Organizational Mismatch:

Startup Acquisitions and Employee Departures

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Abstract

This study investigates the effectiveness of high-tech startup acquisitions as a hiring strategy ("acqui-hiring") versus traditional hiring. Unlike regular hires who choose to join a new firm on their own volition, most acquired employees do not have a voice in the decision to be acquired. I theorize that this lack of choice instigates organizational mismatch, thereby elevating turnover rates among acquired workers. Using employee-level data from US Census, I find empirical support for higher turnover among acquired workers relative to regular hires, as well as the moderating role of organizational mismatch. Moreover, analysis of serial acquirers suggests that firms learn over time how to effectively retain acquired employees. Together, these results elucidate the conditions under which firms can harness new talent by acquiring startups.

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Introduction

Strategy scholars have long explored how firms can gain advantage by hiring and retaining human capital (Castanias and Helfat 1991; Hatch and Dyer 2004; Karim and Williams 2012; Campbell, Coff, and Kryscynski 2012). Alongside traditional hiring, an important alternative channel for ushering in new talent is through acquiring other companies that employ talented workers. Commonly known as "acqui-hiring," this practice is especially prevalent among startup companies because their most valuable – and often the only – asset is their human capital (Selby and Mayer 2013; Chatterji and Patro 2014). Consistent with this view, Mark Zuckerberg once remarked, "We buy companies to get excellent people."

While M&A literature has traditionally focused on new technological capabilities sourced from startup acquisitions (Granstrand and Sjölander 1990; Ahuja and Katila 2001; Puranam and Srikanth 2007), talent is a key acquired resource that has received much less attention. Given the prominence of human assets for young firms (e.g., Agarwal et al. 2015; Honore and Ganco 2019), startup acquisitions are an important alternative method of hiring external talent. And yet, there is a limited understanding of how the two hiring strategies – "acqui-hiring" and traditional hiring – systematically differ in their underlying motives as well as performance outcomes.

In this study, I fill this gap by investigating the effectiveness of startup acquisitions as a hiring strategy relative to traditional hiring. I propose a theory building on the fundamental premise that acquisitions occur outside the purview of most employees.[1] Specifically, unlike regular hires who choose to join a new employer, most acquired workers do not have a voice in the decision to be acquired – much less by which firm to be acquired. I posit that this inability to

[1] Typically, a startup firm's decision to be acquired is directed by a small party including founders and early investors. Therefore, founders do not pertain to this theoretical argument and thus excluded from the empirical analysis. Nonetheless, results are consistent when including founders.

choose their new employer (i.e., acquiring firm) increases the salience of an *organizational mismatch*, elevating turnover among acquired workers. This logic does not hold for regular hires, precisely because they voluntarily choose their new employer and hence any organizational mismatch resulting from this decision to join. Furthermore, I hypothesize that high-earning individuals are more sensitive to the sudden organizational mismatch since they tend to face better outside options, thereby leaving at a higher rate than low earners following an acquisition.

I test these hypotheses in a large-scale sample of high-tech startup acquisitions that I assemble using comprehensive employee-employer matched data from the US Census. I find that acquired startup workers systematically exhibit higher turnover relative to observationally similar regular hires at the same acquiring firm. Moreover, I construct a new measure of organizational mismatch, and demonstrate that turnover sharply increases with organizational mismatch for acquired workers, but not for regular hires. Consistent with the theory, turnover is more pronounced for high-earning individuals, suggesting costly departures for the acquirer.

A key managerial implication from this study is that firms can learn from prior startup acquisitions. Analyses focusing on serial acquirers show that past experience enables firms to mitigate the negative effect of an organizational mismatch on retention. Another managerial takeaway is the novel measure of organizational mismatch, which managers can use prior to the acquisition to assess their likelihood of retaining employees from potential acquisition targets.

This study makes several contributions. First, it theorizes and tests the key differences between acqui-hiring and regular hiring. Building on prior research on employee mobility and firm performance (Wezel et al. 2006; Agarwal et al. 2009; Campbell et al. 2012; Raffiee 2017), this study compares two important but distinct channels through which firms can hire and retain new talent. Though acqui-hiring has several advantages including the ability to hire the entire team, this paper sheds light on the limitations on this increasingly popular approach by demonstrating the challenges of retaining acquired workers – especially the star employees.

Second, this paper builds on the existing technology M&A literature by examining talent as a key asset purchased through an acquisition. While existing studies have examined the turnover patterns of top management teams (Cannella and Hambrick 1993; Walsh 1988; Ranft and Lord 2000), this study is the first to investigate the impact of acquisitions on the entire workforce of the target firm, with special attention paid to rank-and-file employees who are unwittingly transferred through an acquisition. Taken together, this study advances our understanding of technology M&A as a strategic channel to gain not only new technological innovations and market advantage, but also valuable talent held by other firms.

Theory and Hypotheses

A seminal line of research in strategy has examined capabilities as a source of firm performance (e.g., Barney 1991; Dosi, Nelson, and Winter 2001). In turbulent competitive environments, dynamic capabilities are posited to enable firms to gain and sustain long-run advantage in response to external change (Teece, Pisano, and Shuen 1997; Helfat and Peteraf 2003). Extending this theory, Teece (2007) decomposes dynamics capabilities as a firm's capacity to (1) *sense,* (2) *seize,* and (3) *reconfigure* new opportunities.

Given the importance of human capital for firm performance (Castanias and Helfat 1991; Hatch and Dyer 2004), talent is a key asset that can be viewed through the theoretical lens of dynamic capabilities. Implicating Teece's (2007) framework, Chatterji and Patro (2014) contend that a firm needs to assemble the necessary human assets to pursue ("seize") a business opportunity after identifying its market potential ("sense"). Building on its capacity to seize new opportunities, the firm can coalesce talent by either internally re-deploying existing workforce or externally hiring new talent. If the firm's existing personnel is not sufficient to address the new opportunity, then it must externally garner the necessary human capital.

Generally, there are two modes of hiring outside talent: (1) individuals from traditional labor markets and (2) teams through acquisitions (Selby and Mayer 2013). This decision to hire individuals or acquire an existing team is a *strategic choice* that firms must weigh when mobilizing talent resources in pursuit of a business opportunity. This choice involves complex uncertainties because unlike other assets such as physical capital or intellectual property, human assets cannot be purchased and owned outright; that is, once acquired, individuals can voluntarily exit the firm (Ranft and Lord 2000). Therefore, the decision between acqui-hiring and traditional hiring must consider not only the potential value of the human asset once brought in, but also the likelihood of retaining the new employees.

Startup Acquisitions as a Hiring Strategy

Why might a firm choose to hire through startup acquisitions, rather than the traditional labor market? Relative to regular hiring, the primary advantage of acqui-hiring is the ability to hire an entire team in a single transaction. Team-based hiring is beneficial for several reasons. First, acquirers can capture the team complementarities that startups accumulate over time. These complementarities arise likely due to the benefits associated with a team's collective diversity in experience and expertise (Teodoridis 2017; Choudhury and Haas 2018), leading to outperformance of teams over individuals (e.g., Wuchty, Jones, and Uzzi 2007). Meanwhile, these team-specific complementarities may disappear once the team dissolves. For instance, exogenously losing a member in a startup founding team (Choi et al. 2019) or a patenting team (Jaravel, Petkova, and Bell 2018) leads to a large long-run decline in the remaining group's performance. Therefore, wholly purchasing the entire team allows the acquirer to preserve and capture the target startup's team complementarities.

Second, acqui-hiring bypasses the difficulty of inferring an individual's contribution to a group's outcome. Attribution of credit in team-based work is especially limited in knowledge-intensive settings where an individual's input is difficult to quantify (Vakili, Teodoridis, and Bikard 2019). Therefore, a potential acquirer may be unable to identify and thus poach the best employees from a startup team. Conversely, the same logic applies to identifying and selecting out subpar (or free-riding) employees as described in the problem of moral hazard in teams (Holmstrom 1982). Given the limitations in the ability to properly attribute team output to individual inputs, startup acquisitions may therefore generate efficiency gains in hiring by bringing in the entire team rather than a collection of individuals.

In addition to the benefits derived from hiring an entire team, the acquiring firm can enhance employee retention by offering stronger employment contracts upon the acquisition than they would with regular hires. New employment contracts for acquired workers commonly include both economic incentives and restrictive clauses designed to reinforce employee retention. Typically, employment contracts used in startup acquisitions offer equity incentives with a vesting schedule of three to four years, along with restrictive clauses like non-competition agreements.[2] By and large, startup acquisitions provide several advantages as a hiring strategy – including contractual levers to increase worker retention – in comparison to conventional hiring.

[2] See Coyle and Polsky (2013) for discussion on standard equity incentives used in startup acquisitions. Regarding non-compete agreements and startup acquisitions, see Schneid (2006) and Younge, Tong, and Fleming (2014).

Worker Choice in Acqui-hiring vs. Regular Hiring

A key feature in acqui-hiring is that acquisitions occur outside the purview of the acquired employees. Unlike regular hires who *choose* to join the new employer on their own volition, acquired workers have limited to no discretion in their employer's ownership change. This is because the target company's decision to be acquired is directed by a few major stakeholders, typically the founders and early investors. In other words, non-founding employees are generally excluded from the pre-acquisition talks regardless of their personal desire to work for the presumed acquirer.[3] Even if these employees are able to anticipate that their firm may be acquired in the future, it is unlikely that they can foresee by exactly whom they might be acquired – essentially rendering these individuals devoid of choice. Building on this premise, I theorize that the lack of choice among acquired workers leads to elevated rates of turnover. This leads to the first hypothesis.

Hypothesis 1: Acquired workers exhibit greater rates of turnover than near-identical regular hires who voluntarily join the same acquiring firm.

Organizational Mismatch

Moreover, employee turnover likely depends on the extent to which the new employer is dissimilar from the prior employer. An "organizational mismatch" may arise if there is a stark contrast between the two firms. In the context of startup acquisitions, organizational mismatch may be especially prevalent because the startups (target) and established firms (acquirer) are fundamentally different types of organizations. These stark organizational differences manifest

[3] Although this premise is not empirically testable, there are many supporting anecdotes among practitioners. For example, Eric Jackson, a former executive at PayPal, describes in his book "The PayPal Wars" that he along with most of the PayPal employees were not aware of the acquisition decision until the final deal was reached and publicly announced. Only the top management team from both companies as well as early investors were involved in the deal-making.

in several dimensions including organizational structure (Hannan and Freeman 1984; Sorensen 2007) as well as norms and routines (Stuart and Sorenson 2003; Turco 2016). For simplicity, the multi-dimensional contrast between the two groups can be summarized as startups being more "entrepreneurial" than established firms – hence the organizational mismatch that frequently emerges when these two dissimilar firm types are combined through an acquisition.

In several interviews with various early employees of acquired startups, many of the respondents highlighted the difficulty of acclimating to a less-entrepreneurial acquirer.[4] In particular, many interviewees pointed to the tradeoff between bureaucracy and speed when comparing their experiences at the acquired startup and acquirer. A former early employee of a startup, who unexpectedly landed at a large technology firm through an acquisition in 2014, remarked: "[Acquirer]'s internal processes, language, and rules took months to learn. More importantly, incentives are inverted at big firms. Big companies are process-oriented… and with so much invested and publicized, the priority is minimizing mistakes. Small companies are results-oriented, so we swing for the fences." In such cases invoking sizeable change, acquired workers are likely to experience significant frictions in acclimating to their new employer. Since they did not initially choose to work for their new employer, the difficult transition likely heightens their likelihood of leaving the firm.

However, this logic does not theoretically hold true for regular hires, even for those who also experience an organizational mismatch in their transition. This divergence results from the fact that regular hires voluntarily choose their employer and hence any organizational mismatch resulting from the decision to join. Because they exercise choice, regular hires may stay with the new employer *in spite of* the (anticipated) organizational mismatch. Consequently, organizational

[4] Interviews conducted by the author between 2015 and 2018.

mismatch should not influence regular hires' turnover patterns since it had already been factored into their initial decision to join. This prediction leads to the second hypothesis:

Hypothesis 2: Organizational mismatch leads to a greater turnover among acquired workers, but not among regular hires.

Who is most affected by organizational mismatch? While organizational mismatch is a firm-level construct, there may be significant within-firm variation in the types of individuals who are more or less likely to leave the firm as a consequence. An important mediator may be the acquired workers' outside options. Generally, an individual's likelihood of leaving a firm increases with the level of outside options she faces in the external labor market (e.g., Zenger 1992). In the same way, the decision to part ways with the acquirer likely depends on the person's career prospects outside the firm. In theory, even though employees do not choose to be acquired, those who have limited outside options may be constrained to stay with the acquirer despite the organizational mismatch. This leads to the next hypothesis:

Hypothesis 3: *Within an acquired startup, turnover among acquired workers will be greater for those with better outside options.*

Do Firms Learn Over Time?

Some firms – including Cisco as the leading example – are generally renowned for their ability to acquire and effectively integrate the target companies (Chaudhuri and Tabrizi 1999). From a strategy perspective, a key question is whether and how firms accumulate such capability to retain and integrate the new employees. A plain view is that such ability is fixed inside each firm and therefore some firms are innately better than others.

In contrast, a large literature on dynamic capabilities contends that firms can learn to improve their M&A performance by harnessing specific capabilities (e.g., Eisenhardt and Martin

2000; Trichterborn, Knyphausen- Aufsess, and Schweizer 2016). Relatedly, Arora, Fosfuri, and Roende (2018) theoretically argue that firms must invest in "absorptive capacity" (Cohen and Levinthal 1990) to be able to effectively integrate the newly acquired startup. Therefore, acquirers are likely to learn how to better manage startup acquisitions as they gain experience in acquiring nascent firms.

How and which specific dynamic capabilities do firms develop through their repeated acquisitions of startup companies? In Teece's (2007) framework, the two important capabilities in initially approaching new opportunities are the ability to *sense* and *seize*. In the context of learning from prior startup acquisitions, the first capability may involve "sensing" and therefore identifying certain types of startups as promising acquisition targets. In other words, prior experience may enable firms to spot and avoid acquiring startups that would invoke an organizational mismatch. Moreover, the second capability may involve "seizing" resources from the acquired firm once the buyout is completed. In this aspect, prior experience may allow firms to better manage and retain the new employees. Leading to the final set of hypotheses, these two capabilities convey distinct types of learning – both of which are expected to increase acquisition performance.

Hypothesis 4A – Learning to Sense: As serial acquirers gain experience in acquiring startups, they are less likely to acquire a startup with an organizational mismatch.

Hypothesis 4B – Learning to Seize: As serial acquirers gain experience in acquiring startups, they are more likely to retain employees from the acquired startup.

Data and Methods

For this study, I use employee-employer matched data from the US Census Bureau to build a large sample of high-tech startup companies – and their non-founding employees – that are acquired between 1990 and 2011. Along with the acquired workers, I also identify the employees who join the acquiring firm as regular hires in the same year as the acquisition. This approach ensures that all employees are new to the firm, meaning that tenure at the firm is fixed to zero for both groups of workers. In addition, to make sure that the differences in retention outcomes are not endogenously driven by worker characteristics, I use a matching algorithm to find observationally equivalent organic hires for each acquired employee. Then I compare the mobility decision of acquired workers and regular hires in the first, second, and third year following the year of joining. The following section provides a detailed description of the construction of firm- and individual-level data, and the resulting final sample.

Identifying High-Tech Startups

While M&A activity covers many industries and different types of firms, this study focuses on high-tech startup targets for several reasons. First, in order to examine a setting where human capital – more so than the tangible assets such as land and machinery – is a key asset to acquire, I restrict the sample of acquisition targets to startups. Startups are defined as firms that are younger than ten years old, where a firm's birth is the year when the first employee is hired.

Second, I focus on the high-tech sector in order to differentiate small businesses from high-growth startups. While many researchers and practitioners alike broadly use the term entrepreneurship, there are different forms of entrepreneurship. Most notably, small businesses and growth-oriented startups are two distinct types of entrepreneurship albeit both tend to consist of young firms. On the one hand, high-growth startups are a small subset of new firms that quickly scale and account for a disproportionately high share of job (Decker et al. 2014; Guzman and Stern 2016). On the other hand, small businesses tend to remain small because they typically do not have a desire to grow large or innovate in a meaningful way (Hurst and Pugsley 2011).

In the same way, acquisitions of young firms include both high-growth startups and small businesses. According to the M&A database constructed for this study (as further described in Section 3.2), acquisitions – whereby one firm is subsumed under the ownership of another existing firm – among young firms occur predominantly in the small business sector, most frequently restaurants and dentist offices. As Figure 1 shows, roughly 85% of startup acquisitions take place in non-high tech industries. Therefore, given that the prevailing view on startup acquisitions concerns high-growth ventures, it is critical to distinguish the two forms of entrepreneurship in this study.

To differentiate between high-growth startups and small businesses, many studies in the entrepreneurship literature limit their study to venture capital-backed startups or young firms that are granted a patent (Azoulay et al. 2018). Since venture capital financing and patenting are early firm outcomes that reflect the firm's underlying quality – rather than innate traits of the firm – this study does not use these markers in order to avoid selecting on firm quality.

Instead, I attempt to focus on high-growth startups by restricting the sample to high-tech startups. This approach has several advantages. First, the categorization of high-tech versus non-high-tech is a time-invariant measure that is determined at the time of the establishment's birth. Second, high-tech industries are objectively defined by the Bureau of Labor Statistics as the set of NAICS-4 industries with the highest share of STEM-oriented workers. Accordingly, I follow Hecker (2005) and Goldschlag and Miranda (2016) to define the high-tech sector (See Table A1 in the Appendix for a complete list). While I impose the high-tech condition on the target startup firms, acquirers can operate in any industry.

Firm Characteristics

The Longitudinal Business Database (LBD) is the primary firm-level dataset in this study. The LBD is a panel dataset of all establishments in the U.S. with at least one paid employee. The LBD covers all industries in the private non-farm economy and every state in the US. The LBD begins in 1976 and currently runs through 2015. While the underlying observations are at the level of the establishment, the LBD assigns a unique firm identifier to each establishment. This is a useful feature especially for firms with multiple establishments. Furthermore, the longitudinal nature of the LBD allows researchers to identify the birth of startup companies and track important business characteristics including firm age, employment, payroll, and exit.

More importantly, I identify acquisitions in the LBD based on firm ownership changes. The main benefit of relying on the LBD for detecting M&A activity is the systematic coverage of young, private firms, for which standard M&A databases (e.g., SDC Thomson) are known to be limited in coverage. When a firm undergoes an acquisition, its firm-identifier changes to that of the surviving (parent) firm in the following year. I construct a set of firms that experience such change. In order to exclude non-M&A-based changes to firm ownership (e.g., false positives) such as divestitures and corporate restructuring, I leverage the pre-acquisition establishment-level name and EIN information to carefully validate the detected cases of acquisitions. In short, I rule out cases in which (1) the ex-ante names of the acquired and acquiring establishments are highly similar and (2) EINs do not change. Consequently, I build a comprehensive database of firm acquisitions in the LBD between 1985 and 2015. See Figure 1 for trends in startup acquisitions over time.

[Insert Figure 1 here]

In addition, I use the Longitudinal Linked Patent-Business Database (See Graham et al. 2018) to measure whether the target firm owns (or has applied for) a patent prior to the acquisition year. This allows me to distinguish patent-owning from non-patenting target firms.

Worker Characteristics

Worker-level information is based on the Longitudinal Employer-Household Dynamics (LEHD), which is an employee-employer matched dataset that covers 95% of private sector jobs. The study uses the full available version of the LEHD, which includes all US states except Massachusetts. The current LEHD time coverage spans from 1985 to 2014, although most states are not available before 2000 (See Figure 2 for a map of included states and their earliest year of coverage).[5] The LEHD tracks individuals at a quarterly basis and provides information on earnings, linked employer identifier, and demographic characteristics (e.g., age and gender). These quarterly worker-firm observations allow me to precisely determine whether and when acquired workers transition to the acquiring firm as well as their post-acquisition mobility decisions. Employers in the LEHD are observed at the state EIN level. I merge the LEHD to the LBD using the crosswalk developed by Haltiwanger et al. (2014).

I use the earnings and join date information in the LEHD to categorize startup employees as founders, early joiners, or late joiners. Similar to Kerr and Kerr (2017) and Azoulay et al. (2018), I define founders as employees who join the firm in the first quarter of operation and are

[5] States vary in their first time of entry in the LEHD data. The earliest entrant is Maryland in 1985Q2. Most states enter the data by 2000. See Vilhuber (2018) for a detailed description of the LEHD.

among the top three earners during the firm's first year. Relatedly, early joiners are those who join the firm in the first quarter but are not among the top three earners. Lastly, late joiners are those who join the firm after the first quarter. In order to focus on individuals who are unwittingly acquired, I exclude from the sample the founders and early joiners, who represent 13% of the acquired workers. Nonetheless, all results are consistent when including the founding team in the analyses.

One limitation of the worker-level data is that the LEHD does not distinguish voluntary from involuntary turnover. While this study puts forth a narrative around voluntary departures driven by worker choice, many employees at the target firm may simply be fired. Unfortunately, the data do not allow for careful distinction between the two types of departures. However, to mitigate this potential issue, I take two concrete steps in the analysis. First, I restrict my sample of acquired workers to those who work for the acquirer at least two quarters, meaning that they initially receive job offers for employment at the acquirer. That is, these workers are not outright dismissed upon the acquisition. The "never-joiners" comprise roughly 10% of the sample of acquired workers, and are removed in the main analyses. Second, I check whether acquired workers who leave are systematically more likely to enter into unemployment relative to regular joiners who leave. The intuition is that higher unemployment rates among acquired workers would validate the concern around involuntary dismissals. Fortunately, the two groups do not appear to show major differences in the propensity for unemployment upon leaving the acquirer.

Analytic Sample

Beginning with the full set of acquisitions in the LBD, I identify roughly 6,000 cases in which high-tech startups are acquired. After matching to the LEHD and restricting to years between 1990 and 2011 to allow for at least three years of observation following the acquisition, the sample is reduced to 3,700 acquired startups.[6]

At the worker level, there are 300,000 non-founding employees from target startups who transition to the acquirer, along with several million workers who are conventionally hired at the acquirer in the same year as the acquisition. For comparability, I exclude regular hires for whom this is their first job. By construction, acquired workers are experienced workers given their tenure at the target firm prior to the acquisition. By restricting the set to having some prior experience, this provides a comparable set of 5.3 million regular hires.

To ensure that the differences in retention outcomes are not driven by unobserved characteristics such as worker quality or seniority, each acquired worker is matched, using Coarsened Exact Matching (Iacus, King, and Porro 2012), to an observationally equivalent organic hire who joins the same acquiring firm during the acquisition year. While worker roles are not observed in the LEHD, I use detailed worker characteristics – namely earnings, age, and gender in the year prior to the acquisition – to adjust for inherent differences in human capital between the two groups.[7] By conditioning the acquisition year to be the join year for regular hires, tenure at firm is mechanically set to zero for both the acquired workers and regular hires. To ensure comparability in career trajectories, I restrict to regular hires with prior labor market experience (i.e., exclude first-time workers) because, by construction, their acquired counterparts have prior work experience from the target firm prior to the acquisition. Therefore, differences in retention outcomes in this study are not driven by differences in tenure. The final sample

[6] Several factors contribute to the reduction in sample size when matching LBD firms to the LEHD. First, because of the imperfect EIN-based matching between the two data sources, roughly 30% of the firms in the LBD are not found in the LBD-LEHD crosswalk. Second, Massachusetts is not included in the LEHD, meaning that the identified firm-level acquisition is dropped from the sample if the target or the acquiring firm is based in Massachusetts.
[7] In order to avoid partial annual earnings, I use "full quarter earnings" which are calculated as the wages in a quarter for which the person receives non-zero wages from the preceding and subsequent quarters.

includes 3,700 startup acquisitions, 230,000 acquired workers, and 1.6 million regular hires. Tables 1A and 1B present the summary statistics of the final sample's firms (both the target and acquirer) and their employees.

[Insert Tables 1A and 1B here]

Main Variables

The main dependent variables in this study are worker-level retention outcomes. $Depart_{ijt}$ is a binary outcome equal to 1 if worker *i* is no longer employed at the acquiring firm *j* in year *t* since the acquisition. The variable remains as 0 if the worker is employed at the firm for any amount of time during the year of interest. For example, if a worker acquired in 2005 leaves the firm in 2006, then the $Depart_{ij1}$ would equal 0 while $Depart_{ij2}$ would equal 1.

The primary independent variable is $Acquired_{ij}$, which is a dummy variable equal to 1 if worker *i* in acquiring firm *j* is hired through a startup acquisition, and 0 if the worker is organically hired.

Measuring Organizational Mismatch

As explained in Section 2, organizational mismatch in startup acquisitions occurs when the acquired target firm is starkly more "entrepreneurial" than the acquiring firm. A naïve approach to quantify the "entrepreneurial" nature of firms is by using firm size or firm age. However, there are numerous examples (e.g., Cisco) of large and old firms that are unusually entrepreneurial as an organization. To allow for this heterogeneity beyond firm age and size, I construct a novel measure "Startup Affinity Score" by leveraging each firm's entire stock of employment patterns, which are enabled by the use of population-level administrative data.

For each firm, I quantify its *Startup Affinity Score* by examining its turnover events along with the destinations of the departing employees.[8] More specifically, for every departure event occurring before the acquisition year, I track whether the leaving individual subsequently joins a startup or an established firm. A departing employee's intentional choice to join a startup, rather than a mature firm, reveals her preferences for employment conditions (Sorkin, 2018). When aggregated up, these mobility choices characterize the firm's tendency to attract workers who prefer to transition to startups rather than established firms. While these former employees do not directly influence the behavior of the acquired employees because they are not present at the time of the acquisition, their subsequent decisions to join a young firm or an established company provide useful and relevant information to characterize their former employers.

Peer turnover patterns are a useful and relevant empirical frame to quantify each firm's "entrepreneurial nature" for two main reasons. First, usefulness comes from the fact that job transitions are not random: they are intentional choices that reveal workers' preferences for employers. Simply put, a worker's decision to join a particular firm – and thereby not join another employer – demonstrates her relative value of the two firms based on both pecuniary and non-pecuniary factors (Sorkin 2018). Second, relevance of peer job transitions stems from the fact that organizations tend to attract similar individuals. Since both the departing and incumbent employees initially selected into joining a particular organization rather than other potential employers, these workers likely exhibit similar preferences for employment. Following this logic, I define a firm to have high *Startup Affinity Score* if its former employees – who leave prior to the acquisition – systematically tend to move to other young companies.

[8] Only employer-to-employer flows are considered. In other words, turnover events resulting in unemployment (e.g., retirement) are excluded.

To construct this measure, I track the departures of each firm's employees prior to the acquisitions along with their destinations. Using the LEHD to track their career histories, I find roughly 1 million employer-to-employer transitions – before the acquisition – among the employees of the target firms. Similarly, I find 78 million pre-acquisition departures for the acquirers. I aggregate all of the pre-acquisition mobility decisions, and then calculate the share of transitions to other startups versus old firms. The resulting firm-level shares characterize each target and acquiring firm's affinity for entrepreneurial organizations.

Figure 3 illustrates the distribution of the firms' pre-acquisition share of departures to startups (henceforth "Startup Affinity Score"). The blue kernel density curve for the target firms suggests that, even after selecting on the relatively homogenous group of young high-tech firms, there is a significant variation in the share of departures to young vs. old employers. In other words, not all startups are entrepreneurial: While some targets exhibit a strong affinity for startups, others show weak affinity for startups. The fact that some startups are more entrepreneurial than others is consistent with recent evidence that startups substantially vary in how "flat" they are organizationally structured (Lee 2019). In turn, this rich variation among target startups largely generate high versus low organizational mismatch in startup acquisitions.

Moreover, the distribution of the acquiring firms is also shown to provide a benchmark for older firms and their share of employee departures to startups. Relative to that of the target firms, the curve for the acquiring firms is shifted to the left. This shows that that workers at the acquiring firms tend to flow to other established firms. Therefore, *Startup Affinity Score* is expectedly correlated with firm maturity, reflecting the systematic and persistent endogenous sorting of workers into nascent versus old firms.

[Insert Figure 3 here]

Lastly, I similarly compute *Startup Affinity Score* for the set of regular hires based on their prior employers. This is possible because, as described in Section 3, the control group is restricted to individuals with some labor market experience prior to joining the acquiring firm. Such condition makes the two groups comparable, as all acquired workers possess work experience at the target firm prior to being acquired by another employer. Therefore, each worker has a prior employer, whose *Startup Affinity Score* can be determined.

Finally, I define organizational mismatch as a binary variable that equals 1 if the prior employer has a higher *Startup Affinity Score* than the acquiring firm, and 0 otherwise. For acquired workers, their prior employer is the target startup; for regular hires, it is simply their previous employer. As a robustness check, organizational mismatch can also be measured as the continuous difference in Startup Affinity Score between the two firms.

Econometric Framework

The main results in this study are based on a series of linear worker-level regressions. These regressions are a variation of the following simple econometric framework with worker *i* in acquiring firm *j*:

$$Y_{ij} = \beta_0 + \beta_1 Acquired_{ij} + \delta_j + \varepsilon_{ij} \quad (1)$$

Y_{ij} is a set of binary outcome variables including departing from firm *j* by year *k* since the acquisition, where $k \in \{1,2,3\}$. Furthermore, δ_j is a suite of target-acquirer firm fixed effects, meaning that all firm-specific traits including industry, geography, and year of the acquisition are subsumed by these parameters. In other words, workers who are acquired by firm *j* are solely compared to those who join firm *j* as organic hires during the same year as the acquisition.

It is important to note why linear (ordinary least squares) regression models are used instead of non-linear models (e.g., probit, logit) given that the dependent variables are binary outcomes. While probit and logit models have the benefit of bounding the estimates between 0 and 1, the resulting estimates may be biased due to the incidental parameters problem. Unlike linear regressions which provide the best linear approximation to the conditional expectation function, logit and probit models may produce biased estimates as the number of parameters grows relative to the number of observations.[9] This issue may be particularly problematic when including many fixed effects in the regression.

Firm fixed effects δ_j in Equation (1) are crucial in this empirical design because they allow β_1 to be interpreted as within-firm effects. In other words, estimates of β_1 identify the effect of being acquired versus hired on the worker's likelihood of exiting the firm, after accounting for firm-specific effects including region, industry, and join year. Therefore, the inclusion of δ_j mitigates the endogeneity concerns that would otherwise arise when comparing across firms, stemming from both observable and unobservable differences. Given the importance of firm fixed effects as the identification strategy in this empirical framework, this study uses a linear probability model in order to avoid the incidental parameters problem.

Empirical Results

Turnover Rates: Acquired vs. Regular Hires

Figure 4 shows the unconditional rates of employee retention for acquired workers versus regular hires. Since the set of acquired workers in the sample are those who work for the acquirer for at least two quarters, retention rates are mechanically set to 100% in the year of the

[9] See Angrist and Pischke (2009) for a detailed discussion on limited dependent variables (e.g., binary), non-linear models, and the incidental parameter problem.

acquisition. In the following years, acquired workers noticeably exhibit lower retention rates. While 88% of the regular joiners are retained by the year after the join (acquisition) year, the rate for acquired workers is 66%. However, the stark differences in retention rates appear to wane over time.

[Insert Figure 4 here]

In parallel to Figure 4, Table 2 presents the linear probability regression estimates on employee turnover, accounting for individual and firm characteristics. The dependent variable is a binary indicator that equals 1 if the employee leaves the acquiring firm by year *k*. All specification include target-acquirer firm fixed effects. While the first three specifications include all workers, the latter three specifications include only the workers that are closely matched in earnings, age, and gender. As a result, acquired workers and traditional hires in the matched specifications are observationally equivalent with regards to key human capital characteristics. Nonetheless, results are consistent with and without matching, suggesting that retention outcomes are not explained by innate individual characteristics.

Overall, all specifications indicate that acquired workers are significantly more likely to leave the acquirer. The effect ranges from 8 to 22 percentage points and is statistically significant at the 1% level. While only 12% of the comparable regular hires leave the firm in the first year after the acquisition, 34% of the acquired workers leave in the same time period. In a three-year window, acquired workers are approximately 15% more likely to leave the firm relative to regular hires. Therefore, even after controlling for important worker traits such as earnings and age, acquired workers exhibit greater turnover relative to regular hires, confirming hypothesis 1.

[Insert Table 2 here]

It is important to note that the differences in retention between the groups become much smaller over time. This is consistent with the view that the elevated rates of turnover among acquired workers is largely driven organizational mismatch, which is further tested in the next section. Following the canonical model of worker tenure and turnover, acquired workers who learn that they are a good match tend to stay with their new employer. Consequently, rates of employee exits among the two groups appear to converge over time. Taken together, these results imply that new employees learn about the quality of their match with the firm relatively quickly, as reflected by the large share of employee outflows in the first year of employment.

Organizational Mismatch and Turnover

In this section, I test organizational mismatch as the primary mechanism behind the elevated rates of turnover among acquired workers. To do so, acquired worker indicator is fully interacted with a binary variable *Organizational Mismatch* equalling 1 if the individual's prior employer has a higher *Startup Affinity Score* than the acquirer. For acquired workers, the prior employer is the target startup while for the regular hires, it is simply their previous employer. Since *Organizational Mismatch* is separately measured for acquired workers and regular hires, this term can be separately included to estimate its independent effect on turnover.

[Insert Figure 5 here]

Before the regression analysis with a full suite of controls, Figure 5 plots the unconditional rates of employee departures based on whether the individual experiences an organizational mismatch or not. The sample is split into acquired workers (Panel A) and regular hires (Panel B) to illustrate whether organizational mismatch differentially impacts the two groups.[10] For acquired workers, organizational mismatch group exhibits an upward level shift, indicating that these individuals systematically have higher rates of employee departures. However, this pattern does not hold for regular hires, implying that organizational mismatch has no significant impact on these individuals' turnover. Table 3 statistically estimates these differences in an OLS model with target-acquirer fixed effects.

[Insert Table 3 here]

Consistent with prior results, the second row in Table 3 shows that acquired workers generally exhibit significantly greater rates of turnover than regular hires. More importantly, the first row shows a positive and statistically significant interaction effect between acquired worker indicator and organizational mismatch. This demonstrates that among acquired workers, those who experience an organizational mismatch are much more likely to leave the firm.[11] In the first year following the acquisition, relative to regular hires, acquired workers with an organizational mismatch are roughly 50% more likely to leave than their counterparts who do not experience such mismatch. By year three, this difference is roughly 140%. These findings demonstrate that organizational mismatch is a key driver of post-acquisition turnover.

Equally important for testing Hypothesis 2 is understanding the impact of organizational mismatch on regular hires' turnover patterns. As articulated in Section 2.3, theory predicts a null relationship because, unlike acquired individuals, regular hires voluntarily choose their next employer along with any organizational mismatch incurred by the decision to join. The third row in Table 3 estimates the impact of organizational mismatch on turnover among regular hires. In

[10] Organizational Mismatch equals 1 for 56% and 55% of acquired workers and regular hires, respectively.
[11] These results are robust to using organizational mismatch measured as a continuous variable (i.e., Prior employer's *Startup Affinity Score* minus acquirer's *Startup Affinity Score*.

all three specifications, though sometimes statistically significant at the 10% level due to the large sample size, the point estimate is economically close to zero – roughly 0.6% change relative to a mean of 35%. A more compelling case for a null effect is that the sign flips across the specifications, reflecting an imprecise relationship with turnover. Taken together, these results demonstrate that organizational mismatch significantly increases turnover for acquired workers, but not for regular hires. This confirms hypothesis 2.

Next, Table 4 tests whether high-earning individuals are more likely to leave, addressing the hypothesis that they are particularly sensitive to organizational mismatch given their more attractive outside options. In this interaction regression, high earners are workers in the top quartile in the firm's wage distribution. This leads to the empirical testing of whether high-earning acquired workers are more or less likely to leave the firm than low earners, while holding constant the baseline (e.g., regular hires) differences in leaving across income groups.

[Insert Table 4 here]

First, it is important to note that the baseline effect (row 3) of being a high earner is negative and significant, meaning that top earners are generally less likely to leave. This is consistent with the existing prior literature which also documents the negative link between higher compensation and risk of exiting, and attributes it to higher opportunity costs (Coff 1997; Zenger 1992; Campbell et al. 2012).

However, the interaction effect is positive and significant. In other words, among the acquired workers, high-earning individuals demonstrate a greater propensity to leave. This confirms hypothesis 3. Interestingly, the departure effect among top earners does not appear until two years after the acquisition. While specific employment contractual terms are unobservable, it may be the case that – aligned with the typical one-year cliff in equity vesting schedule – these individuals wait until a significant portion of the equity vests. Overall, though not immediately, the exodus of startup employees following an acquisition is disproportionately prominent among the high earners. Insofar as firms aim to hire and retain top talent through startup acquisitions, these pronounced departure patterns among highest-paid employees appear to be especially costly for the acquiring firm.

Do Firms Learn Over Time?

As discussed in Section 2.4, firms may develop dynamic capabilities that enable them to exhibit greater performance over time. The two hypothesized capabilities revolve around "sensing" and "seizing". The former is the ability to avoid acquiring startups that would result in an organizational mismatch. The latter is the ability to better retain acquired employees following the buyout. I empirically test these two channels of learning by transitioning to firm-level analyses and focusing on serial acquirers, which account for roughly half of the acquisitions in the sample.[12]

[Insert Table 5 here]

Panel A of Table 5 presents the relationship between the serial acquirer's number of prior startup acquisitions and the propensity to acquire a startup with an organizational mismatch. While the first specification does not include any controls, the second specification includes acquirer firm fixed effects to account for time-invariant unobservable characteristics of the firm such as industry. In both specifications, there does not seem to be a systematic relationship

[12] In other words, half of the deals are done by one-time acquirers. However, it is possible that these one-time acquirers actually have prior deal experience before the starting point of this study's sample (e.g., 1990).

between prior experience and organizational mismatch. In support of rejecting Hypothesis 4A, firms do not appear to learn to "sense" which startups to pursue or avoid acquiring.

Panel B tests the link between acquired employee turnover and prior startup acquisitions. As a baseline, consistent with prior results, row 2 indicates that a startup acquisition resulting in an organizational mismatch exhibits greater rates of turnover. However, the interaction term demonstrates that the negative impact of organizational mismatch declines with prior experience. Each additional prior startup acquisition experience is linked to 0.9 percentage point reduction in employee turnover, relative to a mean departure rate of roughly 60%. Albeit seemingly small, this estimated effect is economically significant effect given that prolific acquirers such as Cisco and Google have each acquired dozens of startups in the past decade.[13] Consistent with hypothesis 4B, these results suggest that serial acquirers learn how to "seize" new opportunities as they accumulate experience with acquiring startups.

Alternative Explanation: Technology vs. Talent

An important alternative explanation is that firms acquire startups primarily for their technology, not necessarily for their talent. As a result, acquirers may decide to dismiss a sizeable portion of the acquired workforce after purchasing its underlying technology, mechanically leading to higher rates of observed turnover. Though they do not directly address the talent purchased through M&A, prior studies highlight firms' desire to bring in new technology when acquiring young firms (Granstrand and Sjölander 1990; Ahuja and Katila 2001; Puranam and Srikanth 2007).

[13] Savannah Dowling, "Cisco Acqiusitions Drive Company Growth," *Crunchbase News*, December 2018 https://news.crunchbase.com/news/cisco-acquisitions-drive-company-growth/ (Accessed December 2019).

I address this concern in two ways. First, as described in Section 3.3, I emphasize the fact that the acquired workers in this study are those who work for the acquirer for at least two quarters. This condition implies that these individuals were vetted and subsequently hired by the acquirer, reflecting a desire to, at least initially, hire the new talent. Second, I directly test whether the turnover premium for acquired workers is higher for target startups with a patent. In this alternative view, turnover for acquired workers is expected to be much higher for target firms with a patent since acquirers presumably dismiss the acquired workers after procuring the technology. To test this prediction, I use the Longitudinal Linked Patent-Business Database (Graham et al. 2018), and define a target firm to be patent-owning if has applied for or been granted a patent prior to the acquisition year.

[Insert Table 6 here]

Table 6 presents the turnover differential by target firm's patenting. Acquired worker status is interacted with whether the target firm owns a patent prior to being acquired. Since prior patenting, by construction, is identified only for the acquired workers, the baseline effect on patenting status is not included in the regressions. The first three specifications show the results on target firm's patent ownership and employee departures within the first three years of the acquisition. With respect to the baseline effect of being an acquired worker versus a regular hire, the higher rates of employee exits among acquired workers consistently remain positive and statistically significant. However, the interaction term indicates that target firm's patenting status does not lead to meaningful differences in retention outcomes among the acquired workers. Thus, these results reject the view that the acquirer is likely to dismiss workers en masse after purchasing a target firm and its intellectual property.

Conclusion

Acquisitions of high-tech startups in the US have experienced a steady rise in the past several decades (See Figure 1). While other factors are certainly relevant, talent inside entrepreneurial firms is a linchpin asset that plays an important role in driving the demand for acquiring startups. Though this approach of "acqui-hiring" is an important alternative way of ushering in external talent, there has been limited understanding how the various methods of hiring systematically differ. This study fills this gap by providing the first, large-scale empirical and theoretical investigation on the effectiveness of startup acquisitions as a hiring strategy versus regular hiring.

At the heart of these two hiring strategies is a theory based on the lack of choice among acquired workers: unlike regular hires who choose to join a new employer, acquired workers seldom have a choice in their employer's ownership change. Because they do not choose, acquired workers are theorized to exhibit pronounced rates of turnover – especially when encountering organizational mismatch that often results from the startup acquisition. Using comprehensive administrative data from the US Census between 1990 and 2011, I find strong empirical support for the proposed theory.

Despite the apparent benefits of hiring entire teams rather than individuals, these results highlight the challenges and limitations of startup acquisitions as a hiring strategy. Nevertheless, it appears that firms can learn to develop their capabilities in acquiring startups. Analyses on serial acquirers demonstrate that prior experience in acquiring startups enables acquirers to adequately manage the difficulties of an organizational mismatch, thereby helping keep the acquired team intact.

There are several limitations to this study worth highlighting. First, the underlying data do not capture each's occupation inside the firm. In order to avoid comparing fundamentally different types of workers – for example, executives to entry-level employees – I use earnings and age to proxy for the worker's level of human capital. Nonetheless, it would be informative to clarify the nature of the work that is assigned to individual. For instance, the results on departures may differ between technical versus non-technical workers.

Second, the inability to observe employment contracts is a constraint in this study. A common view of startup acquisitions is that target employees become much wealthier upon being acquired, financially enabling these individuals to leave and pursue other career opportunities. However, liquidity effects from an acquisition greatly vary by the specific terms of the employment contract including the equity vesting schedule. Moreover, personal wealth gains from startup acquisitions tend to be heavily concentrated among the founders, with much smaller shares distributed among the non-founding employees. Since this study focuses on the non-founding employees by excluding both the founders and the early joiners from the sample, it is unlikely that wealth effects are the primary driver of employee turnover among the acquired employees. Nevertheless, it would be informative to understand how much of the post-acquisition retention patterns can be accounted for by each individual's financial gains from the buyout.

This study concludes by highlighting a few areas for future research. An important question is how the price of startup acquisitions – which frequently surpass a billion dollar valuation in spite of the uncertainties associated with new markets and technologies – accounts for the post-acquisition retention patterns of the target workers. Put differently: What is the price of (retained) entrepreneurial talent? Although acquirers may rationally price their transactions by accurately predicting the likelihood of preserving the human capital, it could be the case that acquirers systematically overpay in light of the markedly high turnover documented in this study.

Another avenue is to explore how the acquired technology is integrated and implemented inside the acquiring firm. Building on a broad literature on technology M&A and integration (e.g., Graebner 2004; Puranam, Singh, and Zollo 2006; Paruchuri, Nerkar, and Hambrick 2006), a novel topic is the duality of technology and individuals that flow via an acquisition. Although this study documents nuanced effects depending on whether the target firm owns a patent, more attention should be paid to the interplay between the actual inventor and the underlying patents. Given that startup acquisitions are an empirical setting in which there is co-mobility of patents and individuals – including cases when one asset moves but not the other – the complementarity between knowledge and individuals can be empirically assessed. In other words, how useful is knowledge without the original source? Insofar as knowledge and talent are valuable assets for firms, this seems to be a first-order line of scholarly inquiry. More broadly, the increasingly popular use of comprehensive employee-employer datasets is promising for future research streams on how human capital not only shapes the creation and growth of new ventures, but also how incumbent firms can acquire such entrepreneurial talent.

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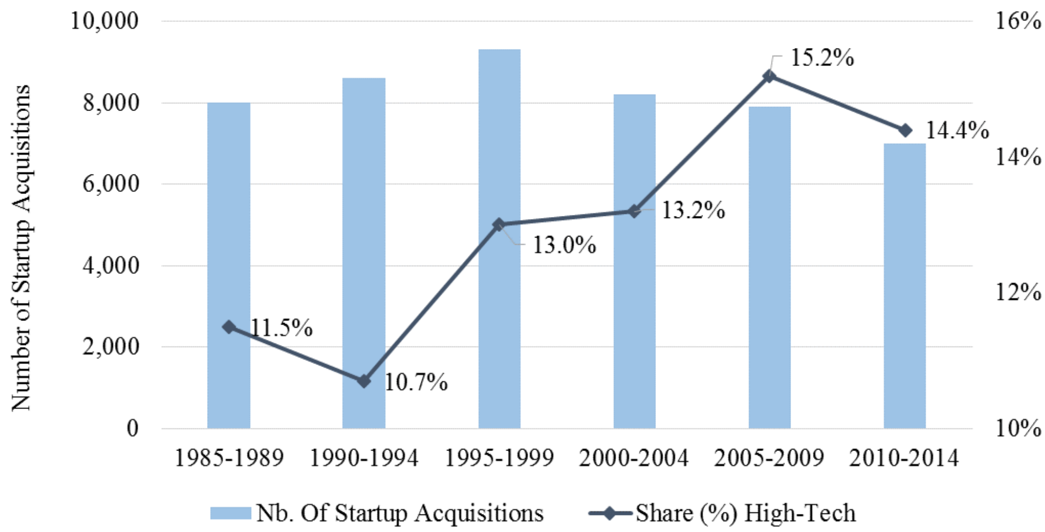
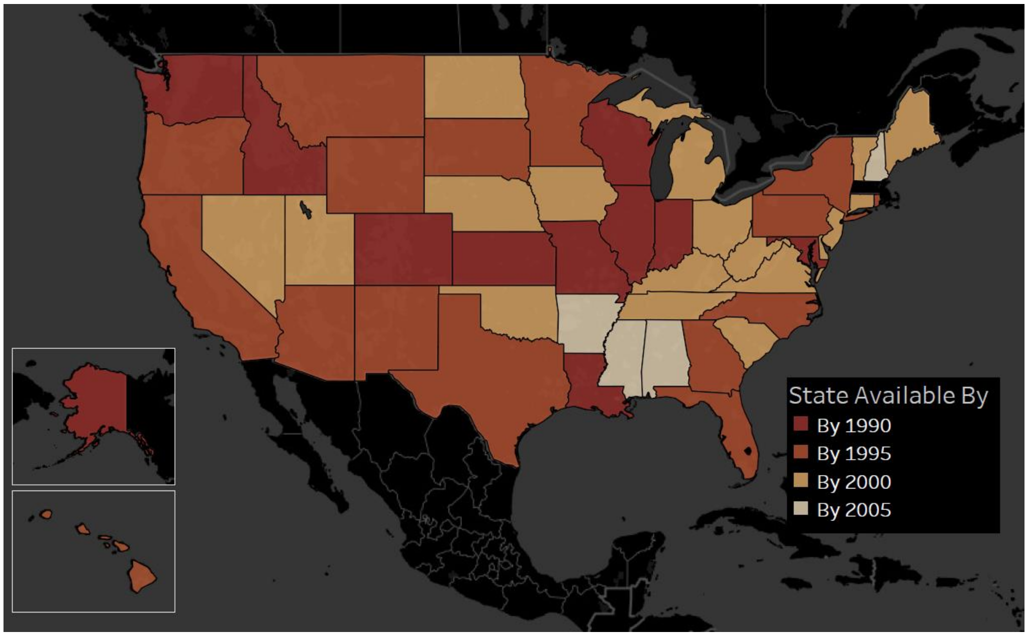
Figures

Figure 1: Time Trends in US Startup Acquisitions



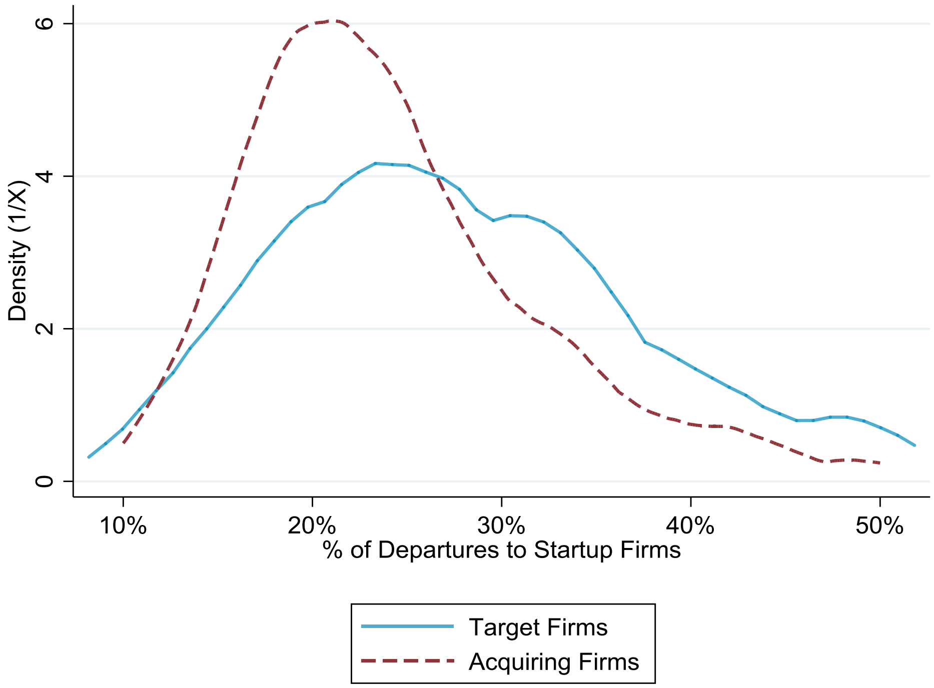
Note: This figure counts the number of times that startups, defined as younger than ten years old, are acquired by existing firms in a given five-year window. Acquisition activity is measured using the author's algorithm based on firm ownership changes in the LBD. Share of high-tech is the percentage of startup acquisitions that occur in industries with the highest shares of STEM-oriented workers (See Section 3 for detailed description of defining high-tech industry).

Figure 2: Coverage of US States and Entry Year in LEHD



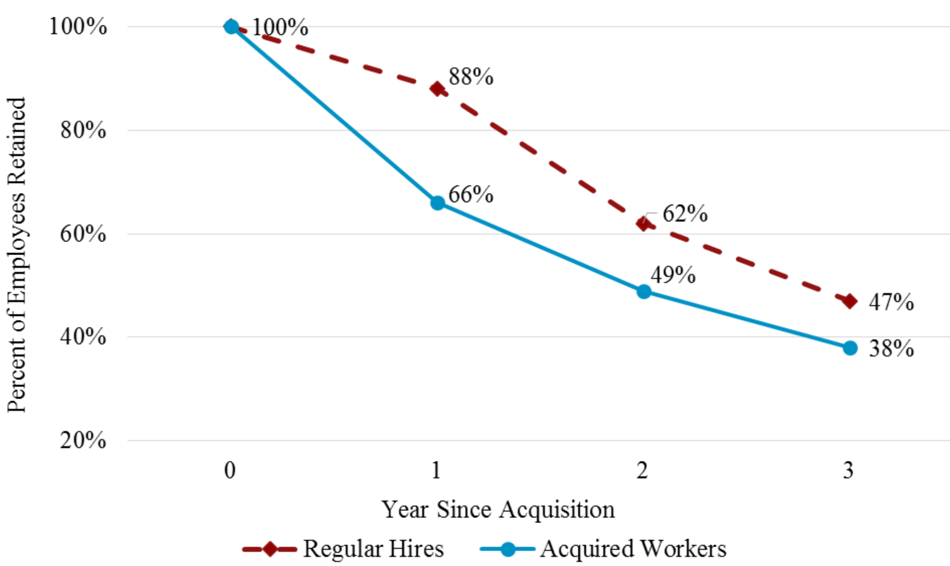
Note: See Vilhuber (2018) for a detailed description of the LEHD. This study uses all available states in the LEHD.

Figure 3: Distribution of Startup Affinity Score



Note: This figure is the kernel density plot of firns' *Startup Affinity Score*, defined as the share of pre-acquisition employee departures to startup firms (5 years old or younger). Since the age of the receiving firm is the variable of interest, only employer-to-employer flows are counted.

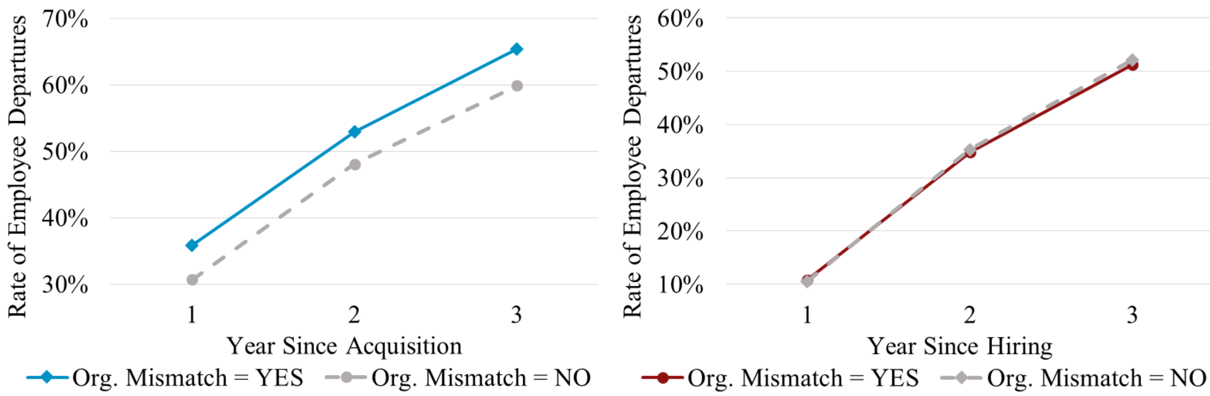
Figure 4: Employee Retention Rates: Acquired Workers vs. Regular Hires



Note: This figure plots the unconditional retention rates. Both acquired workers and regular hires join the acquiring firm in year 0. Employee is retained in year *t* if she works for the firm for at least a quarter in year *t*.

Figure 5: Organizational Mismatch and Turnover

Panel A: Acquired Workers *Panel B: Regular Hires*



Note: These figures plot the unconditional (%) rates of employee departures for acquired workers and regular hires in Panels A and B, respectively. In each plot, workers are divided into those who experience an organizational mismatch versus those who do not. Organizational Mismatch is a binary variable that equals 1 if the individual's prior employer has a higher *Startup Affinity Score* than the acquirer; prior employer for the treated group is the target startup while for regular hires it is simply the previous employer.

Tables

Table 1A: Firm-level Summary Statistics

	Target Firms (N=3,700)			Acquirers		
Characteristics	**Mean**	**Median***	**SD**	**Mean**	**Median***	**SD**
Firm Size (Employee Count)	150	42	460	12,500	1,900	31,100
Firm Age	4.1	4.0	2.9	22.4	23.0	8.6
Payroll ($M)	10	3	30	860	130	2,700
Top NAICS-4 Industries (%)						
Computer Systems Design And Services	0.20		0.40	0.08		0.27
Mgmt., Scientific, and Technical Consulting Svcs.	0.12		0.32	0.02		0.15
Architectural, Engineering, and Related Services	0.11		0.31	0.06		0.24
Scientific R&D Services	0.07		0.26	0.03		0.16
Professional and Commercial Equipment & Supplies	0.07		0.26	0.05		0.22
Software	0.06		0.24	0.05		0.21
Data Processing, Hosting, and Related Services	0.06		0.24	0.03		0.17

Note: Observations are at the level of distinct target firms. Serial acquirers are counted multiple times based on their characteristics at the time of each acquisition. Following Census disclosure rules, quasi-medians (the average of observations in between the 41st and 59th percentile values) are shown.

Table 1B: Worker-level Summary Statistics

Panel A: Before Matching

Characteristics	Acquired Workers (N=295,000) Mean	Median*	SD	Regular Hires (N=5,267,000) Mean	Median*	SD
Annual Earnings ($)	81,000	54,700	980,600	65,500	45,900	160,000
Age	38.5	37.0	10.3	36.5	35.0	11.0
Male (%)	0.66		0.47	0.60		0.49

Panel B: After Matching

Characteristics	Acquired Workers (N=226,000) Mean	Median*	SD	Regular Hires (N=1,648,000) Mean	Median*	SD
Annual Earnings ($)	77,000	55,900	238,000	75,800	58,500	147,000
Age	37.5	36.5	9.6	36.3	35.5	9.2
Male (%)	0.67		0.47	0.68		0.46

Note: Observations are at the worker level. Founders and early joiners are removed from this sample. In other words, only late joiners (employees hired in or after second quarter since firm's birth) are included. Following Census disclosure rules, quasi-medians (the average of observations in between the 41st and 59th percentile values) are shown.

Table 2: Employee Departure Rates: Acquired Workers vs. Regular Hires

	Full Sample			Matched Sample		
	Departure by *t+1*	Departure by *t+2*	Departure by *t+3*	Departure by *t+1*	Departure by *t+2*	Departure by *t+3*
	(1)	(2)	(3)	(4)	(5)	(6)
Acquired Worker	0.217***	0.132***	0.086***	0.217***	0.136***	0.090***
	(0.013)	(0.013)	(0.013)	(0.015)	(0.015)	(0.015)
Mean DV of Regular Hires	0.122	0.376	0.535	0.108	0.350	0.517
Target-Acquirer Firm FE	YES	YES	YES	YES	YES	YES
Observations	5,562,000	5,562,000	5,562,000	1,874,000	1,874,000	1,874,000
R-squared	0.107	0.115	0.109	0.119	0.112	0.114

Note: This table is a set of worker-level regressions using OLS. Specifications 4-6 are based on matched workers using Coarsened Exact Matching. Depart by *k* equals 1 if the worker does not receive any wages from the firm in year *k*. Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Organizational Mismatch and Turnover

	Departure by *t+1* (1)	Departure by *t+2* (2)	Departure by *t+3* (3)
Acquired Worker × Org. Mismatch	0.081***	0.087***	0.079***
	(0.028)	(0.030)	(0.031)
Acquired Worker	0.169***	0.085***	0.044
	(0.023)	(0.026)	(0.028)
Org. Mismatch	0.006*	-0.000	-0.006*
	(0.003)	(0.004)	(0.003)
Mean DV of Regular Hires	0.108	0.350	0.517
Matched Workers	YES	YES	YES
Target-Acquirer Firm FE	YES	YES	YES
Observations	1,874,000	1,874,000	1,874,000
R-squared	0.120	0.112	0.114

Note: This table is a set of worker-level regressions using OLS. All specifications are based on matched workers using Coarsened Exact Matching. Organizational Mismatch is a binary variable that equals 1 if the individual's prior employer has a higher *Startup Affinity Score* than the acquirer; prior employer for the treated group is the target startup while for regular hires it is simply the previous employer. Depart by *k* equals 1 if the worker does not receive any wages from the firm in year *k*. Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: High Earners and Turnover

	Departure by *t+1* (1)	Departure by *t+2* (2)	Departure by *t+3* (3)
High Earner × Acquired Worker	0.005	0.026***	0.025***
	(0.009)	(0.009)	(0.008)
Acquired Worker	0.217***	0.131***	0.085***
	(0.016)	(0.016)	(0.015)
High Earner	-0.026***	-0.046***	-0.040***
	(0.002)	(0.004)	(0.004)
Matched Workers	YES	YES	YES
Target-Acquirer Firm FE	YES	YES	YES
Observations	1,874,000	1,874,000	1,874,000
R-squared	0.120	0.113	0.115

Note: This table is a set of worker-level regressions using OLS. All specifications are based on matched workers using Coarsened Exact Matching. High earner is a binary variable that equals 1 if the individual's annual wages are among the top 25% within the acquiring firm. Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Serial Acquirers and Learning Over Time

Panel A: Learning to "Sense" - Acquiring targets with lower organizational mismatch

Dependent Variable	**Org. Mismatch = 1/0**	
	(1)	(2)
Number of Prior Deals	-0.002	-0.003
	(0.005)	(0.008)
Constant	0.636***	
	(0.014)	
Acquiring Firm FE	NO	YES
Observations	1,700	1,700
R-squared	0.003	0.393

Panel B: Learning to "Seize" - More effectively integrating acquired startups

Dependent Variable	**% Acq. Employee Turnover**	
	(1)	(2)
Nb. of Prior Deals × Org. Mismatch	-0.009***	-0.010**
	(0.003)	(0.005)
Org. Mismatch	0.037**	0.062***
	(0.015)	(0.019)
Constant	0.658***	
	(0.011)	
Acquiring Firm FE	NO	YES
Observations	1,700	1,700
R-squared	0.005	0.436

Note: This table represents startup acquisitions done by serial acquirers, which are firms that have more than one startup acquisition in the underlying sample. Number of prior deals is the count of startup acquisitions by the same acquirer prior to the focal deal. Organizational Mismatch is a binary variable that equals 1 if the target firm has a higher *Startup Affinity Score* than the acquirer. The dependent variable in Panel B is the percent rate of acquired employee departures by year 3 since the acquisition. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Patenting Firms and Turnover

	Departure by *t+1* (1)	Departure by *t+2* (2)	Departure by *t+3* (3)
Acquired Worker × Patenting Firm	0.001	0.015	-0.004
	(0.031)	(0.030)	(0.028)
Acquired Worker	0.217***	0.132***	0.091***
	(0.018)	(0.019)	(0.020)
Matched Workers	YES	YES	YES
Target-Acquirer Firm FE	YES	YES	YES
Observations	1,874,000	1,874,000	1,874,000
R-squared	0.119	0.112	0.114

Note: This table is a set of worker-level regressions using OLS. All specifications are based on matched workers using Coarsened Exact Matching. Patent is a binary indicator on whether the target firm applies for or is granted a patent prior to the acquisition year. Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.