

When Autonomy Backfires: Adverse Selection in Startup Recruitment*

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November 28, 2025

* Authors contributed equally. We thank Matthew Bidwell, Peter Cappelli, Waverly Ding, Justin Frake, Claudine Gartenberg, David Hsu, Manav Raj, Evan Starr, and Matteo Tranchero for providing valuable comments on the earlier versions of this manuscript. We also appreciate the helpful suggestions from seminar participants at the Wharton School, UC Irvine, the Duke Fuqua Junior Strategy Conference, the Junior Faculty Organizational Theory Conference, and the Smith Entrepreneurship Research Conference. All errors in this paper are the sole responsibility of the authors.

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Abstract

To compete with established firms for talent, startups often highlight their distinctive organizational attributes in recruitment efforts. Using a dataset of 228 million job postings, we first document that autonomy is a particularly prominent attribute: startups increasingly emphasize this organizational design feature, especially when targeting more educated candidates. To assess the efficacy of this strategy, we conduct a pre-registered field experiment in partnership with an actual startup. The results reveal a counterintuitive effect: explicitly emphasizing autonomy attracts less educated candidates while deterring their more educated counterparts. We propose that this adverse selection may arise from education-contingent differences in interpretation. Specifically, more educated job seekers are more likely to construe this emphasis as (1) a marker of generalist work misaligned with their specialized human capital, (2) a sign of organizational dysfunction stemming from excessive autonomy, (3) a compensating differential substituting for inadequate pecuniary compensation, or (4) simply “cheap talk” that undermines employer credibility. Together, our findings demonstrate that, although autonomy is a core attribute that distinguishes entrepreneurial ventures from established firms, its explicit emphasis can paradoxically backfire—undermining efforts to attract the high-ability human capital critical to entrepreneurial success.

Keywords: entrepreneurship, early joiner, human capital, autonomy, organizational design

1 Introduction

Early joiners—non-founder employees who join a startup during its formative stages—play a pivotal role in shaping venture growth and long-term success. By contributing complementary forms of human, social, and reputational capital, these early hires influence not only a startup’s financial performance (Choi et al. 2023, Lee and Kim 2024, Marx and Hsu 2022) but also its ability to acquire and deploy critical external resources (Clough et al. 2019, Engel et al. 2023, Kim 2018). Recognizing this strategic importance, recent scholarship has begun to investigate how early-stage ventures compete with established firms to attract these early employees. This literature suggests that, given their resource constraints, startups frequently offer deferred pecuniary compensation (e.g., equity stakes and stock options; Andersson et al. 2009, Hand 2008, Hellmann and Puri 2002, Oyer and Schaefer 2005, Roach and Sauermann 2015) and strategically highlight distinctive non-pecuniary attributes—such as unique strategic positioning, commitments to social responsibility, flat hierarchies, remote work arrangements, and unconventional or inflated job titles—to differentiate themselves from established employers (Cohen et al. 2023, Hsu and Tambe 2025, Hurst and Lee 2024, Hurst et al. 2024, Teng et al. 2025, van Balen and Tarakci 2024).

Extending this line of inquiry, this study examines a distinct non-pecuniary organizational attribute commonly emphasized in startup recruitment: autonomy. Autonomy refers to the discretion employees possess in determining how they perform their tasks and make meaningful, consequential decisions within their organizations (Boss et al. 2023, Gambardella et al. 2015:39, Hackman and Oldham 1976:257–258, Sauermann 2018:428). Prior research has documented that, like founders, current employees or offer-holders at early-stage ventures often prioritize autonomy over traditional pecuniary compensations (e.g., higher salaries) and other non-pecuniary benefits (e.g., organizational prestige and status) (Elfenbein et al. 2010, Gambardella et al. 2020, Roach and Sauermann 2010, 2015, 2024, Sauermann 2018, Stern 2004). However, by focusing primarily on individuals who have already opted into startup employment, this research has overlooked a crucial antecedent: whether prospective candidates decide to apply in the first place. Consequently, how an explicit emphasis on autonomy in startup recruitment shapes the composition of the applicant pool remains theoretically and empirically underexplored.

This omission represents a notable gap in understanding how autonomy operates in the context

of entrepreneurial human capital acquisition. Because the applicant pool defines the set of individuals from which a startup can select and hire talent, recruitment strategies that reduce the average quality of this pool could carry adverse consequences for venture performance. First, such strategies may impose *observable* screening costs: when the applicant pool is disproportionately composed of lower-quality applicants, startups—which typically operate under significant resource constraints—must invest additional time and effort to identify viable candidates. Second, and perhaps more critically, these strategies entail *unobservable* opportunity costs: startups may unknowingly lose access to higher-quality job seekers who choose not to apply in response to particular recruitment messages. These concerns highlight the importance of understanding how autonomy-oriented language in startup recruitment influences the composition of the applicant pool.

We examine this question through two complementary empirical exercises. First, to document the prevalence of autonomy-related language in startup recruitment, we analyzed a corpus of over 228 million job postings from approximately 3 million U.S. employers spanning the years 2010 to 2019. This descriptive analysis reveals that early-stage startups—particularly in high-tech industries—have increasingly leveraged autonomy as a core non-pecuniary recruitment strategy, and do so at significantly higher rates than established firms. This emphasis is especially pronounced in startup job postings targeting more educated candidates or recruiting for knowledge-intensive occupations such as legal, scientific, engineering, sales, and managerial roles.

These descriptive patterns inform and motivate our second empirical exercise: a pre-registered, reverse-audit field experiment designed to causally identify the effect of emphasizing autonomy in startup recruitment on human capital attraction. We undertook this experiment in partnership with an early-stage high-tech startup recruiting for engineering and sales positions. Leveraging an online job platform tailored to startup employment opportunities, we identified 11,135 qualified job seekers and invited them to apply for open positions at the partner startup. Using our pre-registered outcome measure (i.e., whether a candidate expressed interest by clicking the hyperlink to the company’s application webpage), we find that emphasizing autonomy did not significantly increase the number of interested job seekers but did reduce the average quality of the interested candidate pool. Specifically, this emphasis increased interest among less educated job seekers without bachelor’s degrees by 2.69 percentage points (a 51.53% increase), while reducing interest among more educated candidates holding master’s or doctoral degrees by 2.91 percentage points (a 27.98% decrease). In

exploratory analyses, we observe a similar pattern in actual application behavior: application rates among graduate degree holders declined by 1.72 percentage points (a 42.36% decrease). Notably, across both the primary behavioral indicator (i.e., click-through) and the downstream outcome (i.e., job application), these negative effects were most pronounced among doctoral degree holders.

Given the established evidence that workers—especially those with higher education—value autonomy at work (e.g., Roach and Sauermann 2010, 2024, Stern 2004), we propose that the observed pattern of adverse selection is likely driven by education-contingent, second-order interpretations of an explicit emphasis on autonomy in startup recruitment. Specifically, compared with their less educated counterparts, more educated individuals are more likely to construe this emphasis as (1) a marker of generalist work misaligned with their specialized human capital, (2) a sign of organizational dysfunction from excessive autonomy, (3) a compensating differential substituting for inadequate pecuniary compensation, or (4) “cheap talk” that undermines the employer’s credibility.

Our study offers several contributions to the literature. First, this study contributes to entrepreneurship research by demonstrating that, although autonomy is highly valued by founders and early joiners, its explicit emphasis in recruitment efforts may inadvertently undermine startups’ ability to attract more educated talent. This finding highlights a previously underexplored paradox in entrepreneurial talent acquisition: the organizational attributes preferred by founders and early joiners may induce adverse selection when prominently highlighted to prospective applicants. Second, we extend the human capital literature by underscoring the importance of accounting for cognitive heterogeneity among job seekers when designing recruitment strategies. Our findings suggest an education-contingent recruitment communication dynamic, in which the effectiveness of recruitment strategies depends not only on aligning organizational attributes with worker preferences but also on how different audiences interpret these attributes based on their cognitive capacities. Finally, our work advances the literature on organizational design by showing that the communication of organizational structure to external audiences—particularly job seekers—constitutes a distinct strategic choice with implications that extend beyond the internal architecture of the organization itself. This finding suggests that an effective organizational design should consider not only the cognitive abilities of current employees but also the sophisticated inferences made by prospective candidates whom firms seek to hire.

2 Theoretical background

2.1 Early joiners in new ventures

A firm’s competitive advantage fundamentally depends on its ability to acquire, organize, and retain human capital (Barney 1991, Campbell et al. 2012a, Coff 1997). This strategic imperative is particularly salient in entrepreneurial ventures, where early joiners—non-founder employees who join during a startup’s formative stages—play a critical role in shaping both short-term performance and long-term viability (Choi et al. 2023, Marx and Hsu 2022, Roach and Sauermann 2015).

A growing body of research has highlighted the multifaceted contributions of early joiners. First, these hires contribute specialized knowledge and skills that complement the capabilities of the founding team, filling critical functional gaps in domains such as R&D and sales (Clough et al. 2019, Klotz et al. 2014). Their expertise becomes especially valuable during the scaling phase, when startups contend with resource constraints and managerial complexity that require effective cross-functional coordination (DeSantola and Gulati 2017, Lee and Kim 2024). Beyond their functional contributions, early joiners shape foundational organizational processes by helping to establish values, norms, and routines that persist as the firm grows (Baron and Hannan 2002). Through these formative inputs, they imprint the organization’s emerging structure and culture in ways that shape long-term decision-making and adaptability (Alexy et al. 2021, Choi and Lee 2025). In addition to their influence on internal operations, early joiners play a central role in mobilizing external resources. Drawing on their social and reputational capital, they help attract talent, secure funding, and forge strategic partnerships (Hegde and Tumlinson 2014, Kim 2018, Shane and Cable 2002). Furthermore, the composition of a startup’s early hires can have lasting effects on the firm’s broader workforce composition and diversity by shaping the types of candidates who are attracted to the organization in subsequent recruitment cycles (Engel et al. 2023, Hurst et al. 2024).

2.2 Recruitment strategies to attract early joiners

While early joiners make critical contributions to startup growth and development, early-stage ventures face substantial challenges in attracting these employees. Compared to established firms, startups contend with heightened risks of failure as they operate under severe resource constraints (Baker and Nelson 2005) while confronting the liabilities of newness and smallness (Stinchcombe

1965). Consequently, startups are often unable to offer competitive financial compensation in the form of salaries or wages (Burton et al. 2018, Hamilton 2000, Roach and Sauermann 2024) or non-pecuniary benefits such as job stability, predictable career advancement, and organizational prestige (Sorenson et al. 2021, Stinchcombe 1965, Tan and Rider 2017). The absence of such pecuniary and non-pecuniary offerings places startups at a distinct disadvantage in competing for top talent against more established employers.

To mitigate this disadvantage in human capital acquisition, startups frequently adopt a range of alternative recruitment strategies. A commonly used approach involves offering deferred pecuniary benefits—such as equity stakes and stock options (Hand 2008, Hellmann and Puri 2002, Oyer and Schaefer 2005, Roach and Sauermann 2015)—to supplement lower base salaries and align incentives over the long term (Andersson et al. 2009, Hamilton 2000, Sorenson et al. 2021). In tandem, startups strategically leverage distinctive non-pecuniary attributes to differentiate themselves from established firms. For instance, to appeal to values-driven job seekers, many startups craft mission-oriented narratives that highlight their strategic positioning, corporate purpose, and commitments to social responsibility (Hurst and Lee 2024, Teng et al. 2025, van Balen and Tarakci 2024). Startups also frequently offer remote work arrangements (Hsu and Tambe 2025) or underscore their flatter organizational structures, which foster egalitarian work environments and grant employees greater flexibility and voice (Hurst et al. 2024). To further enhance their appeal, some even adopt unconventional or inflated job titles (e.g., “Growth Hackers” or “Director of First Impressions”) to compensate for limited pecuniary benefits, while signaling the value they place on their employees and the multifaceted roles and responsibilities that traditional titles may not adequately capture (Cohen et al. 2023). Collectively, these non-pecuniary recruitment strategies enable startups to differentiate themselves from established employers and compete for top talent, despite their limited capacity to compete on traditional pecuniary dimensions.

2.3 Emphasizing autonomy as a non-pecuniary recruitment strategy

One prominent non-pecuniary, organizational design feature that startups commonly emphasize in their recruitment efforts is autonomy. For example, Figure 1 illustrates a representative startup job posting that explicitly highlights “autonomy” in an effort to attract early joiners. As we systematically document in Section 3, the use of such autonomy-oriented language in startup recruitment

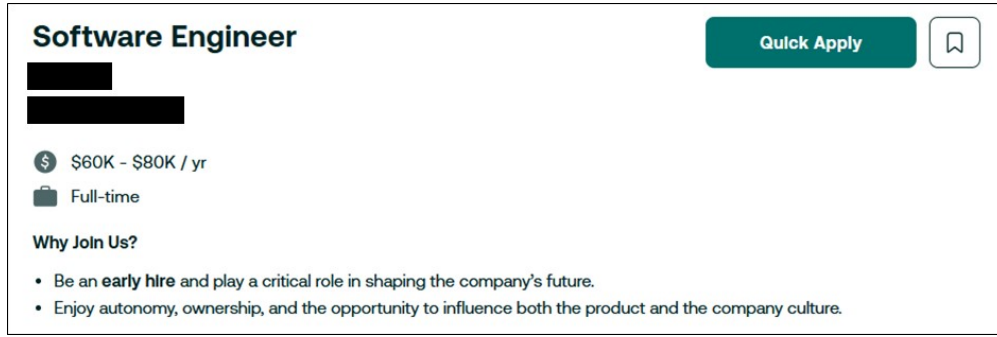


Figure 1 An example of a startup’s job posting explicitly highlighting autonomy to attract early joiners. In this example, the company’s name and location are redacted.

materials has increased substantially in recent years. This trend suggests that entrepreneurial ventures are strategically leveraging autonomy to differentiate themselves from established firms and enhance their appeal to prospective employees.

This strategic emphasis on autonomy aligns with the documented preferences of the entrepreneurial talent pool. Prior research indicates that, like founders, individuals who receive employment offers from early-stage startups tend to exhibit a strong preference for autonomy (Elfenbein et al. 2010, Roach and Sauermann 2015, Sauermann 2018, Stern 2004). In pursuit of greater autonomy, these individuals often willingly forgo traditional pecuniary compensation (e.g., higher salaries) and other non-pecuniary benefits (e.g., organizational prestige or career stability).

The theoretical rationale for these strong preferences is grounded in the literature on organizational design. Autonomy refers to the discretion employees exercise over their tasks and organizational decisions (Boss et al. 2023, Gambardella et al. 2015:39, Hackman and Oldham 1976:257–258, Sauermann 2018:428). Beyond its instrumental value in affording employees greater influence over organizational outcomes, autonomy also holds intrinsic value (Bartling et al. 2014). It satisfies fundamental psychological needs for independence, ownership, and self-determination, which in turn enhance intrinsic motivation and psychological well-being (Deci and Ryan 1985, Deci et al. 2017, Gambardella et al. 2015, Sauermann and Cohen 2010) and reduce evaluation apprehension (Hackman and Oldham 1976). These psychological benefits have been linked to a range of favorable individual and organizational outcomes, including greater job satisfaction and work engagement (Baard et al. 2004, Gagné and Deci 2005), increased productivity (Langfred 2004), enhanced creativity and innovation (Amabile et al. 1996, Boss et al. 2023, Lee 2022, Sauermann

and Cohen 2010), and lower voluntary turnover (Liu et al. 2011).

Given the well-documented preferences for and benefits of autonomy, emphasizing this non-pecuniary attribute in recruitment appears, at first glance, to be a strategically sound approach for entrepreneurial ventures seeking a competitive advantage in the labor market. While autonomy is often cited as a core organizational attribute that differentiates nascent ventures from established firms (Knight et al. 2020, Lee 2022, Roach and Sauermann 2024, Sorenson et al. 2021, Stinchcombe 1965), this attribute may be overshadowed during the job search process by more salient information on traditional pecuniary and non-pecuniary benefits, such as salary, organizational prestige, or job security. Hence, by significantly elevating its salience, explicitly highlighting autonomy in recruitment materials may attract candidates who might otherwise gravitate toward more established employers.

Moreover, this strategy may serve to differentiate the focal startup from its peers. Given that organizational structures often vary substantially even among new ventures at similar stages of development (Alexy et al. 2021, Lee 2022, Sine et al. 2006), an explicit emphasis on autonomy may convey to prospective applicants that the focal startup affords uniquely high levels of discretion. Accordingly, this emphasis may not only differentiate the startup from established firms but also position it more favorably within the broader entrepreneurial labor market. Taken together, these arguments suggest that by elevating the salience of an otherwise implicit attribute and conveying a distinctive organizational environment, highlighting autonomy in recruitment communications may enable startups to attract talent in a competitive and information-asymmetric labor market.

However, a key limitation of this logic is that it draws primarily on the preferences of *founders* and *offer-holders* at early-stage ventures or on the observed effects of autonomy among *current* employees. This perspective neglects a critical antecedent in the hiring process: the application stage, where job seekers decide whether to apply in the first place. Thus, it remains an open question how an explicit emphasis on autonomy shapes the initial sorting of *prospective* applicants.

The following sections address this gap through a multi-method approach. In Section 3, we first assess a large-scale dataset of job postings to document the prevalence of autonomy-related language in startup recruitment. Building on the observed regularities, we implement a natural field experiment in Section 4 to causally identify the effect of this recruitment strategy on human capital attraction. Finally, in Section 5, we ex-post theorize potential mechanisms that may underlie the observed results.

3 Study 1: Descriptive analysis of startup job postings

3.1 Data

To document the prevalence of autonomy-oriented language in startup recruitment, we first analyze 228,483,442 job postings from 3,020,059 firms in the U.S. between 2010 and 2019. This dataset was sourced from Lightcast, which provides comprehensive coverage of U.S. job postings (Cammeraat and Squicciarini 2021) and has been extensively used in prior research (e.g., Hansen et al. 2023, Hurst 2023, Lee and Kim 2024). The dataset contains detailed information at the job-posting level, such as employer name, geographic location, posting date, occupational code, and minimum educational requirements. To identify early-stage ventures, we merged this dataset with a database of 1.2 million companies from Crunchbase, which is widely regarded as “the premier data asset on the tech/startup world” (Dalle et al. 2017:5). This database includes comprehensive firm-level information, such as company name, geographic location, industry classification, and founding year.

3.2 Measurement

Emphasis on autonomy: To measure whether an employer emphasizes autonomy in its recruitment efforts, we identified job postings that contain expressions commonly used to convey this non-pecuniary attribute. Specifically, we first compiled a dictionary of autonomy-related expressions based on prior literature (e.g., Hackman and Oldham 1976, Knight et al. 2020, Reineke et al. 2025), interviews with talent acquisition professionals, and a manual review of job postings.¹ Using Python’s natural language processing library `spacy`, we then searched for the presence of these expressions within each job posting. To ensure high precision, the algorithm incorporated contextual filters to exclude false positives, such as negated phrases (e.g., “no autonomy”) or unrelated technical usages (e.g., “autonomous vehicle”). As this measurement approach is limited to a predefined dictionary, it may omit more subtle or unconventional linguistic variations (e.g., “independence” or “decide how

¹This dictionary includes lemmas for individual terms “autonomy” (excluding instances followed by terms like “control,” “drone,” “infrastructure,” “learning,” “machinery,” “navigation,” “network,” “operation,” “platform,” “robot,” “sensor,” “software,” “system,” or “vehicle”), “discretion,” “empower,” “self-define,” “self-direct,” “self-initiate,” “self-govern,” “self-lead,” “self-manage,” “self-motivate,” and “self-organize.” The dictionary also contains autonomy-relevant phrases commonly found in recruitment language: “bottom-up decision,” “build the future,” “define your own,” “drive initiatives,” “end-to-end responsibility,” “freedom to experiment,” “lead your projects,” “make decisions independently,” “manage your own,” “minimal guidance,” “minimal management,” “minimal oversight,” “minimal supervision,” “no micromanagement,” “not micromanaged,” “run with your,” “set your own,” “shape the direction,” “shape the future,” “take initiative,” “think like an owner,” “work independently,” and “work your own.”

to get things done”). Therefore, the descriptive patterns reported below likely represent conservative estimates of the overall prevalence of autonomy-oriented language in recruitment materials.

Startup: Following prior entrepreneurship research (e.g., Decker et al. 2014, Haltiwanger et al. 2013, Lee and Kim 2024), we classify a firm as a startup if it is less than ten years old in a given year. For example, a firm founded in 2009 is categorized as a startup from 2010 to 2018, but is considered an established firm in 2019.

We identified 77,750 startups founded in the U.S. between 2001 and 2019 by merging data from Crunchbase and Lightcast using the following procedure. First, we refined Crunchbase’s dataset by excluding investment firms, non-profit organizations, and any companies without a founding year or founded before 2001. We then performed an exact match based on company name and geographic location (i.e., state in the U.S.), which yielded 55,230 startups. For the remaining unmatched records, we employed a fuzzy string-matching procedure using Python’s `RapidFuzz` library. This process involved standardizing company names by removing punctuation and corporate suffixes (e.g., “Inc.”) and then, within each state, identifying the best match above a similarity threshold of 95%. To improve accuracy, we excluded any firm whose job postings predated its matched founding year. We then manually reviewed the remaining fuzzy matches to resolve ambiguous or erroneous pairings, resulting in an additional 22,520 matched startups.

This data construction procedure has some potential limitations that likely render our estimates conservative. First, although Crunchbase offers extensive data on new ventures, its coverage is not exhaustive and is skewed toward venture-capital-backed, high-growth startups (Dalle et al. 2017, Lee and Kim 2024). Furthermore, approximately 20% of U.S.-based firms in the Crunchbase dataset lack information on the founding year, making them ineligible for the matching procedure. Lastly, the matching procedure may have failed to pair some startups, thereby misclassifying them as established firms. However, given that startups are more likely than established firms to emphasize autonomy in job postings—a premise substantiated in Figure 2—any under-coverage or misclassification would artificially inflate the prevalence of this recruitment practice among established firms. Accordingly, observed differences between startups and established firms should be interpreted as a conservative lower bound on the true extent of divergence.

Industry: We classify each startup’s industry using Crunchbase’s taxonomy of 47 overlapping

industry groups.² We use this classification in lieu of North American Industry Classification System (NAICS) codes in the Lightcast data, as the latter are largely missing for early-stage ventures.

Occupation: We categorize each job posting’s occupation based on the two-digit occupational code provided in the Lightcast dataset, which corresponds to major occupational groups in the U.S. Department of Labor’s O*NET classification system.

Educational requirement: We code the required education level for each job using Lightcast’s data on the minimum degree qualification specified in the job posting.

3.3 Stylized facts

We begin by examining differences between startups and established firms in their use of autonomy-related language in job postings, as illustrated in Figure 2. Panel (a) shows that startups consistently place greater emphasis on autonomy in their recruitment materials than do established firms. From 2010 to 2019, the proportion of established firms referencing autonomy-related terms increased modestly from 14% to 19%, while the corresponding share among startups rose more sharply from 22% to 34%. Panel (b) presents a more conservative measure, focusing exclusively on the use of the exact term “autonomy.” Here, the divergence is even more pronounced: the proportion of established firms referencing “autonomy” in their job postings grew slightly from 0.6% to 1.1%, whereas the respective share among startups more than tripled from 1.1% to 3.5%.

To gain a more granular understanding of where autonomy-related language is most concentrated, Table 1 presents a cross-sectional breakdown of its usage in startup job postings by industry and occupation. For brevity, the table displays only the top 10 industries and occupations ranked by the frequency of autonomy-related expressions (for a full breakdown, see Appendix A). Panel (a) shows that autonomy is most frequently emphasized in high-tech sectors such as ‘Biotechnology,’ ‘Payments,’ ‘Privacy and Security,’ ‘Science and Engineering,’ and ‘Data and Analytics.’ Panel (b) reveals a parallel pattern across occupations: startups most commonly highlight autonomy in job

²The industry groups in Crunchbase’s dataset include: “Administrative Services,” “Advertising,” “Agriculture and Farming,” “Apps,” “Artificial Intelligence,” “Biotechnology,” “Clothing and Apparel,” “Commerce and Shopping,” “Community and Lifestyle,” “Consumer Electronics,” “Consumer Goods,” “Content and Publishing,” “Data and Analytics,” “Design,” “Education,” “Energy,” “Events,” “Financial Services,” “Food and Beverage,” “Gaming,” “Government and Military,” “Hardware,” “Health Care,” “Information Technology,” “Internet Services,” “Lending and Investments,” “Manufacturing,” “Media and Entertainment,” “Messaging and Telecommunications,” “Mobile,” “Music and Audio,” “Natural Resources,” “Navigation and Mapping,” “Payments,” “Platforms,” “Privacy and Security,” “Professional Services,” “Real Estate,” “Sales and Marketing,” “Science and Engineering,” “Software,” “Sports,” “Sustainability,” “Transportation,” “Travel and Tourism,” “Video,” and “Other.”

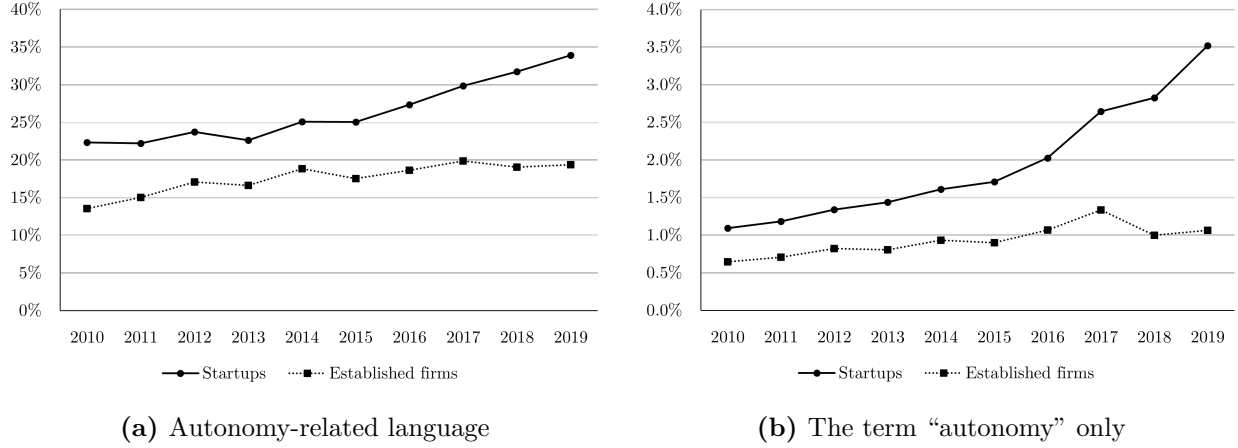


Figure 2 The comparison between startups and established firms in their emphasis on autonomy in recruitment materials. Panel (a) demonstrates that startups are more likely than established firms to include autonomy-related language in job postings. Panel (b) shows that this difference is even more pronounced when focusing specifically on the use of the exact term “autonomy.”

postings for knowledge-intensive roles that demand cognitive ability and advanced education, such as legal professions (“Legal”), science and engineering fields (e.g., “Life, Physical, and Social Science,” “Computer and Mathematical,” and “Architecture and Engineering”), and managerial functions (e.g., “Business and Financial Operations,” “Management,” and “Sales”).

To further investigate whether startups strategically emphasize autonomy to attract more educated candidates, Figure 3 examines how the use of autonomy-related language varies with the minimum educational requirement specified in job postings. Consistent with the occupational patterns described above, panel (a) shows that startups are more likely to highlight autonomy in postings for roles requiring higher levels of formal education. This educational gradient becomes even more pronounced in panel (b), which isolates job postings that use the exact term “autonomy.”

Overall, these descriptive findings establish three stylized facts. First, early-stage startups are increasingly emphasizing autonomy in their recruitment efforts—and doing so at significantly higher rates than established firms. Second, this emphasis is concentrated among high-tech startups hiring for cognitively demanding, knowledge-intensive roles. Third, the pattern exhibits a clear educational gradient: autonomy-related language appears more frequently in job postings that specify advanced educational qualifications. Collectively, these patterns suggest that startups strategically deploy autonomy as a non-pecuniary recruitment lever to compete for more educated talent. These findings provide empirical motivation for our core research question—how does an explicit emphasis on

Industry category	Autonomy-related language	The term “autonomy” only
Biotechnology	35.1%	2.11%
Government and Military	33.4%	2.65%
Payments	33.3%	3.14%
Privacy and Security	33.2%	3.20%
Science and Engineering	32.5%	2.34%
Data and Analytics	32.4%	3.24%
Artificial Intelligence	32.0%	3.04%
Education	31.8%	3.41%
Financial Services	31.1%	2.49%
Software	31.1%	2.96%

(a) By industry

O*NET occupation code	Autonomy-related language	The term “autonomy” only
23: Legal	26.4%	0.85%
19: Life, Physical, and Social Science	20.0%	0.42%
13: Business and Financial Operations	20.0%	0.57%
43: Office and Administrative Support	18.4%	0.32%
11: Management	17.8%	0.87%
15: Computer and Mathematical	17.2%	0.87%
17: Architecture and Engineering	15.9%	0.48%
27: Arts, Design, Entertainment, Sports, and Media	15.6%	0.73%
37: Building and Grounds Cleaning and Maintenance	14.6%	0.01%
41: Sales	14.6%	0.66%

(b) By occupation

Table 1 The emphasis on autonomy in recruitment materials by industry and occupation. For brevity, this table reports only the top 10 industries and occupations ranked by the frequency of autonomy-related language (for a complete breakdown, see Appendix A). Panel (a) shows that startups most frequently emphasize autonomy in high-tech industries. Panel (b) reveals that this emphasis is especially common in knowledge-intensive occupations.

autonomy in startup recruitment shape the composition of the applicant pool—and inform the design of our field experiment to causally test this relationship.

4 Study 2: Field experiment

While the descriptive analysis in Section 3 demonstrates that startups increasingly emphasize autonomy in their recruitment efforts, credibly estimating how this emphasis shapes the applicant pool poses three key empirical challenges. First, although linking job postings to employer-employee matched data could reveal the composition of a firm’s current workforce, it is difficult to disentangle whether this composition is driven by attraction (i.e., who chooses to apply), selection (i.e., whom the employer decides to hire), or attrition (i.e., who chooses to stay). Second, because the decision

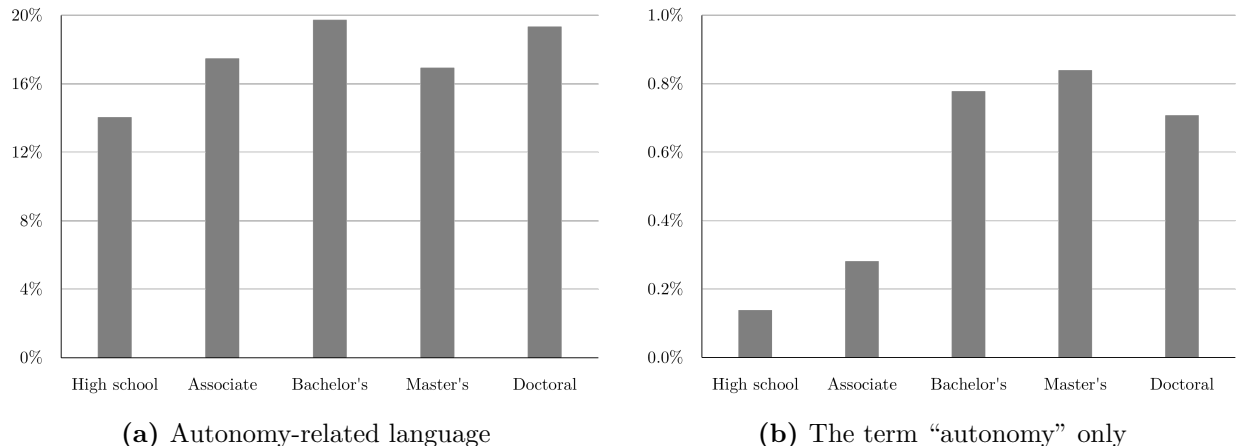


Figure 3 The emphasis on autonomy in recruitment materials by educational requirement. Panel (a) illustrates that startups are more likely to include autonomy-related language in job postings for positions requiring higher levels of formal education. Panel (b) illustrates that this educational gradient is even more pronounced when focusing on the use of the exact term “autonomy.”

to emphasize autonomy in recruitment materials is inherently endogenous, any observed association between this emphasis and workforce composition may be confounded by unobservable factors that simultaneously influence both outcomes. Finally, while some studies have used surveys to examine job seekers’ preferences for autonomy (e.g., Baard et al. 2004, Roach and Sauermann 2015, 2024), growing evidence suggests that stated preferences in survey responses often diverge from revealed preferences in actual behaviors (Gandhi et al. 2024, Levine et al. 2023), particularly in employment contexts (e.g., Hurst and Lee 2024, Hurst et al. 2024, Portocarrero and Burbano 2024).

To address these challenges, we conducted a natural field experiment, which was both approved by the Institutional Review Board and pre-registered on the Open Science Framework.³ For this experiment, we partnered with a U.S.-based high-tech startup that had recently raised Series B funding to scale its business and recruit early joiners for engineering and sales positions—two occupations for which startups frequently emphasize autonomy (see Table 1). Using a prominent online recruitment platform specializing in startup employment opportunities, we identified 11,135 job seekers who met the partner startup’s criteria: (1) currently residing in the U.S., (2) actively seeking startup employment in the U.S., and (3) expressing interest in engineering or sales roles. We then sent recruitment emails to these candidates via a mass email delivery service. After excluding

³The experiment was implemented on June 10, 2025, one day after the pre-registration. The pre-analysis plan is available at: https://osf.io/j5yze/?view_only=09a34d0daaa84ae58b2559fc9ba45471.

Hi {*Job candidate’s name*},

We’re excited to invite you to apply for our team at {*Partner company’s name*}.

Why Join Us

- {*Manipulation in panel (b) inserted here, if “Autonomy” condition*}
- **Mentorship:** Our industry experts provide invaluable mentorship to help you grow.
- **Competitive salary**
- **Comprehensive benefits:** Health, dental, and vision insurance, 401(k) match, and more.

About Us: Founded in {*Partner company’s founding year*}, we’re a fast-paced, high-growth {*Partner company’s industry*} startup with {*Partner company’s product*}. We’ve raised over {*Partner company’s funding amount*} from top-tier investors.

Open Roles: Full-time, on-site positions available in engineering and sales for both entry-level and senior roles.

How to Apply: Click here {*Hyperlink to the partner company’s careers web page*} to learn more and apply.

(a) The body of the email

Autonomy: At {*Partner company’s name*}, autonomy isn’t just a buzzword—it’s how we operate. You’ll have the freedom to define your area of expertise, propose creative solutions, and influence the company’s future.

(b) The manipulation inserted for the treatment condition

Figure 4 Recruitment email to job candidates. In this email, company-specific information is redacted to protect organizational anonymity, in accordance with the partner company’s request.

417 individuals whose emails failed to deliver, our final analytical sample consisted of 10,718 subjects.

4.1 Experimental manipulation

Following the methodology of prior reverse-audit studies (e.g., Flory et al. 2021, Hurst and Lee 2024, Hurst et al. 2024, Snellman and Younkin 2021, Teng et al. 2025), we embedded our experimental manipulation into the recruitment materials sent to potential applicants. As illustrated in Figure 4, these materials were structured in five sections.

In the second section, the randomized manipulation was included for the treated group but excluded for the control group. For the treated group, the manipulation featured autonomy-

oriented language adapted from the partner startup’s official “Careers” webpage and was reviewed and approved by the company. Specifically, this manipulation stated: “Autonomy: At {*Partner company’s name*}, autonomy isn’t just a buzzword—it’s how we operate. You’ll have the freedom to define your area of expertise, propose creative solutions, and influence the company’s future.” This statement was designed to operationalize the theoretical construct of autonomy—defined as the discretion and influence employees possess over their tasks and organizational decisions (Boss et al. 2023, Gambardella et al. 2015:39, Hackman and Oldham 1976:257–258, Sauermann 2018:428).

For the control group, we omitted this statement, rather than inserting a filler statement. We opted for this “pure control” design for theoretical, phenomenological, and methodological reasons. First, it represents the most relevant theoretical counterfactual: the common practice of not explicitly emphasizing autonomy in startup recruitment. Second, a statement highlighting limited autonomy was not viable. Given that such a statement was not observable in our descriptive analysis (Section 3), its abnormality itself might cause subjects to respond negatively. Furthermore, our partner company did not grant permission to use such a statement, as it would misrepresent the company. Lastly, any content within the “Why Join Us” section of a concise, targeted recruitment email might not be perceived as truly inert and could instead introduce an unintended effect.

The other sections were held constant across the treated and control groups. The first section invited recipients to apply for open positions. The third introduced the partner firm as an early-stage, high-tech startup seeking early joiners. The fourth described the open positions in engineering and sales. The final section included a hyperlink to the company’s application webpage, which participants were encouraged to visit if they were interested in applying. This landing page featured the official job posting and application form, which were identical for all participants.

4.2 Measurement

Attraction: To measure job seekers’ attraction to the partner startup, we use a binary variable $Click_i$, which indicates whether subject i showed interest in the open positions by clicking on the hyperlink to the application webpage. To identify who clicked, each hyperlink contained a unique identifier, but all hyperlinks redirected to the same application webpage, irrespective of treatment condition. Click-through data were collected two weeks after the recruitment emails were distributed.

We pre-registered this click-through measure as the primary behavioral indicator of attraction

for two main reasons. First, because both the treatment and the hyperlink were embedded in the recruitment emails, clicking the hyperlink to access the partner company’s application webpage constitutes the first observable behavioral expression of interest. Although submitting an application through this webpage may more directly reflect attraction, this subsequent behavior is conditioned on the preceding action of clicking the hyperlink. Hence, due to “phantom counterfactuals” (Slough 2023), the average treatment effect on actual applications may not be identifiable.

Second, the click-through measure is unlikely to be influenced by other information not specified in the recruitment email that subjects may encounter after landing on the application webpage. Notably, because the application webpage—which is identical for both groups—explicitly highlights autonomy at the partner company, job seekers in the control group are also exposed to the treatment (i.e., an explicit emphasis on autonomy) after clicking the hyperlink. Moreover, the webpage’s “Nice to have” section lists optional qualifications (e.g., “A bachelor’s degree in [relevant majors] from a top institution”), which likely influence application decisions independently of our treatment. Consequently, due to post-randomization information exposure, the estimated treatment effect for subsequent application behavior may be contaminated and/or biased toward zero.

Nevertheless, the click-through measure may imperfectly capture a subject’s genuine interest in applying to the partner startup. For example, some individuals in the treated group may have clicked the hyperlink purely out of curiosity about a startup that emphasizes autonomy, without any intention of applying. To address this concern, we construct an alternative outcome variable, $Apply_i$, which indicates whether subject i submitted an application via the partner company’s webpage. This measure was designated as exploratory in our pre-analysis plan, as the partner company was initially unable to confirm whether application data would be made available. The partner company subsequently provided this data approximately one month after we sent the recruitment emails.

Treatment: To estimate the effect of explicitly emphasizing autonomy, we employ a binary indicator $Autonomy_i$, which equals one if subject i received an email with the manipulation emphasizing autonomy (as detailed in panel (b) of Figure 4); otherwise, zero.

Candidate quality: To examine heterogeneity in the treatment effect by candidate quality, we pre-registered educational attainment as our primary proxy. To operationalize educational attainment, we construct three mutually exclusive binary variables— $Non-bachelor_i$, $Bachelor_i$, and

$Graduate_i$ —which indicate subject i ’s highest reported educational level. For more granular analysis, we further disaggregate the graduate category by creating separate indicators for master’s degrees ($Master_i$) and doctoral degrees ($Doctoral_i$).

We selected this proxy for empirical and conceptual reasons. First, from an empirical standpoint, an explicit emphasis on autonomy is more pronounced when startups target more educated job seekers (see Figure 3). Second, from a conceptual standpoint, educational attainment represents a widely used measure for latent ability (e.g., Bidwell 2011:380–381, Dahl and Klepper 2017:827, Hamilton 2000:607, Spence 1973). Although educational attainment is an imperfect indicator of “quality”—which encompasses cognitive, non-cognitive, and physical abilities, as well as social and reputational capital—prior research demonstrates that it is positively correlated with cognitive ability (Berry et al. 2006, Heckman et al. 2006, Neisser et al. 1996). Specifically, while individuals with greater innate cognitive aptitude are more likely to select into and succeed in extended periods of formal education, educational attainment can enhance cognitive ability by placing sustained demands on critical thinking, inferential reasoning, and creative problem-solving (Becker 1964).

Given its positive association with cognitive ability, educational attainment commonly serves as a key proxy of unobservable productivity in the labor market (Arcidiacono et al. 2010, Arrow 1973, Spence 1973), functions as an initial screening mechanism employers commonly use to narrow large applicant pools to manageable shortlists (Layard and Psacharopoulos 1974, Riley 1979, Stiglitz 1975), and is rewarded by employers (Bidwell 2011, Castex and Kogan Dechter 2014, Mincer 1958). Consistent with this logic, empirical studies on high-ability individuals in startup contexts frequently focus on those with advanced degrees, particularly doctorates (e.g., Agarwal and Ohyama 2013, Roach and Sauermann 2010, 2015, 2024, Sauermann 2018, Sauermann and Cohen 2010, Stern 2004).

Other individual attributes: Using self-reported data from the online job search platform, we obtain a range of individual-level characteristics for each job seeker. As alternative pre-registered proxies for candidate quality, we include four measures: whether job seeker i earned a bachelor’s degree from a university ranked among U.S. News’ Best 100 Global Universities ($Top\ University_i$), whether they hold a managerial role at their current employer ($Manager_i$), their total years of work experience ($Work\ Experience_i$), and their predicted desired annual salary ($Desired\ Salary_i$). In addition, we capture predicted gender ($Woman_i$), predicted race/ethnicity ($Race_i$), geographic

Variable	Full sample					<i>Treated</i> = 0			<i>Treated</i> = 1		
	No. Obs.	Mean	Std. Dev.	Min	Max	No. Obs.	Mean	Std. Dev.	No. Obs.	Mean	Std. Dev.
Outcome											
<i>Click</i>	10,718	0.0675	0.2510	0	1	5,419	0.0681	0.2519	5,299	0.0670	0.2500
<i>Apply</i>	10,718	0.0169	0.1289	0	1	5,419	0.0175	0.1313	5,299	0.0162	0.1264
Treatment											
<i>Autonomy</i>	10,718	0.4944	0.5000	0	1	5,419	0	0	5,299	1	0
Educational attainment											
<i>Non-bachelor</i>	10,718	0.2055	0.4041	0	1	5,419	0.2045	0.4033	5,299	0.2066	0.4049
<i>Bachelor</i>	10,718	0.6060	0.4887	0	1	5,419	0.6032	0.4893	5,299	0.6088	0.4881
<i>Graduate</i>	10,718	0.1885	0.3911	0	1	5,419	0.1923	0.3941	5,299	0.1846	0.3880
<i>Master</i>	10,718	0.1785	0.3829	0	1	5,419	0.1808	0.3849	5,299	0.1761	0.3809
<i>Doctoral</i>	10,718	0.0100	0.0994	0	1	5,419	0.0114	0.1064	5,299	0.0085	0.0918
Alternative proxies of quality											
<i>Top University</i>	10,718	0.0822	0.2747	0	1	5,419	0.0806	0.2723	5,299	0.0838	0.2771
<i>Manager</i>	10,718	0.3359	0.4723	0	1	5,419	0.3300	0.4702	5,299	0.3420	0.4744
<i>Work Experience</i> (log)	9,007	2.5697	0.7877	0	4.0943	4,562	2.5600	0.7984	4,445	2.5797	0.7766
<i>Desired Salary</i> (log)	10,718	11.0768	0.4253	9.1167	12.0279	5,419	11.0781	0.4223	5,299	11.0754	0.4283
Predicted gender											
<i>Woman</i>	8,446	0.2582	0.4377	0	1	4,285	0.2492	0.4326	4,161	0.2675	0.4427
Predicted race/ethnicity											
<i>Asian</i>	7,215	0.1355	0.2779	0	1	3,653	0.1354	0.2777	3,562	0.1357	0.2782
<i>Black</i>	7,215	0.0843	0.1157	0	1	3,653	0.0834	0.1127	3,562	0.0854	0.1187
<i>Hispanic</i>	7,215	0.1239	0.2495	0	1	3,653	0.1247	0.2500	3,562	0.1230	0.2490
<i>White</i>	7,215	0.6562	0.3255	0	1	3,653	0.6565	0.3255	3,562	0.6559	0.3255
Location											
<i>CA</i>	10,718	0.1973	0.3980	0	1	5,419	0.1891	0.3917	5,299	0.2057	0.4042
<i>TX</i>	10,718	0.1161	0.3203	0	1	5,419	0.1161	0.3203	5,299	0.1161	0.3203
<i>NY</i>	10,718	0.0923	0.2894	0	1	5,419	0.0987	0.2983	5,299	0.0857	0.2799
<i>FL</i>	10,718	0.0704	0.2559	0	1	5,419	0.0692	0.2538	5,299	0.0717	0.2580
<i>Others</i>	10,718	0.5239	0.4995	0	1	5,419	0.5268	0.4993	5,299	0.5209	0.4996
Interested role											
<i>Engineering</i>	10,718	0.3585	0.4796	0	1	5,419	0.3659	0.4817	5,299	0.3508	0.4773

Note. For work experience, gender, and race/ethnicity, the number of observations are smaller due to missing data or the limitations of prediction algorithms.

Table 2 Summary statistics.

location (measured at the U.S. state level), and whether the job seeker indicated interest in engineering rather than sales roles on the online job search platform (*Engineering_i*).⁴

4.3 Summary statistics and randomization balance

Table 2 presents summary statistics. Among 10,718 job seekers who successfully received our recruitment email, 6.75% expressed interest by clicking the hyperlink to the partner company’s application webpage, and 1.69% submitted an application. In terms of educational attainment, 20.55% did not hold a bachelor’s degree, while 60.60% earned a bachelor’s degree and 18.85% held a graduate degree as their highest level of education. In turn, summary statistics by treatment condition reveal that differences between treated and control groups are statistically indistinguishable from zero, suggesting that the randomization procedure was successful.

⁴Because only 5,961 job seekers in our sample self-reported their desired annual salary on the online job search platform, we employed machine learning algorithms to impute values for the remaining 4,757 individuals. Using educational attainment and other individual attributes described in Section 4.2 as input features, these algorithms were trained on self-reported desired salaries from a broader sample of 444,028 job seekers on the same platform. In addition, as information on gender and race/ethnicity was not available, we inferred these attributes from individuals’ names using Python’s `gender_guesser` and `ethnicolr` libraries, respectively.

4.4 Estimation

We assess the effect of emphasizing autonomy in startup recruitment on job seekers' attraction using the following specification:

$$Attraction_i = \beta_0 + \beta_1 Autonomy_i + \varepsilon_i \quad (1)$$

where $Attraction_i$ stands for one of the two outcome variables (i.e., $Click_i$ or $Apply_i$). β_1 represents the average treatment effect, while β_0 and ε_i are the intercept and the random error term, respectively.

To examine heterogeneity with respect to candidate quality, we extend our analysis in two ways. First, we estimate Equation 1 on subsamples stratified by educational attainment. Second, to test for differences between educational groups, we estimate a fully specified interaction model:

$$\begin{aligned} Attraction_i = & \beta_0 + \beta_1 Autonomy_i + \beta_2 Non-bachelor_i + \beta_3 Graduate_i \\ & + \beta_4 Autonomy_i \times Non-bachelor_i + \beta_5 Autonomy_i \times Graduate_i + \varepsilon_i \end{aligned} \quad (2)$$

where the baseline group is job seekers with a bachelor's degree. The coefficients on the interaction terms, β_4 and β_5 , capture the differential treatment effects for candidates with a non-bachelor's degree and a graduate degree, respectively, relative to this baseline. All equations are estimated as linear probability models with robust standard errors.

4.5 Main results

The results are displayed in Figure 5 (and reported in Table B1 in Appendix Appendix B). We first estimate Equation 1 on the full sample to assess the average treatment effect of emphasizing autonomy on job seekers' attraction, as measured by the likelihood of clicking the hyperlink to the partner company's application webpage ($Click$). As shown in panel (a) (and Model 1 of Table B1), the estimated average treatment effect is small, negative, and statistically indistinguishable from zero ($\hat{\beta} = -0.0011$, $p = .8205$). Hence, we do not find evidence to suggest that emphasizing autonomy in startup recruitment increases the size of the applicant pool.

This estimated null effect may reflect two distinct possibilities. One possibility is a true null effect—namely, our treatment had no substantive impact on the behavior of the target population. Notably, job seekers in our sample had already indicated interest in startup employment by joining the online job search platform designed specifically for startup employment opportunities. If these candidates already hold strong priors that startups generally offer autonomous work environments

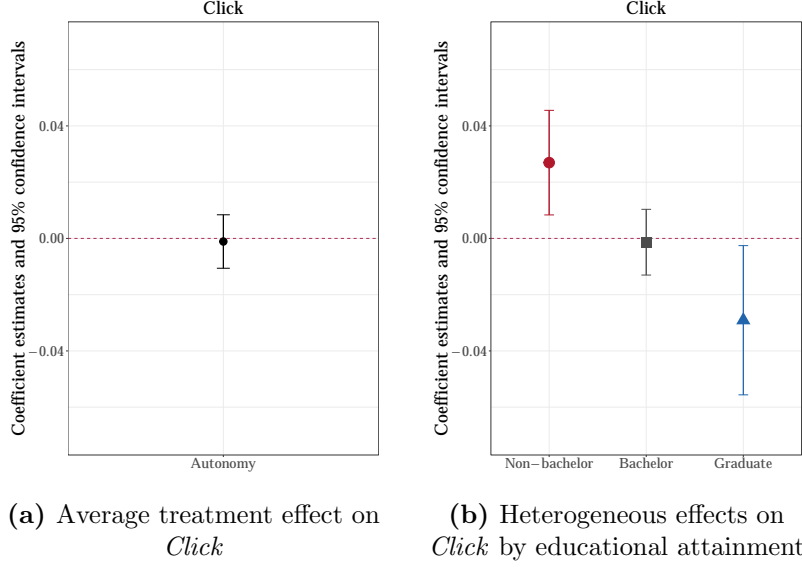


Figure 5 Main results: The effects of emphasizing autonomy in a startup’s recruitment efforts on job seekers’ attraction, as measured by their likelihood of clicking the hyperlink to the partner company’s application webpage (*Click*).

or are already aware that our partner startup emphasizes autonomy in its recruitment materials, the treatment may have conveyed little incremental informational value, thereby exerting minimal influence on their job-seeking behavior. An alternative possibility is that the observed null effect masks meaningful underlying heterogeneity. Specifically, the treatment may have indeed shaped job seekers’ attraction but elicited offsetting responses across subgroups: increasing interest among less educated candidates while deterring more educated ones. These countervailing responses may manifest as a statistically null effect in aggregate, even though the underlying treatment heterogeneity is theoretically and economically significant.

To investigate this potential heterogeneity, we estimate Equation 1 on subsamples stratified by educational attainment. The results, depicted in panel (b) (and detailed in Models 2 to 5 of Table B1), reveal a stark divergence across educational groups. For job seekers without a bachelor’s degree (*Non-bachelor*), emphasizing autonomy significantly enhances attraction by 2.69 percentage points ($p = .0045$), representing a 51.53% increase relative to their baseline click rate of 5.22%. In contrast, for bachelor’s degree holders (*Bachelor*), the treatment effect is negligible and statistically insignificant ($\hat{\beta} = -0.0013$, $p = .8218$). Most notably, among individuals with a graduate degree (*Graduate*), the treatment acts as a significant deterrent, reducing attraction by 2.91 percentage points ($p = .0317$), which corresponds to a 27.98% decrease from their baseline click rate of 10.40%.

To formally assess whether these differences are statistically meaningful, we employ Equation 2, a fully specified interaction model where job seekers with a bachelor’s degree serve as the reference group. The results, presented in Model 6 of Table B1, indicate that, compared to this baseline group, individuals without a bachelor’s degree (*Non-bachelor*) are 2.83 percentage points more likely to express interest in the treatment condition than in the control condition ($p = .0115$). Conversely, individuals holding a graduate degree (*Graduate*) are 2.77 percentage points less likely to show interest in the treatment condition than in the control condition ($p = .0605$).

These heterogeneous effects translate into material shifts in the composition of the interested candidate pool. Among individuals who expressed interest in the control condition, those without a bachelor’s degree accounted for 11.65% (43 out of 369). In the treatment condition, this proportion rose to 20.28% (72 out of 355)—a relative increase of 74.05%. In contrast, while graduate degree holders comprised 33.33% (123 out of 369) among all interested candidates in the control condition, their representation in the treatment condition declined to 24.51% (87 out of 355)—a relative decrease of 26.48%.

Overall, these results demonstrate that emphasizing autonomy in startup recruitment may lower the average quality of interested candidates by attracting less educated individuals while deterring more educated ones. This pattern of adverse selection poses a fundamental challenge in entrepreneurial talent acquisition—one that has remained underexplored in prior research due to its predominant focus on post-application populations (i.e., current employees at startups).

4.6 Exploratory analyses

4.6.1 Using the alternative outcome measure based on job applications

As discussed in Section 4.2, the pre-registered click-through measure (*Click*) may serve as an imperfect proxy. To address this potential measurement concern, we analyze an alternative, exploratory outcome based on actual application behavior (*Apply*). The results based on this alternative outcome measure are reported in Figure 6 (and Table B2 in Appendix Appendix B).

First, panel (a) confirms that emphasizing autonomy in startup recruitment has a precise null effect on the size of the applicant pool. Consistent with our primary analysis, the estimated effect is small, negative, and statistically indistinguishable from zero ($\hat{\beta} = -0.0013$, $p = .6010$).

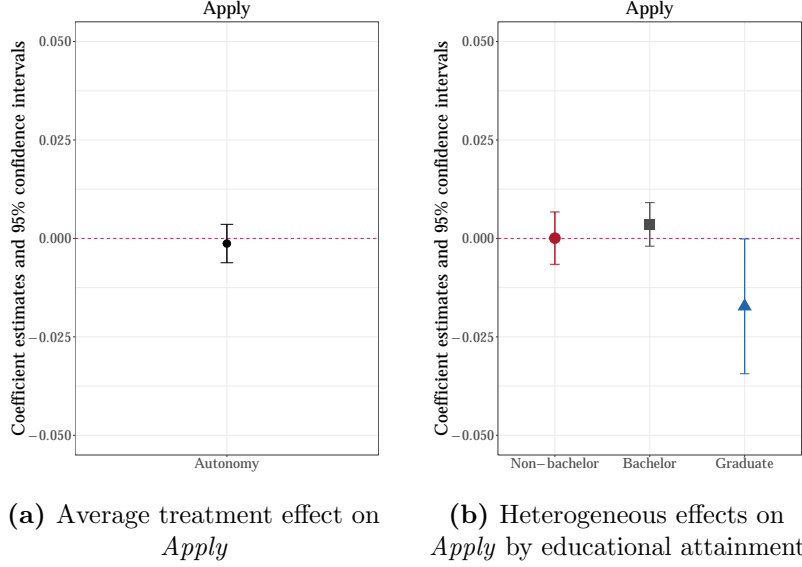


Figure 6 Exploratory analyses: (1) Using an alternative, exploratory outcome measure of *Apply*, which indicates whether a subject submitted an application.

More importantly, the heterogeneous effects displayed in panel (b) largely align with our pre-registered analysis using the click-through measure. Among bachelor’s degree holders (*Bachelor*), the estimated effect remains negligible ($\hat{\beta} = 0.0036$, $p = .2072$). Among those with a graduate degree (*Graduate*), the deterrent effect persists. Specifically, the emphasis on autonomy reduces their likelihood of applying by 1.72 percentage points ($p = .0482$), representing a 42.36% decrease from the baseline application rate of 4.06%. This effect is reflected in the composition of the applicant pool. Graduate degree holders comprised 53.68% (51 out of 95) of applicants in the control condition but only 36.05% (31 out of 86) in the treatment condition—a relative decrease of 32.85%.

However, while the click-through analysis revealed a significant positive treatment effect among job seekers without a bachelor’s degree (*Non-bachelor*), the application-based outcome yields a precise null effect for this group ($\hat{\beta} = 0.0001$, $p = .9823$). We attribute this divergence to additional information presented on the partner company’s application webpage but not included in our recruitment emails. As described in Section 4.2, the “Nice to have” section of the application webpage listed optional qualifications, including “A bachelor’s degree in [relevant majors] from a top institution.” This post-treatment information likely discouraged job seekers without a bachelor’s degree from completing their applications, even though the emphasis on autonomy in the recruitment email initially piqued their interest in the partner company.

In sum, across both the primary behavioral indicator (i.e., click-through) and the downstream

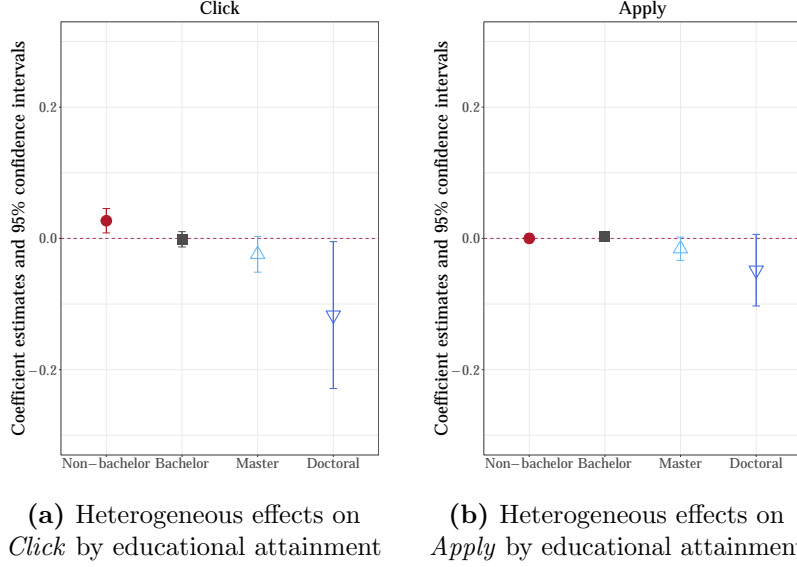


Figure 7 Exploratory analyses: (2) Disaggregating job seekers with a graduate degree into individuals holding a master’s degree and those holding a doctoral degree. Panel (a) presents the results based on the pre-registered outcome measure *Click*, while panel (b) displays the results based on the alternative, exploratory measure *Apply*.

consequential outcome (i.e., job application), our findings suggest that explicitly emphasizing autonomy in startup recruitment can degrade the quality of the applicant pool.

4.6.2 Disaggregating job seekers with a graduate degree

To further explore how the effect of emphasizing autonomy varies across types of graduate degrees, we disaggregate the graduate category and re-estimate Equation 1 separately for the 1,913 individuals holding a master’s degree and the 107 individuals holding a doctoral degree. The results of these more granular exploratory analyses are presented in Figure 7 (and Table B3 in Appendix Appendix B). Because doctoral degree holders represent only approximately 1% of our sample, we interpret these non-pre-registered results as suggestive rather than conclusive.

First, panel (a) shows that, while emphasizing autonomy reduces interest among both master’s and doctoral degree holders, the deterrent effect is substantively more pronounced for the latter. Specifically, this emphasis reduces the likelihood of click-through among master’s degree holders by 2.42 percentage points ($p = .0817$), representing a 23.38% decline relative to their baseline click rate of 10.35%. Among doctoral degree holders, the estimated reduction is 11.68 percentage points ($p = .0409$), corresponding to a 104.19% decrease relative to their baseline click rate of 11.21%. These effects are also reflected in the pool of interested job seekers. The share of master’s degree

holders among interested candidates fell from 30.62% (113 out of 369) in the control condition to 23.94% (85 out of 355) in the treatment condition—a relative decline of 21.81%. More strikingly, the proportion of doctoral degree holders plummeted from 2.71% (10 out of 369) in the control condition to just 0.56% (2 out of 355) in the treatment condition—a 79.21% relative decrease.

A similar pattern emerges in actual application behavior, as shown in panel (b). Among master’s degree holders, the treatment reduces the likelihood of applying by 1.58 percentage points ($p = .0822$), which represents a 38.26% decrease from their baseline application rate of 4.13%. The deterrent effect is again more pronounced for doctoral degree holders, with an estimated reduction of 4.84 percentage points ($p = .0815$)—a 172.86% decline relative to their baseline application rate of 2.80%. These shifts also manifest in the applicant pool. The share of master’s degree holders among all applicants fell from 50.53% (48 out of 95) in the control condition to 36.05% (31 out of 86) in the treatment condition—a relative decrease of 28.66%. More notably, doctoral degree holders, who represented 3.16% (3 out of 95) of applicants in the control condition, were absent (0 out of 86) from the applicant pool in the treatment condition—a complete (100%) elimination.

Although these disaggregated results were not pre-registered, they suggest that the deterrent effect of emphasizing autonomy in startup recruitment is disproportionately concentrated among the most highly educated candidates, specifically those with doctoral degrees.

4.7 Supplementary analyses

Examining alternative proxies for quality: While educational attainment offers a well-ordered, interpretable, and theoretically grounded proxy for cognitive ability (as discussed in Section 4.2), prior research has employed a range of alternative indicators to capture candidate quality (e.g., Bidwell 2011, DeVaro and Waldman 2012, Elfenbein et al. 2010, Hsu and Tambe 2025, Lee and Csaszar 2020). These measures include whether an individual earned a bachelor’s degree from an elite institution (*Top University*), whether they hold a managerial position at their current employer (*Manager*), their years of work experience (*Work Experience*), and their desired annual salary (*Desired Salary*). As pre-registered, we examine heterogeneity in treatment effects using these alternative proxies and report the results in Table B4 in Appendix Appendix B.

Interestingly, across both outcomes (i.e., *Click* and *Apply*), the interaction coefficients between the treatment and these alternative proxies are substantively modest and statistically indistinguish-

able from zero (at least $p > .1980$). We interpret these null findings *ex post* as potentially providing further support for our theoretical reasoning that the observed adverse selection is driven by educational attainment, rather than by other dimensions of candidate quality captured by these alternative measures. For instance, attending an elite university may reflect socioeconomic background or personality traits (Borghans et al. 2016, Breen and Jonsson 2007, Coleman 1988, Spence 1973). Managerial status often captures non-cognitive ability, particularly leadership and interpersonal skills (Adams et al. 2018, Benson et al. 2019). Years of work experience can conflate chronological age, job tenure, and preferences for employment stability (Lazear 1976, Lorence and Mortimer 1985, Williams 1991). Desired annual salary is heavily influenced by self-perception, negotiation style, and labor market positioning (Leibbrandt and List 2015, Raiffa 1985), as evidenced by the prevalence of missing or implausible extreme values (e.g., \$0 or more than \$10 million) self-reported on the online job search platform. The absence of treatment heterogeneity along these alternative proxies may, therefore, imply that the observed adverse selection induced by autonomy-oriented language in startup recruitment could specifically be education-contingent.

Controlling for demographic characteristics: Although the summary statistics by treatment condition in Table 2 suggest a successful randomization, the observed effects might be influenced by demographic characteristics that correlate with educational attainment. To address this potential concern, we re-estimate our models while controlling for the full set of observable individual-level attributes described in Section 4.2. As reported in Table B5 in Appendix Appendix B, the results remain robust with tighter 95% confidence intervals across both outcome measures, *Click* and *Apply*.

Using alternative model specifications: To verify that our findings are robust to alternative model specifications, we replicate our analyses using logistic regressions, instead of linear probability models. As shown in Table B6 in Appendix Appendix B, the direction, statistical significance, and economic magnitude of the coefficient estimates all remain consistent across both outcome measures.

5 Post hoc theorizing

Taken together, our field evidence reveals a counterintuitive pattern: an explicit emphasis on autonomy in startup recruitment attracts less educated candidates while simultaneously deterring more educated counterparts. This finding is striking given robust empirical evidence that workers—

especially those with higher education—value autonomy (e.g., Roach and Sauermann 2010, 2024, Stern 2004), as discussed in Section 2.3. Given these well-documented preferences, we do not attribute the observed adverse selection to differences in underlying taste for autonomy itself.

We first consider a potential methodological explanation rooted in our pure-control experimental design. As detailed in Section 4.1, a mechanical consequence of this design is a marginal increase in email length in the treatment condition relative to the control condition. However, for this potential confound to account for our main findings, its effects would have to operate in a highly asymmetric and opposing manner across educational strata. Specifically, the additional text would need to exert a substantially positive effect on candidates without a bachelor’s degree, a negligible effect on bachelor’s degree holders, and a strongly negative effect on graduate degree holders. While we cannot definitively rule out this possibility, we view such heterogeneous sensitivity to minor variations in email length as an unlikely primary driver of the observed behavioral divergence.

We instead posit a more theoretically grounded explanation: the observed behavioral divergence may stem from systematic, education-contingent differences in interpretation. The central premise of this reasoning is that a high degree of autonomy constitutes a baseline expectation in startup contexts (Knight et al. 2020, Lee 2022, Roach and Sauermann 2024, Sorenson et al. 2021). When employers explicitly highlight an attribute that job seekers already anticipate, the message becomes informationally redundant and invites second-order inference: why would an employer emphasize the obvious? This interpretive process may manifest through mechanisms related to the nature of the work, the organizational structure, the incentive system, and the employer’s credibility.

First, with respect to the nature of the work, more educated individuals may infer a misalignment between the job’s requirements and their human capital. Through extensive formal education, individuals accumulate specialized human capital concentrated within narrow domains of expertise (Becker 1964). These candidates may interpret an explicit emphasis on autonomy not as professional freedom, but as an indicator of loosely scoped work that demands broad generalist capabilities (Morgeson et al. 2005). This interpretation implies a potential mismatch between the specialized human capital they have accumulated and the general human capital required for highly autonomous work. Such anticipated misfit may raise concerns about inefficient allocation of expertise (Dahlander 2022) and suboptimal deployment of time (Mazmanian et al. 2013).

Second, more educated individuals may draw negative inferences about the employer’s organiza-

tional structure. Given that autonomy is already a baseline expectation in startup contexts (Knight et al. 2020, Lee 2022, Roach and Sauermann 2024, Sorenson et al. 2021), these individuals—many of whom have been socialized in highly autonomous academic environments—may interpret its explicit emphasis as implying an excessive degree of autonomy. This perceived extreme may be construed as “too much of a good thing,” symptomatic of underlying organizational dysfunction, including ambiguous role definitions (Lee and Kim 2024:1645, Sorenson et al. 2021:589, Stinchcombe 1965), insufficient managerial supervision (Hurst et al. 2024, Langfred 2004, Lee 2022), and unclear performance evaluation criteria (Prendergast 1999). For candidates who have made substantial irreversible investments in their human capital (Becker 1962, Schultz 1961), these structural deficiencies may not only heighten the perceived risk of startup failure but also create uncertainty around stable career progression (Hurst et al. 2024, Lee 2022).

Third, as for the incentive system, more educated job seekers may perceive the explicit emphasis on autonomy as a compensating differential—a non-pecuniary benefit offered in lieu of competitive pecuniary compensation. This interpretation may trigger concerns about inadequate recognition and reward for their contributions. Cognizant of the value they can bring and command, these candidates may instead seek more structured environments where their efforts are more likely to be properly identified, evaluated, and remunerated (Campbell et al. 2012a, Card et al. 2018, Lazear 2000). Alternatively, rather than accepting potentially undercompensated employment, they may opt to found their own venture to fully reap the returns on their specialized human capital (Agarwal and Ohyama 2013, Roach and Sauermann 2024, Stuart and Ding 2006).

Lastly, regarding the employer’s credibility, more educated individuals may construe the redundant emphasis as “cheap talk”—a costless claim that any startup can make, regardless of its actual organizational practices. Because such a claim entails negligible cost and conveys no individuating information, it invites second-order inference. More educated candidates, who are better equipped through formal education to engage in such inferential reasoning (Berry et al. 2006, Heckman et al. 2006, Neisser et al. 1996), may look beyond what the emphasis directly communicates to deduce what its presence implies and question its veracity. This skepticism may generalize, leading these candidates to infer broader deficiencies in organizational transparency or strategic clarity. Consequently, the explicit emphasis on autonomy may function as a negative diagnostic signal, prompting a broader devaluation of the employer’s overall credibility and attractiveness.

In summary, although autonomy remains broadly valued across educational levels, its explicit emphasis in startup recruitment may invite education-contingent interpretation. Specifically, more educated candidates may interpret the same informational cue with greater sophistication and skepticism, potentially perceiving it as (1) a marker of generalist work misaligned with their specialized human capital, (2) a sign of organizational dysfunction stemming from excessive autonomy, (3) a compensating differential substituting for inadequate pecuniary compensation, or (4) a “cheap talk” that undermines employer credibility. These negative interpretations—whether individually or jointly—may contribute to the observed adverse selection pattern.

6 Discussion

Early joiners play a critical role in the growth and long-term success of entrepreneurial ventures. Our descriptive analysis of job postings reveals that early-stage startups are increasingly emphasizing autonomy in their recruitment efforts, especially when targeting more educated job seekers. However, our field experiment conducted in collaboration with a U.S.-based high-tech startup demonstrates that explicitly emphasizing this non-pecuniary attribute may inadvertently induce adverse selection by attracting less educated candidates while deterring more educated individuals. Given the robust empirical evidence that workers—especially those with higher education—value autonomy at work (e.g., Roach and Sauermann 2010, 2024, Stern 2004), we propose that this pattern of results is likely driven by education-contingent differences in interpretation about the nature of work, the organizational structure, the incentive system, and the employer’s credibility. Below, we elaborate on the theoretical and practical implications of these findings.

6.1 Theoretical contributions

6.1.1 Entrepreneurship

First, we contribute to entrepreneurship research by uncovering a hidden adverse selection dynamic in early-stage startups’ human capital acquisition. While prior work has predominantly centered on founders (e.g., Carnahan 2017, Eisenhardt and Schoonhoven 1990, Hegde and Tumlinson 2021, Lee et al. 2024, Shah et al. 2019), a growing body of work highlights the critical role of early joiners—non-founder employees who join startups during their formative stages—in shaping venture

growth and performance (Choi et al. 2023, Roach and Sauermann 2024). This body of work shows that early joiners, like founders, exhibit a strong preference for autonomy (Elfenbein et al. 2010, Gambardella et al. 2020, Roach and Sauermann 2015, Stern 2004), often forgoing traditional pecuniary rewards (e.g., higher salaries) and other non-pecuniary benefits (e.g., organizational prestige or status) in exchange for this non-pecuniary attribute.

These documented preferences suggest that startups may attract high-ability early joiners by strategically emphasizing autonomy—a distinctive non-pecuniary attribute that sets new ventures apart from established firms (Knight et al. 2020, Lee 2022, Roach and Sauermann 2024, Sorenson et al. 2021, Stinchcombe 1965). Consistent with this intuition, our descriptive analysis reveals that early-stage startups, particularly in high-tech sectors, are increasingly using autonomy-oriented language, especially when targeting more educated job seekers. However, this seemingly rational recruitment strategy is grounded in the observed preferences of individuals who founded or have already joined startups (Roach and Sauermann 2015), thus overlooking a critical antecedent in the recruitment funnel: the initial decision to apply. As a result, this strategy may fail to account for job seekers who may be valuable to startups but self-select out of the application process.

Our study addresses this gap through a pre-registered natural field experiment that captures job-seeking behavior at the earliest stage of the recruitment process. The findings reveal that an explicit emphasis on autonomy in startup recruitment may, in fact, backfire—inadvertently inducing adverse selection within the applicant pool. Specifically, this emphasis disproportionately attracts less educated job seekers while deterring more educated candidates. This counterintuitive result suggests that, despite its broad appeal (Elfenbein et al. 2010, Puranam 2018:125, Roach and Sauermann 2015, Sauermann 2018, Stern 2004), autonomy may produce outcomes directly opposite to strategic intentions when prominently highlighted in startup recruitment. More broadly, our findings underscore that startup recruitment strategies informed by the preferences of post-application samples (e.g., offer holders or current employees) may be detrimental to startups, as they fail to capture the behavior of job seekers who opt out of the recruitment process before applying.

6.1.2 Human capital

Second, our research extends the literature on human capital by identifying strategic external communication as a critical mechanism through which firms compete for talent. A foundational

premise of this literature is that a firm’s competitive advantage hinges on its ability to acquire, organize, and retain human capital (Barney 1991, Campbell et al. 2012a, Coff 1997). While prior work has largely focused on how employers align internal organizational attributes with worker preferences to retain existing employees (e.g., Bode et al. 2015, Campbell et al. 2012b, Carnahan et al. 2012, Kryscynski 2021), more recent research has turned toward how employers externally communicate these attributes to attract prospective applicants (e.g., Flory et al. 2021, Hsu and Tambe 2025, Hurst and Lee 2024, Snellman and Younkin 2021, Teng et al. 2025). This emerging stream of work reveals that even well-intentioned or seemingly positive recruitment messages can inadvertently repel the very talent they are designed to attract. For instance, explicit non-discrimination statements can discourage job seekers of color (Leibbrandt and List 2018), while highlighting egalitarian structures can deter female applicants (Hurst et al. 2024). Our study contributes to this line of inquiry by demonstrating that these complex sorting dynamics extend beyond identity-based considerations (e.g., race, gender) to encompass core individual capabilities (e.g., educational attainment).

Specifically, we introduce a broader theoretical principle of education-contingent organizational messaging, which posits that the effectiveness of organizational recruitment messages depends systematically on the cognitive abilities of the target audience. More educated individuals, equipped with greater capacity for critical thinking, inferential reasoning, and creative problem-solving (Gottfredson 1997:13, Neisser et al. 1996:77, O’Reilly and Chatman 1994:603), are more likely to engage in second-order reasoning when interpreting recruitment messages. That is, they may not only evaluate what the informational cue explicitly conveys but also make sophisticated inferences about what the cue implies *ex ante* unobservable organizational characteristics. This deeper level of interpretation, while advantageous for organizational performance, may create challenges in recruitment. Recruitment messages intended to convey positive attributes—such as autonomy—may be interpreted by more educated candidates as signals of employer credibility deficits, human capital mismatch, organizational dysfunction, or compensating differentials for below-market pecuniary benefits, leading them to self-select out of the applicant pool.

This differential interpretation, which has been largely overlooked in prior research, underscores the importance of accounting for the cognitive heterogeneity of prospective job seekers when designing recruitment strategies. The principle of education-contingent organizational messaging suggests that effective human capital acquisition strategies should move beyond simplistic models of aligning

organizational attributes with worker preferences. Instead, these strategies should adopt a more targeted, audience-specific approach that reflects how prospective candidates may interpret these attributes differently through the lens of their cognitive abilities. Tailoring recruitment strategies to account for the interpretive frameworks of different cognitive segments can help employers more effectively attract the talent most essential to firm performance, particularly in dynamic and complex organizational settings such as early-stage ventures.

6.1.3 Organizational design

Lastly, we advance the literature on organizational design by demonstrating that communicating organizational structure constitutes a distinct strategic decision—one with implications that extend beyond the internal architecture of the organization. This literature has traditionally focused on the internal functionality of structural choices, building on Simon’s (1947) foundational insight that organizations must accommodate the bounded cognitive abilities of their current employees. From this perspective, effective organizational design involves setting clear decision boundaries by decomposing complex tasks into manageable subtasks and allocating them across employees to facilitate coordination and manage interdependence (Burton and Obel 2004, Joseph and Gaba 2020, Joseph and Sengul 2025, Puranam 2018). However, a growing body of research has challenged the efficacy of such conventional “bureaucratic” approach, arguing that restricting employee discretion can stifle critical thinking, inferential reasoning, and creative problem-solving (Amabile et al. 1996, Keum and See 2017, Lee 2022). This evolving perspective has led to increased interest in more autonomous organizational forms, which grant employees greater decision-making authority and operate with less hierarchical oversight (Reineke et al. 2025).

By shifting the analytical focus from existing employees to prospective applicants, our study uncovers an underexplored strategic dimension of organizational design: the external communication of structural choices. Structural attributes such as autonomy—while highly valued by current employees for its intrinsic and instrumental value (Bartling et al. 2014, Deci and Ryan 1985, Deci et al. 2017, Hackman and Oldham 1976)—may produce adverse consequences when explicitly communicated during recruitment. These unintended effects may arise because job seekers with different cognitive abilities may interpret the same structural attributes in divergent ways.

Our findings suggest that the effectiveness of organizational design choices operates not only

through *internal* coordination mechanisms among current employees but also through *external* sorting mechanisms among prospective applicants. This dual function underscores the need for a more nuanced perspective on organizational design—one that considers both how structural choices function internally within the organization and how they are interpreted externally in the labor market. Organizations should, therefore, align internal structural choices with external recruitment strategies. When not carefully calibrated to the cognitive abilities and interpretive frameworks of potential hires, well-intended recruitment messages about these organizational design choices may inadvertently repel, rather than attract, the very talent critical to organizational success.

6.2 Practical implications

Our study carries important practical implications for entrepreneurs navigating the challenges of early-stage talent acquisition. As startups typically encounter substantial resource constraints, they often seek to attract talent by strategically leveraging distinctive non-pecuniary organizational attributes—notably, autonomy—that differentiate themselves from established firms in the labor market. In this context, autonomy functions not only as an internal management practice but also as a form of external recruitment communication aimed at shaping how prospective applicants perceive the organization. However, our findings suggest that making autonomy salient in startup recruitment warrants greater strategic nuance.

The central managerial insight from our findings is that a prominent emphasis on autonomy is not a one-size-fits-all solution in startup recruitment. While autonomy is broadly appealing in theory, its explicit promotion can backfire—inadvertently attracting less educated job seekers while deterring more educated candidates. This adverse selection imposes two distinct costs. The first is an *observable* screening cost: an over-representation of less educated applicants increases the burden on hiring managers—already stretched in resource-constrained environments—to sift through a larger, lower-quality pool to identify qualified candidates. The second, and more insidious, cost is an *unobservable* opportunity cost: hiring managers may remain entirely unaware of the more educated job seekers who never applied, having been repelled by the autonomy-related language.

The solution, therefore, lies in carefully calibrating how autonomy is communicated to prospective applicants. Our findings point to two potential recruitment strategies. The first, somewhat counterintuitive, approach involves *externally* de-emphasizing autonomy in recruitment materials to

potential candidates while *internally* fostering an autonomous work environment for current employees. A second, more balanced approach entails communicating *structured* autonomy. Specifically, if a startup chooses to emphasize autonomy in its recruitment efforts, it may pair this emphasis with clear assurances of (1) robust organizational infrastructure, including clear role definitions, accessible managerial guidance, transparent performance evaluation criteria, and developmental support systems, and (2) competitive pecuniary compensation that reflects market value rather than positioning autonomy as a compensating differential. This more nuanced and contextualized communication may help more educated candidates interpret autonomy not as a negative diagnostic signal, but as a marker of meaningful empowerment, thus preserving its appeal without incurring the costs of adverse selection. Ultimately, effective startup recruitment requires not just knowing which organizational attributes to communicate but also understanding how different candidates will interpret these attributes.

6.3 Limitations and future research

Like all research, this study has limitations that open promising avenues for future inquiry. First, although our field experiment provides greater external validity compared to typical laboratory or survey studies, it was conducted in partnership with a single startup operating in a high-tech sector—an industry where autonomy-oriented language is prevalent in recruitment materials. Furthermore, given that startups are particularly inclined to emphasize autonomy when hiring for engineering and sales positions, the experiment focused on these two occupations. Future research could enhance the generalizability of our findings or clarify their boundary conditions by replicating the study across a broader set of startup jobs and industries. Second, while our field experiment identifies a causal effect, its design provides limited insight into the precise mechanisms underlying the observed patterns (Chatterji et al. 2016). Future studies could complement our findings by employing controlled laboratory or survey experiments that directly manipulate and isolate the proposed mechanisms. Second, although we propose a set of potential mechanisms through which emphasizing autonomy may influence a startup’s applicant pool, our study is not exhaustive in its exploration of alternative explanations. Future studies could build on this work by identifying and testing additional psychological or contextual mechanisms that shape job seekers’ responses to the emphasis on autonomy in startups’ recruitment efforts. Lastly, our study focuses on the

startup context, where autonomy serves as a differentiating organizational attribute commonly emphasized in recruitment. The effects we document in this setting might not generalize—and could even reverse—in the context of established firms, where clear organizational structures, evaluation metrics, and career paths are presumed to exist. For these firms, autonomy-related language may be interpreted as a sign of empowerment and trust, thereby attracting more educated candidates seeking to make an impact within a stable work environment. Future research could examine such potential differences across diverse organizational contexts.

6.4 Conclusion

In conclusion, our study offers a cautionary insight for entrepreneurs navigating the challenges of early-stage talent acquisition. While autonomy is widely regarded as a desirable organizational attribute—particularly valued by founders and early joiners at startups—explicitly emphasizing this attribute in startup recruitment may have unintended consequences. In particular, this emphasis may trigger adverse selection by disproportionately attracting less educated applicants while deterring the more educated candidates. These findings highlight the importance of understanding how diverse audiences perceive recruitment messages. We hope this research lays the groundwork for future inquiry into the complex dynamics of human capital acquisition in entrepreneurial contexts and the strategic tradeoffs involved in communicating organizational attributes to prospective talent.

References

- Adams, R., M. Keloharju, S. Knüpfer. 2018. Are CEOs born leaders? Lessons from traits of a million individuals. *Journal of Financial Economics* **130**(2) 392–408.
- Agarwal, R., A. Ohyama. 2013. Industry or academia, basic or applied? Career choices and earnings trajectories of scientists. *Management Science* **59**(4) 950–970.
- Alexy, O., K. Poetz, P. Puranam, M. Reitzig. 2021. Adaptation or persistence? Emergence and revision of organization designs in new ventures. *Organization Science* **32**(6) 1439–1472.
- Amabile, T. M., R. Conti, H. Coon, J. Lazenby, M. Herron. 1996. Assessing the work environment for creativity. *Academy of Management Journal* **39**(5) 1154–1184.
- Andersson, F., M. Freedman, J. Haltiwanger, J. Lane, K. Shaw. 2009. Reaching for the stars: Who pays for talent in innovative industries? *Economic Journal* **119**(538) 308–332.
- Arcidiacono, P., P. Bayer, A. Hizmo. 2010. Beyond signaling and human capital: Education and the revelation of ability. *American Economic Journal: Applied Economics* **2**(4) 76–104.
- Arrow, K. J. 1973. Higher education as a filter. *Journal of Public Economics* **2**(3) 193–216.
- Baard, P. P., E. L. Deci, R. M. Ryan. 2004. Intrinsic need satisfaction: A motivational basis of performance and well-being in two work settings. *Journal of Applied Social Psychology* **34**(10) 2045–2068.
- Baker, T., R. E. Nelson. 2005. Creating something from nothing: Resource construction through entrepreneurial bricolage. *Administrative Science Quarterly* **50**(3) 329–366.
- Barney, J. 1991. Firm resources and sustained competitive advantage. *Journal of Management* **17**(1) 99–120.
- Baron, J. N., M. T. Hannan. 2002. Organizational blueprints for success in high-tech start-ups: Lessons from the Stanford Project on Emerging Companies. *California Management Review* **44**(3) 8–36.
- Bartling, B., E. Fehr, H. Herz. 2014. The intrinsic value of decision rights. *Econometrica* **82**(6) 2005–2039.
- Becker, G. S. 1962. Investment in human capital: A theoretical analysis. *Journal of Political Economy* **70**(5) 9–49.
- Becker, G. S. 1964. *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. Columbia University Press, New York.
- Benson, A., D. Li, K. Shue. 2019. Promotions and the Peter principle. *Quarterly Journal of Economics* **134**(4) 2085–2134.
- Berry, C. M., M. L. Gruys, P. R. Sackett. 2006. Educational attainment as a proxy for cognitive ability in selection: Effects on levels of cognitive ability and adverse impact. *Journal of Applied Psychology* **91**(3) 696–705.
- Bidwell, M. 2011. Paying more to get less: The effects of external hiring versus internal mobility. *Administrative Science Quarterly* **56**(3) 369–407.
- Bode, C., J. Singh, M. Rogan. 2015. Corporate social initiatives and employee retention. *Organization Science* **26**(6) 1702–1720.
- Borghans, L., B. H. H. Golsteyn, J. J. Heckman, J. E. Humphries. 2016. What grades and achievement tests measure. *Proceedings of the National Academy of Sciences* **113**(47) 13354–13359.
- Boss, V., L. Dahlander, C. Ihl, R. Jayaraman. 2023. Organizing entrepreneurial teams: A field experiment on autonomy over choosing teams and ideas. *Organization Science* **34**(6) 2097–2118.
- Breen, R., J. O. Jonsson. 2007. Explaining change in social fluidity: Educational equalization and educational expansion in twentieth-century Sweden. *American Journal of Sociology* **112**(6) 1775–1810.
- Burton, M. D., M. S. Dahl, O. Sorenson. 2018. Do start-ups pay less? *ILR Review* **71**(5) 1179–1200.
- Burton, R. M., B. Obel. 2004. *Strategic Organizational Diagnosis and Design: The Dynamics of Fit*. Springer, Boston, MA.
- Cammeraat, E., M. Squicciarini. 2021. Burning Glass Technologies’ data use in policy-relevant analysis. Retrieved from <https://doi.org/10.1787/cd75c3e7-en>.
- Campbell, B. A., R. Coff, D. Kryscynski. 2012a. Rethinking sustained competitive advantage from human capital. *Academy of Management Review* **37**(3) 376–395.

- Campbell, B. A., M. Ganco, A. M. Franco, R. Agarwal. 2012b. Who leaves, where to, and why worry? Employee mobility, entrepreneurship and effects on source firm performance. *Strategic Management Journal* **33**(1) 65–87.
- Card, D., A. R. Cardoso, J. Heining, P. Kline. 2018. Firms and labor market inequality: Evidence and some theory. *Journal of Labor Economics* **36**(S1) S13–S70.
- Carnahan, S. 2017. Blocked but not tackled: Who founds new firms when rivals dissolve? *Strategic Management Journal* **38**(11) 2189–2212.
- Carnahan, S., R. Agarwal, B. A. Campbell. 2012. Heterogeneity in turnover: The effect of relative compensation dispersion of firms on the mobility and entrepreneurship of extreme performers. *Strategic Management Journal* **33**(12) 1411–1430.
- Castex, G., E. Kogan Dechter. 2014. The changing roles of education and ability in wage determination. *Journal of Labor Economics* **32**(4) 685–710.
- Chatterji, A. K., M. Findley, N. M. Jensen, S. Meier, D. Nielson. 2016. Field experiments in strategy research. *Strategic Management Journal* **37**(1) 116–132.
- Choi, J., S. Lee. 2025. Span of control as a dynamic strategic lever for early-stage firm growth. Retrieved from <https://ssrn.com/abstract=4949699>.
- Choi, J., N. Goldschlag, J. Haltiwanger, J. D. Kim. 2023. Early joiners and startup performance. *Review of Economics and Statistics* 1–46.
- Clough, D. R., T. P. Fang, B. Vissa, A. Wu. 2019. Turning lead into gold: How do entrepreneurs mobilize resources to exploit opportunities? *Academy of Management Annals* **13**(1) 240–271.
- Coff, R. W. 1997. Human assets and management dilemmas: Coping with hazards on the road to resource-based theory. *Academy of Management Review* **22**(2) 374–402.
- Cohen, L., U. Gurun, N. B. Ozel. 2023. Too many managers: The strategic use of titles to avoid overtime payments. Retrieved from <https://nber.org/papers/w30826>.
- Coleman, J. S. 1988. Social capital in the creation of human capital. *American Journal of Sociology* S95–S120.
- Dahl, M. S., S. Klepper. 2017. Whom do new firms hires? *Industrial and Corporate Change* **24**(4).
- Dahlander, L. 2022. The role of autonomy and selection at the gate in flat organizations. *Journal of Organization Design* **11**(1) 27–29.
- Dalle, J.-M., M. den Besten, C. Menon. 2017. Using Crunchbase for economic and managerial research. Retrieved from <https://doi.org/10.1787/6c418d60-en>.
- Deci, E., R. M. Ryan. 1985. *Intrinsic Motivation and Self-Determination in Human Behavior*. Springer, New York.
- Deci, E. L., A. H. Olafsen, R. M. Ryan. 2017. Self-determination theory in work organizations: The state of a science. *Annual Review of Organizational Psychology and Organizational Behavior* **4** 19–43.
- Decker, R., J. Haltiwanger, R. Jarmin, J. Miranda. 2014. The role of entrepreneurship in U.S. job creation and economic dynamism. *Journal of Economic Perspectives* **28**(3) 3–24.
- DeSantola, A., R. Gulati. 2017. Scaling: Organizing and growth in entrepreneurial ventures. *Academy of Management Annals* **11**(2) 640–668.
- DeVaro, J., M. Waldman. 2012. The signaling role of promotions: Further theory and empirical evidence. *Journal of Labor Economics* **30**(1) 91–147.
- Eisenhardt, K. M., C. B. Schoonhoven. 1990. Organizational growth: Linking founding team, strategy, environment, and growth among U.S. semiconductor ventures, 1978–1988. *Administrative Science Quarterly* **35**(3) 504–529.
- Elfenbein, D. W., B. H. Hamilton, T. R. Zenger. 2010. The small firm effect and the entrepreneurial spawning of scientists and engineers. *Management Science* **56**(4) 659–681.
- Engel, Y., T. Lewis, M. S. Cardon, T. Hentschel. 2023. Signaling diversity debt: Startup gender composition and the gender gap in joiners’ interest. *Academy of Management Journal* **66**(5) 1469–1500.
- Flory, J. A., A. Leibbrandt, C. Rott, O. Stoddard. 2021. Increasing workplace diversity: Evidence from a recruiting experiment at a Fortune 500 company. *Journal of Human Resources* **56**(1) 73–92.

- Gagné, M., E. L. Deci. 2005. Self-determination theory and work motivation. *Journal of Organizational Behavior* **26**(4) 331–362.
- Gambardella, A., P. Khashabi, C. Panico. 2020. Managing autonomy in industrial research and development: A project-level investigation. *Organization Science* **31**(1) 165–181.
- Gambardella, A., C. Panico, G. Valentini. 2015. Strategic incentives to human capital. *Strategic Management Journal* **36**(1) 37–52.
- Gandhi, L., A. Kiyawat, C. F. Camerer, D. J. Watts. 2024. Hypothetical nudges provide misleading estimates of real behavior change. Retrieved from <https://doi.org/10.5465/AMPROC.2024.13002abstract>.
- Gottfredson, L. S. 1997. Mainstream science on intelligence: An editorial with 52 signatories, history and bibliography. *Intelligence* **24**(1) 13–23.
- Hackman, J. R., G. R. Oldham. 1976. Motivation through the design of work: Test of a theory. *Organizational Behavior and Human Performance* **16**(2) 250–279.
- Haltiwanger, J., R. S. Jarmin, J. Miranda. 2013. Who creates jobs? Small versus large versus young. *Review of Economics and Statistics* **95**(2) 347–361.
- Hamilton, B. H. 2000. Does entrepreneurship pay? An empirical analysis of the returns to self-employment. *Journal of Political Economy* **108**(3) 604–631.
- Hand, J. R. 2008. Give everyone a prize? Employee stock options in private venture-backed firms. *Journal of Business Venturing* **23**(4) 385–404.
- Hansen, S., P. J. Lambert, N. Bloom, S. J. Davis, R. Sadun, B. Taska. 2023. Remote work across jobs, companies, and space. Retrieved from <https://www.nber.org/papers/w31007>.
- Heckman, J. J., J. Stixrud, S. Urzua. 2006. The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics* **24**(3) 411–482.
- Hegde, D., J. Tumlinson. 2014. Does social proximity enhance business partnerships? Theory and evidence from ethnicity's role in U.S. venture capital. *Management Science* **60**(9) 2355–2380.
- Hegde, D., J. Tumlinson. 2021. Information frictions and entrepreneurship. *Strategic Management Journal* **42**(3) 491–528.
- Hellmann, T., M. Puri. 2002. Venture capital and the professionalization of start-up firms: Empirical evidence. *Journal of Finance* **57**(1) 169–197.
- Hsu, D. H., P. B. Tambe. 2025. Remote work and job applicant diversity: Evidence from technology startups. *Management Science* **71**(1) 595–614.
- Hurst, R. 2023. Countervailing claims: Pro-diversity responses to stigma by association following the Unite the Right Rally. *Administrative Science Quarterly* **68**(4) 1094–1132.
- Hurst, R., S. Lee. 2024. Sociopolitical stance-taking and labor market sorting: Evidence from experiments. Retrieved from <https://ssrn.com/abstract=4846170>.
- Hurst, R., S. Lee, J. Frake. 2024. The effect of flatter hierarchy on applicant pool gender diversity: Evidence from experiments. *Strategic Management Journal* **45**(8) 1446–1484.
- Joseph, J., V. Gaba. 2020. Organizational structure, information processing, and decision-making: A retrospective and road map for research. *Academy of Management Annals* **14**(1) 267–302.
- Joseph, J., M. Sengul. 2025. Organization design: Current insights and future research directions. *Journal of Management* **51**(1) 249–308.
- Keum, D. D., K. E. See. 2017. The influence of hierarchy on idea generation and selection in the innovation process. *Organization Science* **28**(4) 653–669.
- Kim, M. 2018. Hiring through networks and employee performance: Evidence from R&D workers in the semiconductor industry. *Management Science* **64**(11) 5315–5333.
- Klotz, A. C., K. M. Hmieleski, B. H. Bradley, L. W. Busenitz. 2014. New venture teams: A review of the literature and roadmap for future research. *Journal of Management* **40**(1) 226–255.
- Knight, A. P., L. L. Greer, B. De Jong. 2020. Start-up teams: A multidimensional conceptualization, integrative review of past research, and future research agenda. *Academy of Management Annals* **14**(1) 231–266.

- Kruscynski, D. 2021. Firm-specific worker incentives, employee retention, and wage–tenure slopes. *Organization Science* **32**(2) 352–375.
- Langfred, C. W. 2004. Too much of a good thing? Negative effects of high trust and individual autonomy in self-managing teams. *Academy of Management Journal* **47**(3) 385–399.
- Layard, R., G. Psacharopoulos. 1974. The screening hypothesis and the returns to education. *Journal of Political Economy* **82**(5) 985–998.
- Lazear, E. 1976. Age, experience, and wage growth. *American Economic Review* **66**(4) 548–558.
- Lazear, E. P. 2000. Performance pay and productivity. *American Economic Review* **90**(5) 1346–1361.
- Lee, H., S. K. Shah, R. Agarwal. 2024. Spinning an entrepreneurial career: Motivation, attribution, and the development of organizational capabilities. *Strategic Management Journal* **45**(3) 463–506.
- Lee, S. 2022. The myth of the flat start-up: Reconsidering the organizational structure of start-ups. *Strategic Management Journal* **43**(1) 58–92.
- Lee, S., F. A. Csaszar. 2020. Cognitive and structural antecedents of innovation: A large-sample study. *Strategy Science* **5**(2) 71–97.
- Lee, S., J. D. Kim. 2024. When do startups scale? Large-scale evidence from job postings. *Strategic Management Journal* **45**(9) 1633–1669.
- Leibbrandt, A., J. List. 2018. Do equal employment opportunity statements backfire? Evidence from a natural field experiment on job-entry decision. Retrieved from <https://nber.org/papers/w25035>.
- Leibbrandt, A., J. A. List. 2015. Do women avoid salary negotiations? Evidence from a large-scale natural field experiment. *Management Science* **61**(9) 2016–2024.
- Levine, S. S., O. Schilke, O. Kacperczyk, L. G. Zucker. 2023. Primer for experimental methods in organization theory. *Organization Science* **34**(6) 1997–2025.
- Liu, D., S. Zhang, L. Wang, T. W. Lee. 2011. The effects of autonomy and empowerment on employee turnover: Test of a multilevel model in teams. *Journal of Applied Psychology* **96**(6) 1305–1316.
- Lorenz, J., J. T. Mortimer. 1985. Job involvement through the life course: A panel study of three age groups. *American Sociological Review* **50**(5) 618–638.
- Marx, M., D. H. Hsu. 2022. Revisiting the entrepreneurial commercialization of academic science: Evidence from “twin” discoveries. *Management Science* **68**(2) 1330–1352.
- Mazmanian, M., W. J. Orlikowski, J. Yates. 2013. The autonomy paradox: The implications of mobile email devices for knowledge professionals. *Organization Science* **24**(5) 1337–1357.
- Mincer, J. 1958. Investment in human capital and personal income distribution. *Journal of Political Economy* **66**(4) 281–302.
- Morgeson, F. P., K. Delaney-Klinger, M. A. Hemingway. 2005. The importance of job autonomy, cognitive ability, and job-related skill for predicting role breadth and job performance. *Journal of Applied Psychology* **90**(2) 399–406.
- Neisser, U., G. Boodoo, T. J. Bouchard Jr., A. W. Boykin, N. Brody, S. J. Ceci, D. F. Halpern, J. C. Loehlin, R. Perloff, R. J. Sternberg, S. Urbina. 1996. Intelligence: Knowns and unknowns. *American Psychologist* **51**(2) 77–101.
- O’Reilly, C. A., J. A. Chatman. 1994. Working smarter and harder: A longitudinal study of managerial success. *Administrative Science Quarterly* **39**(4) 603–627.
- Oyer, P., S. Schaefer. 2005. Why do some firms give stock options to all employees? An empirical examination of alternative theories. *Journal of Financial Economics* **76**(1) 99–133.
- Portocarrero, F. F., V. C. Burbano. 2024. The effects of a short-term corporate social impact activity on employee turnover: Field experimental evidence. *Management Science* **70**(9) 5871–5895.
- Prendergast, C. 1999. The provision of incentives in firms. *Journal of Economic Literature* **37**(1) 7–63.
- Puranam, P. 2018. *The Microstructure of Organizations*. Oxford University Press, Oxford, UK.
- Raiffa, H. 1985. *The Art and Science of Negotiation*. Harvard University Press, Cambridge, MA.
- Reineke, P., R. Katila, K. M. Eisenhardt. 2025. Decentralization in organizations: A revolution or a mirage? *Academy of Management Annals* **19**(1) 298–342.

- Riley, J. G. 1979. Testing the educational screening hypothesis. *Journal of Political Economy* **87**(5) S227–S252.
- Roach, M., H. Sauermann. 2010. A taste for science? PhD scientists’ academic orientation and self-selection into research careers in industry. *Research Policy* **39**(3) 422–434.
- Roach, M., H. Sauermann. 2015. Founder or joiner? The role of preferences and context in shaping different entrepreneurial interests. *Management Science* **61**(9) 2160–2184.
- Roach, M., H. Sauermann. 2024. Can technology startups hire talented early employees? Ability, preferences, and employee first job choice. *Management Science* **70**(6) 3619–3644.
- Sauermann, H. 2018. Fire in the belly? Employee motives and innovative performance in start-ups versus established firms. *Strategic Entrepreneurship Journal* **12**(4) 423–454.
- Sauermann, H., W. M. Cohen. 2010. What makes them tick? Employee motives and firm innovation. *Management Science* **56**(12) 2134–2153.
- Schultz, T. W. 1961. Investment in human capital. *American Economic Review* **51**(1) 1–17.
- Shah, S. K., R. Agarwal, R. Echambadi. 2019. Jewels in the crown: Exploring the motivations and team building processes of employee entrepreneurs. *Strategic Management Journal* **40**(9) 1417–1452.
- Shane, S., D. Cable. 2002. Network ties, reputation, and the financing of new ventures. *Management Science* **48**(3) 364–381.
- Simon, H. A. 1947. *Administrative Behavior: A Study of Decision-Making Processes in Administrative Organization*. 4th ed. Free Press, New York.
- Sine, W. D., H. Mitsuhashi, D. A. Kirsch. 2006. Revisiting Burns and Stalker: Formal structure and new venture performance in emerging economic sectors. *Academy of Management Journal* **49**(1) 121–132.
- Slough, T. 2023. Phantom counterfactuals. *American Journal of Political Science* **67**(1) 137–153.
- Snellman, K., P. Younkin. 2021. Who’s the boss? Evidence of job seeker bias from a field experiment. Retrieved from <https://ssrn.com/abstract=3785311>.
- Sorenson, O., M. S. Dahl, R. Canales, M. D. Burton. 2021. Do startup employees earn more in the long run? *Organization Science* **32**(3) 587–604.
- Spence, M. 1973. Job market signaling. *Quarterly Journal of Economics* **87**(3) 355–374.
- Stern, S. 2004. Do scientists pay to be scientists? *Management Science* **50**(6) 835–853.
- Stiglitz, J. E. 1975. The theory of “screening,” education, and the distribution of income. *American Economic Review* **65**(3) 283–300.
- Stinchcombe, A. L. 1965. Social structure and organizations. J. G. March, ed., *Handbook of Organizations*, vol. 7. Rand McNally, Chicago, IL, 142–193.
- Stuart, T. E., W. W. Ding. 2006. When do scientists become entrepreneurs? The social structural antecedents of commercial activity in the academic life sciences. *American Journal of Sociology* **112**(1) 97–144.
- Tan, D., C. Rider. 2017. Let them go? How losing employees to competitors can enhance firm status. *Strategic Management Journal* **38**(9) 1848–1874.
- Teng, N., N. Wright, A. Kacperczyk. 2025. Do disruptive startups attract better talent? Evidence from a hiring field experiment in India. Retrieved from <https://ssrn.com/abstract=5231552>.
- van Balen, T., M. Tarakci. 2024. Recruiting talent through entrepreneurs’ social vision communication. *Organization Science* **35**(1) 326–345.
- Williams, N. 1991. Reexamining the wage, tenure and experience relationship. *Review of Economics and Statistics* **73**(3) 512–517.

Appendix A Study 1: Descriptive analysis of startup job postings

Industry category	Autonomy-related language	The term “autonomy” only
Biotechnology	35.1%	2.11%
Government and Military	33.4%	2.65%
Payments	33.3%	3.14%
Privacy and Security	33.2%	3.20%
Science and Engineering	32.5%	2.34%
Data and Analytics	32.4%	3.24%
Artificial Intelligence	32.0%	3.04%
Education	31.8%	3.41%
Financial Services	31.1%	2.49%
Software	31.1%	2.96%
Information Technology	30.9%	2.61%
Mobile	30.8%	2.95%
Health Care	30.6%	2.33%
Lending and Investments	30.6%	2.44%
Messaging and Telecommunications	30.5%	3.17%
Hardware	30.4%	2.53%
Natural Resources	30.2%	1.56%
Energy	29.9%	1.73%
Agriculture and Farming	29.9%	1.87%
Apps	29.8%	3.13%
Internet Services	29.8%	3.01%
Consumer Electronics	29.7%	2.45%
Administrative Services	29.5%	2.18%
Sports	29.4%	2.59%
Professional Services	29.1%	2.26%
Community and Lifestyle	29.1%	2.03%
Sustainability	29.1%	1.64%
Video	28.9%	2.45%
Travel and Tourism	28.8%	2.43%
Gaming	28.7%	2.55%
Real Estate	28.4%	1.66%
Commerce and Shopping	28.4%	2.61%
Transportation	28.3%	2.76%
Content and Publishing	28.1%	2.23%
Sales and Marketing	28.1%	2.48%
Media and Entertainment	28.1%	2.34%
Consumer Goods	27.9%	1.86%
Navigation and Mapping	27.5%	2.16%
Advertising	27.5%	2.43%
Design	27.4%	2.22%
Clothing and Apparel	27.4%	2.46%
Manufacturing	27.2%	1.50%
Music and Audio	26.9%	1.71%
Food and Beverage	26.8%	1.68%
Platforms	26.0%	2.85%
Events	25.2%	1.92%

Table A1 The emphasis on autonomy in startup recruitment by industry.

O*NET occupation code	Autonomy-related language	The term “autonomy” only
23: Legal	26.4%	0.85%
19: Life, Physical, and Social Science	20.0%	0.42%
13: Business and Financial Operations	20.0%	0.57%
43: Office and Administrative Support	18.4%	0.32%
11: Management	17.8%	0.87%
15: Computer and Mathematical	17.2%	0.87%
17: Architecture and Engineering	15.9%	0.48%
27: Arts, Design, Entertainment, Sports, and Media	15.6%	0.73%
37: Building and Grounds Cleaning and Maintenance	14.6%	0.01%
41: Sales	14.6%	0.66%
45: Farming, Fishing, and Forestry	14.1%	0.37%
47: Construction and Extraction	13.9%	6.04%
21: Community and Social Service	13.8%	0.49%
55: Military	13.3%	0.49%
51: Production	11.7%	0.25%
49: Installation, Maintenance, and Repair	11.6%	0.13%
33: Protective Service	9.6%	0.10%
53: Transportation and Material Moving	9.2%	0.05%
39: Personal Care and Service	9.2%	0.10%
29: Healthcare Practitioners and Technical	8.5%	0.66%
25: Educational Instruction and Library	8.1%	0.27%
31: Healthcare Support	6.4%	0.14%
35: Food Preparation and Serving	6.1%	0.06%

Table A2 The emphasis on autonomy in startup recruitment by occupation.

Appendix B Study 2: Field experiment

Outcome Model Sample	<i>Click</i>				
	(1) All	(2) Non-bachelor only	(3) Bachelor only	(4) Graduate only	(5) All
<i>Autonomy</i>	−0.0011 (0.0048) [0.8205]	0.0269** (0.0095) [0.0045]	−0.0013 (0.0060) [0.8218]	−0.0291* (0.0135) [0.0317]	−0.0013 (0.0060) [0.8218]
<i>Non-bachelor</i>					−0.0233** (0.0072) [0.0012]
<i>Graduate</i>					0.0559*** (0.0109) [0.0000]
<i>Autonomy × Non-bachelor</i>					0.0283* (0.0112) [0.0115]
<i>Autonomy × Graduate</i>					−0.0277 [†] (0.0148) [0.0605]
Constant	0.0681*** (0.0034) [0.0000]	0.0388*** (0.0058) [0.0000]	0.0621*** (0.0042) [0.0000]	0.1180*** (0.0100) [0.0000]	0.0621*** (0.0042) [0.0000]
No. observations	10,718	2,203	6,495	2,020	10,718
R ²	0.0000	0.0037	0.0000	0.0023	0.0063

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, [†] $p < 0.1$

Note. Heteroskedasticity-robust standard errors in parentheses. P-values in brackets.

Table B1 Main results: The effects of emphasizing autonomy in a startup’s recruitment efforts on job seekers’ attraction, as measured by their likelihood of clicking the hyperlink to the partner company’s application webpage (*Click*).

Outcome Model Sample	<i>Apply</i>				
	(1) All	(2) Non-bachelor only	(3) Bachelor only	(4) Graduate only	(5) All
<i>Autonomy</i>	−0.0013 (0.0025) [0.6010]	0.0001 (0.0034) [0.9823]	0.0036 (0.0028) [0.2072]	−0.0172* (0.0087) [0.0482]	0.0036 (0.0028) [0.2073]
<i>Non-bachelor</i>					−0.0050 [†] (0.0030) [0.0973]
<i>Graduate</i>					0.0376*** (0.0069) [0.0000]
<i>Autonomy × Non-bachelor</i>					−0.0035 (0.0044) [0.4293]
<i>Autonomy × Graduate</i>					−0.0208* (0.0092) [0.0233]
Constant	0.0175*** (0.0018) [0.0000]	0.0063** (0.0024) [0.0080]	0.0113*** (0.0019) [0.0000]	0.0489*** (0.0067) [0.0000]	0.0113*** (0.0019) [0.0000]
No. observations	10,718	2,203	6,495	2,020	10,718
R ²	0.0000	0.0000	0.0002	0.0019	0.0092

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, [†] $p < 0.1$

Note. Heteroskedasticity-robust standard errors in parentheses. P-values in brackets.

Table B2 Exploratory analyses: (1) Using an alternative, exploratory outcome measure of *Apply*, which indicates whether a subject submitted an application through the partner company's application webpage.

Outcome	<i>Click</i>				
Model	(1)	(2)	(3)	(4)	(5)
Sample	All	Non-bachelor only	Bachelor only	Master only	Doctoral only
<i>Autonomy</i>	−0.0011 (0.0048) [0.8205]	0.0269** (0.0095) [0.0045]	−0.0013 (0.0060) [0.8218]	−0.0242 [†] (0.0139) [0.0817]	−0.1168* (0.0564) [0.0409]
Constant	0.0681*** (0.0034) [0.0000]	0.0388*** (0.0058) [0.0000]	0.0621*** (0.0042) [0.0000]	0.1153*** (0.0102) [0.0000]	0.1613*** (0.0472) [0.0009]
No. observations	10,718	2,203	6,495	1,913	107
R ²	0.0000	0.0037	0.0000	0.0016	0.0334

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, [†] $p < 0.1$

Note. Heteroskedasticity-robust standard errors in parentheses. P-values in brackets.

(a) *Click*

Outcome	<i>Apply</i>				
Model	(1)	(2)	(3)	(4)	(5)
Sample	All	Non-bachelor only	Bachelor only	Master only	Doctoral only
<i>Autonomy</i>	−0.0013 (0.0025) [0.6010]	0.0001 (0.0034) [0.9823]	0.0036 (0.0028) [0.2072]	−0.0158 [†] (0.0091) [0.0822]	−0.0484 [†] (0.0275) [0.0815]
Constant	0.0175*** (0.0018) [0.0000]	0.0063** (0.0024) [0.0080]	0.0113*** (0.0019) [0.0000]	0.0490*** (0.0069) [0.0000]	0.0484 [†] (0.0275) [0.0815]
No. observations	10,718	2,203	6,495	1,913	107
R ²	0.0000	0.0000	0.0002	0.0016	0.0209

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, [†] $p < 0.1$

Note. Heteroskedasticity-robust standard errors in parentheses. P-values in brackets.

(b) *Apply*

Table B3 Exploratory analyses: (2) Disaggregating job seekers with a graduate degree into individuals holding a master's degree and those holding a doctoral degree. Panel (a) presents the results based on the pre-registered outcome measure *Click*, while panel (b) displays the results based on the alternative, exploratory measure *Apply*.

Outcome	Click			
Model	(1)	(2)	(3)	(4)
Sample	All	All	All	All
Alternative proxy for quality	<i>Top University</i>	<i>Manager</i>	<i>Work Experience</i> (log)	<i>Desired Salary</i> (log)
<i>Autonomy</i>	−0.0008 (0.0049) [0.8673]	−0.0017 (0.0063) [0.7934]	0.0097 (0.0175) [0.5781]	0.0631 (0.1231) [0.6085]
<i>Alternative Proxy</i>	0.0603*** (0.0161) [0.0002]	−0.0298*** (0.0067) [0.0000]	0.0062 (0.0044) [0.1552]	0.0292*** (0.0077) [0.0001]
<i>Autonomy</i> × <i>Alternative Proxy</i>	−0.0056 (0.0225) [0.8020]	0.0027 (0.0096) [0.7796]	−0.0028 (0.0066) [0.6650]	−0.0058 (0.0112) [0.6046]
Constant	0.0632*** (0.0034) [0.0000]	0.0779*** (0.0044) [0.0000]	0.0534*** (0.0115) [0.0000]	−0.2554** (0.0845) [0.0025]
No. observations	10,718	10,718	9,007	10,718
R ²	0.0040	0.0029	0.0003	0.0020

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, [†] $p < 0.1$

Note. Heteroskedasticity-robust standard errors in parentheses. P-values in brackets.

(a) *Click*

Outcome	Apply			
Model	(1)	(2)	(3)	(4)
Sample	All	All	All	All
Alternative proxy for quality	<i>Top University</i>	<i>Manager</i>	<i>Work Experience</i> (log)	<i>Desired Salary</i> (log)
<i>Autonomy</i>	−0.0020 (0.0026) [0.4361]	−0.0017 (0.0034) [0.6245]	−0.0080 (0.0104) [0.4430]	−0.0734 (0.0555) [0.1858]
<i>Alternative Proxy</i>	−0.0016 (0.0063) [0.7937]	−0.0136*** (0.0033) [0.0000]	−0.0064* (0.0028) [0.0253]	0.0051 (0.0036) [0.1584]
<i>Autonomy</i> × <i>Alternative Proxy</i>	0.0085 (0.0096) [0.3756]	0.0016 (0.0046) [0.7326]	0.0027 (0.0037) [0.4583]	0.0065 (0.0051) [0.1980]
Constant	0.0177*** (0.0019) [0.0000]	0.0220*** (0.0024) [0.0000]	0.0354*** (0.0080) [0.0000]	−0.0391 (0.0400) [0.3275]
No. observations	10,718	10,718	9,007	10,718
R ²	0.0001	0.0023	0.0010	0.0009

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, [†] $p < 0.1$

Note. Heteroskedasticity-robust standard errors in parentheses. P-values in brackets.

(b) *Apply*

Table B4 Robustness checks: (1) Using alternative proxies for quality. Panel (a) presents the results based on the pre-registered outcome measure *Click*, while panel (b) displays the results based on the alternative, exploratory measure *Apply*.

Outcome	<i>Click</i>				
Model	(1)	(2)	(3)	(4)	(5)
Sample	All	Non-bachelor only	Bachelor only	Graduate only	All
<i>Autonomy</i>	0.0052 (0.0058) [0.3780]	0.0299* (0.0122) [0.0143]	0.0074 (0.0073) [0.3106]	-0.0359* (0.0174) [0.0393]	0.0077 (0.0072) [0.2897]
<i>Non-bachelor</i>					-0.0100 (0.0096) [0.3024]
<i>Graduate</i>					0.0438** (0.0138) [0.0015]
<i>Autonomy × Non-bachelor</i>					0.0226 (0.0141) [0.1091]
<i>Autonomy × Graduate</i>					-0.0452* (0.0182) [0.0132]
Controls	Yes	Yes	Yes	Yes	Yes
No. observations	7,060	1,420	4,558	1,082	7,060
R ²	0.0195	0.0624	0.0265	0.0622	0.0222

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, [†] $p < 0.1$
Note. Heteroskedasticity-robust standard errors in parentheses. P-values in brackets.

(a) *Click*

Outcome	<i>Apply</i>				
Model	(1)	(2)	(3)	(4)	(5)
Sample	All	Non-bachelor only	Bachelor only	Graduate only	All
<i>Autonomy</i>	-0.0003 (0.0030) [0.9225]	-0.0007 (0.0054) [0.8917]	0.0056 (0.0036) [0.1244]	-0.0241* (0.0101) [0.0171]	0.0052 (0.0036) [0.1492]
<i>Non-bachelor</i>					0.0032 (0.0047) [0.4885]
<i>Graduate</i>					0.0225** (0.0083) [0.0069]
<i>Autonomy × Non-bachelor</i>					-0.0059 (0.0062) [0.3465]
<i>Autonomy × Graduate</i>					-0.0279** (0.0104) [0.0071]
Controls	Yes	Yes	Yes	Yes	Yes
No. observations	7,060	1,420	4,558	1,082	7,060
R ²	0.0221	0.0320	0.0229	0.0491	0.0242

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, [†] $p < 0.1$
Note. Heteroskedasticity-robust standard errors in parentheses. P-values in brackets.

(b) *Apply*

Table B5 Robustness checks: (2) Controlling for individual characteristics listed in Section 4.2. Panel (a) presents the results based on the pre-registered outcome measure *Click*, while panel (b) displays the results based on the alternative, exploratory measure *Apply*.

Outcome	<i>Click</i>				
Model	(1)	(2)	(3)	(4)	(5)
Sample	All	Non-bachelor only	Bachelor only	Graduate only	All
<i>Autonomy</i>	-0.0175 (0.0770) [0.8206]	0.5557** (0.1978) [0.0050]	-0.0233 (0.1034) [0.8219]	-0.3153* (0.1479) [0.0330]	-0.0233 (0.1034) [0.8219]
<i>Non-bachelor</i>					-0.4946** (0.1717) [0.0040]
<i>Graduate</i>					0.7038*** (0.1204) [0.0000]
<i>Autonomy</i> \times <i>Non-bachelor</i>					0.5790** (0.2232) [0.0095]
<i>Autonomy</i> \times <i>Graduate</i>					-0.2921 (0.1805) [0.1056]
Constant	-2.6163*** (0.0539) [0.0000]	-3.2095*** (0.1557) [0.0000]	-2.7149*** (0.0725) [0.0000]	-2.0111*** (0.0961) [0.0000]	-2.7149*** (0.0725) [0.0000]
No. observations	10,718	2,203	6,495	2,020	10,718

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $^{\dagger}p < 0.1$

Note. Heteroskedasticity-robust standard errors in parentheses. P-values in brackets.

(a) *Click*

Outcome	<i>Apply</i>				
Model	(1)	(2)	(3)	(4)	(5)
Sample	All	Non-bachelor only	Bachelor only	Graduate only	All
<i>Autonomy</i>	-0.0785 (0.1501) [0.6013]	0.0119 (0.5367) [0.9823]	0.2771 (0.2203) [0.2083]	-0.4524 † (0.2325) [0.0516]	0.2771 (0.2203) [0.2083]
<i>Non-bachelor</i>					-0.5881 (0.4140) [0.1554]
<i>Graduate</i>					1.5030*** (0.2191) [0.0000]
<i>Autonomy</i> \times <i>Non-bachelor</i>					-0.2653 (0.5802) [0.6475]
<i>Autonomy</i> \times <i>Graduate</i>					-0.7296* (0.3202) [0.0227]
Constant	-4.0261*** (0.1035) [0.0000]	-5.0581*** (0.3795) [0.0000]	-4.4699*** (0.1654) [0.0000]	-2.9669*** (0.1437) [0.0000]	-4.4699*** (0.1654) [0.0000]
No. observations	10,718	2,203	6,495	2,020	10,718

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $^{\dagger}p < 0.1$

Note. Heteroskedasticity-robust standard errors in parentheses. P-values in brackets.

(b) *Apply*

Table B6 Robustness checks: (3) Using logistic regressions, instead of linear probability models. Panel (a) presents the results based on the pre-registered outcome measure *Click*, while panel (b) displays the results based on the alternative, exploratory measure *Apply*.