How Do Entrepreneurs Set Wages?

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Abstract

Hiring beyond the founding team is essential to scaling a venture, but labor and search are extremely costly. What hiring strategies do entrepreneurs use, and how do they think about setting compensation for their employees? I conduct a novel survey and experiment with 540 founders of growth-capable U.S. startups that have, on average, 18 employees and $6.8 million of funding. Entrepreneurs initially described hiring and compensation-setting at their own firms and then were asked for their best advice about wages for four fictitious job postings. This paper shows that founders report being involved in all aspects of the hiring process, even at the minority of startups that have human resources staff. Startups are less likely than established firms to use paid consultants or wage benchmarking data, relying instead on word-of-mouth advice and free online services to research compensation. Entrepreneurs' wage advice is highly dispersed and sensitive to information, particularly when the entrepreneur is a first-time founder or lacks experience with a given job. Finally, soliciting a "fair" wage rather than framing wages as a cost induced non-male entrepreneurs to recommend wages that were $11,000 higher, on average. Taken together, these results suggest that startup hiring is a founder-centric process and that wages at startups may be influenced both by available information and by founders' own utility, beliefs, and preferences.

1 Introduction

Successfully scaling and running a high-performing startup requires hiring and retaining talented employees (Coff and Kryscynski 2011; Wasserman, 2012). A large literature in economics, sociology, and management has addressed different aspects of firm-worker matching including worker preferences and information (Roach and Sauermann, 2022; Bryan et al., 2022; Bernstein et al., 2022), referral-based hiring (Fernandez et al., 2000; Burks et al., 2015; Friebel et al., 2023), delegation in hiring (Cowgill and Perkowski, 2020), and firm-driven search (Black et al., 2020). A common assumption of much of this literature is that wages are determined by the marginal product of labor, as in canonical economic models of competitive labor markets (e.g. Katz and Murphy (1992)) or by a negotiation over joint surplus resulting from the firm-worker match (e.g. Diamond (1982)). These negotiations may in turn be impacted by internal firm structures, bureaucracies, or personnel (Adler, 2022) but labor demand and wage-setting are fundamentally firm-level processes.

However, in entrepreneurial ventures, the founders often *are* the firm, and their utility, beliefs, and preferences may determine who is hired and how wages are set. Entrepreneurial strategy is fundamentally an individual choice process under constraint and uncertainty (Gans et al., 2019) and entrepreneurs' own preferences and values have been shown to affect a wide range of business decisions including the decision to start a firm in the first place (Hurst and Pugsley, 2011; Shah et al., 2019), the firm's geographic location and re-location (Dahl and Sorenson, 2009; Bryan and Guzman, 2022), and the split of initial equity among founders (Hellmann et al., 2019). In fact, prior work has shown that high-tech founders have distinct mental models of the employment relationship and organizational "blueprint" they plan to develop (Baron and Hannan, 2002). This is not to say that labor market competition does not impact wages, but rather that entrepreneurial wage-setting is a process where individual founder judgements may play a large role in determining compensation.

In this paper, I investigate how young, growth-capable startups search for employees and choose compensation, drawing on a novel survey and experiment that I conducted with 540 growth-capable U.S. startups. The Hiring at Top Startups (HATS) Study first asked participants about hiring and compensation-setting practices at their own firms before soliciting their best advice about wages appropriate to four fictitious job postings. Advice-giving is extraordinarily common among high-growth tech entrepreneurs and is an important way that information and business practices diffuse (Saxenian, 1996; Chatterji et al., 2019; Howell and Nanda, 2019; Lerner and Malmendier, 2013). Respondents were incentivized to participate and offer truthful advice by the promise of a final study report about participating companies' responses (a similar tactic was employed by the CompStudy, see Wasserman (2006)). The companies that participated in the

HATS Study are less than six years old and, on average, have raised \$6.8 million and have 18 employees. Ninety-two percent of survey respondents were founders, and most participating founders are male (80%), white (67%), U.S. citizens (84%), and have postgraduate degrees (56%), with a large share reporting that their highest degree obtained is an MBA (20%).

This paper first draws on the survey portion of the HATS Study to illustrate the central role that founders play in the startup hiring process. An overwhelming majority of founders report designing job ads, assessing candidates, and choosing compensation packages, even when they have an HR person (which less than a quarter of firms do). Founders are much more likely than HR managers at established firms to rely on free, online data sources to benchmark salaries, and they rely heavily on word-of-mouth advice to benchmark compensation. Founders rate their own professional networks and employee referrals as the most useful tools to find employees. This founder-centric hiring process suggests that the idiosyncratic information and tastes of individual founders may play a large role in determining compensation.

The paper then proceeds to illustrate that these entrepreneurs' wage judgements are influenced both by information and (for some entrepreneurs) concerns about fairness by presenting the results of two experimental manipulations embedded in the advice-giving exercise. In this exercise, entrepreneurs were asked for their advice about wages appropriate to four fictitious job postings which were constructed based on real job advertisements and chosen to represent a range of technical and non-technical roles common at startups in the industry sectors surveyed. After making their four initial recommendations, all entrepreneurs were given the opportunity to revise their advice along with a wage benchmark sourced from a popular job-posting website. This allows me to observe entrepreneurs' prior beliefs about wage levels, as well as their updating behavior.

In a first experimental manipulation, I varied the information available to entrepreneurs when they revised their advice, randomizing them to see wage benchmarks either from Glassdoor.com or Indeed.com. These are two of the most popular job search websites in America, and 55% of survey respondents report having consulted at least one of these sites when benchmarking salaries. However, these benchmarks can vary widely: for example, at the time of the survey, Glassdoor suggested that the average base salary for an administrative assistant in Washington State was \$42,456, while Indeed.com suggested it was \$55,919 (32% higher).

From this exercise, I show that founders give widely varying advice about wages that is responsive to information, and that the information content does matter. Providing information substantially compresses the distribution of wage advice: this compression is evident visually and can be summarized by the absolute value of the percent deviation of the advice from the wage benchmark. Initially, wage advice is on average 31.12 percentage points off the benchmark, and when information is revealed this drops to 19.9 percentage points, a difference of 36% ((31.12-19.9)/31.1). However, not all entrepreneurs were equally likely to use information: first-time founders, founders with no experience performing or hiring somebody to perform a given role, and founders who are not male are more likely to update their advice in response to information, even conditional on their initial advice.[1] Finally, entrepreneurs randomly assigned to the higher of the two benchmarks for a given position in a given state recommend wages that are about $4,000 higher, on average. This suggests that in the constrained world of startup hiring, the quality of information (which is highly variable) may impact entrepreneurs' assessments of wages, particularly if they lack experience hiring for a particular job.

A second experimental manipulation aimed to test whether prompting entrepreneurs for a fair wage changed their advice. Preferences over fairness have been shown to impact how economic agents allocate resources both in general (Fehr and Schmidt, 1999; Bewley, 1999; Akerlof and Yellen, 1990) and at high-potential startups specifically (Hellmann and Wasserman, 2017; Hellmann et al., 2019; Shah et al., 2019). The entrepreneur's view of fairness is also particularly interesting because of management's role in establishing norms of cooperation within the firm (Gartenberg and Zenger, 2022). Entrepreneurs were randomly allocated to one of two different sets instructions for this advice-giving exercise. In the first treatment arm (the cost treatment), the instructions described wages as a cost paid while a startup tries to stay lean. In the second treatment arm (the fairness treatment), the instructions reminded entrepreneurs that managers exercise power over their employees and asked them to recommend a fair wage for the employee to receive. Importantly, the goal of this exercise was not to define fairness as a construct, but to see how this group of employers understood the construct, and whether fairness concerns could be activated to change founders' advice about wages.

I show that, in the overall sample, this treatment did not impact the wage advice given by entrepreneurs, but the fairness treatment did induce non-male entrepreneurs to recommend wages about $11,000 higher than non-male entrepreneurs in the cost treatment arm. This effect was reduced, but not eliminated by, the provision of the wage benchmark. This finding is in line with other work that finds heterogeneous responses by male and female entrepreneurs to prosocial messaging (Guzman et al., 2020), and descriptive work that finds "altruism" ranks highly as a motivation for female professionals and entrepreneurs early in their careers, but becomes important for men much later (Wasserman, 2012). This suggests that members of different demographic groups may react differently to calls to incorporate prosocial goals into their organizations which could impact relative firm performance.

[1] Survey respondents self-identified as "male," "female," or "some other gender" with two respondents selecting the last option. Throughout the analysis, I group "female" and "some other gender" together and refer to "non-male" entrepreneurs. All results in the paper are robust to dropping these two observations and considering only those who identify as male and female. I consider grouping non-male entrepreneurs to be appropriate for this analysis given the social context of these top startups.

In sum, this paper provides evidence that hiring at entrepreneurial ventures is a founder-centric process and that founder beliefs and values may play a role in determining wages which in turn impact firm performance. This study is a first attempt to respond to calls from personnel economists (Oyer and Schaefer, 2011) and entrepreneurship scholars (Burton et al., 2019a) for more investigation into firms' internal hiring processes, and for greater connection between literature about entrepreneurship and studies of broader labor market institutions (Burton et al., 2019b). It also highlights a critical problem in entrepreneurial strategy: how to hire and compensate the talent which can be a key competitive advantage (Barney, 1991; Campbell et al., 2012) and source of technical and market knowledge (Agarwal et al., 2004; Singh and Agrawal, 2011). This is fundamental, as many startups operate under severe resource constraints, making the cost of a bad hire or high turnover potentially devastating (Baron et al., 2001; Li et al., 2022).

The paper proceeds as follows: Section 2 situates this paper within three strands of related literature before describing the survey and experiment in greater detail in Section 3. Section 4 describes survey insights on entrepreneurial hiring, and Section 5 reports the two sets of experimental results. Section 6 discusses further implications of startup hiring and robustness tests, and Section 7 concludes and offers thoughts on future directions for subsequent work.

2 Related Literature

Hiring as a phenomenon is of broad interest to scholars across disciplines. This section situates this paper in the context of three streams of work: literature that deals with the startup labor market specifically, hiring and personnel economics more generally, and the role of individual judgements and values in economic exchange.

First, this paper aims to complement and extend existing work about entrepreneurial hiring and careers of startup employees. Classic work in management scholarship on entrepreneurial ventures has tended to focus on founding team formation, the impact of first hires for functional roles (Burton and Beckman, 2007) and executive compensation (notably the CompStudy, detailed in (Wasserman, 2006)). These studies have drawn on a variety of data including surveys and interviews to uncover firm's otherwise unobserved internal processes. In this tradition, the Hiring at Top Startups (HATS) Study described in the next section asks founders about their hiring and compensation practices, but broadens the focus to hiring beyond non-executive roles. Hiring for these roles is both practically important for firms that successfully grow, and conceptually interesting as it may involve the founding team hiring for roles with which they have less experience, or hiring people from more distant educational and class backgrounds. Recent work has similarly focused on this aspect of scaling using large-scale data from job postings (Lee and Kim, 2022). This paper complements this work by exploring the hiring processes and decision-making behind this startup job posting activity. These hiring process are important because they may impact who gets pursue a startup career (discussed further in Section 6), the quality of those jobs, and the returns to startup careers (Burton et al., 2018; Sorenson et al., 2021; Roach and Sauermann, 2022).

Second, this paper complements work from personnel and labor economics by providing evidence about how young firms actually approach the hiring problem. This paper is a first step to understanding which aspects of the labor market, from benchmarking data (Cullen et al., 2022) to outbound recruiting (Black et al., 2020) to the use of referrals (Burks et al., 2015) to delegation in hiring (Cowgill and Perkowski, 2020) are most relevant for entrepreneurs. HATS aims to fill a gap in our understanding of the labor market, as data about the internal process of young firms are particularly difficult to obtain (Burton et al., 2019a). In addition to this empirical contribution, HATS makes a conceptual point that theories of firm-worker matching that describe hiring as a firm-level problem may not accurately capture the complexity of compensation-setting at young firms, where entrepreneurs play a central role and their own tastes, utility, beliefs, and values may influence who gets hired and how much they are compensated. This is important conceptually, and also practically because entrepreneurial ventures are critical to job creation and destruction (Haltiwanger et al., 2013).

Finally, this paper relates to literature about the role of individual judgments and values in economic decision making in general, and hiring/compensation specifically. It has long been understood that agents have heterogeneous preferences for inequality which affect how they behave when allocating resources (Fehr and Schmidt, 1999; Bewley, 1999) and how they behave when they recieve less than they think they deserve (Akerlof and Yellen, 1990). Founding teams specifically have been shown to have different degrees of inequality aversion that impacts the split of initial equity (Hellmann and Wasserman, 2017) and that these fairness preferences persist over time (Hellmann et al., 2019). This paper investigates whether founders of top U.S. startups are responsive to fairness concerns in their wage advice about non-executive roles, and only finds a response among non-male founders. This mirrors other work in entrepreneurship that finds founders of different genders and from different cultural backgrounds may be differentially responsive to pro-social motivations (Guzman et al., 2020) and that female entrepreneurs and non-entrepreneurs rank "altruism" in the top five career motivations beginning in their 20s, while "altruism" enters the top-five for men much later in life (Wasserman, 2012).

Managerial discretion in wage-setting has important practical and theoretical implications. The rise in managerial discretion in pay has been linked to aggregate increases in inequality (Massenkoff and Wilmers, 2023). In particular, it has been suggested that managers with business school educations depress wages and reduce labor share at large U.S. firms and in the Danish labor market (Acemoglu et al., 2022). This has practical implications for how economic gains are divided between workers and managers. Theoretically, the influence of managerial discretion and values is important for two reasons. First, theories of the firm as a subsociety explicitly define the managers' role in defining and sustaining principles of justice and common purposes within firms (Gartenberg and Zenger, 2022). The establishment of these principles has important implications for firm functioning. Definitions of shared purpose may be especially important in small firms, which generally provide weaker monetary incentives to employees. Second, there is renewed interest among management scholars in incorporating strategic goals beyond profit maximization, for example, the simultaneous pursuit of 'Purpose' and 'Profit'. This 'purpose' is often a prosocial value. HATS joins other work in highlighting that different groups may be differentially responsive to clarion calls to pursue goals like fairness or social impact (Guzman et al., 2020).

3 The Hiring at Top Startups Study

3.1 Study Recruitment and Sample

The Hiring at Top Startups (HATS) Study aimed to survey young startups with growth potential about their hiring and compensation setting strategies. To identify this population of firms, I used Pitchbook, a company database and research services firm owned by American financial services firm Morningstar Incorporated. Pitchbook is used extensively by venture capital and private equity professionals, as well as by entrepreneurship researchers (Eisenmann, 2021).

In April 2023, I attempted to contact all privately held companies with founder contact information in the Business-to-Business Product and Services and IT industries that were founded between January 1, 2016 and December 31, 2022 and had between 1 and 75 employees. The search was limited to companies with headquarters in 14 U.S. states: California, Massachusetts, New York, Rhode Island, North Carolina, South Carolina, Georgia, Florida, Texas, Colorado, Oregon, Michigan, Illinois, and Washington. This was a total of 11,656 companies.

I attempted to contact entrepreneurs three times using both physical mail and email. For the vast majority businesses (N=9,997 or 86.2% of the target population) with a physical address, the initial survey invitation was sent by mail. Where no physical address was available, the initial survey invitation was sent by email (N=1,596). Letters were mailed by a third-party printing and mailing service on April 12-13 while I sent initial emails from a study-specific institutional email address on April 14th. A follow-up email was sent to all entrepreneurs who had not yet responded to the survey on April 20-21.[2] On May 2, a final email

[2] A small number of emails were sent on the 21st because, despite my best efforts to prepare with university technical staff, the study email account was blocked by Microsoft due to the volume of email sent on a single day. This issue was addressed by

reminder was sent to all individuals with valid emails (that did not bounce) and who had not yet participated in the study. The survey stopped recording responses on May 8.

Study participants completed the survey (hosted by Qualtrics) online, and were advised it would take approximately fifteen minutes. Respondents were incentivized to participate by the promise of a report at the study's conclusion (similar to the CompStudy (Wasserman, 2006)) and a lottery for one of two $100 gift cards.

Of the companies I attempted to contact, 4.6% completed the study in its entirety. Excluding the 618 companies whose survey invitations (both mail and email) were returned, the response rate rises to 5.17%. This is lower than the typical response rate of surveys targeting C-level executives of large companies: for example, Graham et al. (2015) achieve an 11% response rate from CEOs, and a 6% response rate from CFOs. However, email bounces are an imperfect measure of outdated contact information: it is possible that a larger share of firms failed to receive their survey invitation, for example if emails continued to receive mail despite an individual changing roles or a company exiting.

For a more exhaustive description of the survey procedure, including other minor restrictions to the sample (Pitchbook search criteria), and rate of returned mail and email bounce back rate, please see the Survey Appendix in Section A2.

Firms that participated in the study are remarkably similar in size, age, and funding to the sample of companies invited to participate. Table 1 compares the overall set of firms invited to participate in the study (Column 1) to the HATS study participants (Column 2). There are differences in industry and geography with a higher share of the HATS participants headquartered in Massachusetts (10% vs. 6% of invited participants), perhaps reflecting greater responsiveness to the study's HBS affiliation. In terms of industry sector, a smaller share of the HATS companies are in IT and a larger share in Business Product and Services, which is likely correlated with the geographic selection (as top IT startups are clustered in California). Because industry sector is a somewhat noisy classification, and because many business products and services are heavily reliant on software, it is unclear whether this imbalance is particularly meaningful.

There are two more caveats about the sample which, while they do not bias the experimental results, have implications for generalizability to the overall population of startups. First, the sampling criteria limited the invited firms to those with fewer than seventy-five employees founded from 2016-2022. This opens up potential selection issues, since the sample excludes any firms founded during that time which managed to grow larger. This selection will vary by founding year cohort: the share of companies exceeding seventy-five employees two years after founding likely differs from those exceeding seventy-five employees five years after founding (this also applies to the share of firms surviving at all). Further, as the incentives to participate

the time of the final reminder email.

Table 1: HATS Sample vs. Survey Respondents

	(1) Invited to Participate	(2) HATS Repondents	(3) Difference in Means
Panel A: Size, Age, Industry Sector			
Employees	17.01	17.63	0.62
Age (2023 - Year Founded (Pitchbook))	4.21	4.26	0.05
Information Technology	0.66	0.60	-0.06***
Business Product and Services (B2B)	0.19	0.26	0.07***
Panel B: Funding			
Raised a Founding Round, Including Angel	0.88	0.90	0.02
Total Size all Deals (Millions USD)	8.00	6.81	-1.18
Panel C: HQ Location			
California	0.43	0.34	-0.09***
New York	0.18	0.14	-0.04**
Texas	0.08	0.09	0.01
Florida	0.06	0.06	0.00
Massachusetts	0.06	0.10	0.04***
Washington	0.04	0.06	0.02**
Illinois	0.03	0.04	0.01
Colorado	0.03	0.04	0.01
Observations	10912	540	11452

Tables compares the companies invited to participate in HATS (Column 1) with the companies that participated (Column 2). Column 3 shows the difference in means between the Pitchbook sample and the HATS respondents, with stars indicating the significance from a two-sided test of equality of means (* p <0.1, ** p<0.05, *** p<0.01).

in HATS were relatively weak, it is likely that the respondents are founders who are particularly interested in hiring and human resources, though it is unclear whether this interest is because the firm has already thoughtfully invested in its hiring practices, or because it is less experienced with hiring than the average startup.

3.2 Experimental Intervention

The experimental intervention asked all entrepreneurs for their "best advice" about wages appropriate to four fictitious job postings. Entrepreneurs' advice is both informative and important. First, if entrepreneurs took the exercise seriously and gave honest advice, this exercise reveals their beliefs about wage rates for jobs common among the startup workforce. The volume of comments about the exercise, as well as the fact that most entrepreneurs revised at least some of their advice, suggests that entrepreneurs took this task seriously. Making the exercise about advice to a fictitious startup rather than asking for competitively sensitive information about actual salaries also aimed to make it less risky for entrepreneurs to be honest. Respondents' lying would also make the study's report to participants less useful, and people may cooperate when they hope others will cooperate. In sum, while the study cannot guarantee respondents were truthful, it did not include obvious ways to lie and gain advantage. Second, while this advice does not represent actual wage offers, entrepreneurs' advice is itself meaningful because networking and word-of-mouth advice is extraordinarily common among high-growth tech entrepreneurs, and is an important way that information and business practices diffuse (Saxenian, 1996; Chatterji et al., 2019; Howell and Nanda, 2019; Lerner and Malmendier, 2013). Responses from the survey portion of HATS also reinforce that word-of-mouth advice plays a role in transmitting information about wages specifically, as will be discussed in Section 4.

Entrepreneurs were randomly assigned to two different versions of this advice-giving exercise, depicted in Figure 1. In both sets of directions, the firm was described as having raised a Series A funding round and having around twelve employees (a number that ended up being the median number of employees in the HATS sample). The firm was held constant across the four job postings in order to minimize respondents' cognitive burden, and in order to focus on the entrepreneurs' value of different positions rather than the value of different positions at different firms.

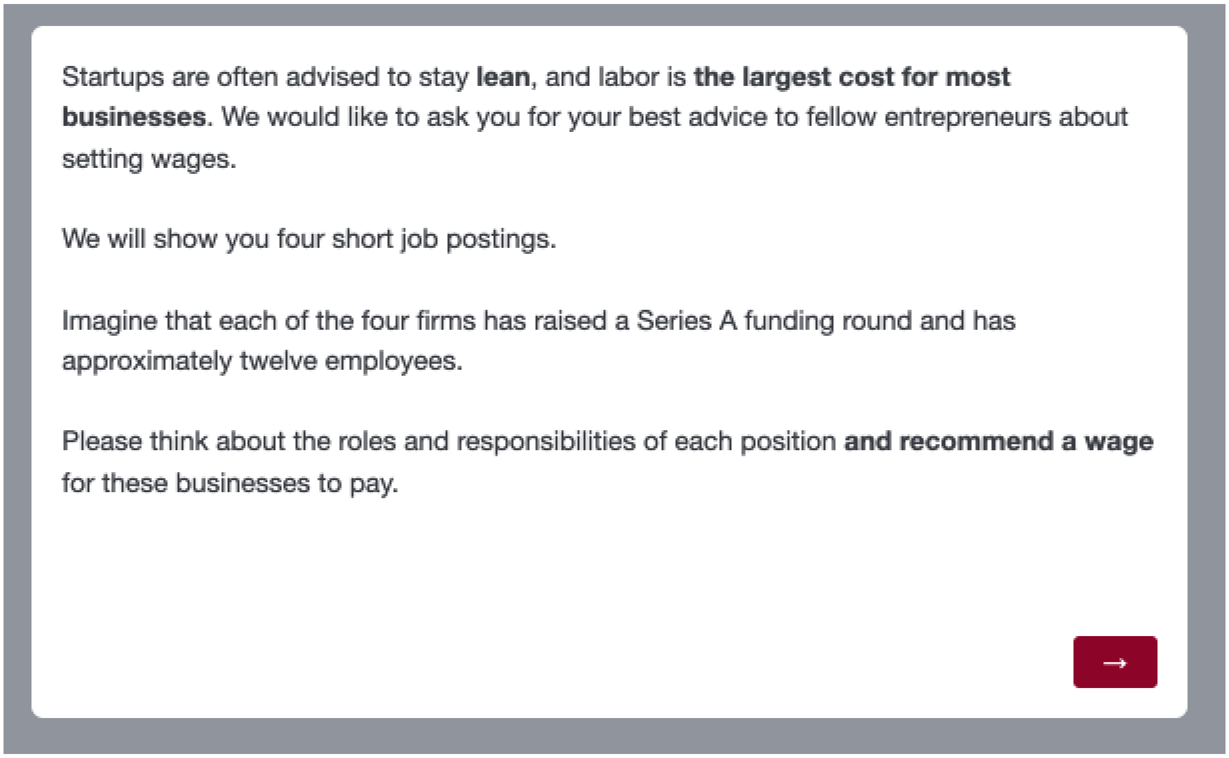
Randomization was done by Qualtrics, and characteristics of respondents and their firms were balanced across the two treatment arms with the exception of gender (for a balance table, see Table 2). A larger share of the fair wage treatment are non-male entrepreneurs (21% vs. 15%) and that difference is significant at the 10% level (p-value of difference=.06).

Entrepreneurs then made initial wage recommendations for four job positions: an administrative assistant, a software engineer, a data scientist, and a customer service representative (reproduced in Figure 2). Panel (a) of Figure 3 provides an example of this part of the exercise. These four positions were chosen because they are a substantial part of the startup workforce, have different technical and educational requirements, and different worker demographics. Worker demographics not only differ across these positions (for example, women are a much higher share of administrative assistants than software engineers) but between these positions and the demographic composition of the entrepreneurs themselves.

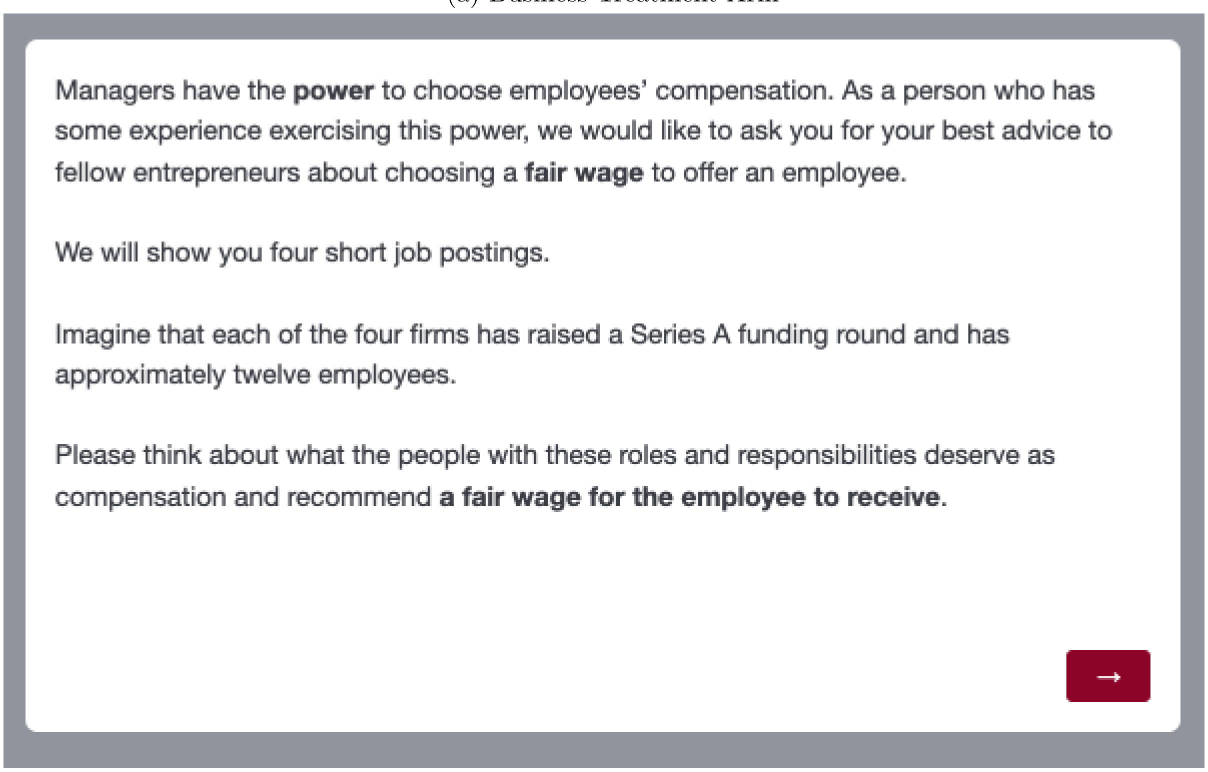
I wrote these job postings based on actual job advertisements, primary from Wellfound (formerly AngelList talent). Postings were abridged to minimize the burden on respondents. The four job postings were randomly presented in four different fixed orders so each job appeared first for at least some respondents, in case subsequent advice was influenced by prior advice.[3] Importantly, entrepreneurs were prevented from returning to their initial four recommendations after proceeding to the next part of the exercise.

Finally, entrepreneurs were given the opportunity to revise their advice in light of a state-specific wage benchmark (as illustrated in Figure 3, Panel (b)). The benchmarks given to respondents were real screenshots from either Indeed or Glassdoor, two of the most common job search websites in the United States. In the survey portion of HATS, 46% of respondents report having consulted Glassdoor, 35% having consulted Indeed, and 26% report having consulted both websites when determining how much an employee should

[3] Full randomization of the post order would have been ideal, but the additional technical complexity was prohibitive.



(a) Business Treatment Arm



(b) Fairness Treatment Arm

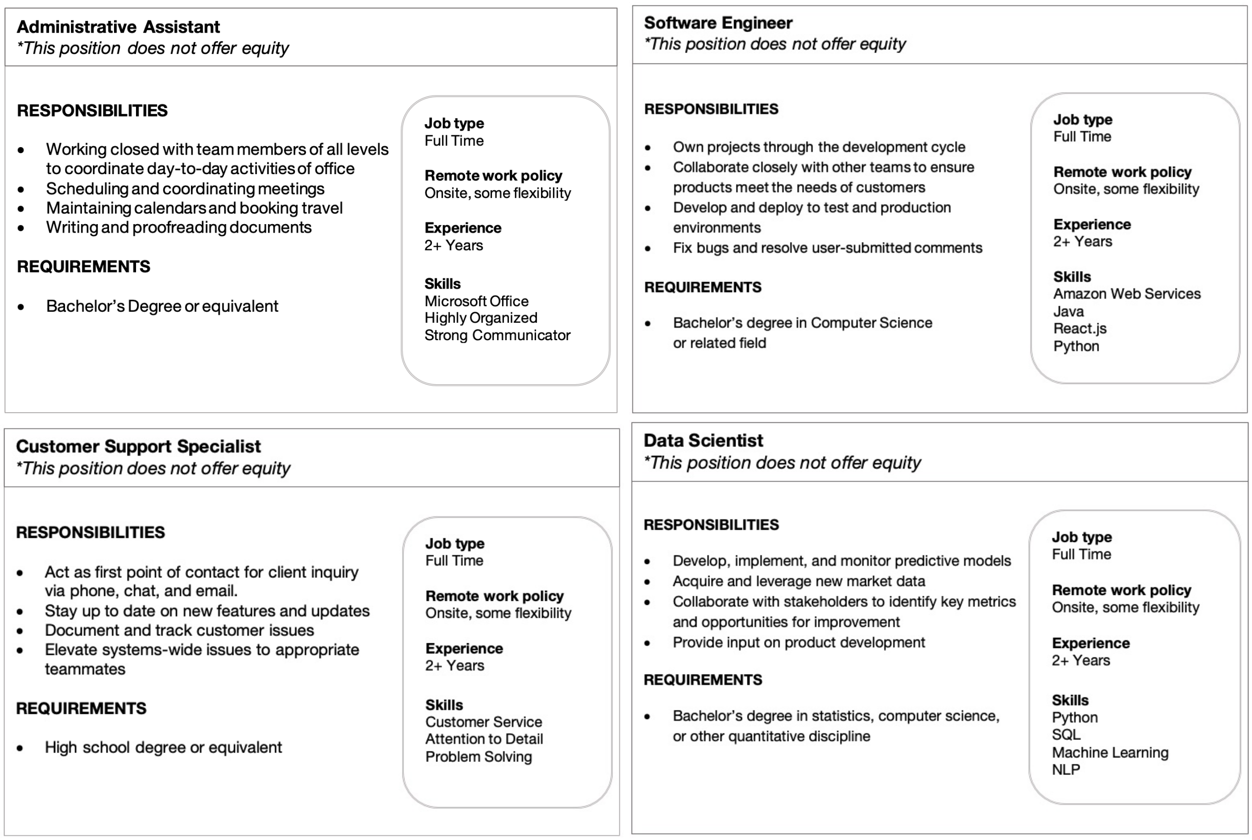
Figure 1: The two treatment arms in the experimental portion of HATS. Participants were randomized to one of these two versions of the wage-advice exercise.

Table 2: Balance Between Treatment Arms

	(1) Business Treatment	(2) Fairness Treatment	(3) Difference
Founder	0.91	0.94	-0.04
Not Male	0.15	0.21	-0.06*
Serial Entrepreneur (Self-Identified)	0.51	0.50	0.01
Worked at other startups	0.33	0.34	-0.01
White	0.67	0.67	-0.00
U.S. Citizen	0.84	0.86	-0.02
Highest Level Edu, BA	0.35	0.36	-0.01
Highest Level Edu, MBA	0.22	0.18	0.04
Highest Level Edu, Master's	0.20	0.20	-0.00
Highest Level Edu, Doctorate	0.10	0.14	-0.04
Highest Level Edu, Postgraduate Degree	0.56	0.57	-0.01
Under 25	0.02	0.03	-0.01
Age 25-34	0.24	0.25	-0.01
Age 35-44	0.32	0.32	0.01
Age 45-54	0.25	0.25	0.00
Age 55-64	0.13	0.11	0.02
65 or over	0.03	0.03	-0.00
Employees (Pitchbook March 2023)	18.61	17.25	1.36
Age (2023 - Year Founded (Pitchbook))	4.34	4.29	0.05
Raised a Founding Round, Including Angel	0.90	0.88	0.02
Total Size all Deals (Millions USD)	6.22	7.77	-1.55
Information Technology	0.57	0.61	-0.05
Business Product and Services (B2B)	0.27	0.22	0.05
California	0.30	0.35	-0.05
New York	0.14	0.14	0.00
Massachusetts	0.10	0.10	0.00
Observations	266	262	528

Table shows characteristics of respondents and their firms assigned to the cost language treatment (Column 1) and those assigned to the fairness language treatment (Column 2). Column 3 shows the difference in means, with stars indicating significance levels (* $p<0.1$, ** $p<0.05$, *** $p<0.01$).

be paid. Which benchmark the respondent received (Indeed or Glassdoor) was cross-randomized across treatment groups.



Administrative Assistant
**This position does not offer equity*

RESPONSIBILITIES

- Working closed with team members of all levels to coordinate day-to-day activities of office
- Scheduling and coordinating meetings
- Maintaining calendars and booking travel
- Writing and proofreading documents

REQUIREMENTS

- Bachelor's Degree or equivalent

Job type
Full Time

Remote work policy
Onsite, some flexibility

Experience
2+ Years

Skills
Microsoft Office
Highly Organized
Strong Communicator

Software Engineer
**This position does not offer equity*

RESPONSIBILITIES

- Own projects through the development cycle
- Collaborate closely with other teams to ensure products meet the needs of customers
- Develop and deploy to test and production environments
- Fix bugs and resolve user-submitted comments

REQUIREMENTS

- Bachelor's degree in Computer Science or related field

Job type
Full Time

Remote work policy
Onsite, some flexibility

Experience
2+ Years

Skills
Amazon Web Services
Java
React.js
Python

Customer Support Specialist
**This position does not offer equity*

RESPONSIBILITIES

- Act as first point of contact for client inquiry via phone, chat, and email.
- Stay up to date on new features and updates
- Document and track customer issues
- Elevate systems-wide issues to appropriate teammates

REQUIREMENTS

- High school degree or equivalent

Job type
Full Time

Remote work policy
Onsite, some flexibility

Experience
2+ Years

Skills
Customer Service
Attention to Detail
Problem Solving

Data Scientist
**This position does not offer equity*

RESPONSIBILITIES

- Develop, implement, and monitor predictive models
- Acquire and leverage new market data
- Collaborate with stakeholders to identify key metrics and opportunities for improvement
- Provide input on product development

REQUIREMENTS

- Bachelor's degree in statistics, computer science, or other quantitative discipline

Job type
Full Time

Remote work policy
Onsite, some flexibility

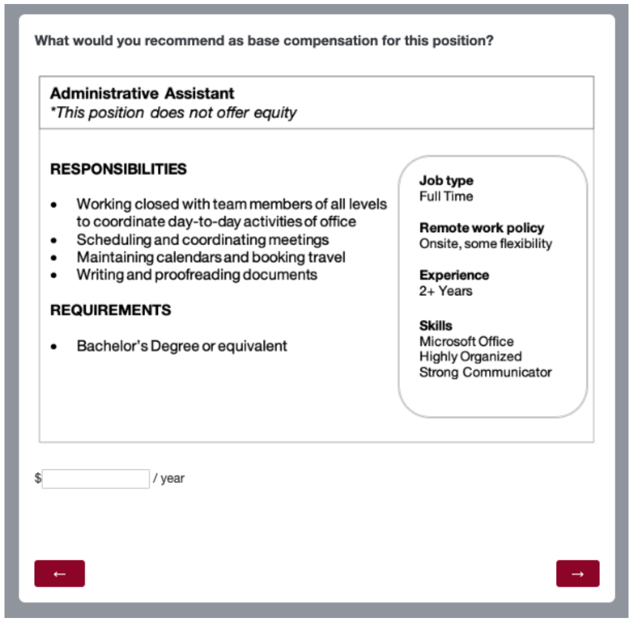
Experience
2+ Years

Skills
Python
SQL
Machine Learning
NLP

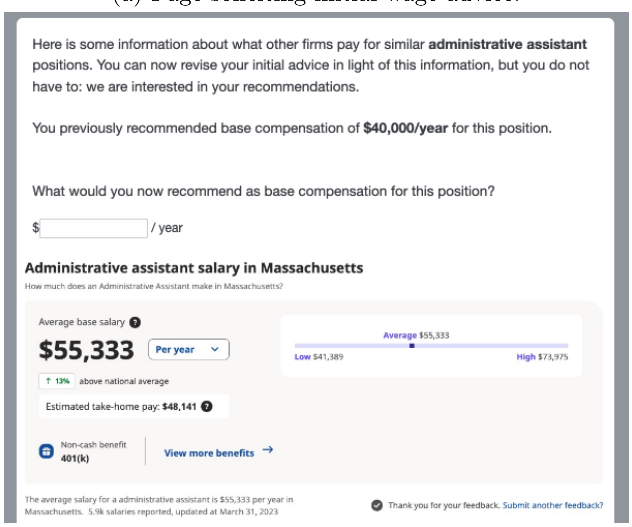
Figure 2: The four job postings.

Allowing entrepreneurs to revise their advice accomplishes four things. First, it mimics how people make decisions, starting with a prior guess or estimate and then updating based on information. Second, while the initial advice is informative about entrepreneurs' mental models of the labor market, the updating (extensive and intensive margin) is informative about how they do or do not respond to information. Third, in in the absence of any information, it would be difficult to tell if any interesting correlations (higher bids in the fairness group, or among different demographic groups of entrepreneurs, for instance) were the result of underlying beliefs or disparities in information about prevailing wage rates. Finally, providing information about other firms explicitly introduces the notion of labor market competition.

At the end of this exercise, entrepreneurs were shown their (up to) eight recommendations and asked to share why they did or did not change their advice.



(a) Page soliciting initial wage advice.



(b) Page soliciting revised wage advice (job posting was repeated below the benchmark).

Figure 3: This figure provides screenshots of the experimental portion of the HATS survey described in Section 3.2. These images depict the survey as it would have appeared to a respondent reporting a Massachusetts zip code. Panel (a) shows how the the initial wage advice was elicited. After making all four initial recommendations, Panel (b) shows how the respondent would have been offered the ability to revise their recommendation.

4 Hiring Practices at Growth-Capable Startups

The survey portion of HATS underscores the central role that founders play in hiring at their firms and illustrates important ways that startup hiring differs from hiring at larger, more established firms. Overall, this reveals that founders are deeply embedded in the hiring process and drawing on a variety of resources, often informal or cheap, to hire the workers they need to grow their firms.

Founders are highly involved with all aspects of the startup hiring process, as illustrated by Table 3. Most founders report that they (either alone or with other people) design job advertisements (86%), assess candidates (92%), and choose a compensation packages to offer a candidate (98%). Founders are still extremely influential in the startup hiring process even if firms have HR personnel: fewer founders with HR at their firms design job ads (70%) but 86% still assess candidates and 96% still determine compensation. Founders' influence over compensation specifically is also distinct because, while only 6 and 10 percent of founders reports that they *alone* design job ads or assess candidates, 20% of respondents report that they alone choose a compensation package to offer a candidate. Entrepreneurs also report having hired many people: half the sample estimates they have hired more than 25 people in the past five years, and 25% of the sample estimates that they have hired over 100 people over their entire career (this includes hiring that may have taken place at other organizations).

Table 3: Share of Founders Involved in the Hiring Process

	(1) All	(2) With HR
Designing Job Ads	86.3	70.0
Assessing Candidates	91.8	80.9
Determining Compensation	98.2	96.4
Observations	497	110

Table shows, for respondents who indicate they are one of the founders of the firm, the share who answered either *You Alone* or *You With Other People* in response to the question, *At your firm, who is responsible for the following parts of the hiring process?*

However, despite being intimately involved in the process and relatively experienced with hiring people, entrepreneurs are operating without the hiring personnel or data resources of large firms. Only one-quarter of the sample reports having a person or people responsible for human resources. Even among firms with more than 10 employees (the sample median), this share only rises to 41% and among firms with more than 18 employees (the sample average), the share is 53%. While low, these numbers could be higher than in the general startup population; for example, founders who are especially interested in hiring may be both more likely to hire a human resources professional and to participate in the HATS study.

A majority of survey respondents (85%) report that they consult external data when determining how much an employee should be paid, and these sources differ from those consulted by HR professionals at medium and large firms. Table 4 juxtaposes the data sources used by these respondents with those used by experienced HR professionals as reported in Cullen et al. (2022). These authors survey 1,350 HR managers across a variety of industries who have on average six years of hiring experience and most of whom (77.95%) work at companies with more than 50 employees (see Cullen et al., 2022, Online Appendix). Startup founders are much more likely than these HR professionals to use free online data sources (71.48% vs. 58.07%) and less likely to use paid online data sources, industry surveys, government data, compensation consultants, or payroll data services to benchmark salaries. The gaps are particularly noticeable for the resources that are likely most costly (compensation consultants and payroll data services).

Table 4: Sources of Compensation Data

	Entrepreneurs (HATS Respondents)	HR Professionals (Cullen et. al 2022)
Free online data sources	71.48	58.07
Paid online data sources	24.63	34.37
Industry surveys	43.15	68
Government data	17.41	37.11
Compensation consultants	6.67	26.3
Payroll data services	18.7	23.19
Observations	467	1350

Column (1) presents responses from the HATS survey (*Which data sources does your organization use to determine how much a new employee should be paid? Please select all that apply.*) and Column (2) presents results from a survey of 1,350 HR professionals conducted by Cullen, Li, and Perez-Truglia (*Which sources do you use to obtain salary benchmarks? (Select all that apply).*)

In this resource-constrained environment, founders rely heavily on their professional networks and word-of-mouth, both to recruit candidates and make assessments about prevailing wage levels. This was revealed both by open and closed-ended survey responses. In response to the open-ended question, "How do you choose a compensation package to offer for a given position?" many founders referenced free data sources, and "asking around" for advice. Table 5 presents some examples. These comments illustrate that entrepreneurs' advice is used to form expectations about wages and that asking for advice within the context of the survey was a reasonably realistic task. They also suggest that founders are not entirely satisfied with the quality of data available to them.

Entrepreneurs who scour job-postings for salary comparisons (as several mentioned doing) may also face challenges finding information from comparable firms: 15% of the HATS firms report that they do not post job advertisements, and another 44% reported that they would only include salary information on a job ad (even a range) where required by law.

Finally, Figure 4 shows that, in closed-ended survey responses, respondents rate their personal networks

Table 5: Founders on choosing compensation [Open Response]

"Based on budgetary constraints and informal networking." *TX, 35-40 employees, $20-25M raised*
"I do research on Glassdoor and by asking friends. But, sometimes the data are very outdated, especially during periods of volatility." *IL, 10-15 employees, $5-10M raised*
"Compensation data tends to be very poor quality with low sample rates, inconsistent ranges, and most notably suffer from no shared leveling or job title reference making comparison exceedingly difficult." *CA, 30-35 employees, $25-30M raised*
"We made an internal compensation table for it. Most of the information is gathered from websites or asking other people in similar industries." *CA, 20-25 employees, $5-10M raised*
"We have real limits on the cash compensation we can offer. To develop a range, we ask other startups and look at other postings." *WA, 10-15 employees, <$1M raised*
"Ask around to determine compensation." *GA, 5-10 employees, $1-5M raised*
"I use word of mouth to get a sense of market value for the type of role" *TX, 1-5 employees, <$1M raised*

Table shows select responses to the open-ended survey question, "How do you choose a compensation package to offer for a given position?" that reference the importance of informal networking and word-of-mouth information to determine compensation.

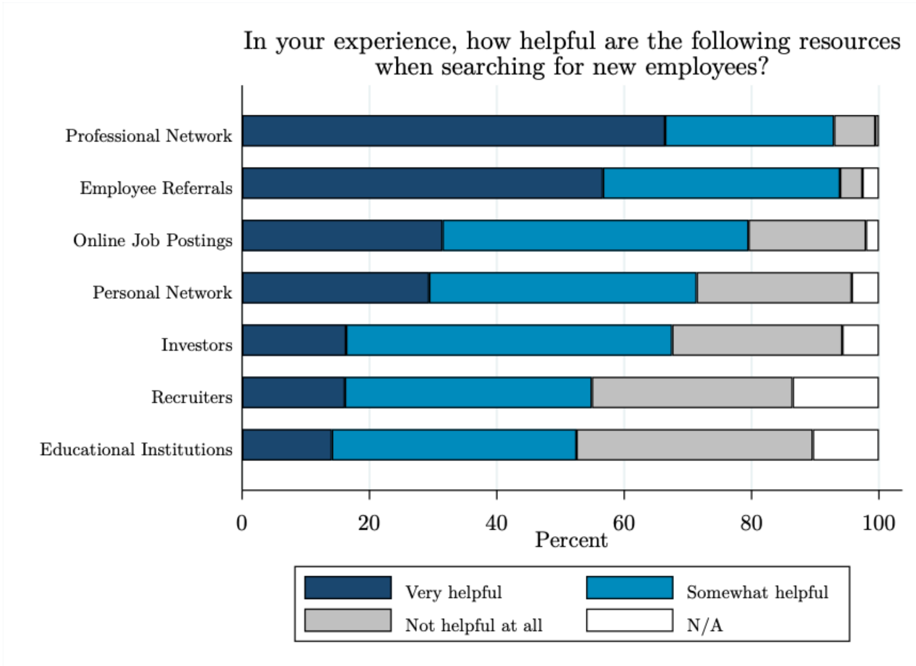


Figure 4: Figure depicts all respondents' ratings of the helpfulness of seven sources when searching for new employees. Professional networks and employee referrals were rated as "very" or "somewhat" helpful by the largest share of respondents.

and employee referrals as most helpful in searching for employees.

5 Experimental Results

Having established that founders are central to startup hiring and supplementing free online hiring resources with advice from professional networks, what does their advice look like? Is it sensitive either to information or concerns about fairness?

5.1 Wage Benchmarking

5.1.1 Wage advice is dispersed and sensitive to information

In Figure 5, each dot is a survey respondent, with their initial wage advice plotted on the x-axis and their revised advice (once shown the wage benchmark) on the y-axis. Two things are immediately apparent from these plots. First, for all positions the wage advice has enormous range: for data scientists, wage advice ranges from $20,000 to $300,000.[4] Second, the number of dots off of the 45-degree line illustrates that many

[4]Every effort was make to ensure that very low and very high values were not typos. Sometimes it was clear from the survey comments that somebody wrote 200,000 when they intended to write 20,000 (or vice versa). While it is impossible to be completely sure all of these cases were fixed, all results in the paper are robust to dropping outliers at the top and bottom of the distribution of advice.

respondents did revise their advice when given information. Overall, in 57 percent of cases, the respondent revised their advice when given information, with 85 percent of respondents making at least one update to their four pieces of advice.

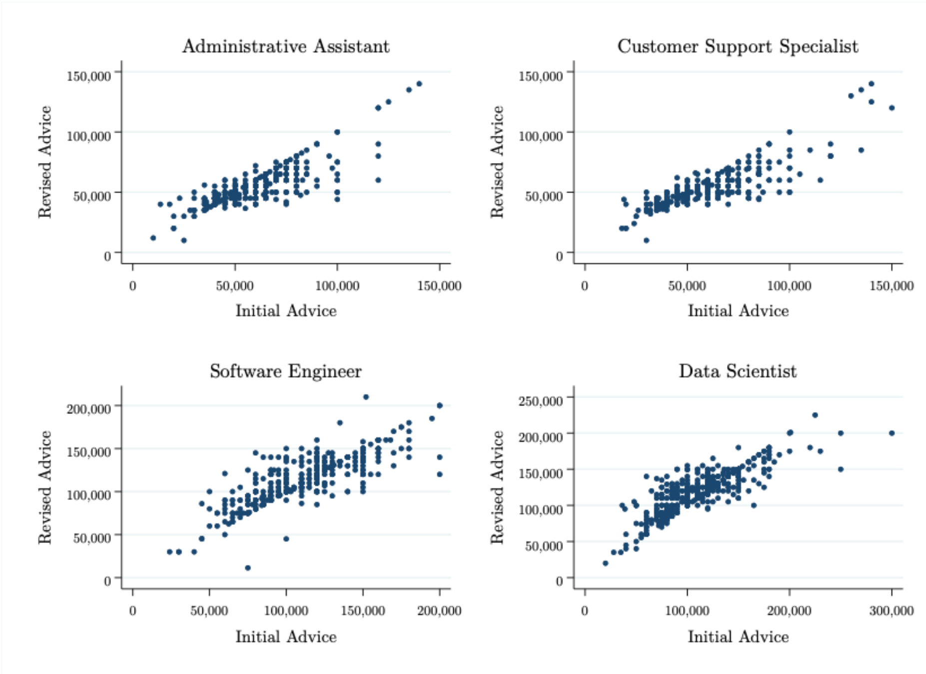


Figure 5: Each panel of this figure illustrates the wage advice given for a single position, across all states. Each dot represents a survey respondent with their initial wage advice on the x-axis and their revised advice on the y-axis.

The above figure also captures variation due to geography: to illustrate the variance of advice net of state-level and position-level variation in wage levels, Figure 6 is a density plot of the residuals from a regression of wage advice on indicators for state and position. This plot illustrates two things: even controlling for state-level variation, there is enormous variance in entrepreneurs' wage advice, and providing information results in a substantial reduction in this variance.

This reduction in the variance in advice is due to respondents' advice compressing towards the benchmark provided. In Figure 7, entrepreneurs' advice is transformed into percent deviation from the benchmark, with initial advice presented in black and revised advice in red. Initial wage advice before entrepreneurs had seen the benchmark is, on average, 14.2 percent higher than the benchmark. Once entrepreneurs see the benchmark, this falls to 9.2 percent, a decline of 35% ((14.2-9.2)/14.2). This is larger than the estimated compression of actual wage offers associated with the rollout of a benchmarking tool by a major payment service provider (25%), detailed in Cullen et al. (2022). A likely explanation for this is that entrepreneurs' initial wage assessments were very far from the benchmarks for the lower-paid roles. Percent deviations from

Residualized Wage Advice, All Positions

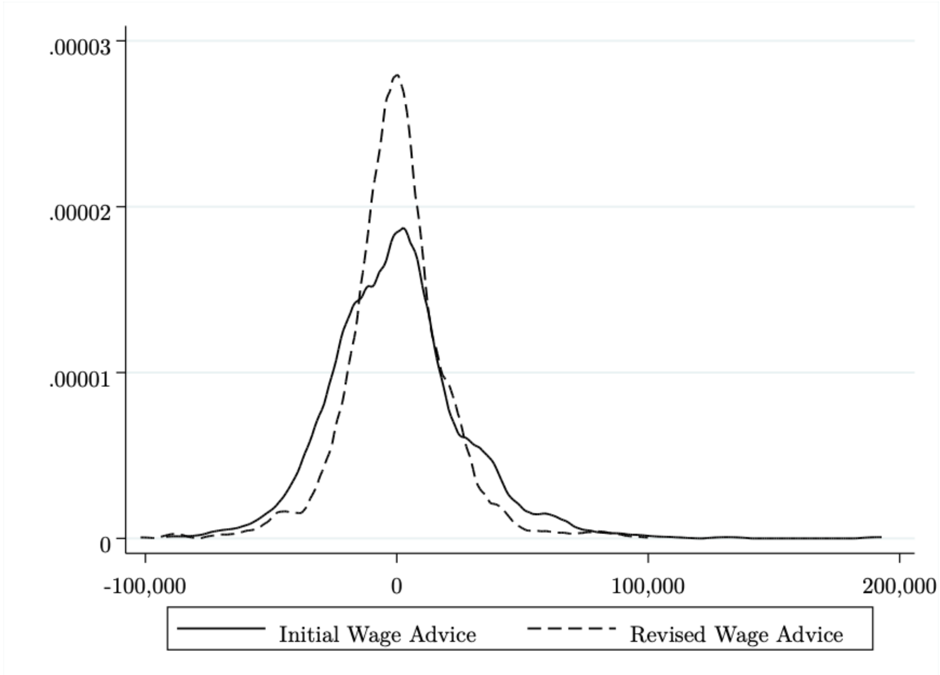


Figure 6: Figure shows the residuals from a regression of initial (solid line) and revised (dashed line) wage advice on an indicator for job (eg. administrative assistant) and state.

the benchmark of initial and revised advice for each position are reported in the survey appendix. It is also not surprising that wage advice moves more dramatically than actual wage offers, which are constrained by actual budgets, internal firm policies, and the compensation of existing employees.

5.1.2 Less experienced respondents are more likely to respond to information

Finally, while most people updated at least some of the wage advice, less-experienced entrepreneurs were more likely to update their advice when exposed to the wage benchmark. Table 6 illustrates that first-time founders are about 6 percentage points more likely to update their advice (about 10% more likely to revise, as 55 percent of advice was changed), and founders that had no experience either performing or hiring for a similar role (i.e. administrative assistant, etc.) were about 9 percentage points more likely to update (about 16% more likely to update). Also more likely to update are non-male founders. These estimates are virtually unchanged when controlling for the respondent's initial advice (columns 2 and 3). Founders were not deferentially likely to update based on race or education (having an MBA or not). Interestingly, having below-median hiring experience (either over one's entire career, or over the past year) did not impact the probability of updating one's advice.

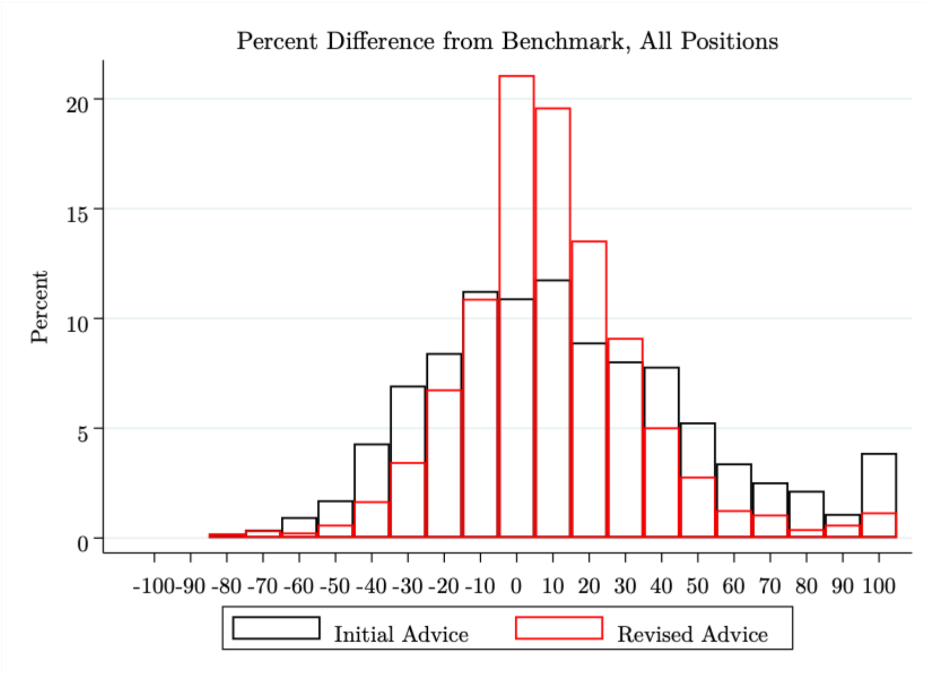


Figure 7: Figure shows initial advice (black) and revised wage advice (red), expressed as percent difference from the benchmark average wage shown to a survey respondent.

Table 6: Probability of Updating Wage Advice

	(1) Any Update	(2) Any Update	(3) Any Update
No Experience with Position	0.0972***	0.0927***	0.0894***
	(0.0296)	(0.0297)	(0.0308)
First-time Founder	0.0514*	0.0540*	0.0544*
	(0.0308)	(0.0307)	(0.0311)
Not Male	0.0910***	0.0871**	0.0872**
	(0.0349)	(0.0350)	(0.0354)
N	1951	1951	1951
Initial Advice Control	No	Yes	Yes
Job FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Job x State FE			Yes

The outcome variable for all columns is a dummy equal to one if a survey respondent revised their initial wage advice when presented with a wage benchmark. All regressions control for the benchmark variation shown to survey respondents (Glassdoor or Indeed). Standard errors are shown in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.1.3 The content of the benchmark impacts the advice

Since entrepreneurs respond to information, which they often get at least partially from free, online sources, this raises the question of whether the quality of that information could be impacting beliefs about wages, especially for less experienced founders who may be more likely to update their beliefs based on that information.

Publicly available information about wages can vary tremendously across sources. There are myriad possible reasons for this, as data are crowd-sourced, potentially aggregated across positions with different requirements and firms at different stages of development, and summarized with opaque adjustments made by the site owner. As part of the advice-giving exercise, entrepreneurs were randomized to receive a benchmark either from Glassdoor.com or Indeed.com, and Figure 8 illustrates the range of these benchmarks. Each line represents, for a given position in a given state, the distance between the Glassdoor and Indeed estimates of average salary in March 2023. The y-axis shows the state ("NAT" indicates the national benchmark). For example, in the panel on the top left, the average base salary for an administrative assistant in New York State was \$41,684 according to Glassdoor, and \$61,159 according to Indeed (45% higher). This figure illustrates both that the range of estimated compensation can be wide, and that one site does not always produce higher estimates than the other: while Indeed most often reports a higher average, this is not always the case. This is further complicated by the fact that Glassdoor reports estimates of salaries and bonuses (See Appendix Figure A2 for illustrations of the gap between Indeed and Glassdoor when this extra compensation is included).

Entrepreneurs randomly assigned to the higher of the two benchmarks on average recommended wages that were about \$4,000 higher than entrepreneurs randomly assigned to the lower benchmark for the same position in the same state. Table 7 regresses initial and revised wage advice on an indicator for being assigned to the benchmark with a higher number. As expected, the benchmark has no impact on entrepreneurs' initial wage advice (which is given before the benchmark is revealed). The impact of the benchmark persists when controlling for the benchmark brand (Columns 5-7) and is robust to controlling for entrepreneurs' initial wage advice (Column 7), though the effect shrinks in magnitude. These effects are economically significant, particularly for the lower-paid positions which earn around \$50,000 per year.

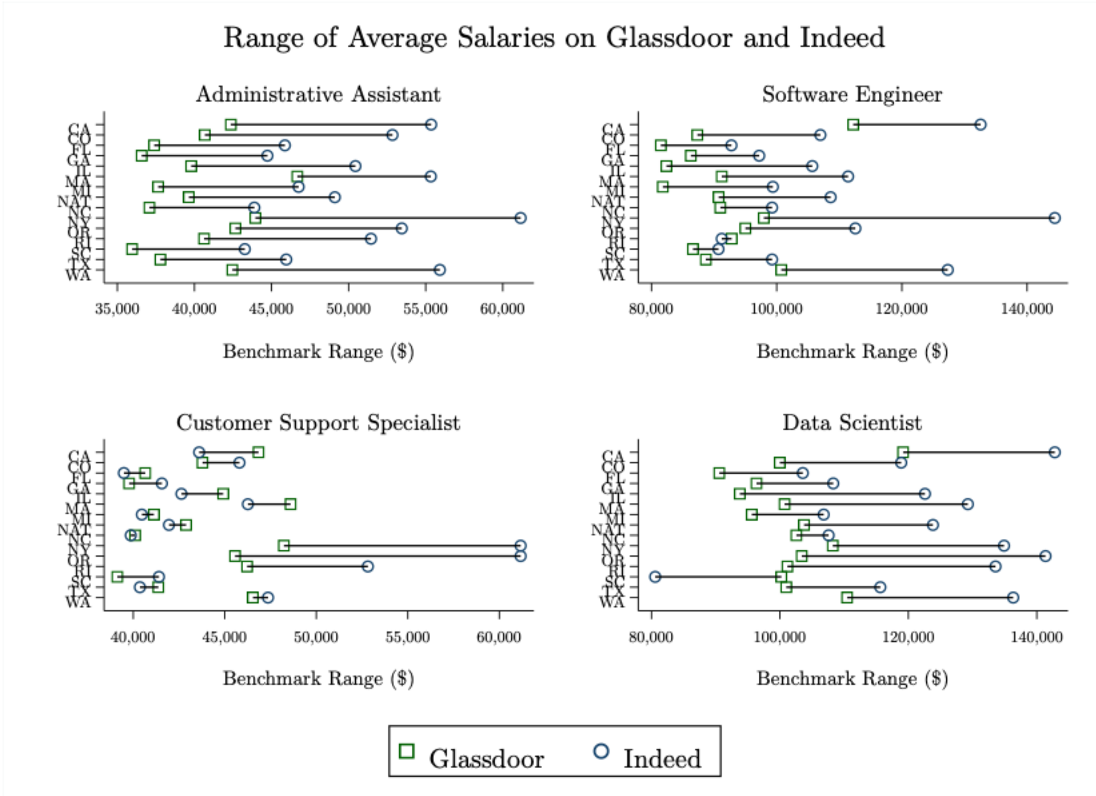


Figure 8: Figure illustrates the difference between the average base compensation reported by the Glassdoor and Indeed benchmarks shown to survey participants.

Table 7: Impact of Being Assigned to Higher Benchmark

	Initial Advice			Revised Advice			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Higher Benchmark (Number)	1506.6	1484.2	1515.6	4034.0***	3755.6***	3718.6***	2527.2***
	(1546.9)	(1072.0)	(1087.8)	(1207.1)	(845.2)	(798.0)	(508.0)
Benchmark Brand (Glassdoor)		-35.47	-22.11		-440.2	-501.5	-80.03
		(1741.7)	(1751.5)		(1273.0)	(1263.6)	(630.8)
N	2088	2088	2088	1963	1963	1963	1951
R-squared	0.507	0.507	0.514	0.721	0.721	0.737	0.920
Job FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Job x State FE			Yes			Yes	Yes
Control for Intial Advice							Yes

Table regresses the initial and revised wage advice on an indicator for being assigned to the higher of the two wage benchmarks. There are fewer observations in Columns 4-7 because not all respondents who provided initial advice gave revised advice. All regressions control for treatment arm (cost vs. fairness language). Standard errors are shown in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Fairness Intervention

Having considered how founders incorporate information into their wage advice, I now turn to the question of how values around fairness may impact their advice.

5.2.1 Main Effect

Asking entrepreneurs for a fair wage did not produce different wage recommendations in the overall sample. Table 4 presents the results of a regression of initial wage advice (columns 1 and 2) and revised wage advice (columns 3 and 4) on an indicator equal to one if an entrepreneur was assigned to the fair wage treatment. These regressions include initial and revised bids for all positions (up to four initial and four revised bids for each entrepreneur). All regressions include controls for job (administrative assistant, software engineer, customer support specialist, and data scientist), the firm's headquarter state (based on ZIP code), and the randomly assigned benchmark. The coefficients are positive, but not statistically significant.

Table 8: Fairness Treatment: Main Effect

	Initial Advice		Revised Advice	
	(1)	(2)	(3)	(4)
Fairness Treatment	1529.8	1530.5	885.9	868.6
	(1830.0)	(1847.7)	(1392.7)	(1408.1)
N	2088	2088	1963	1963
R-squared	0.507	0.513	0.719	0.736
Job FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Job x State FE		Yes		Yes

Standard errors in parentheses, clustered at the individual level (the level of treatment). Columns 1 and 2 illustrate the impact of the fairness treatment on initial wage advice and columns 3 and 4 illustrate the impact of the fairness treatment on revised wage advice when the entrepreneurs had access to a state-specific wage benchmark. Columns 1 and 3 include fixed effects for the four job postings and the firm's state, columns 2 and 4 add a state-specific job fixed effect. All regressions control for the benchmark source (Glassdoor or Indeed).

This null effect is true across all four job postings, though this analysis is not well-powered.

Finally, there was no differential propensity to update based on treatment status, conditional on the entrepreneur's initial wage advice. That is, there is no statistically significant impact of the treatment language on the probability that an entrepreneur makes any update to their initial advice, updates their advice to recommend a higher wage, or updates their advice to recommend a lower wage, conditional on their initial advice.

Table 9: Fairness Treatment, by Position

	Initial Advice		Revised Advice	
	(1)	(2)	(3)	(4)
Software Engineer x Fairness	4454.7	3680.6	888.0	43.63
	(2280.9)	(2289.4)	(2043.3)	(1908.9)
Customer Support x Fairness	1243.1	1113.3	684.8	717.7
	(1429.9)	(1442.0)	(1036.9)	(1037.6)
Data Scientist x Fairness	2592.3	2937.1	591.2	549.0
	(2824.0)	(2799.5)	(2174.6)	(2135.8)
N	2088	2088	1963	1963
R-squared	0.507	0.514	0.719	0.736
State FE	Yes	Yes	Yes	Yes
Job x State FE		Yes		Yes

Standard errors in parentheses, clustered at the individual level (the level of treatment). Columns 1 and 2 illustrate the impact of the fairness treatment on initial wage advice and columns 3 and 4 illustrate the impact of the fairness treatment on revised wage advice when the entrepreneurs had access to a state-specific wage benchmark. Columns 1 and 3 include fixed effects for the four job postings and the firm's state, columns 2 and 4 add a state-specific job fixed effect. All regressions control for the benchmark source (Glassdoor or Indeed).

5.2.2 Heterogeneity by Gender

While there was no fairness effect on average, the fairness treatment did induce non-male entrepreneurs to recommend higher wages. Figure 9 plots the residuals from a regression of initial and revised wage advice on an indicator for position and geography by gender and treatment arm (as wages vary widely between jobs and across states). For male entrepreneurs, the distribution of these residuals in both treatment arms is nearly identical. For non-male entrepreneurs, the fairness distribution (the dashed purple line) is shifted to the right.

Table 6 illustrates this in a regression framework. Initial wage advice given by non-male entrepreneurs in the fairness treatment is \$11,000 higher than non-male entrepreneurs in the cost treatment. This shrinks to \$8,000 when entrepreneurs are given benchmark information. Non-male entrepreneurs recommend lower wages than male entrepreneurs for jobs in the same geography (a fact discussed in Section 5), but the fairness treatment completely offsets this effect.

Non-male entrepreneurs in the fairness treatment recommend higher wages for all positions, but these differences are particularly large for the software engineer and the data scientist. This could be a function of non-male entrepreneurs having less familiarity with these roles (hiring experience is discussed further below). However, deviations from a larger salary are also simply easier to detect in small samples. Appendix Figure A1 plots the distribution of residuals of a regression of non-male entrepreneurs' wage advice on state

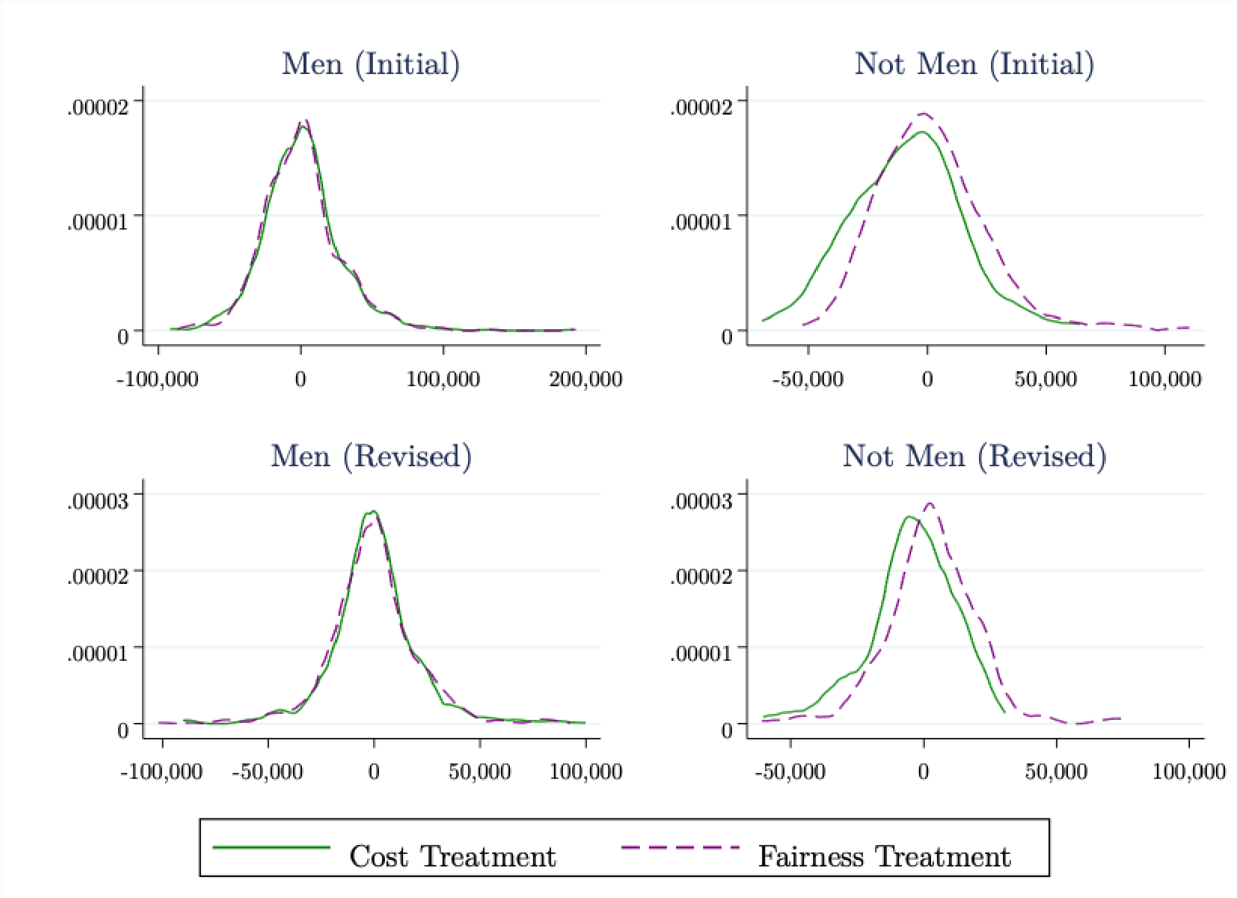


Figure 9: This figure plots the residual from a regression of entrepreneurs' wage advice on an indicator for position (job) and state (geography), plotted by treatment arm. Male entrepreneurs' advice is on the left, not male entrepreneurs' on the right.

indicators for each job separately.

Table 10: Fairness Treatment: Heterogeneity by Entrepreneur Gender

	Initial Advice		Revised Advice	
	(1)	(2)	(3)	(4)
Fairness Treatment x Not Male	11047.1**	11041.6**	8191.0**	8298.5**
	(4601.6)	(4649.2)	(3208.3)	(3242.2)
Not Male	-9785.4***	-9779.6***	-4629.4*	-4643.7*
	(3535.3)	(3571.5)	(2438.2)	(2469.1)
Fairness Treatment	-188.8	-187.4	-626.9	-667.0
	(2088.0)	(2108.2)	(1613.3)	(1631.0)
N	2088	2088	1963	1963
R-squared	0.511	0.518	0.721	0.737
Job FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Job x State FE		Yes		Yes

Standard errors in parentheses, clustered at the individual level (the level of treatment). Columns 1 and 2 illustrate the impact of the fairness treatment on initial wage advice and columns 3 and 4 illustrate the impact of the fairness treatment on revised wage advice when the entrepreneurs had access to a state-specific wage benchmark. Columns 1 and 3 include fixed effects for the four job postings and the firm's state, columns 2 and 4 add a state-specific job fixed effect. All regressions control for the benchmark source (Glassdoor or Indeed).

6 Discussion and Robustness Checks

6.1 Additional Challenges of the Entrepreneurial Hiring Process

Entrepreneurial hiring is centered on founders who are running organizations that are often capital constrained, and are relying extensively on informal networks for referrals and advice. This poses a number of challenges beyond the poor quality of available data (which was highlighted in Section 4 and was the focus of the first experimental intervention). This section presents other challenges described by entrepreneurs in the survey responses which raise important questions for future work.

Founders' open-ended comments also highlighted two additional challenges of network-based hiring: scale and homophily. For example, these two founders, both in California, highlight that in dense labor markets, startups can grow large without ever posting a job, but they do eventually need employ additional hiring strategies:

> Initially (nearly up to 50 FTEs) we used our networks for referrals and were very successful. Now, we use job boards, our website, our LinkedIn, and sometimes we engage recruiters (recently ... after we crossed 50 employees and when our referral networks had been used extensively).
> *(CA, $25-30M raised, 70-80 employees).*

> Of our first 40 employees, a large amount were sourced via our own network. Post 40, we are hitting the limits of our network and have recently hired a recruiter to help.

(CA, $50-55M raised, 40-50 employees).

This raises an important question for future work: when is the optimal time to move from a network-based hiring approach to another strategy, like using a recruiter? Does this depend on age, stage, or what functional role the company is seeking?

A few founders also reflected on the fact that network-based hiring limited them to finding employees with whom they already had a connection. This conflicted with a desire for diversity in hiring.

> Employee networks tend to be the least expensive and fastest way to fill a position, but can suffer from reinforcing monocultures and bias.
> *(CA, $25-30M raised, 30-35 employees)*

> At a company of our size, we are primarily focused on achieving a low "false positive" rate (avoiding hires that would need to be let go within short order). As such, we primarily focus on hiring from the pool of candidates that we already know or that are referred to us from trusted sources . . . The major downside to this methodology is that we restrict ourselves to those folks that we already know, which makes it difficult to achieve our diversity goals.
> *(TX, $1-5M raised, 5-10 employees)*

> We've found good people through Linkedin but it's a real mess. Too many people spam apply for jobs. The barrier to apply is probably too low. Leveraging our networks has been far and away the most effective way to hire people who've been successful at our company. The bummer there is that sometimes leads to building a less diverse staff, but on the average, the people are way better. Hiring is hard.
> *(OR, $5-10M raised, 25-30 employees.)*

Finally, while this paper has focused on base compensation, this is only one aspect of compensation at growth-capable startups. Founders are aware that they cannot compete with salaries offered by top established companies, and describe using equity compensation and things like culture or firm mission to balance lower wage offers. This is notable, given that founders and employees may have different assessments of the potential value of equity in the venture, and in light of recent work that suggests startup employees often misunderstand fundamental aspects of equity compensation (Aran and Murciano-Goroff, 2023).

> The largest question is tradeoff between cash and options - we get input from the candidate on what would work best for them. Competing with large tech firms (Google, FB, AWS, ...) and large banks who are hiring similar candidates is an issue - we can't compete on salary.
> *(MA, $5-10M raised, 25-30 employees)*

> [...] Many candidates are looking for increased base compensation. They are not a fit for our company, The better candidates understand that equity grants at a very early stage (i.e. penny shares at fair company value) are potentially far more valuable over the long run. They are generally willing to accept a lower base comp rate and make it up with options. At our current company, CEO, SVP of Engineering, and Principal Architect made the same amount - significantly below-market-rate salaries. Everyone is working towards increasing the value of equity.
> *(CO, $5-10M raised, 10-15 employees)*

Reliance on networks and compensating for lower pay with other benefits has important implications for who gets to participate in the startup workforce. This was summarized nicely by one survey respondent who, after describing balancing cash compensation with equity and viewing their firm as a genuine launchpad for employees' future careers, wrote:

> The difficulty here is restricted stock doesn't pay the bills, so not everyone has the privilege to be able to join our company. That's an issue for sure in terms of the diverse workforce we'd like to foster.
> *(OR, Series A-backed, 5-10 employees)*

6.2 What Drives the Fairness Effect?

Non-male entrepreneurs assigned to the fairness treatment suggested higher wages: is this due to differences in values, or a function of some other difference between male and non-male entrepreneurs like hiring experience? This question is natural, but slightly misleading, because gender impacts many facts of an individual entrepreneur's experiences, from early education and socialization to professional networking (Howell and Nanda, 2019) to access to funding (Hebert, 2020) to the questions they are asked by potential investors (Kanze et al., 2018). I now offer alternative explanations for the fairness effect, but with the caveat that gender is potentially a contributor to many of these explanations.

First, it seems unlikely that gender differences in information are driving the fairness effect, as all survey respondents are eventually given some information about the wage distribution, and this fails to fully erode the fairness effect. Gender differences in information are more likely to play a role in explaining differences between wage advice given by male and non-male entrepreneurs, rather than in explaining different wage advice between treatment arms among non-male entrepreneurs.

A lack of entrepreneurial or hiring experience also does not appear to be driving the fairness effect. One could imagine that founders with more experience are more reluctant to incur hiring costs given the high rates of startup failure, or are more hard-nosed negotiators with prospective employees. Those less experienced with the difficulties of running a startup or employing people could find it easier to recommend higher fair wages. If non-male entrepreneurs have less hiring experience, this could be driving the fairness effect. It is true that, on average, male entrepreneurs have more previous hiring experience and slightly more cumulative hiring experience than non-male entrepreneurs. Cumulative hiring experience could be due to previous work experience in different roles or longer careers due to higher average age or fewer career interruptions (for example, due to family or childcare responsibilities). However, the fairness effect is not being driven by a few particularly young or inexperienced non-male entrepreneurs. Of the non-male entrepreneurs in the fairness group who recommended the highest wages (are in the top 90th percentile of wage advice), 40% are serial entrepreneurs and 95% of them have raised some funding with a median total amount raised of 1.7 million USD. Half of this group have hired at least 30 people (and none report zero hiring experience), and nearly three-quarters are over the age of 35.

Gender differences in attention could also explain the fairness effect, but I see no evidence that male entrepreneurs paid less attention to the survey directions than non-male entrepreneurs. First, this paper only uses complete survey responses, so all participants made it to the end of the survey. Second, men and non-men were equally likely to revise their wage advice, and there was no differential propensity to skip questions. Finally, the average survey completion time (recorded by Qualtrics) did not differ by gender.

7 Conclusion

Hiring and wages are central to firm performance (Barney, 1991; Campbell et al., 2012) particularly for new ventures where employees are a critical source of technical and market knowledge and expertise (Agarwal et al., 2004; Singh and Agrawal, 2011). In addition, many startups operate under severe resource constraints, making the cost of a bad hire or high turnover potentially devastating (Baron et al., 2001; Li et al., 2022).

How should scholars think about the critical task of hiring and setting compensation at entrepreneurial firms? This paper draws upon a novel survey of growth-capable U.S. startups to characterize entrepreneurial hiring as a phenomenon that depends heavily on founders. Founders do not fully delegate hiring, even if they have HR. A substantial share of startups do not post jobs, relying instead on founder networks and employee referrals to recruit effectively. In contrast to HR professionals at larger firms, startups rely more heavily on word-of-mouth advice and free, online data sources to benchmark compensation. This involvement of top management, coupled with the path-dependence inherent in relying on employee referrals and founders' own professional networks, makes startup hiring not only an important challenge, but also a strategic one (Elfenbein and Sterling, 2018). In addition to uncovering the internal hiring processes of contemporary growth-capable startups, this characterization, and entrepreneurs' own survey responses, raises important questions for future work, including how to trade-off between the uncertainty reduction of hiring via referrals and network homophily, when it may be optimal for a founder to delegate hiring responsibilities, or whether intermediaries like investors or accelerators could be more useful to startups seeking employees.

Given that hiring is a process undertaken by individuals rather than purely profit-maximizing firms, entrepreneurs' own experiences, beliefs, and values may impact wage-setting at startups. This paper uses an advice-giving experiment to probe the possible importance of two elements of founder judgements for wage-setting: beliefs about market wages and values around fairness.

Founders' advice about wages was widely dispersed, with founders recommending very different wages for the same job at the same hypothetical firm in the same state. This advice was also highly responsive to information, suggesting that this dispersion was not entirely due to well-informed employers making different strategic decisions about pricing labor. This variation is remarkable because it is the advice of entrepreneurs making actual decisions about compensation, and because word-of-mouth advice is an important way that entrepreneurs seek out information about compensation when making actual hiring decisions. Further, entrepreneurs randomized to see the higher of two benchmarks recommended higher wages, on average. While it is unsurprising that people respond to information, this finding is important given founders' reliance on free, online data, and the wildly different estimates of average compensation provided by these sources. This highlights that information frictions are likely important in the startup hiring process. This raises the question of whether public data resources could better assist entrepreneurs, or whether there is a market opportunity for intermediary platforms to profitably address this problem (for example, as Carta and Pave/OptionsImpact have attempted to do).

Finally, this paper suggests that 'fair' compensation at startups may be in the eye of the beholder: invoking fairness as a construct seemed to induce only non-male entrepreneurs to advise higher wages. This is important because it suggests that different groups of entrepreneurs may behave differently when asked to consider factors like fairness or justice in the construction of their organization. Overall, this suggests that simply appealing to managerial discretion in wage-setting is insufficient to change compensation on average. It also underscores that the entrepreneurs most sensitive to calls to consider broader goals like fairness may themselves be from groups that face particular challenges in succeeding in entrepreneurship.

References

D. Acemoglu, A. He, and D. Le Maire. Eclipse of rent-sharing: The effects of managers' business education on wages and the labor share in the us and denmark. 2022.

L. Adler. What's a job candidate worth? explaining variation in pay-setting practices. 2022.

R. Agarwal, R. Echambadi, and A. M. Franco. Knowledge transfer through inheritance: Spin-out generation, development, and survival. *Academy of Management journal*, 47(4):501–522, 2004.

G. A. Akerlof and J. L. Yellen. The fair wage-effort hypothesis and unemployment. *The Quarterly Journal of Economics*, 105(2):255–283, 1990.

Y. Aran and R. Murciano-Goroff. Equity illusions. *Journal of Law, Economics, and Organizations*, 2023.

J. Barney. Firm resources and sustained competitive advantage. *Journal of management*, 17(1):99–120, 1991.

J. N. Baron and M. T. Hannan. Organizational blueprints for success in high-tech start-ups: Lessons from the stanford project on emerging companies. *California Management Review*, 44(3):8–36, 2002. doi: 10.2307/41166130.

J. N. Baron, M. T. Hannan, and M. D. Burton. Labor pains: Change in organizational models and employee turnover in young, high-tech firms. *American journal of sociology*, 106(4):960–1012, 2001.

S. Bernstein, K. Mehta, R. R. Townsend, and T. Xu. Do startups benefit from their investors' reputation? evidence from a randomized field experiment. Technical report, National Bureau of Economic Research, 2022.

T. F. Bewley. Why wages don't fall during a recession. 1999.

I. Black, S. Hasan, and R. Koning. Hunting for talent: Firm-driven labor market search in the united states. *Available at SSRN 3576498*, 2020.

K. A. Bryan and J. Guzman. Entrepreneurial migration. 2022.

K. A. Bryan, M. Hoffman, and A. Sariri. Information frictions and employee sorting between startups. Technical report, National Bureau of Economic Research, 2022.

S. V. Burks, B. Cowgill, M. Hoffman, and M. Housman. The value of hiring through employee referrals. *The Quarterly Journal of Economics*, 130(2):805–839, 2015.

M. D. Burton and C. M. Beckman. Leaving a legacy: Position imprints and successor turnover in young firms. *American Sociological Review*, 72(2):239–266, 2007.

M. D. Burton, M. S. Dahl, and O. Sorenson. Do start-ups pay less? *ILR Review*, 71(5):1179–1200, 2018.

M. D. Burton, M. G. Colombo, C. Rossi-Lamastra, and N. Wasserman. The organizational design of entrepreneurial ventures. *Strategic Entrepreneurship Journal*, 13(3):243–255, 2019a.

M. D. Burton, R. W. Fairlie, and D. Siegel. Introduction to a special issue on entrepreneurship and employment: Connecting labor market institutions, corporate demography, and human resource management practices. *ILR Review*, 72(5):1050–1064, 2019b. doi: 10.1177/0019793919866409.

B. A. Campbell, R. Coff, and D. Kryscynski. Rethinking sustained competitive advantage from human capital. *Academy of Management Review*, 37(3):376–395, 2012. doi: 10.5465/amr.2010.0276. URL https://doi.org/10.5465/amr.2010.0276.

A. Chatterji, S. Delecourt, S. Hasan, and R. Koning. When does advice impact startup performance? *Strategic Management Journal*, 40(3):331–356, 2019.

B. Cowgill and P. Perkowski. Delegation in hiring: Evidence from a two-sided audit. *Columbia Business School Research Paper*, (898), 2020.

Z. Cullen, S. Li, and R. Perez-Truglia. What's my employee worth? the effects of salary benchmarking. *The Effects of Salary Benchmarking (october 01, 2022)*, 2022.

M. S. Dahl and O. Sorenson. The embedded entrepreneur. *European management review*, 6(3):172–181, 2009.

P. A. Diamond. Wage determination and efficiency in search equilibrium. *The Review of Economic Studies*, 49(2):217–227, 1982.

D. A. Dillman, J. D. Smyth, and L. M. Christian. *Internet, phone, mail, and mixed-mode surveys: The tailored design method*. John Wiley & Sons, 2014.

T. Eisenmann. *Why Startups Fail*. Penguin Random House, 2021.

D. W. Elfenbein and A. D. Sterling. (when) is hiring strategic? human capital acquisition in the age of algorithms. *Strategy Science*, 3(4):668–682, 2018.

E. Fehr and K. M. Schmidt. A theory of fairness, competition, and cooperation. *The Quarterly Journal of Economics*, 114(3):817–868, 1999.

R. M. Fernandez, E. J. Castilla, and P. Moore. Social capital at work: Networks and employment at a phone center. *American journal of sociology*, 105(5):1288–1356, 2000.

G. Friebel, M. Heinz, M. Hoffman, and N. Zubanov. What do employee referral programs do? measuring the direct and overall effects of a management practice. *Journal of Political Economy*, 131(3):633–686, 2023.

J. Gans, S. Stern, and J. Wu. Foundations of entrepreneurial strategy. *Strategic Management Journal*, 40, 02 2019. doi: 10.1002/smj.3010.

C. Gartenberg and T. Zenger. The firm as a subsociety: Purpose, justice, and the theory of the firm. *Organization Science*, 2022.

J. R. Graham, C. R. Harvey, and M. Puri. Capital allocation and delegation of decision-making authority within firms. *Journal of financial economics*, 115(3):449–470, 2015.

J. Guzman, J. J. Oh, and A. Sen. What motivates innovative entrepreneurs? evidence from a global field experiment. *Management Science*, 66(10):4808–4819, 2020.

J. Haltiwanger, R. S. Jarmin, and J. Miranda. Who creates jobs? small versus large versus young. *Review of Economics and Statistics*, 95(2):347–361, 2013.

C. Hebert. Gender stereotypes and entrepreneur financing. In *10th Miami behavioral finance conference*, 2020.

T. Hellmann and N. Wasserman. The first deal: The division of founder equity in new ventures. *Management Science*, 63(8):2647–2666, 2017.

T. F. Hellmann, P. H. Schure, C. Tergiman, and D. H. Vo. Ownership dynamics within founder teams: The role of external financing. *Strategic Entrepreneurship Journal*, 13(3):256–287, 2019.

S. T. Howell and R. Nanda. Networking frictions in venture capital, and the gender gap in entrepreneurship. Technical report, National Bureau of Economic Research, 2019.

E. Hurst and B. W. Pugsley. What do small businesses do? Technical report, National Bureau of Economic Research, 2011.

D. Kanze, L. Huang, M. A. Conley, and E. T. Higgins. We ask men to win and women not to lose: Closing the gender gap in startup funding. *Academy of Management Journal*, 61(2):586–614, 2018.

L. F. Katz and K. M. Murphy. Changes in relative wages, 1963–1987: supply and demand factors. *The quarterly journal of economics*, 107(1):35–78, 1992.

S. R. Lee and J. D. Kim. When do startups scale? large-scale evidence from job postings. *Working Paper*, 2022.

J. Lerner and U. Malmendier. With a little help from my (random) friends: Success and failure in post-business school entrepreneurship. *The Review of Financial Studies*, 26(10):2411–2452, 2013.

Q. Li, B. Lourie, A. Nekrasov, and T. Shevlin. Employee turnover and firm performance: Large-sample archival evidence. *Management Science*, 68(8):5667–5683, 2022.

M. Massenkoff and N. Wilmers. Wage stagnation and the decline of standardized pay rates, 1974–1991. *American Economic Journal: Applied Economics*, 15(1):474–507, 2023.

P. Oyer and S. Schaefer. Personnel economics: Hiring and incentives. In *Handbook of labor economics*, volume 4, pages 1769–1823. Elsevier, 2011.

M. Roach and H. Sauermann. Can early-stage startups hire talented scientists and engineers? ability, preferences, and employee job choice. *Ability, Preferences, and Employee Job Choice (September 12, 2022)*, 2022.

A. Saxenian. *Regional advantage: Culture and competition in silicon valley and route 128, with a new preface by the author*. Harvard University Press, 1996.

S. K. Shah, R. Agarwal, and R. Echambadi. Jewels in the crown: Exploring the motivations and team building processes of employee entrepreneurs. *Strategic Management Journal*, 40(9):1417–1452, 2019.

J. Singh and A. Agrawal. Recruiting for ideas: How firms exploit the prior inventions of new hires. *Management science*, 57(1):129–150, 2011.

O. Sorenson, M. S. Dahl, R. Canales, and M. D. Burton. Do startup employees earn more in the long run? *Organization Science*, 32(3):587–604, 2021.

N. Wasserman. Stewards, agents, and the founder discount: Executive compensation in new ventures. *Academy of Management Journal*, 49(5):960–976, 2006.

N. Wasserman. *The Founder's Dilemmas: Anticipating and Avoiding the Pitfalls That Can Sink a Startup*. Princeton University Press, 2012.

A1 Appendix Tables

This section contains appendix tables and figures referenced in the main text of the paper.

Table A1: Wage Advice, Percent Deviations from Benchmark

	Initial	Revised
All	14.2	9.6
Administrative Assistant	26.5	15.6
Customer Support Specialist	30.1	16.7
Software Engineer	2.8	4.5
Data Scientist	-2.8	1.6

Table shows the average percent deviations from the benchmark of initial and revised wage advice for each position.

This table shows the average percent deviations of respondents' wage advise from the wage benchmarks. Respondents were in generally much closer to the benchmarks, on average, for the software engineer and data scientist roles. Importantly, this does not mean that entrepreneurs' advice was incorrect: the benchmarks shown likely aggregate administrative and customer-facing roles across firms and industries, and combine positions with radically different expectations. This is perhaps supported by the fact that the revised wage advice remains 9.6% and 15.6% above the benchmarks, on average.

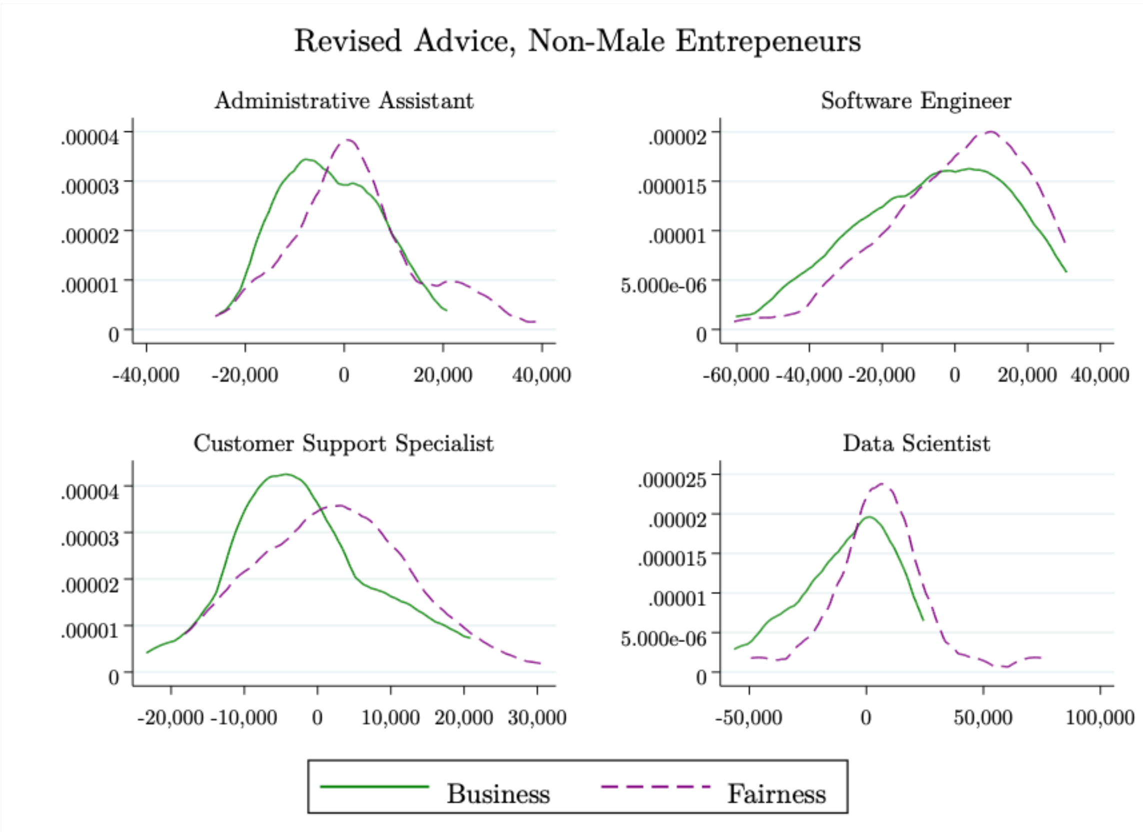


Figure A1: This figure has the same structure as Figure 9, plotting the residual of a regression of non-male entrepreneurs' revised wage advice on an indicator for state, but now separating the plots by position. These distributions are noisy, given the restriction to non-male entrepreneurs (N=98). For all positions, non-male entrepreneurs in the fairness treatment recommend a higher wage on average, but these differences are particularly pronounced for the software engineer and data scientist positions. This could be a function of non-male entrepreneurs having less familiarity with these role (hiring experience is discussed further below). However, deviations from a larger salary are also simply easier to detect in small samples.

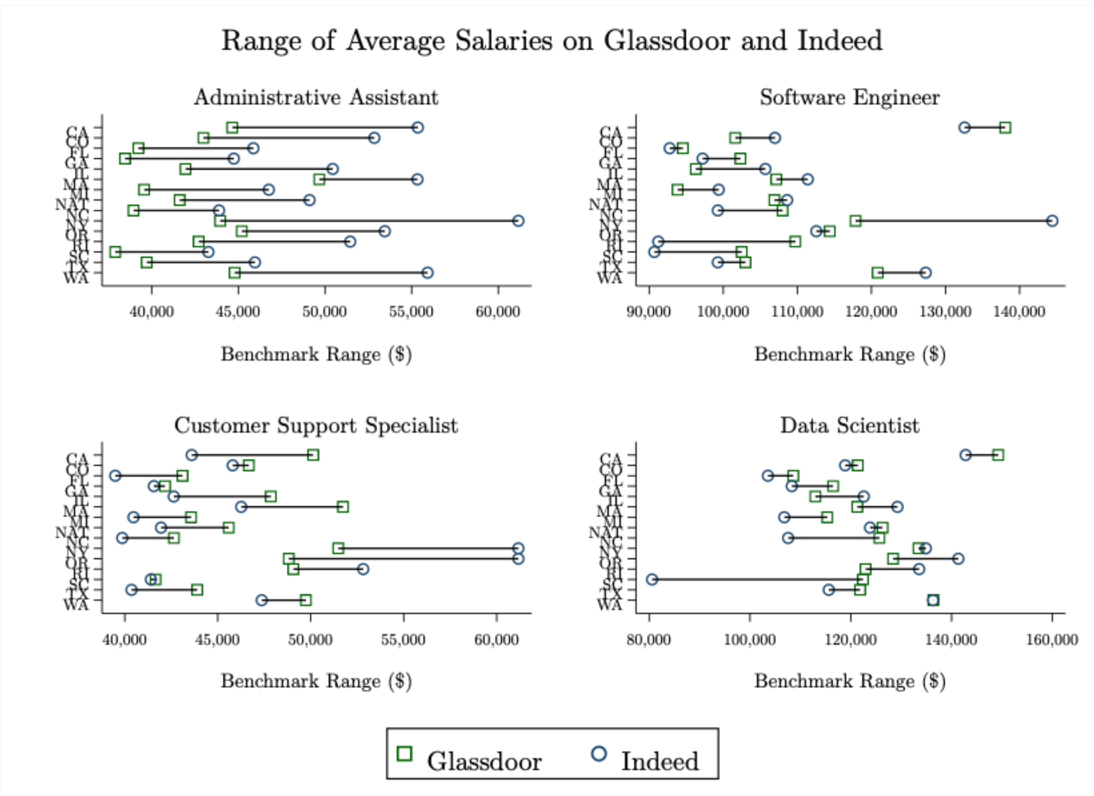


Figure A2: This figure has the same structure as Figure 8 in the main text and illustrates the range between the Glassdoor and Indeed benchmarks. While Figure 8 uses average base compensation in Glassdoor graphic, this figure uses average total compensation (a higher number).

A2 Survey Appendix

This section provides a more comprehensive description of the design and implementation of the Hiring at Top Startups (HATS) Survey.

A2.1 Sample

The intention of HATS is to investigate hiring at young startup companies. Company information was obtained from Pitchbook, a service owned by Morningstar Incorporated, an American financial services firm. Pitchbook contains a company database and research that is used by Venture Capital and Private Equity professionals.

The study population consisted of all privately held companies (both with and without backing) listed in Pitchbook in the Business-to-Business Products and Services and Information Technology industries which were founded between January 1, 2016 and December 31, 2022 with between 1 and 75 employees. The search was limited to companies with headquarters in 14 U.S. states: California, Massachusetts, New York, Rhode Island, North Carolina, South Carolina, Georgia, Florida, Texas, Colorado, Oregon, Michigan, Illinois, and Washington. This limitation was due to project budget, but these states in fact comprise the majority of companies in Pitchbook that met the search criteria due to the strong agglomeration of startup and venture capital activity in America.

The population was further limited to companies listed as “profitable,” “startup,” or “generating revenue/not profitable,” excluding those listed as “product development” “bankruptcy” or “stealth.” This was done to restrict to companies with a higher probability of actively hiring for a reasonable variety of roles. The search was also limited to the “pre-venture” and “venture capital” universes, excluding “private equity,” “M&A”, “debt financed,” “publicly listed,” and “other private companies.” This was done on the advice of a colleague in order to exclude private equity purchases of mature companies.

Finally, a small number of profiles were excluded if the company was sourced from Dun & Bradstreet, or the profile was “technologically generated.” For the purposes of ensuring the study was limited to U.S.-based founders, companies sourced from European regulatory filings were also excluded, though this choice was redundant to the choice of HQ location.

The search described above yielded 13,429 companies. 11,593 of these companies were included in the study because the company had a contact person and email listed. That is, companies with no contact person, or only listed generic contacts of the form *contact@company.com* or *info@startup.com* were excluded. This was done to limit the target population to companies likely to respond.

This left 11,593 companies that HATS attempted to contact.

A2.2 Recruitment

Entrepreneurs were contacted three times. The vast majority businesses (N=9,997 or 86.2% of the target population) had a physical address and the initial survey invitation was sent by mail. This was done because some evidence suggests that contacting people by multiple means improves response rate (Dillman et al., 2014) and is the standard practice of many administrative surveys like the Census Bureau. Where no physical address was available, the initial survey invitation was sent by email (N=1,596). Letters were mailed by a third-party printing and mailing service on April 12-13, and initial emails were sent by the principal investigator (Innessa Colaiacovo) from a study-specific email, hats_study@hbs.edu) on April 14 2023.

A follow-up email was sent to all entrepreneurs who had not yet responded to the survey on April 20-21, 2023.

A final email reminder was sent to all individuals with valid emails (that did not bounce) and who had yet responded to the survey on May 2 advising them that the survey would end on May 3rd. The survey actually stopped recording responses on May 8th.

A non-trivial fraction of mail and email was returned to sender. Of the 9,997 initial invitation letters, 2,422 (2422/9998 = 24%) were returned to sender (and processed by the PI). The share of mail returned to sender was higher for older companies, which was predictable given the high failure rate of startups. Also clear is a jump in the fraction of returned mail for companies founded prior to 2020, the onset of the COVID-19 pandemic.

Of the 1,596 initial emails to businesses without a physical address, 251 (19.47%) bounced due to incorrect or non-existent email addresses. Of the 10,797 follow-up email contacts, 1,464 bounced due to incorrect or non-existent email addresses (13.56%). At least 646 firms (5.8%) were never reached at all, as both the mail and email contacts were returned to sender. This number is likely a lower-bound, as it is possible email addresses are still actively receiving mail after companies have failed or people have changed roles, resulting in the company failing to receive the survey invitation.