Confidence in Ability and Job Search

Maxim Massenkoff
Naval Postgraduate School

Nagisa Tadjfar
MIT

Nancy Wang
MIT

October 2023

Workers' beliefs, not ability, may limit their opportunities

- Access to elite firms remains highly unequal, shaped by university pedigree and social networks (Zimmerman, 2019; Chetty *et al.*, 2022; Blair and Chung, 2022)
- Asymmetric information about worker ability leads firms to inefficiently screen out high-potential candidates—especially early-career workers (Pallais, 2014; Terviö, 2009)
- A related mechanism is that workers may *self-screen out* of applying to elite firms when application costs (e.g., time, effort) are non-trivial (Beam, 2021)
- This self-screening is inefficient if workers are miscalibrated about:
  - Second-order beliefs about employer screening (e.g., employers are more selective than they actually are)
  - Their own ability (e.g., workers, especially those without elite credentials, may believe they are less talented than they are)

This project: How does self-confidence affect job search?

This project: partner with a large interviewing platform and link platform data for 7,000+ software engineers with downstream employment outcomes

- Fuzzy RD design: Platform provides a salient signal of their coding ability when performance exceeds a company-determined threshold
  - Exceeding threshold $\uparrow$ likelihood of signal by 41pp (robust F-stat: > 300)
- Estimate the effects of receiving positive signal on job switches, firm quality, and average compensation levels
- Examine role of self-confidence using sentiment analysis of worker self-assessments and video recordings of interviews

Preview of Findings

- **Downstream job search and employment:** Receiving the ability signal ...
  - Increased job search: likelihood of switching companies $\uparrow$ by 20-22pp
  - More ambitious job search: likelihood of working at an elite firm $\uparrow$ by 15-27pp
  - Increased earnings: workers switch to companies with 12-20% higher compensation
- **Heterogeneous effects:** Largely driven by users who come from lower-ranked universities with <5 years of work experience
- Comparing on- vs. off-platform search, we find evidence that effects are due to belief-updating on the worker side (i.e., $\uparrow$ self-confidence), not changes in screening by firms

Related Literature

Worker screening and match quality: Farber and Gibbons (1996), Autor (2001), Lange (2007), Pallais (2014), Blair and Chung (2022), Goldin and Rouse (2000), Amer *et al.* (2023), Pallais (2014), Blair and Chung (2022), Zimmerman (2019), and Terviö (2009)

→ We study coding interviews in the Tech sector to document how interview performance affects job search and employment outcomes.

Self-confidence and labor market outcomes: Benabou and Tirole (2000), Niederle and Vesterlund (2007), Mobius, Niederle, *et al.* (2011), Mobius and Rosenblat (2006), Exley and Kessler (2022), Bandiera *et al.* (2022), Enke *et al.* (2023), Aksoy *et al.* (2024), Tekleselassie *et al.* (2025), and Demiral and Mollerstrom (2024)

→ We bridge thies literature with the screening literature by directly separating the effects of gaining access to job opportunities with receiving a signal of ability, which are often bundled.

Overview of Data

- **Interviewing platform**
  - Interview details (e.g., performance scores for coding/communication/problem solving, self evaluations, interview topic, coding language, video recordings) for >88K interviews
  - User demographics (e.g., age, race, gender, years of experience)
  - Job search activity on the platform (e.g., applications, interviews)
- **LinkedIn**: Employment and education history for 88% of relevant sample
- **Levels.fyi**: ∼60k individual compensation packages (salary, equity, bonus, sign-on) by company, level, location, gender in 2019-2023
- **Other**: US News and Times university rankings; tech company rankings from prestigehunt

We partner with a leading tech-sector interviewing platform

Free, anonymous technical interview practice with engineers from Google, Facebook, and more

Get actionable feedback, get awesome at interviewing, get fast-tracked at top companies.

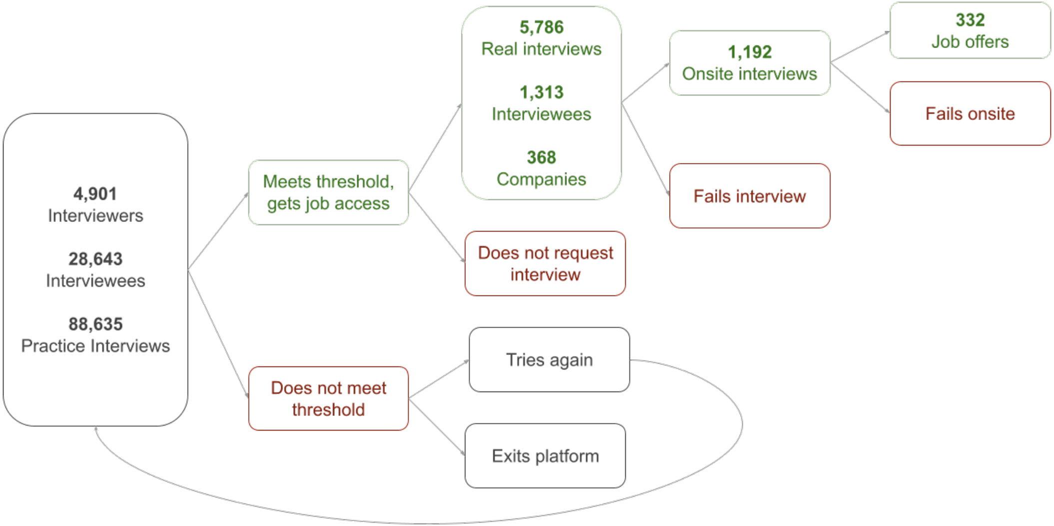
GIVE IT A TRY

Everything is free and always will be.

Users are trained, screened, and matched to firms

- Users complete *anonymous* practice interviews with *real professionals*
- Scored on coding, communications, problem solving, and "would hire" that are combined into rolling performance score
  - Users significantly improve as they practice ▸ Figure
- Users who exceed the performance score threshold receive access to interviews from 300+ companies ▸ Company List
- These interviews can lead to onsite interviews and full-time job offers

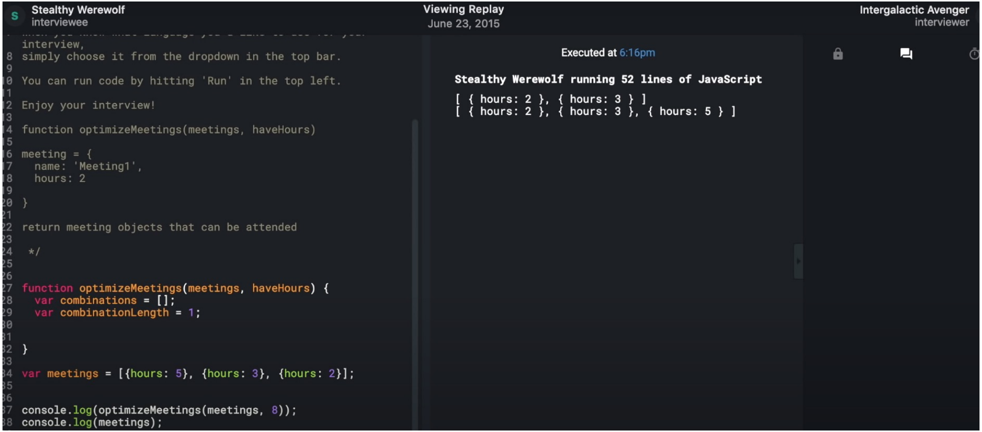
A subset of platform users convert interviews into job offers



Highly educated and high-earning user base

	Mean	SD
Demographics		
Top 50 University	0.36	0.48
Female	0.19	0.39
Years of Experience	4.74	4.61
Master's	0.48	0.50
PhD	0.05	0.21
Employed at Signup	0.50	0.50
Job History		
Ever Ranked Company	0.71	0.45
Best Company Rank	36.39	31.42
Current Avg. Company Comp. ($)	203,411	48,387
Platform Metrics		
Has Jobs Board Access	0.33	0.47
# of Practice Interviews	3.63	5.58
# of Real Interviews	0.18	1.21
N = 8,506		

Example of a practice technical interview



Interviewers score candidates and provide feedback

This candidate received:

- **Coding Score:** 2/4
- **Problem Solving Score:** 1/4
- **Communication Score:** 2/4
- **Would you hire?** No

"I could see that you were struggling with this problem a bit. You solved the first version really well, including a good analysis of runtime, etc, but the second version with a different optimization strategy was tough. I could tell that you grasped the challenge of the problem and the general style of solution, but in practice I would have liked to see the solution come faster and with less guidance. I would suggest brushing up on combinatorics and dynamic programming, as they come up a lot in algorithmic-style questions."

Users who gain access receive salient ability signal

Hey Nagisa,

Our goal at [this platform] is to make the job search better for excellent software engineers like you. As one of our best-performing users, you can now book real (and still anonymous!) interviews with top companies.

Why do your job search on [this platform]? With us, you skip right to the technical interview, which means you can interview tomorrow without resumes, recruiter calls, or haranguing your friends for referrals. Also, your interview takes place on [this platform], so everything is anonymous unless you both decide to move forward. There's no harm in trying it out!

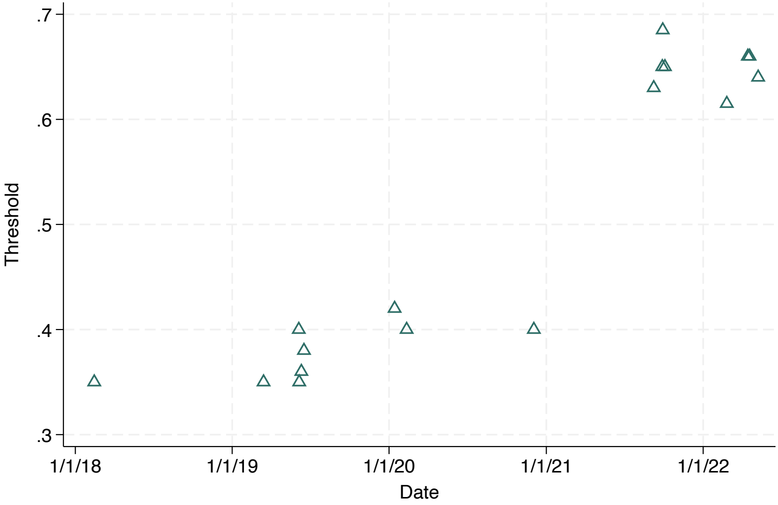
Check out the companies hiring on [this platform] right now!

Access to interviews motivates fuzzy RD (IV)

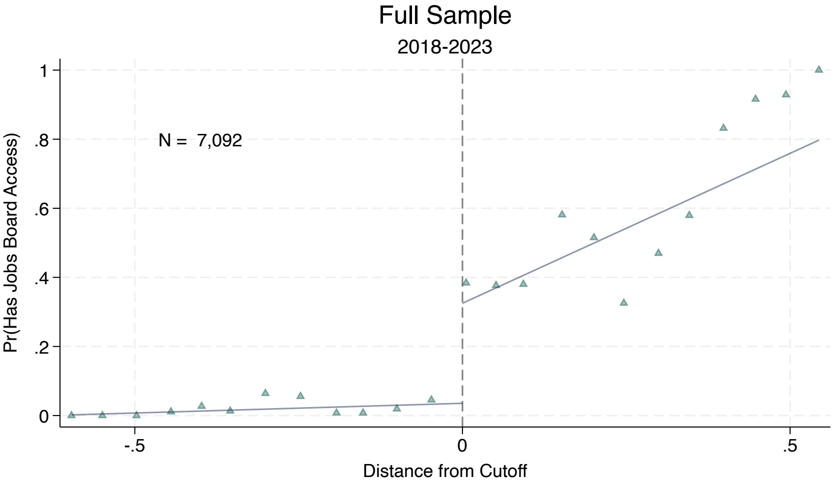
$$Y_i = \beta A_i + f(Score_i) + \gamma X_i + \varepsilon_i$$

- $Y_i =$ outcome for individual i
- $Score_i \in (-0.60, 0.56)$ is the rolling performance score relative to cutoff τ
- $A_i = \mathbb{1}[Score_i \geq 0]$ is an instrument for gaining jobs board access
- $f(\cdot)$ is max order 2 polynomial, interacted with A_i (Imbens and Lemieux, 2008; Cattaneo *et al.*, 2019)
- $X_i =$ controls (e.g., gender, degree type, educational background)
- Sample restricted to US users who gained access prior to 2023

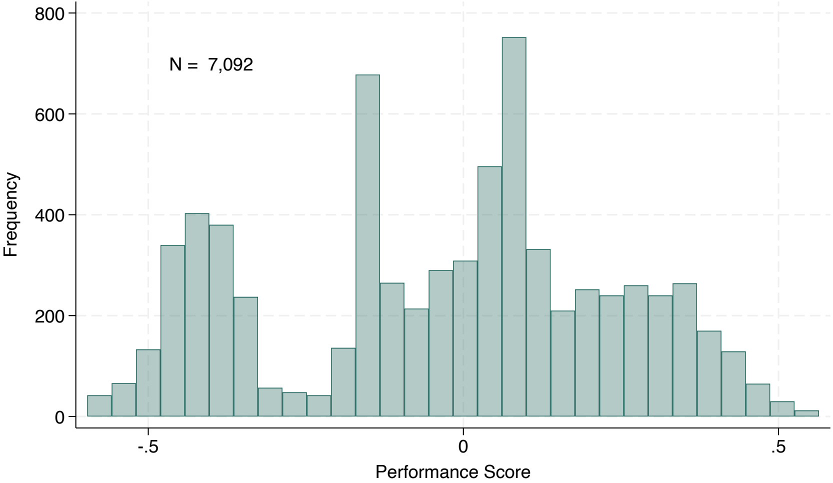
Cutoff τ changed 15 times between 2018-2023



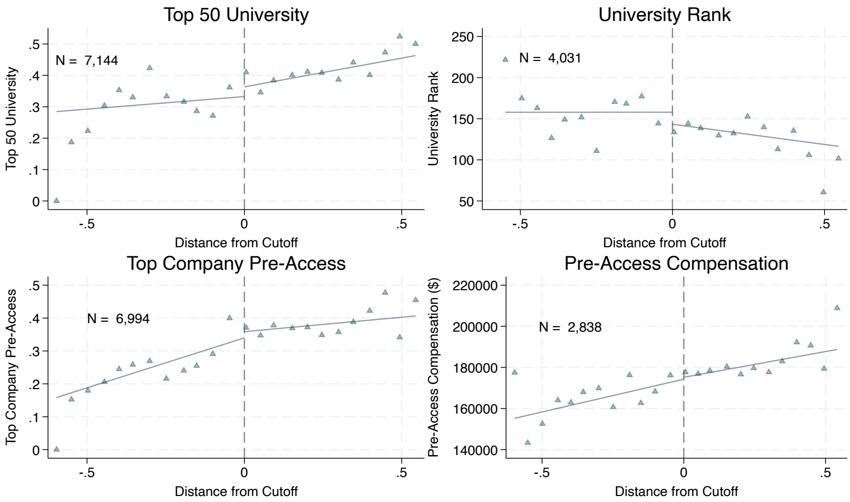
Access to interviews motivates fuzzy RD ▸ Cleaner RD



No bunching in running variable at cutoff



Covariates are stable across the threshold



Jobs board access induces users to switch jobs

	Switch Job Within 1 Year				
	Full Sample		Discontinuity Sample ($\pm$0.2)		Discontinuity Sample ($\pm$0.08)
	(1)	(2)	(3)	(4)	(5)
Has Jobs Board Access	0.209**	0.203**	0.223***	0.085	0.114*
	(0.090)	(0.084)	(0.038)	(0.112)	(0.068)
Observations	7,092	5,847	3,171	3,171	1,363
Polynomial Order	2	2	–	1	–
Interacted Instruments	Y	Y	N	Y	N
Degree FE	N	Y	N	Y	N
Visa Control	N	Y	N	Y	N
Gender FE	N	Y	N	Y	N
Experience Controls	N	Y	N	Y	N
Mean Outcome	0.264	0.271	0.235	0.235	0.225

More specifically, to move across companies

	Switch Company Within 1 Year				
	Full Sample		Discontinuity Sample (±0.2)		Discontinuity Sample (±0.08)
	(1)	(2)	(3)	(4)	(5)
Has Jobs Board Access	0.227***	0.219***	0.218***	0.102	0.111*
	(0.085)	(0.079)	(0.037)	(0.107)	(0.066)
Observations	7,092	5,847	3,171	3,171	1,363
Polynomial Order	2	2	–	1	–
Interacted Instruments	Y	Y	N	Y	N
Degree FE	N	Y	N	Y	N
Visa Control	N	Y	N	Y	N
Gender FE	N	Y	N	Y	N
Experience Controls	N	Y	N	Y	N
Mean Outcome	0.242	0.246	0.214	0.214	0.208

Increased likelihood of working at a "top firm"

▸ Top Firm Details

	Work At A Top Tech Company Within 1 Year				
	Full Sample		Discontinuity Sample ($\pm$0.2)		Discontinuity Sample ($\pm$0.08)
	(1)	(2)	(3)	(4)	(5)
Has Jobs Board Access	0.153*	0.210***	0.271***	0.085	0.112
	(0.079)	(0.081)	(0.044)	(0.126)	(0.079)
Observations	6,966	5,793	3,142	3,142	1,350
Polynomial Order	2	2	–	1	–
Interacted Instruments	Y	Y	N	Y	N
Degree FE	N	Y	N	Y	N
Visa Control	N	Y	N	Y	N
Gender FE	N	Y	N	Y	N
Experience Controls	N	Y	N	Y	N
Mean Outcome	0.388	0.402	0.416	0.416	0.453

Which translates to higher expected compensation

	Log Avg. Company Compensation Within 1 Year				
	Full Sample		Discontinuity Sample ($\pm$0.2)		Discontinuity Sample ($\pm$0.08)
	(1)	(2)	(3)	(4)	(5)
Has Jobs Board Access	0.123**	0.119*	0.193***	-0.063	0.034
	(0.060)	(0.070)	(0.040)	(0.125)	(0.069)
Observations	3,183	2,751	1,540	1,540	702
Polynomial Order	2	2	–	1	–
Interacted Instruments	Y	Y	N	Y	N
Degree FE	N	Y	N	Y	N
Visa Control	N	Y	N	Y	N
Gender FE	N	Y	N	Y	N
Experience Controls	N	Y	N	Y	N
Mean Outcome ($)	186,484	185,706	184,772	184,772	187,467

Effects persist and grow stronger over time

	Works at Top Firm in 2023				
	Full Sample		Discontinuity Sample (±0.2)		Discontinuity Sample (±0.08)
	(1)	(2)	(3)	(4)	(5)
Has Jobs Board Access	0.271***	0.325***	0.415***	0.196	0.238***
	(0.073)	(0.077)	(0.044)	(0.126)	(0.079)
Observations	7,004	5,821	3,156	3,156	1,355
Polynomial Order	2	2	–	1	–
Interacted Instruments	Y	Y	N	Y	N
Degree FE	N	Y	N	Y	N
Visa Control	N	Y	N	Y	N
Gender FE	N	Y	N	Y	N
Experience Controls	N	Y	N	Y	N
Mean Outcome	0.547	0.567	0.561	0.561	0.591

Key Takeaways

- 20-22pp higher likelihood of switching to a new company within 1 year
- 15-27pp higher likelihood of working at a top firm within 1 year
- 12-20% higher expected compensation within 1 year

Who is most resposive to this ability signal?

1. *Direct:* workers gain access to interviews that convert into job offers
   - $\sim$ 150 individuals accept job offers through the platform while $\sim$ 800 workers with access switch jobs $\rightarrow$ cannot explain the full effect
   - Preparing for real interviews on platform reduces the cost/increases the benefit of additional interviews off platform

2. *Indirect:* workers gain a credible signal on their ability which give workers new information about their ability

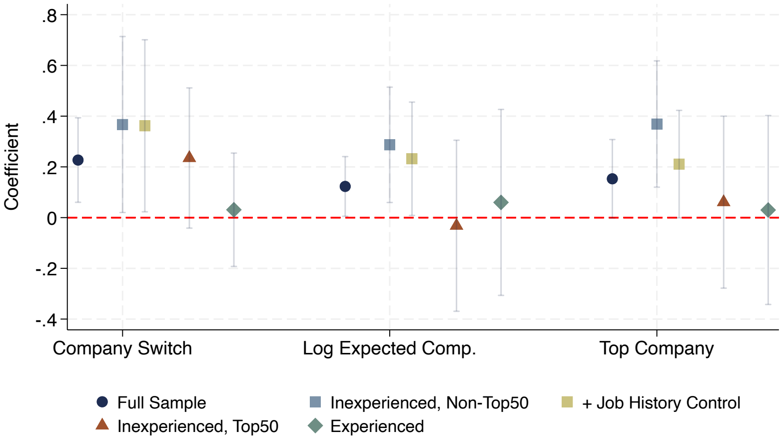
In both cases, we expect workers who had (1) less access to credible signals on their ability or (2) had noisier resume signals of ability to employers prior to the platform to be most responsive

Who has a harder time signaling ability?

	(1) Log Avg. Pre-Comp	(2) Prior Company Is Top Company	(3) Prior Company Rank
Top 50 University	0.093***	0.066***	-4.377***
	(0.009)	(0.010)	(1.255)
Years of Experience	0.020***	0.028***	-0.153
	(0.003)	(0.003)	(0.403)
Observations	4,099	10,122	3,270
R^2	0.035	0.022	0.009
Controls	Y	Y	Y

- Less experienced workers from less prestigious educational pedigrees worked at lower-paid jobs at lower-ranked companies
- These workers may have noisier resume signals of ability and/or have had fewer reliable signals of their own ability relative to the pool of software engineers

Effects driven by novice workers from lower-ranked universities



Mechanisms: self-confidence or a foot in the door?

Next steps to isolate self-confidence as a mechanism:

- Quantifying self-confidence among platform users
  - videos
  - self-assessment on perceived interview performance
- Heterogeneity by self-confidence
- Sentiment analysis on users' confidence before vs. after access in interviews
- Tenure at firms from Linkedin to quantify worker-firm match quality

Conclusion

- Using data from an interviewing platform that matches users to tech jobs based on performance, we employ a fuzzy RD design to estimate the effect of a credible ability signal on labor market outcomes
- We find that jobs board access increases the one-year probability of switching companies by 20%, probability of working at a top firm by 15%, and expected compensation by 12%
- Effects are driven by inexperienced workers from less prestigious educational and job history backgrounds

Thank you!

References I

[1] S. D. Zimmerman, "Elite Colleges and Upward Mobility to Top Jobs and Top Incomes," en, *American Economic Review*, vol. 109, no. 1, pp. 1–47, Jan. 2019, ISSN: 0002-8282. DOI: 10.1257/aer.20171019. [Online]. Available: https://pubs.aeaweb.org/doi/10.1257/aer.20171019 (visited on 10/09/2023).

[2] R. Chetty *et al.*, "Social capital I: Measurement and associations with economic mobility," en, *Nature*, vol. 608, no. 7921, pp. 108–121, Aug. 2022, Publisher: Nature Publishing Group, ISSN: 1476-4687. DOI: 10.1038/s41586-022-04996-4. [Online]. Available: https://www.nature.com/articles/s41586-022-04996-4 (visited on 05/09/2024).

[3] P. Q. Blair and B. W. Chung, "Job Market Signaling through Occupational Licensing," *The Review of Economics and Statistics*, pp. 1–45, Nov. 2022, ISSN: 0034-6535. DOI: 10.1162/rest_a_01265. [Online]. Available: https://doi.org/10.1162/rest_a_01265 (visited on 10/16/2023).

[4] A. Pallais, "Inefficient Hiring in Entry-Level Labor Markets," en, *American Economic Review*, vol. 104, no. 11, pp. 3565–3599, Nov. 2014, ISSN: 0002-8282. DOI: 10.1257/aer.104.11.3565. [Online]. Available: https://www.aeaweb.org/articles?id=10.1257/aer.104.11.3565 (visited on 10/13/2023).

[5] M. Terviö, "Superstars and Mediocrities: Market Failure in the Discovery of Talent1," *The Review of Economic Studies*, vol. 76, no. 2, pp. 829–850, Apr. 2009, ISSN: 0034-6527. DOI: 10.1111/j.1467-937X.2008.00522.x. [Online]. Available: https://doi.org/10.1111/j.1467-937X.2008.00522.x (visited on 10/13/2023).

[6] E. A. Beam, "Search costs and the determinants of job search," *Labour Economics*, vol. 69, p. 101 968, Apr. 2021, ISSN: 0927-5371. DOI: 10.1016/j.labeco.2021.101968. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0927537121000038 (visited on 05/09/2024).

[7] H. S. Farber and R. Gibbons, "Learning and Wage Dynamics," *The Quarterly Journal of Economics*, vol. 111, no. 4, pp. 1007–1047, 1996, Publisher: Oxford University Press, ISSN: 0033-5533. DOI: 10.2307/2946706. [Online]. Available: https://www.jstor.org/stable/2946706 (visited on 10/16/2023).

References II

[8] D. H. Autor, "Why Do Temporary Help Firms Provide Free General Skills Training?" *The Quarterly Journal of Economics*, vol. 116, no. 4, pp. 1409–1448, 2001, Publisher: Oxford University Press, ISSN: 0033-5533. [Online]. Available: https://www.jstor.org/stable/2696463 (visited on 10/16/2023).

[9] F. Lange, "The Speed of Employer Learning," en, Jan. 2007. DOI: 10.1086/508730. [Online]. Available: https://www.journals.uchicago.edu/doi/epdf/10.1086/508730 (visited on 10/16/2023).

[10] C. Goldin and C. Rouse, "Orchestrating Impartiality: The Impact of "Blind" Auditions on Female Musicians," en, *American Economic Review*, vol. 90, no. 4, pp. 715–741, Sep. 2000, ISSN: 0002-8282. DOI: 10.1257/aer.90.4.715. [Online]. Available: https://www.aeaweb.org/articles?id=10.1257%2Faer.90.4.715&source=post_page-----deda93da109b---------------------- (visited on 03/27/2023).

[11] A. Amer, A. C. Craig, and C. Van Effenterre, "Does Better Information Reduce Gender Discrimination in the Technology Industry?" en, 2023.

[12] R. Benabou and J. Tirole, "Self-Confidence and Social Interactions," en, National Bureau of Economic Research, Cambridge, MA, Tech. Rep. w7585, Mar. 2000, w7585. DOI: 10.3386/w7585. [Online]. Available: http://www.nber.org/papers/w7585.pdf (visited on 10/09/2025).

[13] M. Niederle and L. Vesterlund, "Do Women Shy Away From Competition? Do Men Compete Too Much?*," *The Quarterly Journal of Economics*, vol. 122, no. 3, pp. 1067–1101, Aug. 2007, ISSN: 0033-5533. DOI: 10.1162/qjec.122.3.1067. [Online]. Available: https://doi.org/10.1162/qjec.122.3.1067 (visited on 10/09/2025).

[14] M. M. Mobius, M. Niederle, P. Niehaus, and T. S. Rosenblat, "Managing Self-Confidence: Theory and Experimental Evidence," en, May 2011.

[15] M. M. Mobius and T. S. Rosenblat, "Why Beauty Matters," en, *American Economic Review*, vol. 96, no. 1, pp. 222–235, Mar. 2006, ISSN: 0002-8282. DOI: 10.1257/000282806776157515. [Online]. Available: https://www.aeaweb.org/articles?id=10.1257/000282806776157515 (visited on 10/09/2025).

References III

[16] C. L. Exley and J. B. Kessler, "The Gender Gap in Self-Promotion*," *The Quarterly Journal of Economics*, vol. 137, no. 3, pp. 1345–1381, Aug. 2022, ISSN: 0033-5533. DOI: 10.1093/qje/qjac003. [Online]. Available: https://doi.org/10.1093/qje/qjac003 (visited on 10/09/2025).

[17] O. Bandiera, N. Parekh, B. Petrongolo, and M. Rao, "Men are from Mars, and Women Too: A Bayesian Meta-analysis of Overconfidence Experiments," en, *Economica*, vol. 89, no. S1, S38–S70, 2022, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ecca.12407, ISSN: 1468-0335. DOI: 10.1111/ecca.12407. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1111/ecca.12407 (visited on 10/09/2025).

[18] B. Enke, T. Graeber, and R. Oprea, "Confidence, Self-Selection, and Bias in the Aggregate," en, *American Economic Review*, vol. 113, no. 7, pp. 1933–1966, Jul. 2023, ISSN: 0002-8282. DOI: 10.1257/aer.20220915. [Online]. Available: https://www.aeaweb.org/articles?id=10.1257/aer.20220915 (visited on 10/09/2025).

[19] B. Aksoy, C. L. Exley, and J. B. Kessler, "The (Unexpected) Gender Minority Gap in Confidence," en, National Bureau of Economic Research, Tech. Rep. w32061, Jan. 2024. DOI: 10.3386/w32061. [Online]. Available: https://www.nber.org/papers/w32061 (visited on 10/09/2025).

[20] T. Tekleselassie, M. Witte, J. Radbruch, L. Hensel, and I. E. Isphording, *Feedback, Confidence and Job Search Behavior*, en, SSRN Scholarly Paper, Rochester, NY, Mar. 2025. DOI: 10.2139/ssrn.5195741. [Online]. Available: https://papers.ssrn.com/abstract=5195741 (visited on 10/09/2025).

[21] E. E. Demiral and J. Mollerstrom, "Signaling confidence," *Journal of Economic Behavior & Organization*, vol. 226, p. 106 691, Oct. 2024, ISSN: 0167-2681. DOI: 10.1016/j.jebo.2024.106691. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S016726812400297X (visited on 10/09/2025).

[22] G. W. Imbens and T. Lemieux, "Regression discontinuity designs: A guide to practice," en-US, *Journal of Econometrics*, vol. 142, no. 2, pp. 615–635, Feb. 2008, Publisher: North-Holland, ISSN: 0304-4076. DOI: 10.1016/j.jeconom.2007.05.001. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0304407607001091 (visited on 10/16/2023).

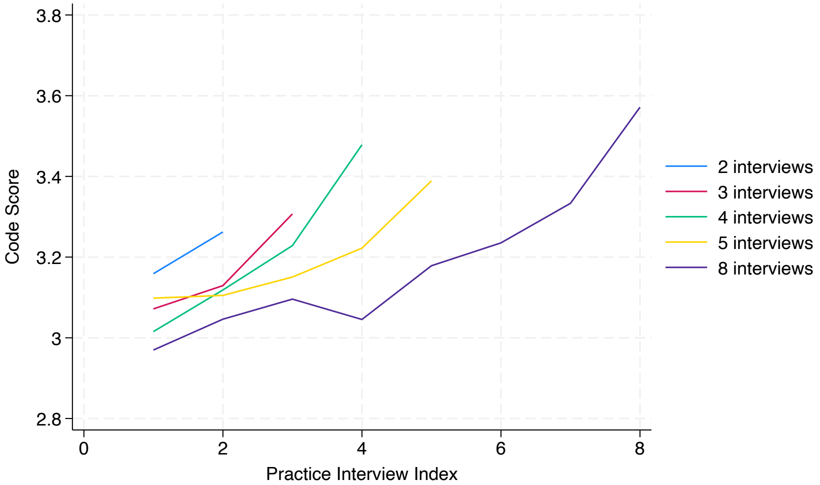
References IV

[23] M. D. Cattaneo, N. Idrobo, and R. Titiunik, *A Practical Introduction to Regression Discontinuity Designs: Foundations*. Nov. 2019, arXiv:1911.09511 [econ, stat]. DOI: 10.1017/9781108684606. [Online]. Available: http://arxiv.org/abs/1911.09511 (visited on 10/17/2023).

Appendix

Users improve as they practice on the platform

Back

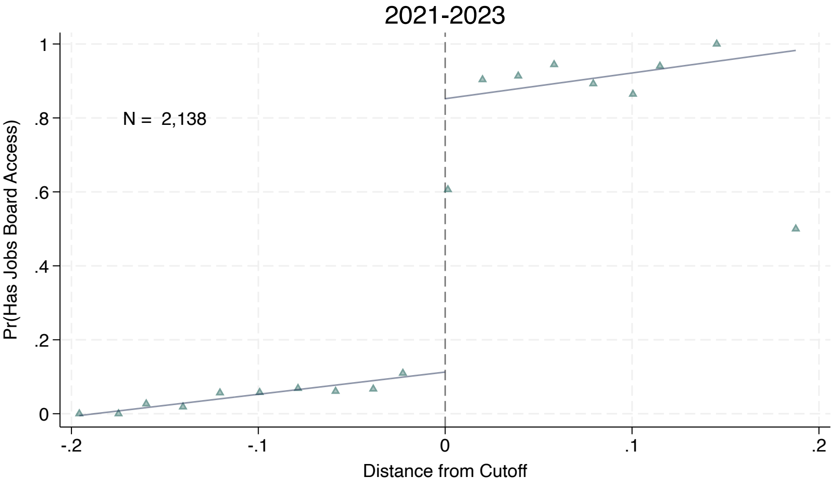


Back to platform details

Summary Statistics of Interviews

	Practice	Real	Real + Top 20 Univ.	Real + US-educated
Interviewee Scores				
Would Hire (0, 1)	.55	.62	.68	.63
Code Score (1-4)	2.88	3.08	3.17	3.08
Problem Solving Score (1-4)	2.82	3.06	3.17	3.07
Comm. Score (1-4)	3.26	3.27	3.4	3.33
Self Eval. (1-4)	2.48	2.85	2.91	2.85
Interviewer Scores				
Would Work With (0, 1)	.92	.94	.91	.94
Question Quality (1-4)	3.68	3.57	3.52	3.58
Hint Quality (1-4)	3.67	3.67	3.65	3.68
Excited to Work With (1-4)	3.57	3.55	3.52	3.55
Interview Length (min.)	57	62	58	59
N	80,688	6,226	1,008	2,479

Fuzzy RD: First Stage (2021-2023) ▸ Back



What companies hire on this platform? ▸ Back

	# of Technical Interviews	# of Onsites	Rank
Lyft	258	107	36
Uber	172	68	40
X	168	28	74
Commure	157	40	–
Asana	152	61	73
Flexport	138	66	92
Liftoff	132	43	–
Checkr	112	55	–
Cruise	111	49	53
Edo	109	34	–
Indeed	96	19	117

Reassuringly, no changes in pre-access variables ▸ Back

	Log Avg. Compensation, Pre-Access			
	(1)	(2)	(3)	(4)
Has Access	0.035	0.033	0.065	0.074
	(0.074)	(0.071)	(0.061)	(0.066)
Performance Score	0.168**	0.165**	0.160	0.013
	(0.070)	(0.072)	(0.320)	(0.339)
Performance Score Sq.		-0.063	-0.080	-0.375
		(0.096)	(0.581)	(0.609)
Observations	2,813	2,813	2,813	2,510
R^2	0.035	0.035	0.037	0.027
Polynomial Order	1	2	2	2
US Only	Y	Y	Y	Y
Interacted Instruments	N	N	Y	Y
Controls	N	N	N	Y
Sample	Full	Full	Full	Full

Practice performance varies by university tiers

University Rank:	*Top 20*	*20-50*	*50-200*	*>200*
Would Hire	0.55	0.50	0.51	0.44
Code Score	2.86	2.79	2.81	2.69
Comm Score	3.33	3.23	3.26	3.15
Problem-solving Score	2.80	2.71	2.75	2.62
Starting Code Score	2.80	2.73	2.76	2.64
Starting Comm Score	3.32	3.21	3.26	3.14
Starting Problem-solving Score	2.71	2.64	2.68	2.55
Gets Access (%)	30	25	26	22
Interview Duration (min)	57	56	57	56
# Practice Interviews	4	4	3	3
Observations	2363	3445	1449	10740

But much less so conditional on getting access

University Rank:	*Top 20*	*20-50*	*50-200*	*>200*
Would Hire	0.77	0.72	0.75	0.72
Code Score	3.15	3.14	3.12	3.13
Comm Score	3.50	3.46	3.46	3.42
Problem-solving Score	3.08	3.06	3.06	3.04
# Practice Interviews	6	6	6	6
Switches Jobs within 1 year (%)	28	28	30	26
Post-access expected compensation	203,867	196,244	193,531	189,778
Pre-access expected compensation	194,023	182,768	184,738	179,209
Observations	710	860	374	2376

Real performance varies by university tiers

University Rank:	*Top 20*	*20-50*	*50-200*	*>200*
Would Hire	0.66	0.61	0.62	0.58
Code Score	3.14	2.98	3.08	3.00
Comm Score	3.44	3.28	3.28	3.23
Problem-solving Score	3.17	3.00	3.03	2.98
# Interviews	3	3	3	3
Switches Jobs within 1 year (%)	20	27	20	22
Post-access expected compensation	213,094	200,736	187,703	193,553
Pre-access expected compensation	199,359	183,414	185,375	177,351
Observations	286	325	145	914

What is a "top" tech firm? ‣ Back to intro ‣ Back to 2nd stage

- We obtained a ranking of 132 companies that are considered "prestigious" from prestigehunt
- Within these 132 companies, companies are put in head-to-head matches and are then evaluated by users. Rankings are determined using the Elo rating system with a dynamic K-factor based upon number of matches played.
- New companies are added to the list once they have participated in enough head-to-head matches
- Companies include (in order): Nvidia, Databricks, Meta, Netflix, Two Sigma, Jane Street, Deepmind, Optiver, Citadel, Palantir, D.E. Shaw, Jump Trading, Renaissance Technologies, LinkedIn, Google