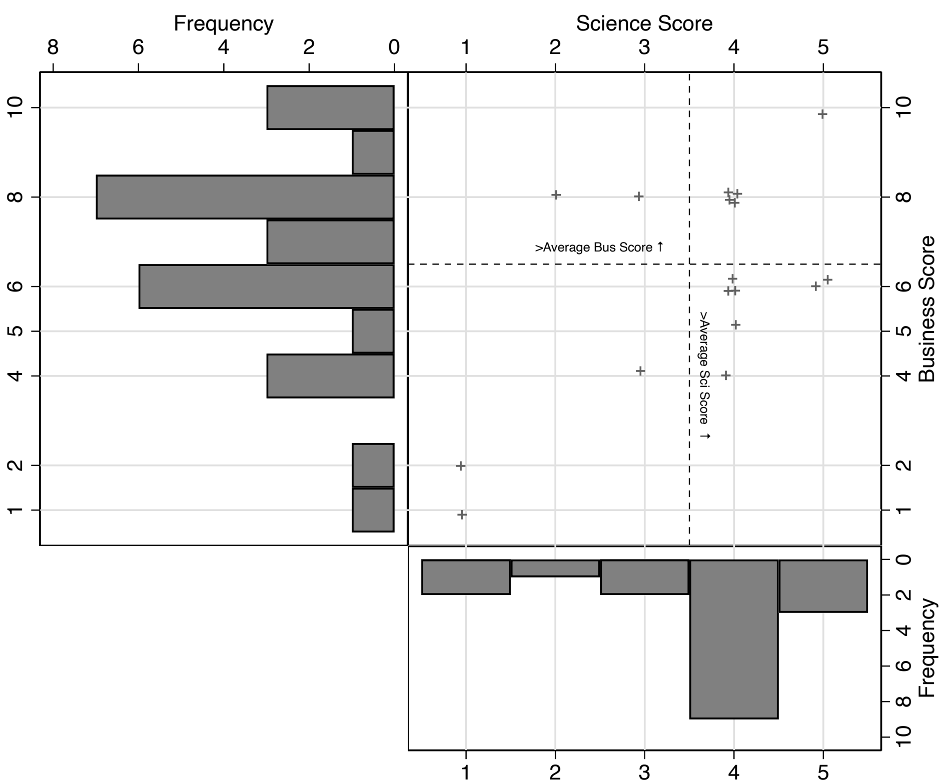
Supplemental Appendix for "Information Frictions and Employee Sorting Between Startups" by Kevin Bryan, Mitchell Hoffman, Amir Sariri

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 E is a Data Appendix containing definitions of variables and details on the creation of the sample. Appendix F provides key documents from the Secondary RCT. Appendix G provides further details on the survey of economist experts. Appendix H shows the detailed explanation of the quadratic scoring rule that was made available to subjects (in addition to the simpler and intuitive explanation that was provided to subjects and that can be seen in Appendix D).

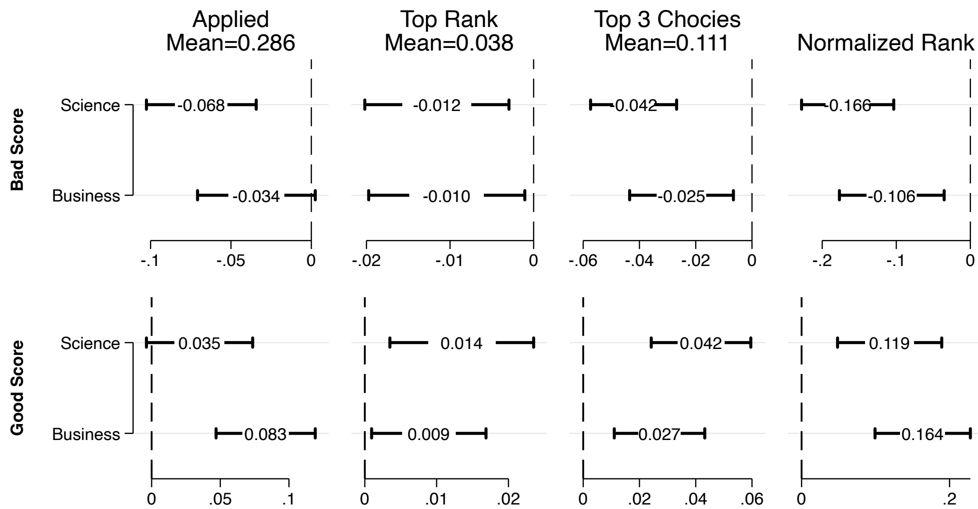
Appendix A Additional Figures and Tables

Figure A1: Distribution Plots of Science and Business Scores

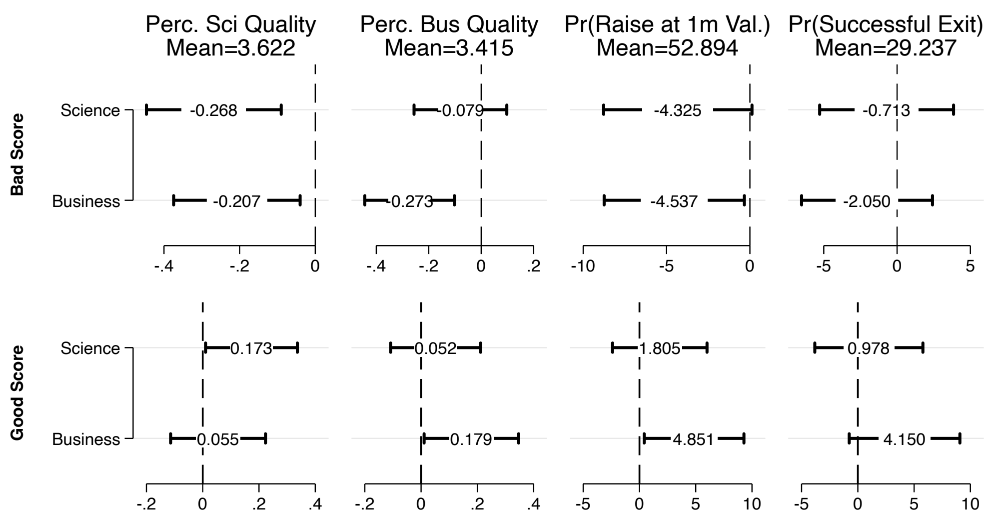


Notes: This figure shows the distribution of startup scores in the Primary RCT, excluding 9 startups that were missing the science score. Scatterplot points are jittered for clarity.

Figure A2: The Effect of Expert Ratings on Job Applications and Beliefs: A Visual Summary



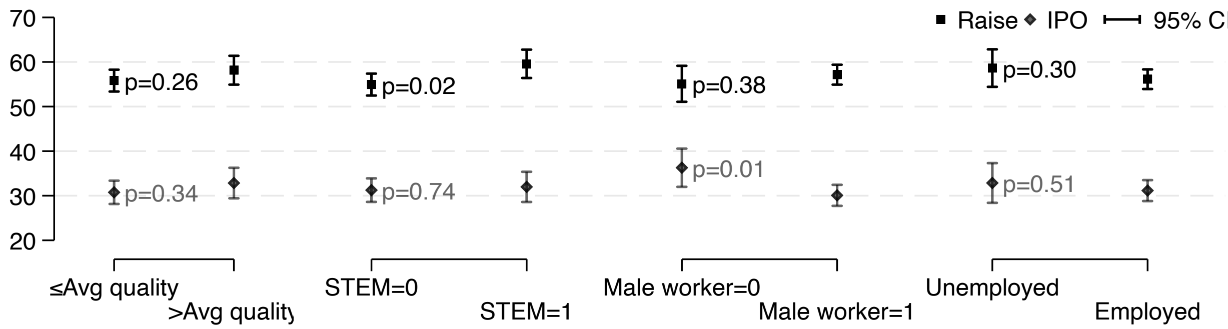
(a) Effect of showing positive and negative expert ratings on job application rankings



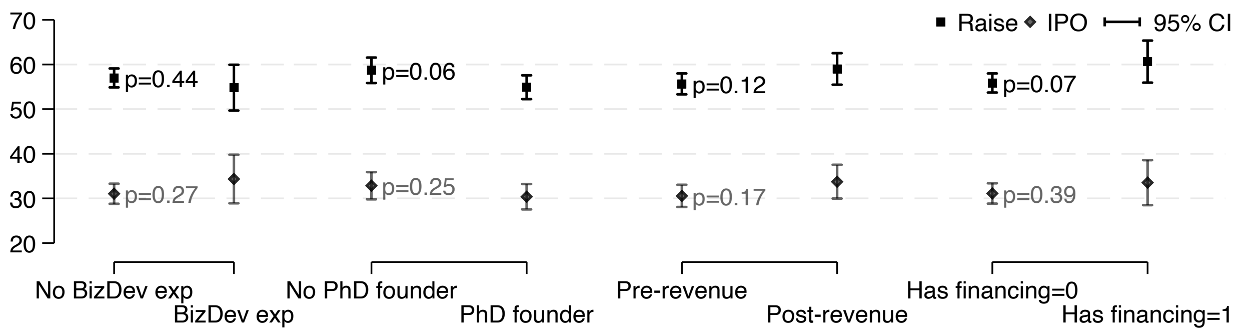
(b) Effect of positive and negative expert ratings on worker beliefs

Notes: Figure A2a plots the estimated effect of expert ratings on job applications from the Primary RCT. Figure A2b shows the same effect on worker beliefs using pooled data from the Primary and Secondary RCTs. *Bad/Good Score* estimates show percentage point change in the probability of applying to a bad/good firm conditional on showing expert ratings. The left two subgraphs show standard error change in the perceived quality of the firm's science and business. The right two subgraphs show the percentage point change in the estimated probability of raising capital at a valuation of at least \$1 million within 1 year and successful exit via IPO or getting acquired for at least \$50 million within 1 year. All confidence intervals depicted are at the 95% level.

Figure A3: 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 Firms into the Primary RCT

	Firm Characteristic Means by RCT Treatment Arm					
	Bad Biz Bad Sci (1)	Bad Biz Good Sci (2)	Good Biz Bad Sci (3)	Good Biz Good Sci (4)	Non-RCT Firm Means (5)	All Firms, Selection Regression (6)
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)
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 A2: Share of Workers by Number of Applications and Treatment Group

	Sci & Biz Info	Biz Info	Sci Info	No Info	All
Applications:					
=10	0.45	0.52	0.32	0.47	0.45
=1	0.02	0.00	0.08	0.02	0.02
≤ 3	0.16	0.06	0.19	0.14	0.13
≥ 5	0.75	0.91	0.74	0.79	0.80

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. "All" means all treatment four arms pooled together.

Table A3: Impact of Expert Ratings on Unincentivized Job Interest

	(1)	(2)	(3)
Panel A: Sample = Pooled			
Science info X Good science	0.159		0.160
	(0.160)		(0.159)
Science info	−0.226*		−0.227*
	(0.130)		(0.129)
Business info X Good business		0.303**	0.308**
		(0.150)	(0.151)
Business info		−0.225**	−0.224*
		(0.113)	(0.114)
F(Sci + Sci X GoodSci = 0)	0.542		0.543
F(Bus + Bus X GoodBus = 0)		0.499	0.470
Observations	1,104	1,104	1,104
Panel B: Sample = Primary RCT			
Science info X Good science	−0.079		−0.086
	(0.253)		(0.253)
Science info	−0.024		−0.011
	(0.238)		(0.237)
Business info X Good business		0.175	0.175
		(0.206)	(0.206)
Business info		−0.197	−0.193
		(0.156)	(0.158)
F(Sci + Sci X GoodSci = 0)	0.486		0.517
F(Bus + Bus X GoodBus = 0)		0.899	0.920
Observations	553	553	553
Panel C: Sample = Secondary RCT			
Science info X Good science	0.309		0.306
	(0.217)		(0.216)
Science info	−0.316**		−0.324**
	(0.155)		(0.154)
Business info X Good business		0.419*	0.432*
		(0.221)	(0.223)
Business info		−0.256	−0.266
		(0.165)	(0.165)
F(Sci + Sci X GoodSci = 0)	0.964		0.911
F(Bus + Bus X GoodBus = 0)		0.286	0.279
Observations	551	551	551

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 A4: The Effect of Expert Ratings on Worker Beliefs – Primary RCT

	(1)	(2)	(3)
Panel A: Dep. Var. = Perc. Sci Quality			
Science info X Good science	0.070		0.059
	(0.211)		(0.211)
Science info	−0.048		−0.037
	(0.199)		(0.199)
Business info X Good business		0.246	0.246
		(0.169)	(0.170)
Business info		−0.169	−0.168
		(0.133)	(0.132)
F(Sci + Sci X GoodSci = 0)	0.853		0.854
F(Bus + Bus X GoodBus = 0)		0.585	0.588
Observations	542	542	542
Panel B: Dep. Var. = Perc. Biz Quality			
Science info X Good science	0.083		0.081
	(0.208)		(0.206)
Science info	−0.087		−0.084
	(0.194)		(0.191)
Business info X Good business		0.436**	0.438**
		(0.172)	(0.173)
Business info		−0.243*	−0.241*
		(0.134)	(0.134)
F(Sci + Sci X GoodSci = 0)	0.974		0.983
F(Bus + Bus X GoodBus = 0)		0.170	0.164
Observations	544	544	544
Panel C: Dep. Var. = Pr(Raise at 1m Valuation)			
Science info X Good science	−2.933		−2.987
	(4.367)		(4.439)
Science info	2.029		2.192
	(4.087)		(4.151)
Business info X Good business		8.667**	8.665**
		(4.124)	(4.119)
Business info		−4.824	−4.848
		(3.216)	(3.237)
F(Sci + Sci X GoodSci = 0)	0.757		0.788
F(Bus + Bus X GoodBus = 0)		0.272	0.278
Observations	538	538	538
Panel D: Dep. Var. = Pr(Successful Exit)			
Science info X Good science	−11.247**		−11.019**
	(4.790)		(4.853)
Science info	8.219		7.851
	(4.998)		(5.024)
Business info X Good business		9.603**	9.519**
		(4.110)	(4.060)
Business info		−1.640	−1.689
		(3.622)	(3.588)
F(Sci + Sci X GoodSci = 0)	0.369		0.346
F(Bus + Bus X GoodBus = 0)		0.050	0.052
Observations	541	541	541

Notes: This table shows the effect of information on employee beliefs using pooled data from the Primary RCT. Dependent variable for each panel shown at the beginning of the panel. Standard errors clustered by worker in parentheses.

Table A5: The Effect of Expert Ratings on Worker Beliefs – Secondary RCT

	(1)	(2)	(3)
Panel A: Dep. Var. = Perc. Sci Quality			
Science info X Good science	0.784***		0.783***
	(0.138)		(0.137)
Science info	−0.367***		−0.374***
	(0.095)		(0.095)
Business info X Good business		0.292**	0.291**
		(0.146)	(0.144)
Business info		−0.257**	−0.257**
		(0.103)	(0.101)
F(Sci + Sci X GoodSci = 0)	0.000		0.000
F(Bus + Bus X GoodBus = 0)		0.737	0.746
Observations	552	552	552
Panel B: Dep. Var. = Perc. Biz Quality			
Science info X Good science	0.215		0.214
	(0.138)		(0.138)
Science info	−0.070		−0.079
	(0.100)		(0.099)
Business info X Good business		0.473***	0.471***
		(0.153)	(0.153)
Business info		−0.307***	−0.305***
		(0.106)	(0.106)
F(Sci + Sci X GoodSci = 0)	0.149		0.174
F(Bus + Bus X GoodBus = 0)		0.114	0.116
Observations	551	551	551
Panel C: Dep. Var. = Pr(Raise at 1m Valuation)			
Science info X Good science	13.119***		13.077***
	(3.726)		(3.736)
Science info	−6.951**		−7.103***
	(2.711)		(2.709)
Business info X Good business		9.816**	9.854***
		(3.789)	(3.764)
Business info		−4.179	−4.228
		(2.775)	(2.752)
F(Sci + Sci X GoodSci = 0)	0.039		0.044
F(Bus + Bus X GoodBus = 0)		0.056	0.055
Observations	552	552	552
Panel D: Dep. Var. = Pr(Successful Exit)			
Science info X Good science	11.970***		11.954***
	(3.647)		(3.645)
Science info	−4.480*		−4.551*
	(2.434)		(2.429)
Business info X Good business		3.512	3.371
		(3.493)	(3.477)
Business info		−2.479	−2.418
		(2.593)	(2.564)
F(Sci + Sci X GoodSci = 0)	0.026		0.028
F(Bus + Bus X GoodBus = 0)		0.739	0.757
Observations	551	551	551

Notes: This table shows the effect of information on employee beliefs using pooled data from the Secondary RCT. Dependent variable for each panel shown at the beginning of the panel. Standard errors clustered by worker in parentheses.

Table A6: 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 A7: 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

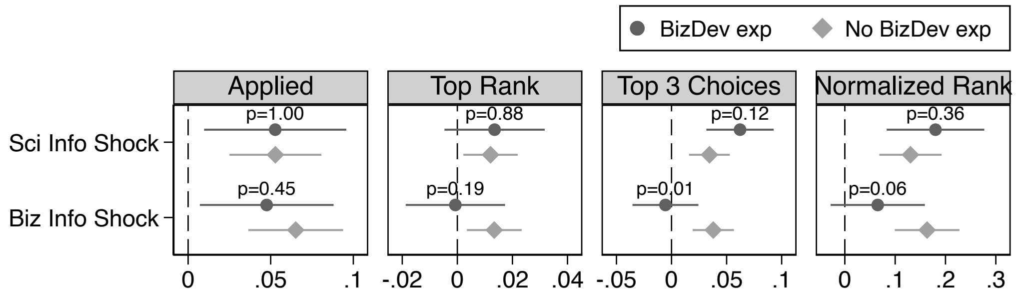
Notes: This table shows worker and firm predictors of beliefs about firm success in the Primary RCT. The dependent variables are at the top of columns. Workers were asked to submit their beliefs about three randomly selected firms. Data is 604 belief responses, of which 7 are missing Pr(Raise at 1m Valuation),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

Table A8: Multiple Hypothesis Testing
Multiplicity of Outcomes

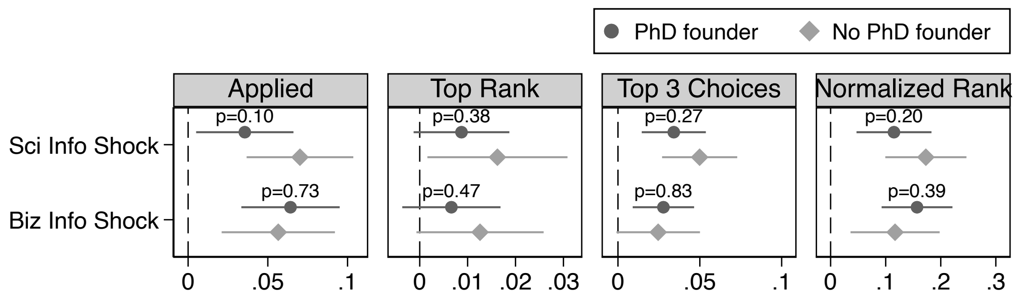
Dependent Variables	Applied	Top Rank	Top 3 Choices	Normalized Rank
Science info X Good science	{0.000}	{0.010}	{0.000}	{0.000}
Science info	{0.001}	{0.010}	{0.000}	{0.000}
Business info X Good business	{0.000}	{0.033}	{0.006}	{0.000}
Business info	{0.082}	{0.068}	{0.026}	{0.016}

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 4, 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 A11 provides a multiple hypothesis testing correction related to multiple dimensions of heterogeneity.

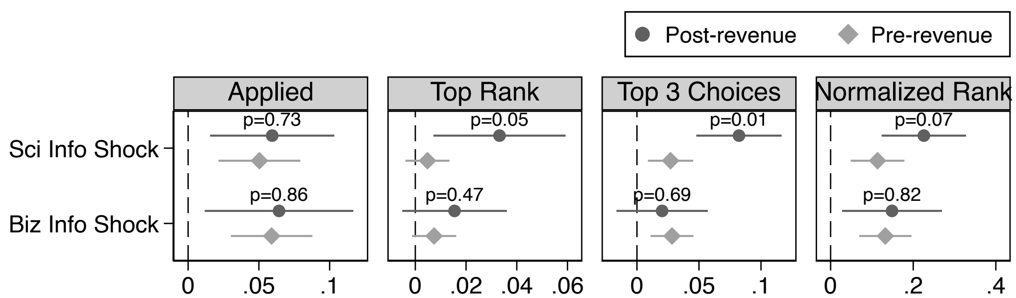
Figure A4: Treatment Effect Heterogeneity by Firm Characteristics



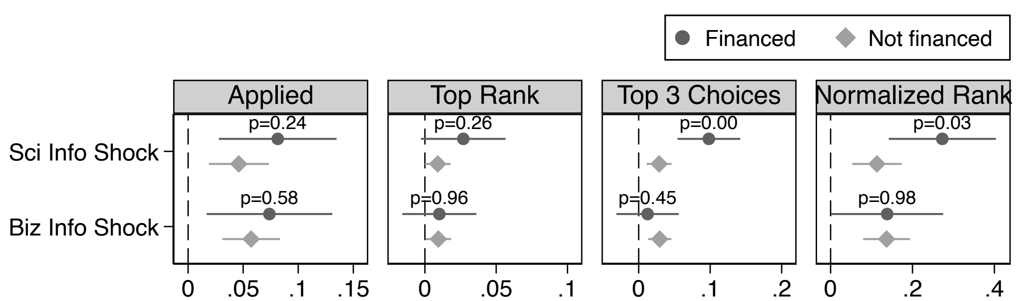
(a) By whether founders have prior business development experience



(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: 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 4, except for the addition of the interaction variables *Biz Info X Sci Info* and *Biz Info X Sci Info X Good Firm*.

Table A10: Treatment Effect Heterogeneity by Worker Characteristics

	Applied	Top Ranked	Top 3 Choices	Normalized Rank
Panel A:				
Sci Info Shock	0.051***	0.011*	0.038***	0.143***
	(0.014)	(0.006)	(0.010)	(0.032)
>Avg quality × Sci Info Shock	0.005	0.005	0.010	0.002
	(0.021)	(0.007)	(0.014)	(0.049)
Bus Info Shock	0.050***	0.009*	0.019*	0.113***
	(0.015)	(0.005)	(0.010)	(0.034)
>Avg quality × Bus Info Shock	0.030	0.002	0.020*	0.065
	(0.020)	(0.006)	(0.012)	(0.041)
Panel B:				
Sci Info Shock	0.012	−0.002	0.029**	0.057
	(0.019)	(0.007)	(0.013)	(0.044)
Male × Sci Info Shock	0.057***	0.020***	0.018	0.123**
	(0.021)	(0.007)	(0.015)	(0.049)
Bus Info Shock	0.032*	0.005	0.021	0.088**
	(0.017)	(0.007)	(0.013)	(0.042)
Male × Bus Info Shock	0.038*	0.007	0.006	0.066
	(0.019)	(0.007)	(0.014)	(0.045)
Panel C:				
Sci Info Shock	0.054***	0.012**	0.046***	0.150***
	(0.015)	(0.006)	(0.010)	(0.034)
STEM × Sci Info Shock	−0.002	0.000	−0.008	−0.014
	(0.020)	(0.007)	(0.013)	(0.047)
Bus Info Shock	0.061***	0.011**	0.030***	0.141***
	(0.015)	(0.005)	(0.010)	(0.034)
STEM × Bus Info Shock	−0.002	−0.003	−0.011	−0.011
	(0.020)	(0.006)	(0.012)	(0.043)
Panel D:				
Sci Info Shock	0.081***	0.014*	0.057***	0.209***
	(0.020)	(0.008)	(0.013)	(0.043)
Employed × Sci Info Shock	−0.038*	−0.002	−0.020	−0.087*
	(0.022)	(0.008)	(0.014)	(0.048)
Bus Info Shock	0.068***	0.008	0.023*	0.144***
	(0.020)	(0.006)	(0.012)	(0.042)
Employed × Bus Info Shock	−0.010	0.003	0.005	−0.009
	(0.022)	(0.006)	(0.013)	(0.045)

Notes: This table shows heterogeneity in worker response to information shocks in the Primary RCT. It shows the same estimates from Figure 3, but in tabular form. In addition, Figure 3 presents treatment effects for both values of a characteristics (e.g., for men and for women), whereas this table presents interaction effects. Each panel analyzes interaction terms involving a different worker characteristic. There are four regressions presented per panel, each with a different dependent variable shown in the column headers. Each regression includes the characteristic by itself as a regressor, as noted in the regression equation in the main text, but this coefficient is suppressed for clarity. As described in the main text, worker quality is measured by a startup-focused HR expert.

Table A11: 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 3, 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 $y_{nf} = \alpha_0 + \alpha_1 \text{BizInfoShock}_n + \alpha_2 \text{SciInfoShock}_n + \alpha_3 \text{C}_n + \alpha_4(\text{BizInfoShock}_n \times \text{C}_n) + \alpha_5(\text{SciInfoShock}_n \times \text{C}_n) + \boldsymbol{X}_{nf} + \varepsilon_{nf}$, where y_{nf} is the key dependent variable of applying to a job.

Table A12: 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 A13: 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 A14: 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, Ouimet & Zarutskie (2014) use US census data to show that young workers are more likely to work at startups. Bernstein *et al.* (2024) 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 Selection into Applying for at Least One Job

This appendix investigates whether the propensity for participants to apply to at least one job differs by treatment arm, conditional on having visited the job board. Since jobseekers are unaware of their treatment status until they arrive at the job board, selection can only occur after that point.

Could selection into applying—based on treatment—bias our primary outcome, which is the probability of applying to a given firm conditional on applying at all? While this may seem difficult to test—as we only observe individuals in the SEP dataset if they apply to at least one job—we can indirectly test for selection using aggregate data.

The key idea is to assume that the number of workers arriving at the job board is similar across treatment arms, consistent with treatment being unobserved prior to that point. We consider two versions of this assumption: (i) that the number of arrivals is exactly equal across arms, or (ii) that arrivals are equally likely across arms but subject to sampling noise. Under either version, we can use a generalized chi-squared test to assess whether the share of visitors who apply to at least one job differs by treatment.

Empirical setup: A total of 587 workers clicked the email link to visit the job board. Then, 250 workers apply for at least one job, with 66, 53, 67 and 64 coming from the four treatment arms. The number of workers who apply to at least one job K_i depends on both the number of clickers N_i who view the job board under a given treatment, and the conditional probability of applying given a website visit p_i.

There are two ways to investigate whether the 250 jobseekers are randomly drawn from the treatment arms or whether there is selection. In the first way, we assume the number of job board visitors from arm i, N_i, is distributed such that $N_i \sim \text{Multinomial}(n_{\text{click}}; \frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4})$, or 146.75 per arm. The variance of job board visitors per arm: $\text{Var}(N_i) = 587; (\frac{1}{4})(1 - \frac{1}{4}) = 587 \times 0.25 \times 0.75 \approx 110$. However, this model does not account for the fact that random variation in who opens and clicks an email means that the number of jobseekers who see the job board will not be identically distributed across arms. Therefore, our second and preferred method is to correct for the random number of email clickthroughs across each arm N_i by adjusting the variance used in the test with a delta-method approximation $\hat{p}_i = K_i/N_i$ for the variance $\text{Var}(\hat{p}_i) \approx \text{Var}(K_i)/(E[N_i])^2$.

In this first method, using a generalized chi-squared test statistic, we have $\chi^2_{\text{fixed}} = \sum_{i=1}^4 \frac{(K_i - \hat{p}\, n_i)^2}{\hat{p}\,(1-\hat{p})\, n_i} \approx 3.48$. Comparing this to a χ^2 distribution with 3 degrees of freedom, the p-value is $P(\chi^2_3 \geq 3.48) \approx 0.32$. In the preferred method, via the law of total variance, we can compute $\text{Var}(K_i) = \mathbb{E}[\text{Var}(K_i \mid N_i)] + \text{Var}(\mathbb{E}[K_i \mid N_i]) \approx 55.84$, hence $\text{Var}(\hat{p}_i)_{\text{adj}} \approx \frac{55.84}{(146.75)^2} \approx 0.0026$. The test statistic is calculated using a generalized chi-square because the denominators (job board visitors per arm) are random rather than fixed, so their sampling variance must be included in the test. Therefore, $\chi^2_{\text{adj}} = \sum_{i=1}^4 \frac{(\hat{p}_i - \hat{p})^2}{\text{Var}(\hat{p}_i)_{\text{adj}}} \approx 2.24$, with the p-value of $P(\chi^2_3 \geq 2.24) \approx 0.53$. Accounting for the extra variance due to random arrivals increases the p-value, providing even less evidence against H_0.

Overall, we see no evidence of the treatments affecting selection into applying for at least one job. This is also true if, instead of looking at equality across all four treatments, we look separately at the impact of the business rating treatment ($p = 0.32$ under assumption (i) and $p = 0.42$ under assumption (ii)) or the impact of the science rating treatment ($p = 0.18$ under assumption (i) and $p = 0.28$ under assumption (ii)).

B.4 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 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,

[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.

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 job-seekers 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 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

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

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:*

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]This requires that the worst firm is not so bad that workers would avoid applying even if they were guaranteed a job at that firm as the only applicant. That is, $\min_j Q_j$ needs to be sufficiently high.

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

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

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.

[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.

Appendix D Screenshots from the Primary RCT

Figure D1: Primary RCT Survey Instructions

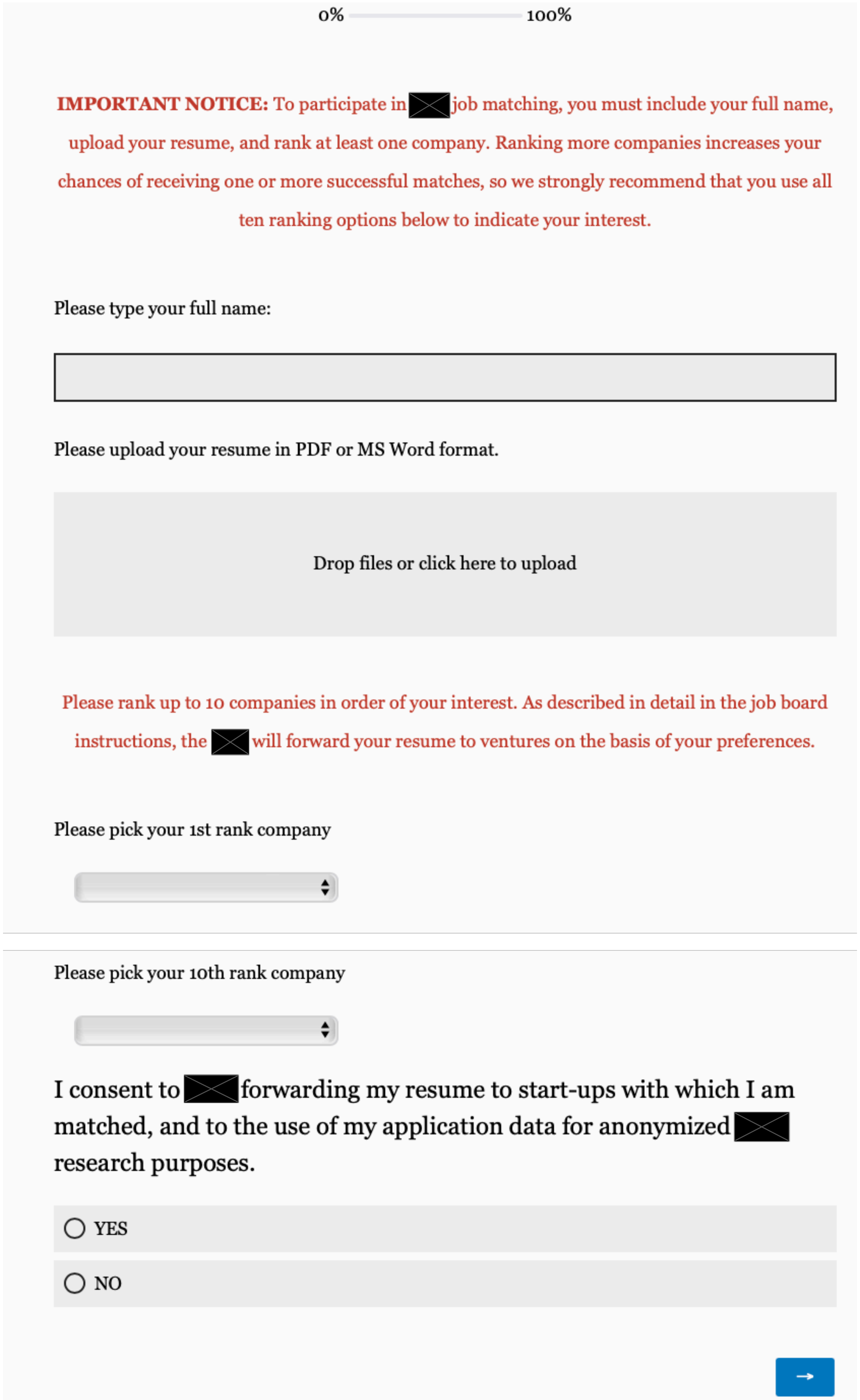
Instructions

Welcome to the inaugural [redacted] job board. [redacted] is the largest science-based start-up mentorship program in the world. 26 start-ups in this year's cohort expressed interest in talking to [redacted] alumni interested in business development jobs. Through this system, we will forward your resume and information to start-ups of interest.

Clicking on company logos brings up brief descriptions written by each venture. After examining these companies, upload your resume in the form to the right, and list the 10 companies of greatest interest in your order of preference from most preferred ("1") on down. **If you do not see a form on the right side of this page to rank companies, please turn off your ad blocker or try with a different browser**.

To avoid inundating these start-ups with an excessive number of resumes, we have agreed to forward a limited number of resumes to each start-up. **It is in your interest to state your true preference ranking!** Specifically, the probability your information is sent to a given venture is strictly higher the higher you rank a venture. An algorithm by leading economists ensures that there is no benefit to manipulating your true preference about which ventures you would like to meet.

Figure D2: Screenshots from the Primary RCT (highlighting from the original)



0% 100%

IMPORTANT NOTICE: To participate in [redacted] job matching, you must include your full name, upload your resume, and rank at least one company. Ranking more companies increases your chances of receiving one or more successful matches, so we strongly recommend that you use all ten ranking options below to indicate your interest.

Please type your full name:

Please upload your resume in PDF or MS Word format.

Drop files or click here to upload

Please rank up to 10 companies in order of your interest. As described in detail in the job board instructions, the [redacted] will forward your resume to ventures on the basis of your preferences.

Please pick your 1st rank company

Please pick your 10th rank company

I consent to [redacted] forwarding my resume to start-ups with which I am matched, and to the use of my application data for anonymized [redacted] research purposes.

YES

NO

→

0% 100%

Your response has been recorded.

The next 5 questions are optional and will not affect job matching. However, if you complete them, you may win up to $250 and will inform [redacted] design of its Job Board.

What is your assessment of the **quality of the science/technology** in the below ventures, on a scale from 1 (lowest score) to 5 (highest score)?

NOTE: In this setting, the quality of the science is defined as your overall assessment of the quality of the underlying science and its potential for forming the basis of a commercial product.

	(lowest score) 1	2	3	4	(highest score) 5
[redacted]	○	○	○	○	○
[redacted]	○	○	○	○	○
[redacted]	○	○	○	○	○

← →

0% 100%

What is your assessment of the **quality of the business model** for these company, on a scale of 1 (lowest score) to 5 (highest score)?

NOTE: In this setting, the business model may be defined broadly, as the overall quality and execution potential of the company's business strategy in building a scalable technology-based start-up.

	(lowest score) 1	2	3	4	(highest score) 5
[redacted]	○	○	○	○	○
[redacted]	○	○	○	○	○
[redacted]	○	○	○	○	○

← →

0% 100%

PROBABILITY:

The below questions ask you to think about the **percent chance** that something will happen in the future.

The **percent chance** can be thought of as the number of chances out of 100. You can use any number between 0 and 100.

For example, numbers like:
2 and 5 percent may be "almost no chance",
20 percent or so may mean "not much chance",
a 45 or 55 percent chance may be a "pretty even chance",
80 percent or so may mean a "very good chance",
and a 95 or 98 percent chance may be "almost certain"

INCENTIVES ON PROBABILITY QUESTIONS:

As added encouragement on probability questions, five people who complete this survey will be chosen at random to be paid via a lottery system. For those chosen, payment will be $0 or $250. Payment will be based on one of two questions below. This lottery system has been used to elicit people's probability beliefs in various contexts and is specially designed so that **it's mathematically optimal for you to state your true belief about the probability an event will occur.**

For further detail, please see here.

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?

NOTE: A $1,000,000 valuation is historically the absolute minimum valuation for a firm which raises a "seed" financing round. Seed financing is generally the first financing round with institutional rather than angel investors. The firm you are evaluating was randomly selected from a sample where historically similar firms have a 35% chance of reaching a $1,000,000 valuation.

Almost No Chance		Not Much Chance			Pretty Even Chance		Very Good Chance		Almost Certain	
0	10	20	30	40	50	60	70	80	90	100

[redacted]

[redacted]

[redacted]

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?

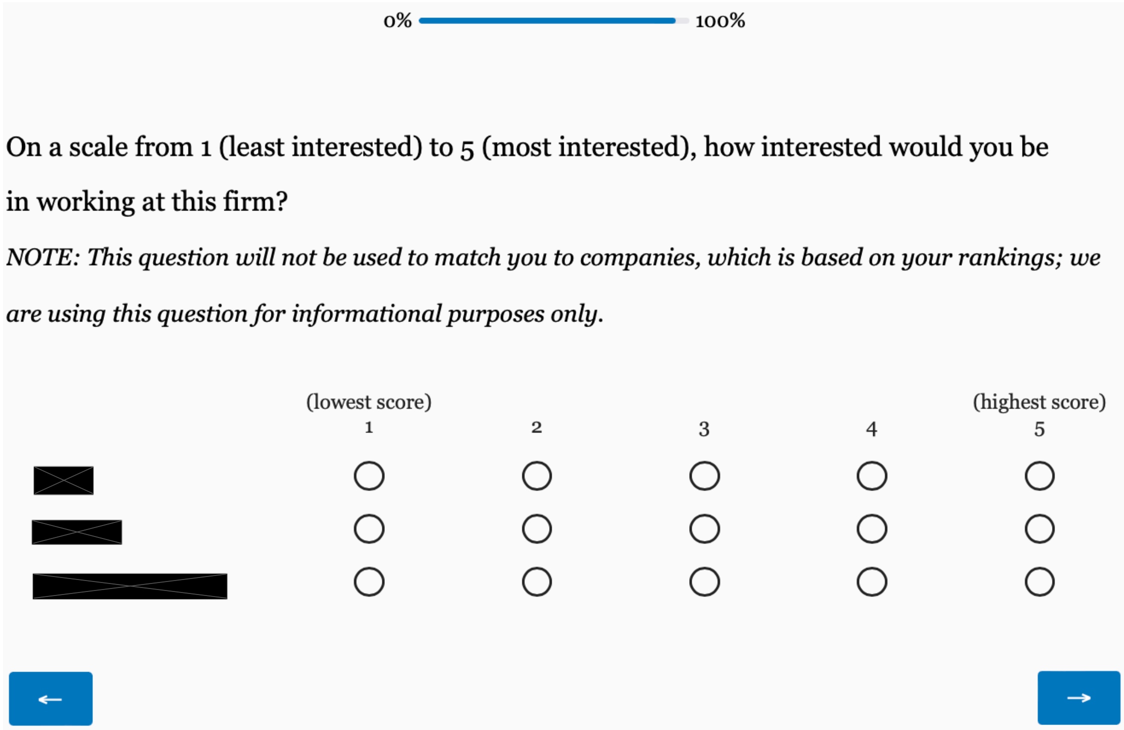
Almost No Chance		Pretty Even Chance			Very Good Chance		Almost Certain		Not Much Chance	
0	10	20	30	40	50	60	70	80	90	100

[redacted]

[redacted]

[redacted]

← →



0% 100%

On a scale from 1 (least interested) to 5 (most interested), how interested would you be in working at this firm?

NOTE: This question will not be used to match you to companies, which is based on your rankings; we are using this question for informational purposes only.

	(lowest score) 1	2	3	4	(highest score) 5
[redacted]	○	○	○	○	○
[redacted]	○	○	○	○	○
[redacted]	○	○	○	○	○

← →

Appendix E Data Appendix

E.1 Creating Our Samples of Workers and Firms

Candidates contacted. For the Primary RCT, we contacted business school alumni from two North American business schools in three different email campaigns. From the first business school, we reached out to 7,894 Master's alumni on May 27, 2019 with a reminder sent on June 21, to 5,721 undergraduate alumni from the same school on June 25, 2019 with a reminder sent on July 9. For the second business school, we reached out to 3,701 undergraduate and 2,083 Master's alumni on August 6, 2019, though the school preferred not to send a second reminder. Furthermore, 40 double-degree alumni from the first school were contacted twice. In calculating our balance tables, we remove these individuals from the undergraduate subsample, resulting in 5,681 undergraduate alumni. Thus, we contacted 19,359 unique alumni. PhD alum were not emailed.

Subjects. We received 264 survey submissions. We dropped from this set 4 repeat submissions from identical individuals where we only kept their earlier time-stamped submission. We dropped 1 dummy submission by a staff member of the SEP. Finally, we dropped 9 submissions by individuals who we could not match to our original contact lists. We managed to contact 5 of these individuals; they all told us that their friends and family had forwarded the Job Board email invitation to them. The remaining 250 submissions constitute our Primary RCT data.

In Section 3 of the main text, we discuss the tracking data which allow us to provide information on the participation rate conditional on clicking on the job board link. There were 587 recipients who opened the email and clicked on the job board link. 93 out of 587 recipients clicked the link in the reminder email. It is possible that some of those 93 people overlap with the initial 494 people who clicked from the original email. This makes the lower bound of unique individuals equal to 494, which would make the participation rate even higher than 43%. Within each individual email, people are unique.

Startups. Primary RCT ventures are 26 startups recruited from the SEP's 2018-19 cohort. The Secondary (pilot) RCT ventures are 26 startups selected from the 2017-18 cohort. The analysis in Table 1, which shows the correlation between expert ratings and performance, uses the full cohort of 130 startups in 2017-18, from which 24 startups were dropped due to missing one or both scores.

E.2 Random Assignment using Unique URLs

It would not be possible for a job seeker to know from the website link that an experiment was going on. The randomization trigger was part of a non-descript block of text such as "nytimes.com/sports?id=Aa674k". The text following the question mark is referred to as a "url query". In nine cases, dropped from our analysis, we received applications from people who were not the original targeted recipient of the job board invite.

E.3 Description of Variables

Gender. Obtained by linking first names to the US Social Security Administration's list of most common names by gender. Names with a greater than 50% chance of being male are classified as male, whereas names with a greater than 50% chance of being female are classified as female. When a name does not match, we manually code gender by using an Internet search.

Race. By clicking on the link provided on the resume, race is obtained by checking the social media (typically LinkedIn) profile of the candidate. In the absence of a web link, individual names are searched online and identification is ensured by cross referencing profile information with resume information. All other cases are obtained by linking last names with census information on the distribution of race by last name.

City is SEP HQ is an indicator equal to 1 if worker's lives in the same city as SEP HQ.

Graduation year is a worker's year of graduation obtained from the business school registrar's office records.

Startup founder is an indicator from resumes equal to 1 if the applicant founded a business.

Startup employee is an indicator from resumes equal to 1 if the worker has startup employment experience.

Employed is an indicator from resumes equal to 1 if the worker is currently employed.

Years of experience is an integer from resumes equal to the total years of worker experience rounded to the nearest year. Includes internships.

STEM is a binary variable from the applicant's resume that is equal to 1 if the candidate listed an undergraduate degree in natural, formal, or engineering sciences.

Worker Quality (1-10) is a number from 1 to 10 that reflects candidate quality for a business development job at a fast-growing, science-based startup that has just received early venture capital investment (10 is the highest score). An independent startup-focused HR expert determined these scores based on de-identified worker resumes.

Predicted Salary (Thousand) is the annual salary the worker should be offered in order for the startup to have a chance at hiring them. An independent experienced HR consultant determined these salaries based on de-identified worker resumes.

Number of founders is an integer that is equal to the size of the founding team reported on the application form of the firms submitted to SEP in the summer of 2018.

Number of employees is an integer that is equal to the number of non-founding employees reported on the application form of the firms submitted to SEP in the summer of 2018.

PhD founder is an indicator from startup applications to SEP equal to 1 if the startup had at least one PhD founder.

Technology fixed effects are a series of dummy variables reflecting the core technology of the startup. These include machine learning, quantum machine learning, blockchain, space, cities, and health.

Pct SEP Activities Completed is the fraction of high-priority business objectives firms completed during SEP. Every eight weeks, founders and mentors set three objectives that constitute the highest priorities of startups. SEP then verifies whether each objective is completed.

BizDev experience is an indicator from startup applications to SEP equal to 1 if the startup had at least one founder with business development professional experience.It includes experience in marketing, operations, finance, or other executive roles.

Top 1/3 Page is an indicator equal to 1 if the startup's profile is positioned in the top one-third of the website.

Raised capital is an indicator obtained from SEP internal data equal to 1 if the firm raised external capital before the experiment.

E.4 Description of AngelList classification

We examine the full text of all 1017 advertisements for a full-time job posted on AngelList's job board between October 30 and November 13, 2020 by a startup with between 1 and 10 employees. 40.4% of the advertisements are for non-technical roles, including sales, marketing, upper management, HR, communications, and finance. The remainder are technical roles, largely engineering. From each advertisement, we hand-code the following variables.

Founder Education. The advertisement lists the university at least one founder holds a degree from.

Academic Spinout. The advertisement describes the firm as based on, or a spinout from, an academic lab or academic research performed by the founding team.

Other spinout. The advertisement describes the firm as based on, or a spinout from, work done at an incumbent firm or government agency.

Incubator Participation. The advertisement lists participation in a named incubator or accelerator.

Formal IP. The advertisement notes that the firm holds formal IP such as a patent or pending patent.

Named Buyer or Partner. The advertisement specifically names a current customer or partner.

International Sales. The advertisement notes the company has made sales beyond its country of origin.

Named Investor or Large Grant. The advertisement notes that the company has received funding from a named investor, foundation, or government agency.

Unnamed Investor's Prior Exits. The advertisement describes the company as receiving investment from the backer of a prior named successful startup.

Prize or Contest Winner. The advertisement describes the company as a winner (including non-first prize winners) of any business model, technical, or product contest.

Prominent Advisor. The advertisement describes the firm as being advised or mentored by a specific named person.

Founder's Startup/Corporate Experience. The advertisement describes the founders as having previously led a successful exit, founded a named startup, or worked in an executive position at a related incumbent firm.

Founder's Award for Related Work. The advertisement notes that a founder has won a prize, or is well-known for, work related to the startup.

Media Mention. The advertisement listed a named media source as having written up the company, or the company has participated in a popular entrepreneurship program like Dragon's Den or Shark Tank, or the company has appeared on Product Hunt.

Tech Based on Published Science. The firm's technology is described as being derived from published, peer-reviewed scientific work.

Specific Sales Traction. Specific sales success, such as a high position on an App Store, are included in the advertisement.

Product Description. The advertisement describes the company's primary product. In general, "stealth" startups are the only ones who do not give this detail.

Technical Description. The advertisement gives specific technical details about the operation or production or nature of the product (e.g., "We use a generative adversarial network to investigate financial fraud...").

Business Model/Monetization Strategy. The advertisement specifically describes how the product is being monetized or scaled (e.g., "We operate a two-sided platform where we charge banks to connect to our high net-worth investors...").

Appendix F Key Documents from the Secondary RCT

The two figures below show a sample startup dossier and treatment shown to MBA students in the Secondary RCT. The top panel shows the background information provided, while the bottom panel shows how expert ratings were displayed for the group that received both the Business Model and Science scores.

[redacted]

Prospectus ID: 67139

VENTURE OVERVIEW:
Company's patent-pending technology employs a novel generative synthesis approach to dramatically reduce the size of deep neural networks while maintaining (and sometimes improving) their functional characteristics. The applications of this IP are numerous, most notably the optimization of neural networks for both cloud and edge systems.

PRODUCT DETAILS

Describe how your product or service works.
Company's engine is employed as follows: 1) the user provides a model or task, training inputs, and hardware and performance specifications; 2) the Company engine builds an optimized deep neural network up to three orders of magnitude more compact than the original; 3) the network is deployed and significant performance gains are realized; 4) the network is re-optimized using the platform as new training data becomes available and/or new features are added.

What is the value proposition for your customers?
The value proposition for customers is twofold: 1) a dramatic reduction in the cost to run deep learning solutions (Company achieved an 80 percent reduction in cloud costs for one of its clients); 2) enabling real-time deep learning solutions on the edge, such as a cell phone or stand-alone GPUs (Company can enable powerful convolutional neural networks on modest hardware chips that would otherwise require large computing infrastructures).

Do you have a working prototype or demo?
Company's technology is currently being used by clients across numerous verticals, including automotive, security & surveillance, and manufacturing. In addition, Company has used the engine to construct prototypes and demos that illustrate the power of the platform: (link to video demonstration – omitted)

How do you sell to your customer?
Company currently generates revenues from constructing end-to-end solutions for enterprise clients. Company's future commercialization strategy will be based on a B2B licensing and a SaaS model, as well as, secondarily, a B2C model, charging fees to individuals to use the self-service platform (primarily for its academic benefits).

Who else is selling to your customer and why will your customer buy your product or service instead of your competitor's?
Although there are other players in the deep learning optimization space (e.g., SigOpt, XNOR.AI), Company's technology provides: 1) better performance without sacrificing accuracy (the neural networks generated by Company are smaller, faster and have equal or better accuracy compared to other models); 2) flexible hardware endpoints (optimizes neural networks for CPUs, GPUs, FGPAs and DSPs on cloud and embedded systems); 3) AI at the edge (enables AR/VR, IoT, real-time visual and audio perception possible on edge devices); 4) scope and flexibility (works against any deep neural network architecture).

What is the long-term vision of your company and how is your product going to change the world?
The ultimate goal of Company is to increase scope, power and efficacy of AI solutions through its deep learning optimization technology. Company wants to unearth new possibilities for deep learning (medical, aerospace, education) and accelerate those areas where it is already being employed.

1

Treatment Shown to the Group Receiving both Business Model and Science Scores

Advisor	14.5%

SCIENTIST OPINION OF FIRM'S SCIENCE

Below Average

A scientist from Canada's National Research Council with expertise in the technical area where this Company operates was asked to evaluate this firm's ***underlying science quality and the team's technical ability****. Scientists score companies as 1, 2, 3, 4, or 5. We excluded the 1's and 2's, which are fairly uncommon. The most common (or modal) score is 4. We randomly selected firms from the 3's and 5's. Thus, a score of 5 is Above Average and 3 is Below Average. Among the 20 CDL firms chosen, about half are 3's and half are 5's.*

ANALYST OPINION OF BUSINESS MODEL

Below Average

People with experience in the evaluation of technology-based start-ups were asked to evaluate this firm's ***business model, scalability, and potential to execute****, on the basis of information like what you have seen. Two to four evaluators scored each start-up on a 1-10 scale. The average score among all firms is about 6.5. Thus, Above Average means 7 or higher, and Below Average means 6 or below. Among the 20 CDL firms chosen, about half are Above Average and half are Below Average.*

Notable Talent:

- [redacted] PhD, Systems Design Engineering

Appendix G Survey of Economist Experts

Of the 270 NBER economists contacted, 120 were attendees from NBER Personnel, 100 were attendees from NBER Entrepreneurship, and 50 were attendees from NBER Labor.[5] Our 32% response rate from NBER economists is slightly higher than that in a leading recent study by Deshpande & Dizon-Ross (2023) who receive a response rate of 24% in surveying members from the NBER Children and Education groups. Note that we do not know the job titles (e.g., full professor, associate professor, ...) for the 10 responses from the Social Science Prediction Platform. Results in the economist survey are qualitatively similar when restricting to faculty members.

As in any expert prediction exercise, it is critical that experts are not already familiar with the results of the study. We addressed this point in two ways. First, in drawing our base survey sample of 270 NBER economists, we manually excluded several economists we believed were familiar with the results (e.g., by seeing the paper at a seminar). Second, as described in the main text, we began the survey by asking a screener question.

Question 1: As a screening question, are you familiar with the main findings from the NBER working paper "Information Frictions and Employee Sorting between Startups?" For example, have you read the paper or its abstract?

- Yes
- No

If the respondent answers "Yes" to being aware of the study's main results, the survey terminates. If the answer is "No," then the respondent sees an overview of the study before proceeding to the prediction questions. Below is the description that respondents saw about our study:

[5] Some economists attend multiple meetings from our set of Personnel, Entrepreneurship, and Labor. We drew first from Personnel attendees, second from Entrepreneurship, and third from Labor. Thus, an economist who attended Personnel and Entrepreneurship would count as a Personnel attendee, and an economist who attended Entrepreneurship and Labor would count as an Entrepreneurship attendee.

Overview of the study

Alum of two North American business schools were invited to participate in a startup job board. This job board featured 26 early-stage science-based startups who had 1) participated in a world-leading entrepreneurship program, and 2) chose to be on the job board. To fix ideas, a typical startup in our setting would be one founded by two computer science professors with an advancement in artificial intelligence for autonomous vehicles.

Treatments

Each job seeker was randomly selected to receive a customized link to one of the four versions of the job board. The **control group** saw a job board with just the ads written by the startups. The remaining three groups saw those ads alongside a note indicating whether the startup's **science** and/or **business** quality received an above-average expert rating.

The science expert rating was determined by a PhD scientist from Canada's National Research Council with expertise in the startup's technological domain. This rating was based on a 30-minute interview with founders and detailed written materials the venture provided in advance of the meeting. The business expert rating was provided by experts with experience in the evaluation of technology-based startups who were asked to evaluate the startups' business models, scalability, and potential to execute. The business rating was based on an in-person interview and extensive documents, as well as informal interactions.

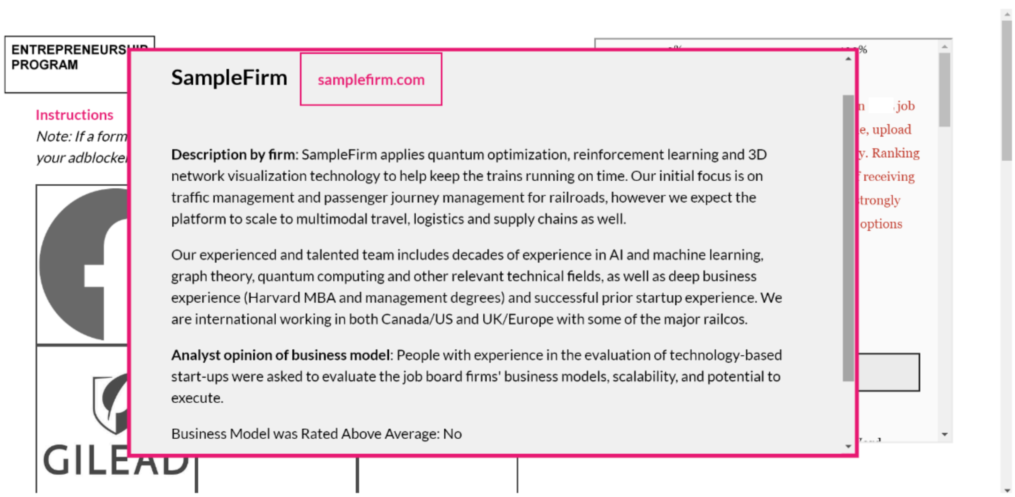
The image below summarizes our 2X2 RCT design:

	Hide Business Rating	Show Business Rating
Hide Science Rating	Standard Job Ad	Standard Job Ad + Business Rating
Show Science Rating	Standard Job Ad + Science Rating	Standard Job Ad + Science & Business Rating

Note: Standard Job Ad includes the firm's description, names of the founders, and link to the firm's website.

Overview of the study

The below screenshot shows a sample anonymized job ad with a negative business rating. Note that the expert rating treatment was at the **market level** and not at the job ad level--job seekers in a given job board either saw or did not see a given expert rating treatment for all job ads.



Next, we provide the full list of questions in the survey following the screener.

Question 2: Which had a larger effect on job applications, science or business expert ratings?

- Science expert ratings
- Business expert ratings
- Science and business expert ratings had about the same effect
- Both had no effect

Question 3: Which had a larger effect in terms of magnitude on job applications, positive or negative information?

- Positive information (i.e., information that firm quality is above-median within our sample) has a larger effect
- Negative information (i.e., information that firm quality is below-median within our sample) has a larger effect
- Positive and negative information had about the same effect in terms of magnitude
- Both had no effect

Question 4: Were science ratings and business ratings complements or substitutes in terms of their impact on job applications?

- Complements
- Substitutes
- Both had no effect

For the next questions, we define a good firm as one rated above-average in terms of both its science and business by experts. We define a bad firm as one rated below-average in terms of both its science and business by experts.

Please use a response of "X" to predict that good firms received X% more applications than bad firms, and use a response of "-X" to predict that bad firms received X% more applications than good firms. X is the number that you provide.

Question 5: Baseline: In the control group where we showed no expert ratings, how many percent (%) more or less applications did good firms receive compared to bad firms?

Question 6: Impact of Science Expert Ratings: When jobseekers viewed expert science ratings, how many percent (%) more or less applications did good firms receive compared to bad firms?

Question 7: Impact of Business Expert Ratings: When jobseekers viewed expert business ratings, how many percent (%) more or less applications did good firms receive compared to bad firms?

Question 8: Impact of Science and Business Expert Ratings: When jobseekers viewed both expert science and business ratings, how many percent (%) more or less applications did good firms receive compared to bad firms?

Question 9: Do you think the effect of expert ratings on job applications varied based on whether the job seeker had an undergraduate STEM degree?

- Yes, significantly smaller effect for those with a STEM degree than those without
- No difference based on worker STEM background
- Yes, significantly larger effect for those with a STEM degree than those without
- Expert ratings had no effect

Question 10: Do you think the effect of expert ratings on job applications varied based on the "quality" of the job seeker? To measure the job seeker quality, the project partnered with an HR expert who focuses on startup hiring. This HR expert rated the resumes of the job seekers based on suitability for working at a startup, and we divided these into above-median quality and below-median quality.

- Yes, significantly smaller effect for above-median quality candidates than for below-median
- No difference based on worker quality
- Yes, significantly larger effect for above-median quality candidates than for below-median
- Expert ratings had no effect

Question 11: Do you think the effect of expert ratings on job applications varied based on the gender of job seeker?

- Yes, significantly smaller effect for women than men
- No difference based on worker gender
- Yes, significantly larger effect for women than men
- Expert ratings had no effect

Appendix H Detailed Explanation of the Quadratic Scoring Rule

The figure below displays the more detailed explanation of the risk-invariant quadratic scoring rule that was made available to subjects (in addition to the simpler and intuitive explanation that was also provided to subjects, and that can be seen in Appendix D). This explanation was used in both the primary and secondary RCTs. The quadratic scoring rule is used to provide incentives on the probability questions. In the primary RCT, the more detailed explanation was accessed by clicking a link "For Further Detail". In the secondary RCT, the more detailed explanation was given on a separate sheet of paper.

Quadratic Scoring Rule Explanation Sheet

INCENTIVES ON SOME PROBABILITY QUESTIONS:

As added encouragement on probability questions, five people who complete this survey will be chosen at random to be paid via a lottery system. Payment will be based on one of two questions below. This lottery system has been used to elicit people's probability beliefs in various contexts, and is specially designed so that **it's mathematically optimal for you to state your true belief about the probability an event will occur.**

Specifically, if you are randomly chosen for possible payment, you will receive $250 CAD or $0. The probability of receiving $250 is equal to $2p-p^2$ if the event occurs, and is equal to $1-p^2$ if the event does not occur, where p is the probability that you give. The below table gives examples of your probability of winning $250 depending on the probability that you state and whether the event in question occurs or not.

Your Stated Probabilty	Your probability of winning $250 if event occurs	Your probability of winning $250 if event does not occur
0	0.0000	1.0000
5	0.0975	0.9975
10	0.1900	0.9900
15	0.2775	0.9775
20	0.3600	0.9600
25	0.4375	0.9375
30	0.5100	0.9100
35	0.5775	0.8775
40	0.6400	0.8400
45	0.6975	0.7975
50	0.7500	0.7500
55	0.7975	0.6975
60	0.8400	0.6400
65	0.8775	0.5775
70	0.9100	0.5100
75	0.9375	0.4375
80	0.9600	0.3600
85	0.9775	0.2775
90	0.9900	0.1900
95	0.9975	0.0975
100	1.0000	0.0000

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