AEA Papers and Proceedings 2023, 113: 432–435
https://doi.org/10.1257/pandp.20231061

Do Financial Incentives Encourage Women to Apply for a Tech Job? Evidence from a Natural Field Experiment†

By Jan Feld, Edwin Ip, Andreas Leibbrandt, and Joseph Vecci

There have been many attempts to reduce women's underrepresentation in high-paying, male-dominated professions such as those in the technology sector (tech). In recruitment, companies provide diversity and inclusion trainings for their hiring managers (Dobbin and Kalev 2022), introduce gender quotas and other affirmative action policies (Niederle, Segal, and Vesterlund 2013; Ip, Leibbrandt, and Vecci 2020), make applications gender blind (Goldin and Rouse 2000), use gender-balanced evaluation panels (Bagues and Esteve-Volart 2010; Bagues, Sylos-Labini, and Zinovyeva 2017), and switch to artificial intelligence recruitment technologies to reduce human bias (Avery, Leibbrandt, and Vecci 2023). Many of these attempts have had modest success (Beasley and Fischer 2012; Kong et al. 2020).

One reason for women's underrepresentation might be that many tech jobs are highly competitive. Tech jobs often involve substantial application costs that only pay off for a small subset of applicants who get the job. Compared to men, women might shy away from applying to these jobs because they are more risk averse (Croson and Gneezy 2009; Charness and Gneezy 2012), are less confident (Buser, Ranehill, and van Veldhuizen 2021; Sarsons and Xu 2021), and dislike competitions (Niederle and Vesterlund 2007).

In this study, we test whether financial incentives for applying for a tech job (even if applicants do not get the job) encourage more female job seekers to complete their applications. The financial incentive has a "piece rate" component—that is, an amount that gets paid regardless of applicants' performance. Women's higher risk aversion and lower confidence suggest that they would find such a piece rate incentive more attractive than, for example, lottery-type incentives that get paid to random applicants or making the job more attractive.

I. Experimental Design and Empirical Approach

A. *Experimental Design*

We test the effectiveness of financial incentives for completing applications using a natural field experiment that is preregistered (Feld et al. 2019) and received ethics approval from Monash University.

We advertised for a Python programmer job across major job sites in the United States (e.g., Indeed.com and Dice.com). The job consisted of 80 hours of programming work over 2 months at US$40 per hour and was open to anyone who was based in the United States. To start an application, applicants had to upload their resume and fill out a short form asking, among other things, their demographic and contact information as well as how they learned to program. We advertised the same job twice (in September 2019 and in February 2020) using identical protocols. Each time, we posted the job ad for one month. We hired one programmer for each advertised job (for more details, see Feld et al. 2022).

We received 2,183 applicants who met our criteria for inclusion in our analysis. That is, these applicants lived in the United States, knew how to program in Python, were either female or male, and were not excluded for other reasons (e.g., they did not apply for job 1 *and* job 2). We invited all eligible female applicants ($n = 310$) and a random sample of all eligible

* Feld: Victoria University Wellington (email: jan.feld@vuw.ac.nz); Ip: University of Exeter (email: e.ip@exeter.ac.uk); Leibbrandt: Monash University (email: andreas.leibbrandt@monash.edu); Vecci: Gothenburg University (email: joseph.vecci@gu.se). We acknowledge support from the Australian Research Council (grant number FT180100252). We also thank participants at the 2023 ASSA meetings.

† Go to https://doi.org/10.1257/pandp.20231061 to visit the article page for additional materials and author disclosure statement(s).

male applicants ($n = 1{,}298$) to a second stage of their application.

In this stage, applicants were asked to complete an online skill assessment, which consisted of a Python programming test and either an aptitude or a personality assessment. The programming test consisted of two programming tasks. Applicants had up to 115 minutes to complete the tasks. These types of assessments are common and form an important part of the job application process (Chamorro-Premuzic 2015).

We randomize eligible job applicants into two treatments. In the control treatment, applicants were invited to perform the online skill assessment without any financial incentive. This treatment resembles the standard practice of not paying applicants for completing an assessment. In the incentive treatment, job applicants were offered \$5 for completing the assessment, plus a bonus payment of up to \$5 depending on their performance in the programming test.[1]

Our estimation sample consists of 309 female applicants and 1,296 male applicants who we invited to the second stage across the 2 treatments.[2] The modal female and male applicant has completed a four-year college degree. Of female applicants, 53 percent are employed, and 30 percent are studying. Of male applicants, 58 percent are employed, and 30 percent are studying. Female applicants have less Python experience (1.9 years compared to 2.6 years); the majority of both female and male applicants learnt to program at university. Of 1,605 applicants in our estimation sample, 635 (39.6 percent) completed the assessments across the 2 treatments.

[1] In particular, the emails that invited applicants to the second stage of the job applications were identical except for the following text: "*To compensate you for your time, you will receive \$5 for completing the assessment plus an additional amount of up to \$5 which depends on your performance on the Python programming task. You may choose to be paid via Amazon gift voucher, PayPal or Bank transfer.*"

[2] This number is lower than the number of invited eligible applicants, because we exclude one female applicant and two male applicants for whom we have missing data on some control variables.

B. *Empirical Approach*

To measure the effect of offering financial incentives on the application behavior of female applicants, we use ordinary least squares regressions to estimate the following model for the sample of female applicants only:

$$(1) \qquad Y_i = \alpha_1 Incentive_i + \gamma' X_i + u_i,$$

where Y_i is a binary indicator that is equal to 1 if applicant i completed the Python programming test and 0 if the applicant was invited but did not complete the test (this variable is missing for applicants who were not invited). We classify an applicant as completing the test if they attempted both programming tasks (regardless of whether the programs actually worked). $Incentive_i$ is an indicator showing whether the applicant was randomly assigned to the incentive treatment, and X_i consists of the following control variables: five indicators of applicants' level of education; one dummy variable indicating whether the applicant is currently studying; one dummy variable indicating whether the applicant is currently employed; four dummy variables showing whether the applicant learned to program at university, learned in an online course, was self-taught, or learned in another way; years of Python programming experience; and years of Python programming experience squared.

To test whether the effect of offering financial incentives differs by applicant gender, we use ordinary least squares to estimate the following model using the full sample of both male and female applicants:

$$(2) \quad Y_i = \beta_1 Incentive_i + \beta_2 male_i + \beta_3 male_i \times Incentive_i + \gamma' X_i + \epsilon_i,$$

which is identical to equation (1) except for additionally including a male dummy as well as an interaction term of the male dummy and the incentive dummy. In this model, β_1 shows the effect of offering the incentive for female applicants, and $\beta_1 + \beta_3$ shows the effect of offering the incentive for male applicants.

II. Results

Table 1 shows no statistically significant effect of being offered a financial incentive for

Table 1—The Impact of Incentives on Attempting the Python Test

	(1)	(2)	(3)	(4)
Incentive	−0.035	−0.035	−0.035	−0.028
	(0.057)	(0.056)	(0.057)	(0.056)
Male			−0.092	−0.101
			(0.045)	(0.044)
Male × Incentive			0.017	0.003
			(0.063)	(0.062)
Constant	0.481	0.296	0.481	0.361
	(0.040)	(0.198)	(0.040)	(0.099)
Observations	309	309	1,605	1,605
R^2	0.001	0.118	0.005	0.037
Controls	No	Yes	No	Yes
Sample	Female applicants	Female applicants	Female and male applicants	Female and male applicants

Notes: The dependent variable for all columns is an indicator variable that is equal to 1 if the applicant attempted the Python programming test and 0 if the applicant did not attempt the test. The main independent variable in columns 1 and 2 is an indicator variable that is equal to 1 if the applicant was assigned to the incentive treatment and 0 if the applicant was assigned to the nonincentive treatment. The main variables in columns 3 and 4 are the incentive indicator, a male indicator that is equal to 1 if the applicant is male and 0 if the applicant is female, and an interaction term of the incentive and male indicator variables. We include controls in columns 2 and 4. See Section I for more details on the included controls. Heteroskedasticity robust standard errors in parentheses.

female applicants. The point estimates in column 1 suggest that being offered an incentive statistically insignificantly *reduces* the probability of female applicants completing the Python test by 3.5 percentage points. The 95 percent confidence interval allows us to rule out effects of the incentive offer of smaller than −14.7 percentage points and larger than 7.6 percentage points. The result look identical when we add control variables (see column 2), where we also see an estimated 3.5 percentage point reduction.

Furthermore, this result holds for both genders. Columns 3 and 4 show the estimated effect of offering incentives is −1.9 percentage points for men (−2.5 percentage points with controls). The small differences between the estimated effects for men and women are also not statistically significant.

III. Discussions

There are a few plausible reasons why we did not see an economically meaningful or statistically significant effect of being offered an incentive to complete the application.

Introducing financial incentives within a job application process is nonstandard, so applicants may treat it with some skepticism.

The incentive may have also been too low. Maybe many of those who did not provide their payment details did not think that a payment between \$5 and \$10 was worth the hassle.

Providing financial incentives may also signal that there will be a larger applicant pool, increasing competition and reducing the probability of obtaining the job. Since women are more likely to shy away from competition, this signal may reinforce this behavior.

Finally, while the aim of the experiment is to increase the number of women entering a competitive job tournament, it is interesting that in our sample, women are more likely to complete their applications than men (see the male coefficient in columns 3 and 4 of Table 1). One possible reason for this finding is gender differences in opportunity costs. If our male applicants have higher-paid job opportunities than our female applicants, then they may exert their effort on jobs that pay more.

Another possible reason is that the kind of women already self-selected into a male-dominant programming profession may be different from women in the general population (Feld et al. 2022). For instance, unlike many studies of gender differences in the general population or student samples, we find no significant gender differences in self-reported risk attitude among our applicants. Perhaps guaranteed financial incentives would be more effective targeting women who are still choosing their career or specialization instead of women who have already self-selected into such an environment.

REFERENCES

Avery, Mallory, Andreas Leibbrandt, and Joseph Vecci. 2023. "Field Experiments on Disrupting Gender Imbalances in Recruitment with Artificial Intelligence." Unpublished.

Bagues, Manuel, and Berta Esteve-Volart. 2010. "Can Gender Parity Break the Glass Ceiling? Evidence from a Repeated Randomized Experiment." *Review of Economic Studies* 77 (4): 1301–28.

Bagues, Manuel, Mauro Sylos-Labini, and Natalia Zinovyeva. 2017. "Does the Gender Composition of Scientific Committees Matter?" *American Economic Review* 107 (4): 1207–38.

Beasley, Maya A., and Mary J. Fischer. 2012. "Why They Leave: The Impact of Stereotype Threat on the Attrition of Women and Minorities from Science, Math and Engineering Majors." *Social Psychology of Education* 15 (4): 427–48.

Buser, Thomas, Eva Ranehill, and Roel van Veldhuizen. 2021. "Gender Differences in Willingness to Compete: The Role of Public Observability." *Journal of Economic Psychology* 83: 102366.

Chamorro-Premuzic, Tomas. 2015. "Ace the Assessment." *Harvard Business Review*, July. https://hbr.org/2015/07/ace-the-assessment.

Charness, Gary, and Uri Gneezy. 2012. "Strong Evidence for Gender Differences in Risk Taking." *Journal of Economic Behavior and Organization* 83 (1): 50–58.

Croson, Rachel, and Uri Gneezy. 2009. "Gender Differences in Preferences." *Journal of Economic Literature* 47 (2): 448–74.

Dobbin, Frank, and Alexandra Kalev. 2022. *Getting to Diversity: What Works and What Doesn't*. Cambridge, MA: Belknap Press.

Feld, Jan, Edwin Ip, Andreas Leibbrandt, and Joseph Vecci. 2019. "Pay for Applications." AEA RCT Registry. August 29. https://doi.org/10.1257/rct.4625-1.0.

Feld, Jan, Edwin Ip, Andreas Leibbrandt, and Joseph Vecci. 2022. "Identifying and Overcoming Gender Barriers in Tech: A Field Experiment on Inaccurate Statistical Discrimination." CESifo Working Paper 9970.

Goldin, Claudia, and Cecilia Rouse. 2000. "Orchestrating Impartiality: The Impact of 'Blind' Auditions on Female Musicians." *American Economic Review* 90 (4): 715–41.

Ip, Edwin, Andreas Leibbrandt, and Joseph Vecci. 2020. "How Do Gender Quotas Affect Workplace Relationships? Complementary Evidence from a Representative Survey and Labor Market Experiments." *Management Science* 66 (2): 805–22.

Kong, Stephanie, Katherine Carroll, Daniel Lundberg, Paige Omura, and Bianca Lepe. 2020. "Reducing Gender Bias in STEM." *MIT Science Policy Review* 1: 55–63.

Niederle, Muriel, Carmit Segal, and Lise Vesterlund. 2013. "How Costly Is Diversity? Affirmative Action in Light of Gender Differences in Competitiveness." *Management Science* 59 (1): 1–16.

Niederle, Muriel, and Lise Vesterlund. 2007. "Do Women Shy Away from Competition? Do Men Compete Too Much?" *Quarterly Journal of Economics* 122 (3): 1067–101.

Sarsons, Heather, and Guo Xu. 2021. "Confidence Men? Evidence on Confidence and Gender among Top Economists." *AEA Papers and Proceedings* 111: 65–68.