STANFORD BUSINESS GRADUATE SCHOOL OF

Effective and scalable programs to facilitate labor market transitions for women in technology

Susan Athey & Emil Palikot

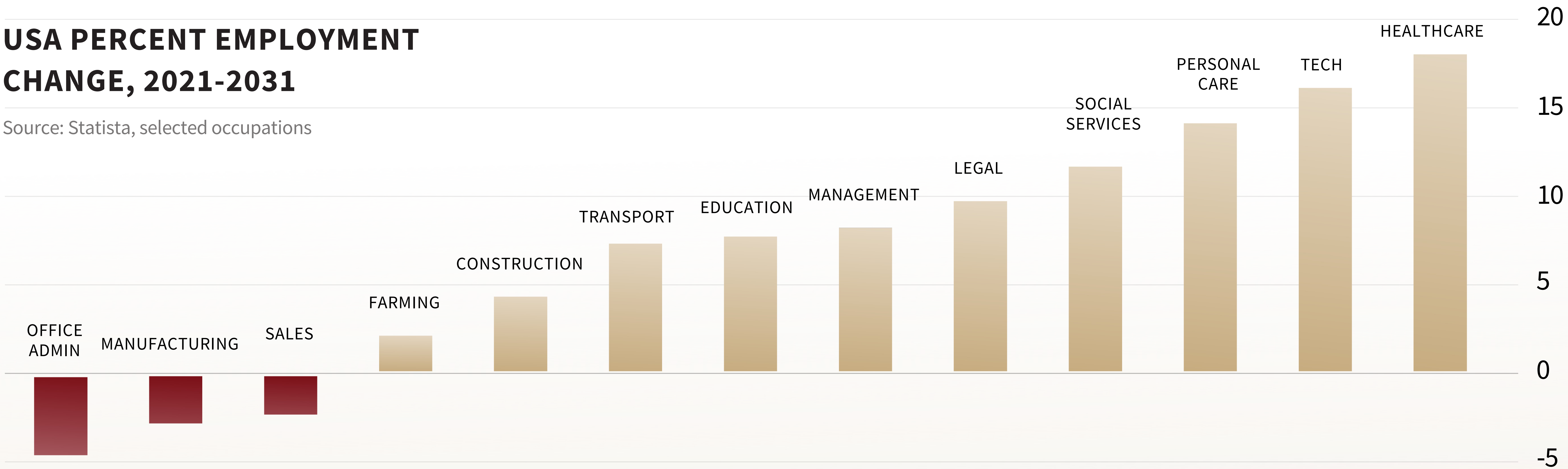
NBER SI | 7/22/2024

Structural changes in the labor market

STANFORD GRADUATE SCHOOL OF BUSINESS

USA PERCENT EMPLOYMENT CHANGE, 2021-2031

Source: Statista, selected occupations



- In 2021, 53% of U.S. workers that switched jobs, changed occupation
- Important policy challenge to support transitions into growing occupations

The top 15 emerging jobs in the U.S.

STANFORD BUSINESS GRADUATE SCHOOL OF

Fastest growing high-paying jobs

1. AI Specialist
2. Robotics Engineer
3. Data Scientist
4. Full Stack Engineer
5. Site Reliability Engineer
6. Customer Success Specialist
7. Sales Development Representative
8. Data Engineer
9. Behavioral Health Technician
10. Cybersecurity Specialist
11. Back End Developer
12. Chief Revenue Officer
13. Cloud Engineer
14. JavaScript Developer
15. Product Owner

Source: LinkedIn

The top 15 emerging jobs in the U.S.

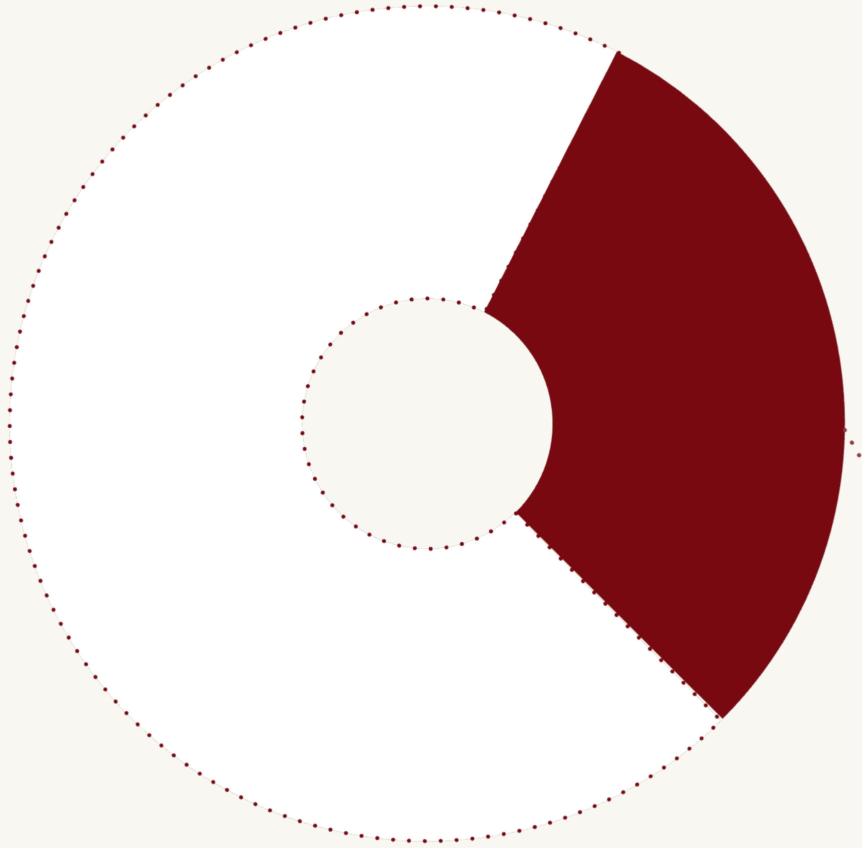
STANFORD BUSINESS GRADUATE SCHOOL OF

Fastest growing high-paying jobs

1. AI Specialist
2. Robotics Engineer
3. Data Scientist
4. Full Stack Engineer
5. Site Reliability Engineer
6. Customer Success Specialist
7. Sales Development Representative
8. Data Engineer
9. Behavioral Health Technician
10. Cybersecurity Specialist
11. Back End Developer
12. Chief Revenue Officer
13. Cloud Engineer
14. JavaScript Developer
15. Product Owner

Source: LinkedIn

Women are **underrepresented** in tech



~30%

of tech jobs worldwide is occupied by women

Source: United Nations (2022)

STANFORD BUSINESS GRADUATE SCHOOL OF

Which specific solutions or programs can help women transition to the technology sector?

?

This project

Carries out a randomized evaluation of a traditional 1-1 in-person mentoring program (***Mentoring***)

Designs, develops, implements, and evaluates an online program called ***Challenges*** with a focus on portfolio development

Develops and counterfactually evaluates targeting and scaling policies

Main findings

STANFORD BUSINESS GRADUATE SCHOOL OF

40%

Challenges as well as *Mentoring* increase probability of finding a job in the technology sector by over 40%

$15

Challenges is cost effective (only $15 per person), easy to scale, and transfer (already offered in multiple languages and tech specializations)

10pp

Targeting admission based on the characteristics of applicants further increases programs' effectiveness by 10 percentage points (pp)

Literature review

STANFORD BUSINESS GRADUATE SCHOOL OF

1. Mentoring:
   - Evidence from other contexts: Alfonsi et al. (2022), Ginther et al. (2020)
   - Not scalable, particularly in the context of growing occupations
     - Group mentoring, peer mentoring – observational/small-scale evidence mostly from academic settings – Nisbet & McAllister (2015), Mitchell (1999)
     - Technology-assisted mentoring – evidence mostly from education and small-scale – Lindsay et al. (2018), Li (2018)

2. Non-traditional more scalable approaches: Boot camps, coding academies, MOOCs, etc.:
   - Effectiveness of blended (in-person & online) offerings - Chirikov (2020)
   - Shortage of empirical evidence
     - MOOCs - No RCT-based evidence; studies based on observational data show mixed results Hadavand et al. (2018), Castano-Munoz & Rodrigues (2021)
     - Athey & Palikot (2023) – effective way to signal skills *(not yet posted)*

Literature review

STANFORD BUSINESS GRADUATE SCHOOL OF

3. Active labor market programs
   - Mostly blue-collar jobs and gov. funded programs
     - Most of programs are ineffective- on average close to zero impact on short term employment, some small positive impact in medium term
       - Meta study Card et al. (2018)
       - Barnow (1987), Bloom et al. (1997), Heckman et al. (1999)
   - The effective programs tend to focus on practical skills Lechner & Gerfin (2010), Sianesi (2008), YearUp – Fein & Hamadyk (2018), or signal of skills Adebe et al. (2020)

4. Off-policy methods for policy targeting
   - Highest impact vs. highest outcomes - Customer churn - Ascarza (2018), development - Haushofer et al. (2022), financial aid - Athey et al. (2023)

Agenda/ Project Timeline

Dare IT operates *Mentoring*

1

Challenges ideation and project development

2

Challenges and *Mentoring* experiment design

3

Summer & Autumn 2021

Programs take place

Winter & Spring 2022

Evaluation

4

Summer 2022/ Spring 2023

5

Targeting policies and further scaling

Dare IT & the Mentoring Program

Dare IT Mentoring Program

- **Mentees** – women that have the skills to get a job in tech, but no job
- **Mentors** – mid-career tech workers, women, volunteers
- **Format** – 1:1 over 3 months
- **Free-of-charge**

Dare IT Mentoring Program

- **Repeatedly over-subscribed** –10 eligible candidates per spot
- **Hard to scale:**
  - 1:1 format requires matching, supervision, conflict resolution etc.
  - Recruitment and training of mentors
- Applicants actively seek out this opportunity – Dare IT does not advertise
- Applications are manually reviewed for eligibility
  - Everyone has the skills to do the job

Scaling-up Dare IT operations

Interviews with HR & hiring managers

STANFORD BUSINESS GRADUATE SCHOOL OF

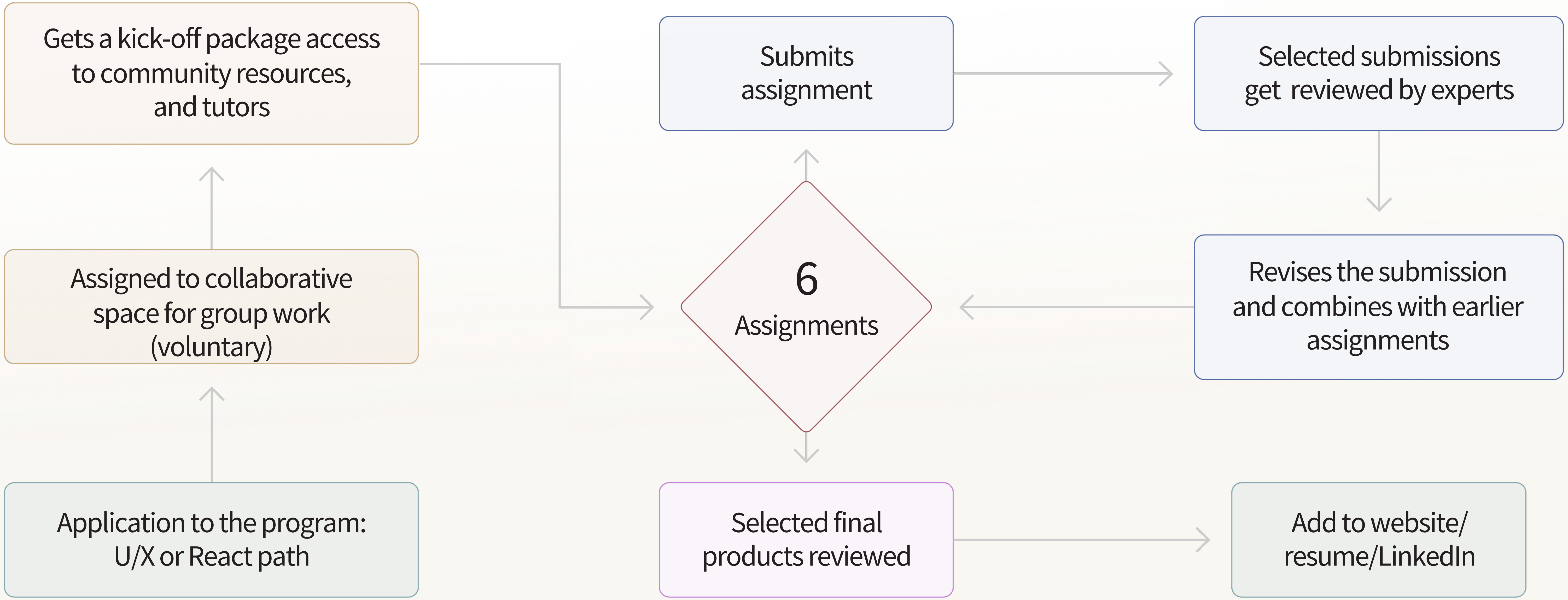
"Interviews with candidates with no practical experience lack dynamism, they focus on high level stuff … which hurts the candidate"

- Interviews with HR employees and hiring managers from over a dozen of Polish tech firms
- Each interviewee mentioned lack of practical experience or signals of practical skills

Challenges program

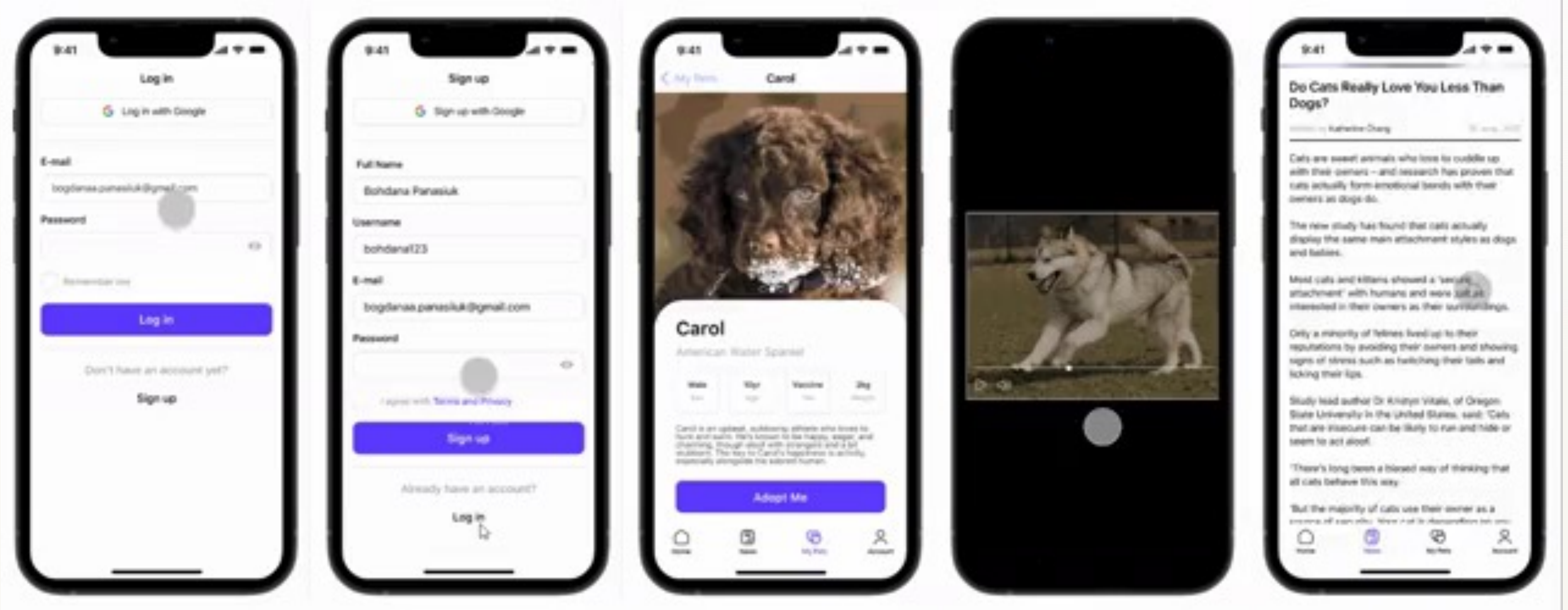
Participants:

- Need to have skills to participate
- Solve assignments prepared by practitioners to build a portfolio item



Challenges – example of a final product

- In U/X path the goal was to develop a design of a mobile app
- Example, *Promyk* an app for adoption of animals (link)



Experiment design and evaluation

Experiment design

STANFORD GRADUATE SCHOOL OF BUSINESS

Mentoring

~ 1000 applicants after screening

each mentor shortlists 2 applicants

160 pairs

treatment

control

Challenges

~ 600 applicants

100 first applicants

admitted to the program and removed from the analysis

treatment

control

Both experiments pre-registered in the AEA RCT Registry

Primary outcome – “tech job”

STANFORD BUSINESS GRADUATE SCHOOL OF

A job that a candidate added to their LinkedIn profile during or after the program that is:

- In a technology company other than positions finance, regulatory, legal, accounting, and HR, where technology companies include firms in software development, testing, and sales; data analytics; IT services; digital marketing; and online platforms.
- Jobs in non-technology companies that involve software development and testing, IT support, and data analytics; mostly banks and management consultancies.

Mentors, mentees, Challenges participants and the control groups

STANFORD BUSINESS GRADUATE SCHOOL OF

Mentors

- 45% are Dare IT mentors for the first time
- 52% have managerial experience
- 70% are career-changers

Mentoring groups

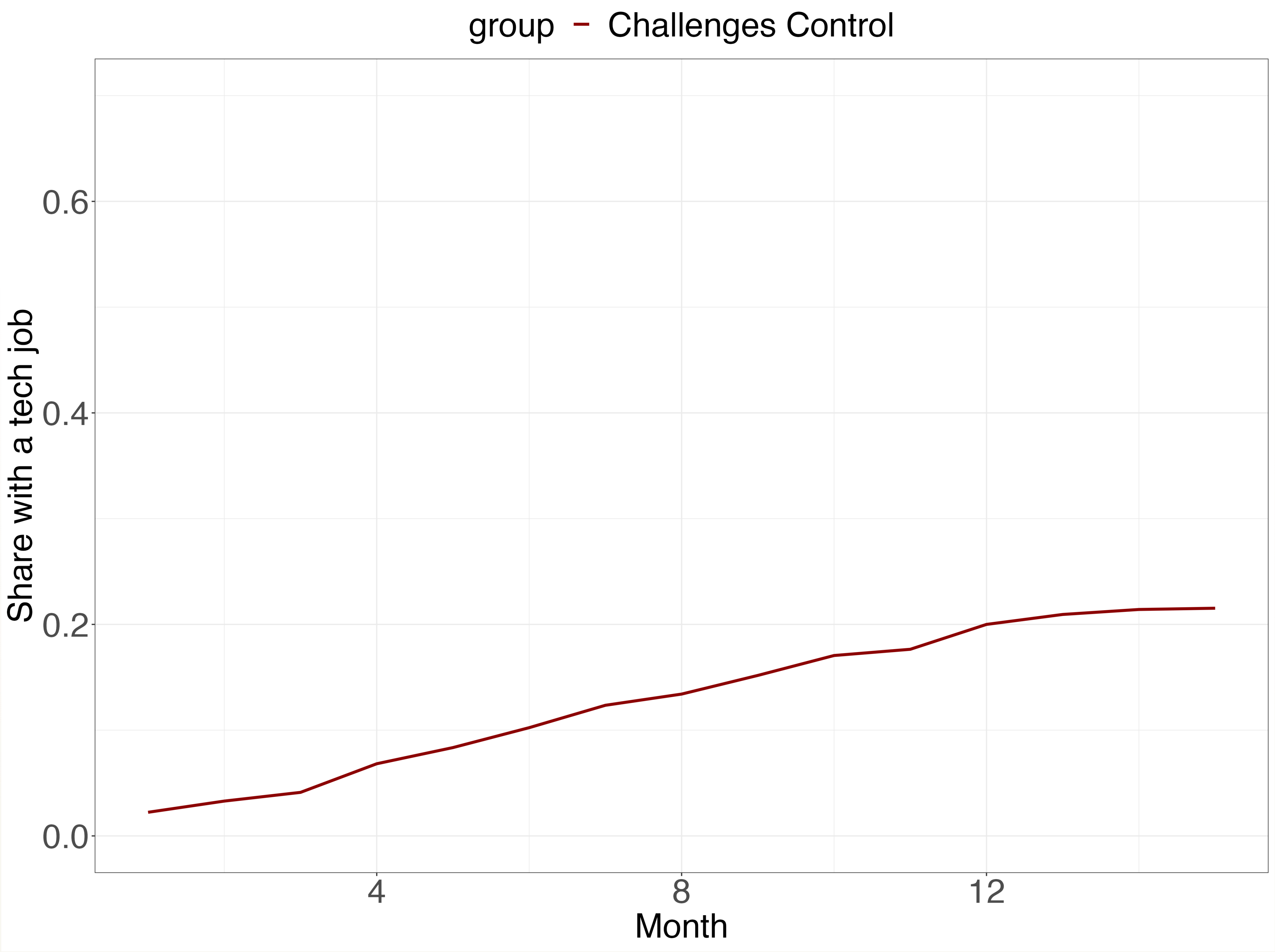
- 13% social sciences, 50% STEM
- 24% live in smaller towns
- On average 7 years prof. exp
- 50% above 30 years old

- 70% have family or friends in tech
- 26% are mothers

Challenges groups

- 23% social sciences, 40% STEM
- 50% live in smaller towns
- On average, 7.5 years of prof. exp
- 52% above 30 years old

Average treatment effects



Mentoring experiment – 300 subjects, Challenges – 400 subjects

Average treatment effects

Mentoring experiment – 300 subjects, Challenges – 400 subjects

Average treatment effects

STANFORD BUSINESS GRADUATE SCHOOL OF

In the 8th month after application*

Mentoring increases the probability of having a tech job by 13pp (S.E. 5pp)

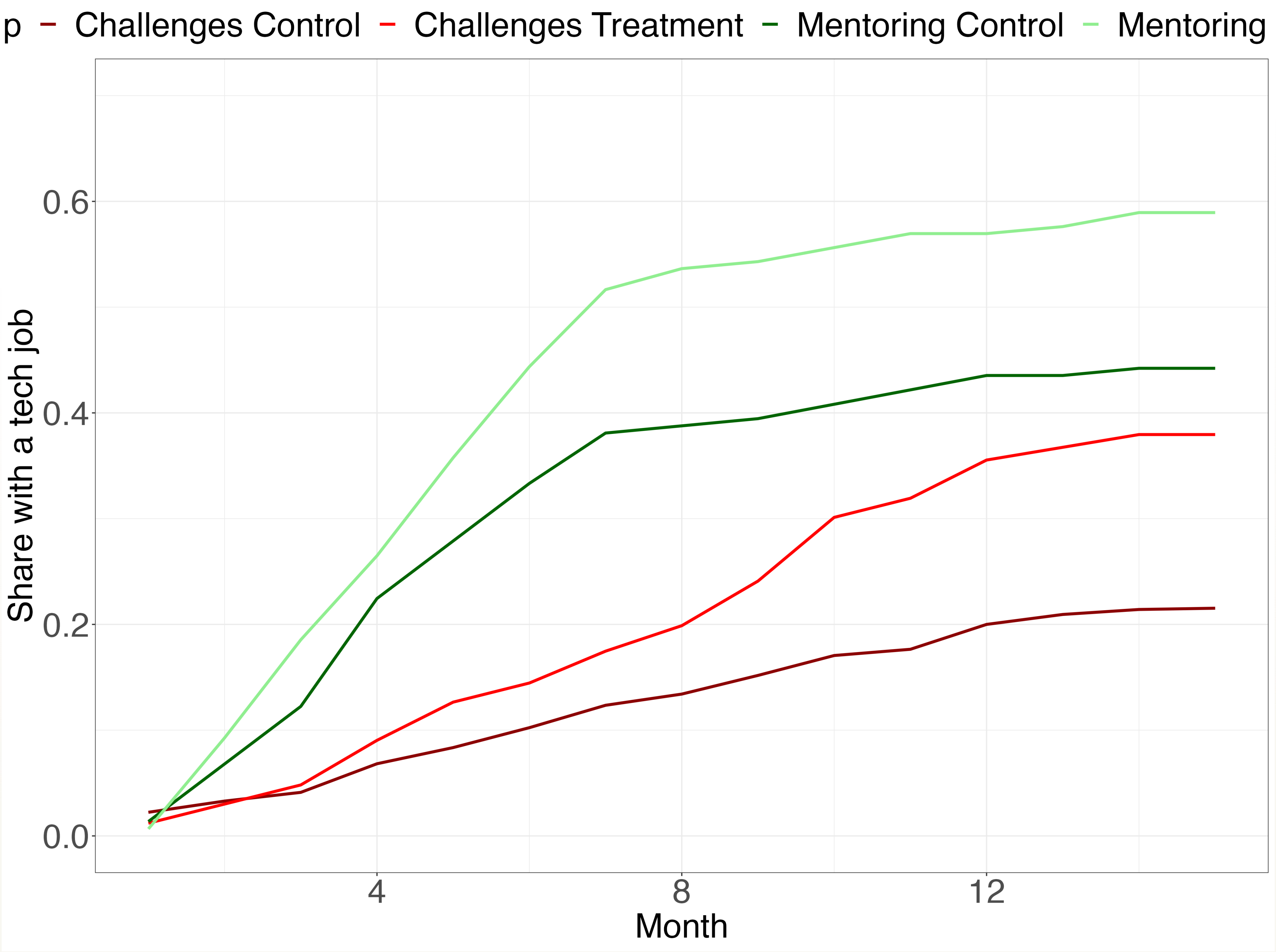
Challenges by 9pp (S.E. 4pp)

Across 16 months after application**

Mentoring increases the probability of having a tech job by 13pp (S.E. 2.5pp)

Challenges by 7pp (S.E. 2pp)

**Difference in means estimator, **Cox model*



Mentoring experiment – 300 subjects, Challenges – 400 subjects

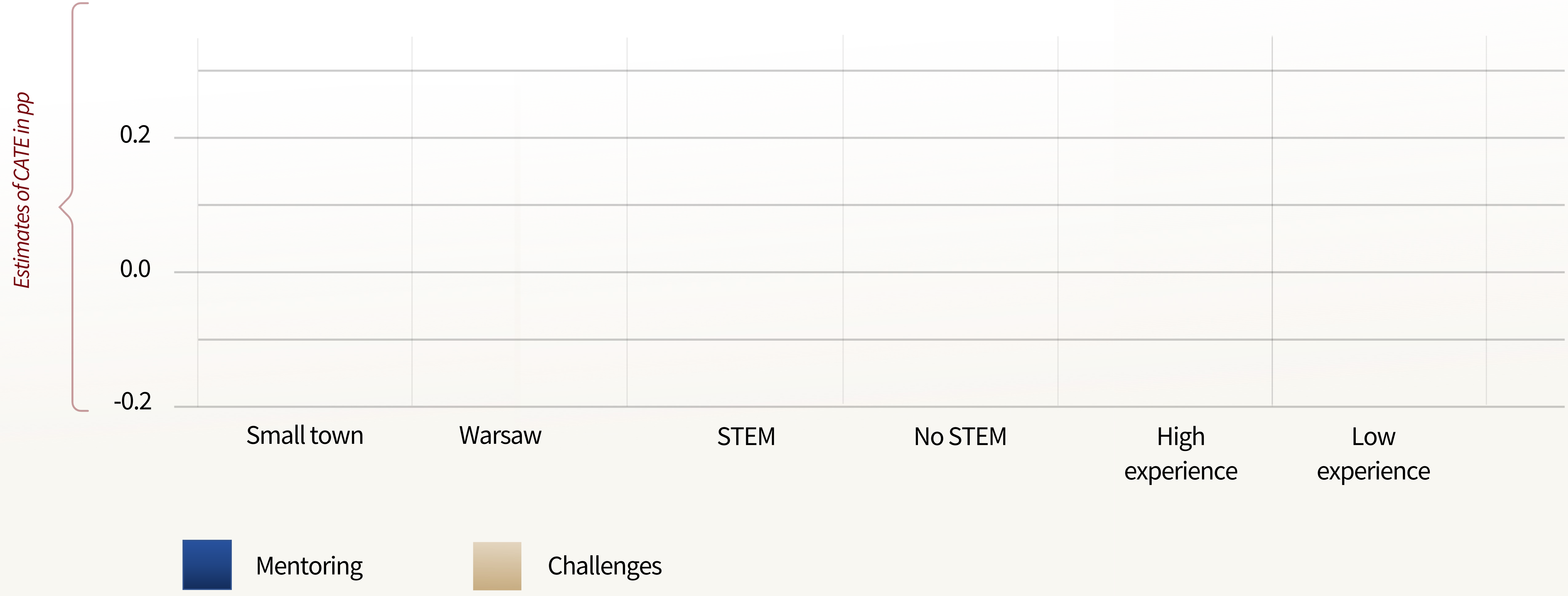
BUT

Treatment effects are highly heterogenous

Heterogenous treatment effects – tech job 16 months

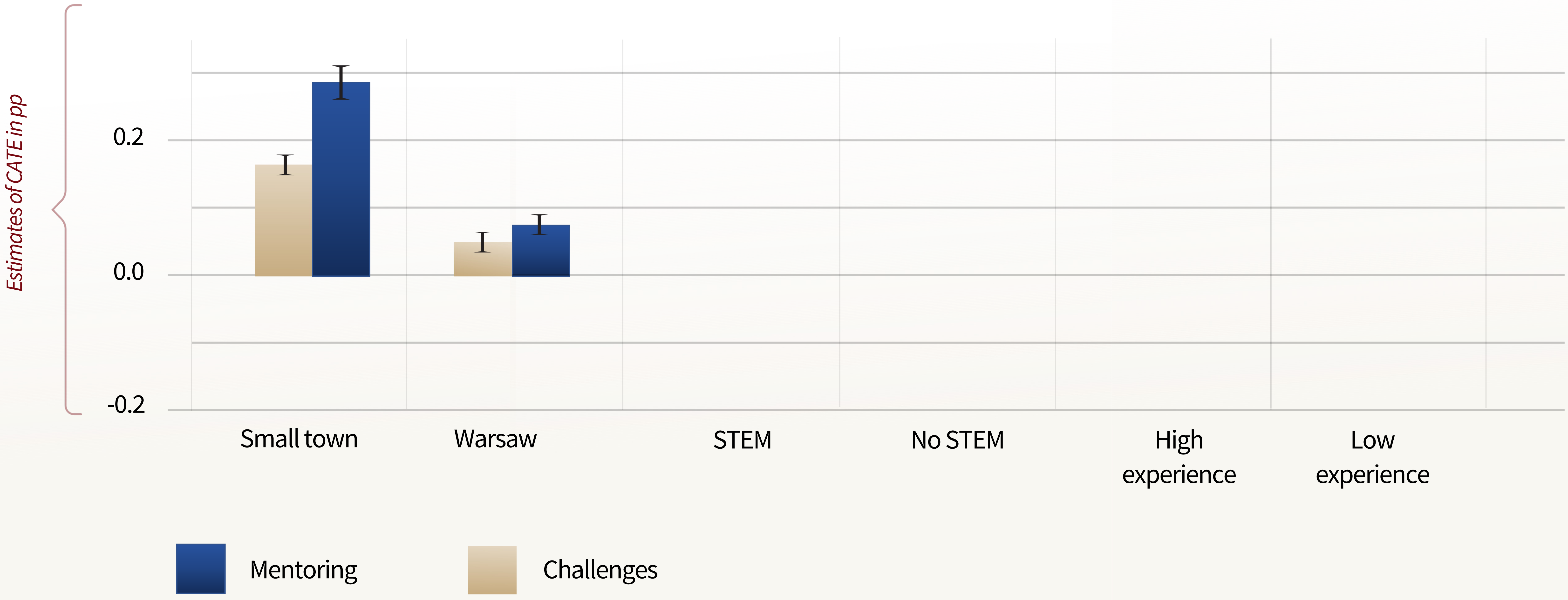
STANFORD BUSINESS GRADUATE SCHOOL OF

Estimates of the conditional average treatment effects in percentage points. In blue for Mentoring and in yellow for Challenges. Whiskers show standard errors.



Heterogenous treatment effects – tech job 16 months

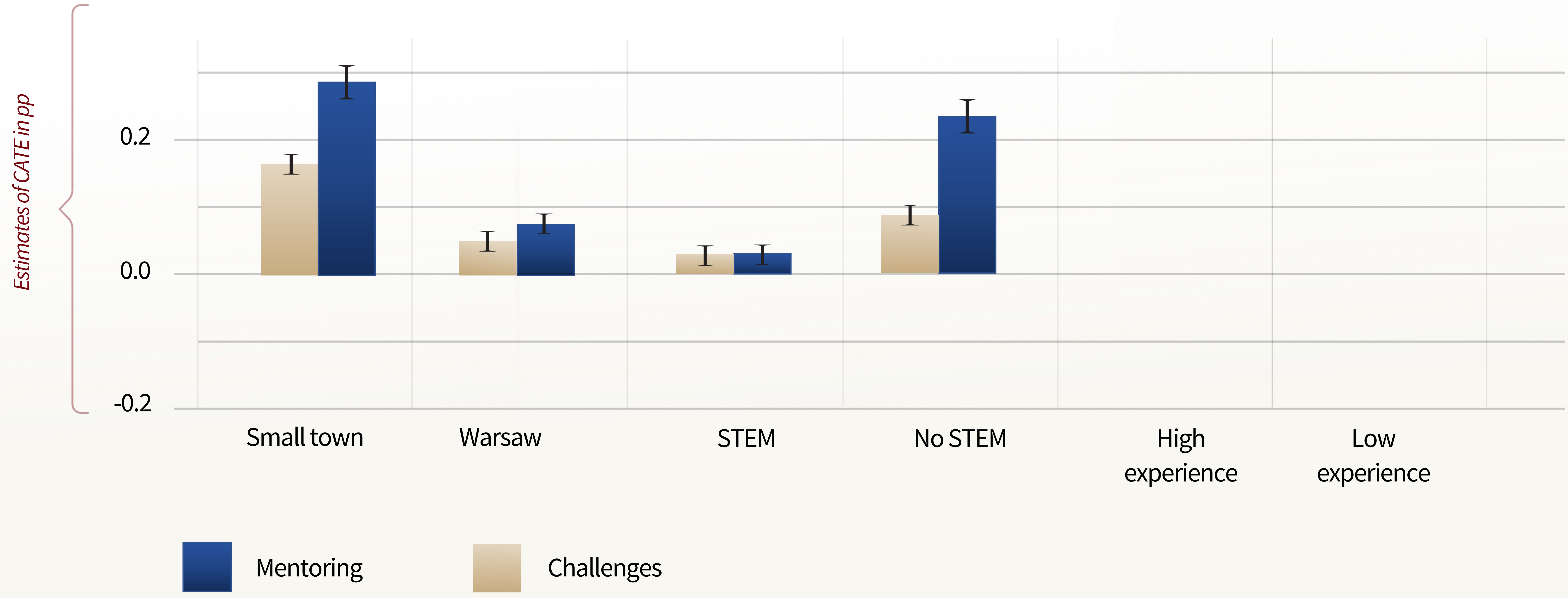
Estimates of the conditional average treatment effects in percentage points. In blue for Mentoring and in yellow for Challenges. Whiskers show standard errors.



Heterogenous treatment effects – tech job 16 months

STANFORD GRADUATE SCHOOL OF BUSINESS

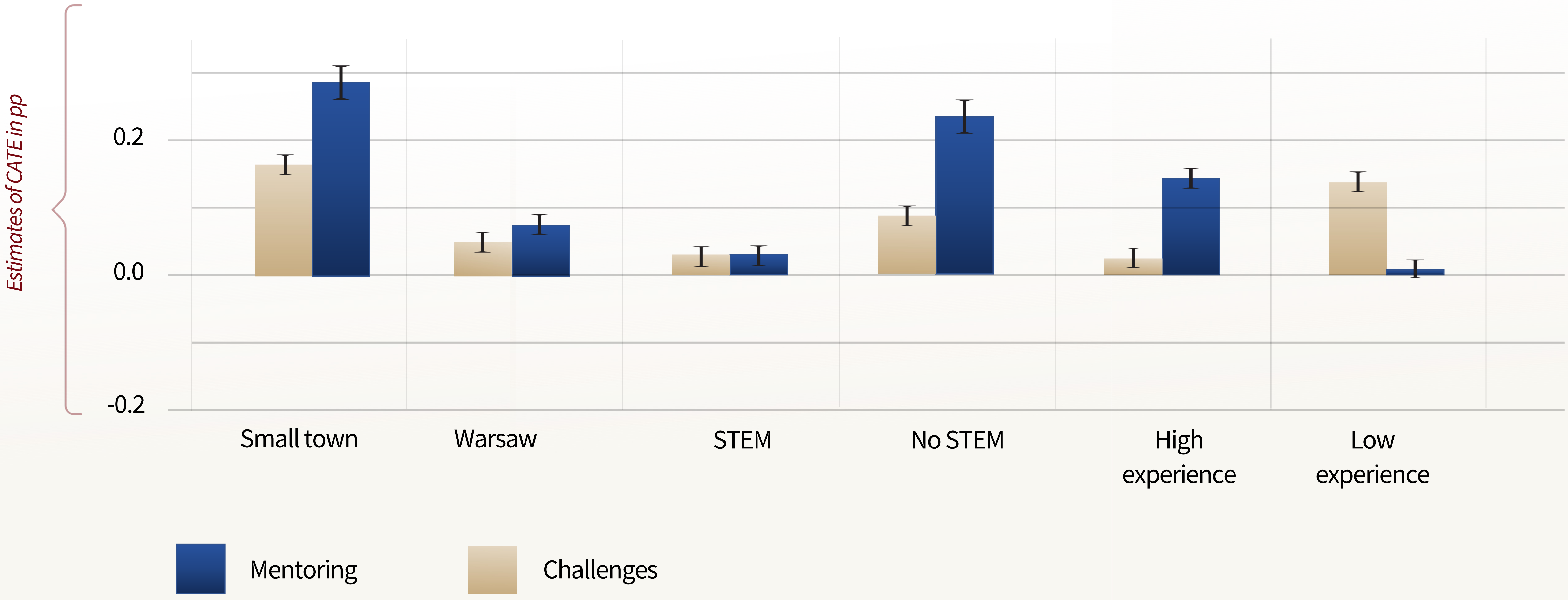
Estimates of the conditional average treatment effects in percentage points. In blue for Mentoring and in yellow for Challenges. Whiskers show standard errors.



Heterogenous treatment effects – tech job 16 months

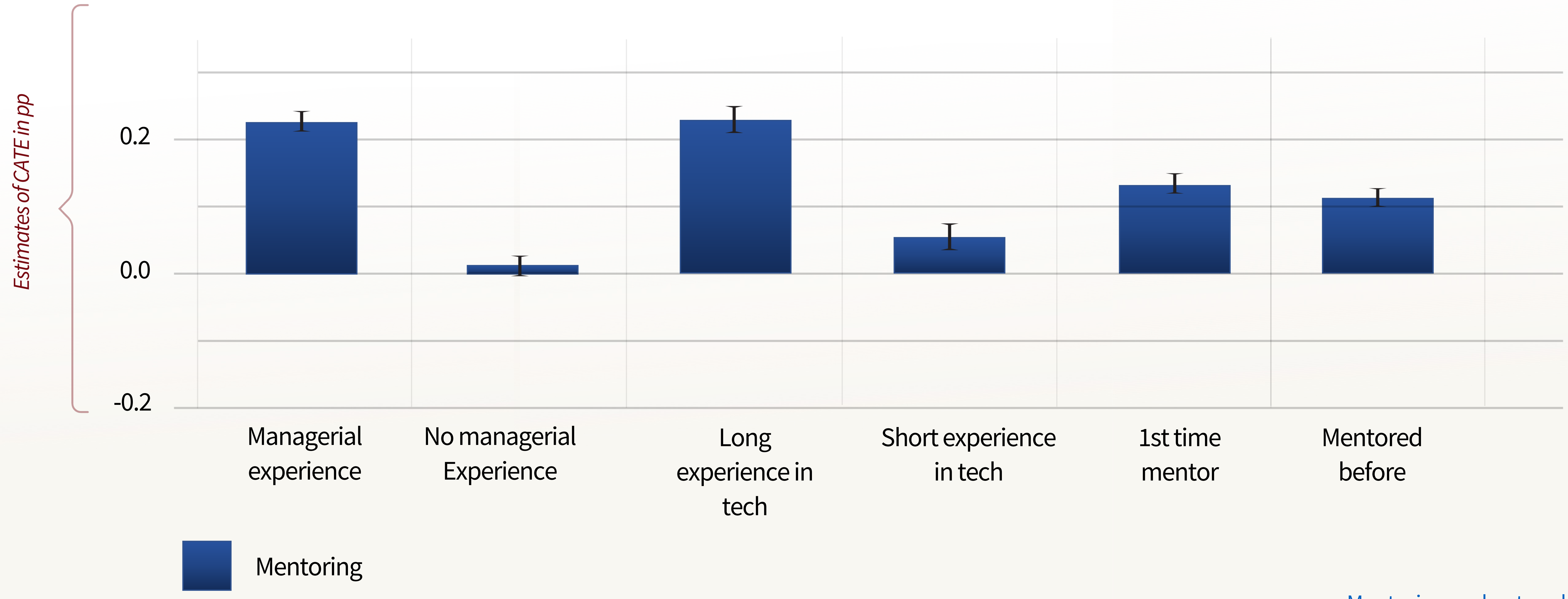
STANFORD BUSINESS GRADUATE SCHOOL OF

Estimates of the conditional average treatment effects in percentage points. In blue for Mentoring and in yellow for Challenges. Whiskers show standard errors.



Heterogenous treatment effects – tech job 16 months

Estimates of the conditional average treatment effects in percentage points.
Characteristics of mentors. Whiskers show standard errors.



Mentoring and networking

Off-policy evaluation of alternative assignment rules and capacity levels

Increasing impact w/o changing programs' content

STANFORD BUSINESS GRADUATE SCHOOL OF

Current state:

- 13% of applicants get into *Mentoring* and 15% to *Challenges*
- Applicants get into programs 'randomly'
    - in Challenges fully random, in Mentoring selected by mentors (not informed about the HTE and often 1st time mentors)

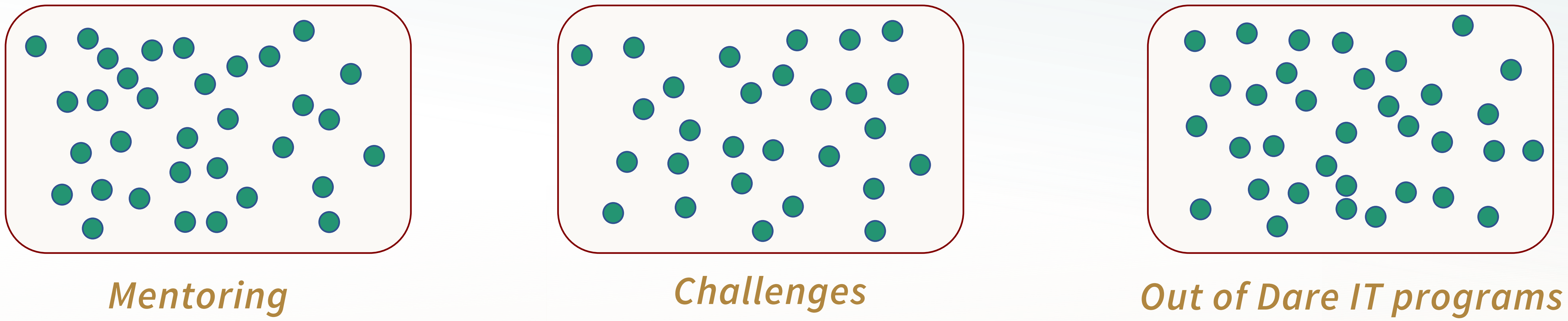
ATE/HTE results suggest:

- High ATE suggests that increasing the number of spots will benefit additional participants
- Admitting participants based on characteristics can increase programs' impact
    - Targeting should be feasible - 23% of applicants to Challenges were interested in Mentoring before

Off-policy analysis goals:

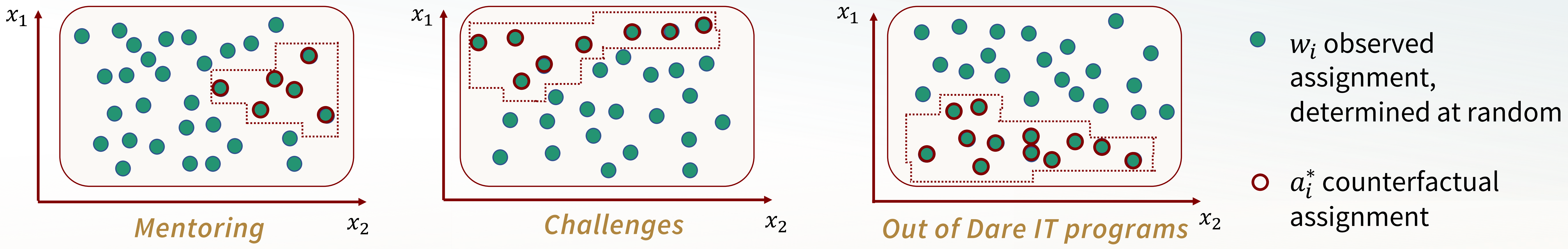
- Quantify benefits from prioritizing admission based on applicants' characteristics
- Quantify benefits from relaxing capacity constraints

Off-policy framework



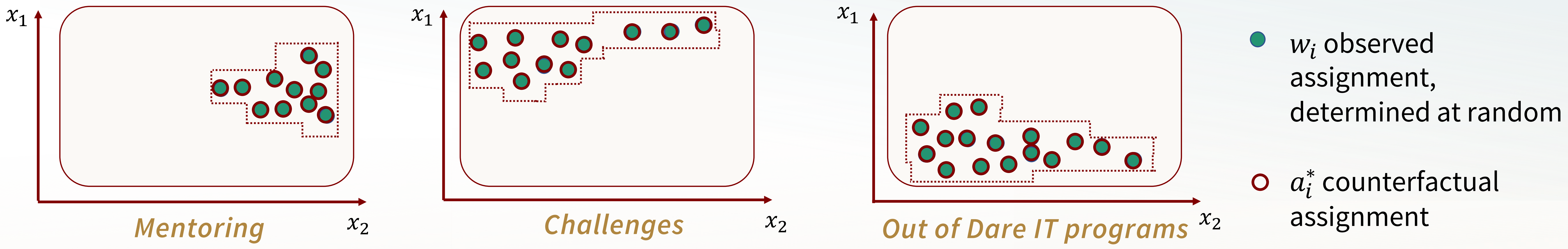
w_i observed assignment, determined at random

Off-policy framework



Off-policy framework

STANFORD GRADUATE SCHOOL OF BUSINESS



Assignment rules

- Assignment policy is a mapping from applicants' characteristics and programs' capacity levels to assigned programs

$$\pi: (X, Q) \to \mathcal{A} \in \{0, M, C\}$$

- Thus, a policy π applied to a pool of applicants with characteristics x_i and capacity levels Q^M and Q^C results in counterfactual assignments $a_i^\pi \in \{0, M, C\}$

Targeted assignment rule - estimation

1. **Train & test split**
   - Train set to estimate the policy and test set to evaluate
2. **Estimate treatment effect for each applicant**
   - In the train set - AIPW estimator (Robins et al., 1994, Athey et al., 2019), estimate treatment effects $\tau^A(X)$, and outcomes $Y(A, X)$
   - Predict into test set and obtain $\hat{\tau}_i{}^a$ and $\hat{Y}_i{}^a$
3. **In test set, obtain assignments: $a_i^* \in \{0, M, C\}$ under policy $\pi^*(X, Q)$**

Obtain a_i^*'s by maximizing treatment effects subject to capacity constraints

$\max_{z_{ia}} \sum_i \sum_a z_{ia} \hat{\tau}_i^a$ subject to $\sum_i z_{ia} < Q^a \forall a$ & $\sum_a z_{ia} = 1\ \forall i$ where z_{ia} equals 1 when i is assigned to program a and 0 otherwise; Q^a is the number of slots in program a

Targeted assignment rule – evaluation

STANFORD GRADUATE SCHOOL OF BUSINESS

4. **Estimate the value of the policy**

- Let $V(\pi(X,Q)) = E[Y(\pi(X,Q))]$ be the value of the policy $\pi(X,Q)$
- However, $\widehat{Y}_i^a$ was used for policy assignment, so cannot use it for evaluation

- New model; AIPW using the test set and cross-fitting (Chernozhukov et al., 2016), obtain $\widehat{Y}_i^{c,a}$

- We consider following estimator of the value of the policy

$$\hat{V}(\pi(X,Q)) = \frac{\sum \widehat{Y}_i^{c,a}}{N_{test}}$$

Targeted assignment rule – evaluation

STANFORD BUSINESS GRADUATE SCHOOL OF

4. **Estimate the value of the policy**

- Let $V(\pi(X,Q)) = E[Y(\pi(X,Q))]$ be the value of the policy $\pi(X,Q)$
- However, $\hat{Y}_i^{a}$ was used for policy assignment, so cannot use it for evaluation
- New model; AIPW using the test set and cross-fitting (Chernozhukov et al., 2016), obtain $\hat{Y}_i^{c,a}$
- We consider following estimator of the value of the policy

$$\hat{V}(\pi(X,Q)) = \frac{\sum \hat{Y}_i^{c,a}}{N_{test}}$$

5. **Evaluation**

- Compare outcomes under optimal counterfactual assignments with alternative assignments per group
- Compare value of the optimal policy with value under policies assigning participants at random

Outcomes per targeted assignment group

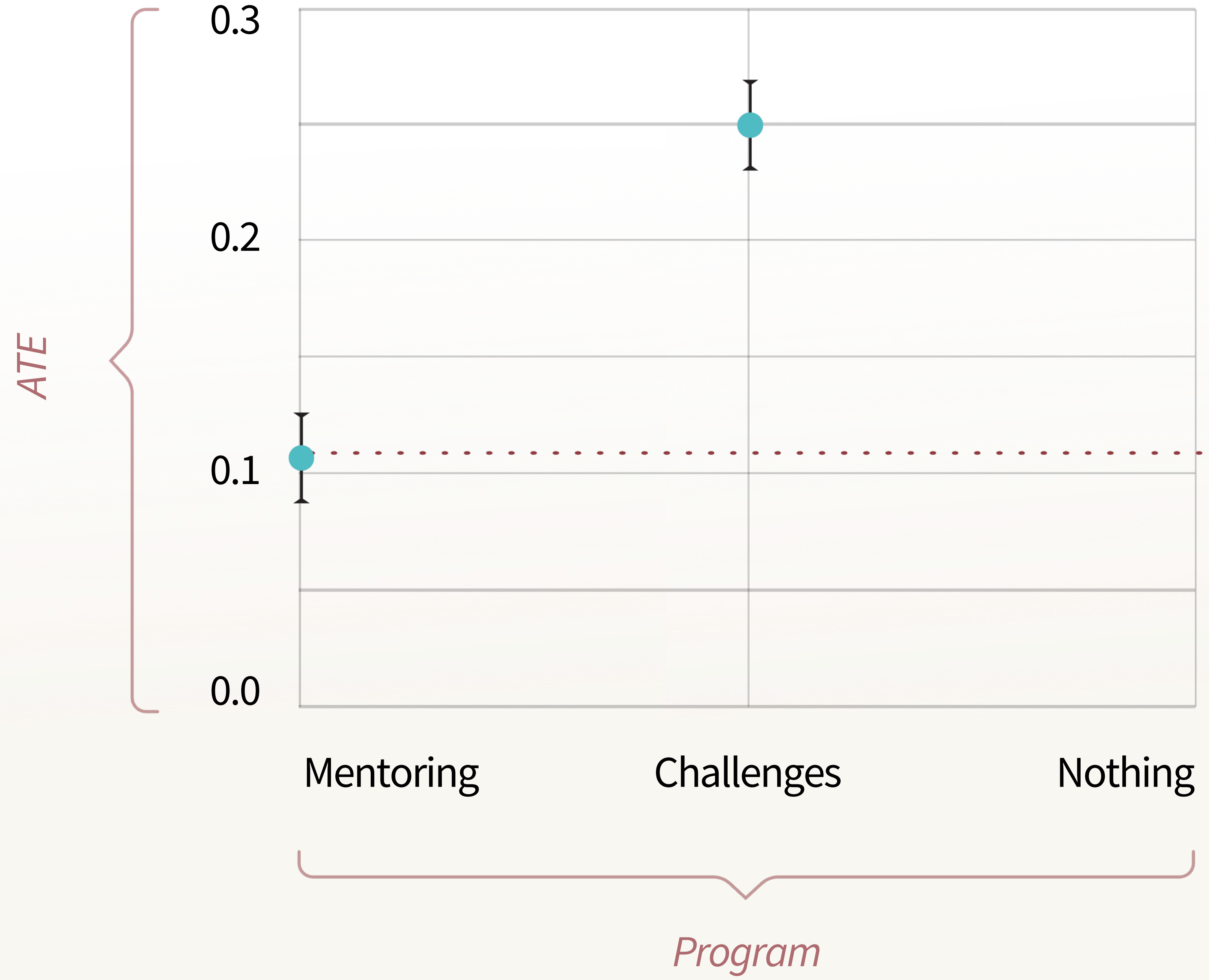
Policy: optimal assignment, capacity limits 13% of applicants in Mentoring and 15% in Challenges

ATE of the challenges group (C^*) if they would participate in Challenges

$$\bar{Y}_{C^*=C}$$

Outcomes per targeted assignment group

Policy: optimal assignment, capacity limits 13% of applicants in Mentoring and 15% in Challenges

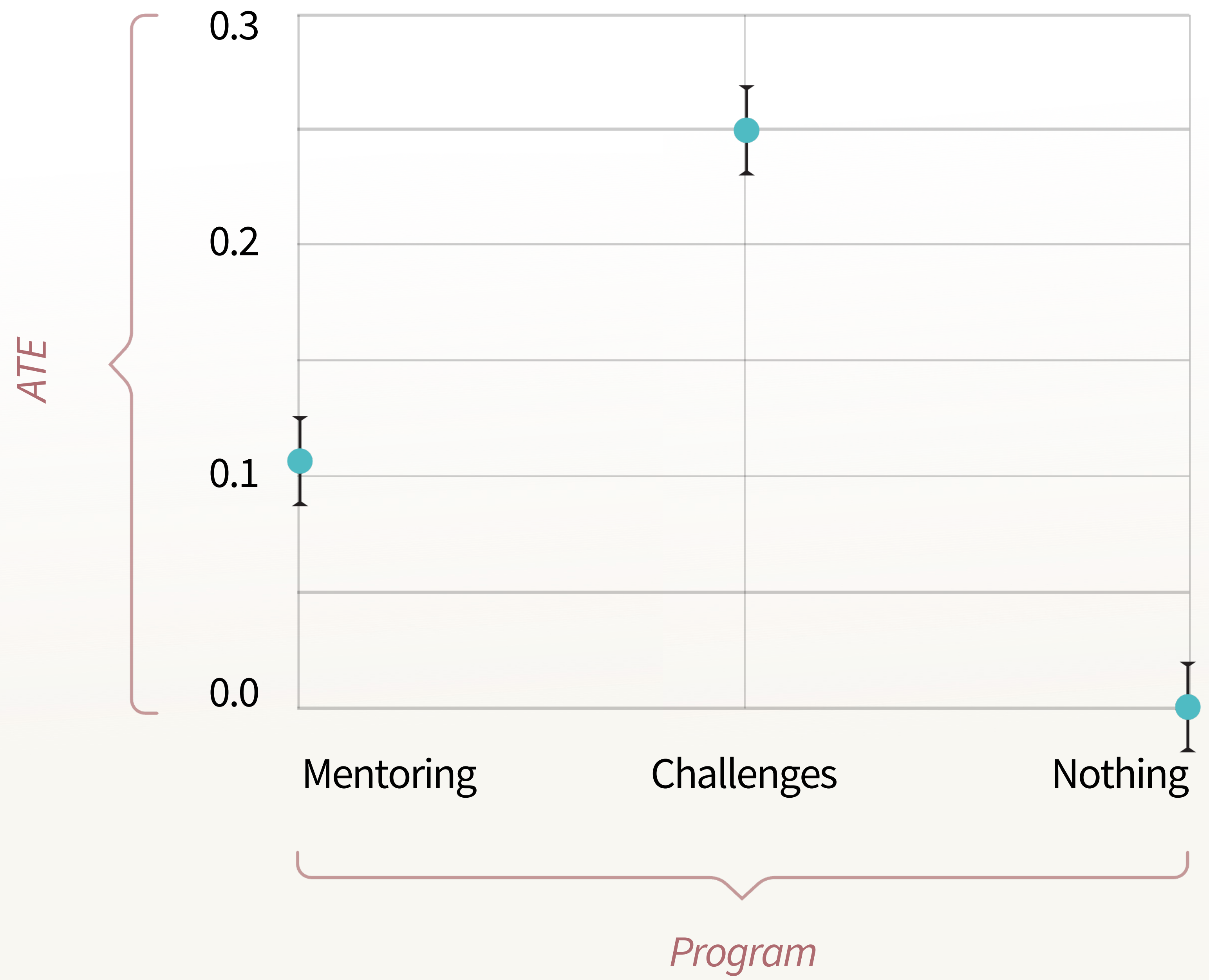


ATE of the challenges group (C^*) if they would participate in Mentoring

$$\bar{Y}_{C^*=M}$$

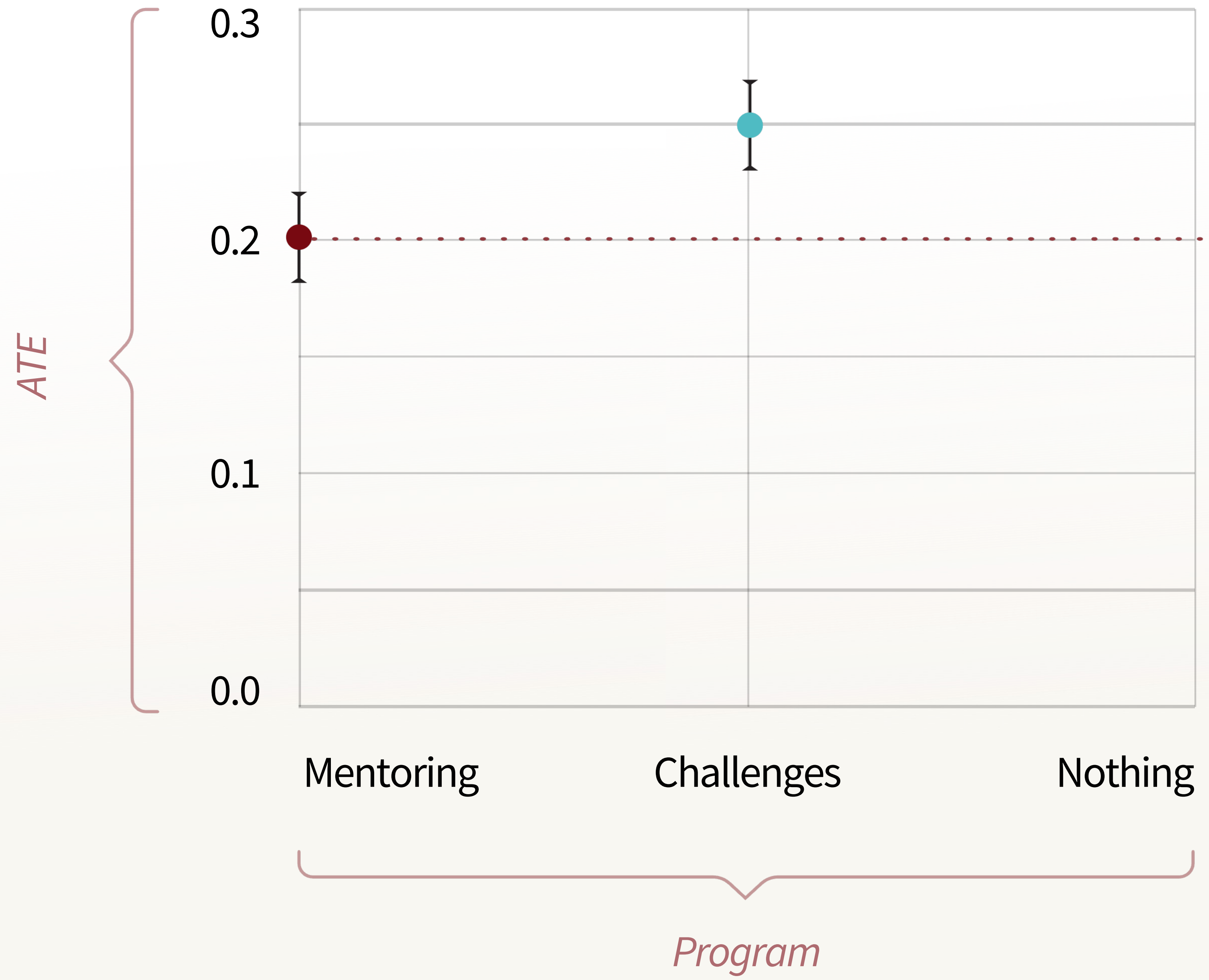
Outcomes per targeted assignment group

Policy: optimal assignment, capacity limits 13% of applicants in Mentoring and 15% in Challenges



Outcomes per targeted assignment group

Policy: optimal assignment, capacity limits 13% of applicants in Mentoring and 15% in Challenges

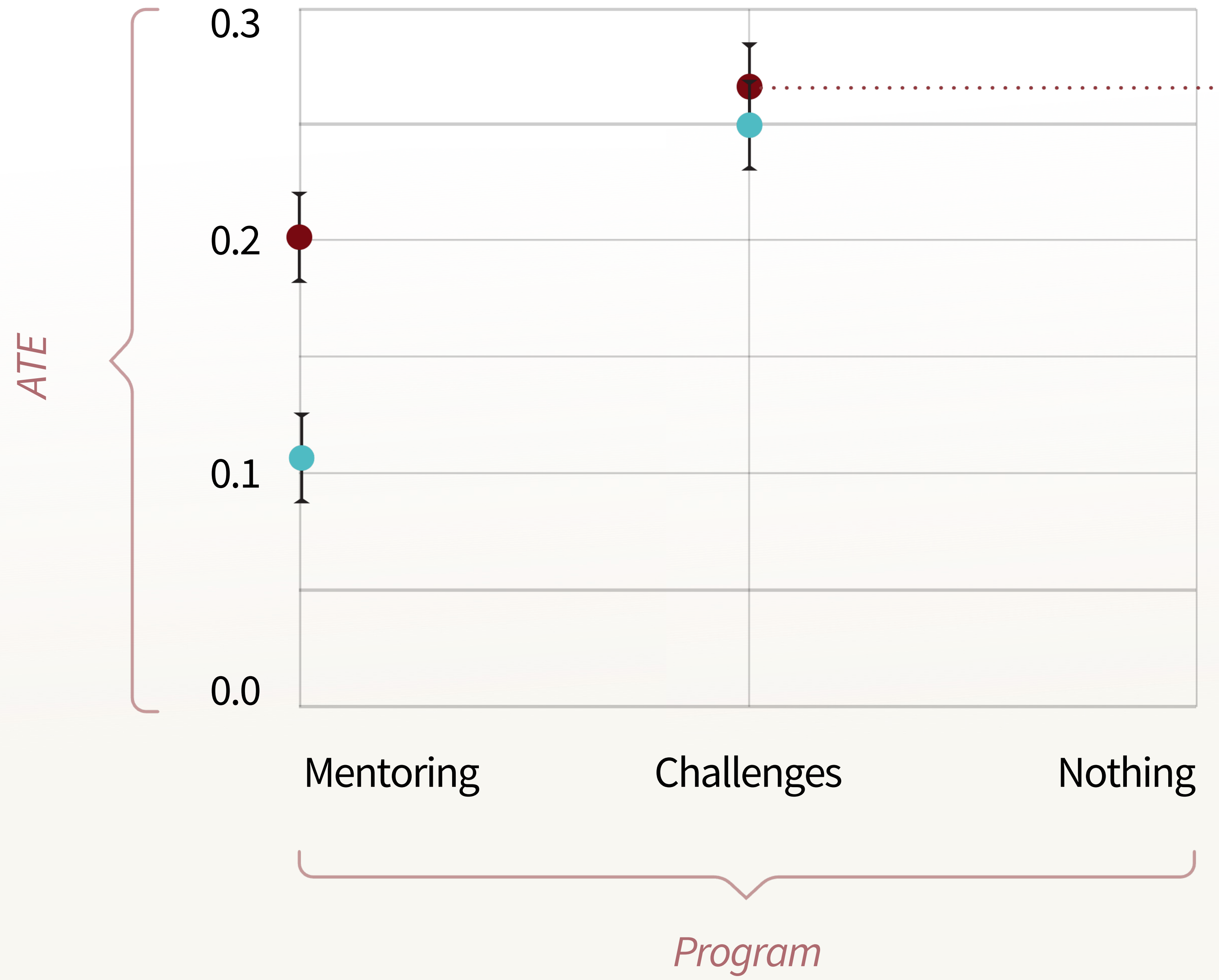


ATE of the mentoring group (M^*) under optimal assignment

$$\bar{Y}_{M^*=M}$$

Outcomes per targeted assignment group

Policy: optimal assignment, capacity limits 13% of applicants in Mentoring and 15% in Challenges

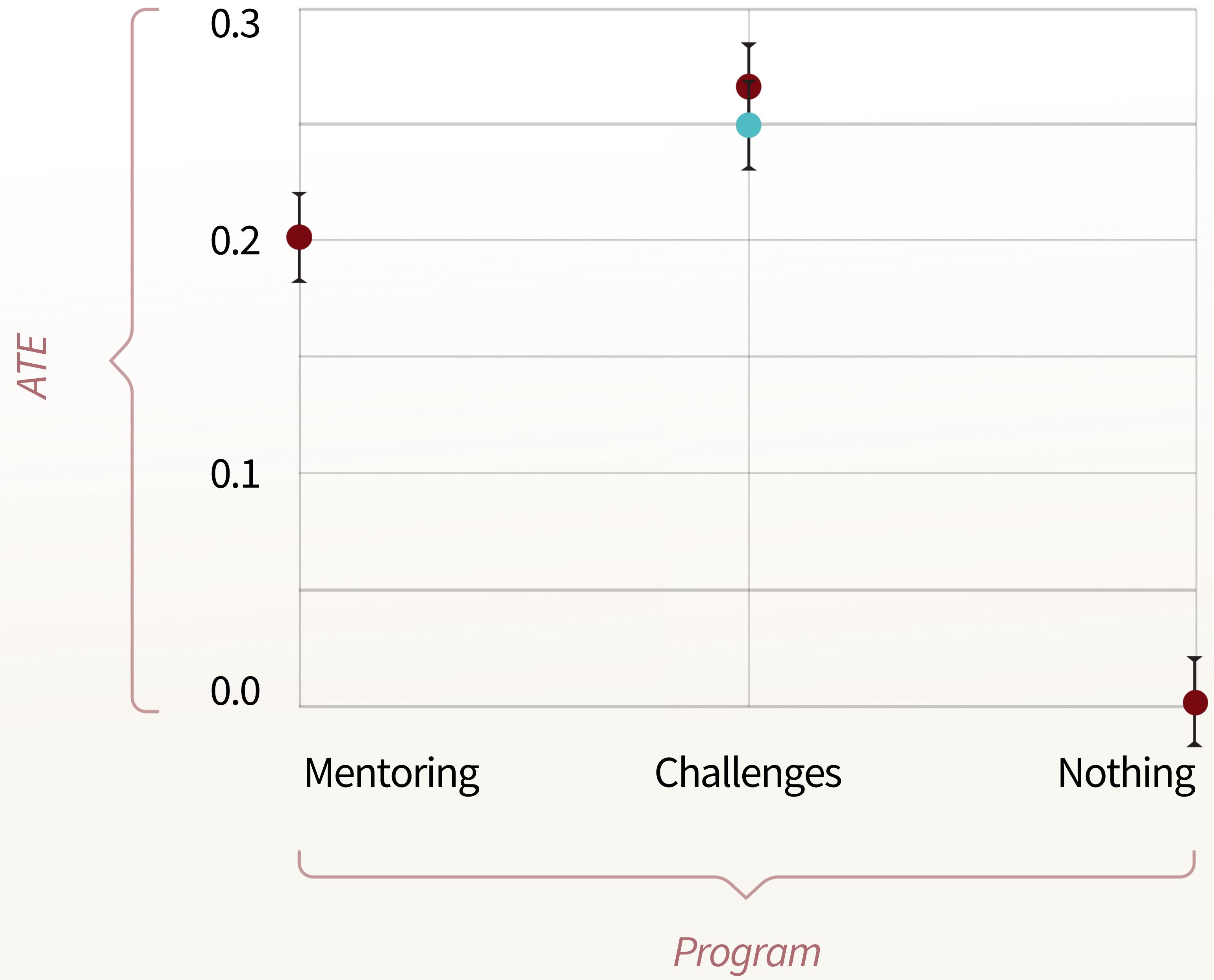


ATE of the mentoring group (M^*) if they would participate in Challenges

$$\bar{Y}_{M^*=C}$$

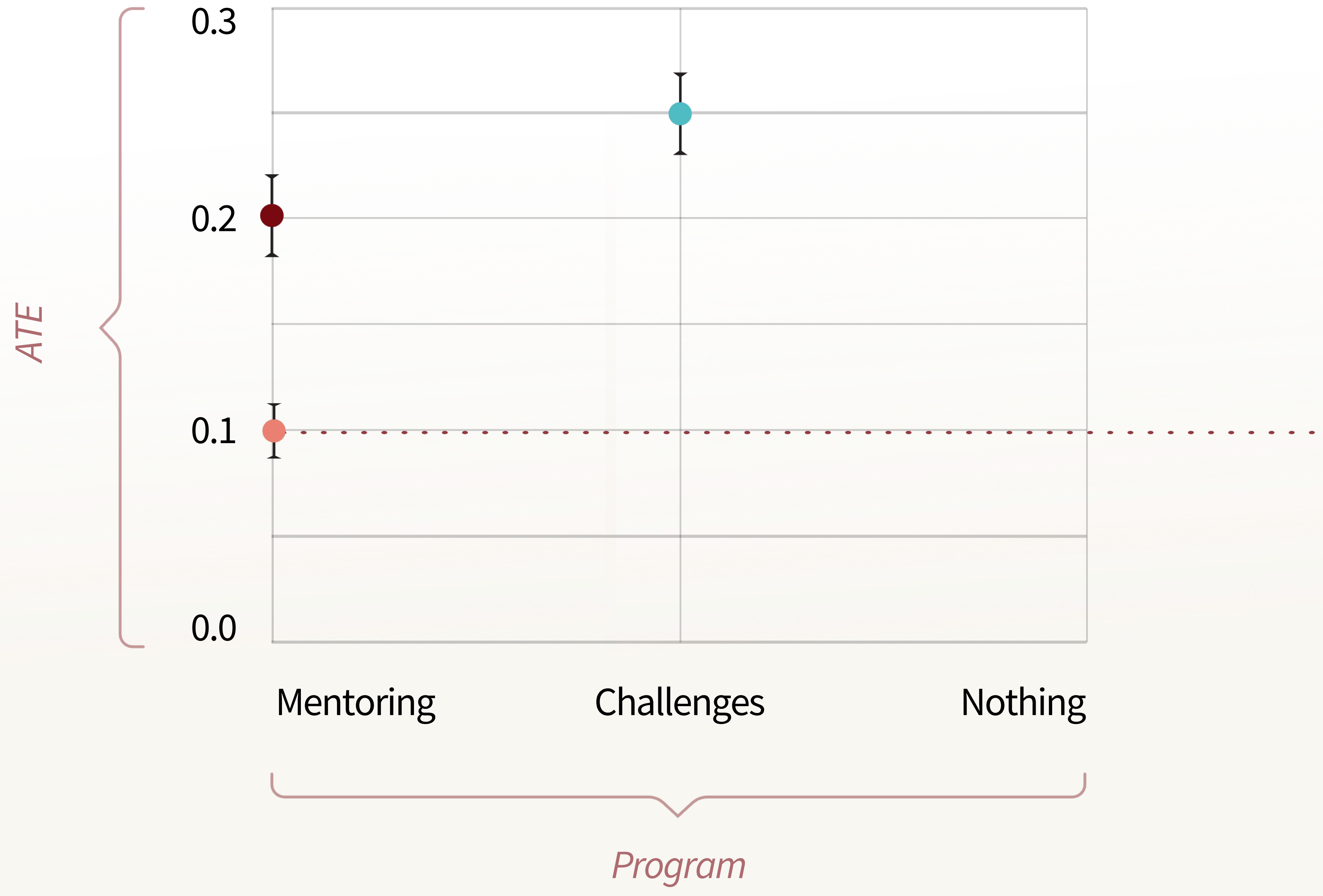
Outcomes per targeted assignment group

Policy: optimal assignment, capacity limits 13% of applicants in Mentoring and 15% in Challenges



Outcomes per targeted assignment group

Policy: optimal assignment, capacity limits 13% of applicants in Mentoring and 15% in Challenges

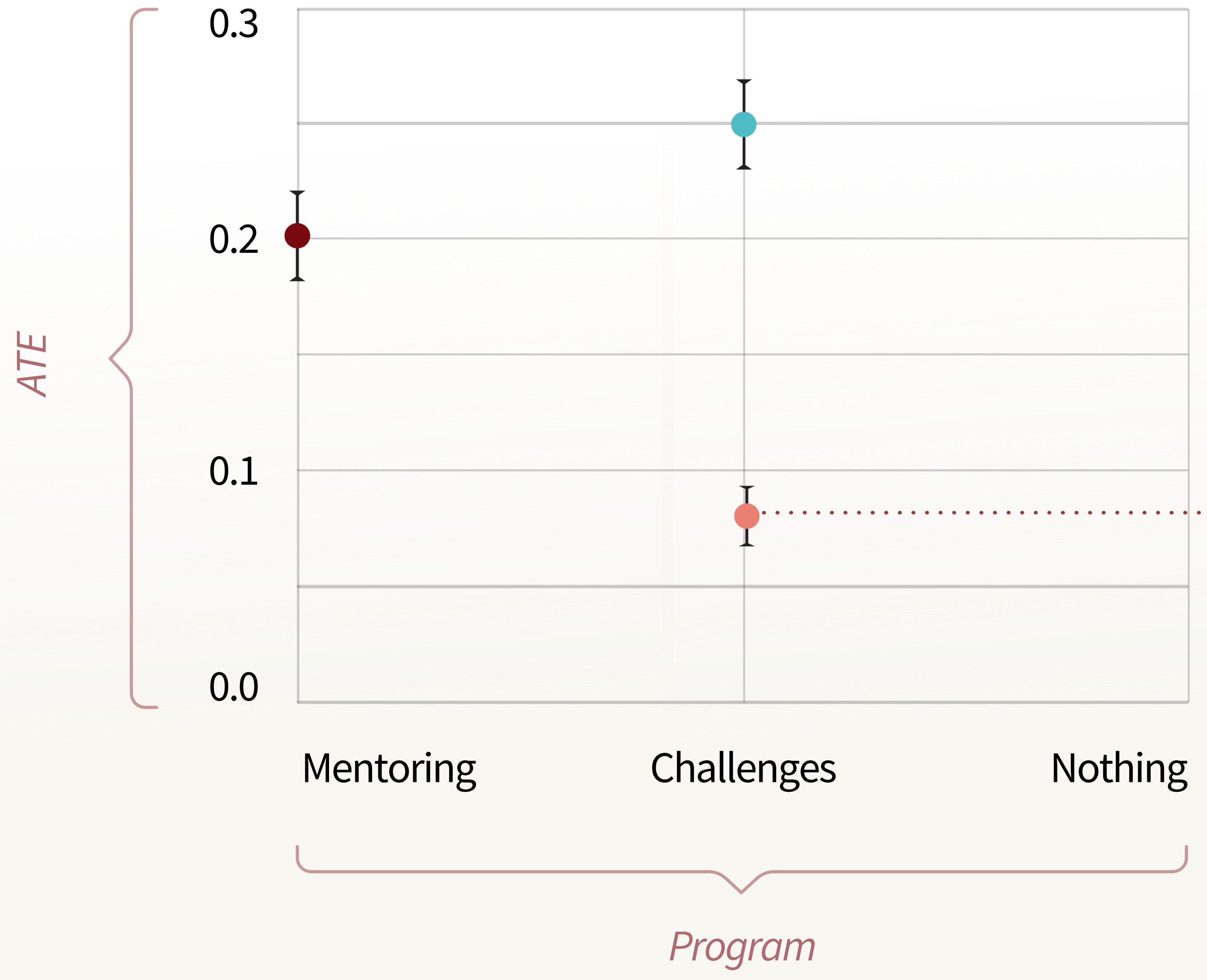


ATE of the nothing group (0^*) if they participate in Mentoring

$$\bar{Y}_{0^*=M}$$

Outcomes per targeted assignment group

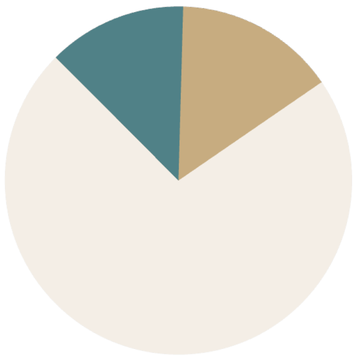
Policy: optimal assignment, capacity limits 13% of applicants in Mentoring and 15% in Challenges



ATE of the nothing group (0^*) if they participate in Challenges

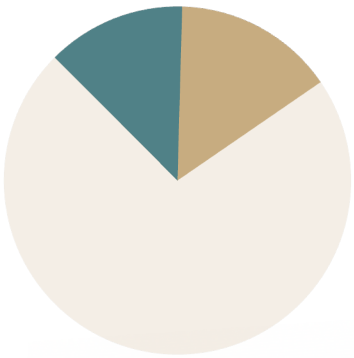
$$\bar{Y}_{0^*=C}$$

Policy comparison



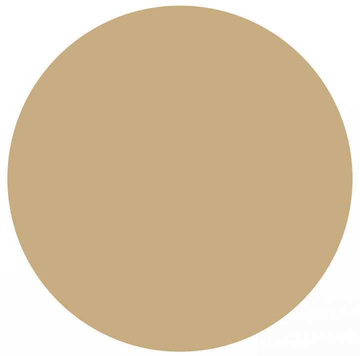
Status Quo:

13% to Mentoring
15% to Challenges
assignment at random



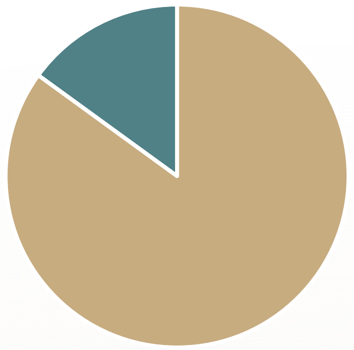
Targeted 1:

13% to Mentoring
15% to Challenges
optimal assignment



All Challenges:

0% to Mentoring
100% to Challenges

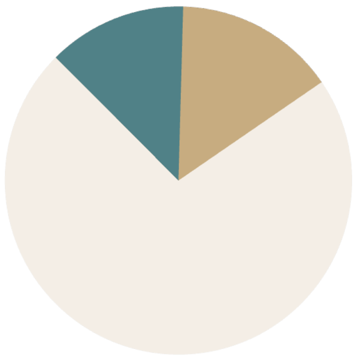


Targeted 2:

Up to 13% to Mentoring
Up to 100% to Challenges
optimal assignment

Policy comparison

STANFORD BUSINESS GRADUATE SCHOOL OF

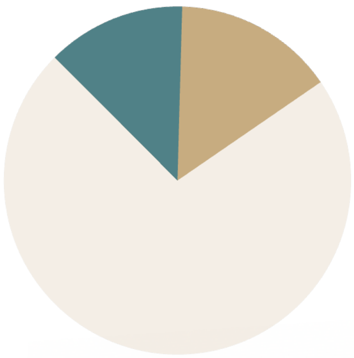


Status Quo:

13% to Mentoring

15% to Challenges

assignment at random

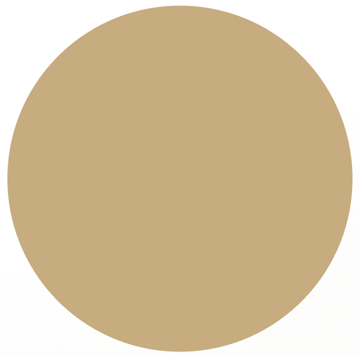


Targeted 1:

13% to Mentoring

15% to Challenges

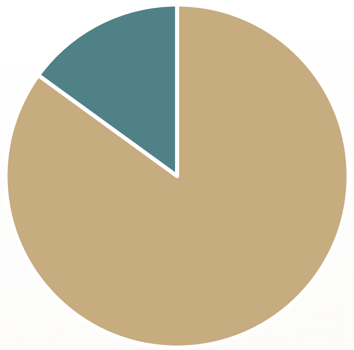
optimal assignment



All Challenges:

0% to Mentoring

100% to Challenges

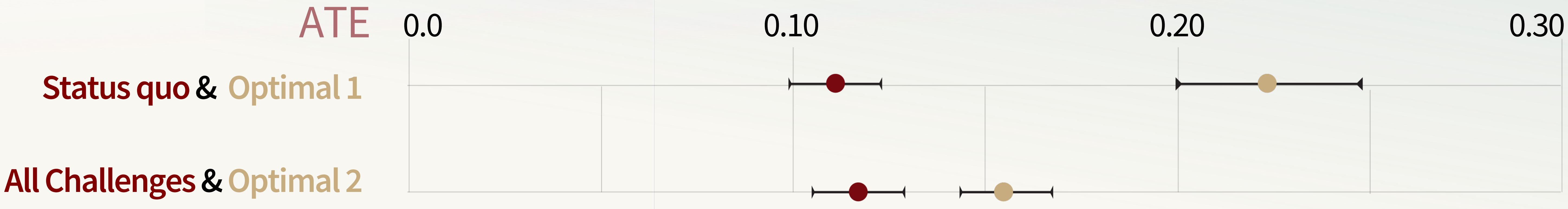


Targeted 2:

Up to 13% to Mentoring

Up to 100% to Challenges

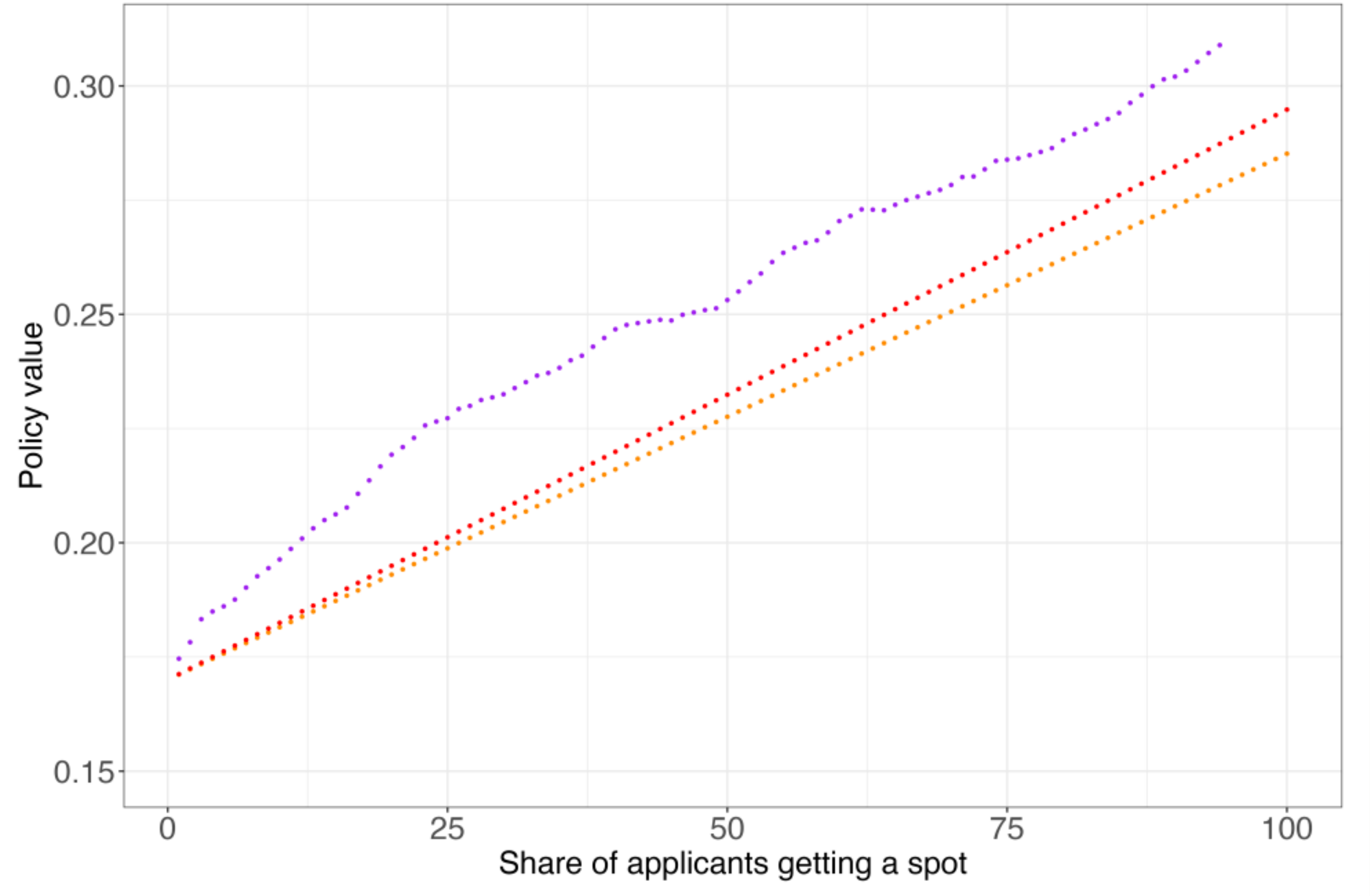
optimal assignment



The value of targeting

The value of keeping Mentoring

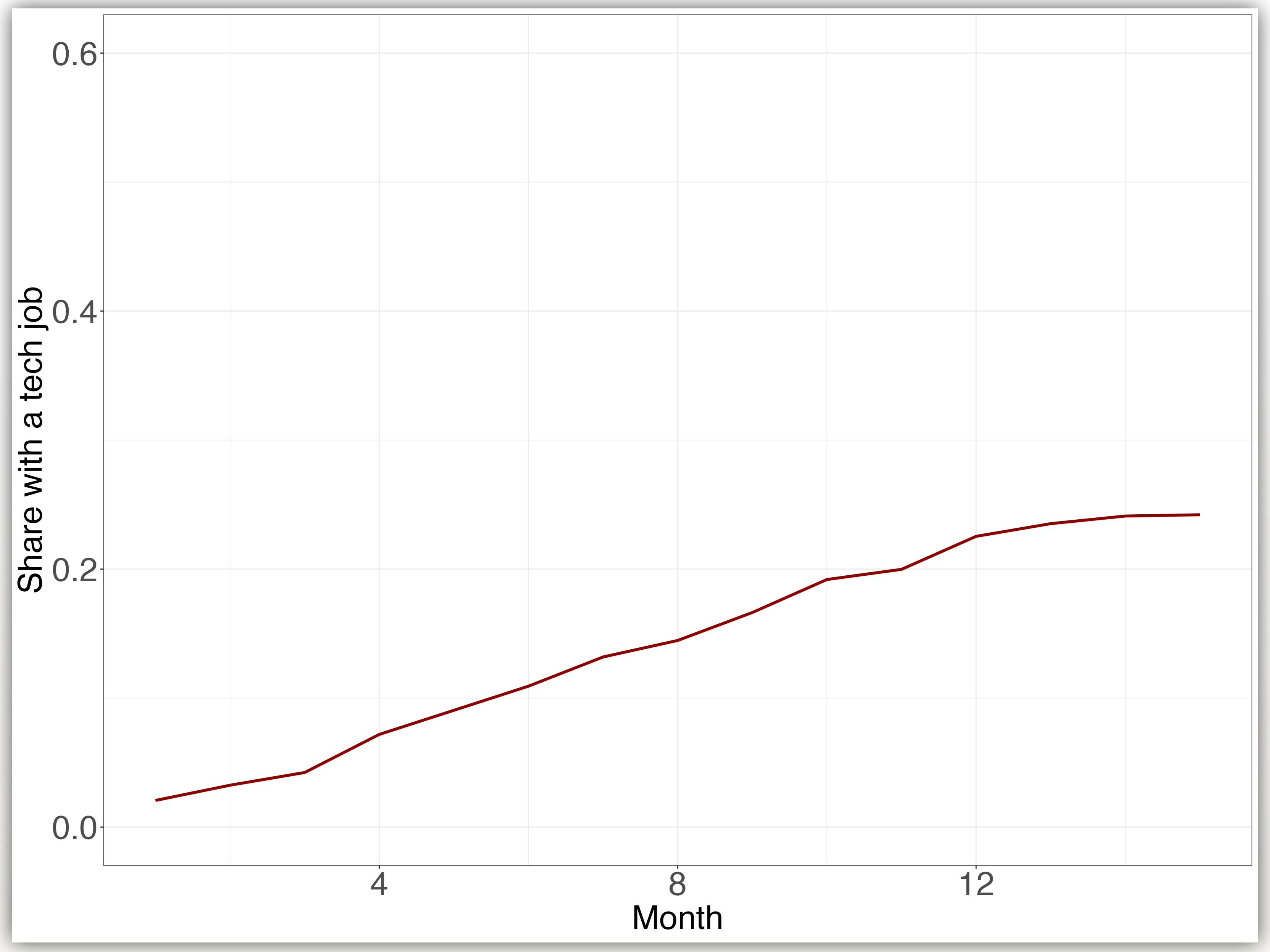
Value of targeting



- randomly assign to *Mentoring*
- randomly assign to *Challenges*
- optimally assign across the two programs

Mentors' select promising candidates

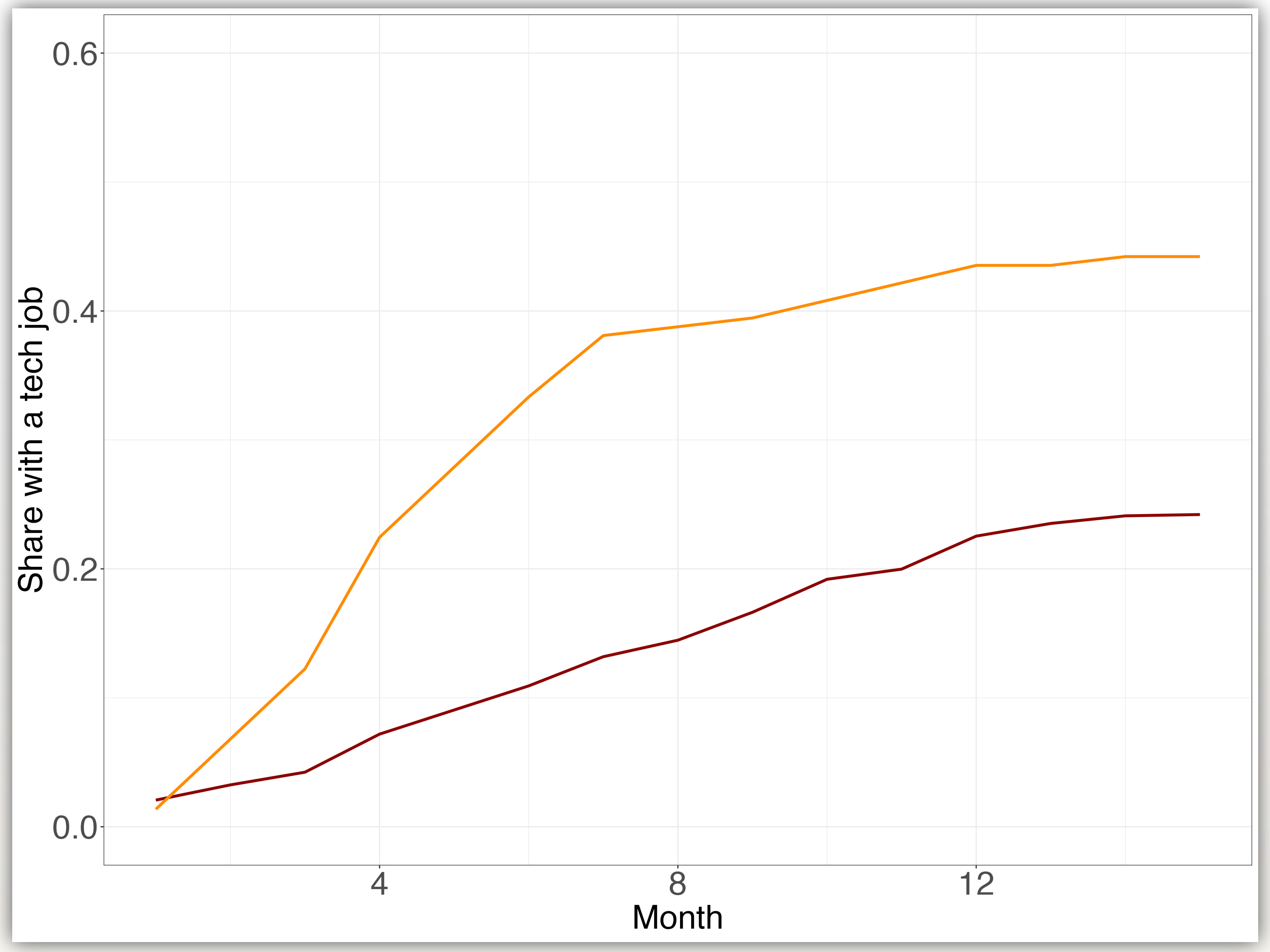
STANFORD BUSINESS GRADUATE SCHOOL OF



Not selected

Mentors' select promising candidates

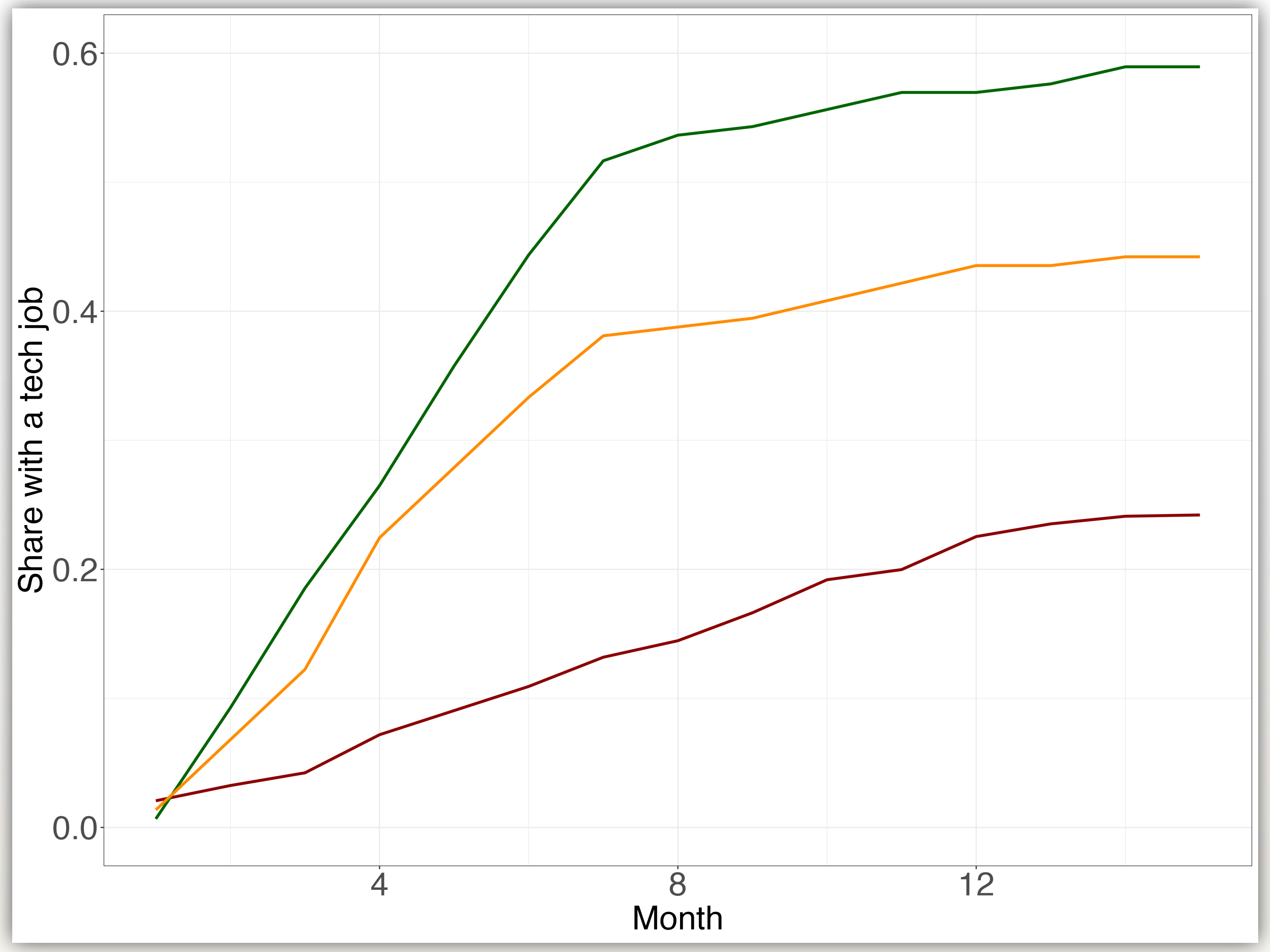
STANFORD BUSINESS GRADUATE SCHOOL OF



Not selected　　Selected and randomized to control

Mentors' select promising candidates

STANFORD BUSINESS GRADUATE SCHOOL OF

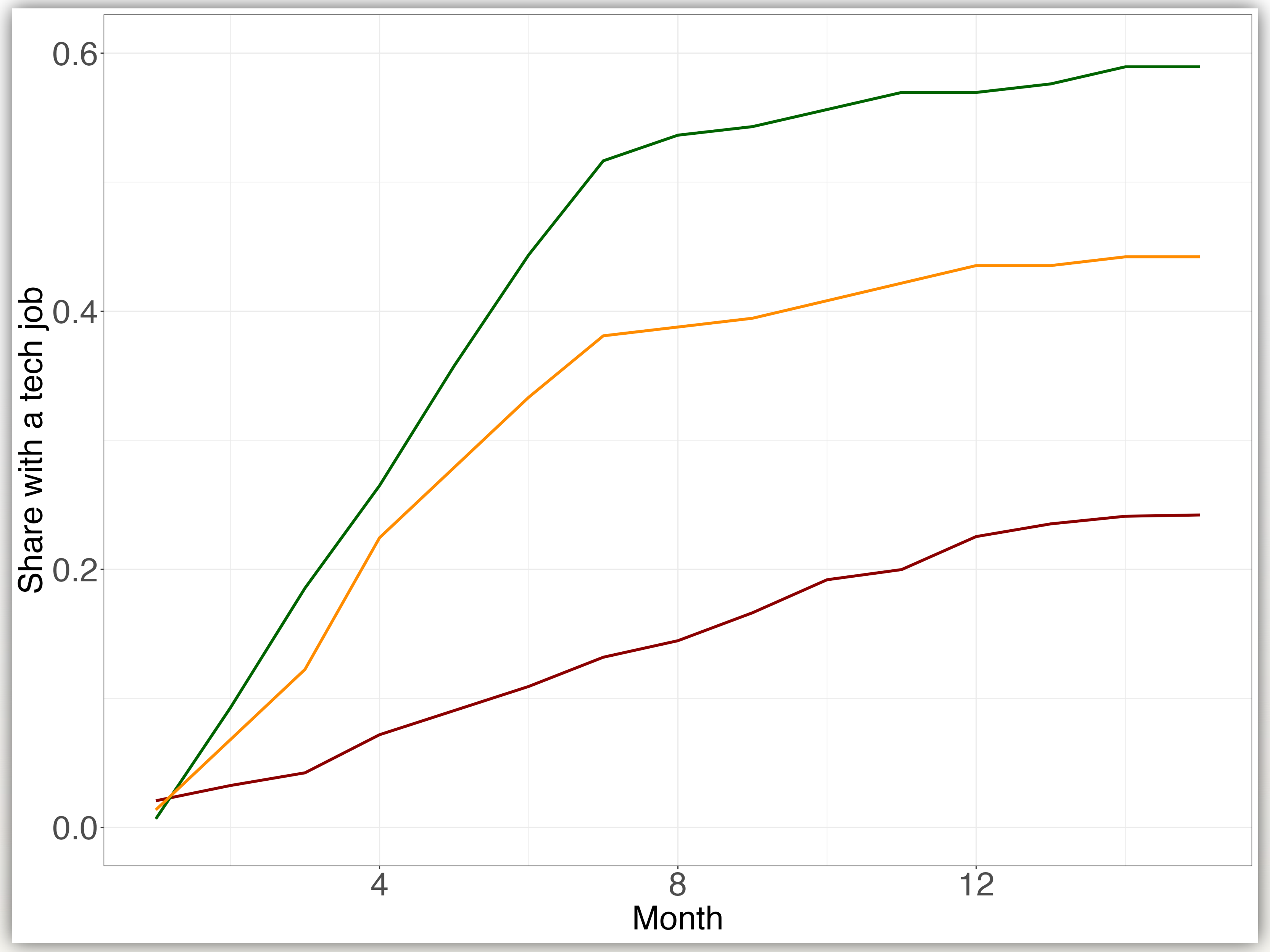


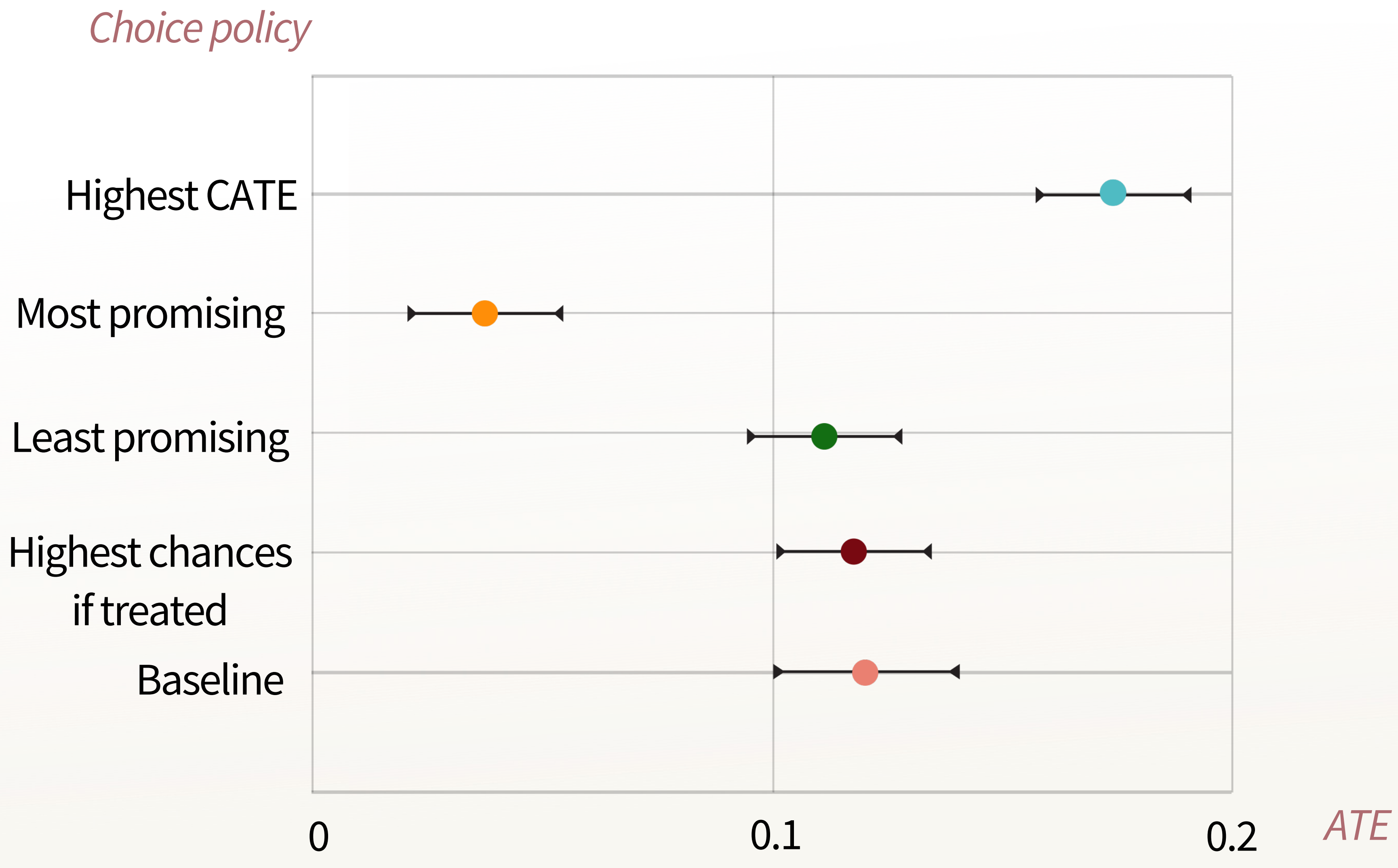
Not selected

Selected and randomized to control

Selected and treated

Mentors' select promising candidates





Not selected
Selected and randomized to control
Selected and treated

Summary: 1300 Polish women with tech skills but not tech jobs

Mentoring

- 160 mentors selected two applicants
- Paired randomized experiment
- 13pp increase in the probability of having a tech job
- Effective but hard to scale

Challenges

- New offering created during this research
- Development of portfolio signaling skills
- Cheap & highly-scalable
- 300 participants
- 9pp increase in the probability of having a tech job

Off-policy evaluation

- High heterogeneity in treatment effects
- 10pp increase in the effectiveness of programs from *targeted* assignment