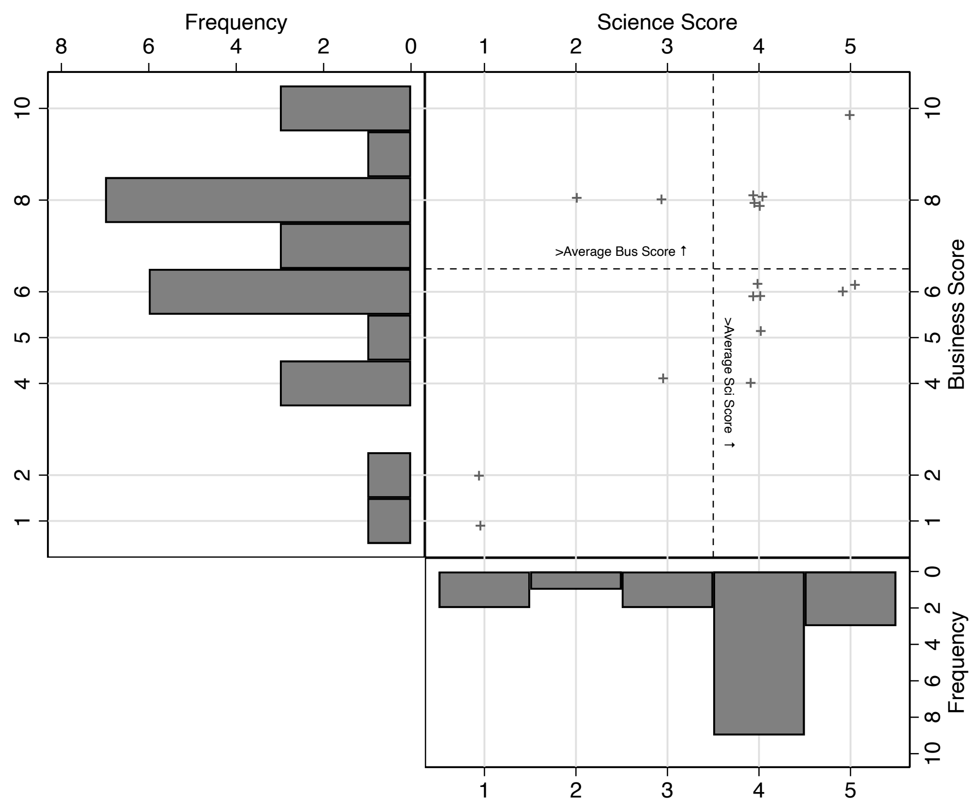
Online Appendix: "Information Frictions and Employee Sorting Between Startups"

The Online Appendix consists of the following parts. Appendix A provides additional figures and tables. Appendix B provides further discussion on different parts of the main text. Appendix C provides the Theory Appendix. Appendix D provides screenshots from the Primary RCT.

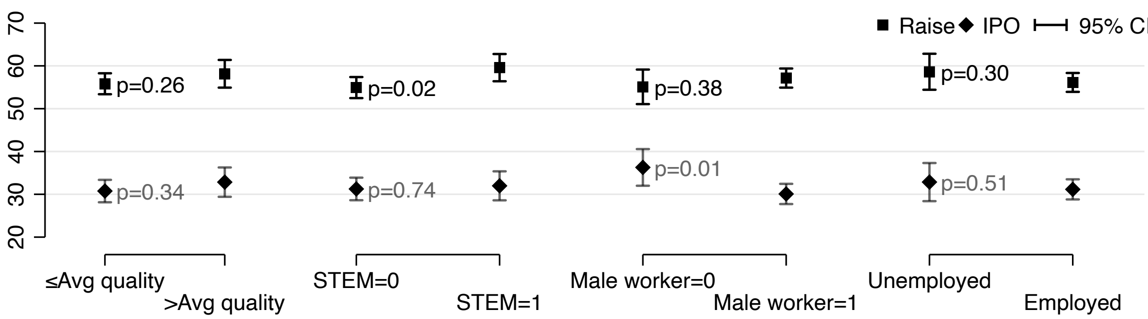
Appendix A Additional Figures and Tables

Figure A1: Distribution Plots of Science and Business Scores

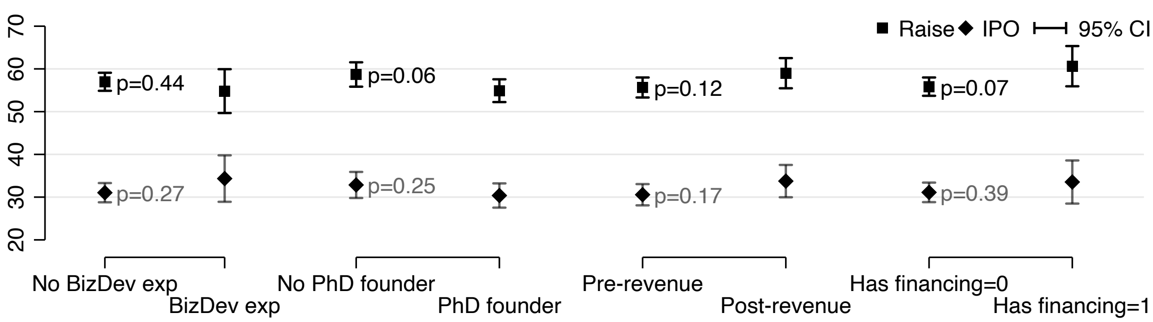


Notes: This figure shows the distribution of startup scores in the Primary RCT, excluding 9 startups that were missing the science score. Scatterplot points are jittered for clarity.

Figure A2: Distribution of Worker Beliefs for Raise and Exit in 1 Year by Worker and Firm Characteristics



(a) By worker characteristics



(b) By firm characteristics

Notes: This figure shows the mean and 95% confidence interval of the Primary RCT incentivized beliefs about the probability of successful funding (square symbols) and successful exit (diamond symbols). Difference in means test p-values are reported beside symbols. For raise, workers are asked "What is the probability that the firms below raise money at a valuation of at least CAD$1,000,000 within 1 year of the time this information was prepared?" For exit, workers are asked "What is the probability that the firm in question has an initial public offering (IPO) or is acquired at CAD$50,000,000 or more within 1 year of the time the information was prepared?"

Table A1: Selection of Alumni into the Primary RCT

	Submitted job app
Male	1.030***
	(0.163)
City is SEP HQ	0.758***
	(0.183)
Graduation Year, Base Level = 1980	
1985	0.402
	(0.455)
1995	0.392
	(0.409)
2005	1.110***
	(0.404)
2013	1.152***
	(0.352)
2018	0.867**
	(0.360)
2019	4.560***
	(0.771)
Treatment Group, Base Level = No Info	
Business + Science info	−0.037
	(0.233)
Business info	0.025
	(0.235)
Science info	−0.268
	(0.223)
R^2	0.01
Observations	19,359

Notes: This table examines overall selection into the Primary RCT. It shows a linear probability model, where RCT participation (defined as applying to at least one firm on the job board) is regressed on subject characteristics. Coefficients are multiplied by 100 for readability. Robust standard errors in parentheses. An observation is an alumni who is emailed. More details on the selection process are provided in Section 3 of the main text.

Table A2: Selection of Firms into the Primary RCT

	Firm Characteristic Means by RCT Treatment Arm					
	Bad Biz Bad Sci	Bad Biz Good Sci	Good Biz Bad Sci	Good Biz Good Sci	Non-RCT Firm Means	All Firms, Selection Regression
Has financing	0.0	0.1	0.2	0.4	0.2	-0.028
						(0.061)
Num. employees	0	7	0	3	4	-0.002
						(0.006)
Num. founders	3	3	2	3	2	0.044*
						(0.025)
PhD Founder	0.4	0.7	0.3	0.6	0.5	-0.013
						(0.054)
BizDev exp	0.2	0.0	0.6	0.2	0.5	-0.109*
						(0.055)
Female founder	0.6	0.3	0.2	0.2	0.2	0.017
						(0.063)
Patent (pending/granted)	0.6	0.9	0.7	0.0	0.7	-0.023
						(0.056)
Log(Revenue)	0.00	3.92	3.23	6.89	3.57	-0.000
						(0.005)
Log(Capital)	11.35	6.94	4.72	9.52	6.88	0.003
						(0.004)
R^2						0.05
Observations	5	7	9	5	157	183

Notes: This table shows descriptive statistics for the 26 startups in the Primary RCT (Job Board), and the remaining 157 startups in the same SEP cohort; these 183 firms make up the full cohort of 2018-2019 firms who participated in streams at SEP's primary location. The first four columns present means of variables in the four RCT treatment arms in the Primary RCT. The fifth column presents means for the firms who chose not to participate in the RCT. The final column presents results from a selection regression, where the dependent variable is whether a startup chose to participate in the Job Board (0 or 1), and with robust standard errors in paretnehses. As can be seen, observable characteristics are generally weak predictors of whether a startup participates in the job board.

Table A3: Share of Workers by Number of Applications and Treatment Group

	Sci & Biz Info	Biz Info	Sci Info	No Info
#Apps Submitted:				
=10	0.45	0.52	0.32	0.47
=1	0.02	0.00	0.08	0.02
≤ 3	0.16	0.06	0.19	0.14
≥ 5	0.75	0.91	0.74	0.79

Notes: This table shows the intensity of job applications by different treatment groups in the Primary RCT. Rows show the share of workers in each treatment group who used all, one, less than four, and at least half of the possible application slots by ranking startups among their top ten places to work.

Table A4: Non-Experimental Predictors of Job Applications

	Applied	Top Ranked	Top 3 Choices	Normalized Rank
Panel A: No Information				
Has financing	−0.071	−0.091**	−0.099*	−0.221
	(0.073)	(0.039)	(0.051)	(0.140)
Num. founders	0.033	0.026**	0.023	0.060
	(0.021)	(0.012)	(0.015)	(0.041)
Num. employees	−0.002	−0.000	−0.002	−0.008*
	(0.002)	(0.001)	(0.002)	(0.004)
Pct SEP activities completed	0.157*	0.000	−0.012	0.159
	(0.087)	(0.030)	(0.045)	(0.158)
PhD Founder	−0.097**	−0.008	−0.049**	−0.188**
	(0.037)	(0.010)	(0.022)	(0.079)
BizDev exp	−0.008	0.012	0.032	0.028
	(0.034)	(0.016)	(0.023)	(0.068)
Female founder	0.009	−0.059***	−0.023	−0.011
	(0.035)	(0.022)	(0.033)	(0.089)
Log(Revenue)	0.008**	0.005**	0.009***	0.026***
	(0.003)	(0.002)	(0.003)	(0.007)
Log(Capital)	0.002	0.001	0.001	0.005
	(0.002)	(0.001)	(0.002)	(0.005)
Top 1/3 Page	0.036	0.042***	0.031	0.117*
	(0.032)	(0.016)	(0.024)	(0.069)
R^2	0.08	0.08	0.11	0.12
Observations	1,716	1,716	1,716	1,716
Panel B: Full Sample				
Has financing	0.014	−0.059***	−0.045	−0.018
	(0.043)	(0.022)	(0.028)	(0.086)
Num. founders	0.010	0.013**	0.014	0.024
	(0.014)	(0.007)	(0.010)	(0.030)
Num. employees	−0.002**	−0.002***	−0.003***	−0.009***
	(0.001)	(0.001)	(0.001)	(0.002)
Pct SEP activities completed	0.098**	−0.004	−0.005	0.074
	(0.044)	(0.017)	(0.027)	(0.088)
PhD Founder	−0.062***	−0.019***	−0.037***	−0.139***
	(0.017)	(0.006)	(0.011)	(0.037)
BizDev exp	−0.048***	0.001	−0.014	−0.082**
	(0.017)	(0.008)	(0.012)	(0.039)
Female founder	−0.007	−0.034***	−0.034**	−0.040
	(0.020)	(0.010)	(0.015)	(0.044)
Log(Revenue)	0.010***	0.006***	0.009***	0.028***
	(0.002)	(0.001)	(0.001)	(0.004)
Log(Capital)	−0.000	0.000	0.000	−0.001
	(0.001)	(0.001)	(0.001)	(0.003)
Top 1/3 Page	0.022	0.028***	0.036***	0.077**
	(0.017)	(0.008)	(0.012)	(0.037)
R^2	0.05	0.05	0.06	0.07
Observations	6,500	6,500	6,500	6,500

Notes: This table shows non-experimental predictors of job applications. All models include fixed effects for the specialized technology stream of the SEP program to which startups were admitted. Streams are based on core technology or industry, and include machine learning, quantum machine learning, blockchain, space, cities, and health. Standard errors clustered by worker in parentheses.

Table A5: Impact of Expert Ratings on Unincentivized Job Interest

	(1)	(2)	(3)
Science info X Good science	0.117		0.118
	(0.125)		(0.125)
Science info	-0.171^{*}		-0.172^{*}
	(0.101)		(0.100)
Business info X Good business		0.235^{**}	0.239^{**}
		(0.118)	(0.118)
Business info		-0.176^{**}	-0.176^{*}
		(0.090)	(0.090)
F(Sci + Sci X GoodSci = 0)	0.535		0.536
F(Bus + Bus X GoodBus = 0)		0.520	0.491
Observations	1,104	1,104	1,104

Notes: This table shows the within-startup effect of information on the candidate's normalized interest in working for the start-up using pooled data from the Primary and Secondary RCTs. Worker interest is a score from 1 to 5 (highest). Standard errors clustered by worker in parentheses.

Table A6: Correlations between Heterogeneity Dimensions and Worker Beliefs

	Raise at \$1m Valuation	IPO or \$50m Acquisition
Panel A: Worker Characteristics		
>Avg quality	1.702	2.258
	(2.687)	(3.560)
Male worker	1.420	−6.739
	(2.903)	(4.114)
STEM	4.986^{*}	1.272
	(2.804)	(3.570)
Employed	−3.671	−1.400
	(3.346)	(4.540)
R^2	0.02	0.02
Panel B: Firm Characteristics		
BizDev exp	−2.763	3.186
	(3.127)	(3.184)
PhD Founder	-4.157^{**}	−3.382
	(1.836)	(2.055)
Post-revenue	1.982	2.938
	(2.165)	(2.166)
Has financing	5.139^{*}	1.355
	(2.746)	(2.642)
R^2	0.02	0.01
Observations	534	534
Mean of DV	56.64	31.28

Notes: This table shows worker and firm predictors of beliefs about firm success in the Primary RCT. The dependent variables are shown at the top of each column. Worker were asked to submit their beliefs about three randomly selected firms. Data is 604 belief responses from Primary RCT, of which 7 are missing Pr(Raise at 1m Valuation), 4 are missing Pr(Successful Exit), and 59 are missing both. Standard errors clustered by worker in parentheses.

Table A7: Multiple Hypothesis Testing
Multiplicity of Outcomes

Dependent Variables	Applied	Top Rank	Top 3 Choices	Normalized Rank
Science info X Good science	{0.000}	{0.010}	{0.000}	{0.000}
Science info	{0.001}	{0.010}	{0.000}	{0.000}
Business info X Good business	{0.000}	{0.033}	{0.006}	{0.000}
Business info	{0.082}	{0.068}	{0.026}	{0.016}

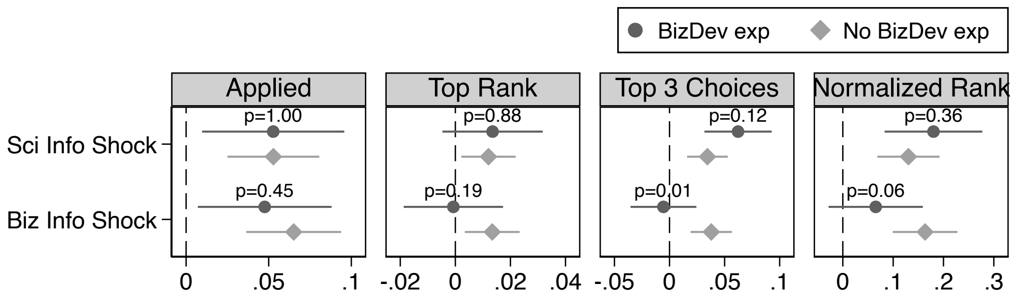
Notes: This table displays family-wise error rate (FWER) adjusted p-values to account for analyzing the impact of information on multiple outcome variables shown in Table 3, based on Westfall & Young (1993) free step-down procedure (5,000 replications) and while accounting for clustering by worker in bootstrapping. Each p-value adjusts for testing four hypotheses on whether the treatment equals zero for 4 outcome variables. The specification is $y_{nf} = \alpha_0 + \alpha_1 \text{GotBizInfo}_n + \alpha_2 \text{GotBizInfo}_n \times \text{GoodBizFirm}_f + b_1 \text{GotScienceInfo}_n + b_2 \text{GotScienceInfo}_n \times \text{GoodScienceFirm}_f + \boldsymbol{X}_{nf} + \varepsilon_{nf}$.

Table A8: Tests of Complementarity between Science and Business Ratings

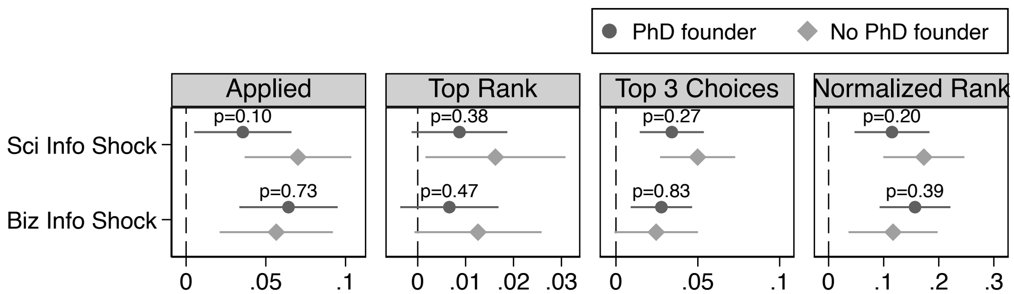
	Applied	Top Rank	Top 3 Choices	Normalized Rank
Biz info	−0.055	−0.019*	−0.022	−0.124*
	(0.035)	(0.011)	(0.021)	(0.072)
Sci info	−0.129***	−0.027**	−0.058***	−0.298***
	(0.035)	(0.011)	(0.020)	(0.068)
Biz Info X Sci Info	0.107**	0.038**	0.053*	0.245**
	(0.051)	(0.015)	(0.029)	(0.104)
Biz info X Good firm	0.137**	0.030	0.045	0.295***
	(0.054)	(0.019)	(0.033)	(0.110)
Sci info X Good firm	0.061	0.022	0.067**	0.228**
	(0.046)	(0.018)	(0.031)	(0.100)
Biz Info X Sci Info X Good Firm	−0.062	−0.014	−0.015	−0.141
	(0.078)	(0.027)	(0.050)	(0.169)
R^2	0.07	0.03	0.04	0.07
Observations	2500	2500	2500	2500

Notes: This table shows tests of complementarity between science and business rating information on job applications. The sample is restricted to good and bad firms, defined as whether the firm is rated as above-average on both dimension or it is not rated as above-average on both dimension. The specification is identical to that of Table 3, except for the addition of the interaction variables *Biz Info X Sci Info* and *Biz Info X Sci Info X Good Firm*.

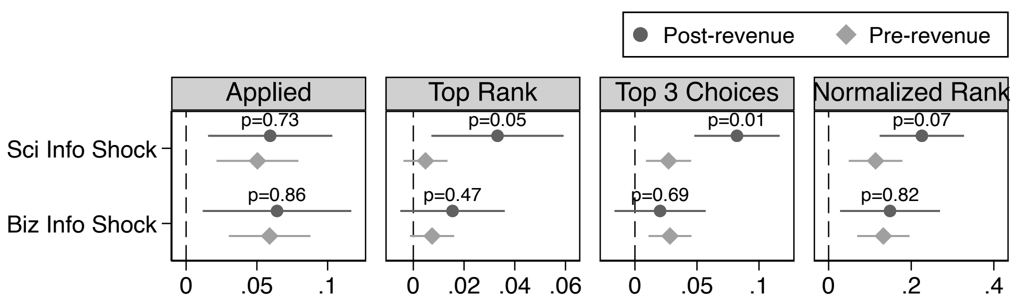
Figure A3: Treatment Effect Heterogeneity by Firm Characteristics



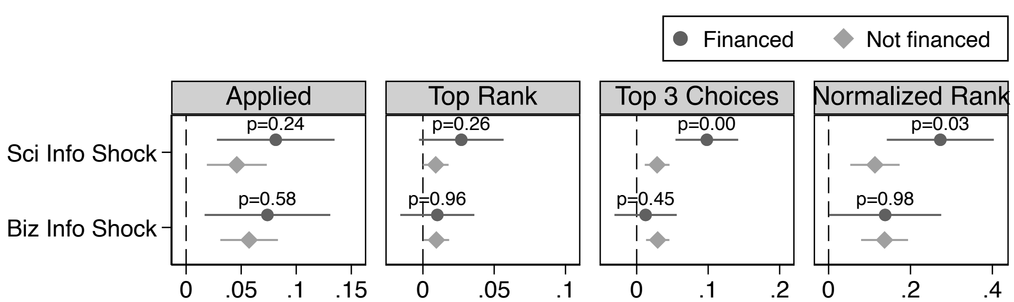
(a) By whether founders have prior business development experience



(b) By whether the firm has a PhD founder



(c) By whether the firm is generating revenue



(d) By whether the firm is externally financed

Notes: This figure shows heterogeneity in worker response to information shocks in the Primary RCT. Estimates are from regressing application outcomes on science and business treatments and their interactions with worker characteristics. Regressions include venture and strata fixed effects. The lines shown are 95% confidence intervals.

Table A9: Multiple Hypothesis Testing
Multiplicity of Heterogeneity Dimensions

	Worker is male	Worker is high quality
Science info shock	{0.044}	{0.968}
	[0.028]	[1.000]
Business info shock	{0.181}	{0.314}
	[0.201]	[0.392]

Notes: This table displays family-wise error rate (FWER) adjusted p-values in curly brackets (Bonferroni adjusted p-values in square brackets) to account for multiple hypothesis testing in analyzing worker treatment effect heterogeneity shown in Figure 4, based on Westfall & Young (1993) free step-down procedure (5,000 replications) and while accounting for clustering by worker in bootstrapping. The first row's family of hypotheses is four tests on whether the coefficient for Science Info Shock X Characteristics equals zero for the 4 worker characteristics considered in our heterogeneity analysis (quality, gender, STEM degree, and current employment). The second row is analogous to the first row, but for business info shock. The specification is $y_{nf} = \alpha_0 + \alpha_1 \text{BizInfoShock}_n + \alpha_2 \text{SciInfoShock}_n + \alpha_3 \text{C}_n + \alpha_4(\text{BizInfoShock}_n \times \text{C}_n) + \alpha_5(\text{SciInfoShock}_n \times \text{C}_n) + \boldsymbol{X}_{nf} + \varepsilon_{nf}$.

Table A10: Differences in Worker and Venture Average Characteristics in the 20% Most and Least Affected Observations by Responsiveness to Information Shocks

	Science Info Shock				Business Info Shock			
	Estimate	S.E.	*jp*-value	*p*-value	Estimate	S.E.	*jp*-value	*p*-value
Panel A: Worker characteristics								
>Avg quality	−0.05	0.25	1.00	0.43	1.01	0.25	0.01	0.00
Male worker	0.89	0.20	0.00	0.00	0.69	0.25	0.10	0.00
STEM	−0.09	0.23	1.00	0.34	−0.10	0.33	1.00	0.38
Employed	−0.34	0.22	0.60	0.06	0.03	0.24	1.00	0.45
Panel B: Venture characteristics								
BizDev exp	0.44	0.32	0.54	0.08	−1.17	0.33	0.01	0.00
PhD Founder	−0.51	0.28	0.33	0.03	0.61	0.42	0.52	0.07
Post-revenue	0.88	0.25	0.02	0.00	0.19	0.42	0.98	0.33
Has financing	1.09	0.28	0.01	0.00	0.02	0.43	1.00	0.48

Notes: This table shows the difference in average characteristics of workers (Panel A) and ventures (Panel B) between the 20% most and least affected job applications by science and business information shocks in the Primary RCT. Results are based on the Sorted Effects method of Chernozhukov *et al.* (2018) and is implemented using the R package by Chen *et al.* (2019).

Table A11: Credible Quality Signals in Startup Job Advertisements

Signal	% of All Jobs	% of Business Development Jobs
Founder Education	3.4	2.9
Academic Spinout	1.3	1.0
Other Spinout	0.2	0.2
Incubator Participation	4.8	3.6
Formal IP	2.0	2.4
Named Buyer or Partner	5.6	7.1
International Sales	1.4	1.5
Named Investor or Large Grant	7.5	8.5
Unnamed Investor's Prior Exits	0.2	0.2
Prize or Contest Winner	1.3	1.7
Prominent Advisor	0.2	0.5
Founder's Startup/Corporate Experience	1.8	1.2
Founder's Award for Related Work	0.5	1.0
Media Mention	1.4	1.2
Tech Based on Published Science	0.4	0.2
Specific Sales Traction	0.2	0.2
At least one credible signal	22.7	24.3
Product Description	92.6	94.4
Technical Description	24.6	17.8
Business Model/Monetization Strategy	5.4	9.5

Notes: This table shows characteristics of the universe of job advertisements (N=1017) on AngelList Careers during a two-week period from startups with 1-10 employees. "% of All Jobs" refers to the fraction of job ads which mention each feature. "% Business Development Jobs" restricts to the 411 job ads which are not technical or engineering hires. See Appendix E for the description of the features.

Table A12: Correlation between Success Beliefs and Applications

	(1)	(2)	(3)
Panel A: Dep. Var. = Applied			
Pr(Raise at 1m Valuation)	0.005***		0.006***
	(0.001)		(0.001)
Pr(Successful Exit)		0.002***	−0.000
		(0.001)	(0.001)
R^2	0.14	0.09	0.14
Observations	534	534	534
Panel B: Dep. Var. = Top Rank			
Pr(Raise at 1m Valuation)	0.000		0.000
	(0.000)		(0.000)
Pr(Successful Exit)		0.000	0.000
		(0.000)	(0.000)
R^2	0.03	0.03	0.03
Observations	534	534	534
Panel C: Dep. Var. = Top 3 Choices			
Pr(Raise at 1m Valuation)	0.002***		0.002***
	(0.001)		(0.001)
Pr(Successful Exit)		0.001	−0.000
		(0.001)	(0.001)
R^2	0.07	0.05	0.07
Observations	534	534	534
Panel D: Dep. Var. = Normalized Rank			
Pr(Raise at 1m Valuation)	0.011***		0.011***
	(0.002)		(0.003)
Pr(Successful Exit)		0.005**	−0.000
		(0.002)	(0.002)
R^2	0.13	0.08	0.13
Observations	534	534	534

Notes: This table shows within-startup correlations between worker success beliefs and job applications in the Primary RCT. Beliefs are the incentivized probabilities that the startup will raise external capital at $1m valuation, and experience an IPO or an acquisition with $50m or above valuation. Data is 604 responses from Primary RCT, of which 7 are missing Pr(Raise at 1m Valuation), 4 are missing Pr(Successful Exit), and 59 are missing both. Standard errors clustered by worker in parentheses.

Appendix B Additional Discussion

B.1 Other Related Work in Management and Finance

While our paper primarily contributes to the literature in personnel economics and labor economics, there is also work related to our paper in management and finance. In management, Aran & Murciano-Goroff (2023) conduct a survey experiment with college-educated workers in startups, finding that many exhibit limited financial literacy about the value of startup equity. Focusing on engineers, Tambe *et al.* (2020) show that many workers in information technology place significant value on learning new skills. This suggests that there are other non-pay considerations besides probability of a successful exit that could be important for startup employees. Roach & Sauermann (2023) argue that PhD scientists join startups despite lower wages because ability and preference for startups are uncorrelated, allowing startups to hire high-ability, strong-preference candidates. Beckman & Burton (2008) find that startups who do not hire important functional business roles early on, when they don't have those skills on the founding team, have a lot of trouble hiring those roles as the firm grows. Honoré & Ganco (2022) show that workers avoid startups that are not spinouts (i.e., that do not have obvious pre-existing links to an industry) unless they have a large founding team that serves as a substitute measure of quality. In finance, Bernstein *et al.* (2020) show that workers on AngelList became more likely to apply to safer startups during covid. Overall, we view our results as highly consistent with and complementary to these other studies, which also paint a picture of limits to sophistication and significant information frictions for startup employees.

B.2 Discussion on the Quadratic Scoring Rule

We further discuss our system for incentivizing beliefs (i.e., our quadratic scoring rule), expanding further on footnote 11 and Section 5.1 in the main text. One concern with our results on worker beliefs is whether they are driven by our use of a quadratic scoring rule. Danz *et al.* (2022) show in a lab that the binarized scoring rule, which is broadly similar to our risk-invariant quadratic scoring rule of McKelvey & Page (1990), often exhibits measurement error in measuring subject beliefs. If there is classical measurement error in beliefs, this will not lead to bias for our regressions of belief on treatment, nor will it bias our conclusion that workers are overoptimistic about the probability of positive firm events. It will contribute to larger standard errors. A key thing about our use of a quadratic scoring rule is that we explicitly tell workers that it is incentive-compatible to state their true beliefs following work such as Hoffman (2016). Wang (2011) finds that quadratic scoring rules yield more accurate beliefs than non-incentivized beliefs, and Palfrey & Wang (2009) find that quadratic scoring produce more accurate beliefs relative to an improper scoring rule (namely, a simple linear penalty scoring rule), though not all work supports that incentives improve accuracy. For example, Hoffman & Burks (2020) randomize whether workers receive a quadratic scoring rule incentive in guessing about their productivity, and find that the scoring rule has little effect on beliefs. Haaland *et al.* (2023) provide general discussion on measuring beliefs, arguing that belief questions can yield meaningful data even without incentives. In our setting, we believe the quadratic scoring rule incentives serve to draw in job applicants' focus, and that it is highly unlikely the incentives decrease the quality of the belief elicitation.

B.3 Details on RCT Timing/Registration, Scientific Scores, and RSD Procedure

Here, we expand more on timing for the two RCTs, including when they were registered. We also provide details on the science expert scores and the procedure for the random serial dictatorship (RSD) mechanism.

Timing and registration. The primary RCT was conducted during May-August 2019. The RCT was registered with a pre-analysis plan in the AEA RCT Registry in August 2019 before data collection had completed and before data analysis had occurred. The secondary RCT was conducted before this in March 2018. The secondary RCT was used to help select students for entrance into the SEP MBA class, and it was unclear at the time whether the results would be used for research purposes, or whether we could move forward with a broader research study, which also required buy-in from the business schools, so that their alum could be contacted about the job board.

Is it any concern for our paper's conclusions that data from the secondary RCT were analyzed before the RCT was registered? In our view, the answer is strongly no. Our paper's main outcome variables (i.e., job applications and the incentivized firm ranking list) are exclusively from the primary RCT and thus do not face this concern. The paper's key findings are robust to restricting to data from the primary RCT.

Scientific scores. No scientific evaluations were done for 9 of the 26 startups in the primary RCT, generally because their product did not rely on novel science.[1] These firms were considered below-median (or not above-median), keeping with the idea that quality of the underlying science is not a source of competitive advantage for these firms. Nonetheless, our main results on job applications are highly robust to excluding these 9 firms. Figure A1 shows the distribution of both science and business scores. For each job seeker in the primary RCT, the 3 startups randomly chosen for

[1]For 8 of the 9 firms, SEP is confident that the firm's product did not rely on novel science. The 9th firm's science quality was uncertain and was a late entry to SEP for idiosyncratic reasons.

belief questions were selected from the 17 firms for which scientific evaluations were done.

RSD procedure. In the primary RCT, workers are informed that their job applications will be passed along to firms according to the RSD mechanism, where a job application would be passed along to a startup based on their ranking. Once workers had already submitted all their job applications, the actual implementation by SEP was slightly different, though still very much in line with what workers were informed. Firms received a zip folder containing the resumes of all workers who ranked the firm, but firms were provided a short list of applicants whose names were included based on the RSD mechanism. That is, workers ended up receiving slots on the special short list of applicants passed along to the firms, and firms were informed that the slots were allocated based on RSD. That implementation occurred in this manner has no effect on the conclusions or interpretation of the paper. Since the zip folder contained many resumes, being on the short list is akin to have your application forwarded by SEP, with the other applications arriving through another channel.

Appendix C Theory Appendix

A Model of Hiring with Asymmetric Information

In this Appendix, we present a stylized model of hiring under imperfect information about firm quality. We use it to show that providing expert ratings (1) increases the number of applicants who apply to above-average firms, (2) decreases the number who apply to below-average firms, and (3) increases the total surplus generated, and wage inclusive of firm equity, paid by high-quality startups.

There are two fundamental assumptions in the model, both of which match our experimental setting. First, workers do not perfectly learn the quality of startups they apply to until they make a costly application. Second, the nature of this imperfect information is that workers are sometimes unable to tell the difference between more promising and less promising startups, not that workers simply observe firm quality with noise. That is, in expectation, both high-quality and low-quality startups will be seen as being closer to the median firm that they actually are.

The reason the model is game-theoretic (in a very simple way) is to account for jobseekers potentially competing with one another for jobs.

Primitives: Let there be M firms and $N \geq M$ workers. Let the surplus generated from firm j hiring worker i be $\Pi_{ij} = q_{ij}Q_j$, where $Q_j > 0$ are fixed firm qualities and $q_{ij} > 0$ are worker match qualities drawn from an i.i.d. distribution with mean q.[2] That is, the surplus created by a given firm and given worker is weakly

[2]With some algebraic complexity, this model can be extended to handle workers with hetero-

complementary in the quality of the other.

Information Asymmetry: Workers do not observe Q_j directly before applying. Rather, all workers observe a common signal μ_j for each firm. For a fraction $\delta \in (0, 1)$ of firms, drawn randomly, $\mu_j = Q_j$, the true firm quality. For the remaining fraction $1 - \delta$ firms, $\mu_j = 0$, an uninformative signal that pools each of these firms. Neither workers nor firms observe their match-quality q_{ij} until worker i applies to firm j.

Timing: First, all workers commonly observe signals μ_j for each firm j. Second, workers apply to exactly one firm; this is a reduced-form equivalent to assuming a linear cost per application of c such that in equilibrium no worker applies to more than one firm. Third, workers and the firms they apply to observe match-specific qualities q_{ij}. Fourth, firms hire the best worker that applied. Finally, any worker who is hired earns payoff equal to a fixed share of surplus $\alpha\Pi_{ij}, \alpha \in (0, 1)$; that is, workers are given an equity share in the firm they work for. Note that due to the surplus sharing assumption in this model, policies that maximize worker payoff, firm surplus, and total surplus are identical.

Let us now solve the model, denoting with p_{ij} the probability worker i applies to firm j. Since the share δ of firms with an uninformative signal are chosen at random, workers' posterior belief of the quality of these firms will be exactly $\bar{Q}$, the average quality of the firms whose quality is observed. Let $\bar{\mu_j} = \bar{Q}$ for firms with these uninformative signals, and $\bar{\mu_j} = \mu_j = Q_j$ for all other firms.

Workers will maximize their payoff from a given match times the probability they are hired. Since workers are identical other than their idiosyncratic match quality, the probability a worker gets hired is just the probability their idiosyncratic match-quality is highest, or one over the number of other applicants to the same firm. Therefore, worker i chooses the randomization strategy across firms p_i to maximize the expectation

$$\mathbb{E}[\sum_j \frac{p_{ij}\alpha q_{ij}\bar{\mu_j}}{\sum_i p_{ij}}]$$

We now solve for the symmetric mixed-strategy equilibrium.

Lemma 1 *Assume that there exists a symmetric mixed-strategy equilibrium where workers apply to all firms with positive probability.*[3] *Then:*

geneous quality. High-quality workers are equally dissuaded from applying to the best firms due to information asymmetry as low-quality workers: both have imperfect information about the true quality of firms.

[3]This requires that the worst firm is not so bad that workers would avoid applying even if they

1. *In any symmetric mixed-strategy equilibrium, the probability each worker applies to firm j is $p_j = \frac{\bar{\mu_j}}{\sum_{j'} \bar{\mu_j}}$.*

2. *Therefore, the number of applicants for firm j is a binomial distribution with probability $\frac{\bar{\mu_j}}{\sum_{j'} \bar{\mu_j}}$ and N trials.*

Proof: In any mixed-strategy equilibrium, the payoff of applying to firms j and j' in the support must be identical. That is, $\mathbb{E}[\frac{p_{ij}\alpha q_{ij}\bar{\mu_j}}{\sum_i p_{ij}}] = \mathbb{E}[\frac{p_{ij'}\alpha q_{ij'}\bar{\mu_{j'}}}{\sum_i p_{ij'}}]$. Since $\mathbb{E}[\epsilon_{ij}] = 0, \forall i, j$, that equality reduces to $\mathbb{E}[\frac{p_{ij}\alpha q\bar{\mu_j}}{\sum_i p_{ij}}] = \mathbb{E}[\frac{p_{ij'}\alpha q\bar{\mu_{j'}}}{\sum_i p_{ij'}}]$. Hence for any firms j and j', $\frac{p_{ij}}{p_{ij'}} = \frac{\mu_j}{\mu_j'}$, and by symmetry, $\frac{p_j}{p_{j'}} = \frac{\mu_j}{\mu_j'}$. Summing this equality for all $j' \neq j$, we have that $p_j = \frac{\bar{\mu_j}}{\sum_{j'} \bar{\mu_j}}, \forall j$. The second part of the lemma follows immediately. ■

The previous lemma says that the expected number of applicants to a given firm is increasing in the workers' posterior belief $\bar{\mu_j}$ of the firm's quality.

Proposition 2 *Let an information treatment increase δ, the probability workers observe true firm quality.*

1. *Above-average firms receive more applications.*

2. *Below-average firms receive fewer applications.*

3. *The change in the number of applications a firm receives when workers gain perfect information about the firm's quality is increasing in the difference between the firm's true quality and the average quality of all other firms.*

4. *Surplus generated by above-average firms, and hence wages for workers they hire, increases.*

Proof: by the previous lemma, the number of workers that apply to firm j in expectation is increasing in the perceived quality of the firm $\bar{\mu_j}$. When workers do not perfectly observe the quality of firm j, in expectation workers believe that firm to have equal quality to the average of all other firms.[4] Therefore, the expected number of applicants to firm j is

$$\delta \frac{Q_j}{\mathbb{E}[\sum_{j' \neq j} Q_{j'}]} + (1 - \delta) \frac{\mathbb{E}[Q_{j' \neq j}]}{\mathbb{E}[\sum_{j' \neq j} Q_{j'}]}$$

were guaranteed a job at that firm as the only applicant. That is, $\min_j Q_j$ needs to be sufficiently high.

[4]That is, when firm j has its true quality hidden, $\mathbb{E}[\bar{Q}]$ across all realizations of firms that could have their true quality hidden from workers is just the expected true quality of all firms other than the focal firm.

Therefore, for firms with $Q_j > \mathbb{E}[Q_{j' \neq j}]$, an increase in δ raises the probability workers believe the firm to have a higher quality, and hence raises the expected number of applicants. Likewise, for below-average firms where $Q_j < \mathbb{E}[Q_{j' \neq j}]$, an increase in δ decreases the expected number of applicants. Finally, if K_j workers apply for firm j and the firm hires the best worker who applies inclusive of idiosyncratic match quality, total expected surplus is $X(K_j)Q_j$ where $X(K_j)$ is the $K_j th$ order statistic from the distribution q_{ij} is being drawn from. That is, $X(K_j)$ is the expected quality of the best applicant who applies to firm j conditional on getting K_j applications. An increase in the expected number of applicants therefore also increases expected surplus earned by a given firm. ■

The proposition above is not simply the result of asymmetric information about firm quality. For instance, if workers received a signal with mean-zero noise about each firm, that noise could both *increase* or decrease the number of applicants a firm gets: sometimes the noise causes workers to overestimate the quality of even the best firms. The fundamental issue in our empirical setting is not the misperception, but the *pooling* of high- and low-quality firms. Information increases applications when it affects the relative quality of my firm relative to others.