Received: 7 October 2019 | Revised: 4 November 2021 | Accepted: 5 November 2021 | Published on: 2 December 2021

DOI: 10.1002/smj.3361

RESEARCH ARTICLE

STRATEGIC MANAGEMENT JOURNAL WILEY

Acquired employees versus hired employees: Retained or turned over?

Weiyi Ng[1] | **Toby E. Stuart**[2]

[1]NUS Business School, National University of Singapore, Singapore

[2]Haas School of Business, University of California, Berkeley, California, USA

Correspondence
Weiyi Ng, NUS Business School, National University of Singapore, Singapore.
Email: weiyi_ng@nus.edu.sg

Funding information
NUS Business School Start-up Grant, Grant/Award Number: R-313-000-128-133; Erwing Marion Kauffman Foundation Dissrtation Grant

Abstract

Research Summary: Thousands of acquisitions of technology companies result in the de facto hiring of myriad individuals into new employers every year. We analyze the effects of such deals on acquired employee (AE) retention relative to a matched sample of directly hired employees (HEs) joining the same acquirers in the same year. In a dataset with all acquisitions of VC-backed companies in the previous two decades paired to over 30 million resumes, we find that acquired employees (AEs) turnover at a much higher rate than matched, HEs. Importantly, this difference in turnover rates is *larger* for AEs in higher job ranks and with advanced degrees. Likewise, we show that the postacquisition departure rate is highest for AEs in critical executive, technical, business development, and sales roles.

Managerial Summary: Acquisitions of venture-backed tech-companies occur for many strategic reasons, including the acquisition of key managerial and technical human talent. The retention of acquired talent is thus an important consideration for the value of the acquisition. Through a dataset of over 30 million resumes, we examine the turnover rates of employees acquired through technology acquisitions in the previous two decades, comparing these AEs to their similar, organically hired counterparts. In this comparison, we find that AEs are more likely to turnover in general. Importantly, the higher turnover rate of AEs increases with seniority and education attainment and is the

highest in critical executive, technical, business development, and sales roles.

KEYWORDS

careers, dynamic capabilities, large-scale data analysis, mergers and acquisitions, microfoundations

1 | INTRODUCTION

In 2019, there were more than 3,500 technology-based mergers and acquisitions (M&As) exceeding $450 billion in total transaction value. An aggregate number in this dollar range has transpired in most years during the past decade. Indeed, the workforces of the highest-valued companies of our time have been partially assembled through M&As: Facebook, Amazon, Microsoft, Google, and Apple have purchased some 750 companies in the past three decades. A majority of these were small, venture-backed start-ups.

We examine the retention of human capital in tech company acquisitions, relative to an organic-hired benchmark. Specifically, we assess retention rates across two hiring *modes*, acquired employees (AEs) and directly hired employees (HEs). We review theoretical rationales for why turnover may depend on hiring mode, and we develop novel empirical evidence showing this to be so in a comprehensive, matched employer–employee dataset.

We focus on employee retention because it is an important outcome in the technology sector (Coff & Kryscynski, 2011; Stuart & Sorenson, 2003; Younge, Tong, & Fleming, 2015). Although not often the sole reason for purchasing another company, a strategic consideration in many transactions in tech is that a deal is a means to recruit new employees (Ouimet & Zarutskie, 2011; Younge et al., 2015). Retaining this talent is generally desirable. First, an organization's members are stores of its core knowledge (Barney, 1991; Hoetker & Agarwal, 2007). In addition to serving as organizational memory, employees provide creative input into the innovation process and they embody the firm's relationships with vendors and customers. Moreover, when employees depart to fill positions at competing firms, tacit know-how and valuable social capital leaks to competitors (Aime, Johnson, Ridge, & Hill, 2010; Coff, 1997; Starr, Prescott, & Bishara, 2021; Wezel, Cattani, & Pennings, 2006). Therefore, to prevent the seepage of knowledge and relationships through turnover (Chatterjee, 2017; Phillips, 2002; Wezel et al., 2006) and to preclude disruption to the teams and social systems that enable knowledge workers to be productive (Reagans, Argote, and Brooks, 2005; Azoulay, Graff Zivin, & Wang, 2010), employers generally wish to retain members with core expertise (Campbell, Ganco, Franco, & Agarwal, 2012). Indeed, Fedyk and Hodson (2017) show that employee turnover rates significantly contribute to stock market returns for a broad sample of public companies.

An empirical challenge in studying employee departure following M&As is, against what baseline should we compare employee turnover, postacquisition? This issue is salient because labor mobility in the technology sector is notoriously high independent of M&As, which means that retention of AEs can only be assessed relative to a counterfactual that pins down an informative, *employer–employee-time-specific base rate*. In particular, the career experiences and professional backgrounds of AEs may be very different from HEs, and we need to account for these differences *as well as* establish a baseline rate of mobility to surface valid empirical findings of the effect of hiring mode on turnover.

An important contribution of our paper is to compare the turnover rate of AEs and HEs using a matching estimator that imposes equivalence on observables between these two groups. For data, we identify all acquirers of once-VC-backed companies in the United States. We then merge in millions of individual resumes *with full career histories*, which are crucial to our empirical approach. These career histories enable us to match AEs to HEs with very similar educational, career, and employer-level characteristics to provide large-scale empirical evidence for an important phenomenon—turnover rates as a function of hiring mode—for which most of the existing evidence is anecdotal (for an exception, see Kim, 2020).

2 | THEORY

Companies have two, broad modes to recruit talent: they can hire employees on the open labor market or they can acquire an incumbent organization with an established workforce. Here, we develop theoretical reasons to anticipate heterogeneous employment outcomes for individual workers across these two hiring modes. We briefly review the literature on each hiring mode and then formulate predictions concerning the dependence of turnover on hiring mode.

2.1 | Hired employees

Strategy research considers firms' recruitment of human capital—from technical workers to star scientists to CEOs—on the external labor market. On one hand, the literature takes the lens of current employers to posit that *imperfect* resource mobility is necessary for strategic value capture (Dierickx & Cool, 1989; Montgomery & Wernerfelt, 1988; Peteraf, 1993). If human capital is freely mobile, competitive market forces erode any supra-normal value it otherwise might create. Thus, mechanisms that hamper resource mobility have been central tenets of strategic value capture (Peteraf, 1993). Indeed, the many strategic ramifications of employee mobility are the impetus for a recent body of work on noncompete contracts, which slow down interfirm mobility in geographic regions that enforce them (Marx, Strumsky, & Fleming, 2009; Mawdsley & Somaya, 2016; Starr et al., 2021; Starr, Frake, & Agarwal, 2019; Stuart & Sorenson, 2003). Likewise, firms attempt to strategically manage turnover by implementing a multitude of policies to retain key employees or by more aggressive means, such as active litigation strategies to protect intellectual property (Agarwal, Ganco, & Ziedonis, 2009). Ultimately, this work concerns how to retain employees to capture economic value.

Conversely, the "learning-by-hiring" literature considers employee mobility through the lens of the recruiting employer, versus the source of, talent. This work documents that knowledge-expansion occurs when firms recruit technical talent from other organizations (Rosenkopf & Almeida, 2003; Singh & Agrawal, 2011). The migration of engineers and scientists is a channel for the interorganizational diffusion of know-how (Lacetera, Cockburn, & Henderson, 2004; Palomeras & Melero, 2010; Somaya, Williamson, & Lorinkova, 2008; Song, Almeida, & Wu, 2003). Studies have addressed the effect of inbound employee mobility on quite a few dimensions of postrecruitment organizational performance, including whether new hires replicate behaviors from their previous experiences (e.g., Dokko, Wilk, & Rothbard, 2009; Groysberg, Lee, & Nanda, 2008) and whether recruits actively build on the knowledge stock of their former employer (e.g., Almeida, Dokko, & Rosenkopf, 2003; Rosenkopf & Almeida, 2003; Singh & Agrawal, 2011; Song et al., 2003).

Likewise, empirical work considers how new capabilities may be grafted onto an existing organization by recruiting key employees from organizations with desirable routines (Gardner, 2005; Harris & Helfat, 1997; Lacetera et al., 2004; Wezel et al., 2006). Rao and Drazin (2002) explored the effect of external recruitments on product innovation for hiring organizations; Song, Almeida, and Wu (2003) studied patenting outcomes; and Boeker (1997) traced the diffusion of strategic decision-making to interfirm mobility among managers. Scholars have also evaluated the consequences of the loss of essential employees to competitors (Felin & Foss, 2005), finding that employee mobility influences the escape of knowledge and other corporate performance outcomes, possibly even survival rates among firms that lose key employees (Agarwal, Campbell, Franco, & Ganco, 2016; Phillips, 2002).

2.2 | Acquired employees

Acquisitions are daily occurrences in tech. While multiple strategic rationales may underpin any given transaction, access to a target company's core products, technical expertise, and its workforce are primary considerations (Graebner, Eisenhardt, & Roundy, 2010; Younge et al., 2015). Although acquisitions can be an expensive means of "hiring" a workforce, relying on the external labor market for recruiting poses its own obstacles when speed of scaling is a top priority (Chatterji & Patro, 2014; Ranft & Lord, 2002), when recruiting whole teams trumps hiring many individual contributors (Groysberg, 2010), and when tight labor market conditions undermine organic hiring approaches (Cappelli & Keller, 2014; Michaels, Handfield-Jones, & Axelrod, 2001).

Behavioral and knowledge theories of the firm (Cohen & Levinthal, 1989; Nelson & Winter, 1982) also inform motivations to acquire. In times of rapid technical development and the threat of obsolescence, these literatures highlight the strategic importance of acquisitions to revive incumbents' knowledge bases (Coff & Kryscynski, 2011; Younge et al., 2015). Acquisitions of young tech firms by established companies have been a particularly vital, external source of innovation for incumbents (Doz, 1987; Graebner, 2004; Ranft & Lord, 2002). This is especially so for venture-funded companies, which produce significantly more inventions per dollar of invested capital than established firms (Kortum & Lerner, 2000). Thus, venture-funded firms have been especially attractive acquisition targets (Graebner et al., 2010).

The literature on dynamic capabilities also contemplates acquisitions partly aimed at onboarding human capital (e.g., Puranam, Singh, & Zollo, 2006; Teece, 2007) and how these deals potentially can lead to strategic renewal (cf. Agarwal & Helfat, 2009). This work shows that new resources and capabilities can stem from extensions of an acquirer's talent base when the technologies and human capital of a target company are integrated, and that acquisitions may be transformative when they lead to the redeployment and reconfiguration of resources in the acquirer-target pair. There is some evidence that technology-based M&As increase acquirers' postdeal inventive productivity (Ahuja & Katila, 2001; Link, 1988). Moreover, given the vast scale of M&A activity, the dynamic capabilities literature posits that, in and of itself, a firm's capacity to source acquisition opportunities and to extract value from these deals may affect overall firm performance (Bingham, Heimeriks, Schijven, & Gates, 2015; Helfat et al., 2007; Meyer-Doyle, Lee, & Helfat, 2019).

Ranft and Lord (2000) weave together a number of these strands of literature as they pertain to tech deals. They argue that, in contrast to acquisitions aimed at realizing economies of scale, gains in market share, or geographical expansion, deals in tech often are often about access to

deep technical expertise and skilled employees, high-functioning teams in product or other functions, or novel technologies in fast-changing industries. In turn, because talent acquisition and knowledge expansion are factors in tech-based mergers, the retention of critical technical experts and functional leaders, along with the target firms' management, is one measure of the success of merger implementation (Ahuja & Katila, 2001; Link, 1988).

2.3 | Hypotheses: Does hiring mode affect employee retention?

Given that experienced employees arrive to their positions via one of two, principal modes—they either are HEs or AEs—we pose the question: is there an association between mode of hiring and employers' retention rate of talent? In addressing the question, we have in mind a comparison between hired and AEs with very similar professional backgrounds and employment histories.

We posit that there are two, fundamental difference between AEs and HEs. First, for HEs, there is a mutual match between the employer and the employee. Both the individual and the employer selected one another in the context of a competitive labor market. Conversely, for AEs, the individual-employer match occurred at the *ancillary*, *acquired* company, rather than with the eventual acquirer. In other words, AEs are mutually matched to their preacquisition employers but not to their postacquisition employers. How significant is this absence of a match for the likelihood of employee turnover?

One clue comes from sociological work on the association between bureaucracy and organizational size. Large organizations differ from small ones in levels of hierarchy, the prevalence of internal processes and routines, and the formalization of job roles, responsibilities, and tasks (Blau & Schoenherr, 1971; Dobrev & Barnett, 2005; Stuart & Sorenson, 2003). While large organizations are formalized, small firms operate with more fluid structures and less precise job roles (Elfenbein, Hamilton, & Zenger, 2010; Sørensen & Fassiotto, 2011; Sørensen & Stuart, 2000). In addition to the size difference, acquirers tend to be of earlier birth cohorts than their younger acquisition targets. This too implies significant cultural and workplace-feel differences in acquirer-target dyads (Hannan & Freeman, 1984; Sørensen & Stuart, 2000).

Cultural incompatibilities and differences in bureaucratization suggest that AEs may experience a significant, *unplanned* change in their work environment when they transition from employment at an early-stage company to become members of a postacquisition subsidiary of a larger organization. To develop the implications of this change, let us simplistically assume an economy with only two types of firms, "startups" and "established" companies. Further, assume that a meaningful fraction of job seekers holds preferences (that may change) which better align with work roles at one or the other type of firm (Barber, Wesson, Roberson, & Taylor, 1999). Likewise, employers attempt to screen job applicants on matches to the milieu they offer, to maximize productivity and minimize turnover.

In this simplistic account of employee–employer job matching, merging a "startup" into an "established" firm creates a de facto mismatch between the current-job preference of employees and their postacquisition job context. If an employee matches to a startup role because she values a general absence of bureaucratic procedures, that individual may perceive her work role to be less compelling after her startup is acquired. Even if the acquirer attempts to remain "hands off," it is likely that HR policies, resource allocation choices, cultural norms, reporting structures, and so forth, all change in the postacquisition time window.

A second factor—merger integration challenges—may amplify the sense of an employment mismatch in the eyes of AEs, and their tendency to act to rectify it. In the "unfolding model" of

voluntary turnover, Lee and Mitchell (1994) argue that employees' psychological detachment from their current work roles is most likely to occur after a shock of some form, which provides the impetus for workers to consider a search for alternative employment opportunities. Acquisitions punctuate the equilibria of stable employment relationships for many AEs in part because, as the literature on merger integration reveals, myriad obstacles to seamless unions arise, including a host of unplanned challenges when integrating new employees into an acquirer's existing operations (Graebner, 2004; Haspeslagh & Jemison, 1991). Postacquisition integration often is quite disruptive, even when acquired companies are small (Coff, 1999; Ranft & Lord, 2002). Many scholars attribute these challenges to difficulties associated with cultural assimilation between acquirer and target (e.g., Cartwright & Cooper, 1993).

These arguments lead to our baseline hypothesis:

> **Hypothesis 1.** *Relative to hired employees with similar attributes, acquired employees will turnover more frequently.*

We also evaluate a critical follow-on prediction: differences in turnover rates as a function of hiring mode will depend on an employee's job rank, education, and job function. We proceed under two assumptions: turnover rates will be highest for individuals who (a) enjoy the greatest external job market opportunities (pulls) and (b) experience the greatest impetus to depart because of internal organizational (push) factors. Moreover, AEs will be more sensitive than HEs to these factors because postdeal changes cause them to be more likely to evaluate alternative employment options.[1]

2.4 | Pull factors: Differential job opportunities

If an acquisition increases the base rate of employee turnover, it is likely that this will be especially so for the most marketable AEs. This localizes the effect of mergers on turnover rates to employees with the most in-demand career histories, which are likely to include high-ranking employees with specific education and skill profiles.

The overall labor market dynamic has evolved toward frequent, external hiring of high-ranking managerial, technical, and functional talent. In a large-scale survey, Jacoby, Nason, and Saguchi (2005) found that U.S. employers almost never consider only internal candidates for managerial vacancies. Likewise, Bidwell (2011) demonstrated extensive external hiring for mid- and upper-level executives. The internal labor markets that characterized U.S. employers in the post-WWII era have yielded to a preponderance of external hiring into key positions in organizations (Crispin & Mehler, 2013). Demand for experienced employees has been high, to the degree that hyperbolic expressions such as "*The War for Talent*" (Michaels et al., 2001) have become part of the vernacular in technology. Employers have responded to these challenging labor market conditions with a flurry of noncompete and other litigation initiated to stem the tide of talent poaching (Agarwal et al., 2009; Starr et al., 2021). Researchers have found that this

[1]In addition to the aforementioned, acquisition-induced "shock" to their employment relationship, it is a common recruitment strategy for external recruiters and hirers to proactively contact AEs following M&As (Stuart & Sorenson, 2003). If recruiting firms are more likely to target AEs relative to HEs in these overtures, there can be a differential effect in turnover rates based on hiring mode, which is caused by the talent acquisition tactics of external hirers.

is particularly so for employees who possess technical knowledge (Dokko et al., 2009) and essential managerial capabilities (Boeker, 1997). Manifesting the heated external labor market, Starr et al. (2021) report that individuals in high-skill, knowledge-intensive work roles, including engineers, scientists, and senior managers, are more likely to be asked to sign noncompete covenants (also see Marx, 2011).

Furthermore, Somaya et al. (2008) note that in addition to general human capital, social capital also facilitates employee mobility. This applies particularly to employees in external-facing job roles, such as sales and business development, that possess portable social capital: while all employees develop at least a certain measure of internal relational capital, transferable relational capital is more likely to reside in the hands of employees with external-facing work roles.

The literature certainly has spotlighted the heavy demand for and the strategic importance of technical and leadership talent. It is therefore reasonable to believe that when an employee has general human capital and general social capital that transfers with greater value and ease to a different employer, that employee is likely to be more footloose when experiencing employment mismatch arising from an acquisition.

2.5 | Push factors: The impetus for change

For internal reasons as well, we expect the most educated and highest ranking employees to feel the greatest push to depart, postacquisition. Why? The more that a job role changes from pre-to-post acquisition, the greater will be the perception of a postacquisition mismatch among AEs. In turn, a central driver of the degree of mismatch is the level of autonomy an employee enjoys, which depends on job rank and educational attainment. The literature consistently shows that more educated and higher ranking employees enjoy greater on-the-job resources, autonomy, and task variety (Autor & Dorn, 2013; Solomon, Nikolaev, & Shepherd, 2021). This matters because highly educated workers in senior jobs probably experience a greater transformation in their job roles between pre-acquisition and postacquisition periods than will lower-level, administrative workers. For instance, postacquisition, the former Chief Marketing Officer at target company may become a division-level executive reporting to an SVP of Marketing at the new parent company and is thus subject to the organizational practices, politics, and cultural values of the acquirer. These work role differences will be especially pronounced at the level of founders and CEO of acquired companies, as their positions shift from very high levels of control and autonomy, to reporting into a larger corporate structure, with an existing way of thinking about and doing things. Such changes in the nature of work are likely greater than alterations in the work roles of junior employees.

These arguments together suggest that acquirers may face a challenge retaining highly valued employees in the postacquisition period. Compounding this difficulty, acquisitions often are liquidity events for a subset of employees, creating significant wealth for founders, senior managers, and important sales leaders and technologists. These transactions therefore fundamentally alter the opportunity structures confronting employees at the companies experiencing them (Stuart & Sorenson, 2003). Thus, in addition to resulting in job context mismatches, mergers may weaken the financial bonds that tie executives and technologists to their employers. We therefore predict:

> **Hypothesis 2.** *The difference in the turnover rate for AEs relative to HEs will be higher for employees at upper organizational ranks, in technical and externally facing job functions, and with more educational credentials.*

3 | EMPIRICAL APPROACH

Until recently, large sample data to study the employment effects of M&As at a granular, employee level have not existed. To test the hypotheses, we require access to many individual career histories. We also need a compelling sample of counterfactual career trajectories to pin down baseline mobility rates, which is critical to an empirical understanding of how M&As affect the velocity of turnovers relative to organic hiring strategies.

3.1 | Data and sample

To obtain individual career trajectories, we utilize *public* resumes from LinkedIn profiles. The core of our data comprises over 30 million public LinkedIn profiles randomly sampled in the second half of 2013 (Ge, Huang, & Png, 2016). These resumes constitute approximately a 15% random sample of the LinkedIn population at that time.[2]

Online resumes have multiple benefits. Most importantly, they contain extensive, self-reported longitudinal data on career histories. In contrast to the one-page norm for hard-copy resumes, the infinite shelf-space of a web platform invites individuals to describe extensive prior career experiences. As such, although we retrieved the data in 2013, the resumes include many individuals who record their employment histories back to the 1960s.

LinkedIn resumes are unstructured data. When filling out a profile, users are prompted to enter employer names, job titles, and the start and end dates of employment spells. In addition, users frequently supply job descriptions and skill tags. These data allow us to machine learn and classify prior job roles and educational degrees, the identities of past and present employers, educational institution(s), job titles and functions, and major field(s) of study.

There are, however, downsides to these data. First, unstructured data present multiple complexities. We address these issues in detail in appendices. Second, individuals self-select onto the platform, and it is difficult to know the exact, population-level characteristics that are sampled in online resume sites. An advantage of studying the tech sector is that LinkedIn has much better coverage of this segment of the workforce, relative to the overall labor market. As such, coverage issues may be minimized for projects that focus on tech companies.[3]

3.1.1 | Identifying acquired employees

To identify acquisitions, we utilize CrunchBase and PitchBook. CrunchBase chronicles the startup ecosystem. PitchBook is a subscription-only dataset that comprehensively documents VC investments. Together, the two give us broad coverage of M&A deals of VC-backed companies.

[2]We emphasize that we sampled only public LinkedIn profiles. Thus, all individuals in the sample opted to share their data, which complies with LinkedIn's Terms and Conditions at the time of download. The data were collected over a significant duration of time, in a manner that did not place a burden on the company's servers.

[3]The adoption rate of LinkedIn by workers in technology was high at the point of sampling. For example, Archambault and Grudin (2012) report that 77% of Microsoft employees maintained a LinkedIn Profile in a 2011 survey. Ge et al.'s (2016) survey finds that the significant majority of all patent inventors report that they maintain a public LinkedIn profile.

To create a matched employee–employer dataset, we cleaned the "Company Name" field of all three databases using the steps outlined in Online Appendix A. Merging on acquired company names with LinkedIn public profiles gives us the AE (treatment) group. *AEs are defined to be employees of all acquired companies whose tenure crosses the month and year in which the acquisition of their employer transpired*. Collectively, the acquirers in our dataset undertook 7,134 acquisitions from 1995 to 2010.

3.1.2 | Identifying HEs

An intuitive option to create a control group would be to use existing employees of acquirers. This approach, however, has shortcomings. First, the professional backgrounds of AEs are likely to differ from those of previous HEs. The typical background of individuals that select into young, small, technology-focused, VC-backed companies will differ from those that accepted jobs in established, larger organizations. Second, the full workforce of larger organizations will span a greater number and diversity of occupations than smaller start-ups. Third, existing employees with ongoing tenure at their current employers are likely to be well matched to jobs and will turnover at lower rates than new hires.

Instead, we match AEs to new, organically hired workers *that join acquirers during the same year that an M&A occurs*. To do this, we retrieve all employees of *acquirers* in the sample of 30 million LinkedIn resumes. This process yields 1.53 million individuals in 5.73 million job spells across 2,492 distinct acquirer companies. From these 1.53 million HEs, our task is to construct the most persuasive control group that matches to the AEs. In practice, we seek to discern the effect of an acquisition on the subsequent career of the acquired-in workforce, compared to hires whose job characteristics and past career histories are nearly equivalent. To state this in formal terms, we will identify a control group of HEs that exhibit the identical probability of being "acquired" as a member of the actual, acquired employee sample.

Empirically, we construct the control group using a nonparametric coarsened exact matching (CEM) procedure (Iacus, King, & Porro, 2011). We first determine and bin the relevant covariates requiring balance. These covariate bins define strata, which are then populated by observations from both "treatment" (AE) and "control" (HE) groups. Any observation that fails to inhabit a stratum is dropped. Here, it is very important to emphasize that the matching estimator *does a lot*; the group of employees at large companies have very different professional backgrounds and credentials than do the AEs at startups. Without matching on employee backgrounds, the control group of HEs is quite dissimilar from the AEs. Finally, the observations in each stratum are then assigned proportionate weights depending on the size of the strata population and within-strata distributions across treatment and control groups.

3.2 | Information retrieval and data cleaning

3.2.1 | Job roles

We define an individual's job role based on their specific, listed job title. The set of unique job titles in the dataset manifests the challenges of unstructured resume data. We observe over 14.4 million uniquely written job titles. Inspecting the data reveals that the dominant source of heterogeneity is the multitude of synonyms, acronyms, abbreviations, and spelling errors present in the data.

We wish to transform 14.4 million unordered job titles to a hierarchical taxonomy of actually distinct job roles. We do this with a bottom-up, *unsupervised* machine-learning algorithm to categorize job titles. The critical data element for clustering job titles is the text LinkedIn members use to self-characterize their work roles. This approach, outlined in Online Appendix B, will succeed if site users employ common language to describe similar work roles.

3.2.2 | Job ranks

To understand the effect of an individual's job level on subsequent turnover, it is necessary to rank order jobs. After cleaning up job titles, we use individuals' mobility from origin to destination job titles, either within or between companies, to create a seniority order of job titles. We assume that sequential employment spells are most likely to represent upward mobility,[4] so we model each job switch as a game in which the destination job "wins" over the origin job. For instance, if a "software developer" moves to a "VP of Engineering," we model this switch as a victory for "VP of Engineering." With an average of 4.7 employment spells per person in our full resume dataset, we determine the ranking of each job by an Elo rating system (Elo, 1978) described in Online Appendix C.

3.2.3 | Educational degrees

Most of the educational degrees on LinkedIn are tertiary degrees, reflecting the white-collar, professional character of the site's users. Educational degrees are far more systematic than job descriptions. We manually categorize degrees (e.g., BS, BA, AB, SB, B.Eng) into three tertiary degree levels: bachelor's, master's, and doctoral.[5]

3.2.4 | Age (cohort)

Person-age is generally not explicitly reported on LinkedIn. We approximate age based on college-year completion cohorts, defining age to be the number of years since undergraduate graduation year.

3.2.5 | Prior mobility patterns

In past research on turnover, a count of prior job mobility events has proven effective at capturing individual differences in the propensity to remain in a job. Therefore, we calculated, for each individual in the AE and HE samples, the person's average tenure at all previous companies until the point in time of the acquisition or organic hire.

[4]While this assumption is obviously violated in many cases, it is predominantly true for a large majority of resumes. An advantage of large data sets is that the normative signal swamps the noise, so the automated ranking of job titles approaches accuracy.

[5]Only a small proportion of individuals in the data reported secondary diplomas and associate degrees. We drop these cases.

3.2.6 | Previous employer characteristics

We exploit the full sample of 30 million resumes to measure the age and size of the firms in our sample. The unprecedented scale of the resume sample allows us to aggregate individual-level job spell data to approximate these quantities for all company-year observations. Finally, we assign firms industry segment codes using a supervised machine-learned taxonomy that is described in Online Appendix D, with CrunchBase and Pitchbook providing the reference industry categories.

3.3 | Statistical approach

3.3.1 | Turnover

Because employee turnover events are distributed in time and are right censored for all workforce-active individuals that have not moved employers at the end of the observation window, the data are suited to hazard rate models. We examine the differences between the hazard rate of employee departure between treatment (AE) and control (HE) groups. In the regressions, the risk of turnover commences at the point of organizational entry at acquisition or organic hire.[6]

We examine employee turnover by estimating conditional coefficient magnitudes in firm-stratified Cox regressions. Cox proportionate hazard models implement the functional form:

$$H(t|X_i) = H_0(t)^{X_i \cdot \beta},$$

where t is the time to turnover, H_0 is the base hazard function, X_i are variables of interest, and βs are coefficients to be estimated.

We estimate the regression equation on the CEM sample of acquired and HEs. We match HEs to AEs on nine covariates: (a) the time of acquisition and organic hire, so the employment-spell start dates match between treated and control cases, (b) detailed occupational role, (c) job rank in a 5-quantile hierarchy, (d) highest attained educational degree, (e) person age, (f) the average tenure of previously held jobs, (g) the age of individuals' previous employers, (h) the size of individuals' previous employers, and (i) the industry sub-segment of the previous employer.

4 | RESULTS

4.1 | CEM statistics

The CEM procedure imposes equality between AEs and HEs on the matching covariates. When successfully implemented, *none* of the covariates used to match will distinguish between

[6]Employee-level careers are modeled subsequent to joining new companies, but we observe individuals' full prior career histories so there are no left censored observations.

acquired and organically HEs in the postmatch sample. In effect, the matching variables will fail to separate treatment cases (AEs) from controls (HEs).

To construct the control group, we must eliminate HEs who do not resemble AEs. This is the purpose of the CEM procedure—to generate a post-CEM sample in which the treatment and control distributions overlap completely across the full range of predicted probabilities. Online Appendix E describes the CEM sample and shows that the matching procedure successfully eliminates the segment of the HE sample that is nonoverlapping with the AE sample. Conditional on observables, there is no difference in selection into treatment.

Matching procedures generally cause data loss in the treatment and control groups. The greater the number of matching covariates, the more likely observations drop, as there are fewer instances of exact matches. Accordingly, there are 68,660 AEs in the pooled sample, which reduces to 13,673 observations following the CEM procedure.[7]

When we apply the CEM procedure, certain features of individual backgrounds significantly shift in their proportionate representation in the presample and postsample. We have investigated all differences but note one of particular interest: the change in job roles in the CEM sample. Exactly as expected, the CEM sample amps up representation of technical, business, and managerial job titles that are prevalent in VC-backed start-ups (e.g., "software developer"), relative to their representation at large companies. Conversely, it dramatically under-samples, sometimes to the point of excision from the sample, job roles that are rare in the startup sector (e.g., fitness coaches, musicians). To establish a valid empirical result, this underscores the importance of detailed career histories to create a control group of observationally similar employees.

4.2 | Turnover

Table 1 shows the cross-tab of AE and HE tenure lengths in the unmatched and CEM samples. In the unadjusted sample, the average length of tenure of an employee hired through organic channels is about 1,145 days, or 3.1 years. This is in *stark* contrast to AEs: the average AE retains their position for about 600 days, or 1.75 years. The difference in tenure between the treated and control group is a remarkable 44%.

Some of this difference might be attributed to heterogeneity in the professional backgrounds of AEs and HEs. To account for this, we move to the CEM sample. After matching, the effect size attenuates but remains large and statistically meaningful. In the CEM sample, HEs averaged 844 days (2.31 years) of tenure, while AEs averaged 586 days (1.6 years). In the CEM sample, the average AE's tenure is 27% less than that of a typical HE.

In Table 2, we report multivariate Cox regressions, also on the CEM sample. The treatment effect in Model 1 suggests that *AEs turnover at 1.25 the base rate of equivalent HEs*. Hypothesis 2 proposes that due to superior job market opportunities and differential internal organizational experiences, the increase in the turnover hazard for AEs will be amplified for employees at the top of the rank and education distributions and in critical job positions. Therefore, even when assessed relative to HEs with observationally similar attributes, we anticipate that the difference

[7]Of course, there are many more than 68,660 acquired employees in total in the 15-year sample. Recall that we sample < 15% of the professional workforce. After further loss of data in the cleaning and merging processes, we likely observe significantly fewer than 10% of the total number of acquired employees in this time window.

TABLE 1 Cross tabulation of mean employment tenure across AEs and HEs, pooled and CEM sample

	Pooled	CEM
H-Emp tenure (days)	1,145	741
A-Emp tenure (days)	640	538
H-A tenure difference (days)	505 [.0000]	203 [.0000]
Percentage difference (%)	44	27
n (job spells)	5,912,383	45,427

Note: *p*-values in square brackets indicated for two-tailed *t*-tests of mean tenure differences (with CEM weights for CEM sample). Tenure includes right-censored observations.
Abbreviations: AEs, acquired employees; HEs, hired employees; CEM, coarsened exact matching.

in turnover rates between the two groups will be largest for the most senior, highest educated employees in technical and externally facing job roles.

Model 2 shows that as job rank and educational attainment increases, the hazard rate of departure decreases. As we know from prior studies of turnover, without attending to treatment status, more senior employees remain at their employers for a longer duration of time. In this regard, the findings become more striking in the two, subsequent regressions. Models 3 and 4 show that the effect of being acquired on the hazard of employee departure increases in job rank and educational attainment. For instance, an AE, job-rank-quintile-5 experiences an estimated turnover hazard rate that is 1.43 times higher than that of a similarly ranked HE, while an AE in job-rank-quintile-2 experiences only a 1.08× higher hazard rate (a Wald Chi-squared test rejects the null hypothesis of equality of interaction coefficients: $\chi^2 = 105.8$, $df = 4$, $p = .0$). Likewise, an AE doctorate holder turns over at 2.22 the rate of an HE doctorate, while an AE with a BA degree turns over at 1.23 the rate (Wald Chi-squared test rejects null hypothesis of equality of interaction coefficients: $\chi^2 = 28.3$, $df = 2$, $p = .0$).

The examination of job-role heterogeneity in predicting departure presents a challenge of dimensionality. We derived 150 job-role categories from the 30 million random samples of all public 2013 LinkedIn profiles (Online Appendix B). The large number of job categories hampers a parsimonious interpretation of the results. In addition, the majority of the 150 job categories are under-represented in the CEM sample, as the latter is restricted to job roles that appear with some frequency in the startup sector.

To facilitate analysis, we further process job categories by (a) eliminating roles that are under-represented in the CEM sample and (b) joining job roles together by climbing the hierarchical tree from the clustering algorithm that defines job categories. After these steps, we are left with a more parsimonious set of 28 "supra-job" categories. We then regressed time-to-departure on these categories and their interaction with the AE indicator variable in a Cox regression to examine the heterogeneity of departure hazards across these variables. For ease of display, Figure 1 visualizes the largest significant interaction effects. The figure plots the coefficient values and standard error for the largest interaction effects.

Figure 1 shows that AEs which experience the *lowest* relative departure hazard rates comprise a singular group: entry level positions of "analysts, associates and interns." In contrast, AEs in "founding management positions" are the quickest to exit their new employers after an acquisition, followed by employees in the functions, "sales, research scientists, management and engineering." Evidently, acquired talent in these critical technical, managerial, and externally facing job positions are indeed less likely to be retained.

TABLE 2 Cox-proportionate hazard models of turnover

	Model 1	Model 2	Model 3	Model 4
A-Employee	0.2499 (0.0183) [.0000]	0.2380 (0.0184) [.0000]	−0.4341 (0.0735) [.0000]	0.2081 (0.0196) [.0000]
Highest education (Masters)		0.0052 (0.0176) [.7661]	0.0048 (0.0176) [.7850]	−0.0403 (0.0215) [.0614]
Highest education (Doctoral)		−0.1522 (0.0789) [.0538]	−0.1490 (0.0789) [.0591]	−0.3469 (0.0976) [.0004]
Job rank (Rank 2)		−0.0791 (0.0499) [.1134]	−0.2504 (0.0573) [.0000]	−0.0799 (0.0499) [.1094]
Job rank (Rank 3)		−0.2945 (0.0419) [.0000]	−0.5334 (0.0470) [.0000]	−0.2955 (0.0419) [.0000]
Job rank (Rank 4)		−0.2954 (0.0480) [.0000]	−0.5423 (0.0544) [.0000]	−0.2967 (0.0480) [.0000]
Job rank (Rank 5)		−0.3197 (0.0469) [.0000]	−0.5928 (0.0532) [.0000]	−0.3208 (0.0469) [.0000]
A-Emp × Job rank (Rank 2)			0.5066 (0.0937) [.0000]	
A-Emp × Job rank (Rank 3)			0.6953 (0.0743) [.0000]	
A-Emp × Job rank (Rank 4)			0.7183 (0.0844) [.0000]	
A-Emp × Job rank (Rank 5)			0.7920 (0.0826) [.0000]	
A-Emp × Highest education (Masters)				0.1303 (0.0351) [.0002]
A-Emp × Highest education (Doctoral)				0.5887 (0.1477) [.0001]
n	45,427	45,427	45,427	45,427
Concordance	0.608 [.0000]	0.608 [.0000]	0.61 [.0000]	0.609 [.0000]
Wald test	1794 [.0000]	1722 [.0000]	1856 [.0000]	1744 [.0000]
Logrank test	1880 [.0000]	1961 [.0000]	2,105 [.0000]	1982 [.0000]

Note: All models are stratified cox proportional hazard models (firm strata) with CEM-derived weights. Standard errors in parentheses, *p*-values in square brackets. The omitted baseline group comprises bachelor's degree holders, HEs, in job rank 1. Results shown include controls for: job role fixed effects, prior average tenure (days), prior number of jobs, time since bachelor's degree (years).

Abbreviations: CEM, coarsened exact matching.

All told, we find strong support for Hypothesis 2. The difference in turnover rates of AEs compared to similar HEs is highest at top organizational ranks, among critical job roles, and increases with educational attainment.

4.3 | Supplementary analyses

Before concluding, we investigate where employees move, conditional on a turnover event. Our arguments imply that as a function of an individual's mode of hiring, we should expect heterogeneous "destination states" when an employee transitions out of an AE versus an HE employment spell. We have posited that AEs turnover more quickly than HEs because the former group are less well suited to their postacquisition workplace. If this is the case, we expect that,

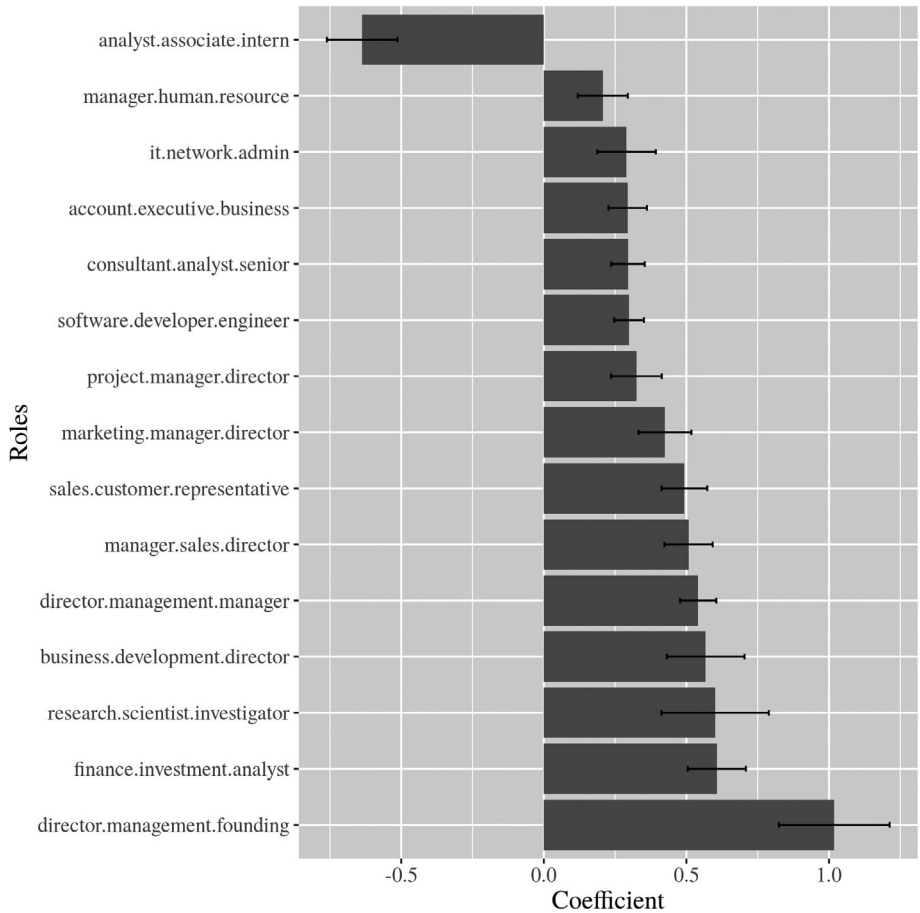

FIGURE 1 Interaction coefficients for AE and specific job roles in cox regressions of the turnover rate. Error bars show 95% confidence intervals. Only effects with error bars not crossing zero are shown. Job roles are labeled with three representative words for each category of job titles. The reference category is a "kitchen sink" categorization of under-represented roles in the CEM sample in comparison with the pooled sample. Results condition on job rank fixed effects, educational level fixed effects, prior average tenure (in days), prior number of jobs, and time since bachelor's degree

even when we condition on departure from the acquiring firm, AEs will be more likely than HEs to accept a work role at a small, high-growth company. In other words, we should observe a greater likelihood of AE's returning to the startup sector, while HE's should be prone to depart for a position at a more established entity.

To investigate this idea, we construct a completely different CEM sample: for an AE that departs an acquirer in year *t*, we find an also-departing HE that matches on age, job role, job rank, and educational credentials. The CEM procedure creates balance between AEs and HEs *at the point of departure*; we report CEM-weighted differences in destination state outcomes in the matched sample. We cross-tabulate (two-tailed *t*-tests) destination outcomes in (a) employer growth (as measured by the ratio of incoming and outgoing employees in each year), (b) the log of employer size, (c) new employer is a "small" firm (as defined by ≤25 employees in our dataset), and (d) new employer is a "very small" firm (as defined by ≤5 employees in our dataset). Table 3 shows exactly what we expect: when AEs turnover, relative to HEs they are more likely to find jobs at smaller, higher growth companies.

5 | DISCUSSION AND CONCLUSION

The level of employee turnover is a consideration in multiple strategic perspectives on the firm, including learning- and knowledge-based theories. We empirically show that employees who join a company via an acquisition depart from their new employers at a higher rate than matched, organically HEs. Importantly, we find that the best educated and highest-ranking AEs as well as those in critical technical, business development, sales, and leadership roles turnover at a much higher rate than comparable individuals who are recruited into established organizations via standard, organic hiring strategies. Our principal contribution is to establish these empirical results in a broad sample of employees and companies in which we carefully match on individuals' career histories. To our knowledge, this is the first paper to do so with data that match on individuals' career backgrounds and former employer characteristics.

A potential concern with the empirical analysis in the paper concerns its reliance on a matching estimator. In this regard, we wish to be clear about both limitations and intentions. To recover a causal treatment effect, selection-on-observed approaches like CEM require the

TABLE 3 Destination state differences between AEs and HEs, CEM sample

	A-Emp	H-Emp	Difference	Difference (%)
Destination growth (in-degree/all-degree)	0.590	0.563	0.0270 [.0000]	4.80
Log (destination size)	5.70	6.06	−0.3600 [.0000]	−25.92
Probability destination small	0.201	0.171	0.0300 [.0000]	17.54
Probability destination very small	0.047	0.041	0.0062 [.0164]	15.12

Note: Statistical significance values indicated for two-tailed CEM weighted *t*-tests of mean employment tenure differences. Growth is measured by considering the inflow $deg^{+}_{i,t}$ and outflow $deg^{-}_{i,t}$ of employees to company *i* in year *t* in the following relation: $deg^{+}_{i,t}/(deg^{+}_{i,t}+deg^{-}_{i,t})$. Inflows do not take into account A-hires. A value of 0.5 therefore indicates a net flow of zero (inflow = outflow), a value of >0.5 indicates positive growth, and anything <0.5 indicates negative growth. Destination size is endogenously measured by yearly representation in the totality of the dataset (~30 million individuals). A "small" destination is any company that has ≤25 employees in the dataset; a "very small" destination is any company that has less than ≤5 employees in the dataset.

Abbreviations: AEs, acquired employees; HEs, hired employees; CEM, coarsened exact matching.

conditional-independence assumption. This states that common variables that affect both treatment assignment and outcomes must be observed, so that conditioning on these variables fully removes the dependence between the two. In this article, however, we do not use CEM to assert a causal claim. Our objective is simply to use it to establish a credible baseline turnover rate for AEs. Because AEs are manifestly different than HEs on multiple dimensions, we cannot approximate a reasonable, counterfactual turnover rate without constraining the comparison group to other employees with similar backgrounds. We consider organic hires matched on time of hire with professional backgrounds that are very similar to AEs to establish the best approximation of a comparative turnover rate.

The paper contributes to the growing literature on the micro-foundations of strategic outcomes (Adner & Helfat, 2003; Felin & Foss, 2005; Gavetti, 2005; Nagle & Teodoridis, 2019). This work often connects characteristics of individuals in technical or leadership roles to organizational behaviors and outcomes. Here, even though we model turnover rates at the person-level, conceptually we take a step up to the meso-scale: if employee retention is important for organizational growth and renewal, theories of knowledge-based competitive differentiation ultimately will be concerned with heterogeneity in how employees are recruited and retained. More broadly, it seems probable that the literature at the crossroads of absorptive capacity, dynamic capabilities, and corporate performance will continue to experience renewed investigation as large-scale resume databases become available. Rich career histories for a near-census of organizational members open up many new research possibilities surrounding individual careers and the micro-foundations of strategic outcomes (e.g., Liu & Stuart, 2014).

We conclude with an avenue for future work. We know from a broad literature on M&A that the strategic rationales for doing deals are diverse: among other factors, cost and revenue synergies, market share gains, geographic expansion, acquiring IP and products, access to new customers, and of course, scaling a workforce, all may enter the calculus to do a deal. Likewise, there are vastly different approaches to postmerger integration, which likely influence how hiring mode affects relative turnover rates. Indeed, a handful of paper establish that postmerger innovative outcomes depend on approaches to merger integration (e.g., Kapoor & Lim, 2007; Puranam & Srikanth, 2007). Our data sources, unfortunately, are silent on the strategic intent of the acquirer and the steps that are taken to implement deals. We know when a transaction for a VC-backed company occurred, but we neither know why it happened nor how it was managed *ex post*. With datasets that are richer on the whys and hows of deals, researchers would be able to explore how the acquirer's motivations and their merger integration plans interact with hiring mode to determine the levels of success at retaining valued employees.

ACKNOWLEDGEMENTS

This paper has benefitted from comments by Melissa Graebner, J. Daniel Kim and participants at the 2018 People and Organizations Conference at the Wharton School. The authors thank Moshe Barach on his work on the dataset, and Fanyi Zhou for her research assistance. The authors would like to acknowledge our financial support: this project was funded in part by a dissertation grant from the Kauffman Foundation for a dissertation grant, and the NUS Business School Start-up Grant (WBS Number: R-313-000-128-133). All errors remain our responsibility.

DATA AVAILABILITY STATEMENT

Historical public data that support the findings of this study are available from the authors upon reasonable request. Restrictions apply to the availability of data obtained from PitchBook

and CrunchBase, which were used under license for this study. These data are available from the authors with the permission of the respective licensors.

ORCID

Weiyi Ng https://orcid.org/0000-0003-4094-0139
Toby E. Stuart https://orcid.org/0000-0002-3858-1360

REFERENCES

Adner, R., & Helfat, C. E. (2003). Corporate effects and dynamic managerial capabilities. *Strategic Management Journal*, *24*(10), 1011–1025.

Agarwal, R., Campbell, B. A., Franco, A. M., & Ganco, M. (2016). What do I take with me? The mediating effect of spin-out team size and tenure on the founder–firm performance relationship. *Academy of Management Journal*, *59*(3), 1060–1087.

Agarwal, R., Ganco, M., & Ziedonis, R. H. (2009). Reputations for toughness in patent enforcement: Implications for knowledge spillovers via inventor mobility. *Strategic Management Journal*, *30*(13), 1349–1374.

Agarwal, R., & Helfat, C. E. (2009). Strategic renewal of organizations. *Organization Science*, *20*(2), 281–293.

Ahuja, G., & Katila, R. (2001). Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management Journal*, *22*(3), 197–220.

Aime, F., Johnson, S., Ridge, J. W., & Hill, A. D. (2010). The routine may be stable but the advantage is not: Competitive implications of key employee mobility. *Strategic Management Journal*, *31*(1), 75–87.

Almeida, P., Dokko, G., & Rosenkopf, L. (2003). Startup size and the mechanisms of external learning: Increasing opportunity and decreasing ability? *Research Policy*, *32*(2), 301–315.

Archambault, A., & Grudin, J. (2012). A longitudinal study of Facebook, LinkedIn, & twitter use. In *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 2741–2750). New York City, NY: ACM Press.

Autor, D., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, *103*(5), 1553–1597.

Azoulay, P., Graff Zivin, J. S., & Wang, J. (2010). Superstar extinction. *The Quarterly Journal of Economics*, *125*(2), 549–589.

Barber, A. E., Wesson, M. J., Roberson, Q. M., & Taylor, M. S. (1999). A tale of two job markets: Organizational size and its effects on hiring practices and job search behavior. *Personnel Psychology*, *52*(4), 841–868.

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

Bidwell, M. (2011). Paying more to get less: The effects of external hiring versus internal mobility. *Administrative Science Quarterly*, *56*(3), 369–407.

Bingham, C. B., Heimeriks, K. H., Schijven, M., & Gates, S. (2015). Concurrent learning: How firms develop multiple dynamic capabilities in parallel. *Strategic Management Journal*, *36*(12), 1802–1825.

Blau, P. M., & Schoenherr, R. A. (1971). *The structure of organizations*. New York City, NY: Basic Books (AZ).

Boeker, W. (1997). Executive migration and strategic change: The effect of top manager movement on product-market entry. *Administrative Science Quarterly*, *42*(2), 213–236.

Campbell, B. A., Ganco, M., Franco, A. M., & Agarwal, R. (2012). Who leaves, where to, and why worry? Employee mobility, entrepreneurship and effects on source firm performance. *Strategic Management Journal*, *33*(1), 65–87.

Cappelli, P., & Keller, J. R. (2014). Talent management: Conceptual approaches and practical challenges. *Annual Review of Organizational Psychology and Organizational Behavior*, *1*(1), 305–331.

Cartwright, S., & Cooper, C. L. (1993). The role of culture compatibility in successful organizational marriage. *Academy of Management Perspectives*, *7*(2), 57–70.

Chatterjee, J. (2017). Strategy, human capital investments, business-domain capabilities, and performance: A study in the global software services industry. *Strategic Management Journal*, *38*(3), 588–608.

Chatterji, A., & Patro, A. (2014). Dynamic capabilities and managing human capital. *Academy of Management Perspectives*, *28*(4), 395–408.

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.

Coff, R. W. (1999). How buyers cope with uncertainty when acquiring firms in knowledge-intensive industries: Caveat emptor. *Organization Science*, *10*(2), 144–161.

Coff, R. W., & Kryscynski, D. (2011). Invited editorial: Drilling for micro-foundations of human capital–based competitive advantages. *Journal of Management*, *37*(5), 1429–1443.

Cohen, W. M., & Levinthal, D. A. (1989). Innovation and learning: The two faces of R & D. *The Economic Journal*, *99*(397), 569–596.

Crispin, G., & Mehler, M. (2013). Sources of hire 2013: Perception is reality. Retrieved from. http://www.careerxroads.com/news/SourcesOfHire2013.pdf

Dierickx, I., & Cool, K. (1989). Asset stock accumulation and sustainability of competitive advantage. *Management Science*, *35*(12), 1504–1511.

Dobrev, S. D., & Barnett, W. P. (2005). Organizational roles and transition to entrepreneurship. *Academy of Management Journal*, *48*(3), 433–449.

Dokko, G., Wilk, S. L., & Rothbard, N. P. (2009). Unpacking prior experience: How career history affects job performance. *Organization Science*, *20*(1), 51–68.

Doz, Y. L. (1987). Technology partnerships between larger and smaller firms: Some critical issues. *International Studies of Management & Organization*, *17*(4), 31–57.

Elfenbein, D. W., Hamilton, B. H., & Zenger, T. R. (2010). The small firm effect and the entrepreneurial spawning of scientists and engineers. *Management Science*, *56*(4), 659–681.

Elo, A. E. (1978). *The rating of chessplayers, past and present*. New York, NY: Arco Pub.

Fedyk, A. & Hodson, J. (2017). Trading on talent: Human capital and firm performance. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3017559

Felin, T., & Foss, N. J. (2005). Strategic organization: A field in search of micro-foundations. *Strategic Organization*, *3*(4), 441–455.

Gardner, T. M. (2005). Interfirm competition for human resources: Evidence from the software industry. *Academy of Management Journal*, *48*(2), 237–256.

Gavetti, G. (2005). Cognition and hierarchy: Rethinking the microfoundations of capabilities' development. *Organization Science*, *16*(6), 599–617.

Ge, C., Huang, K. W., & Png, I. P. (2016). Engineer/scientist careers: Patents, online profiles, and misclassification bias. *Strategic Management Journal*, *37*(1), 232–253.

Graebner, M., Eisenhardt, K., & Roundy, P. (2010). Success and failure in technology acquisitions: Lessons for buyers and sellers. *Academy of Management Perspectives*, *24*, 73–92.

Graebner, M. E. (2004). Momentum and serendipity: How acquired leaders create value in the integration of technology firms. *Strategic Management Journal*, *25*(8–9), 751–777.

Groysberg, B. (2010). *Chasing stars: The myth of talent and the portability of performance*. Princeton, NJ: Princeton University Press.

Groysberg, B., Lee, L. E., & Nanda, A. (2008). Can they take it with them? The portability of star knowledge workers' performance. *Management Science*, *54*(7), 1213–1230.

Hannan, M. T., & Freeman, J. (1984). Structural inertia and organizational change. *American Sociological Review*, *49*(2), 149–164.

Harris, D., & Helfat, C. (1997). Specificity of CEO human capital and compensation. *Strategic Management Journal*, *18*(11), 895–920.

Haspeslagh, P. C., & Jemison, D. B. (1991). *Managing acquisitions: Creating value through corporate renewal* (Vol. 416). New York, NY: Free Press.

Helfat, C. E., Finkelstein, S., Mitchell, W., Peteraf, M. A., Singh, H., Teece, D. J., & Winter, S. G. (2007). *Dynamic capabilities: Understanding strategic change in organizations* (pp. 1–18). Malden, MA: Blackwell Publishing.

Hoetker, G., & Agarwal, R. (2007). Death hurts, but it isn't fatal: The postexit diffusion of knowledge created by innovative companies. *Academy of Management Journal*, *50*(2), 446–467.

Iacus, S. M., King, G., & Porro, G. (2011). Multivariate matching methods that are monotonic imbalance bounding. *Journal of the American Statistical Association*, *106*(493), 345–361.

Jacoby, S. M., Nason, E. M., & Saguchi, K. (2005). The role of the senior HR executive in Japan and the United States: Employment relations, corporate governance, and values. *Industrial Relations: A Journal of Economy and Society*, *44*(2), 207–241.

Kapoor, R., & Lim, K. (2007). The impact of acquisitions on the productivity of inventors at semiconductor firms: A synthesis of knowledge-based and incentive-based perspectives. *Academy of Management Journal*, *50*(5), 1133–1155.

Kim, J.D. (2020). Startup Acquisitions as a Hiring Strategy: Worker Choice and Turnover.Retrieved from SSRN: https://ssrn.com/abstract=3252784

Kortum, S., & Lerner, J. (2000). Assessing the contribution of venture capital to innovation. *RAND Journal of Economics*, *31*(4), 674–692.

Lacetera, N., Cockburn, I. M., & Henderson, R. (2004). Do firms change capabilities by hiring new people? A study of the adoption of science-based drug discovery. *Advances in Strategic Management*, *21*, 133–160.

Lee, T. W., & Mitchell, T. R. (1994). An alternative approach: The unfolding model of voluntary employee turnover. *Academy of Management Review*, *19*(1), 51–89.

Link, A. N. (1988). Acquisitions as sources of technological innovation. *Mergers and Acquisitions*, *23*(3), 36–39.

Liu, C. C., & Stuart, T. (2014). Positions and rewards: The allocation of resources within a science-based entrepreneurial firm. *Research Policy*, *43*(7), 1134–1143.

Marx, M. (2011). The firm strikes back: Non-compete agreements and the mobility of technical professionals. *American Sociological Review*, *76*(5), 695–712.

Marx, M., Strumsky, D., & Fleming, L. (2009). Mobility, skills, and the Michigan non-compete experiment. *Management Science*, *55*(6), 875–889.

Mawdsley, J. K., & Somaya, D. (2016). Employee mobility and organizational outcomes: An integrative conceptual framework and research agenda. *Journal of Management*, *42*(1), 85–113.

Meyer-Doyle, P., Lee, S., & Helfat, C. E. (2019). Disentangling the Microfoundations of Dynamic Capabilities: Evidence from Microdata on Acquisitions. INSEAD Working Paper.

Michaels, E., Handfield-Jones, H., & Axelrod, B. (2001). *The war for talent*. Cambridge, MA: Harvard Business Press.

Montgomery, C. A., & Wernerfelt, B. (1988). Diversification, Ricardian rents, and Tobin's q. *The Rand Journal of Economics*, *19*(4), 623–632.

Nagle, F., & Teodoridis, F. (2019). Jack of all trades and master of knowledge: The role of diversification in new distant knowledge integration. *Strategic Management Journal*, *41*(1), 55–85.

Nelson, R. R., & Winter, S. G. (1982). *An evolutionary theory of economic change*. Cambridge, MA: Harvard University Press.

Ouimet, P., & Zarutskie, R. (2011). Acquiring labor. US Census Bureau Center for Economic Studies Paper No. *CES-WP-11-32*.

Palomeras, N., & Melero, E. (2010). Markets for inventors: Learning-by-hiring as a driver of mobility. *Management Science*, *56*(5), 881–895.

Peteraf, M. A. (1993). The cornerstones of competitive advantage: A resource-based view. *Strategic Management Journal*, *14*(3), 179–191.

Phillips, D. J. (2002). A genealogical approach to organizational life chances: The parent-progeny transfer among Silicon Valley law firms, 1946–1996. *Administrative Science Quarterly*, *47*(3), 474–506.

Puranam, P., Singh, H., & Zollo, M. (2006). Organizing for innovation: Managing the coordination-autonomy dilemma in technology acquisitions. *Academy of Management Journal*, *49*(2), 263–280.

Puranam, P., & Srikanth, K. (2007). What they know vs. what they do: How acquirers leverage technology acquisitions. *Strategic Management Journal*, *28*(8), 805–825.

Ranft, A. L., & Lord, M. D. (2000). Acquiring new knowledge: The role of retaining human capital in acquisitions of high-tech firms. *The Journal of High Technology Management Research*, *11*(2), 295–319.

Ranft, A. L., & Lord, M. D. (2002). Acquiring new technologies and capabilities: A grounded model of acquisition implementation. *Organization Science*, *13*(4), 420–441.

Rao, H., & Drazin, R. (2002). Overcoming resource constraints on product innovation by recruiting talent from rivals: A study of the mutual fund industry, 1986–1994. *Academy of Management Journal*, *45*(3), 491–507.

Reagans, R., Argote, L., & Brooks, D. (2005). Individual experience and experience working together: Predicting learning rates from knowing who knows what and knowing how to work together. *Management science*, *51*(6), 869–881.

Rosenkopf, L., & Almeida, P. (2003). Overcoming local search through alliances and mobility. *Management Science*, *49*(6), 751–766.

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

Solomon, B. C., Nikolaev, B. N., & Shepherd, D. A. (2021). Does educational attainment promote job satisfaction? The bittersweet trade-offs between job resources, demands, and stress. *Journal of Applied Psychology*.

Somaya, D., Williamson, I. O., & Lorinkova, N. (2008). Gone but not lost: The different performance impacts of employee mobility between cooperators versus competitors. *Academy of Management Journal*, *51*(5), 936–953.

Song, J., Almeida, P., & Wu, G. (2003). Learning–by–hiring: When is mobility more likely to facilitate interfirm knowledge transfer? *Management Science*, *49*(4), 351–365.

Sørensen, J. B., & Fassiotto, M. A. (2011). Organizations as fonts of entrepreneurship. *Organization Science*, *22*(5), 1322–1331.

Sørensen, J. B., & Stuart, T. E. (2000). Aging, obsolescence, and organizational innovation. *Administrative Science Quarterly*, *45*(1), 81–112.

Starr, E., Frake, J., & Agarwal, R. (2019). Mobility constraint externalities. *Organization Science*, *30*(5), 961–980.

Starr, E. P., Prescott, J. J., & Bishara, N. D. (2021). Noncompete agreements in the US labor force. *The Journal of Law and Economics*, *64*(1), 53–84.

Stuart, T. E., & Sorenson, O. (2003). Liquidity events and the geographic distribution of entrepreneurial activity. *Administrative Science Quarterly*, *48*(2), 175–201.

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, *28*(13), 1319–1350.

Wezel, F. C., Cattani, G., & Pennings, J. M. (2006). Competitive implications of interfirm mobility. *Organization Science*, *17*(6), 691–709.

Younge, K. A., Tong, T. W., & Fleming, L. (2015). How anticipated employee mobility affects acquisition likelihood: Evidence from a natural experiment. *Strategic Management Journal*, *36*(5), 686–708.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

How to cite this article: Ng, W., & Stuart, T. E. (2022). Acquired employees versus hired employees: Retained or turned over? *Strategic Management Journal*, *43*(5), 1025–1045. https://doi.org/10.1002/smj.3361