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

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Motivation

- Education is important: key determinant of wages, employment, health and other outcomes
- Parental investment is a primary factor influencing educational attainment
- Decisions are based on parents' belief about children's ability *(Bursztyn and Coman, 2012; Dizon-Ross, 2019; Bergman, 2021; List et al., 2021)*
- Parents' belief may be biased
  - Limited access to performance info *(Bursztyn and Coman, 2012; Bergman, 2021)*
  - Illiterate parents *(Dizon-Ross, 2019)*
- What about parents who are educated and have access to academic records?
  - Biases in their belief about children's ability
  - Policies to help optimize their decisions

Question

- Field experiment partnering with a high school in China
  - 748 parents of 12th-grade students
- Combining randomized controlled trails (RCTs), several rounds of surveys, with rich administrative data, this paper
  - Documents two new information frictions from surveys
    - Overconfidence in future performance
    - Underestimate college admission requirement
  - Introduce two novel interventions to solve the problem
    - Machine-learning predictions on future performance
    - Report of colleges corresponding to children's current in-school ranking

Question

- Test impacts of removing information frictions
  - Parents' ability belief
  - Parents' investments
  - Children's academic performance
- Reveal causal effects using exogenous changes caused by treatments
  - How parents' ability beliefs affect investments
  - Educational investments' impacts on performance

Preview of Findings

- The information shocks significantly eliminated the information frictions
  - Parents' belief biases decrease by almost 50%
- Parental educational monetary investments increase by 4.8%
  - Causal effect of ability belief on investments is nonlinear around aspirations
- Children's performance improves by around 5%
  - 1% increase in edu. monetary investment improves performance by 1.4%

Literature Review & Contributions

This paper contributes to three main strands of literature

- Literature on parental educational decisions
  - Evidence on impacts of beliefs about children's effort & return to education
    (Bursztyn and Coman, 2012; Dizon-Ross, 2019; Bergman, 2021; List et al., 2021)
  - Little evidence on causal effects of ability belief
    - Exogenous changes in ability belief
    - Detailed & panel data on parents' general educational investments
  - Identified two types of information frictions
    - Well-educated parents with performance info
    - Individual-level characteristics
  - Proposed novel and low-cost solutions
    - increased educational investment & students' performance

Literature Review & Contributions

- Literature on machine learning application
  - Growing literature: job performance, bail decisions, hiring decisions
    (Mullainathan and Spiess, 2017; Kleinberg et al., 2015; Hoffman et al., 2018)
  - Among the first to implement machine learning in education
  - Came up with machine-learning algorithms based on rich historical academic performance data
  - Eliminate belief biases & help with parents' decision optimization

Literature Review & Contributions

- Literature on the modeling of educational investment decisions (Becker, 1962; Becker and Tomes, 1979; Glomm, 1997; Raut and Tran, 2005)
  - Empirical evidence on the importance of parents' aspirations (Galab et al., 2013; Spera et al., 2008; Bernard et al., 2019)
  - Incorporate aspiration in parents' decision model
  - Test the model predictions empirically
  - Find a non-monotonic correlation between ability belief and investments around aspirations
    - When and why are belief & investments become substitutes or complements

Outline

- Background
- Theoretical Framework
- Experimental Design & Data
- Empirical Results

Background & Context

Location: Guizhou, China

Why China?

- Education investment is **very important** in China
  - The ranking of average spending on education per child: *(CNN Money, 2017)*
    - US: NO. 4 *(2,923 USD per year)*, **5%** of average annual wage
    - China : NO. 6 *(2,145 USD per year)*, **19%** of average annual wage
- It has snowballed in the past few years
  - After-school training market annual increase rate: over 30%
  - Attracted attention from policy-makers
- One-Child policy
  - No sibling tradeoff issues
- Simple college admission system
  - Only one exam matters - College Entrance Exam(CEE)

Theoretical Framework: Set up

Context: parents of high-school students

Parents' optimization equation:

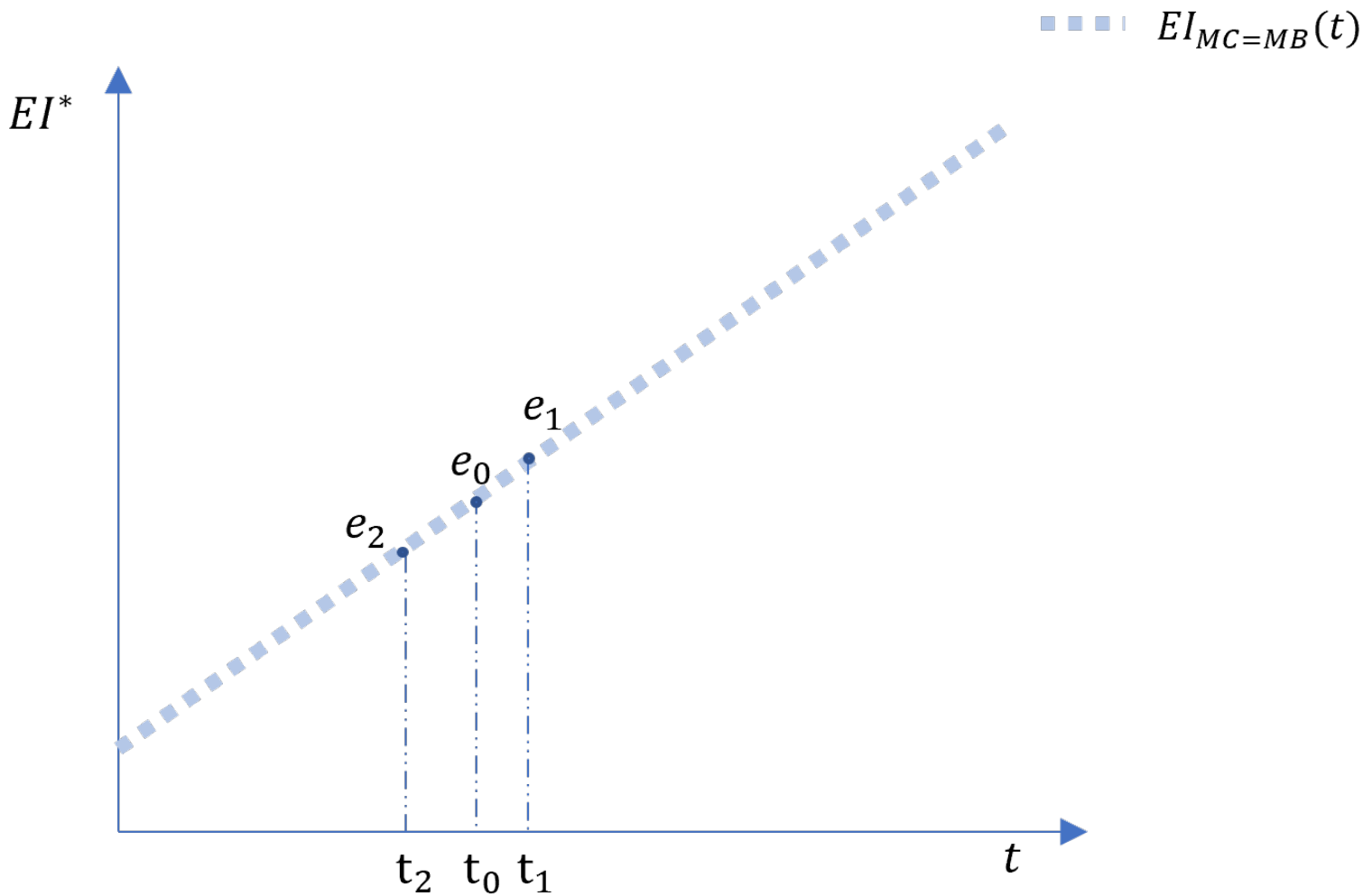
$$u = U(C) + V(P(t, EI), A), \text{ st. } C + EI = I$$

- $U(C)$: the utility from consumption
- $V(.)$: the utility from child's college admission
- $P(t, EI)$: predicted CEE performance
- t : parents'belief of their children's current ability
- EI : parental education investment
- A : parental aspiration (CEE performance needed for ideal college)

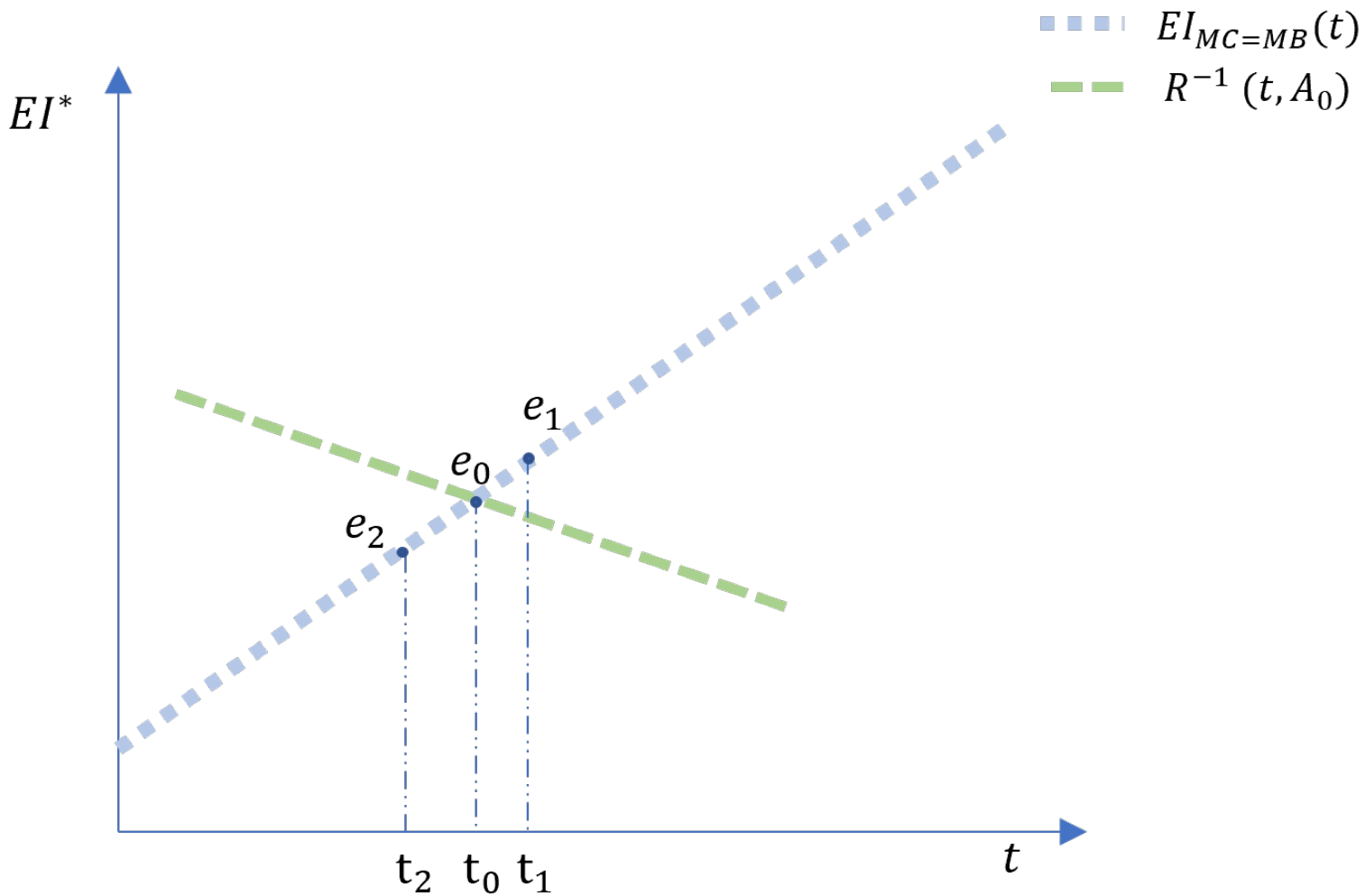
Assumptions:

- Assumption 1: **Utility has a bonus when aspiration is reached**
  $V(P(t, EI), A) = R(P(t, EI)) + k \cdot 1\{P(t, EI) \geq A\}$

Theoretical Framework: Graphic Explanation



Theoretical Framework: Graphic Explanation



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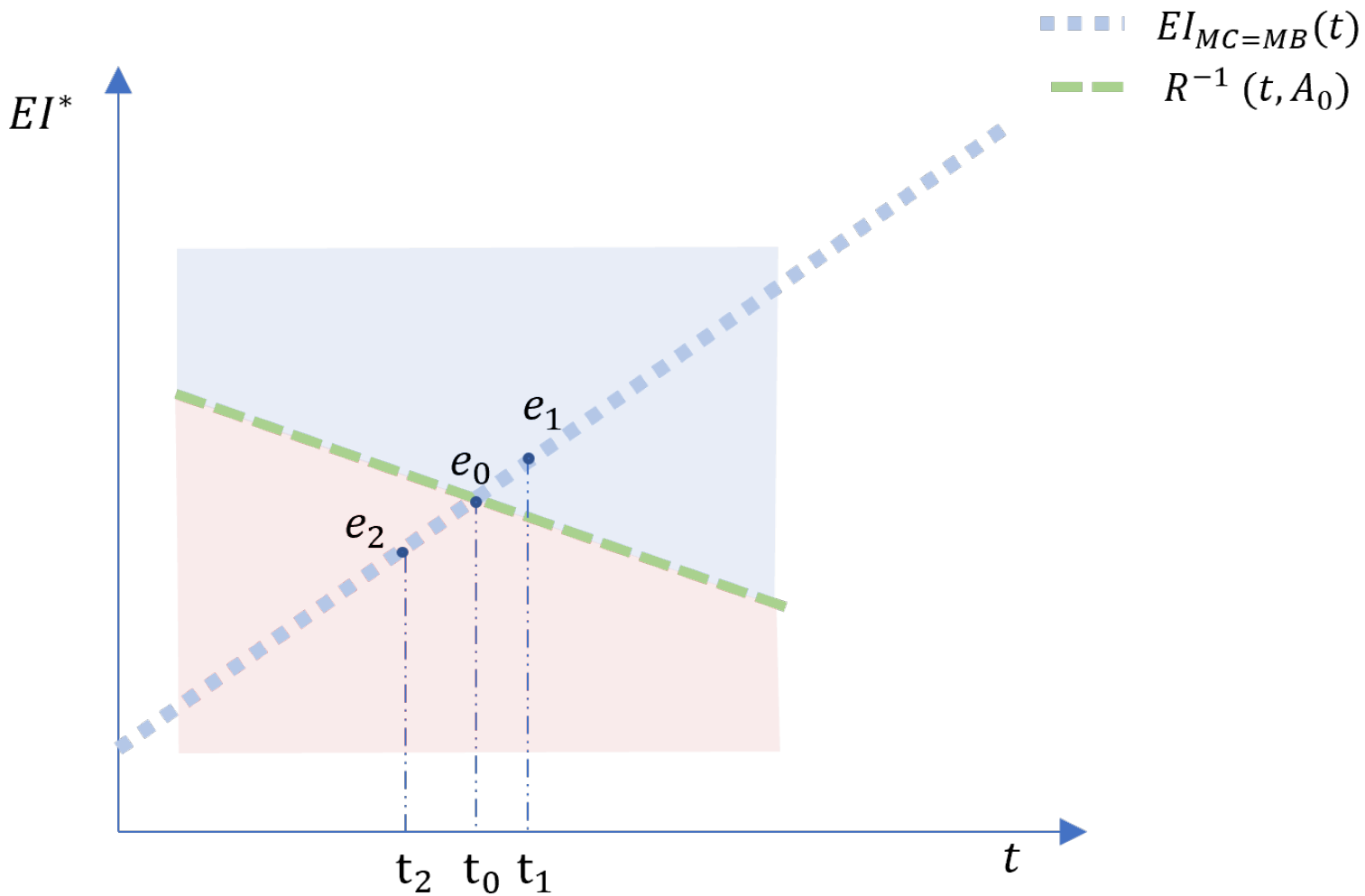

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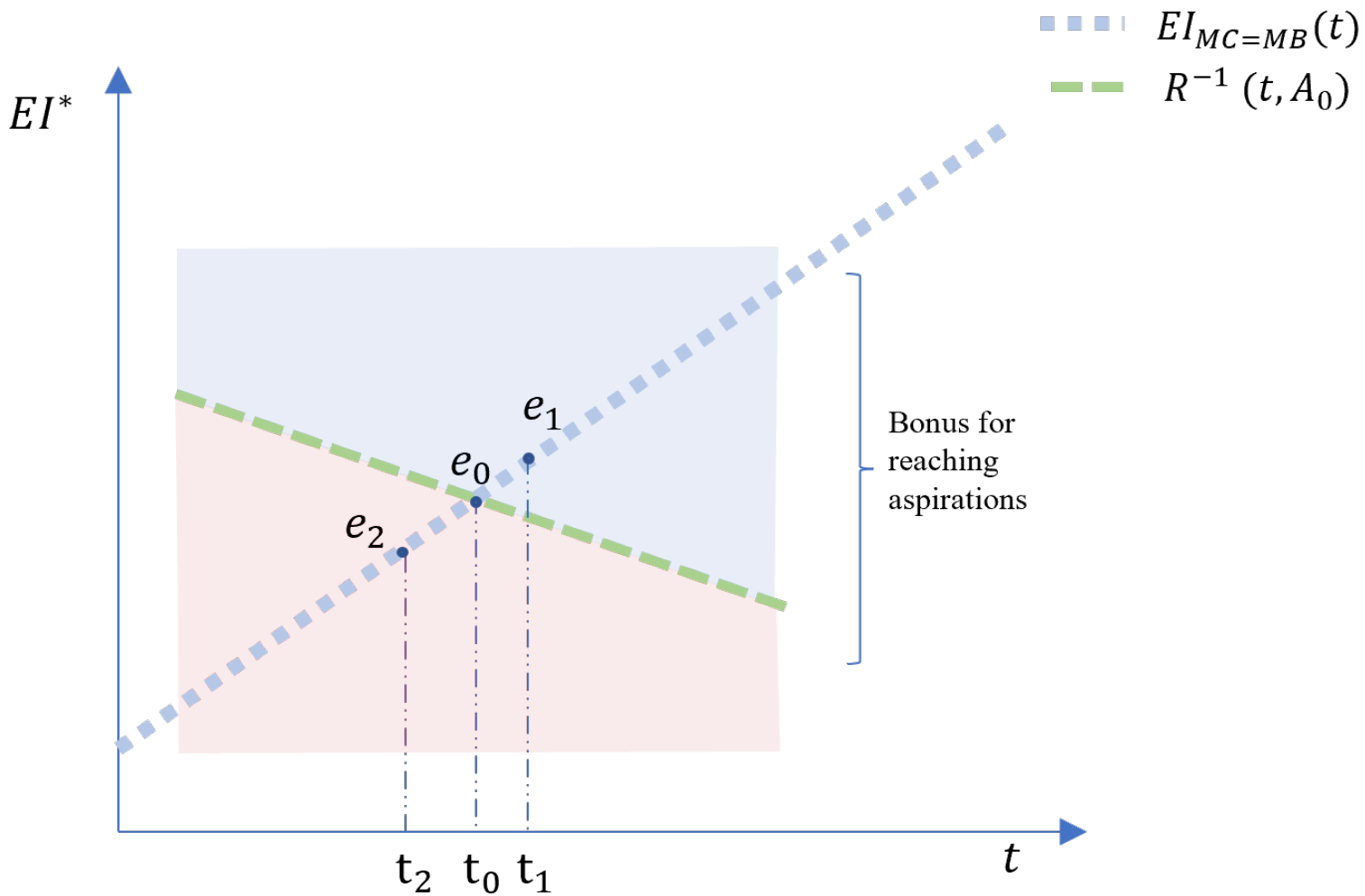

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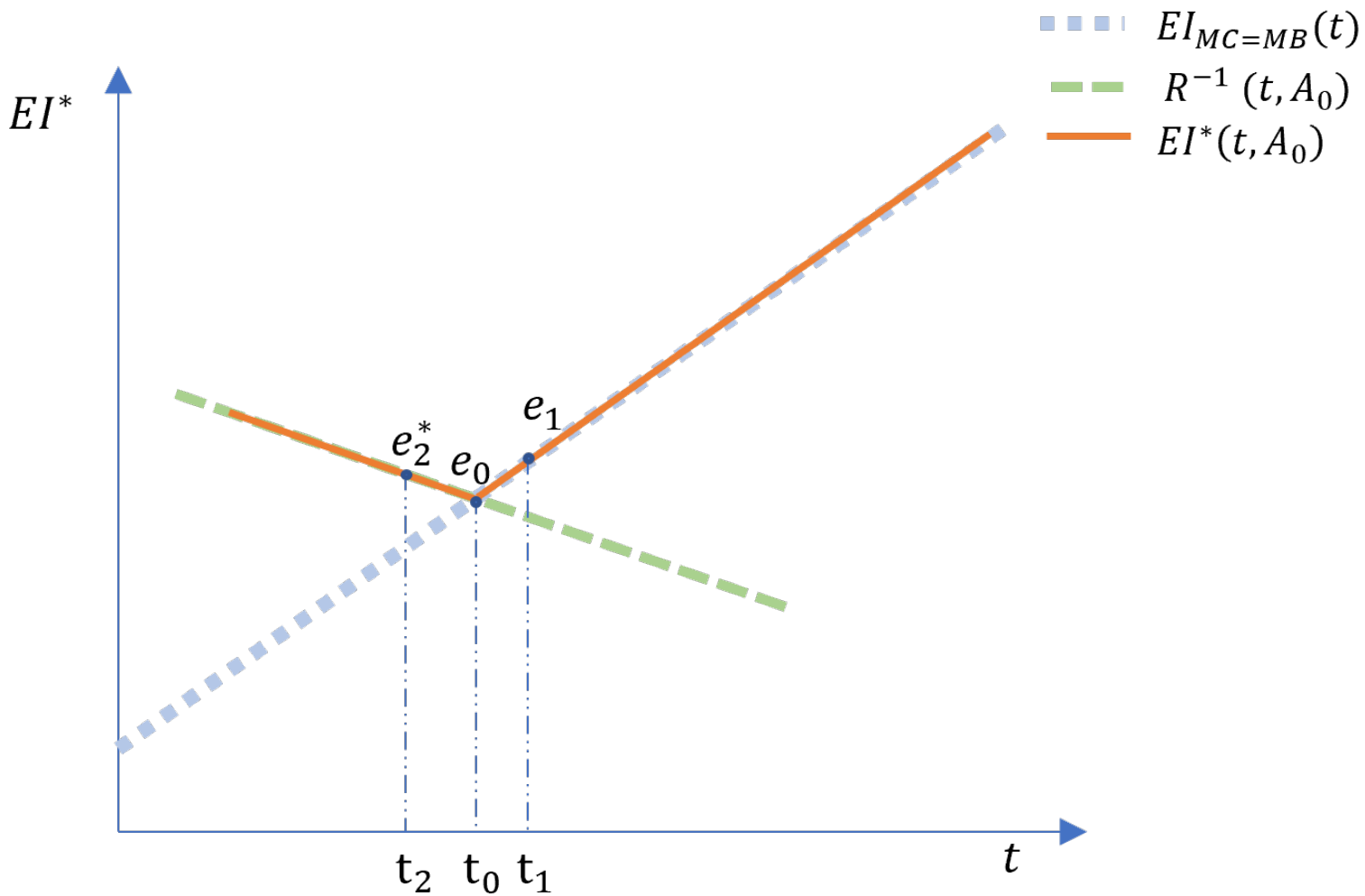

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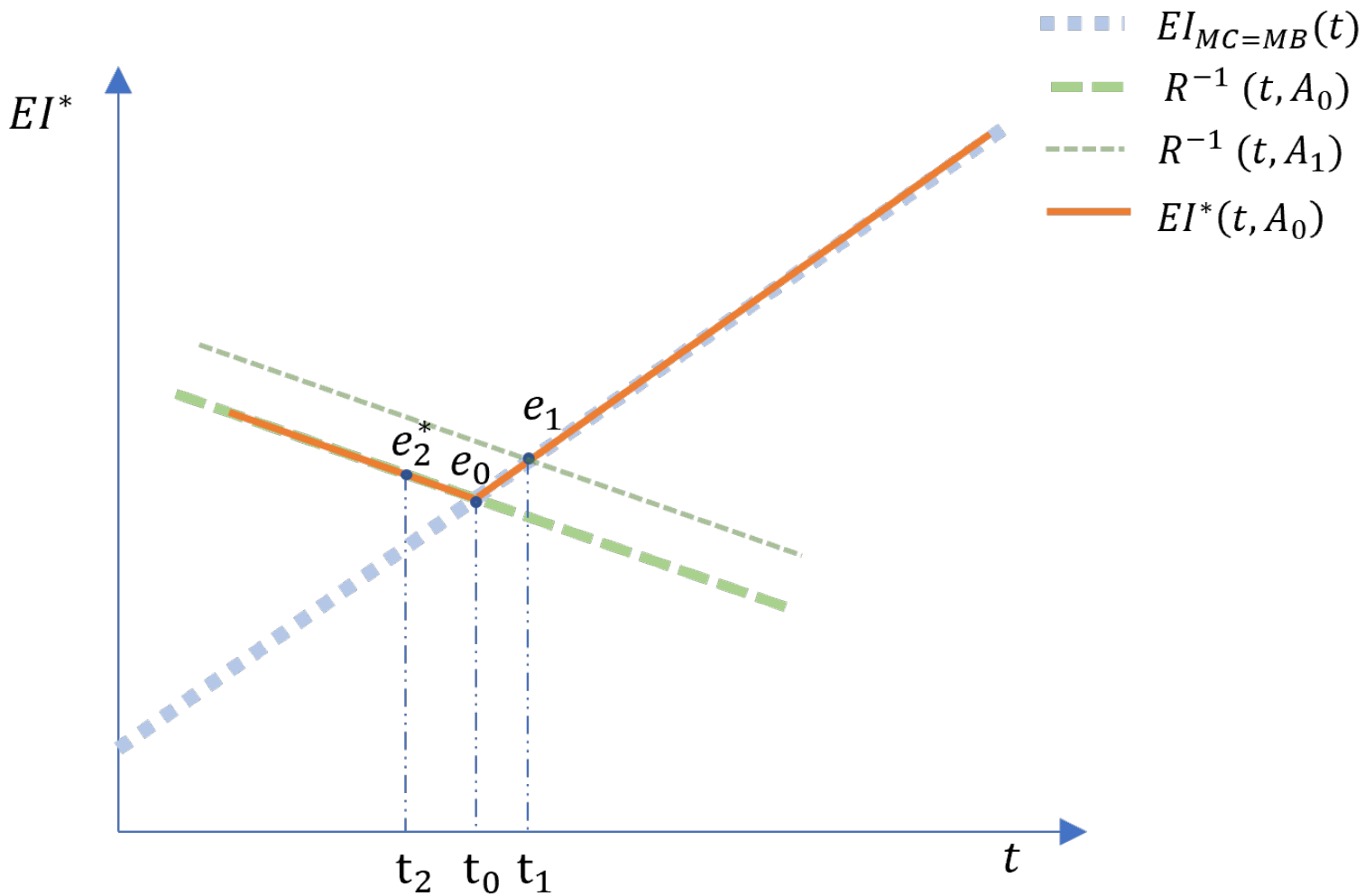

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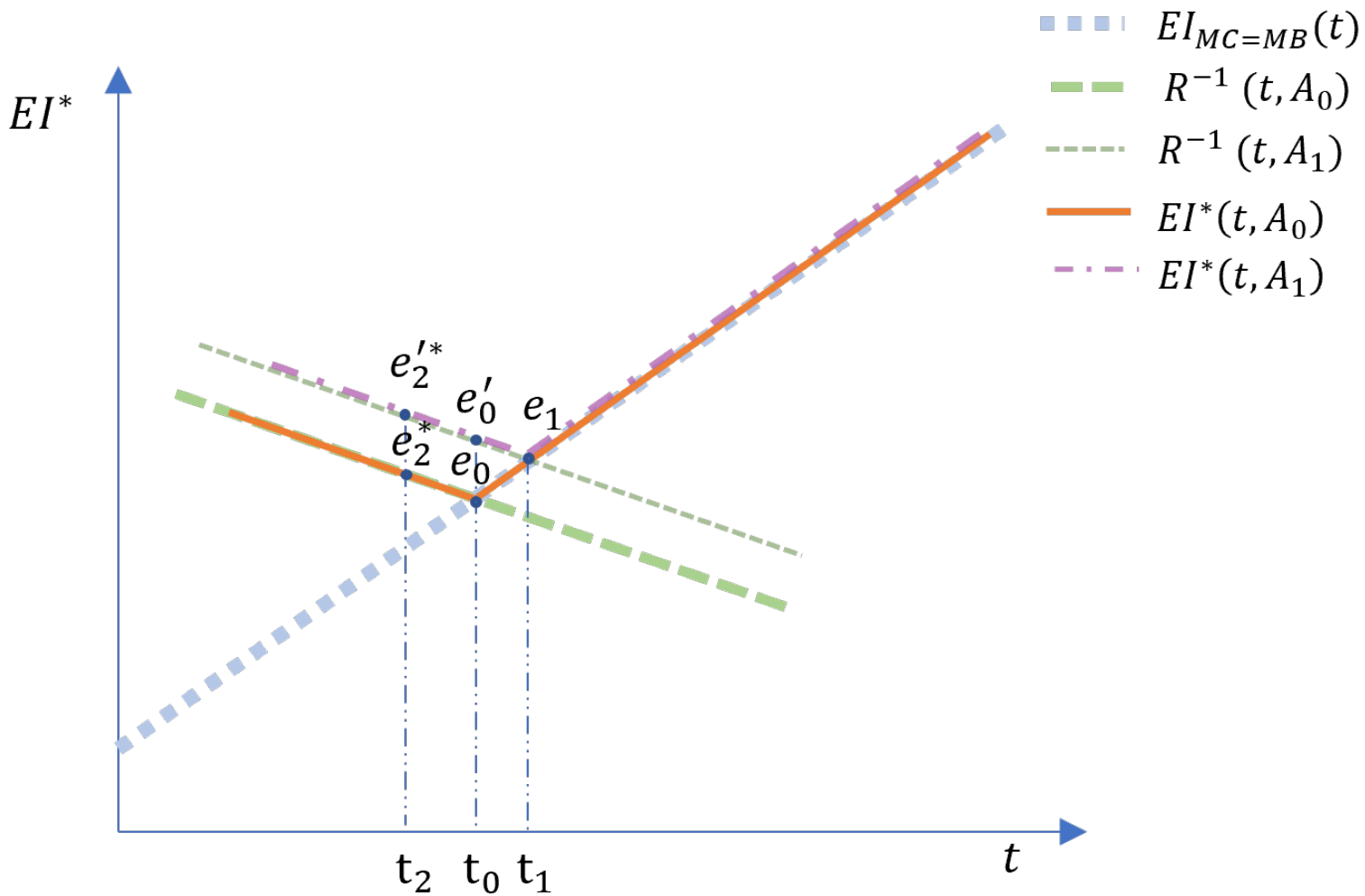
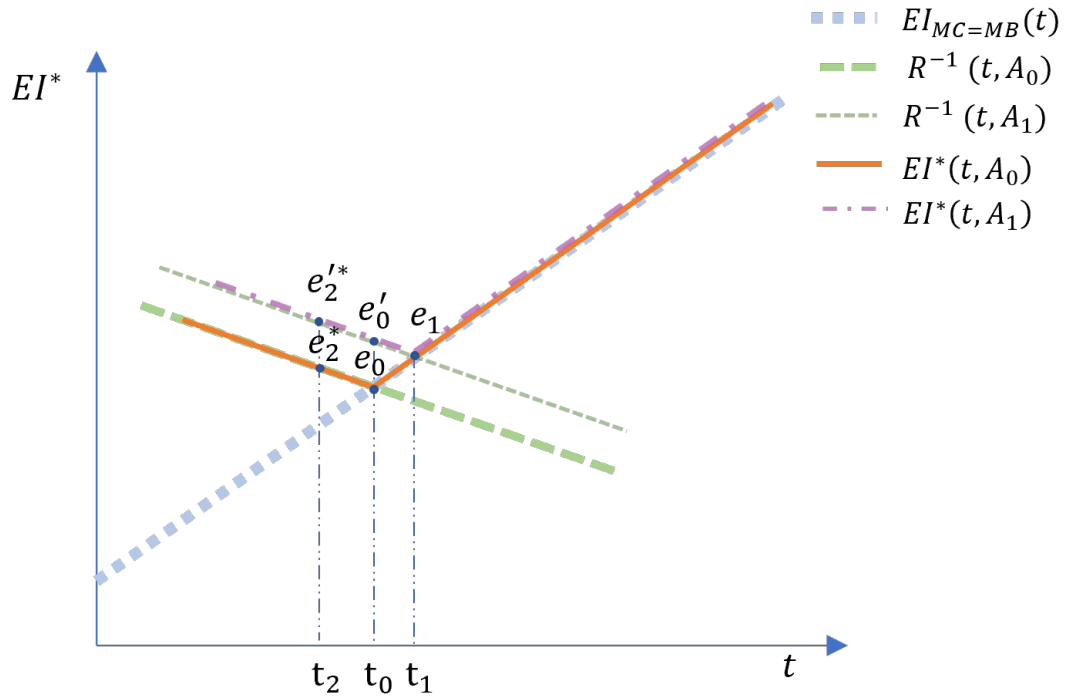


Theoretical Framework: Prediction - Nonlinear



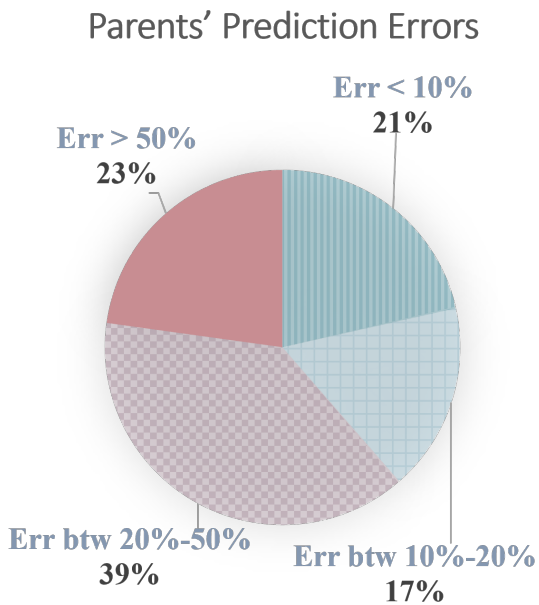
- Aspiration not reached ($t < t_0$):
  - Invest to reach aspiration
  - **Substitute** - the lower the ability belief, the higher the investment
  - The higher the aspiration, the higher the investment
- Aspiration reached ($t \geq t_0$):
  - Invest until $MC = MB$
  - **Complement** - the higher the ability belief, the higher the investment

Experiment

Location: Guizhou, China
Participants: Parents of High-school students (12th grade)
Experiment: Change parents' belief & aspiration exogenously

Remove biases caused by two types of information frictions

- Friction 1: Can't predict future performance
  - e.g. Parents' prediction accuracy



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- Friction 1: Can't predict future performance
  - e.g. Parents' prediction accuracy
- Friction 2: Can't match in-school ranking to colleges
  - Performance information: in-school rank
  - College Admission: in-province rank
  - Cohort sizes: 1,000 v.s. 400,000

Intervention 1: ML Prediction

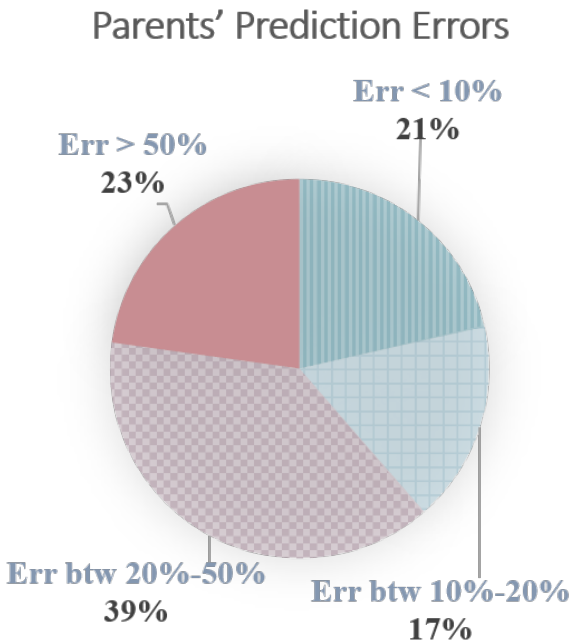
Issue 1: Can't predict future performance

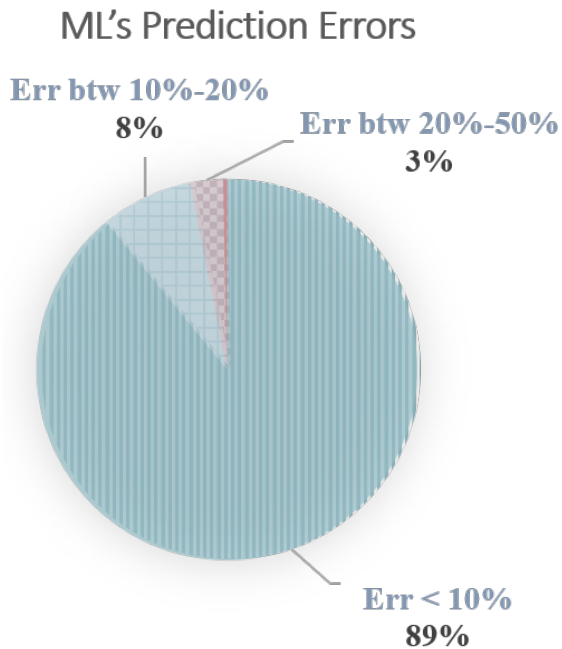
Intervention 1: Machine Learning prediction of future performance

- Prediction of in-school ranking at CEE period
- LASSO algorithm
  - Trained with rich administrative data on alumni's performance
  - 5-fold cross-validation & bootstrapping
  - Pick around 40 most predictive variables out of 4000+
  - Most predictive variables:
    - Performance in late 11th-grade
    - Performance on math & physics

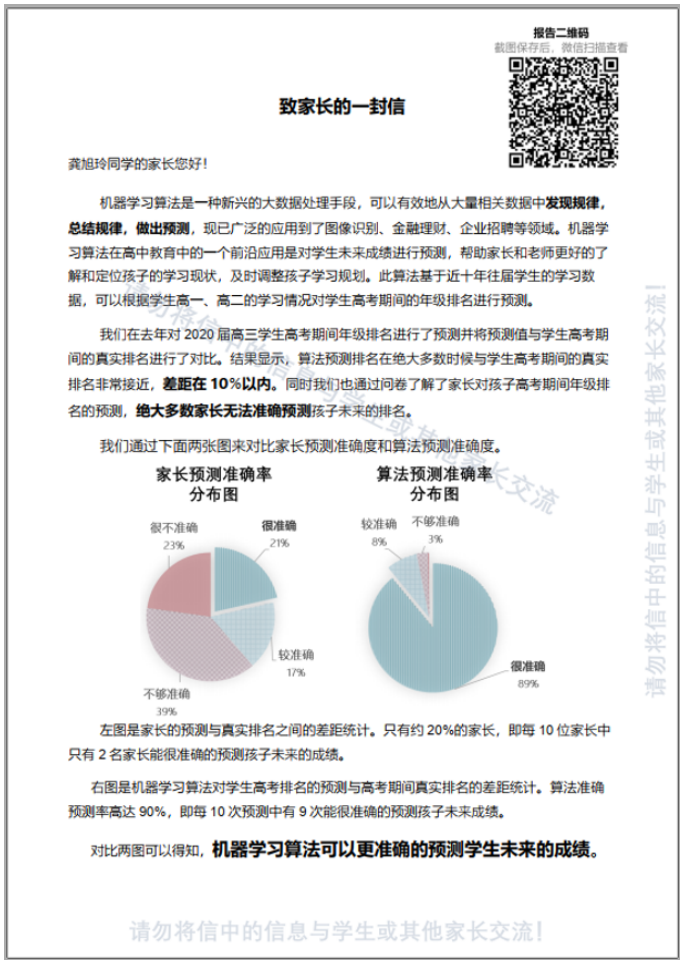
Intervention 1: ML Prediction

- Prediction power:
  - Out-of-Sample prediction power: $R^2 > 96\%$
  - More accurate than parents' predictions





Intervention 1: ML Prediction Report Sample



报告二维码
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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。

家长预测准确率分布图

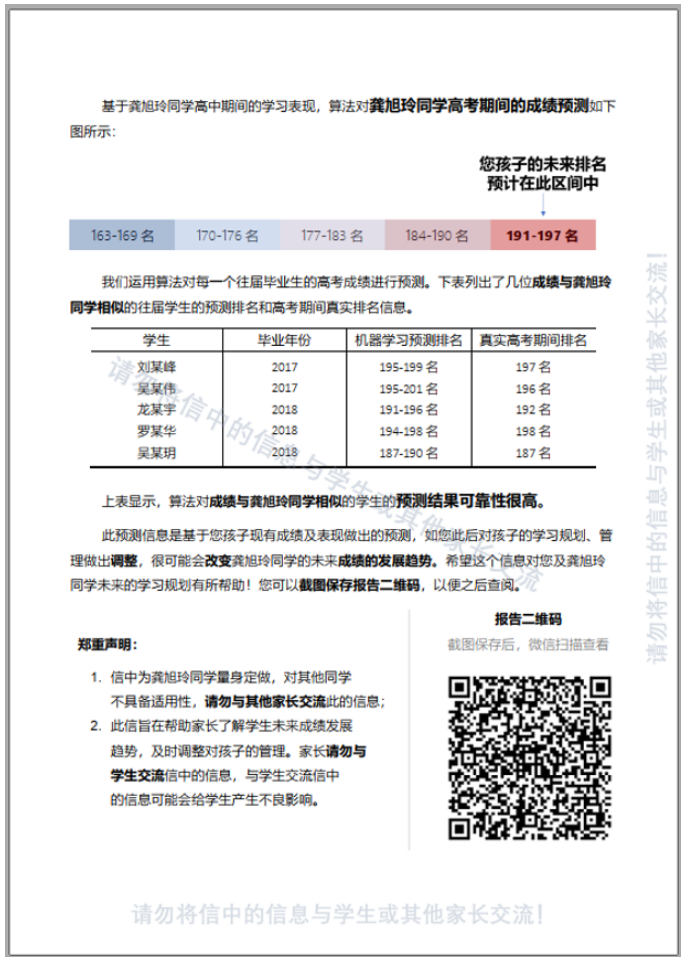
算法预测准确率分布图

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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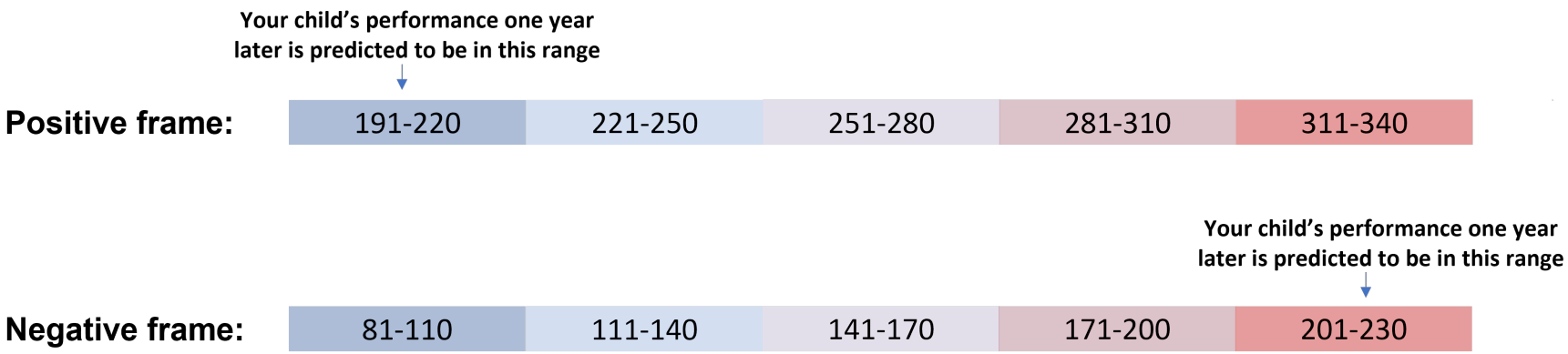
请勿将信中的信息与学生或其他家长交流！

Intervention 1: ML Prediction

The Machine Learning Report includes:

- Introduction to Machine Learning algorithm
- Comparison of algorithm & parents' prediction
- Predicted rank range
  - Randomize framing styles - add random variation to shock intensity
  - e.g. if the student's ML prediction is 201-220



Intervention 2: Rank-to-College Matching

Issue 2: Can't match in-school ranking to college levels

Intervention 2: Rank-to-College Matching Report

- The CEE score of students with similar in-school ranking
- The best three college these students can get in 2017 & 2018
- Random variation in treatment intensity with framing style
  - e.g. real in-school ranking is 200
  - Positive 180 v.s. Negative 220

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

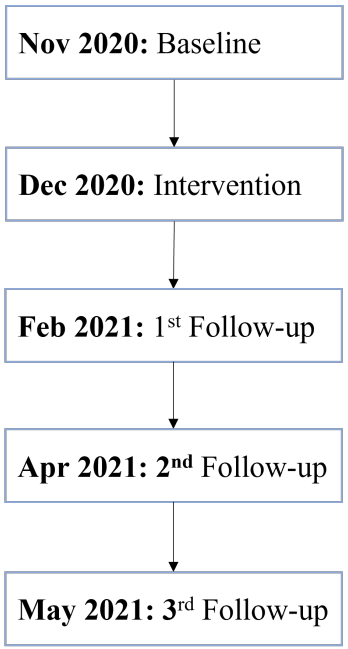
2017 年高考的学子中，年级第 642 名的学生的高考分数为 437 分，可就读的前三所院校信息如下（仅列举 3 所院校作为例子）

	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

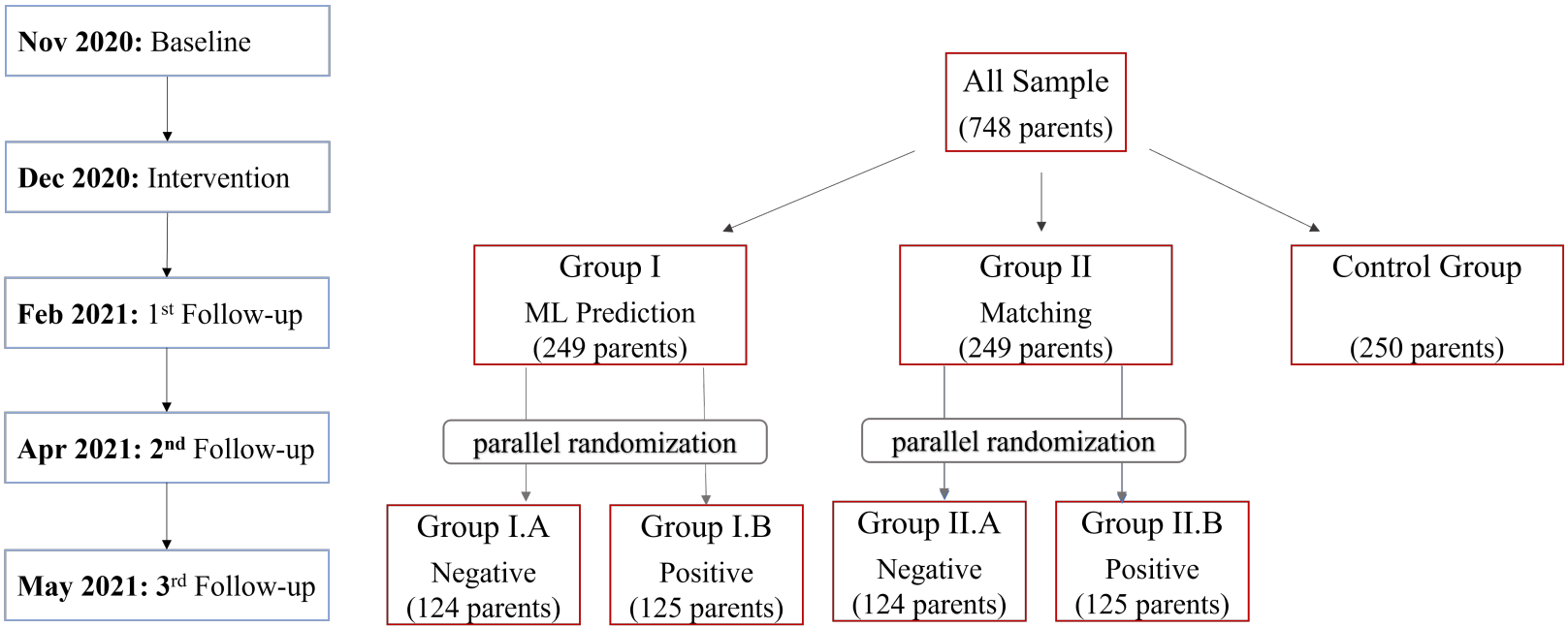
2018 年高考的学子中，年级第 642 名的学生的高考分数为 458 分，可就读的前三所院校信息如下（仅列举 3 所院校作为例子）

	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

Experimental Design & Timeline



Experimental Design & Timeline



Data

Survey data

- Parental Ability Belief: in-school ranking belief
- Aspiration
  - IdealTier: Ideal tier of college (1-7 tiers, Tier 1 are top colleges)
  - GoalRank: Parents' belief about the in-school ranking needed for ideal tier of college
- Parental Investment (in the past two months)
  - Monetary investment
    - Education-related: private tutoring and practice books
    - Other issues: allowance and transportation fees
  - Time investment
    - Education-related: monitor studying, communicate with teachers
    - Other issues: entertainment activities with children
- Demographics
  - Parents' education backgrounds
  - Household's annual income
  - Number of kids
  - Network with other parents

Data

Administrative data

- Cohort 2011-2020
  - Performance data on all monthly exam in high school
  - CEE score & Colleges they can get in
  - Train Machine Learning algorithm & Match in-school ranking to colleges
- Cohort 2021
  - Monthly exam performance data (in-school ranking overtime)
  - Two province-level exams (in-province ranking)
    - Pre: Province-Level mock exam
    - Post: CEE

Summary Statistics - Demographics

Table 1 Pre-Intervention Summary Statistics - Demographics

	ML	Matching	Control	Total
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)
Sample Size	249	249	250	748

- Average household annual income: 50k- 100k Yuan (7.7k - 15.4k USD)
- Average Parents' education background: secondary to high school

Summary Statistics - Parental Investment

Table 2 Pre-Intervention Summary Statistics - Parental Investment

	ML	Matching	Control	Total
Edu. Monetary Inv.[A]	2687.7	2619.2	2608.4	2638.4
	(2832.6)	(2754.0)	(2228.8)	(2617.3)
Oth. Monetary Inv.[A]	1439.9	1396.0	1300.6	1378.6
	(1404.6)	(1364.8)	(1111.2)	(1299.2)
Edu. Time Inv.[B]	26.68	26.37	25.10	26.05
	(25.43)	(24.79)	(22.61)	(24.28)
Oth. Time Inv.[B]	14.67	14.06	13.00	13.91
	(15.43)	(13.93)	(11.69)	(13.76)
Sample Size	249	249	250	748

- Educational investments are twice of non-educational investments
- Edu. monetary investment is around 20% of monthly household income

Summary Statistics - Performance and Belief

Table 3 Pre-Intervention Summary Statistics - Performance& Belief

	ML	Matching	Control	Total
SchoolRank	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^{A}	4.089	4.048	4.084	4.074
	(1.747)	(1.724)	(1.767)	(1.744)
GoalRank	205.7	202.4	198.9	202.4
	(154.5)	(147.0)	(147.2)	(149.4)
Sample Size	249	249	250	748

- Parents are too optimistic:
  RankBelief-Rank = -42
- In parents' belief, most students haven't reached parental aspiration:
  327.8 v.s. 202.4

Summary Statistics - sample balance check

No significant difference across groups in baseline

Table 4 Sample Balance Check with OLS

A. Demographics

VARIABLES	IncomeLevel	ChildNum	FatherEdu	MotherEdu
	(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)	$ln(\lvert RankBelief - SchoolRank\rvert)$	ln(SchoolRank)	IdealTier	ln(GoalRank)
	(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.)	ln(Oth. Monetary Inv.)	ln(Edu. Time Inv.)	ln(Oth. Time Inv.)
	(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

Preview of Empirical Results 1

- Two treatments significantly eliminated existing information frictions
  - Realize children's ability is not as high:
    - Belief about in-school ranking increases by 6%,
    - **Belief inaccuracies** decrease by 50%
  - Realize ideal colleges are more difficult to get into:
    - Perceived difficulty becomes 6% higher
    - Parents aim at colleges below their previous goals (by around 0.11)
- Educational monetary investment significantly increases by 4.8% and 3.1%
- Children's in-province ranking get improved by 6.5% and 4.8%

Preview of Empirical Results 2

- causal impacts of belief on investment is nonlinear around aspiration
  - Aspiration not reached:
    - Ability belief becomes worse by 1% $\Longrightarrow$ edu. monetary investment increases by 1.7%
    - Aspiration becomes higher by 1% $\Longrightarrow$ edu. monetary investment increases by 0.6%
  - Aspiration reached:
    - No significant effects
    - Significantly different from the not-reach case
- Investment driven by the intervention is effective
  - edu. monetary investment increases by 1% $\Longrightarrow$ academic performance get improved by 0.6%

Empirical Model - Pooled Sample

$$\begin{aligned} Y_{it} = \alpha + \gamma_i + \lambda Post + \beta_1 Post \cdot ML_i \cdot LessPositive_i \\ + \beta_2 Post \cdot ML_i \cdot MorePositive_i \\ + \beta_3 Post \cdot Matching_i \cdot LessPositive_i \\ + \beta_4 Post \cdot Matching_i \cdot MorePositive_i + \epsilon_{it} \end{aligned} \tag{1}$$

Y_{it} : belief inaccuracy, ideal tier, etc

$Post_{it}$=1 if the observation is post-intervention

Empirical Model - All Period

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

$Round_t$=1 if the observation is from round t

Empirical Results: Ability Belief

Table 5 Effects on Parental Ability Belief (Pooled)

VARIABLES	$ln(RankBelief)$		$ln(\lvert RankBelief - SchoolRank \rvert)$	
	(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	

- Ability belief become worse in machine-learning groups
- Dramatic reduction in belief inaccuracies
- Negative framing generates larger impacts as it causes a bigger shock

Empirical Results: Aspirations

Table 6 Effects on Parental Aspiration (Pooled)

VARIABLES	*ln(GoalRank)*		*IdealTier*	
	(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			

- Matching treatment make parents realize the difficulty of college admission
- Some parents aim at colleges below their previous goals
- Effects are statistically significant only in the group with negative framing

Empirical Results: Investments

Table 7 Effects on Parental Investments (Pooled)

VARIABLES	*ln(Edu.MonetaryInv.)*		*ln(Oth.MonetaryInv.)*		*ln(Edu.TimeInv.)*		*ln(Oth.TimeInv.)*	
	(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							

- Both interventions significantly increased educational monetary investment
- Effects are significant only for groups with information framed more negatively
- No effects have been identified on the other three types of investments

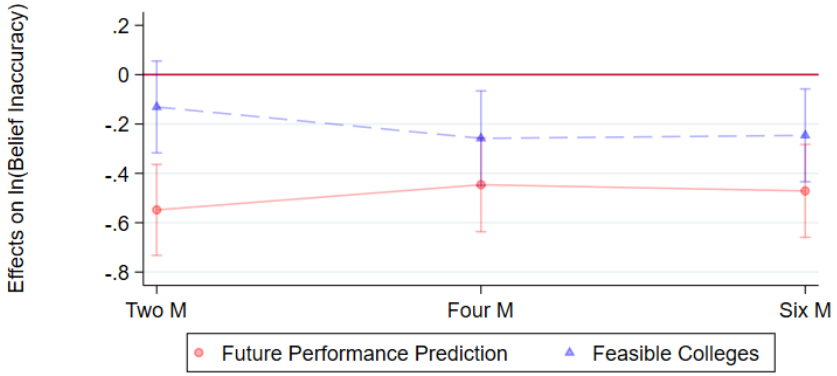
Empirical Results: Performance

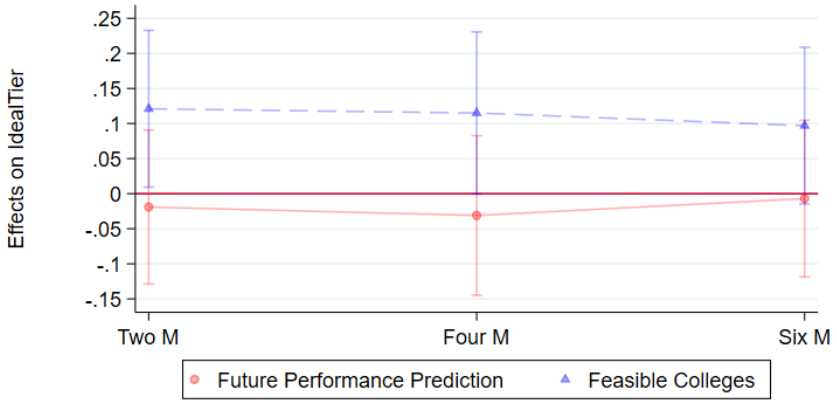
Table 8 Effects on Students' Performance (Pooled)

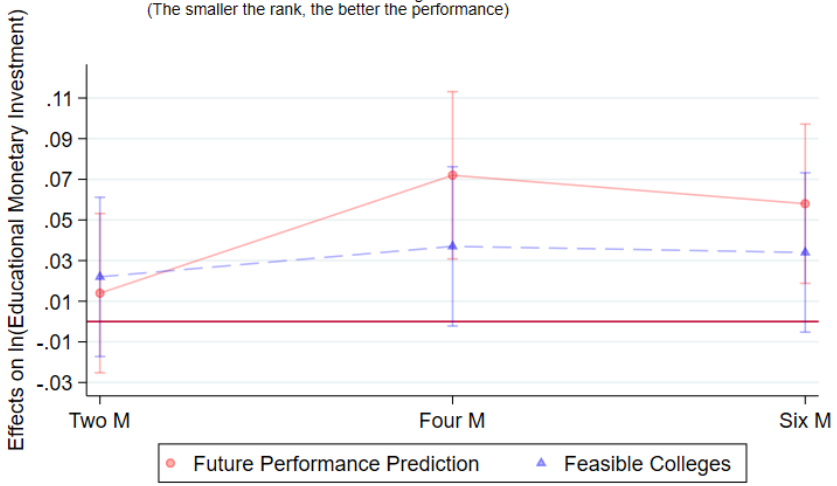
VARIABLES	*ln(SchoolRank)*		*ln(ProvRank)*	
	(1)	(2)	(3)	(4)
Post		0.029***		-0.017
		(0.006)		(0.017)
Post X ML	-0.029***		-0.065***	
	(0.009)		(0.024)	
Post X Matching	-0.020**		-0.048**	
	(0.009)		(0.024)	
Post ML X Negative		-0.034***		-0.069**
		(0.011)		(0.029)
Post X ML X Positive		-0.024**		-0.060**
		(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			

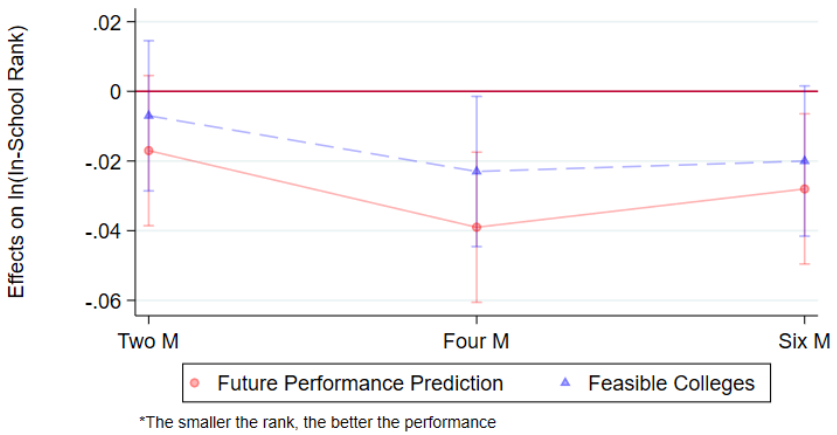
- Performance get significantly improved in both treatment groups
- The impact is especially salient among negative framing

Empirical Results: Dynamic Effects









- Ability beliefs & aspirations get updated shortly and persist overtime
- Educational monetary investment adjustments & performance improvement are lagged by two months

Empirical Model - 2SLS

Reach $= 1$ if $RankBelief_{baseline} \leq GoalRank_{baseline}$
NoReach $= 1$ if $RankBelief_{baseline} > GoalRank_{baseline}$

R_{it}: *NoReach X ln(RankBelief)*, *Reach X ln(RankBelief)*,
NoReach X ln(GoalRank), *Reach X ln(GoalRank)*

1st Stage:

$$\hat{R}_{it} = \alpha + \gamma_i + \sum_{t=1}^{3} (\theta_t Round_t + \theta_t Round_t \cdot Reach_i + \mu_{zt} \cdot Z_i + X_{it}^{'} \beta + \epsilon_{it}) \quad (3)$$

2nd Stage:

$$Y_{it} = \lambda + \eta_i + \tau_1 Round_t + \tau_2 Round_t \cdot Reach_i + \sigma_R \widehat{R}_{it-1} + X_{it}^{'} \beta + \epsilon_{it} \quad (4)$$

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

Empirical Results: Investment 2SLS

Table 9 2SLS - Effects of Belief and Aspiration on Investments

VARIABLES	$ln(Edu.MonetaryInv.)$	$ln(Oth.MonetaryInv.)$	$ln(Edu.TimeInv.)$	$ln(Oth.TimeInv.)$
	(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		

- Find significant nonlinearity around the aspiration
  - Ability belief
  - Aspiration

Empirical Results: Performance 2SLS

Table 10 2SLS - Effects of Investments on Performance

VARIABLES	*ln*(*SchoolRank*)	*ln*(*ProvRank*)
	(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	

- The additional parental educational monetary investments initiated by the treatments are effective
- Lack of power for the identification of causal effects of other types of investments

Conclusion

- reveals two information frictions
  - Prediction bias
  - Poor Matching
- Proposes and tests two novel interventions which significantly eliminate existing information frictions
  - 49% reduction in inaccuracies in parental belief about their children's ability
  - 5% increase in parental educational monetary investments
  - 3% improvement in students' performance
  - Apply big data techniques to help with decision optimization
- Pin down the causal relationship between parental ability belief and educational investments
  - Nonlinear around parents' aspirations
  - Understand when and why parental investments and students' ability become substitutes or complements
  - Prior beliefs and aspirations are important for policy designs

Other On-going Projects

- Parental educational investments
  - Understanding Mechanisms Underlying Peer Effects on Educational Investment Among Parents: Evidence from China
  - Invest in Talented or Invest in Disadvantaged: How Aspirations Affect Parents' Investment Strategy
- The applications of big-data techniques
  - Worker Screening: Applications of Machine Learning Methods to Firm Decision-Making (with Jing Cai and Shing-Yi Wang)
  - How Machine Learning Techniques Help Students' Optimize Their Curriculum Choices and College Admissions
- Future: generalize the methodology to broader settings
  - Poverty alleviation
  - Collaborate with banks,insurance companies, and e-commerce companies

Thanks!

All comments and feedback will be appreciated!

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