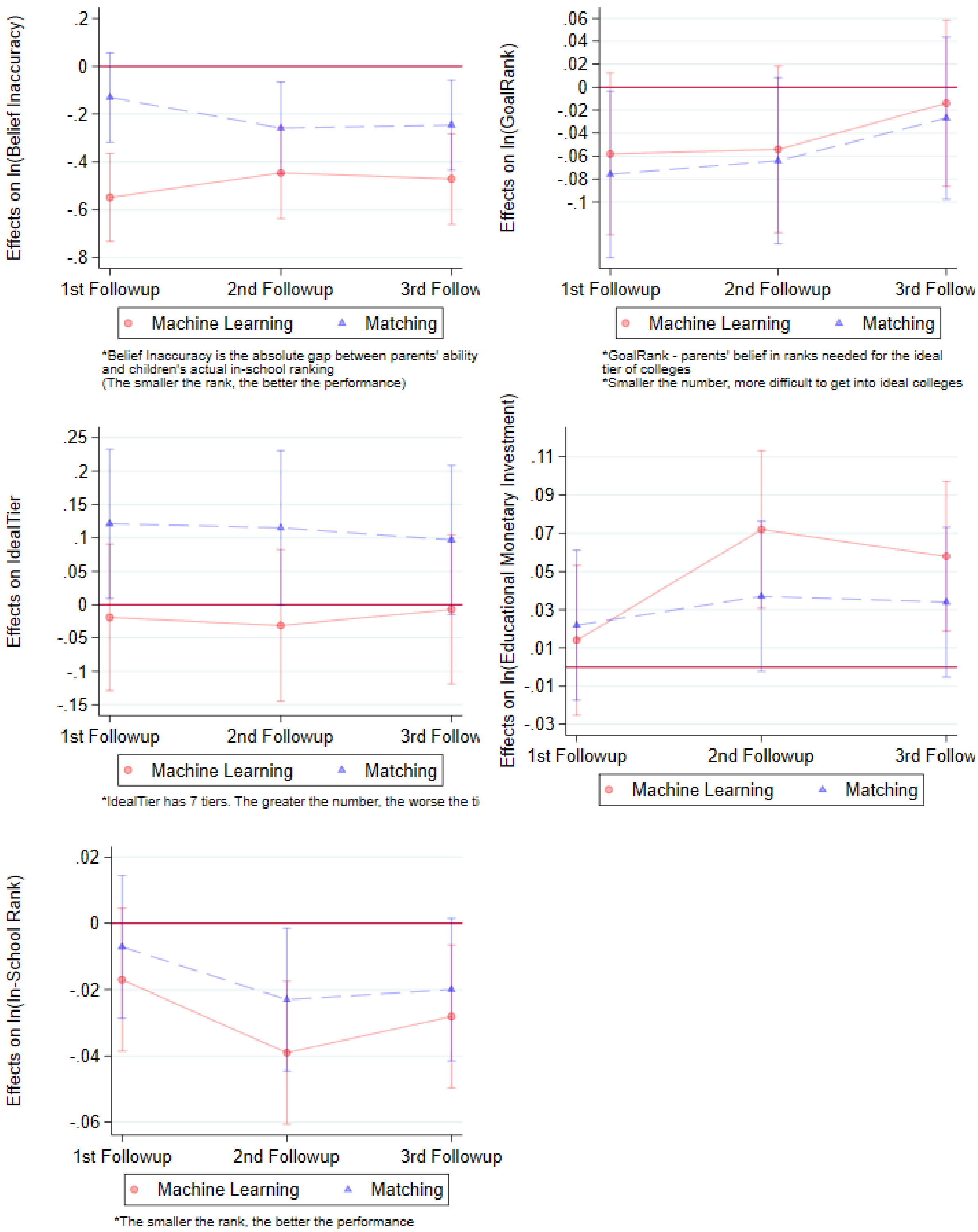


Figure 1.5: Dynamic Effects Across Time

assignments as instrumental variables to identify the following two types of causal effects: the effects of ability belief and aspiration on educational investments, and the causal effects of educational investment on students' performance.

Table 1.8 shows the IV estimation results regarding the impact of ability belief and aspiration on educational investments. I identify a nonlinearity for the impacts around the aspiration. Specifically, the sign and magnitude of the effects depend on parents' prior beliefs about the likelihood of children reaching ideal colleges. For parents who thought their children were struggling to get into ideal colleges in the baseline, when they received negative signals, they negatively adjusted their belief in their children's abilities and their own aspirations and felt that their children needed more help to get into the ideal colleges. To reach this goal, parents increased their investments in children's education. In detail, when parents' belief in their children's in-school ranking increased by 1% (ability belief became worse), they increased the educational monetary investments by 1.19%. When parents' beliefs about the in-school rank needed for ideal colleges decreased by 1% (the difficulty of getting into the ideal colleges became larger), their monetary investments in children's education increased by 0.47%. In contrast, if parents thought their children's ability was good enough for the ideal tier of colleges, the signs of the two effects changed, but they are not statistically different from 0. The causal effects of rank belief under aspirations having been achieved or not achieved are significantly different at the 1% level. The causal effects of aspiration under the two cases are also significantly different from each other at the 5% level. The nonlinearity effects found near the threshold of reaching aspirations coincide with the non-monotonic correlation between parental beliefs and investments predicted in the theoretical framework. Similar to the reduced form results, I find no effects of parental ability beliefs on the other three types of parental investments.

Table 1.8: 2SLS - Effects of Belief and Aspiration on Investments

VARIABLES	$ln(Edu.MonetaryInv.)^{A}$	$ln(Oth.MonetaryInv.)^{B}$	$ln(Edu.TimeInv.)^{C}$	$ln(Oth.TimeInv.)^{D}$
	(1)	(2)	(3)	(4)
$\widehat{NoReach\ X\ ln(RankBelief)}_{t-1}$	1.188***	0.250	-0.280	0.096
	(0.261)	(0.224)	(0.340)	(0.243)
$\widehat{Reach\ X\ ln(RankBelief)}_{t-1}$	-0.483	0.010	0.607	-0.204
	(0.419)	(0.358)	(0.544)	(0.389)
$\widehat{NoReach\ X\ ln(GoalRank)}_{t-1}$	-0.472**	-0.137	-0.326	-0.008
	(0.209)	(0.179)	(0.272)	(0.195)
$\widehat{Reach\ X\ ln(GoalRank)}_{t-1}$	0.121	-0.098	0.436	-0.046
	(0.214)	(0.183)	(0.278)	(0.199)
Observations	2,699	2,699	2,699	2,699
Individual Fixed Effect		Y		
Num of Participants		748		

Notes: *** , ** , * denotes significance at the 1%, 5% and 10% levels respectively. Robust standard errors in parenthesis. Data sources are baseline & followup survey data. Each observation is a survey response, so each parent have 2-4 observations. The 1st stage regress $NoReach\ X\ ln(RankBelief)_{t-1}$, $Reach\ X\ ln(RankBelief)_{t-1}$, $NoReach\ X\ ln(GoalRank)_{t-1}$, and $NoReach\ X\ ln(GoalRank)_{t-1}$ on the interaction terms between time dummies, treatment dummies, and $Reach$ (indicating if parents think children have reached their aspiration) dummies. Because adjustments in investments are observed to be lagged by one round, the belief and aspirations in the last period are used in the 2nd-stage regressions. Both the 1st and 2nd stage regression control for individual FE and time FE.

[A] Total RMB spent in the past two months on issues related to children's education.

[B] Total RMB spent in the past two months on issues not related to children's education.

[C] Average hours spent per week in the past two months on issues related to children's education.

[D] Average hours spent per week in the past two months on issues not related to children's education.

Next, I examine the effectiveness of parental investments in terms of improving students' academic performance. Because the treatments only significantly affected parents' education-related monetary investments, I only have the power to check the causal effects of this type of investment on performance. In the first stage, I regress parental educational monetary investment on instrumental variables and get the predictions. I then regress academic performance indicators on the predicted investment. The results are listed in Table 1.9. It suggests that the additional parental educational monetary investments initiated by the treatments are effective and can significantly improve both the in-school and the in-province rankings. When parental monetary investment in education increased by 1%, students' in-school and in-province rank decreased by 0.43% and 1.37%, respectively.

1.8 Conclusion

This paper reveals two common information frictions among educated parents who have access to school performance: poor predictions of future performance and misunderstanding in the matching between in-school ranking and the requirements of colleges. This results in inaccurate beliefs about children's abilities, inappropriate aspirations, and inefficient educational investments. This paper proposes and tests two novel interventions to solve those problems. Results show that using machine learning to generate predictions on children's future performance and providing the information to parents can significantly eliminate the frictions and lead to a 49% reduction in inaccuracies in parental belief about their children's ability, a 5% increase in parental educational monetary investments, and a 3% improvement in students' performance.

This paper theoretically and empirically demonstrates the importance of aspirations (Genicot

Table 1.9: 2SLS - Effects of Investments on Performance

VARIABLES	$ln(SchoolRank)^{A}$	$ln(ProvRank)^{B}$
	(1)	(2)
$\widehat{ln(Edu.\ Monetary\ Inv.)}$	-0.434***	-1.374***
	(0.063)	(0.379)
Observations	2842	1,490
Num of Participants	748	745
Individual Fixed Effect	Y	

Notes: *** , ** , * denotes significance at the 1%, 5% and 10% levels respectively. Robust standard errors in parenthesis. Data sources are performance records data. As in-school rank is collected with each round of followup survey, each parent have 2-4 observations in the $SchoolRank$. $ProvRank$ only has one observation after the intervention so each parent has 2 observations. The 1st stage regress $ln(Edu.\ Monetary\ Inv.)$ on the interaction terms between time dummies and treatment dummies. Both the 1st and 2nd stage regression control for individual FE and time FE.

[A] $SchoolRank$ is the average ranking of children's academic performance on school's monthly exams among all other students from the same school. The smaller the $SchoolRank$, the better the performance.

[B] $ProvRank$ is the ranking of children's performance on province-level exams among all other students from the same province. The smaller the $ProvRank$, the better the performance.

and Ray (2020)) in parents' investment decisions. It firstly improves the theoretical model for parents' investment decisions by incorporating aspirations into parents' utility, which predicts interesting non-monotonic effects of ability belief on investments around aspirations. It then successfully proves the nonlinear impacts empirically with a field experiment in which parents' beliefs were exogenously changed through information provision. The results suggest that if parents think it will be challenging for their children to achieve parents' aspirations, they increase investments in children's education when receiving adverse shocks, and the additional investment does help improve children's academic performance. When parents believe children's ability is good enough for the level of aspiration, no significant effects of belief or aspiration changes on investments have been identified. The findings help us understand when and why parental investments and students' abilities become substitutes or complements.

The findings of this paper have important policy implications. It shows that policymakers can apply big data techniques to help with decision optimization for households and firms. While my paper shows that machine-learning techniques can be applied to help optimize parents' educational investments, some other decision-making may also involve prediction biases that need to be corrected. For example, similar methodologies can be used to help banks screen borrowers, improve firms' hiring decision-making, etc. Moreover, the evidence on non-monotonic impacts of parents' ability belief on investments around aspirations also suggests that policymakers consider parents' prior beliefs and aspirations for policy designs. Ignoring these factors may result in ineffective or counterproductive policies.

Chapter 2: Understanding Mechanisms Underlying Peer Effects on Educational Investment Among Parents: Evidence from China

2.1 Introduction

People somehow rely their decisions on the choices of people around them. This phenomenon can be observed for decisions as small as the choice of the brand of laundry liquid, or as important as the selection of the location of houses. Such peer effects are also very common among parents. It's not hard to find evidence of herding of parents' decisions on issues related to children's education. Existing literature has explored the role of peers in parenting style and some other factors. However, we still lack evidence on whether peer effects affect parents' investment in children's education, let alone rigorous identifications of the underlying mechanisms.

The identification of the causal effects of peer effects is not easy, especially because of the existence of correlations. As peers are individuals who are related physically or socially, it's hard to find enough exogenous changes for a clean identification of peer effects. In this paper, I use a randomized field experiment with parents of high school students in China to investigate the peer effects on parents' educational investment decisions. I created and introduced a novel educational product to parents and collected their willingness to buy (WTB) for this product at a given price. Before surveying parents' WTB, I provided randomly selected parents with additional information on some peer parents' behaviors as the intervention. The first intervention information is the percentage of parents in a certain peer group who have decided to buy this service. The second intervention information provided parents with information on the percentage of parents in a certain peer group who have been selected to use this service by a lottery. After the delivery of the two intervention information, I collected parents' WTB for this service at a fixed price. Combining the experiment with several rounds of surveys and administrative data from the school, I find significant peer effects on parents' educational investments. More importantly, the experiment design allows me to decouple different channels of peer effects and measure the magnitude and significance of each channel. In addition, the results also reveal how these mechanisms vary across different types of parents.

I start with the discussion of the potential channels for peer effects on parents' educational investments. In general, there are three potential channels of peer effects on parents' educational investment decisions:

1. Social Learning: Parents might learn from peer parents' educational investment decisions by inferring that the products chosen by other parents are more effective.

2. Competition Externality: Parents' children are competing with peer parents' children for limited resources or opportunities, such as college admissions. When one parent starts using an additional educational product, it causes externality to all other parents because it might increase the competition faced by other parents' children. These parents might also want to adopt this product to overcome the potential relative disadvantages.

3. Imitation: Parents may want to copy peer parents' educational investment behavior for reasons other than the "social learning" or the "competition Externality". which is also referred to as the "keep up with the Joneses" phenomenon.

I then estimate the impacts of peer effects on parents' investment in children's education and the underlying mechanisms using a field experiment with 3379 parents from three high schools in China. Two pieces of information were provided to parents to help them know peer parents' behaviors. In the first information, I randomly selected 1517 parents and provided them with information on the WTB rate among a certain group of peer parents. This information not only allows parents to know peer parents' possession (or use) status but also informs them of peers' decisions about whether they'd like to buy this service or not. In the second information, I offer parents information on the percentage of parents among a certain group of peer parents who have been randomly selected to experience this service. This information only reveals the possession status of this product among the peer group. The only difference between the two pieces of information is that parents' decisions are observable in the first information but hidden in the second one. Therefore, the comparison of groups with the two pieces of information can reveal the peer effects through the "social learning" channel. In addition, I add some randomization to the competitiveness of the peer groups constructed for each parent. Comparing the parents assigned with less competitive peers with those assigned with more competitive peers allows me to identify the peer effects through the "competition externality" channel.

The results suggest that the two pieces of information delivered in the intervention have significantly increased parents' WTB for this service. The information on other parents' WTB rates can increase parents' WTB rate by 7.5%, which is around 30% of the WTB rate in the control group. Information on other parents' possession rates can increase parents' WTB rate by 5%, a 20% increase of the initial WTB rate in the control group when the peer groups are parents of students with better performances.

I then identify the magnitude of peer effects through different mechanisms and find strong evidence in both the ”social learning” and the ”competition externality’ channels. The magnitude of peer effects through both channels are similar: they increase parents’ WTB rate by around 5%, which is about 20% of the control group level. In addition, I explored the heterogeneity of the peer effects across characteristics such as education background, income, performance, and child number. I find that parents with relatively lower education, lower income level, and more than one child are more likely to be incentivized by peer effects through the ”competition externality” channel. Parents of students with better performances are also more sensitive to the ”competition externality” type of peer effects.

This paper builds on and contributes to three main strands of literature. First, this paper enriches the existing literature on peer effect by exploring the peer effects on educational investments of parents, a research object which has not been studied in current literature so far. The potential importance of peers has been studied in several fields. Economists in the finance sector have proved the existence of peer effects in investment decisions under a variety of settings. For example, there is a rich volume of literature on the peer effects among individual-level financial decisions (BROWN et al. (2008); Bursztyn et al. (2014); Cai et al. (2015); Hong et al. (2004); HONG et al. (2005); Hvide and Ostberg (2015); OUIMET and TATE (2019)) and firm-level financial decisions (Kaustia and Rantala (2015)). Another important research focus is the peer effects in education field. Some papers explore the effects of peers among students in elementary, secondary, and high schools (Bifulco et al. (2014); Bursztyn and Jensen (2015); Bursztyn et al. (2018); Carrell and Hoekstra (2010); Carrell et al. (2018); Imberman et al. (2012); Lavy and Schlosser (2011); Patacchini et al. (2017); Tonello (2016)) and there are also sizable number of papers exploring the peer effects among college students (Carrell et al. (2013, 2008, 2009, 2011); Foster (2006)). However, the research on peer effects among other participants in education is relatively rare (Farrell (2019)). This paper is one of the very first research which focus on the peer effects among parents and their educational investment decisions.

Secondly, this paper sheds light on the literature investigating the mechanisms of peer effects. Despite the richness of research on peer effects, very few of them have rigorous identification of the underlying mechanisms because of data limitations. Bursztyn et al. (2014) and Cai et al. (2015) have successfully pinned down the potential mechanisms of peer effects on financial and insurance decisions using randomized field experiments. This paper adds to the literature by revealing the mechanisms behind the peer effects observed in parents' educational investment decisions. This paper uses a well-designed field experiment to unbind the possession of a product from the purchase decision, which allows me to disentangle different channels of peer effects. More importantly, I find the primary peer effect mechanisms vary across characterist-ics such as education, income, performance, and child number. These findings can help us to understand herding behavior and involution in education and other settings.

Lastly, this paper also contributes to the literature on parental educational decisions. Existing research has provided suggestive evidence on how parental investments in education are affected by internal issues, such as their beliefs about children's effort (Bergman (2021); Bursztyn and Coffman (2012)), return to education (Jensen (2010); List et al. (2021); Loyalka et al. (2013); Nguyen (2008)), and ability (Barrera-Osorio et al. (2020); Bergman (2021); Bursztyn and Coffman (2012); Dizon-Ross (2019)), However, to the best of my knowledge, there is no existing research investigating the impacts of other parents' educational investment decisions. This paper fills in this knowledge gap by providing strong evidence on the impacts of peer parents' behavior on parents' own educational decisions.

The paper proceeds as follows. Section 2.2 provides details on the experimental design.

Section 2.3 describes the data and summary statistics. Section 2.4 presents the empirical strategies, Section 2.5 discusses the results, and Section 2.6 concludes.

2.2 Experimental Design

The experiment was implemented in three high schools located in Guizhou, China. The sample includes parents of 10th and 11th-grade students in both the science track and the liberal arts track. Parents of 12th-grade students were excluded for two reasons. First, some of the 12th-grade students' parents had participated in another experiment. More important, 12th-grade students had already graduated when this experiment was conducted. In total, 3379 parents were drawn in the baseline. The experiment introduced a novel educational product to parents and asked their willingness to buy for this service at a fixed price. Randomly selected parents received additional information on the WTB rate or possession rate among a specific group of peer parents. The information provided to different treatment groups varies in two directions: 1. Whether peer parents' decision is observable, and 2. The academic competitiveness of the peer parents' children. By comparing the WTB rate across different treatment groups, I can pin down the peer effects through two mechanisms: the ”social learning” and the ”competition externality” channels.

2.2.1 Educational Product

To capture the peer effects among parents, the product used in the experiment needs to satisfy the following requirements. First, the product should be a new type of educational product that no participants have used or experienced before. As parents have no experience to refer to, they are more likely to rely their purchase decisions on others' behaviors. Second, the product should be unique in the market and have no close substitutes. This feature ensures the experiment successfully captures all parents' purchases. Moreover, this product should be beneficial and attractive so that parents are willing to buy it.

To reach these requirements, I generated a new educational service that is novel in the current education market. I worked closely with a group of high-school teachers to estimate students' performance in each exam question tested in the past 3 months and generate a detailed analysis report of each student's recent performance. The report not only summarizes the student's overall general performance in all curriculums, but also provides a detailed analysis of each module in each subject, and a list of weak knowledge points for each subject. The report service updates every month to help parents track their children's performance over time.

This service reaches the three requirements needed for identification. First, this service is very different from the existing educational product so parents cannot make decisions based on their previous experiences. Peer behavior becomes one of the most important sources of information. Second, the service can provide much more detailed performance information than other types of educational services. It requires deep corporations with teachers from each school, so it is unlikely to be substituted by other services available in the market. In the experiment, I also emphasized to the parents that this service is not available through any other channels. Third, this service is attractive to parents since it can give them detailed performance information and proper analysis of it, which can help parents to identify the weakness in their children's studying. I used a pilot to test parents' and students' attitudes to this product. The results show that over 80% of parents and students who have experienced this service think it is beneficial and are willing to pay for it. The average Willingness to Pay for this service among the pilot sample is over 500 yuan per year.

2.2.2 Experiment Implication

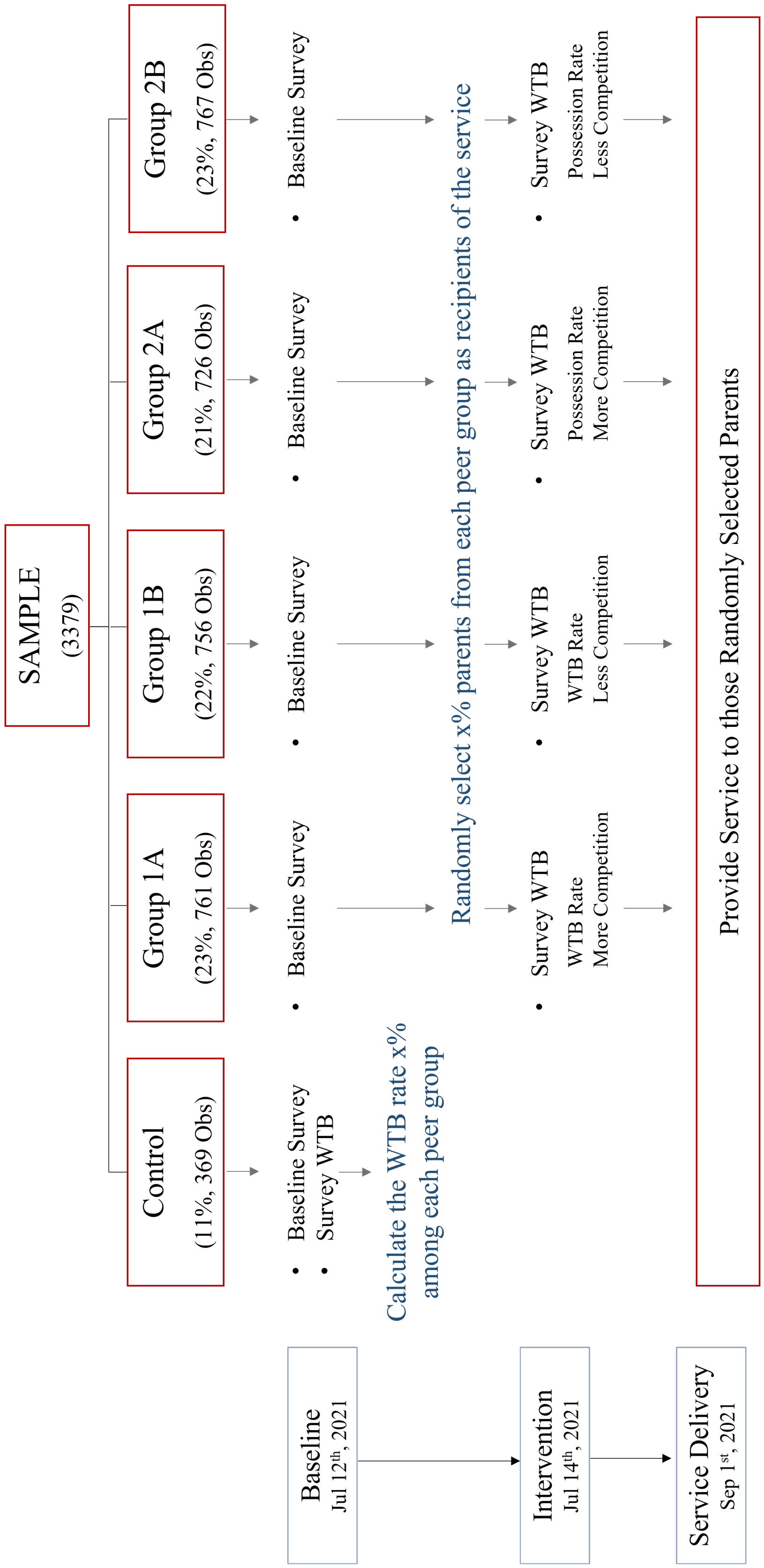


Figure 2.1: Experimental Design

Figure 2.1 summarizes the timeline and interventions of the experiment. I collected the baseline survey on Jul 12th, 2021. For parents in the treatment groups, the baseline survey only collected their demographic information. Parents from the control group, however, had one additional question at the end of the baseline survey which introduced the report service (Figure 2.2) and asked if parents are willing to buy this service with an annual fee of 300 Yuan (Figure 2.3). I, then, generated individualized intervention information for each treated parent based on the answers from the control group. The intervention was embedded in a school survey sent out two days after the baseline survey. Six weeks later, I started to deliver the report service to a randomly selected group of parents for free.

Parents were randomized into three groups: treatment group I, treatment group II, and the control group. Parents in treatment group I received additional information on peer parents' WTB rate of this service whereas parents in treatment group II received information on peer parents' possession rate of this service. Peer groups were individualized for each parent according to his/her child's current in-school performance to ensure the parents in peer groups are close peers to the treated parent. Under both treatment groups, parents were further randomized into two subgroups A and B. Parents in groups I.A and II.A received information on parents of students with performance slightly better than their own children whereas parents in treatment groups I.B and II.B received information on parents of students with slightly worse performance. Here are more details about the two intervention information and peer groups.

Figure 2.2: The Introduction Page

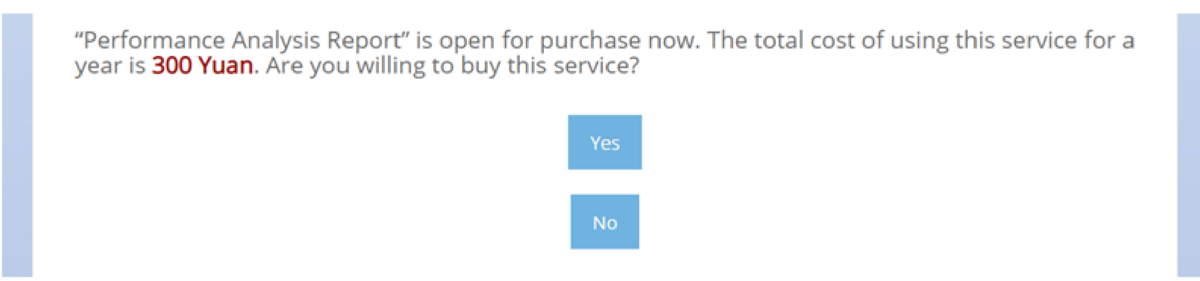


Figure 2.3: The WTB Survey Page

2.2.2.1 Intervention Information I - WTB rate

In this intervention, treated parents (Group I in Figure 2.1) were provided with the percentage of parents, among a certain peer group, who decided to buy this service. Using the control group's baseline data, I calculated the WTB rate (p%) among each peer group. For example, assume the peer group for parent i includes parents of students whose current in-school ranking is between 201-250, I then count the WTB rate among control group parents whose children's current ranking is within this range.

In addition, I randomized the competitiveness of peer groups constructed for parents. Parents assigned to treatment Group I.A had more competitive peer groups than those assigned to treatment Group I.B. More specifically, I varied the competitiveness of the peer groups by informing parents of the decisions among parents of students with performance slightly better or worse than their own children. For example, if the children's current in-school rank is 200, in the more competitive case, parents will receive the WTB rate among parents whose children's ranking is within 151-200, whereas in the less competitive case, they will receive the WTB rate among parents whose children's ranking is within 201-250.

The intervention started with an introduction of the service, and then a paragraph explaining that there is a randomly selected group of parents who have made their purchase decision already. Among these parents, p% of parents whose children's current in-school rank is between 201-250 decided to buy this service.Then, parents were directed to the last question which asked about their WTB for this service at a given price.

2.2.2.2 Intervention Information II - Possession rate

In the second intervention, I provided randomly selected parents (Group II in Figure 2.1) with the percentage of parents, among a certain peer group, who would use this service. From the control group baseline data, I knew the WTB rate (p%) among each peer group, I then randomly selected p% of parents from the peer group as the recipients of this service to make the possession rate of the service among this specific peer group to equal the WTB rate. The allocation of this service was purely randomized and independent of parents' WTB, and the service was provided to parents freely six weeks after the intervention. The possession rate was set to be the same as the WTB rate to avoid differences driven by the gap between the two numbers. Similar to intervention I, I varied the construction of the peer groups to make them more competitive (treatment Group II.A) or less competitive (treatment Group II.B).

The intervention started with an introduction of the service, and then a paragraph explaining that a group of parents have been randomly selected to experience this service. Among these parents, x% of parents whose children's current in-school rank is between 201-250 were selected to experience this service. Once parents finish reading this paragraph, they were directed to the question which collects parents' WTB for this service at a given price.

The random allocation of the chance to experience this service allows me to decouple the purchase decision from possession and then disentangle different channels. In the script, I provided the following justification for the randomized allocation of the experience chance: the company is providing this experience chance to limited parents to collect feedback on the service.

2.2.3 Intervention Delivery

The intervention survey was delivered to parents electronically through WeChat, the most popular instant messaging and social media app in China.To properly individualize the intervention information for each parent, I built up a private website for parents to submit their answers. The headteachers shared the survey link with parents through each class's WeChat group. When parents visited this survey website, the website verified their identities and automatically filled in the tailored intervention information for each parent. Before parents submitted their answers, they were asked to sign electronically to confirm their choices (Figure 2.4). As signatures were required, parents were earnest about their decisions. I also collected the browsing history record to track the progress of the intervention and asked the headteachers to send reminders to parents if needed.

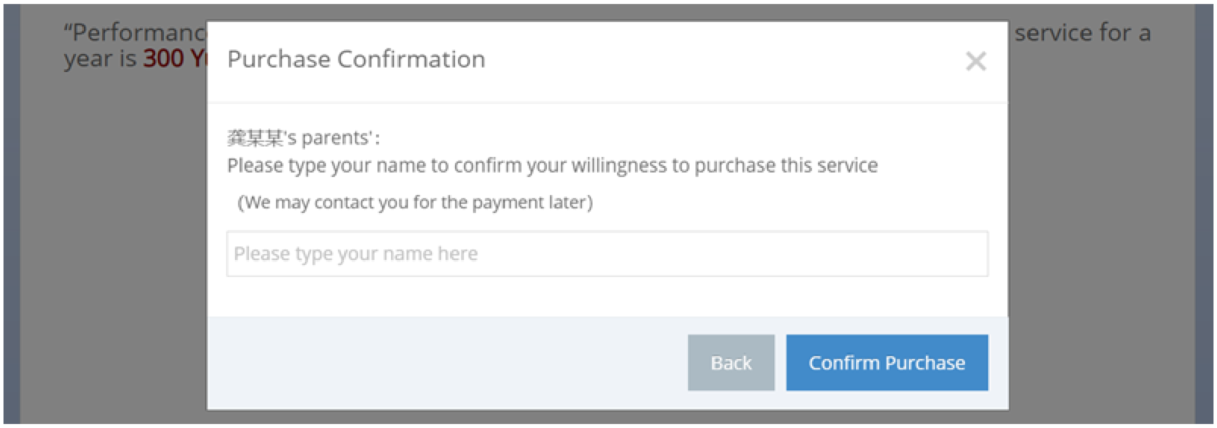


Figure 2.4: The Signature Confirmation Page

2.2.4 Randomization

Parents were randomly assigned to the control or treatment groups. The randomization was at the individual level, and the samples of each group were balanced at the class level. One concern is the communication among parents during the experiment. I took the following four measures to minimize the potential undesired communications among parents. First, I compressed the time gap between the baseline and the intervention into 2 days to avoid communications across the control group and the treatment groups. Second, as communications are more frequent among parents from the same classes, I urged each class to finish all the responses within one day to prevent potential information transfer across treatment groups within the same class. Third, since the intervention was delivered through a mobile app, the biggest concern is that parents may take a screenshot of the intervention information page and share it with others. To deal with this potential threat, I added some individual sensitive information, their children's current ranking, to the intervention information to reduce the sharing of the screenshot of the intervention information page. The children's ranking information can also help adjust the biases in parents' beliefs about children's performance so that they can get a more accurate feeling about the competitiveness of peer parents' children. Forth, I also collected the network information among parents, which can be used to control for potential spillover effects through the network.

2.2.5 Treatment Effects of Interest

Under this experimental design, each treatment group has different combinations of the potential peer effects channels. Table 2.1 lists the information provided, the peer group constructed, and the channels of potential peer effects for each group. The imitation channel is in play for all treatment groups as treatment parents had all aware that some of their peers are going to start using this service. Social learning is only valid for parents from Group I.A and I.B as parents' decisions about the purchase of this service are only observable when the WTB rate is revealed. Parents in Group II.A and II.B, however, cannot know their peers' decisions because of the randomized allocation of the service. The competition channel is complicated. Although all four treatment groups are faced with some level of competition externality from peer parents, groups with more competitive peers are faced with more competition.

This design allows me to estimate the following interesting treatment effects by comparing the WTB rate across different groups. First, I can measure the overall peer impacts through all channels. Parents from the control group made their decisions with no information about other parents' decisions or possession, so peer effects are not playing a role in this case. Parents in treatment group I.A, however, have all three channels active. A comparison of the WTB rates across the two groups can reveal the standard peer effects.

Second, I am also empowered to disentangle the channels of the observed peer effects.

Table 2.1: List of Channels for Each Group

Groups		Control	Group I.A	Group I.B	Group II.A	Group II.B
Information Type		N/A	WTB	WTB	Possession	Possession
Peer group		N/A	Better Performance	Worse Performance	Better Performance	Worse Performance
Channels	Learning	N	Y	Y	N	N
	Competition	N	More Competition	Less Competition	More Competition	Less Competition
	Imitation	N	Y	Y	Y	Y

The only difference between the passion information and the WTB information is that parents' possession of the service is based on their decisions in Group I but this link is removed by the randomized allocation of this service in Group II. Therefore, any differences between the WTB rates across Group I and Group II should reveal the peer effects through the ”social learning” channel. Comparing the WTB rate across groups with the same information but different peer groups (group I.A v.s. group I.B & group II.A v.s. group II.B) can unveil some of the peer effects from the ”competition” channel.

2.3 Data and Summary Statistics

The analysis combines data from two main sources, including survey data collected from parents directly and the administrative data provided by the schools.

2.3.1 Survey data

I conducted two rounds of surveys with parents, including a baseline survey and an intervention survey. Both surveys were distributed through WeChat. In the baseline survey, I collected information on family demographics, parents' belief about their children's abilities, and their aspirations (measured by the expectation of the tier of college that a child could be admitted to). Control group parents' WTB for the service was also surveyed in the baseline. The intervention survey provided treated parents with some information on peer parents' behavior and then collected their WTB for this service. The control group also received an intervention survey, but it only included some unrelated questions.

Table 2.2 lists the summary statistics for key variables collected in the baseline survey. The average level of household income is between the second level (30,000 - 50,000 RMB, around 4,620 - 7,700 USD) and the third level (50,000 - 100,000 RMB, around 7,700 - 15,400 USD), and around 27% of sampled households' annual income is above 100,000 RMB (15,400 USD).

Over 40% of families have at least one parent with a high school or higher degree, and around 28% of families have at least one parent with a bachelor's or higher degree. When looking into more details, I find fathers' average education level is higher than mothers'. 36.3% of fathers have received high school or higher degrees, and 24.2% of fathers' degrees are equal to or higher than college degrees. The two numbers for mothers, however, are 30.9% and 20.6% respectively. About one-quarter of the surveyed households only have one child.

Since I have five randomization groups, I use the following regression to check if the key variables are balanced across groups in the baseline.

$$\begin{aligned} Y_i = \alpha &+ \beta_1 WTBMoreCompetitive_i \\ &+ \beta_2 WTBLessCompetitive_i \\ &+ \beta_3 PossessionMoreCompetitive_i \\ &+ \beta_4 PossessionLessCompetitive_i + \epsilon_i \end{aligned} \tag{2.1}$$

where i denotes the parents and Y_i are the key variables I'd like to check for sample balance in the baseline stage: whether parents are willing to buy this service at the given price or not.

The results are combined in Table 2.3. The results suggest that the randomization was valid as no significant difference across groups has been identified on any of the key variables.

2.3.2 Administrative Data on Student Performance

I also had access to students' performance data for all school-level exams both before and after the intervention. This information is used to check if parents of students with different academic performances behave differently in the experiment.

Table 2.2: Pre-Intervention Summary Statistics

	WTB	Possession	Control	Total
A. Income				
IncomeLevel[A]	2.589	2.545	2.569	2.567
	(1.338)	(1.352)	(1.348)	(1.345)
Income¿100K	0.268	0.269	0.281	0.270
	(0.443)	(0.444)	(0.450)	(0.444)
B. Education				
FatherEdu[B]	2.432	2.4	2.415	2.416
	(1.104)	(1.086)	(1.095)	(1.095)
MotheEdu[B]	2.191	2.199	2.203	2.196
	(1.107)	(1.143)	(1.132)	(1.125)
HighestEdu[C]	2.538	2.536	2.542	2.537
	(1.100)	(1.113)	(1.139)	(1.110)
C. Child Number and Performance				
OnlyChild	0.245	0.251	0.244	0.248
	(0.430)	(0.434)	(0.43)	(0.432)
PercentileRank[D]	0.496	0.497	0.498	0.497
	(0.271)	(0.271)	(0.275)	(0.271)
Sample Size				
Sample Size	1,517	1,493	369	3379

Notes: Data sources are baseline survey and baseline performance records data. Each observation represents a household.

[A] $IncomeLevel$ is the level of household annual income and it has six levels, Level 1-6 represent below 30k, 30k to 50k, 50k to 100k, 100k to 200k, 200k to 500k, and over 500k RMB, respectively.

[B] Parents' education backgrounds are estimated by the highest degree earned. There are 5 levels, Level 1-5 represent less or equal to primary school, secondary school, high school, college, and graduate, respectively.

[C] $HighestEdu$ is the highest degree earned by the two parents.

[D] $PercentileRank$ is the percentile rank of children's academic performance in school's monthly exams among all other students from the same school, cohort, and track.

Table 2.3: Sample Balance Check

A. Income, Child Number, Performance

VARIABLES	IncomeLevel[A]	Income¿100K	OnlyChild	PercentileRank[D]
	(1)	(2)	(3)	(4)
WTBMoreCompetitive	0.040	0.003	-0.007	0.003
	(0.072)	(0.024)	(0.025)	(0.013)
WTBLessCompetitive	0.016	0.005	-0.000	-0.004
	(0.073)	(0.024)	(0.025)	(0.013)
PossessionMoreCompetitive	0.006	0.009	0.006	-0.008
	(0.073)	(0.024)	(0.025)	(0.013)
PossessionLessCompetitive	-0.024	-0.001	0.006	-0.001
	(0.072)	(0.024)	(0.025)	(0.013)
Observations	3,379	3,379	3,379	3,376
R-squared	0.000	0.000	0.000	0.000

B. Education

VARIABLES	FatherEdu[B]	MotheEdu[B]	HighestEdu[C]
	(5)	(6)	(7)
WTBMoreCompetitive	0.007	0.016	-0.017
	(0.059)	(0.058)	(0.059)
WTBLessCompetitive	0.008	-0.051	-0.017
	(0.059)	(0.058)	(0.059)
PossessionMoreCompetitive	-0.006	0.013	0.002
	(0.060)	(0.059)	(0.059)
PossessionLessCompetitive	-0.038	-0.019	-0.030
	(0.059)	(0.058)	(0.059)
Observations	3,379	3,379	3,379
R-squared	0.000	0.001	0.000

Notes: *** , ** , * denotes significance at the 1%, 5% and 10% levels respectively. Robust standard errors in parenthesis. Data sources are baseline survey and baseline performance records data. Each observation is a parent.

[A] $IncomeLevel$ is the level of household annual income and it has six levels, Level 1-6 represent below 30k, 30k to 50k, 50k to 100k, 100k to 200k, 200k to 500k, and over 500k RMB, respectively.

[B] Parents' education backgrounds are estimated by the highest degree earned. There are 5 levels, Level 1-5 represent less or equal to primary school, secondary school, high school, college, and graduate, respectively.

[C] $HighestEdu$ is the highest degree earned by the two parents.

[D] $PercentileRank$ is the percentile rank of children's academic performance in school's monthly exams among all other students from the same school, cohort, and track.

2.4 Estimation Strategy

To identify the overall treatment effects of the two information interventions, I will estimate regression models of the following form:

$$Y_{ic} = \alpha + \gamma_c + \beta_1 WTB_i + \beta_2 Possession_i + \epsilon_i \tag{2.2}$$

where i denotes parent and c denotes the class parent's child was in. Y_i is the parent's decision on whether they wanted to buy this service or not. WTB_i is an indicator for receiving peer parents' WTB rate, $Possession_i$ indicates receiving peer parents' possession rate. β_1 and β_2 are estimates of the treatments effects for the two interventions.

In addition to the overall impacts of the two treatments, I also explore the treatment effects among each group and the following empirical specification will be used to estimate these effects.

$$\begin{aligned} Y_{ic} = \alpha + \gamma_c &+ \lambda_1 WTBMoreCompetitive_i \\ &+ \lambda_2 WTBLessCompetitive_i \\ &+ \lambda_3 PossessionMoreCompetitive_i \\ &+ \lambda_4 PossessionLessCompetitive_i + \epsilon_i \end{aligned} \tag{2.3}$$

In the specification, the four treatment groups are represented separately using four dummy variables: $WTBMoreCompetitive_i$, $WTBLessCompetitive_i$, $PossessionMoreCompetitive_i$, and $PossessionLessCompetitive_i$. The parameters of interest are λ_1, λ_2, λ_3, and λ_4, which measure the differential change in the WTB rate in each treatment group relative to the level in the control group.

More importantly, I'd like to disentangle and measure the magnitudes of peer effects through the "social learning" and "competition externality" channels. The main empirical specification will be:

$$Y_{ic} = \alpha + \gamma_c + \mu Treated_i + \theta Learning_i + \eta Competition_i + \epsilon_i \tag{2.4}$$

$Treated$ is a dummy variable that is equal to 1 for all parents from the treatment groups. $Learning_i$ is a dummy which is equal to 1 for parents received peers' WTB rate. $Competition_i$ is a dummy which is equal to 1 if the information received by parent i reveals the behavior (WTB or possession rate) of parents whose children have better performance than parent i's own child. Here the key parameters are θ, the estimate of peer effects through the "social learning" channel, and η, the estimate of peer effects through the "competition externality" channel.

2.5 Results

I start with showing the take-up rates in the raw data across different groups of parents and then I use several regression models to estimate the peer effects across groups and to quantify the peer effects through different channels. In the end, I discuss the heterogeneity of the effects by education background, income level, performance, and the number of children.

2.5.1 WTB Rates

Before formal estimations of the effects of the interventions, I'd like to present the WTB rates in the raw data across different groups (Figure 2.5). The WTB rate for parents with no information at all (control group) was around 26%. Knowing that some parents of students with worse performance were randomly selected to use this service (group II.B) does not significantly affect parents' decisions. However, if the peer group are parents of students with performances better than their children (group II.A), the WTB rate increases to 29%. Parents with information on other parents' WTB rates are always more likely to purchase this service. When the information is from a less competitive peer group (group I.B), the WTB rate is around 30%, and it increases to 34% (group I.A) if the peer group includes parents of students with more competitive performance.

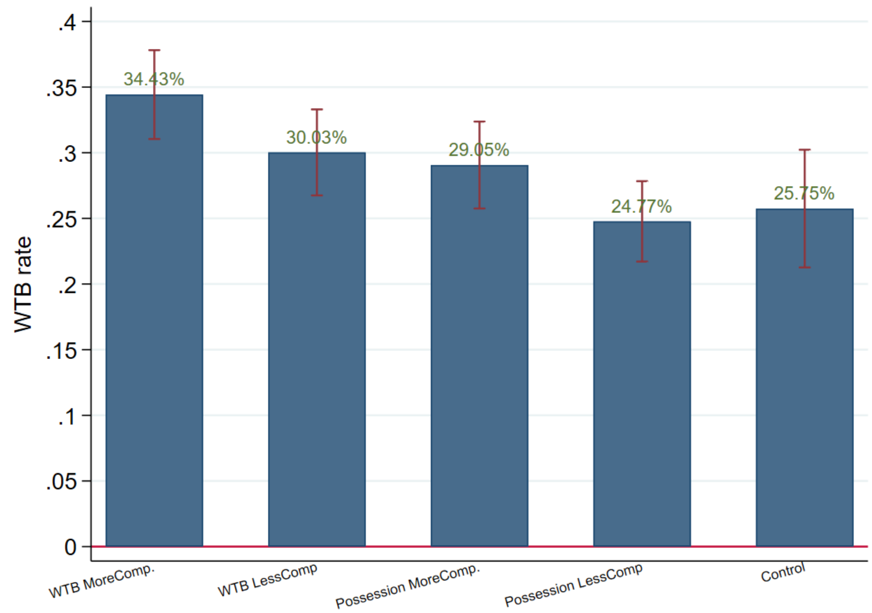


Figure 2.5: Parents' WTB rates By Groups

2.5.2 Treatment Impacts

I first present the treatment effects on parents' WTB rate using estimation Equation (2.2) and (2.3), in Table 2.4. As shown in column 1 in Table 2.4, the WTB rate of the two groups that received peer parents' decisions has significantly increased by 7.5%, which is equal to a 30% increase in the WTB rate in the control group. the WTB rate of the groups with information on peer parents' possession rate has also increased slightly, but it is not statistically significant. In column 2, I test whether the treatment effect varies across the competitiveness of peer parents' children. These results match the results presented in Figure 2.5: in both interventions, parents are more incentivized to buy this service when they received information about peers whose children have better performance than their own children. Specifically, when parents know the decisions of a more competitive peer group, their WTB rate increased by 9.9%, around 40% of the initial WTB rate in the control group. The two numbers become 5% and 20% when the peer group is relatively less competitive. In cases when parents were informed of the possession rate among a more competitive peer group, their willingness to purchase increased by 4.9%, about 20% of the control group level. When the information reveals the possession rate among less competitive peer groups, I don't find significant effects on parents' decisions.

2.5.3 Identification of Channels

Column 3 in Table 2.4 shows the results of the peer effects through different channels using the estimation Equation (2.4). It implies that there are significant peer effects through both the social learning and the competition channels. The magnitude of peer effects through the "social learning" channel increases parents' WTB rate by around 5.2%, which is around 20% of the control group level. The peer effects driven by the competition externality can result in a 5% increase in the WTB rate, about 20% of the control group level. The magnitudes of the peer effects through the two channels are not significantly different from each other.

2.5.4 Heterogeneity of Peer Effects

I present regression estimates of peer effects channels for parents with different characteristics, in Table 2.5.

Table 2.4: Peer Effects on Parents' WTB Rate

VARIABLES	Wanted to purchase the service		
	(1)	(2)	(3)
WTBMoreCompetitive		0.099***	
		(0.028)	
WTBLessCompetitive		0.050*	
		(0.028)	
PossessionMoreCompetitive		0.049*	
		(0.029)	
PossessionLessCompetitive		-0.003	
		(0.028)	
WTB	0.075***		
	(0.026)		
Possession	0.022		
	(0.026)		
Treated			-0.002
			(0.027)
Learning			0.052***
			(0.016)
Competition			0.050***
			(0.016)
Control Group Mean		0.257	
		(0.023)	
Observations		3379	
R-squared	0.004	0.007	0.007
Class-level Fixed Effect		Y	

Notes: *** , ** , * denotes significance at the 1%, 5% and 10% levels respectively. Robust standard errors in parenthesis. Data sources are survey data collected in the two rounds surveys. Each observation represent a parent. The $Treated$ dummy is 1 if the observation is from treatment groups. The $Learning$ is 1 if the intervention information is the WTB rate, and it measures the peer effects through the "social learning" channel. The $Competition$ dummy is 1 if the peer group are parents of students with better performance, and it measures the peer effects through the "competition externality" channel.

Education Background Columns 1-2 in Table 2.5 measure the peer effect via different channels for parents with different educational backgrounds. Column 1 shows the results for households with no parents received college degrees, and Column 2 lists the results for households with at least one parent with college (or higher) degrees. Comparing the WTB rates for the two types of parents in the control group, I find that households with college degrees have significantly higher WTB than those with no college degrees. Interestingly, the results suggest the primary peer effect mechanisms vary across parents' education backgrounds. For families with no college degrees, their key channel of peer effect is the "competition externality", and there is no significant supportive evidence for the learning channel. Families with college degrees, however, are more likely to learn from peer parents' decisions and are immunized to the competition channel.

Income Level Columns 3-4 in Table 2.5 list the estimates of peer effects through different channels for households with relatively low or high income. The threshold used for the classification of high or low income is whether the household annual income is over 100,000 RMB or not. Column 3 shows the results for households with an annual income lower than the threshold and Column 4 is for those with an annual income higher than the threshold. As expected, in the control group, families with higher annual incomes are more willing to buy the service. Wealthier families in all treatment groups show more interest in purchasing this service, regardless of the types of information they received. However, we do find that the exposure to other parents' decisions creates additional incentives for those families to buy this service. In contrast, the competitiveness of peer groups does not have a significant impact.

Current Performance Columns 5-6 in Table 2.5 summarize the results for parents of students with different performances. Column 5 shows the results for parents whose children's current performances are below the average whereas Columns 6 have the results for those whose children are above the average. There is no significant difference between the WTB rate of the two types of parents in the control group. However, they do vary from each other in terms of the main peer effect channels. Parents with children below the average are sensitive to both the learning and the competition channels, whereas those with above-average children are more likely to be driven by the competition channel.

Child Number in Columns 7-8 in Table 2.5, I use the number of children to classify parents into two types. Columns 7 are the estimates for parents with more than one child and Columns 8 shows the measures for parents with only one child. The WTB rates for the two types of parents are statistically different in the control group. Families with only one child have a higher willingness to purchase this service than those with multiple children. The main channels of peer effects also vary across the two types of parents. Parents with more than one child increase their WTB for this service because of the competition externality faced by their children, whereas parents with one child are more likely to be affected through the social learning channel.

2.6 Conclusion

Peer effects are an important but complicated research topic in social science studies. Understanding the peer effects on educational investment among parents is extremely important as parental investment in children is one of the key factors influencing children's academic attainment, which can significantly influence children's income, health, social status, and other

Table 2.5: Heterogeneity Check

VARIABLES	Wanted to purchase the service							
Chracteristics	$CollegeDegree$		$ln(Income > 100K)$		$Performance > Average$		$OnlyChild$	
Reach or Not	N	Y	N	Y	N	Y	N	Y
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated	0.006	-0.009	-0.036	0.105*	-0.041	0.044	0.008	-0.032
	(0.031)	(0.054)	(0.028)	(0.059)	(0.038)	(0.040)	(0.031)	(0.060)
Learning	0.026	0.139***	0.016	0.133***	0.066***	0.038	0.021	0.134***
	(0.018)	(0.033)	(0.017)	(0.036)	(0.023)	(0.024)	(0.018)	(0.035)
Competition	0.068***	0.025	0.064***	0.012	0.041*	0.067***	0.066***	0.010
	(0.018)	(0.033)	(0.017)	(0.035)	(0.023)	(0.024)	(0.018)	(0.036)
Control Group Mean	0.218	0.355	0.215	0.379	0.261	0.254	0.226	0.356
	(0.026)	(0.046)	(0.025)	(0.05)	(0.032)	(0.032)	(0.025)	(0.051)
Observations	2,445	934	2,510	869	1,687	1,692	2,542	837
R-squared	0.008	0.024	0.006	0.031	0.007	0.011	0.007	0.020
Individual Fixed Effect	Y							

Notes: *** , ** , * denotes significance at the 1%, 5% and 10% levels respectively. Robust standard errors in parenthesis. Data sources are survey data collected in the two rounds surveys. Each observation represent a parent. The $Treated$ dummy is 1 if the observation is from treatment groups. The $Learning$ is 1 if the intervention information is the WTB rate, and it measures the peer effects through the "social learning" channel. The $Competition$ dummy is 1 if the peer group are parents of students with better performance, and it measures the peer effects through the "competition externality" channel.

outcomes. This paper successfully measures the peer effects on parents' educational investment decisions. More importantly, the experiment design unjointed the possession of service from the purchase decision which allows me to disentangle and measure the following two peer effect mechanisms: social learning and competition externality. This paper also finds significant heterogeneities of the primary peer effects channels across education background, income, children's performance, and child number.

The findings of this paper have important policy implications. The main finding in this paper speaks on a hotly debated topic in many countries - parents might be investing in education (and especially extracurricular programs) not because of the academic benefits but because of concerns about competition from peers. In a society with limited resources, the relative performance is what really matters. In the extreme case, the ”competition externality” channel can drive up the overall investment in education whereas all students' relative performances stay unchanged. When the average investment level is relatively low, a general increase in educational investment can be beneficial because the increases in productivity overweight the costs. ”Competition externality” peer effect can be employed as an efficient tool to drive up parents' overall investments in children's education in these circumstances. Whereas when the average educational investment is at a relatively high level, the additional benefit from the productivity improvement may not be sufficient to cover the costs, especially when we take into account the extra burden placed on children. Policymakers should take measures to eliminate the undesired peer effects from the competition channel. The recently implemented ”double reduction” [1] policy in China is

[1]The General Office of the Communist Party of China Central Committee released a document on June 26, 2021, in which it lists reducing the educational costs for children as one of six primary goals. The General Office of the Communist Party of China Central Committee and the General Office of the State Council jointly issued a guideline on July 24, 2021, which pledges to adopt a strict approval and supervision system for off-campus tutoring programs in order to reduce parents' educational burden significantly within three years.

one example. In addition, the evidence on the heterogeneity in peer effect mechanisms across different types of parents sheds some light on the sources underlying the observed inequalities in society. Parents with lower educational backgrounds, lower income, and multiple children are more vulnerable to the ”competition externality” channel. The results can help policymakers identify the groups more sensitive to the undesired peer effects, and tailor public policies accordingly to make them more efficient.

This research can be extended in several directions. First, a natural extension is using students' academic performance data after the random allocation of the service to measure how beneficial this service is for different types of students, which allows me to further discuss the welfare impacts of the interventions. Second, this paper focus on parents' purchase decisions on one specific educational service. It will be interesting to explore the peer effects for a more general definition of parental educational investment. Moreover, in this paper, parents received information on the aggregated WTB rate for the product among a certain peer group, one might be interested in how the findings in this paper change would if parents receive information on the decisions or possession status of certain parents in their network. Another potential extension is to vary the way of information delivery. In this paper, parents receive information about peers' behavior or status through a third party (the investigator). It will be great to check if the findings hold when parents are able to observe this information from their peers directly.

Chapter 3: Invest in Talented or Invest in Disadvantaged: How Aspirations Affect Parents' Investment Strategy

3.1 Introduction

How parents invest in children's education is always an interesting topic in labor economics. The classic parental education investment model treats parental human capital investments as intergenerational transfer and parents are willing to invest in children's education until the marginal increase in the children's earnings from one more dollar invested equals the market interest rate (Glomm (1997)). Under this framework, education investment in children is increasing in children's ability (Raut and Tran (2005)).

However, our daily observations suggest that educational investments are not always positively correlated with ability. For example, remedial programs provide additional education investments to students with poor performance (Jacob and Lefgren (2004)). Parents allocate more remedial education investments to children with relatively poor performance (Dizon-Ross (2019)). Parents of disadvantaged children also invest more in the education of their children (Heckman (2006)). There is also empirical evidence showing that parents invest more in children with lower birth weight, which has been proved to be strongly correlated with low in-school performance in the existing literature. These phenomenons suggest that parents increase their investment in children with lower abilities, which conflicts with the classic model's predictions. Some research has explored the reasons underlying this ”bizarre” phenomenon, and the explanations provided in these papers are still rooted in the classic model. One common explanation is that parents invest more in poor-performance children to compensate and another widely accepted explanation is that parents are making mistakes because of inaccurate information (Dizon-Ross (2019); Kinsler and Pavan (2021)). This paper rationalizes the remedial type of investments by incorporating aspirations into the parental investment decision model. Instead of assuming a smooth utility function that only depends on children's performance, this model allows parents' utility function to be discontinuous at the threshold of reaching aspirations by assuming parents receive a one-time additional utility when children achieve their aspirations. When the bonus for reaching aspirations is great enough, parents are willing to increase their investment to help their children reach their aspirations even though this investment level is not preferable without the bonus. In this circumstance, parental educational investment is decreasing in children's ability as children with higher ability are more efficient in studying.

This paper enriches the theoretical work on the modeling of educational investment decisions (Becker (1962); Becker and Tomes (1976); Glomm (1997); Raut and Tran (2005)). There is rich empirical evidence of the impacts of parents' aspirations on children's educational attainments (Galab et al. (2013); Spera et al. (2008)) and parental educational investments (Bernard et al. (2019). However, the importance of aspiration has not yet been demonstrated in theoretical frameworks. My paper advances this literature by incorporating aspiration, a widely used concept in general economics and strategic management decisions (Genicot and Ray (2020); Shinkle (2011)), in the parental investment decision model. The introduction of aspirations causes an interesting non-monotonic between ability belief and investments around aspirations, which illustrates when and why parental investments and students' ability become substitutes or complements.

The paper proceeds as follows. Section 3.2 demonstrates the setting for parental educational investment decisions. Section 3.3 discusses the parental educational investment decisions in a perfect signal setting. Section 3.4 introduces uncertainty and discusses the impacts of the ability signal on investment when the signal is imperfect, Section 3.5 uses a simulation to illustrate the predictions in a more intuitive way, and Section 3.6 concludes.

3.2 Setting

Parents have a certain amount of endowments I and they need to allocate them into two potential investments: consumption C and education investment in a child E. Assume the child's ability is t. With given ability t and parental education investment E, the child's school performance (e.g. score in CEE exam) is $R = R(t, E)$. Parents' utility function is as below.

$$u \equiv U(C) + V(t, E)$$

It has two components, the utility from consumption $U(C)$ and the utility from a child's academic performance $V(t, E)$. Parents need to optimize the allocation of the endowments based on a signal $\hat{t} = t + \Delta t$ observed.

Therefore, the parent's objective function is

$$u(E) \equiv U(I - E) + V(t, E)$$

Based on the real parental educational investment decisions, I made the following reasonable assumptions.

Assumption 1 $U' > 0, U'' < 0$

The utility from consumption is increasing and concave.

Assumption 2 $V(t,E)) = R(t,E) + k \cdot 1\{R(t,E) \geq A\}$

where A is parents' aspiration, which represents the lowest academic performance needed to reach the ideal tier of colleges parents want their child to get into. Parents will get an additional bonus k when their children successfully reach their aspirations. $1\{R(t,E) \geq A\}$ is defined as below:

$$1\{R(t,E) \geq A\} = \begin{cases} 1, \text{ if R(t,E)} \geq \text{A} \\ 0, \text{ Otherwise} \end{cases}$$

The utility of a child's education contains two parts: 1. a "skill" function (e.g. test scores) which is continuous and differentiable in t and E; and 2. a bonus for reaching the aspiration.

Assumption 3 $\frac{\partial R}{\partial t} > 0, \frac{\partial R}{\partial E} > 0, \frac{\partial^2 R}{\partial t^2} < 0, \frac{\partial^2 R}{\partial E^2} < 0, \frac{\partial^2 R}{\partial E \partial t} > 0$

The "skill" function is assumed to be increasing and concave in both ability and education investment. Moreover, individuals with higher abilities will have higher marginal benefits at any given education investment level.

Assumption 4 $\frac{\partial R}{\partial t} = 0$

I assume the aspiration is decided exogenously and it may change for factors such as changes in the public's valuation of schools or variations in the admission competition.

3.3 Perfect Signal

I start with a simplified setting by assuming parents receive full information about the kid's ability. In other words, the additional assumption that $\hat{t} = t$ is made.

For convenience, I use E^* to denote the global maximum for

$$u_1(E) \equiv U(I - E) + R(t, E)$$

E^{**} denotes the unique solution to $R(t, E) = A$.

$$R(t, E^{**}) = A \tag{3.1}$$

As the objective function u is upper semicontinuous and all the necessary and sufficient conditions for a global maximum are satisfied[1] (Rockafellar and Wets (1998)), the global optimum exists and it can only occur at four points: E^*, E^{**}, 0, and I. As the two corner solutions are not common in the setting of this research, this paper will focus on the situations when the global maximum occurs at E^* or E^{**}[2].

3.3.1 Properties of E^*

As E^* is defined as the global maximum for $u_1 = U(C) + R(t, E)$. The following equation is valid at the E^* point.

[1]The detailed proofs can be found in Appendix A.

[2]The corner solutions can be ruled out by an additional assumption as simple as assume $\frac{\partial U(E|E=0)}{\partial E} = \infty$ and $\frac{\partial U(E|E=I)}{\partial E} = -\infty$.

$$\frac{\partial U(I - E^*)}{\partial C} = \frac{\partial R(t, E^*)}{\partial E} \tag{3.2}$$

By taking partial derivatives of both sides with respect to t, I can know that E^* is increasing in ability t.

$$\frac{\partial E^*}{\partial t} = -\frac{\partial^2 R(t, E^*)}{\partial E \partial t} \cdot (\frac{\partial^2 U}{\partial C^2} + \frac{\partial^2 R(t, E^*)}{\partial E^2})^{-1} > 0 \tag{3.3}$$

3.3.2 Properties of E^{**}

As E^{**} is defined as the amount of educational investment needed to reach aspiration A, we find that E^{**} is decreasing in ability t by taking partial derivatives of both sides of Equation (3.1) with respect to t,

$$\frac{\partial E^{**}}{\partial t} = -\frac{\partial R(t, E^{**})}{\partial t} \cdot (\frac{\partial R(t, E^{**})}{\partial E})^{-1} < 0 \tag{3.4}$$

3.3.3 Marginal Change in Ability Signal

Case 1 $E^* > E^{**}$ For all t

In this case, children will always reach the aspiration at the E^* point, so parents' optimal strategy stays at E^*, and it's positively correlated with the ability (as shown in Figure 3.1). This case will be true if parents' aspiration is very easy to achieve for all ability levels.

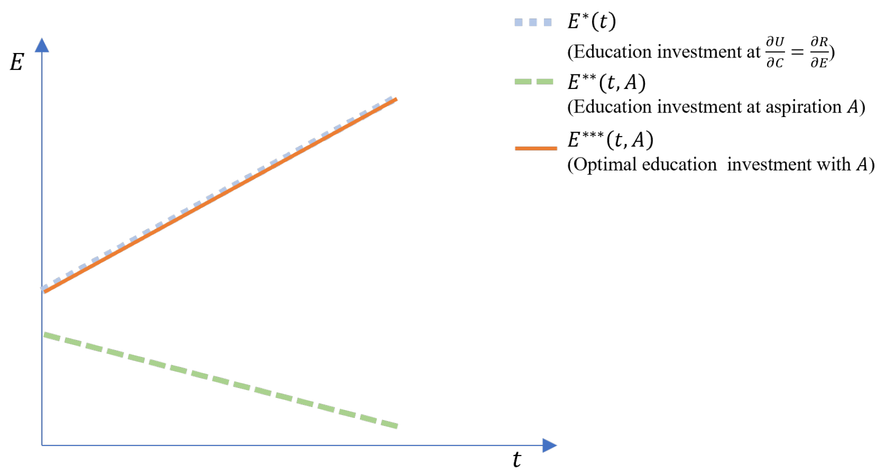


Figure 3.1: Optimal Strategy When E^* is greater than E^{**} For all t

Case 2 $E^* \leq E^{**}$ For all t

In this situation, no children will achieve the aspiration at the E^* point. It will be true if parents set a very hard aspiration that is challenging even for the smartest children. The equilibrium stays at E^* if the utility at E^* ($u(E^*)$) is greater than the utility at the threshold of reaching the aspiration ($u(E^{**})$. Otherwise, it shifts to E^{**}. For convenience, I use $\triangle$ to refer to the difference between the utility at the two potential maximum points.

$$\triangle = u(E^*) - u(E^{**}) = U(I - E^*) + R(t, E^*) - (U(I - E^{**}) + R(t, E^{**})) - k$$

There are three potential cases and here I discuss parents' optimal investment strategy under each case.

Case 2.1 $\triangle$¿0 for all t: One extreme case is that the utility at E^* is consistently higher than the utility at E^{**} for all ability levels. This may be true if the aspiration is too hard to get for all ability levels, or when the bonus for reaching the aspiration is trivial. In this case, parents' optimal investment level always stays at E^*, so the causal effects of a marginal change in ability on parental educational investment are positive (Figure 3.2(a)).

Case 2.2 $\triangle \leq 0$ for all t: Another extreme case is that the utility at E^* is consistently lower than the utility at E^{**} for all ability levels. This can be true if the aspiration is very easy to get at all ability levels, or when the bonus for reaching the aspiration is tremendous. In this case, parents' optimal investment level always stays at E^{**}, which means the causal effects of a marginal change in ability on investment are negative (Figure 3.2(b)).

Case 2.3 $\triangle \leq 0$ for some t: The two extreme cases are relatively rare in the real life. In most cases, the situation is in between - the utility at E^* is the highest for some ability levels, whereas the utility at E^{**} becomes the maximum for the others.

To better understand the distribution of optimal investment over different ability levels, I take partial derivatives of both sides with respect to ability t and get

$$\begin{aligned} \frac{\partial \triangle}{\partial t} =& \frac{\partial E^*}{\partial t} \cdot (\frac{\partial R(t, E^*)}{\partial E} - \frac{\partial U(I - E^*)}{\partial C}) + \frac{\partial R(t, E^*)}{\partial t} \\ & - [\frac{\partial E^{**}}{\partial t} \cdot (\frac{\partial R(t, E^{**})}{\partial E} - \frac{\partial U(I - E^{**})}{\partial C}) + \frac{\partial R(t, E^{**})}{\partial t}] \end{aligned} \tag{3.5}$$

The definition of E^* decides that $\frac{\partial R(t,E)}{\partial E}$ is equal to $\frac{\partial U(I-E)}{\partial C}$ at E^*, so we can simplify the equation above into

$$\frac{\partial \triangle}{\partial t} = -\int_{E^*}^{E^{**}} \frac{\partial^2 R(t, E)}{\partial E \partial t} dE - \frac{\partial E^{**}}{\partial t} \cdot (\frac{\partial R(t, E^{**})}{\partial E} - \frac{\partial U(I - E^{**})}{\partial C}) < 0$$

We know $\frac{\partial^2 R(t,E)}{\partial E \partial t}$ is positive from Assumption 3, I have proved that $\frac{\partial E^{**}}{\partial t}$ is negative in

Equation (3.4) , and $\frac{\partial R(t,E)}{\partial E} - \frac{\partial U(I-E)}{\partial C}$ is negative at E^{**} because it's equal to 0 at E^*, $U(C)$ and $R(t, EI)$ are strictly concave, and E^{**} is greater than E^*. Therefore, it's ot hard to conclude $\triangle$ is decreasing in ability.

Assume $\triangle$=0 at t_0, for $t < t_0$, the optimal investment level is E^*, whereas for $t \geq t_0$, the optimal investment shift to E^{**}, as shown in Figure 3.2(c).

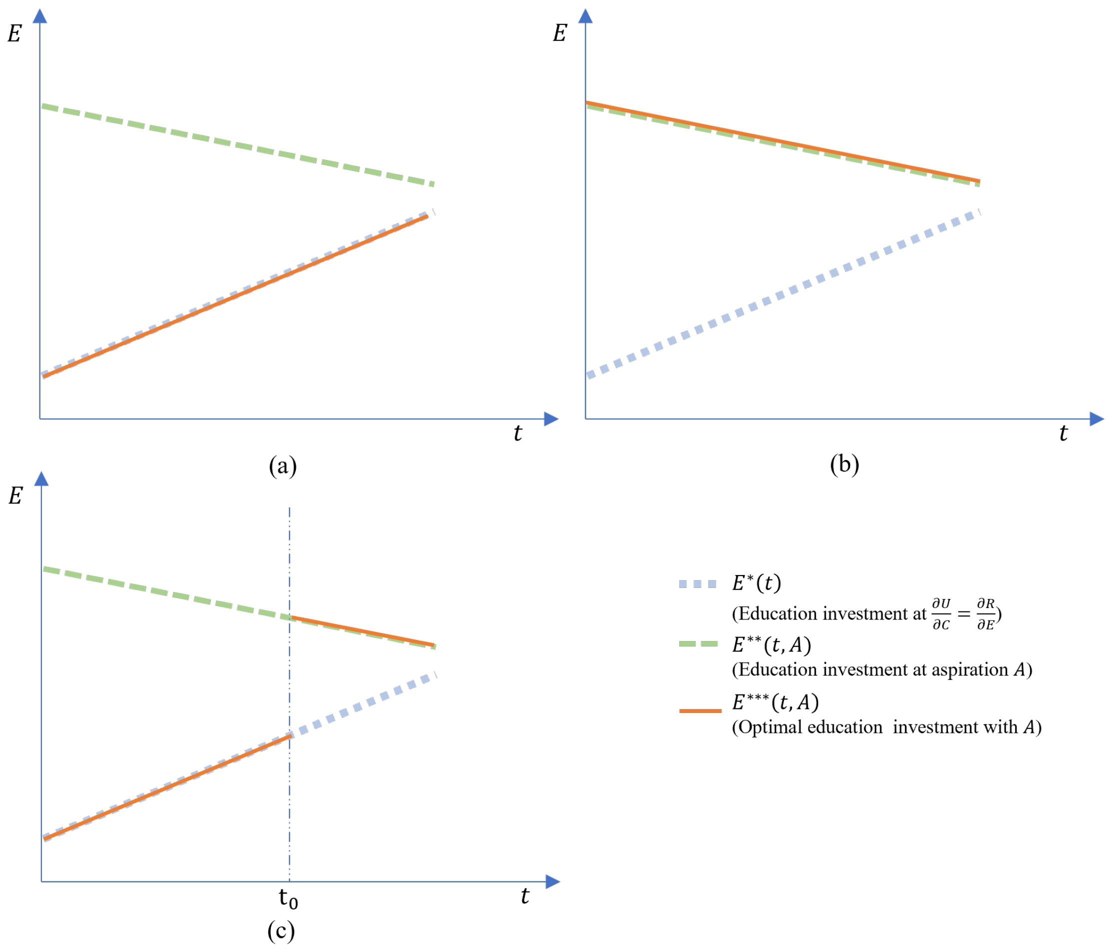


Figure 3.2: Optimal Strategy When E^* is not greater than E^{**} For all t

Parents prefer the E^* point and their investment is positively correlated with ability if the ability is low ($t < t_0$). When ability increases to a certain level $t \geq t_0$, the additional cost for reaching the aspiration A is less or equal to the additional benefit, so parents would prefer adding their investment to the minimum amount needed for the child to reach the aspiration, which causes a jump in the optimal investment curve at t_0. The correlation of the optimal education investment and ability becomes negative for $t \geq t_0$ because education investment in a more capable child is more efficient so the investment needed to reach aspiration is lower.

Case 3 E^* and E^{**} interact with each other at t_1

A more general case would be the two functions (E^* & E^{**}) interact with each other and the ability level at the interaction point is referred to as t_1.

As E^* is increasing in t (Equation 3.3) whereas E^{**} is decreasing in t (Equation 3.4), E^* is smaller than E^{**} for all ability levels that is lower than t_1, and E^* is greater than E^{**} when ability is higher than t_1.

The interaction point t_1 split ability levels into two regions, and the optimal strategy is different in the two regions.

When $t < t_1$: Similar to Case 2, the equilibrium depends on the magnitudes of the utility at E^* and E^{**}. Let's assume the two utilities are equal at t_0[3]. For ability levels lower than t_0, the optimal investment level is E^* which is increasing in ability, whereas for ability levels in between t_0 and t_1, the optimal investment shift to E^{**} which is decreasing in ability.

When $t \geq t_1$: As E^* is not smaller than E^{**}, a child will always reach the aspiration at the E^* point so the equilibrium always stays at E^*, and the optimal investment level is increasing in ability.

[3] In the extreme case where the bonus is large enough, parents always prefer E^{**} regardless of how low the ability is.

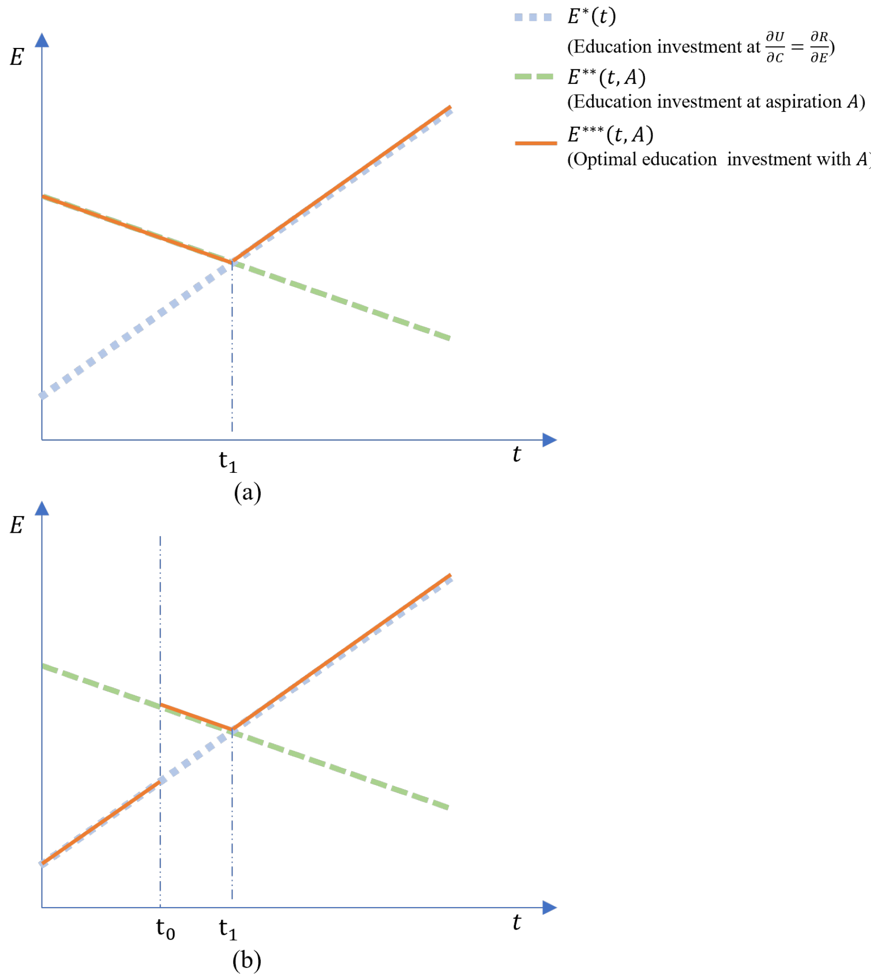


Figure 3.3: Optimal Strategy When E^* interacts with E^{**} at t_1

To sum up, when children can reach the aspiration with E^*, parents' optimal investment level stays at the E^* point and it's increasing in ability. However, when children fail to reach the aspiration with E^*, parents will be incentivized by the bonus to increase their investments in children to help them reach the goal. To optimize their utility, parents will stop investing once the children's performances reach their aspirations, so the lower the ability, the higher the investment. When the children's ability is so low that the bonus will not be sufficient to cover the additional costs for reaching the aspiration, parents' optimal investment level will go back to E^* and the correlation returns to positive again (Figure 3.3).

3.3.4 Marginal Change in Aspiration

Now I discuss how a marginal exogenous change in aspiration affects parents' optimal educational investment level in different situations. As I am focusing on a trivial change in the aspiration that's driven by some exogenous factors, I assume such a minor change in aspiration does not change the amount of bonus (k) for reaching aspiration. This assumption is reasonable and realistic. In real life, the test scores needed to get into a certain college depend on factors such as some unpredictable random variations in the competitiveness of admission across applica-tion seasons. These factors do affect the lowest test score needed for admission (aspiration) but it does not change the reward for reaching the aspiration as the ideal college itself and how it's valued by the society stay unchanged.

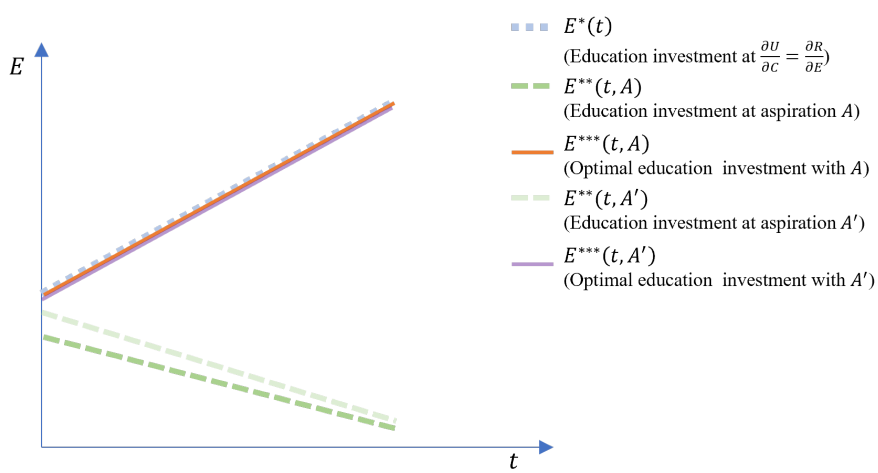


Figure 3.4: Impacts of Aspiration on Optimal Strategy When E^* is greater than E^{**} For all t

As discussed in the last section, the equilibrium stays at E^* in Case 1 and Case 2.1. Changes in aspiration should have no impact on the equilibrium educational investment level unless it's great enough to initiate a dramatic increase in E^{**} (Case 1) or k (Case 2.1). As we are discussing marginal variations in aspiration which are unlikely to result in such a sizable change, it should have no impact on the optimal investment level in Case 1 (Figure 3.4) and Case 2.1 (Figure 3.5(a)).

In Case 2.2, the equilibrium always stays at E^{**}. By taking the partial derivative of Equation (3.1) with respect to A, I can get

$$\frac{\partial E^{**}}{\partial A} = (\frac{\partial R}{\partial E})^{-1}$$

As E^{**} is the equilibrium and it's increasing in aspiration, a marginal increase in aspiration will raise the optimal investment level (Figure 3.5(b)).

In Case 2.3, as the investment needed to reach the aspiration has increased whereas the $\frac{\partial U}{\partial C}$ is greater than $\frac{\partial R}{\partial E}$ at E^{**}, the utility at the new aspiration $A^{'}$ is lower than the utility at the old aspiration. Hence the utilities for E^{*} and E^{**} are equal at $t_0^{'}$, which is slightly higher than t_0. for $t < t_0$, the optimal investment level stay unchanged, whereas for $t \geq t_0^{'}$, the optimal investment slightly increase, as shown in Figure 3.5(c). For ability within $[t_0, t_0^{'})$, their optimal strategy shifts from E^{**} to E^{*}, which result in a significant decrease in educational investments. However, when the change in aspiration is small enough, parents located in this region is negligible.

In other words, changes in aspiration will have no effect on parents' optimal investment level when children's ability is so low that the bonus is insufficient to cover the additional cost needed for reaching the aspiration ($t < t_0$). It has a positive impact on parents' investment for those who decide to increase investment to help children reach their aspiration ($t \geq t_0$).

In Case 3, a marginal change in aspiration can result in a move in both the interaction point for E^{*} and E^{**} (from t_1 to $t_1^{'}$) and the interaction point for utilities at the two levels (from t_0 to

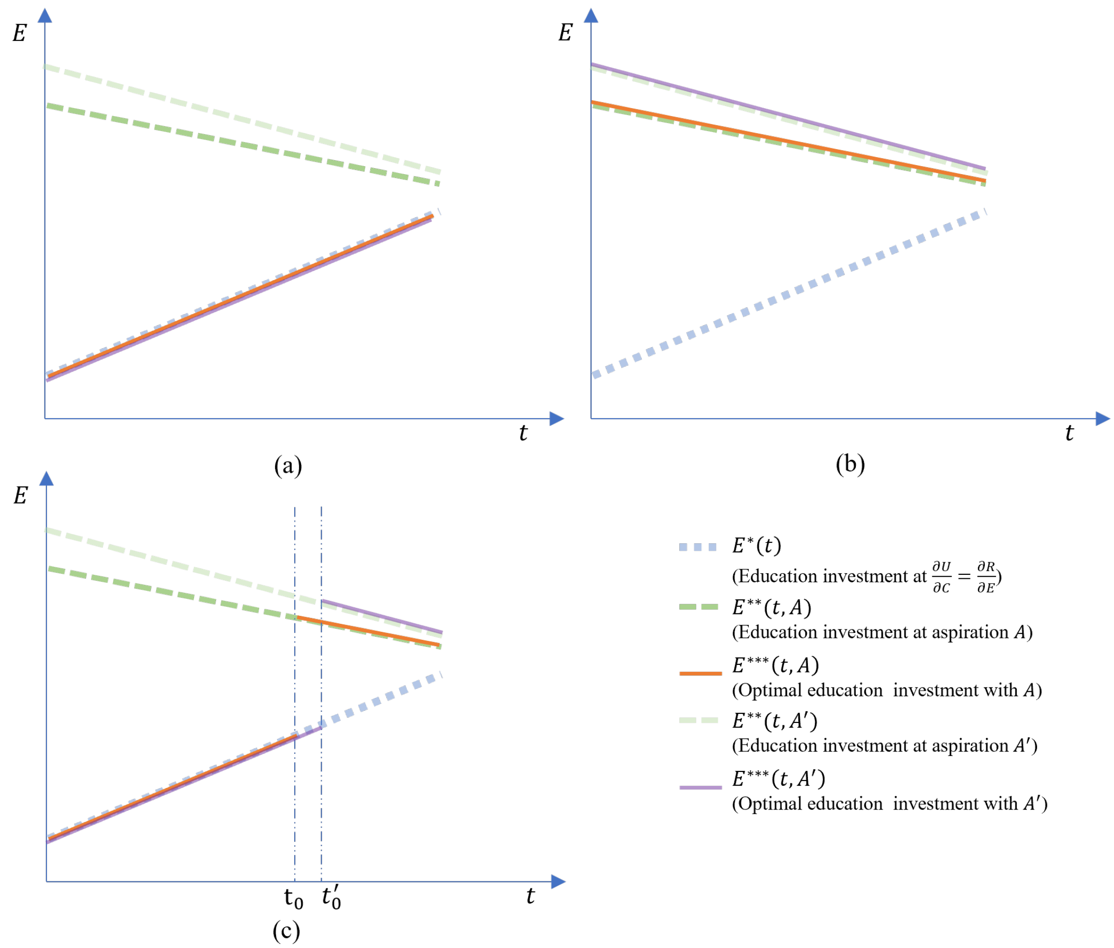


Figure 3.5: Impacts of Aspiration on Optimal Strategy When E^* is not greater than E^{**} For all t

$t_0^{'}$)). A small increase in aspiration will move both interaction points to a slightly higher level as shown in Figure 3.6. For ability lower than t_0 or not smaller than $t_1^{'}$, the equilibrium stays the same. If the ability is within $[t_0^{'}, t_1^{'})$, a marginal increase in aspiration drives up the optimal educational investment level slightly, whereas it results in a significant decrease in the optimal educational investment for ability within $[t_0, t_0^{'})$ (negligible when a change in aspiration is small enough) because the equilibrium shift from E^{**} to E^*.

To sum up, when children's ability is too low (bonus is not enough to cover the additional costs for reaching the aspiration) or too high (can reach aspiration at E^*), parents' optimal

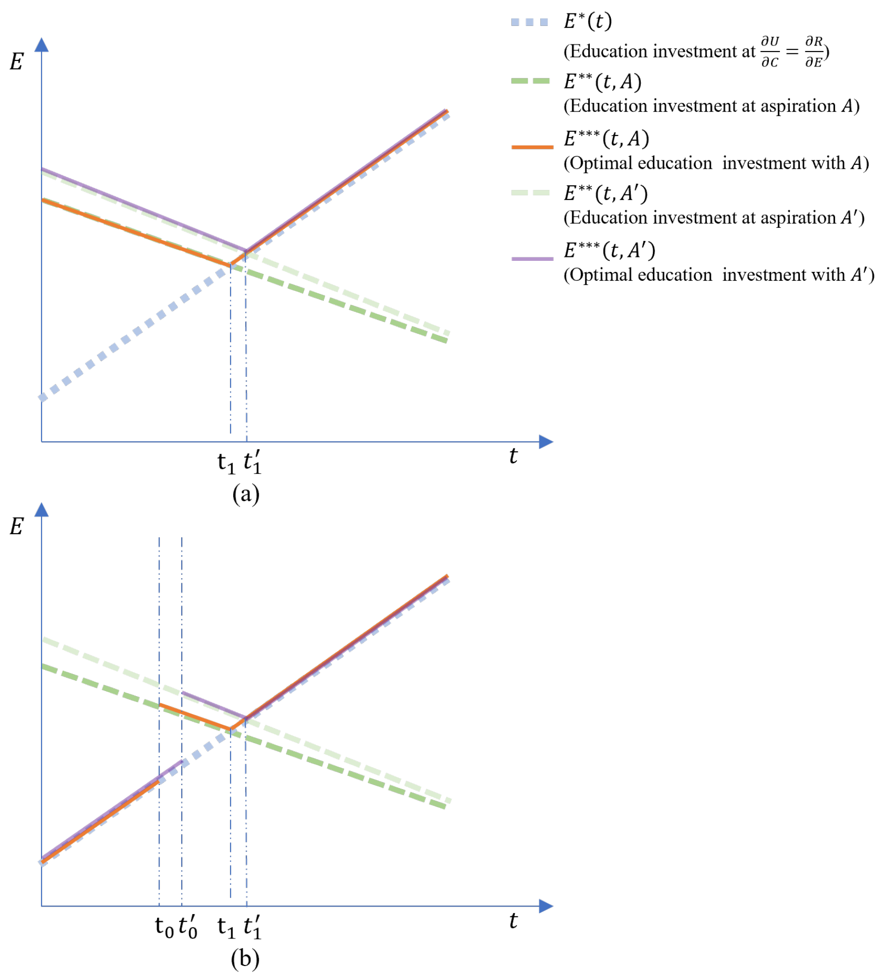


Figure 3.6: Impacts of Aspiration on Optimal Strategy When E^* interacts with E^{**} at t_1

investment stays at the E^* and marginal changes in aspiration do not affect their investment level. When parents are increasing their investment from E^* to E^{**} to help children reach their aspirations, a marginal increase in aspiration will increase parents' investment level.

3.4 Imperfect signaling

In real life, parents are unlikely to observe their children's actual ability, especially for future performances. They receive an imperfect signal of children's ability, instead. I assume parents are aware of the uncertainty and they know the conditional distribution of the true ability ($f(t|\hat{t})$) given the signal they received, $\hat{t}$.

$$\max_E E[u|\hat{t}] = U(I-E) + \int R(t,E) \cdot f(t|\hat{t})dt + k \cdot [1 - F(M(E,A)|\hat{t})]$$

where $f(t|\hat{t})$ and $F(\cdot|\hat{t})$ are the conditional pdf and cdf of the real ability conditional on the signal $\hat{t}$. For convenience I make the following assumption on the distribution of the conditional distribution function.

Assumption 6 $\quad f(t|\hat{t}) = \phi(\frac{t-\hat{t}}{\sigma}) = \frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{(t-\hat{t})^2}{2\sigma^2}}$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the pdf and cdf of standard normal distribution respectively. Here I assume the conditional probability distribution of the true ability is a normal distribution with mean $\hat{t}$ and variance σ^2. $f(t|\hat{t})$ is continuous and differentiable, $\frac{\partial F(t|\hat{t})}{\partial \hat{t}} \leq 0$, $\int \frac{\partial F(t|\hat{t})}{\partial \hat{t}} < 0$.

As shown in Figure 3.7, $\frac{\partial f(t|\hat{t})}{\partial \hat{t}}$ is negative for all t smaller than $\hat{t}$ and it's positive when t is larger than $\hat{t}$.

$M(E,A)$ is the inverse function of $R(\cdot)$ and it represents the lowest ability able to reach the aspiration with education investment E. Therefore, $R[M(E,A),E] = A$.

The first-order derivative is as below:

$$\text{FOC:} \quad \frac{\partial E[u|\hat{t}]}{\partial E} = -U' + \int \frac{\partial R(t,E)}{\partial E} \cdot f(t|\hat{t})dt - k \cdot f(M(E,A)|\hat{t}) \cdot \frac{\partial M}{\partial E}$$

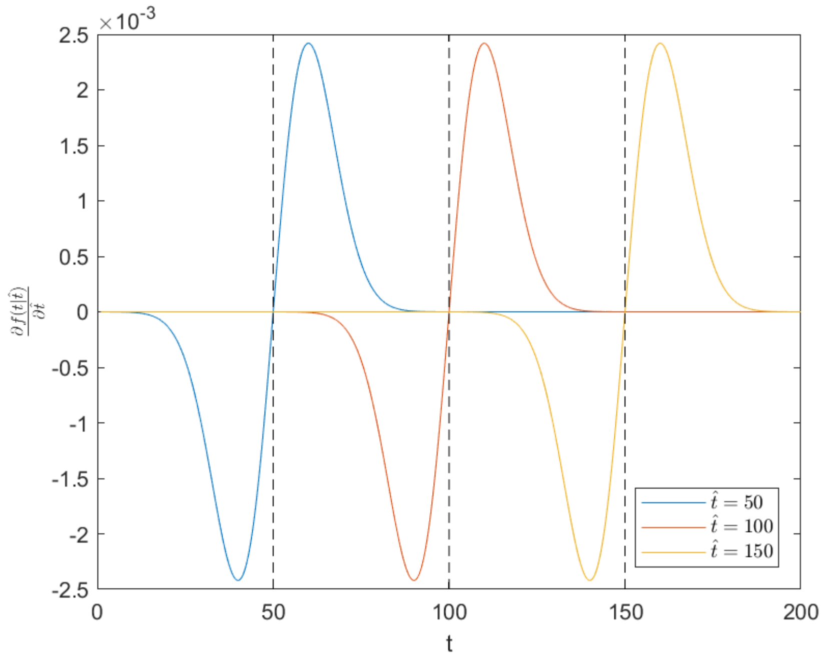


Figure 3.7: Shape of $\frac{\partial f(t|\hat{t})}{\partial \hat{t}}$ when $\hat{t} = 50,\ 100,\ 150$

We can also get the second-order derivative:

$$\text{SOC:} \quad \frac{\partial^2 E[u|\hat{t}]}{\partial E^2} = U'' + \int \frac{\partial^2 R}{\partial E^2} \cdot f(t|\hat{t})dt - k \cdot [\frac{\partial f(M(E,A)|\hat{t})}{\partial t} \cdot (\frac{\partial M}{\partial E})^2 + f(M(E,A)|\hat{t}) \cdot \frac{\partial^2 M}{\partial E^2}]$$

3.4.1 Changes in bonus

From the implicit function theorem, we have

$$\frac{\partial E^{***}}{\partial k} = -\frac{\frac{\partial FOC}{\partial k}}{SOC} = \frac{f(M(E^{***},A)|\hat{t}) \cdot \frac{\partial M}{\partial E}}{SOC}$$

As we are discussing trivial changes at the maximum point, SOC will be negative. From Assumption 2 we know $\frac{\partial M}{\partial E}$ is less than 0, we can get $\frac{\partial E^{***}}{\partial k} \geq 0$, and it will be strictly greater than 0 when $f(M(E^{***},A)|\hat{t})$ is positive. This is to say, when the bonus increases, parents are always willing to invest more in the child's education when reaching the aspiration is not 100% for sure.

3.4.2 Changes in ability signal

From the implicit function theorem, we have

$$\begin{aligned}\frac{\partial E^{***}}{\partial \hat{t}} = -\frac{\frac{\partial FOC}{\partial \hat{t}}}{SOC} &= -\frac{\int \frac{\partial R(t,E^{***})}{\partial E} \cdot \frac{\partial f(t|\hat{t})}{\partial \hat{t}} dt - k \cdot \frac{\partial f(M(E^{***},A)|\hat{t})}{\partial \hat{t}} \cdot \frac{\partial M}{\partial E}}{SOC} \\ &= \frac{\int \frac{\partial^2 R(t,E^{***})}{\partial E \partial t} \cdot \frac{\partial F(t|\hat{t})}{\partial \hat{t}} dt + k \cdot \frac{\partial f(M(E^{***},A)|\hat{t})}{\partial \hat{t}} \cdot \frac{\partial M}{\partial E}}{SOC}\end{aligned} \tag{3.6}$$

It's hard to sign this term in general as the sign of $\frac{\partial f(M(E^{***},A)|\hat{t})}{\partial \hat{t}}$ depends on the relative magnitudes of $\hat{t}$ and $M(E^{***}, A)$. Therefore, I will discuss the sign under different cases.

Case 1 $k \to 0$: When the bonus for reaching the aspiration is small enough, the effects of the additional bonus become negligible.

$$\frac{\partial E^{***}}{\partial \hat{t}} \to \frac{\int \frac{\partial^2 R(t,E^{***})}{\partial E \partial t} \cdot \frac{\partial F(t|\hat{t})}{\partial \hat{t}} dt}{SOC} > 0$$

As we are discussing a marginal change in ability at the global maximizing point, the sign of $\frac{\partial E^{***}}{\partial \hat{t}}$ is the same as the sign of $-\int \frac{\partial^2 R(t,E^{***})}{\partial E \partial t} \cdot \frac{\partial F(t|\hat{t})}{\partial \hat{t}} dt$. With Assumption 6, we know this term is positive. That is to say, when the additional bonus for reaching aspiration is trivial, parents are more willing to invest in the child's education when the signal of ability is high.

Case 2 $k \to \infty$: When the bonus for reaching the aspiration is great enough, the utility from the continuous return to education function R and the cost from the foregone consumption becomes relatively trivial,

$$\frac{\partial E^{***}}{\partial \hat{t}} \to \frac{k \cdot \frac{\partial f(M(E^{***},A)|\hat{t})}{\partial \hat{t}} \cdot \frac{\partial M}{\partial E}}{SOC}$$

Parents are encouraged to ensure the child be able to reach the aspiration with high probability: $1 - F(M(E^{***}, A)|\hat{t}) \to 1$, which means $\frac{\partial f(M(E^{***},A)|\hat{t})}{\partial \hat{t}} \leq 0$, and $\frac{\partial E^{***}}{\partial \hat{t}} \leq 0$. That is to say, when the bonus for reaching the aspiration is great enough, parents' optimal investment level is increasing in the signal of ability if there is some probability that the child will miss the aspiration.

Case 3 $0 \ll k \ll \infty$: Other than the two extreme cases discussed above, parents' decision in the real life is more likely to be between the two. When there is a relatively low probability that their children can reach the aspiration with the current investment level ($M(E^{***}, A) \geq \hat{t}$), parents increase investment when the signal of ability increases. Whereas when there is a relatively high probability for children to reach their aspirations at the current investment level ($M(E^{***}, A) < \hat{t}$), parents' investment may be non-increasing or even decreasing in the signal of ability.

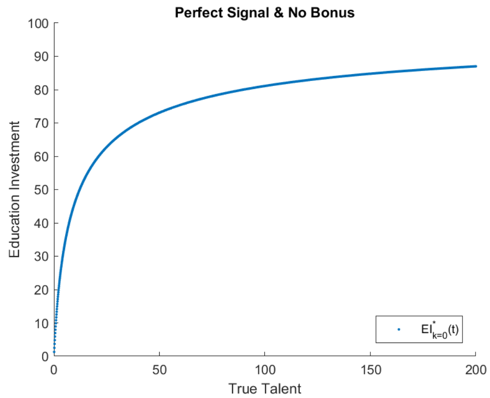
3.5 Simulation

Here is an example to show the predictions above in a more intuitive way.

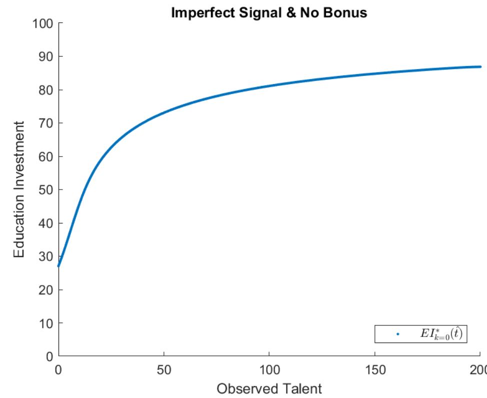
The specifications of the U, R functions are as below.

$$U = a \cdot log(I - E)$$

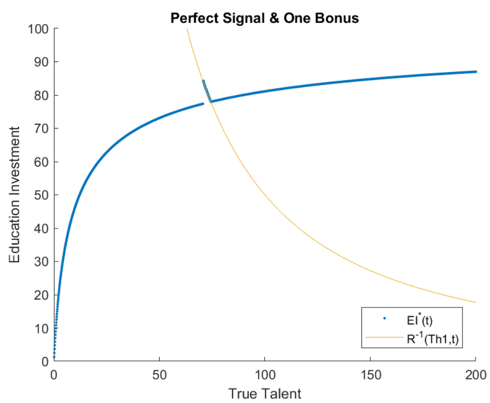
$$R(t, EI) = b \cdot t^{\alpha} E^{1-\alpha}$$



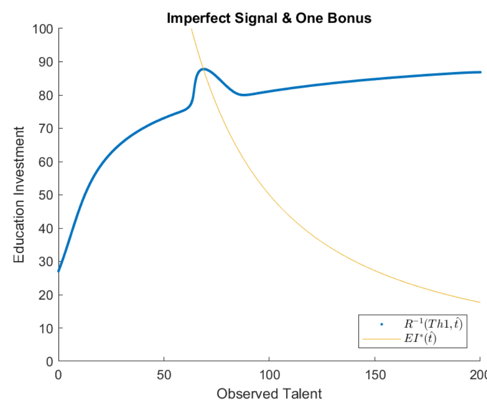
(a) Perfect Signal & No Bonus



(b) Imperfect Signal & No Bonus



(c) Perfect Signal & One Bonus



(d) Imperfect Signal & One Bonus

Figure 3.8: Correlation between optimal education investment and ability signal in different settings

The parameter vector is as below.

$$(a, b, \alpha, I, k, \sigma, \underline{t}, \bar{t}, A_1) = (30, 3.5, 0.6, 100, 30, 5, 0, 200, 212)$$

Figure 3.8 shows the correlation between ability signal and optimal education investment level in six different settings: a. $k = 0$ and perfect signal; b. $k = 0$ and imperfect signal; c. one threshold and perfect signal; d. one threshold and imperfect signal; e. multiple thresholds and perfect signal; multiple thresholds and imperfect signal.

When there is a perfect signal, the curve of the optimal education investment behaves exactly like the prediction in Section 1.2 Case 3. When the ability is low, parents will always prefer the E^* point and their investment is positively correlated with ability. When ability increases to levels at which the additional cost of reaching aspiration A is lower than the bonus, parents shift their investment from E^* to E^{**}, and their optimal education investments decrease as ability increases. The reason is that education investment in a more abled child is more efficient and then the amount of investment needed to reach the aspiration is lower. Moreover, when the ability is high enough so that children's academic performance at the E^* point is sufficient to reach the aspiration, parents will go back to the E^* point and the correlation between optimal education investment and ability is back to positive again. The causal effects of ability on parental educational investment are nonlinear around the threshold or reaching aspiration.

When the signal is imperfect, the general trend is similar, except now parents need to maximize expected utility, so the trend is smoother than the perfect signal case. The larger the variance is, the smoother the curve is.

3.6 Conclusion

This paper builds up a theoretical parental education investment model which employs a discontinuous utility function and introduces uncertainty into the parental education investment decision. With some basic and reasonable assumptions, this paper proves that the correlation between ability signal and optimal parental education investment level is not linear around parents' aspirations. In most situations, the correlation is positive. Parents are more willing to invest in a child if the signal indicates the child has a higher ability. However, if parents can receive some additional bonuses when the child's academic performance reaches certain thresholds (e.g. parents' aspirations), it generates discontinuity in parents' utility function at the thresholds. The bonus can motivate parents to invest in children to help them reach their aspirations. As the goal is to get the additional bonus for reaching the aspiration, parents' investment in children would be just sufficient for them to reach the threshold, which will result in the optimal education investment decreasing in ability. The model can help explain those ”irrational” education investment behaviors which cannot be rationalized in the classic education investment model.

This paper also introduces uncertainty into the decision process. It analyzes parental education investment decisions in two settings: perfect signal and imperfect signal. The analyses show that parental education investment with an imperfect signal is similar to the perfect signal case except for one difference - now parents are maximizing the expected utility. Therefore, the optimal education investment curve is smoothed out by the expectation process. The larger the standard deviation is, the smoother the curve becomes. In the imperfect signal case, the correlation between optimal education investment and ability signal can also be negative in certain situations.

Appendix A: Proofs of Two Propositions

A.1 Proposition 1: u is upper semicontinuous at E^{**}

Proof: Based on the definition of the E^{**}, we have

$$\lim_{E \to \uparrow E^{**}} u(E) = \lim_{E \to \uparrow E^{**}} u_1(E)$$

$$\lim_{E \to \downarrow E^{**}} u(E) = \lim_{E \to \downarrow E^{**}} u_1(E) + k$$

For $y = u(E^{**}) + \Delta y$ ($\Delta y > 0$), we can get

$$y - \lim_{E \to \uparrow E^{**}} u(E) = \lim_{E \to \uparrow E^{**}} [u_1(E^{**}) - u_1(E)] + k + \Delta y$$

$$y - \lim_{E \to \downarrow E^{**}} u(E) = \lim_{E \to \downarrow E^{**}} [u_1(E^{**}) - u_1(E)] + \Delta y$$

As u_1 is a continuous function in E, for every real $y > u(E^{**})$ there exists a neighborhood U of E such that $u(E) < y$ for all $E \in U$. Therefore, u is upper semicontinuous at E^{**}.

A.2 Proposition 2 0$\in \partial u(E)$ where $\partial u(E)$ denotes the superdifferential of u in E

$$\partial u(E) = \{q : q(y - E) \geq u(y) - u(E), \forall y \in [0, I]\}$$

Proof: There are three different situations and I will show that 0 is in the superdifferential of $\partial u(E)$ in E under all three situations.

Case 1 $E^* \geq E^{**}$

Case 1.1 $E^* \geq E^{**}$ and $I \geq E^*$:

$$\begin{aligned} u(y) - u(E^*) &= u_1(y) - u_1(E^*) + k \cdot \{R(t, y) \geq A\} - k \\ &\leq 0 + k \cdot (\{R(t, y) \geq A\} - 1) \\ &\leq 0 \text{ for all } y \in [0, I] \end{aligned}$$

Therefore, the superdifferential of $u(\cdot)$ at E^* includes 0 when childen can reach aspiration with E^* (Figure A.1 (a)).

Case 1.2 $E^* \geq E^{**}$ and $E^{**} \leq I¡E^*$:

$$u(y) - u(I) = u_1(y) - u_1(I) + k \cdot [\{R(t, y) \geq A\} - \{R(t, I) \geq A\}]$$

$$\leq 0 \text{ for all } y \in [0, I]$$

Therefore, the superdifferential of $u(\cdot)$ at E^* includes 0 when childen can reach aspiration with I which is smaller than E^* (Figure A.1 (b)).

The discussion on the case $E^* \geq E^{**}$ and $I < E^{**}$ is omitted because $u(E)$ is continuous and differentiable within $[0, I]$ in this case.

Case 2 $E^* < E^{**}$ and $k < u_1(E^*) - u_1(E^{**})$

Case 2.1 $E^* < E^{**}$, $k < u_1(E^*) - u_1(E^{**})$, $I \geq E^{**}$ and $0 \leq E^*$:

$$u(y) - u(E^*) = u_1(y) - u_1(E^*) + k \cdot \{R(t, y) \geq A\}$$

For $y < E^{**}$:

$$u(y) - u(E^*) = u_1(y) - u_1(E^*)$$

which is not greater than 0 for all $y \in [0, I]$ as E^* is the level of investment that maximizes $u_1(\cdot)$.

For $y \geq E^{**}$: we have

$$u(y) - u(E^*) \leq u_1(E^{**}) - u_1(E^*) + k$$

which is less than 0 for all $y \in \mathbb{R}$.

When the investment at E^* is insufficient for reaching the aspiration and the additional benefits for reaching the aspiration cannot cover the additional costs, 0 is in the superdifferential of $u(\cdot)$ at E^* (Figure A.1 (c)).

Case 2.2 $E^* < E^{**}$, $k < u_1(E^*) - u_1(E^{**})$, $I \geq E^{**}$, $0 > E^*$, and $u(0) > E^{**}$: $\quad 0 \in \partial u(0)$ because $u_1$is decreasing in $[0, I]$, which means $u(0)$ is not less than $u(y)$ for all $y \in [0, E^{**})$ and $u(0) > u(E^{**}) \geq u(y)$ for all $y \in [E^{**}, I]$ (Figure A.1 (d)).

Case 2.3 $E^* < E^{**}$, $k < u_1(E^*) - u_1(E^{**})$, $I \geq E^{**}$, $0 > E^*$, and $u(0) \leq E^{**}$: $\quad 0 \in \partial u(E^{**})$ because $u_1$is decreasing in $[0, I]$, which means $u(E^{**}) \geq u(0) \geq u(y)$ for all $y \in [0, E^{**})$ and $u(E^{**})$ is not less than $u(y)$ for all $y \in [E^{**}, I]$ (Figure A.1 (e)).

The discussion on the case $E^* < E^{**}$, $k < u_1(E^*) - u_1(E^{**}$,and $I < E^{**}$ is omitted because $u(E)$ is continuous and differentiable within $[0, I]$ in this case.

Case 3 $E^* < E^{**}$, $k \geq u_1(E^*) - u_1(E^{**})$, $0 \leq E^{**}$, and $I \geq E^{**}$

$$u(y) - u(E^{**}) = u_1(y) - u_1(E^{**}) + k \cdot \{R(t, y) \geq A\} - k$$

For $y < E^{**}:$ we have

$$u(y) - u(E^{**}) \leq u_1(E^*) - u_1(E^{**}) - k$$

which is not greater than 0 for all $y \in [0, I]$.

For $y \geq E^{**}$: the $u(y) - u(E^{**}) = u_1(y) - u_1(E^{**})$ and it is not greater than 0 for all $y \in \mathbb{R}$ as $u_1$is decreasing in E for all investment level greater than E^*.

The superdifferential of $u(\cdot)$ at E^{**} includes 0 when the investment of E^* is insufficient to reach the aspiration and the additional benefits of reaching the aspiration overweight the additional costs (Figure A.1 (f)).

The discussion on other cases $E^* < E^{**}$, $k \geq u_1(E^*) - u_1(E^{**}$, and $0 > E^{**}$or $I < E^{**}$ are omitted because $u(E)$ is continuous and differentiable within $[0, I]$ in this case.

To sum up, I have proved that 0 is in the superdifferential of the $u(E)$.

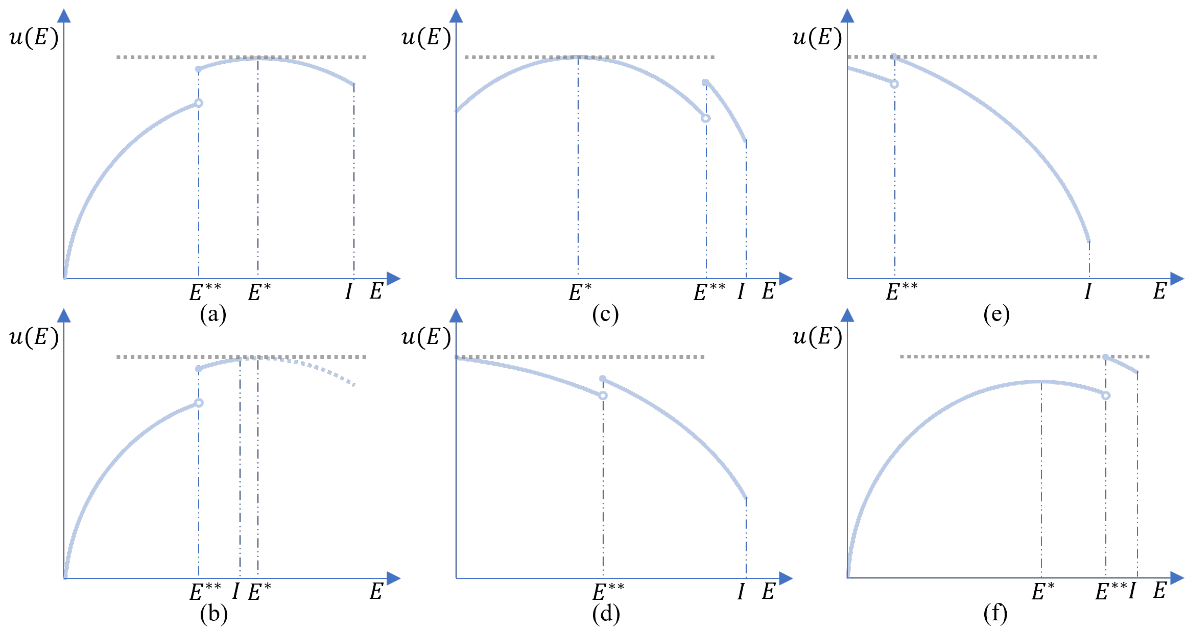


Figure A.1: 0 is in the superdifferential of the $u(E)$ under all situations

Appendix B: Intervention Reports Samples

报告二维码

截图保存后，微信扫描查看

致家长的一封信

龚旭玲同学的家长您好！

机器学习算法是一种新兴的大数据处理手段，可以有效地从大量相关数据中**发现规律，总结规律，做出预测**，现已广泛的应用到了图像识别、金融理财、企业招聘等领域。机器学习算法在高中教育中的一个前沿应用是对学生未来成绩进行预测，帮助家长和老师更好的了解和定位孩子的学习现状，及时调整孩子学习规划。此算法基于近十年往届学生的学习数据，可以根据学生高一、高二的学习情况对学生高考期间的年级排名进行预测。

我们在去年对 2020 届高三学生高考期间年级排名进行了预测并将预测值与学生高考期间的真实排名进行了对比。结果显示，算法预测排名在绝大多数时候与学生高考期间的真实排名非常接近，**差距在 10%以内**。同时我们也通过问卷了解了家长对孩子高考期间年级排名的预测，**绝大多数家长无法准确预测**孩子未来的排名。

我们通过下面两张图来对比家长预测准确度和算法预测准确度。

左图是家长的预测与真实排名之间的差距统计。只有约 20%的家长，即每 10 位家长中只有 2 名家长能很准确的预测孩子未来的成绩。

右图是机器学习算法对学生高考排名的预测与高考期间真实排名的差距统计。算法准确预测率高达 90%，即每 10 次预测中有 9 次能很准确的预测孩子未来成绩。

对比两图可以得知，**机器学习算法可以更准确的预测学生未来的成绩。**

请勿将信中的信息与学生或其他家长交流！

基于龚旭玲同学高中期间的学习表现，算法对**龚旭玲同学高考期间的成绩预测**如下图所示：

您孩子的未来排名
预计在此区间中

163-169 名	170-176 名	177-183 名	184-190 名	**191-197 名**

我们运用算法对每一个往届毕业生的高考成绩进行预测。下表列出了几位**成绩与龚旭玲同学相似**的往届学生的预测排名和高考期间真实排名信息。

学生	毕业年份	机器学习预测排名	真实高考期间排名
刘某峰	2017	195-199 名	197 名
吴某伟	2017	195-201 名	196 名
龙某宇	2018	191-196 名	192 名
罗某华	2018	194-198 名	198 名
吴某玥	2018	187-190 名	187 名

上表显示，算法对**成绩与龚旭玲同学相似**的学生的**预测结果可靠性很高。**

此预测信息是基于您孩子现有成绩及表现做出的预测，如您此后对孩子的学习规划、管理做出**调整**，很可能会**改变**龚旭玲同学的未来**成绩的发展趋势。**希望这个信息对您及龚旭玲同学未来的学习规划有所帮助！您可以**截图保存报告二维码**，以便之后查阅。

郑重声明：

1. 信中为龚旭玲同学量身定做，对其他同学不具备适用性，**请勿与其他家长交流**此的信息；
2. 此信旨在帮助家长了解学生未来成绩发展趋势，及时调整对孩子的管理。家长**请勿与学生交流**信中的信息，与学生交流信中的信息可能会给学生产生不良影响。

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Figure B.1: Machine Learning Report Sample

致家长的一封信

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龚锦洋同学的家长您好！

随着高三生活的深入，高考逐渐为高三家庭中越发重要的一个话题。相信您一直在关注和跟进龚锦洋同学的各次考试成绩，对龚锦洋同学的年级排名信息了然于心。

由于信息的局限性，您现在了解到的绝大部分成绩信息都只列出了龚锦洋同学在年级的排名，并没有市排名或省排名信息，而大学录取是基于考生的高考成绩的省排名由高到低录取的。因此，了解龚锦洋同学现在的成绩所对应的大学可以帮助您更准确的定位您孩子现在的学情，并尽早做出更合适的学习规划。

为了帮助您更好的了解龚锦洋同学的学习情况，此处列出了成绩与龚锦洋同学相近的往届学生在高考时的成绩和对应的大学信息。

我国高校众多，家长们对于绝大多数高校没有足够的了解，我们对大学进行了排名以帮助您了解高校的综合情况。由于考生们在填报大学时会综合考虑学校口碑、学术能力、教学质量、师资力量、就业前景等各项指标，优先选择更优秀的学校，高录取平均分可以很好地反映出各个大学的综合实力和口碑。我们根据**各大学在贵州省的高考录取平均分由高到低对大学进行了排名**。排名越靠前的大学高考录取平均分越高，被更多顶尖的学生喜爱。

这其中：

- 全国前十的大学排名均在前 10 名
- 985 大学的排名均在前 66 名
- 211 大学的排名均在前 231 名
- 一本学校的排名均在前 356 名
- 二本学校的排名均在前 1146 名

请勿将信中的信息与学生或其他家长交流！

2017 届和 2018 届学子中，年级第 642 名的学生的高考成绩及对应大学信息如下

2017 年高考的学子中，年级第 642 名的学生的高考分数为 437 分，可就读的前三所院校信息如下（仅列举 3 所院校作为例子）

	大学名称	类别	大学排名
院校1	浙江海洋大学(二本)	二本	451
院校2	内蒙古医科大学	二本	453
院校3	鲁东大学	二本	455

2018 年高考的学子中，年级第 642 名的学生的高考分数为 458 分，可就读的前三所院校信息如下（仅列举 3 所院校作为例子）

	大学名称	类别	大学排名
院校1	河北地质大学	二本	503
院校2	湖南工程学院(二本)	二本	504
院校3	吉林医药学院	二本	505

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1. 此信息为龚锦洋同学量身定做，对其他同学不具备适用性，**请勿与其他家长交流**此报告中的信息；
2. 此信息旨在帮助家长了解学生成绩所对应的院校，以便及时调整对孩子的管理。家长**请勿与学生交流信中的信息**，以免给学生带来不良影响。

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Figure B.2: Rank-to-College Matching Report Sample

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