

# Understanding Employee Sorting between Startups\*

Kevin A. Bryan<sup>†</sup>

Mitchell Hoffman<sup>‡</sup>

Amir Sariri<sup>§</sup>

## Abstract

Do good startups have difficulty hiring because workers do not know which startups are good? We recruit 26 science-based startups making an early business hire to use a custom-built job board, and invite over 22,000 business school alumni to apply. Applicants are randomly provided coarse expert ratings of all startups' science or business quality: we induce a *market-level* shift in the precision of information. Both business model and science ratings strongly affect application behavior. Firms with positive (negative) information along either margin see applicant interest increase (decrease) by .11 to .18 standard deviations. Stated another way, the information treatment increases the applications gap between firms with above-average overall quality and those below-average from 11% to 89%. Post-application incentivized surveys suggest that the information treatments affect beliefs about quality along each dimension, and therefore beliefs about positive growth outcomes for the startup.

*Keywords:* Hiring, experts, science-based startups

**EXTENDED ABSTRACT: PLEASE DO NOT CITE OR DISTRIBUTE**

---

\*We thank Ajay Agrawal, Jonah Rockoff, and seminar participants at Columbia Business School, Toronto, and Toronto Rotman for helpful comments. We thank Daphne Baldassari for outstanding research assistance. We thank the anonymous science-based entrepreneurship program (SEP) for its generous assistance in conducting the experiments.

<sup>†</sup>University of Toronto Rotman School of Management

<sup>‡</sup>University of Toronto Rotman School of Management and NBER

<sup>§</sup>University of Toronto Rotman School of Management

# 1 Introduction

How firms hire good workers is a central question in economics [Ichniowski et al., 1997, Oyer and Schaefer, 2011, Bloom and Van Reenen, 2011]. Many studies use randomized controlled trials (RCTs) to analyze this process, including a rich tradition of audit studies, though much less is known about how workers select among firms. Management and Entrepreneurship scholars place resource acquisition at the center of their studies, investigating how firms acquire capital and useful partnerships [Lerner, 1995, Hsu and Ziedonis, 2013]. Again, the factors determining how workers select among firms they can work at is less well understood.

Worker interest in firms is particularly interesting for the case of startups. Consider a worker interested in working in a non-technical business role (e.g., sales, operations, marketing). If the worker is choosing among established firms, she may compare compensation packages, consult employer review websites like GlassDoor.com, and talk to social contacts who have worked there. In contrast, small startups often pay similar low wages in terms of base salaries, are unlikely to have online reviews, and there may be few employees (past or present) to discuss with. The process of assessing firms may be particularly challenging for *science-based* startups, such as those in machine learning or quantum computing, where the product or service is often scientifically advanced and market demand uncertain. In the absence of quality signals, workers may apply to work firms with poor technology or business models. Angel investors or venture capitalists often conduct “deep diligence” to address information deficits before investing in startups, e.g., by paying outside computer science professors to evaluate the firms. Potential employees presumably lack both the bargaining power to require such information and the incentive to gather it themselves.

If such expert reviews were made available to workers, would workers change the firms that they apply to? That is, would they apply to *ex ante* better firms? What firm features do workers select on in the absence of expert information? Is there significant misallocation of workers to startups based on limited information?

We address these questions using a unique pair of RCTs. Partnering with a world-leading science-based entrepreneurship program (SEP) with over \$4 billion in equity from its participating firms, we examine worker demand for working at startups on the program’s job board and among applicants to the program’s MBA class.

In the job board experiment, over 22,000 business school alumni are contacted with information about a job board with startups from the SEP looking to make an early business hire. Each potential applicant randomly sees only the information provided by the firms themselves, or sees “above average”/“below average” science quality and business model

quality ratings about firms' science quality in addition to the original job advertisements.<sup>1</sup> These quality ratings are derived from the ratings of subject-matter expert scientists or startup evaluators recruited by the SEP, with evaluators having access to technical documents and other material that is otherwise difficult to access for a potential worker. Applicants were of course free to look at firm websites, search for further information online, and so on. Each applicant was asked to apply to no more than 10 of the 26 firms on the board by rank ordering them, with their CVs sent to startups using the randomized serial dictatorship mechanism to ensure incentive-compatibility of demand. Once applications are sent, we requested completion of a voluntary, incentivized survey about a subset of firms. 261 applicants applied to at least one firm, with just over 2,000 total applications.

In the MBA class experiment, 180 students answered detailed questions about various firms and stated their hypothetical interest in working at the firms after graduation. Students were incentivized to take the questions seriously because their answers (particularly qualitative essays evaluating each firm which we do not use in the present study) determined whether they would get into the SEP course. In both the job board and MBA class RCTs, workers also make incentivized predictions about firm success, such as fundraising or having a successful exit event (IPO or \$50 million+ acquisition), and also stated their beliefs about business and firm quality. Thus, the MBA class RCT is used for our analysis of worker beliefs, but not for the incentivized job rankings.

The RCTs closely mimic a setting where additional information signals are added at the level of the market; that is, we are able to investigate the nature of firm-worker sorting by quality when we improve the precision of applicant knowledge about the quality of the startup's business model or science. Workers are exposed to many firms, but treatment is at the worker level, so that each worker is exposed to the baseline firm information, or additionally ratings on business and/or science quality for all firms.

It is not clear ex-ante whether science or business quality is most important for evaluating firms, or indeed whether potential workers even care about either feature. Perhaps startups have difficulty hiring solely because of the riskiness of the job, or salary issues. However, consider Theranos, a startup once valued at over \$8 billion that promised to revolutionize the web that blood testing is done. There was enormous demand for Theranos' product as marketed by its leaders, leading to an early partnership with Safeway. However, the scientific quality was highly lacking, and expert evaluations of the science were rarely made and deliberately suppressed (note that nonetheless there was much more publicly available information for job applicants about Theranos than the usual early stage startup). In

---

<sup>1</sup>Note that since all firms on the job board are graduates of the well-known SEP, they are all well in the upper tail of quality even among potentially venture-backable firms.

such a case, information on science quality would seem to be very important. On the other hand, entrepreneurs often say that ideas are cheap and what matters is finding untapped demand and executing, suggesting that business model quality is critical. Because our RCTs randomly vary whether information is revealed (and not the underlying quality of firms), the information varies in whether it is bad or good. Thus, within firms, we can examine the impact of a market where information-constrained workers become more aware of which firms have high or low quality among each dimension.

Our main finding is that expert ratings substantially affect how workers rank firms, and thus, the firms their job applications are sent to. Both science and quality information matter for applicant demand, and interestingly, both matter to a similar degree. Furthermore, the impact of positive and negative information is roughly symmetric. Relative to not providing information, providing positive information on science (or business) quality increases workers' ranking of a firm by about 0.15 standard deviations ( $\sigma$ ), and providing negative science(or business) information decreases workers' ranking of a firm by  $0.15\sigma$ . The result is highly robust to different functional forms, all pre-registered in a pre-analysis plan. An alternative way of understanding this result is that when workers receive no expert information, they are 11% more likely to apply to a firm with good science and a good business model than one that is below average along each margin. However, workers in the full information treatment are 89% more likely to apply to a good science/good business startup than one which is below average among both margins. In the absence of expert ratings, workers often select firms based on simple cues, like whether a firm operates in a "hot" technology area or has an aesthetically-pleasing website.

To better understand these effects on worker demand, we examine impacts of the treatments on worker beliefs. Expert ratings substantially affect workers' perceptions of the science and business quality of firms. They also affect workers' beliefs about whether the firms will succeed. To ensure that workers provide thoughtful answers regarding firm success, we incentivized worker beliefs using a risk-invariant quadratic scoring rule, where it is incentive-compatible for any utility-maximizing agent to provide their honest beliefs, and workers can win up to \$250. Interestingly, even under significant incentives, workers show substantial optimism in their beliefs about firm success: the median applicant expects the startup they evaluate to have a 25% change of an IPO or being acquired for more than \$50 million within a year (the empirical probability in our venture sample is 0%). Despite this, workers do update their beliefs about firm success in response to expert ratings about both science and business models, particularly their beliefs about whether firms will raise venture capital. These results support that beliefs about firm quality and success are a key

mechanism for changes in interest.<sup>2</sup>

What is the welfare implication of these results? Assuming that assortative matching between labor and startup is optimal, we derive conditions where information is welfare-improving in a simple model using the incentive compatible relative rank of firms. Though good firms could conceivably attract better workers with higher salaries, the liquidity constraint on startups limits that option. Low-quality firms are *more* willing to offer high equity shares, limiting separating equilibria along wage and equity margins. Credible, precise information about firm quality in job ads is thus useful to workers, endogenously generates a welfare-enhancing separating equilibrium due to the worker response we identify, and improves welfare.<sup>3</sup>

Our paper makes several contributions. First, it is the first RCT on how workers choose between startups, as well as the first RCT about the role of expert ratings in affecting how workers choose among firms. It is thus complementary to a growing body of worker that uses natural experiments or RCTs on how workers choose among jobs or firms [Hedegaard and Tyran, 2018, Mas and Pallais, 2017, Stern, 2004, Wiswall and Zafar, 2015], but that focuses instead on established firms or all firms, and that analyzes other characteristics like whether a firm is family-friendly or allows scientists to the opportunity to publish.<sup>4</sup> Our mechanism results indicate that the overall treatment effects are facilitated by worker beliefs.

Second, our results provide the first evidence that workers would select substantially different firms in the presence of expert-provided information. This shows that there may be significant misallocation in workers to startups. Just as *physical capital* may be misallocated due to frictions between firms [Hsieh and Klenow, 2009], so may *human capital* also be misallocated. Our results indicate that this misallocation may be substantial, particularly in the case where there are complementarities in production between good workers and good firms. Our results suggest that policies to provide more information about firms to workers, whether by governments, business councils, entrepreneurship programs, or job boards, can significantly improve worker welfare. While the issue of workers being allocated to bad firms has not been discussed in the academic literature, there are many parallels. For example, Hastings and Weinstein [2008] provide evidence that poor parents lack easy-to-use information about what schools are good, and Kling et al. [2012] show that seniors are often misinformed about Medicare Part D plans.

---

<sup>2</sup>Beyond positive tail events, workers might have cared a lot instead about other positive attributes, like not losing their job or the chance to gain skills.

<sup>3</sup>Intriguingly, in their self-written firm descriptions for the job board, no firm highlighted external, credible information about the quality of their science or business model.

<sup>4</sup>Beyond the lack of natural experiment or RCT work on how workers choose among startups, we have also found almost no observational work on this question. There is some work on why workers choose to work in startups instead of established firms, but our focus on choices between startups is distinct.

Third, our results relate to several ongoing discussions in the personnel and labor economics literatures on startups. One puzzle is why do startups and other companies often pay workers with equity instead of salary. As discussed by [Oyer and Schaefer \[2005\]](#), common explanations are taxes, credit constraints, or aligning worker beliefs with the firm. Our paper presents the first evidence, and backed by incentivized experimental methods, that workers overestimate the probability of positive events occurring to workers. Thus, our work suggests the possibility that firms may find it cheaper in expected value to pay workers in equity instead of salary. Moreover, since we document that workers respond strongly to expert ratings and otherwise make choices based on cues, our results suggest that workers may have little ability to accurately evaluate expected returns from equity-based compensation. These results provide evidence for recent discussion by legal scholars about whether additional regulation should be considered regarding startup compensation toward employees.

Does the worker apply to the firm at all?			
VARIABLES	(1)	(2)	(3)
Science Score Revealed X Good Science	0.106 (0.027)***		0.109 (0.027)***
Science score revealed	-0.060 (0.019)***		-0.064 (0.019)***
Business Model Score Revealed X Good Business		0.119 (0.028)***	0.122 (0.027)***
Business model score revealed		-0.036 (0.019)*	-0.036 (0.019)*
Observations	5,902	5,902	5,902
R-squared	0.075	0.077	0.081
F(SciRevealed + SciRevealed X GoodScience = 0)	0.0297		0.0310
F(BusRevealed + BusRevealed X GoodBus = 0)		3.83e-05	0
Mean of the dv			0.289

Notes: The DV is a binary variable for whether the worker applies to the firm at all. Standard errors clustered at the subject-level in parentheses. All regressions include firm fixed effect and worker strata (gender, graduation year, location) dummies.

Is a firm the worker's top choice?			
VARIABLES	(1)	(2)	(3)
Science Score Revealed X Good Science	0.018 (0.010)*		0.019 (0.010)*
Science score revealed	-0.009 (0.005)*		-0.009 (0.005)*
Business Model Score Revealed X Good Business		0.020 (0.009)**	0.020 (0.009)**
Business model score revealed		-0.011 (0.005)**	-0.011 (0.005)**
Observations	5,902	5,902	5,902
R-squared	0.057	0.057	0.058
F(SciRevealed + SciRevealed X GoodScience = 0)	0.0658		0.0600
F(BusRevealed + BusRevealed X GoodBus = 0)		0.0337	0.0300
Mean of the dv			0.0380

Notes: The DV is a binary variable for whether the company is the worker's top choice, with incentive compatibility of rankings driven by the RSD mechanism. Standard errors clustered at the subject-level in parentheses.



Is the firm one of the worker's top 3 choices?			
VARIABLES	(1)	(2)	(3)
Science Score Revealed X Good Science	0.080 (0.017)***		0.081 (0.017)***
Science score revealed	-0.039 (0.008)***		-0.040 (0.008)***
Business Model Score Revealed X Good Business		0.058 (0.018)***	0.060 (0.018)***
Business model score revealed		-0.029 (0.010)***	-0.030 (0.010)***
Observations	5,902	5,902	5,902
R-squared	0.074	0.073	0.077
F(SciRevealed + SciRevealed X GoodScience = 0)	2.00e-05		0
F(BusRevealed + BusRevealed X GoodBus = 0)		0.00111	0.00100
Mean of the dv			0.112

Notes: The DV is a binary variable for whether the company is in the worker's top 3 choices, with incentive compatibility of rankings driven by the RSD mechanism. Standard errors clustered at the subject-level in parentheses.

What standardized rank does the company have on a job board?

VARIABLES	(1)	(2)	(3)
Science Score Revealed X Good Science	0.866 (0.191)***		0.888 (0.191)***
Science score revealed	-0.462 (0.108)***		-0.479 (0.107)***
Business Model Score Revealed X Good Business		0.888 (0.197)***	0.909 (0.197)***
Business model score revealed		-0.367 (0.119)***	-0.374 (0.119)***
Observations	5,902	5,902	5,902
R-squared	0.090	0.091	0.096
F(SciRevealed + SciRevealed X GoodScience = 0)	0.000745		0.00100
F(BusRevealed + BusRevealed X GoodBus = 0)		6.62e-06	0
Mean of the dv			1.781

Notes: This table reports linear regression of the standardized rank a company receives from applicants, with firms that are not applied to imputed to a lower rank. Standard errors clustered at the subject-level in parentheses. A higher ranking indicates a more preferred company, with incentive compatibility due to the fact that CVs were sent to firms according to the RSD mechanism.

Reported interest in working for a company in survey given information treatment			
VARIABLES	(1)	(2)	(3)
Science Score Revealed X Good Science	0.198 (0.122)		0.198 (0.122)
Science score revealed	-0.200 (0.099)**		-0.200 (0.098)**
Business Model Score Revealed X Good Business		0.208 (0.118)*	0.210 (0.119)*
Business model score revealed		-0.132 (0.089)	-0.130 (0.089)
Observations	1,054	1,054	1,054
R-squared	0.183	0.182	0.186
F(SciRevealed + SciRevealed X GoodScience = 0)	0.985		0.986
F(BusRevealed + BusRevealed X GoodBus = 0)		0.395	0.374

Notes: This table reports linear regression of interest in working for the company on the external evaluations of the ventures' science and business quality. Dependent variable is the standardized score of the subject's interest in working for the company, measurable on a scale of 1-5. Standard errors clustered at the subject-level in parentheses.

How does the absolute level of application behavior change with information?

Science:	Bad	Good	Bad	Good
Business:	Bad	Bad	Good	Good
<b>Treatment:</b>				
Control	.2	.22	.37	.22
Science Info	.14	.37	.3	.19
Business Info	.14	.17	.44	.24
Sci & Biz Info	.14	.24	.35	.27

Notes: This table shows the share of workers applying to a given firm that scored high or not in different combinations of science and business, by information treatment.

The effect of Science rankings on perceived science and business model quality			
VARIABLES	(1)	(2)	(3)
Science Score Revealed X Good Science	0.473 (0.119)***		0.471 (0.119)***
Science score revealed		-0.297 (0.093)***	-0.295 (0.093)***
Business Model Score Revealed X Good Business		0.243 (0.115)**	0.241 (0.116)**
Business model score revealed		-0.193 (0.090)**	-0.191 (0.090)**
Observations	1,076	1,076	1,076
R-squared	0.199	0.191	0.205
F(SciRevealed + SciRevealed X GoodScience = 0)	0.0450		0.0450
F(BusRevealed + BusRevealed X GoodBus = 0)		0.573	0.573

Notes: This table reports linear regression of the perceived quality of the company's core science on external evaluations of the ventures' science and business quality. Dependent variable is the standardized score of the subject's evaluation of the company's science, measured on a scale of 1-5. Standard errors clustered at the subject-level in parentheses.

The effect of Business Model rankings on perceived science and business model quality

VARIABLES	(1)	(2)	(3)
Science Score Revealed X Good Science	0.166 (0.120)		0.165 (0.120)
Science score revealed	-0.102 (0.095)		-0.101 (0.094)
Business Model Score Revealed X Good Business		0.397 (0.119)***	0.397 (0.119)***
Business model score revealed		-0.239 (0.090)***	-0.238 (0.090)***
Observations	1,062	1,062	1,062
R-squared	0.139	0.148	0.149
F(SciRevealed + SciRevealed X GoodScience = 0)	0.448		0.451
F(BusRevealed + BusRevealed X GoodBus = 0)		0.0755	0.0770

Notes: This table reports linear regression of the perceived quality of the company's business model on external evaluations of the ventures' science and business quality. Dependent variable is the standardized score of the subject's evaluation of the company's business quality, measured on a scale of 1-5. Standard errors clustered at the subject-level in parentheses.

Will the company raise more than \$1 million in external financing within a year?			
VARIABLES	(1)	(2)	(3)
Science Score Revealed X Good Science	7.718 (2.822)***		7.735 (2.838)***
Science score revealed	-5.392 (2.295)**		-5.468 (2.306)**
Business Model Score Revealed X Good Business		9.044 (2.857)***	9.079 (2.866)***
Business model score revealed		-3.808 (2.180)*	-3.789 (2.179)*
Observations	1,036	1,036	1,036
R-squared	0.186	0.188	0.194
F(SciRevealed + SciRevealed X GoodScience = 0)	0.281		0.291
F(BusRevealed + BusRevealed X GoodBus = 0)		0.0229	0.0220

Notes: This table reports linear regression of predicted probability of a \$1 million external financing within one year from the date document was prepared on external evaluations of the ventures' science and business quality. Standard errors clustered at the subject-level in parentheses. Mean of DV is 53.

Will the company have an IPO or be acquired for \$50 million within one year?			
VARIABLES	(1)	(2)	(3)
Science Score Revealed X Good Science	4.346 (2.782)		4.347 (2.788)
Science score revealed	-0.711 (2.319)		-0.769 (2.324)
Business Model Score Revealed X Good Business		6.621 (2.761)**	6.563 (2.765)**
Business model score revealed		-2.875 (2.282)	-2.898 (2.283)
Observations	1,039	1,039	1,039
R-squared	0.109	0.111	0.114
F(SciRevealed + SciRevealed X GoodScience = 0)	0.143		0.148
F(BusRevealed + BusRevealed X GoodBus = 0)		0.143	0.152

Notes: This table reports linear regression of predicted probability of an IPO event or valuation of over \$50 million on external evaluations of the ventures' science and business quality. Standard errors clustered at the subject-level in parentheses. Mean of DV is 30.



## References

- Nicholas Bloom and John Van Reenen. Human resource management and productivity. *Handbook of Labor Economics*, 1:1697–1767, 2011.
- Justine S. Hastings and Jeffrey M. Weinstein. Information, school choice, and academic achievement: Evidence from two experiments\*. *Quarterly Journal of Economics*, 123(4): 1373–1414, 2008.
- Morten Størting Hedegaard and Jean-Robert Tyran. The price of prejudice. *American Economic Journal: Applied Economics*, 10(1):40–63, 2018.
- Chang-Tai Hsieh and Peter J. Klenow. Misallocation and manufacturing tfp in china and india. *Quarterly Journal of Economics*, 124(4):1403–1448, 2009.
- Daniel Hsu and Rosemarie Ziedonis. Resources as dual sources of advantage: implications for valuing entrepreneurial-firm patents,. *Strategic Management Journal*, 2013.
- Casey Ichniowski, Kathryn Shaw, and Giovanna Prennushi. The effects of human resource management practices on productivity: A study of steel finishing lines. *American Economic Review*, 87(3):291–313, 1997.
- Jeffrey R. Kling, Sendhil Mullainathan, Eldar Shafir, Lee C. Vermeulen, and Marian V. Wrobel. Comparison friction: Experimental evidence from medicare drug plans. *Quarterly Journal of Economics*, 127(1):199–235, 2012.
- Josh Lerner. Venture capitalists and the oversight of privately-held firms. *Journal of Finance*, 1995.
- Alexandre Mas and Amanda Pallais. Valuing alternative work arrangements. *American Economic Review*, 107(12):3722–59, 2017.
- Paul Oyer and Scott Schaefer. Why do some firms give stock options to all employees?: An empirical examination of alternative theories. *Journal of Financial Economics*, 76(1): 99–133, 2005.
- Paul Oyer and Scott Schaefer. Personnel economics: Hiring and incentives. *Handbook of Labor Economics*, 2011.
- Scott Stern. Do scientists pay to be scientists? *Management science*, 50(6):835–853, 2004.
- Matthew Wiswall and Basit Zafar. Determinants of college major choice: Identification using an information experiment. *Review of Economic Studies*, 82(2):791–824, 2015.