

When do ideas attract talent?

Evidence from a randomized controlled trial*

SOLÈNE DELECOURT
Berkeley Haas

REMBRAND KONING
Harvard Business School

SAHIBA CHOPRA
Berkeley Haas

Abstract

Startups employ few women, especially at their earliest stages. An underappreciated implication of this underrepresentation is that ideas targeting these groups may struggle to attract the talent needed for venture success. If talent prefers to work on ideas that resonate with their backgrounds, or if workers feel uncomfortable working on ideas focused on other demographic groups, then a lack of workforce diversity may have an unequal impact on which ideas succeed. We test this thesis using field experiment and observational data on the universe of high-tech startup workers in the U.S. Results from our in progress field experiment shows that shifting a non-gender-focused startup idea to be female-focused reduces the probability a candidate applies to the job by 15 percentage points, an effect size equivalent to reducing a job's posted salary by \$30,000 a year. Hiding the gender focused of an already female-focused startup idea has equivalent effects but with flipped signs. These effects stem from the choices of male job seekers, the minority of women who look for startup jobs on our job search platform are more likely to apply to female-focused ideas. Consistent with our experimental results, we use word embedding methods applied to U.S. startups in PitchBook and find female-focused ideas attract 25% fewer employees, that those employees have 30% less work experience, and that these gaps are driven by the fact that 80% of startup employees men. Finally, building on models of bias in entrepreneurial experimentation, we find that these gaps only hold for earlier stage firms, female-focused ventures that raise substantial capital exhibit no talent gap. Our findings illustrate how heterogeneity in beliefs about which early stage ideas are “worthy of working on” can impact the rate and direction of innovation.

*Koning: rem@hbs.edu; Delecourt: solened@berkeley.edu; Chopra: sahiba.chopra@berkeley.edu. We have benefited from thoughtful seminar comments at Berkeley and Harvard. Special thanks to Kelsey Shipman and Katelyn Cranney who provided careful and invaluable research assistance. We thank Berkeley Haas, Harvard Business School, and Harvard's Digital, Data, and Design Institute for funding this work. All errors are our own.

Scholars and managers increasingly recognize the ways in which startup and product ideas can be targeted to benefit historically overlooked and marginalized groups. For example, in the U.S. there is a growing cadre of startups that use AI tools and platform design to improve the hiring and career of people of color. Outside of the U.S., there has been an explosion in startup ideas that apply technology to the needs of businesses and consumers in emerging and developing markets; markets that innovators have historically overlooked. The rise of “FemTech”—startups aimed at the needs of women and especially women’s health—further highlights how technology can be applied to address historically dismissed and overlooked problems (Koning et al., 2021).

Yet, despite the potential for startup ideas to address the needs of these diverse and overlooked groups, the labor market for startup talent—from engineers to product managers to data scientists—remains markedly less inclusive, especially with respect to gender (Koning et al., 2021; Cao et al., 2022; Guzman and Kacperczyk, 2019). As with founders and investors, the workers who scale early-stage ideas are overwhelmingly men, with the share of female startup workers hovering around 25% over the last decade. On the one hand, talent of any gender may be agnostic to whether an idea targets men or women, instead choosing to join startups as long as they show the potential to scale and are well managed (Bernstein et al., 2022; Bryan et al., 2022; Chatterji et al., 2019). On the other, if female-focused ideas tend to attract women but struggle to attract male talent, then the scarcity of women in the startup workforce will make it harder for female-focused ideas to get the talent they need.

Here we unpack this latter possibility using both a field experiment and observational data to explore how the *gendering* of a startup idea impacts its appeal to the male and female workers. Core to our analysis is the idea that a startup idea can be gendered for both systemic or direct reasons. *Systemically gendered* ideas that appeal more to men or women for broad structural, biological, or cultural reasons. These ideas are fundamentally intertwined with gender segregation and biological differences. For example, a startup idea focused on sports betting will overwhelmingly attract male users even if platform is open to both men and women. Similarly, startups like Clue focusing on menstrual health lack a male analogue. However, while systemic differences in an idea’s gender focus matter, the structural gendering implies that differences in an idea’s market potential and gender focus are endogenous, making it difficult to isolate why female-focused ideas struggle to attract talent (Bohren et al., 2022).

Fortunately, there also exist a subset of ideas that are *directly genderable*, ideas for which the genderiness of the startup’s target market can be shifted while holding many other aspects of the idea—from the market potential to the idea’s technical difficulty—relatively constant. In these cases, differences in an idea’s appeal can be at least partially separated from the idea’s quality and a myriad of other (un)observable characteristics. For example, a startup may offer a new hiring platform, wellness product, or financial planning tool could choose to specifically target women. The same founder could also decide pivot to focus on the needs of men (or target genders) without fundamentally changing the entire business idea and model.

We leverage the fact that some ideas are genderable to first design a field experiment testing whether female-focused ideas struggle to attract talent. To estimate labor’s willingness to work on more or less female-focused ideas, we adapt recent work on Incentivized Resume Rating experiments (Kessler et al., 2019; Agan et al., 2021). In our experiment, we present job searchers with 40 “synthetic” startup jobs to measure if the job seeker is more or less interested in working for female-focused ventures. Figure 1 presents a screenshot of the platform we developed for the experiment. For each startup the searcher is asked to indicate whether they would apply or not to the posting. The key to our design is that the searcher might see a real startup description pulled from PitchBook like the following:

Developer of e-bikes intended for **female** urban commuters. The company aims to create a safe, lightweight **women’s** e-bike that is designed for daily use by keeping **women** commuters in focus, offering customers a safe urban e-bike that does not cost a fortune.

Or the searcher might see the same idea, but directly manipulated by us to be gender neutral:

Developer of e-bikes intended for busy urban commuters. The company aims to create a safe, fast, lightweight e-bike that is designed for daily use by keeping commuters in focus, offering customers an efficient urban e-bike that does not cost a fortune.

Crucially, the user’s rating of the 40 startups are then provided to *real* career coaches who use this rating data to find real job postings that reflect the searchers preferences in order to align participant incentives and effort. Crucially, this design lets us randomize whether ideas are (1) more or less female-focused as in the example above and (2) the salary posted for the job while holding all other aspects of the job constant.

In total, of the 40 startups shown to seekers 20 are randomized to be more or less female-focused version of the an actual startup idea pulled form PitchBook. While our field experiment is ongoing, our within subjects design has yielded insights even though only our pilot includes only 17 participants (13 male, 4 female). Table 1 regresses if a job searcher “would apply” to a startup against whether the startup idea is manipulated to be female-focused or not. Regressions are linear probability models with the outcome multiplied by 100 to ease interpretation. Following the advice of Abadie et al. (2017) we cluster at the level of treatment randomizes the gender focus of each individual idea. Model 1 shows that job seekers apply to non-female-focused ideas 61% of the time. The female-focused version of the same idea is just over 16 percentage points less likely to be of interest to job seekers. The effect is economically substantial: when the randomized salary shown with a posting increases by \$1,000 the probability of applying increases by 0.5 percentage points ($p < 0.01$). This suggests a female-focused version of an idea has to increase pay by roughly \$32,000 to attract a similar number of applicants as the non-female-focused version of the idea.

Column 2-5 show these estimates hold even when we include display order, job searcher, and even startup idea fixed effects. Within the same idea, talent is less likely to apply to the female version. Column 5 shows the estimates hold when we restrict to ideas we shifted from non-female focused to being female-focused; Column 6 shows the results also hold for the sample of ideas that were originally female-focused that we manipulated to be non-female-focused. No matter the direction of the manipulation the female-focused version was less likely receive an application.

As expected, these effects are driven by male job seekers. Column 3 of Table 2 interacts our female-focus variable with the gender of the job seeker.¹ Men are 30 percentage points less likely to apply to female-focused ideas; women are 30 percentage points more likely to apply. However, as with the startup workforce, only 23% of the job seekers in our pilot are women. Column 4 shows these patterns hold even when we include job seeker fixed effects and Column 5 shows the results hold with an alternative measure of our gender manipulation.

Given these results, we next turn to testing whether at the macro-level the gender-focus of an idea impacts whether an startup can attract and retain the talent required to scale. To do so we use data on the near universe of of startups founded between 2011 and 2020 in the U.S. that are listed in PitchBook. Using this observational data on 39,704 startups, we build on Cao et al. (2022) and use word embedding methods to classify each startup as more or less female- or male-focused

¹The higher application for rate for women in Table 2 Columns 1-3 is an artifact of the fact that 10 of the 20 manipulated jobs are randomized to be female-focused. Thus our sample simply includes more female-focused listings than exists in reality.

using the startup’s short PitchBook description (Cao et al., 2022). Our measure captures both the genderable startups used in our experiment and *systemic* differences in an idea’s female-focus. For example, the startup “HeyJane” provides online abortion pill access has a normalized female-focus score of 2.6 standard deviations, putting this systemically gendered idea in the top half-percent of female-focused startup ideas. The fantasy football startup “Underdog Fantasy” receives a high male-focused score, putting it in the amongst the most male-focused startups. Medical startups focused on infertility or aimed at the transgender community score highly on both our male- and female-scores highlighting why we treat male- and female-focus as distinct dimensions in this setting rather than a spectrum as in past work.

Table 3 shows OLS regressions of a startup’s workforce size in 2020 against the startup’s gender scores. All models include founding year fixed effects. Consistent with our experimental results, startups that are more female-focused have fewer workers. This effect holds even when we include industry fixed effects. Moreover, the effect is not merely a “gendered” startup discount. More male-focused startups actually have larger work forces than less male-focused firms. Figure 2 presents binned scatter plots of the startup’s inverse-hyperbolic-sine transformed (IHS) number of male and female employees against the startup’s gender score. We see that many fewer men work for female-focused startups—a drop of 1 IHS unit corresponds to roughly a 100% reduction in workforce size—whereas women are more likely to work for female-focused firms. However, because women only make up roughly one-in-five startup workers female-focused startups end up with less talent. As startups become more male-focused the opposite patterns hold.

Finally, Figure 3 show the total number of employees (IHS transformed) against a startup’s female-focus score for the 10% of startups in our sample that have raised \$20 million or more in funding as of 2020. If anything, female-focused startups that are well-funded have more employees than less female-focused ventures. However, for the 90% of ventures with less than \$20 million in funding we see a strong negative relationship. Consistent with models of biased entrepreneurial experimentation (Cao et al., 2022) these results suggest that the dominance of men in the startup workforce may distort the direction of innovation away from the needs of women, but that with sufficient signals and resources female-focused startup ideas are just as enticing to men as to women.

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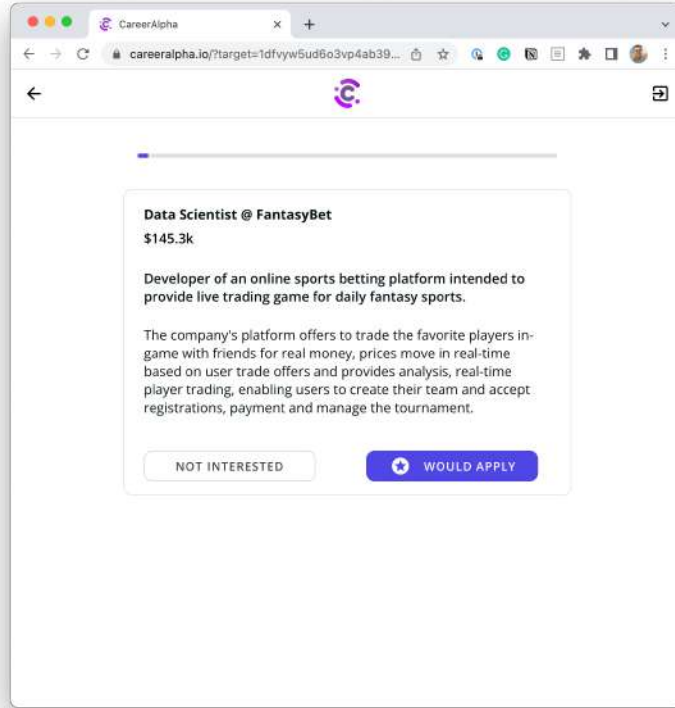


Figure 1: For each description-salary pair users must choose to apply or not apply. The names of the startups are masked and some of the descriptions have been randomized to be more/less female/male-focused.

Table 1: Regressions showing the probability a user applies for job varies with whether the version of the startup idea shown is female-focused or not.

Dependent Variable:	Would apply to startup					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
Constant	61.1*** (3.5)					
Female version	-16.7*** (5.1)	-15.9*** (5.2)	-16.6*** (4.9)	-16.1*** (4.9)	-13.2* (7.6)	-19.0*** (6.7)
Gendering Direction	Both	Both	Both	Both	To Female-focus	From Female-focus
<i>Fixed-effects</i>						
Display Order		Yes	Yes	Yes	Yes	Yes
Job Searcher			Yes	Yes	Yes	Yes
Startup Idea				Yes	Yes	Yes
<i>Fit statistics</i>						
Observations	377	377	377	377	189	188
R ²	0.03	0.09	0.24	0.29	0.37	0.40

Heteroskedasticity-robust standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2: Regressions showing men don't apply to female-focused versions of an idea but women do.

Dependent Variable: Model:	Would apply to startup				
	(1)	(2)	(3)	(4)	(5)
<i>Variables</i>					
Female Job Searcher	17.2*** (5.9)	17.1*** (6.2)	-15.3* (8.0)		
Female version		-15.2*** (5.2)	-30.4*** (5.8)	-31.3*** (5.4)	
Female Job Searcher × Female version			66.2*** (11.7)	66.1*** (11.1)	
Female-focus					-6.9*** (1.5)
Female Job Searcher × Female-focus					13.3*** (2.7)
<i>Fixed-effects</i>					
Display Order	Yes	Yes	Yes	Yes	Yes
Startup Idea	Yes	Yes	Yes	Yes	Yes
Job Searcher				Yes	Yes
<i>Fit statistics</i>					
Observations	377	377	377	377	377
R ²	0.15	0.17	0.24	0.36	0.34

Heteroskedasticity-robust standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: Regressions testing if startups that are more male- and female-focused have hired and retained more or less talent as of 2020.

Dependent Variables: Model:	Employees		Employees (IHS)		Employees: 10+		Has an employee?	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Variables</i>								
Male-focus	0.48*** (0.16)	0.44*** (0.17)	0.04*** (0.01)	0.05*** (0.01)	1.9*** (0.33)	1.7*** (0.34)	-0.01 (0.22)	0.79*** (0.23)
Female-focus	-0.50*** (0.17)	-0.12 (0.18)	-0.07*** (0.01)	-0.04*** (0.01)	-2.2*** (0.34)	-0.88** (0.36)	-0.78*** (0.22)	-0.60** (0.23)
<i>Fixed-effects</i>								
Founding year (10)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry (198)		Yes		Yes		Yes		Yes
<i>Fit statistics</i>								
Observations	39,703	39,703	39,703	39,703	39,703	39,703	39,703	39,703
R ²	0.04	0.09	0.03	0.10	0.04	0.09	0.06	0.11

Heteroskedasticity-robust standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

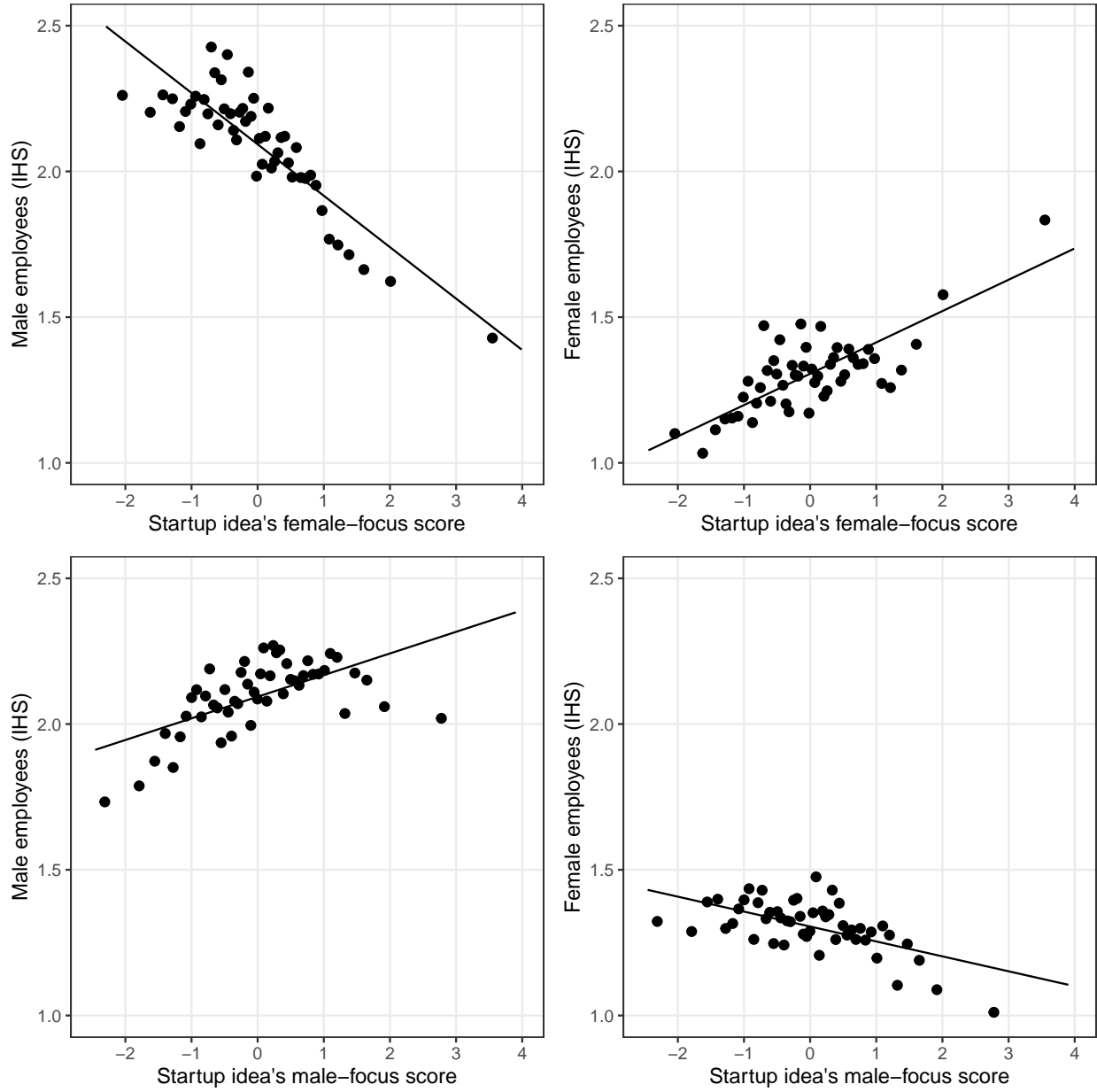


Figure 2: Binscatters showing the inverse hyperbolic sine transformed number of male and female employees in 2020 against the startup's female-and male-focus scores. Each binscatter shows 50 points and includes fixed effects for the year the startup was founded along with controls for the focus score of the opposite gender.



Figure 3: Binscatter—restricted to startups with **over** \$20 million in VC funding—showing the inverse hyperbolic sine (IHS) transformed number of employees in 2020 against the startup’s female-focus score. The binscatter shows 50 points and includes a fixed effects for the startup’s industry and founding year along with controls for the male-focus of the startup. The binscatter shows 50 points.

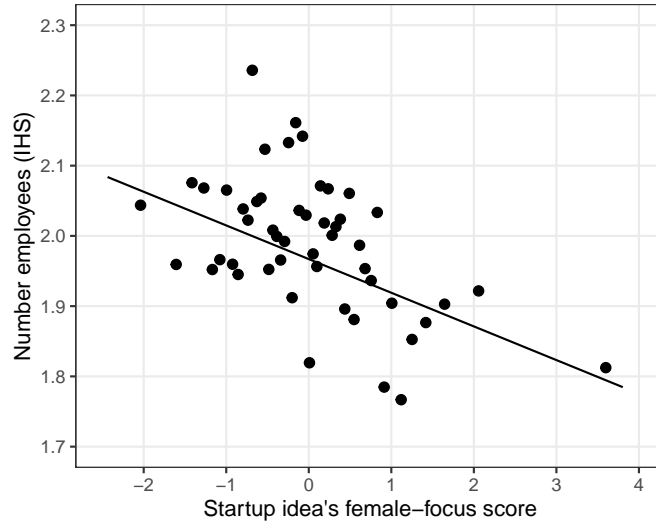


Figure 4: Binscatter—restricted to startups with **under** \$20 million in VC funding—showing the inverse hyperbolic sine (IHS) transformed number of employees in 2020 against the startup’s female-focus score. The binscatter shows 50 points and includes a fixed effects for the startup’s industry and founding year along with controls for the male-focus of the startup. The binscatter shows 50 points.