Predictable Exodus:

Startup Acquisitions and Employee Departures

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Abstract

This paper investigates the effectiveness of startup acquisitions as a hiring strategy. Unlike conventional 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, much less by whom to be acquired. Startup acquisitions therefore provide an empirical setting in which non-founding employees are quasi-randomly assigned to a new employer. I argue that the lack of worker choice lowers the average match quality between the acquired employees and the acquiring firm, leading to elevated rates of turnover. Using comprehensive employee-employer matched data from the US Census, I document that acquired workers are significantly more likely to leave compared to regular hires. This effect is more pronounced among high-earning individuals. Moreover, I demonstrate that these departures can be largely predicted ex-ante. Leveraging population data on career histories, I construct a measure of "startup affinity" for each target and acquiring firm based on pre-acquisition employment patterns, and show that this strongly predicts post-acquisition worker retention. Lastly, an analysis of serial acquirers suggests that firms learn over time how to effectively retain employees from startup acquisitions.

1 Introduction

A vast literature on organizations has long explored how firms gain advantage by hiring, developing, and retaining human capital (Becker 1962; Castanias and Helfat 1991; Coff 1997; Hatch and Dyer 2004; Teece 2011). In addition to conventional hiring, whereby an individual job seeker and an employer agree to an employment contract, firms may bring in talent through other channels. Especially in tight labor markets, firms can hire by acquiring other companies that employ talented workers (Ouimet and Zarutskie 2016). This practice is especially common among startup companies whose most valuable – if not the only – asset is their human capital (Chatterji and Patro 2014). Consistent with this view, Mark Zuckerberg once remarked, "We buy companies to get excellent people."

While startup acquisitions allow the buyer to strategically select and hire a team of workers who have proven to work together productively, this hiring method may be contentious from the perspective of these employees. 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.[1] In other words, startup acquisitions provide an empirical setting in which the acquired workers, and in particular the non-founding employees, are quasi-randomly assigned a new employer. This lack of worker choice may lower the average quality of the match between the acquired workers and the acquiring firm. The resulting mismatch is likely more pronounced when an established company acquires a startup because they are fundamentally different types of organizations with contrasting cultures (Saxenian 1996; Turco 2016) and structures (Hannan and Freeman 1984; Baron, Hannan, and Burton 1999; Sorensen 2007). Following this logic, I hypothesize that startup acquisitions result in high rates of employee exits.

Consider the case of Dialpad Communications,[2] which was acquired by Yahoo in 2005. In addition to Dialpad's nascent internet-based calling technology, Yahoo's key motivation in the acquisition was the talent responsible for the early-stage product. Upon the acquisition, almost all of the 40 employees from Dialpad initially joined the acquirer to help develop its own internet-calling software. However, despite the economic incentives to stay,[3] disagreements inside the organization led more than 70% of the former Dialpad employees to leave the firm within three years. Among the departing individuals, the shared motivation was their incompatibility with a large company's bureaucratic environment that prioritized procedures and coordination at the expense of speed and execution. Yahoo's voice-over-IP business struggled to scale, leading the company to eventually shut down the business.

[1] 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.

[2] Interviewed by the author on May 31, 2018.

[3] Typically, employment contracts used in startup acquisitions offer employee stock options with stay-incentives, such as a vesting schedule of three to four years. See Coyle and Polsky (2013) for more on standard equity incentives used in startup acquisition.

In this paper, I empirically investigate the effectiveness of startup acquisitions as a hiring strategy. To that end, I assemble a comprehensive set of high-tech startup acquisitions in the US between 1990 and 2011 by using employee-employer matched data from the US Census. Unlike many entrepreneurship studies that are limited to observing only the founders, a key advantage of this study is the ability to focus on the non-founding employees, who are unwittingly assigned a new employer upon acquisition.[4] The sample contains roughly 4,000 high-tech startup acquisitions, coupled with 300,000 non-founding employees from the target firms and approximately 2 million workers who are hired at the acquiring firms in the same year as the acquisition. Then, I compare the career paths of the acquired workers versus observationally similar regular hires at the same buyer firm with attention paid to not only the retention outcomes, but also the destinations of the departing employees (e.g., joining another firm vs. founding a new firm).

I provide the first large-scale evidence that acquired startup workers exhibit much higher turnover relative to observationally similar organic hires at the same buyer firm. Acquired workers are almost twice as likely to leave as their counterparts who are conventionally hired. Consistent with the Jovanovic (1979) model of worker tenure and turnover, the differences in departure are highest in the first year and monotonically decline thereafter, as acquired workers who are "good fits" tend to stay with their new employer. Furthermore, the effect is stronger for high-earning individuals, implying a loss of core organizational knowledge from the acquisition.

Next, I advance the theory of organizational mismatch as the mechanism that explains the pronounced turnover when an incumbent firm acquires a startup company. Because the acquired workers do not choose their next employer (i.e., the acquiring firm), I posit that the severity of post-acquisition turnover is moderated by the degree of mismatch between the target and acquiring firms. To measure organizational mismatch, I empirically characterize and compare the two firms' level of "startup affinity" by analyzing the individuals inside each organization, along with the career decisions that they make. In this framework, organizational mismatch is considered high when the target firm exhibits a strong affinity for startups, especially relative to the acquiring firm. To do this, I leverage population-level data on career histories to characterize the target and acquiring firms based on their pre-acquisition employment patterns.

To determine each company's affinity for startups versus more mature employers, I adopt the methodological framework from Sorkin (2018), and construct an ex-ante measure based on the turnover patterns of each firm's former employees. More specifically, I track employee departures *prior* to the acquisition along with their destinations. While these individuals leave before the acquisition, their decisions to join a young firm or an established company provide useful information for predicting their peers' post-acquisition retention outcomes. When aggregated up, these mobility choices reflect the firm's tendency to attract workers who prefer

[4] Nonetheless, all results are consistent when including the founding team.

to transition to startups rather than established firms. Following this reasoning, I define firms to have a strong affinity for startups if their former employees – who leave prior to the acquisition – systematically tend to move to other young companies.

Three central insights lay the foundation for using peer turnover patterns to predict post-acquisition worker retention. First, 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 valuation for the two firms based on both pecuniary and non-pecuniary factors (Sorkin 2018). Second, pre-acquisition turnover activity is an *ex-ante* characteristic of each firm. This is an essential component of a prediction method to ensure that the predictor and the outcome variable are not simultaneously determined. Third, job transitions by former colleagues are relevant because organizations tend to attract similar individuals. Since both the acquired and former employees initially selected into joining a particular organization rather than other potential employers, these workers likely exhibit similar preferences for employment.

I find that the pre-acquisition departure patterns strongly predict the acquired employees' decision to stay with the buyer. In short, target companies with a strong affinity for startups exhibit much higher rates of turnover following an acquisition.[5] Furthermore, these effects are magnified when the acquiring firm has a lower startup affinity than the target firm, lending empirical support to the role of organizational mismatch. Therefore, ex-ante differences in the target and buyer's organizational type largely explain why many acquisition deals fail to retain the new workers while others succeed in capturing talent. While earlier studies describe worker-firm match as an "experience good" whose quality can only be realized and assessed ex-post (Jovanovic 1979; O'Reilly et al. 1991), these results demonstrate that match quality can actually be predicted – in this case, before the startup target is acquired. An important managerial implication is that this prediction method offers a new tool to enhance the due diligence process preceding acquisitions. Acquirers can pre-diagnose their likelihood of retaining the new employees by measuring and learning from the target company's – along with their own – prior employment patterns.

An additional dimension to this study's managerial implications is that firms appear to learn over time how to better retain acquired workers. Analyses focusing on serial acquirers demonstrate that the predictability of post-acquisition departures falls as the firm accumulates experience with acquiring startups, lending support to the learning hypothesis.

More broadly, this study sheds light on the fundamental role of worker choices in two ways. First, when workers do not exercise choice during an organizational change – as in the case of acquisitions for non-founding employees – they tend to negatively respond to the transition,

[5] As a robustness check, I document that this pattern does not hold for the control group of regular hires, based on their prior employers' departure patterns.

primarily by leaving the organization. This is consistent with – and perhaps helps explain – the cultural clash (c.f., Cartwright and Cooper 1992; Van den Steen 2010) and integration issues (Puranam, Singh, and Zollo 2006; Paruchuri, Nerkar, and Hambrick 2006; Hoberg and Phillips 2017) that frequently pervade mergers and acquisitions. Second, when workers leave, their subsequent decisions to join a specific firm rather than others are informative signals of their employer preferences. When these mobility patterns are aggregated up using population-level data, they methodically characterize each firm's organizational type. Building on Cyert and March's (1963) foundational insight that an organization is a coalition of individuals, this study shows how individuals' career decisions provide an empirical lens to better understand the nature of firms based on the individuals they tend to attract, along with the choices that these workers make.

The rest of the paper is as follows. Section 2 develops the theoretical background and presents a set of testable hypotheses. Section 3 describes the approach to predicting post-acquisition employee outcomes. Section 4 describes the empirical setting, measurement, and sources of data. Section 5 presents the main results on employee departures, predictability of outcomes, and heterogeneous effects. Section 6 concludes with the study's key insights, managerial lessons, and questions for future research.

2 Conceptual Framework

2.1 Motivations for Startup Acquisitions

Acquisitions of high-tech startups in the US have experienced a steady rise in the past several decades (See Figure 1). Several factors drive the demand for startup acquisitions. I broadly discuss the three primary motivations behind why incumbent firms choose to acquire startup companies. First, buyers frequently acquire startup companies to eliminate nascent competitors. By construction, acquisitions of startup firms tilt the existing competitive landscape toward the acquirer (Gans and Stern 2000). In support of this view, several studies document that established firms acquire nascent targets with technologies that pose competitive threats, and subsequently shut down the target company, or its core product, following the buyout (Santos and Eisenhardt 2009; Cunningham, Ederer, and Ma 2017). Accordingly, the heightened M&A activity among industry incumbents has raised policy concerns around the anti-competitive effects of acquisitions on the entry and survival of new enterprises.[6]

[6] Betsy Morria and Deepa Seetharaman, "The New Copycats: How Facebook Squashes Competition from Startups," *The Wall Street Journal*, August 9 2017, https://www.wsj.com/articles/the-new-copycats-how-facebook-squashes-competition-from-startups-1502293444 (Accessed August 1 2018).

Second, established firms commonly acquire startups to bring in a new source of technological innovation (c.f., Granstrand and Sjolander 1990; Puranam 2001). The "markets for ideas" allow incumbent firms to transact on the startup's stock of knowledge through, for example, patent licensing and transfers (Arora, Fosfuri, and Gambardella 2001). Relatedly, acquirers can effectively complement – or outright outsource – their R&D efforts by acquiring young firms that invest in risky technologies (Higgins and Rodriguez 2006; Kaplan and Lerner 2010). By bringing in the target firm's knowledge stock, the acquirer can exploit the opportunity to produce new innovations by recombining knowledge (Fleming 2001) shared between the two firms (Puranam and Srikanth 2007). Consistent with this view, the broader literature shows that M&A has a positive impact on the buyer's innovation output (Ahuja and Katila 2001; Sevilir and Tian 2012) especially when it shares a large technological overlap with the target firm (Bena and Li 2014).[7]

Lastly, a major motivation for acquisitions is the talent inside the target firm (c.f., Ouimet and Zarutskie 2016). Organization scholars have long recognized human capital as an important asset and thus a source of competitive advantage for firms (Castanias and Helfat 1991; Hall 1993; Coff 1997; Hatch and Dyer 2004; Teece 2011). However, frictions in external labor markets often limit employers' ability to find, train, and retrain workers. In contrast, acquiring a firm, thereby transferring workers across internal capital markets, bypasses the common frictions in traditional labor markets (Tate and Yang 2016). Since the most valuable – if the not the only – asset of a startup firm is its human capital, acquiring a startup company serves as an alternative channel to capture new talent.

A recent phenomenon, particularly in the technology industry, highlights startup firms as a hotbed of talent. In particular, large technology companies such as Facebook and Cisco have received intense attention in the media for increasingly engaging in "acqui-hiring" – a process in which they buy out startup firms, jettison the core business, and retain the employees.[8] In a hand-collected sample of roughly 100 acqui-hires between 2009 and 2013, Chatterji and Patro (2014) show that the acquirer discontinues the startup's product in a vast majority of the cases. However, roughly 90% of the acquired engineers stay with their new employer for at least a year. This suggests that the acquirers strategically abandon the startup's core business and efficiently allocate the new workers across existing projects in the company. In other words, many startup acquisitions reflect cases in which the acquirer is chiefly interested in talent.

2.2 Startup Acquisitions as a Hiring Strategy

[77] However, for the innovation output of the target firm, several studies including Kapoor and Lim (2007) and Seru (2014) show that M&A has a negative impact.

[8] Coyle and Polsky (2013) as well as Selby and Mayer (2013) provide conceptual discussions of the "acqui-hiring" phenomenon.

Why might a firm choose to hire through startup acquisitions rather than the traditional labor market? Compared to conventional hiring, acquiring a team in a single transaction can be advantageous for three reasons. First, the startup team's productivity is easily observable prior to the acquisition. In other words, the acquirer can reduce the information asymmetry problem in hiring (c.f., Jovanovic 1979; Abraham and Farber 1987) by identifying and purchasing a team that has already proven to work together effectively.

Second, startup teams likely accumulate team-specific complementarities that disappear once the team is dissolved. For instance, Jaravel, Petkova, and Bell (2018) document team-specific capital among inventors. Specifically, the authors show that an inventor's long-run productivity suffers when her collaborator experiences a premature death. Given the work culture that startups generally embody (Turco 2016; Corritore 2018), their workers plausibly also develop team-specific capital that leads to productivity gains. Moreover, team-specific complementarities may increase employee retention. Growing evidence on peer effects and "co-mobility" suggests that co-workers often prefer to work together (Marx and Timmermans 2017), meaning that they jointly influence one another's decision to stay with the firm. Therefore, wholly acquiring the team could lead to higher retention and productivity among the acquired employees.

Third, it is difficult to infer an individual's level of contribution to a group's outcome. In other words, an outside firm may be limited in its ability to identify, and thus poach the best employees from a startup team. To illustrate this "metering problem," Alchian and Demsetz (1972) describe two men lifting a heavy cargo into a truck. By observing the total amount of cargo lifted each day, it is impossible to accurately determine each individual's contribution to the group-level output. As a result, without costly assessment of each worker, it would be difficult for an outside firm to identify and hire the top contributors. In parallel, the problem of moral hazard in teams limits an outsider's ability to select out the low quality workers; since only the joint output of the team can be observed, subpar contributors – as well as free-riders – often cannot be identified (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.

Moreover, 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.[9] By and large, startup

[9] 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).

acquisitions provide several advantages as a hiring strategy – including contractual levers to increase worker retention – in comparison to conventional hiring.

2.3 Acquired Workers vs. Regular Hires

Theoretical Framework

However, this hiring strategy may be contentious from the perspective of the employee. 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 preferences for working at the presumed buyer. 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 *whom* they might be acquired. In this sense, startup acquisitions provide a conceptual framework in which most of the target firm's employees are – from the perspective of these individuals – quasi-randomly assigned to a new employer.

In this theory of organizational mismatch, I posit that the absence of worker choice is the wedge that leads acquired workers to leave the firm at a much higher rate than regular hires in the same firm. The starting premise is that acquired workers do not directly choose their next employer (i.e., the buyer). Suppose a directed search model with labor market frictions in which (1) individuals have idiosyncratic preferences for employment and (2) they choose to accept a job if the expected utility is greater than the reservation wage. But when a group of workers are assigned a new employer without choice, this generates a labor market in which the matches are strictly determined by the employer side. Put another way, the individual preferences are removed from the search process.

Such condition decreases the expected quality of the match between these individuals (e.g., acquired workers) and employers (e.g., the acquirer). This proposition implies that the average worker-firm match quality will be lower for acquired workers than for regular hires, who in contrast, voluntarily select their new employer based on their employment preferences. As a consequence, the mismatch between the target firm's employees and their new employer could lead to higher rates of employee departures. This leads to *Hypothesis 1*: *Compared to observationally similar regular hires, acquired workers are more likely to leave the firm*.

This mismatch issue may be especially severe in the context of startup acquisitions because the target firm (startup) and the acquirer (established firm) are fundamentally different types of organizations. Among the many differences, a primary distinction between the two types is the corporate culture. Unlike established firms, startup organizations tend to reinforce cultural values of openness and autonomy (Turco 2016; Corritore 2018). Relatedly, organizational structure is a key differentiator. While established firms exhibit increasing levels of bureaucracy as they age (Hannan and Freeman 1984; Sorensen 2007) and grow in size (Saxenian 1996), their younger counterparts generally possess a flatter organizational structure that emphasizes execution speed over formal procedures (Slevin and Covin 1990).

In response to their inherent differences, workers endogenously sort into the startups versus established companies based on their personal preferences for employment. More specifically, workers who prefer risk-taking and challenging work environments tend to self-select into startups (Baron, Burton, and Hannan 1996; Roach and Sauermann 2015; Kim 2018). In contrast, individuals who value job security and employer reputation are more likely to join established companies (Kim 2018). This is consistent with the theory of compensating differentials, where individuals take a pay cut to join a firm that closely matches their preferred employment conditions (Rosen 1987; Sorkin 2018) such as autonomy for scientists (Stern 2004). Consequently, the inherent differences between startup employees and their counterparts at more senior firms – as reflected by the endogenous sorting – suggest that startup acquisitions could generate substantial mismatches between the two organizations.

Qualitative Evidence

In my interviews with several founders and early employees of startups that were eventually acquired, many of the respondents discussed the stark contrast between their original startup employer and the acquirer. A central theme emerged across the many acquisition experiences: because the acquirer is typically an older firm, its level of bureaucracy is antithetical to the common entrepreneurial emphasis on speedy execution and learning through experimentation (Ries 2011). A startup founder, reflecting on why he begrudgingly left the acquirer in just a year, corroborated the cultural disparity following the acquisition:

> It's really hard for an entrepreneur – a high-risk, high-speed type of individual – to settle into a methodical, decision-driven culture of meetings... and the slowness of a big company. (Interviewed on February 8th, 2018)

Even for large tech companies that aim to preserve and emphasize an entrepreneurial culture (e.g., Google and Amazon), the tradeoff between bureaucracy and speed was inevitable. A former early employee of a startup, who came to 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. (Interviewed on June 24th, 2016)

While many of the interviewees shared that they became frustrated with the organizational differences and promptly left the acquirer, others were less resentful of their new employer's culture. In fact, some of the acquired workers seemed to embrace the formal hierarchy as well as the job security that the acquirer provided. When asked about why some of his employees stayed while others left with him, a founder of an acquired startup commented:

> Employees who stayed behind with [Acquirer] were those who enjoyed the comfort and security... and slower pace of a large organization. Those who left – like me – are the type that wants to go make things happen fast... Another driver for leaving [Acquirer] was that, in a large organization, you no longer get to *own* a part of the product. But in a startup, you are responsible for a big feature of the product, whose first year is dependent on you to build and make it right.
> (Interviewed on May 31st, 2018)

In other words, startup employees are not uniform in their preferences for work environment. While some strongly prefer an entrepreneurial environment, others may desire a more formal and hierarchical organization. Therefore, there is likely a large variation in the mismatch that results when established firms acquire a startup. This degree of organizational mismatch between the two firms involved in an acquisition may then determine the severity of turnover. This leads to *Hypothesis 2: Turnover among acquired workers is greater when there is a larger organizational mismatch between the target and acquiring firms.*

3 Predicting Post-Acquisition Departures

3.1 Prior Literature on Worker-Firm Match

An important line of inquiry in labor economics and organizational theory concerns the relationship between worker-firm match quality and turnover. In a seminal paper, Jovanovic (1979) presents a theoretical model in which a worker and a firm learn about the quality of their match ex-post, after the worker is hired. In this model, workers who realize that they are highly productive at the firm are retained, while those who learn that they are less productive choose to leave for another job. Similarly, O'Reilly, Chatman, and Caldwell (1991) study the fit between a person and an organization based on the interaction of individual preferences and organizational culture. As expected, they show that workers with favorable person-organization fit tend to have higher job satisfaction and lower rates of turnover.

While these influential studies clarify the relationship between fit and worker turnover, a fundamental challenge underlying these analyses is the inability to account for the initial sorting of workers into firms. Prior to being hired, individuals make a non-random choice to join a firm rather than other potential employers (Sorkin 2018). In support of this view, a vast literature on compensating differentials demonstrates that workers endogenously self-select into firms based on their personal preferences for both monetary and non-pecuniary features of the employer (c.f., Rosen 1987; Stern 2004; Sorkin 2018). Therefore, the link between person-organization fit and turnover is difficult to interpret because both are shaped by the initial sorting of workers into firms.

Thus, the ideal empirical design to identify the impact of fit on turnover is to randomly allocate workers to firms and subsequently observe worker retention patterns. However, it is unrealistic to randomly assign real workers into firms. A notable exception is a study of an Indian technology firm that randomly assigns its entry-level employees to one of its eight locations (Choudhury and Kwon 2018). The authors find that distance between workplace and home has a negative causal impact on long-term worker productivity. However, randomization in this setting occurs within the firm, rather than across firms. Accordingly, a suitable approach to investigate the impact of worker-firm match quality on employee turnover requires an exogenous source of variation in "fit."

In that vein, startup acquisitions provide an empirical setting in which the target firm's employees firm are quasi-randomly assigned to a new employer. As discussed in Section 2.3, the premise turns on the lack of agency that these individuals have in choosing their next employer – contrary to traditional hires who voluntarily choose to join their new employer. This is especially true for the target startup's non-founding members. While the entrepreneurship literature has traditionally focused on founders with little attention paid to "joiners" (Kim 2018; Roach and Sauermann 2015) commonly due to data limitations, the key benefit of employee-employer data from the US Census is the ability to observe the population of workers that earn wages from startup companies – ranging from the founders to early joiners to late joiners. This study is primarily focused on these rank-and-file startup workers whose experience of an acquisition resembles an "exogenous" organizational change. Therefore, founders and early joiners – or the "founding team" – are excluded from the final sample.

It is worth noting that since the change in ownership via acquisitions occurs at the firm-level, the continuing discussion on "fit" regards that between organizations (i.e., target and acquiring firms) rather than between a worker and firm. This is the appropriate level of analysis in the acquisition context because the acquiring firm's decision-making is principally about the (extensive) margin of whether it ought to acquire a particular company, and less about the (intensive) margin of which specific individuals should be retained upon an acquisition.

The main challenge of testing the impact of organizational fit on employee turnover is the empirical measurement of the match quality between the target and acquiring firms. Following the theoretical development in Section 3.1, I define a startup acquisition's organizational mismatch to be high when the target firm tends to attract individuals who have a strong affinity for startups rather than established firms, especially when the buyer has a low affinity for startups. By adopting the methodological framework from Sorkin (2018), I construct a novel measure to characterize the target firm's level of *startup affinity*.

3.2 Measuring Startup Affinity

A fundamental problem in assessing organizational fit is that it can only be observed and measured ex-post – once the match between two parties is realized. As a result, any attempt to understand the impact of organizational fit on M&A performance, including employee retention, is inherently a post-mortem analysis – with no room for pre-diagnosis. This is perhaps why practitioners widely recognize organizational mismatch (e.g., culture clash) as the leading issue in M&A, and yet the various attempts in the M&A literature to measure and diagnose this phenomenon have been elusive.[10,11] To overcome this issue, I empirically characterize both the target and buyer firms based on information prior to the acquisition. This allows me to construct an ex-ante measure of *organizational mismatch*, and thereby predict post-acquisition retention outcomes.

To do so, I leverage each firm's regular turnover events – in particular, employer-to-employer flows – using a revealed preference argument.[12,13] More specifically, I track the departures of employees *prior* to the acquisition along with their destinations. A departing employee's intentional choice to join a startup, rather than an incumbent 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 decisions to join a young firm or an established company provide useful information for peer-based prediction of post-acquisition retention outcomes.

Three core ideas serve as the building blocks for using peer turnover patterns to predict post-acquisition worker retention. First, 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, pre-acquisition turnover activity is an ex-ante characteristic of the target and acquiring firms. This is an essential component of a prediction method to ensure that the predictor and outcome variables are not simultaneously determined. Therefore, this predictor could be utilized during the due diligence process before the acquisition deal is materialized.

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[10] According to the report "A McKinsey perspective on the opportunities and challenges" by McKinsey & Company in June 2010, 92% of surveyed executives claim that their M&A deals "would have substantially benefited from a cultural understanding prior to the merger."
[11] See Bouwman (2013) for a literature review on measuring culture clash in M&A.
[12] Haltiwanger et al. (2012) show that turnover is commonly high at young firms (1-10 years old): in a given quarter, roughly 25% of the workforce separates from their young employer, while separations at older firms is around 15%.
[13] In my data, the average target firm exhibits 160 employee separations in its lifetime prior to the acquisition.

Third, job transitions by former colleagues are relevant because organizations tend to attract similar individuals. Since both the acquired and former 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 the target and acquiring firms to have a strong affinity for startups if their former employees – who leave prior to the acquisition – systematically tend to move to other young companies.

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 buyers. These former colleagues do not directly influence the behavior of the acquired employees because they are not present at the time of the acquisition. Thus, their decisions to join a young firm or an established company are not directly tied to the later acquired workers' choice of departing or staying with the buyer firm. Mechanically, I aggregate all of the pre-acquisition mobility decisions, and then calculate the share of transitions to other startups versus old firms.[14] 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. This is the key variation that generates 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.[15] In the subsequent analysis, I exploit the differences in these two distributions to identify cases of high organizational mismatch – namely, when the acquiring firm has a lower *Startup Affinity Score* than the target firm.

[Insert Figure 3 here]

[14] For this measure, a startup is defined firms that are younger than five years old. All results are consistent when defining startups as younger than ten years old.
[15] Despite that generally negative relationship between firm age and *Startup Affinity Score*, I test and show in the Appendix that this measure among the acquired startups is not solely driven by the target firm's size and age.

Lastly, I similarly compute *Startup Affinity Score* for the set of organically hired workers based on their prior employers. This is possible because, as later described in Section 4.4, 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.[16]

4 Data and Measurement

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 organic 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 organic 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.

4.1 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 the firm's birth year 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

[16] For brevity, the empirical distribution of *Startup Affinity Score* among the control group's prior employers it not shown. Nonetheless, it closely resembles the distribution of the acquiring firms.

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, buyers can operate in any industry.

4.2 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.

4.3 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).[17] 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 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,

[17] 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.

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 buyer 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.

4.4 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.[18]

At the worker level, there are 300,000 non-founding employees from the target firms who are acquired and transition to the buyer, along with several million workers who are conventionally hired at the buyer firm 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 buyer 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.[19] By conditioning the acquisition year to be the join year for organic hires, tenure at firm is mechanically set to zero for both the acquired workers and organic hires. Therefore, differences in retention outcomes in this study are not driven by differences in tenure. The final sample includes 3,700 startup acquisitions, 230,000 acquired workers, and 1.6 million

[18] 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.

[19] 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.

regular hires. Tables 1A and 1B present the summary statistics of the final sample's firms (both the target and buyer) and their employees.

[Insert Tables 1A and 1B here]

4.5 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.

5 Empirical Results

5.1 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 buyer firm j:

$$Y_{ij} = \beta_0 + \beta_1 Acquired_{ij} + \delta_j + \varepsilon_{ij} \tag{1}$$

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-buyer 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.[20] 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.

5.2 Post-Acquisition Employee Departures

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

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

relative to regular hires. Therefore, even after controlling for important worker traits such as earnings and age, acquired workers exhibit greater turnover relative to organic hires.

[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 by the underlying worker-firm match quality. Following the the Jovanovic (1979) 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.

5.3 Mechanism: Organizational Mismatch

In this section, I investigate organizational mismatch as the mechanism that explains the greater turnover among acquired employees in comparison to regular joiners. I test this hypothesis in two ways. First, I assess whether target firms with greater affinity for startups exhibit greater rates of employee departures relative to those with lower affinity for startups. Since acquiring firms tend to be larger and older than targets, strong affinity for startups implies a greater degree of organizational mismatch between the target firm and the buyer. Second, I examine whether the effects are stronger when the buyer has a low affinity for startups – a situation in which organizational mismatch is likely to be especially pronounced. To test these predictions, I use the firm-level measure *Startup Affinity Score*, which is separately measured for each target and buyer, as developed in Section 3.2. As a robustness test to document that this measure is generally uncorrelated with non-acquired workers' retention patterns, it is also calculated for the prior employers of the regular hires.

Figure 5 depicts the 3-year employee departure rates by the prior employer's *Startup Affinity Score* quartiles, where Q1 represents the set with the lowest affinity for startups.[21] For the prior employers of the acquired workers – the target firms – the rate of employee exits are increasing in *Startup Affinity Score*. As shown in Panel A, the rate of departures of acquired workers in Q4 is 20% higher than that of workers in Q4. In other words, target firms that demonstrate higher shares of pre-acquisition departures to startups are more likely to exhibit elevated rates of post-acquisition turnover. However, as illustrated in Panel B, this pattern does not hold for the prior employers of regular hires, whose departure outcomes are unrelated to *Startup Affinity Score*. Therefore, this difference suggests that organizational mismatch

[21] Quartile threshold values are determined based on the target firms. For consistency, the same cutoffs are imposed on the control group, meaning that the quartile bins among the control group does not necessarily contain equal number of observations.

heightens employee turnover only when the workers do not exercise agency in choosing their next employer.

[Insert Figure 5 here]

Table 3 is the regression counterpart to Figure 5. This set of regressions is identical to that in Table 2, but with interaction terms between the acquired worker dummy and the target firm's *Startup Affinity Score* quartiles. *Startup Affinity Score* quartiles are independently included to control for their impact on employee retention for the control group of regular hires. This term can be estimated since *Startup Affinity Score* is separately measured for the control group based on their prior employers. Furthermore, the key omitted group is *Acquired x Startup Affinity Score[Q1]*. Therefore, the regression estimates corresponding to the interaction terms indicate the marginal effect relative to the omitted group.

[Insert Table 3 here]

Consistent with the patterns in Figure 5, the regression estimates for *Startup Affinity Score* quartiles alone – which correspond to the control group – are generally insignificant. In other words, *Startup Affinity Score* is not systematically related to the regular joiners' retention patterns. Although the estimates are statistically significant in the first column given the large sample size, the economic magnitudes are small, translating to a 0.7 percentage point premium for the control group with the highest Startup Affinity Score (Q4). Therefore, as expected, *Startup Affinity Score* does not predict the retention rates of the regular hires.

In contrast, the row corresponding to the acquired workers interacted with the highest *Startup Affinity Score* (Q4) demonstrates the highest rate of turnover. Relative to the acquired workers in the lowest quartile, workers in this category are roughly 12 percentage points more likely to leave the acquirer within three years. Consistent with the trends in Figure 5, the subsequent rows are also positive, albeit smaller in magnitude. While some estimates are statistically indistinguishable from zero, the highest quartiles (Q3 and Q4) are always positive and significant, implying that target firms with the greatest affinity for startups demonstrate the highest rates of employee separations.

In principle, organizational mismatch is determined by not only the characteristic of the target firm, but also that of the acquiring firm. Accordingly, I test whether the effects vary by the acquiring firm's *Startup Affinity Score*. Organizational mismatch is likely more severe when an entrepreneurial target firm is purchased by a less entrepreneurial organization. To test this premise, I re-run the analysis from Table 3 by splitting the sample into high vs. low organizational mismatch: Organizational mismatch is defined as high (low) if the target firm's *Startup Affinity Score* is greater than (less than or equal to) the buyer's *Startup Affinity Score*.

[Insert Table 4 here]

It is first important to note that the subsample of high organizational mismatch is roughly twice as large as the subsample of low organizational mismatch. In other words, high-tech startup acquisitions are generally cases of a high organizational mismatch. This is a sensible pattern given that acquiring firms tend to be significantly older and larger than the targets.

When organizational mismatch is high (Specifications 1-3), target firms with higher *Startup Affinity Score* exhibit much greater rates of employee turnover. Moreover, when using longer time windows of two or three years, the main effect (e.g., difference in employee departures between acquired workers and regular joiners) is statistically insignificant for target firms with the lowest *Startup Affinity Score* (Q1). This means that when the target firm has a low affinity for startups, the acquired workers and regular joiners are statistically equally likely to be retained. However, the departure effects are strongly positive and significant when – hence entirely driven by – the target firms with a higher *Startup Affinity Score* (Q2-Q4). In other words, when there is a substantial organizational mismatch between the acquired and acquiring firms, the target firm's affinity for startup systematically explains the rate of post-acquisition employee exits.

In contrast, Specifications 4-6 show that the target firm's *Startup Affinity Score* has a null effect on explaining employee departures when the acquiring firm has a comparable or higher *Startup Affinity Score*. While the main effect on acquired workers (relative to regular hires) is positive and significant, interaction effects with the target's *Startup Affinity Score* are statistically insignificant from zero. Therefore, when organizational mismatch is low, the target firm's affinity for startups does not account for the variation in employee exits. Taken together, these results validate Hypothesis 2 and empirically support the role of organizational mismatch in explaining post-acquisition employee retention patterns.

5.4 Who Leaves?

Beyond the average departure effect, an equally important dimension is the types of individuals who are most inclined to exit. With respect to firm's advantage gained through hiring, departures are especially costly when the leaving individuals possess firm-specific intangibles such as knowledge and routines that are difficult to replace (Castanias and Helfat 1991; Wezel, Cattani, and Pennings 2006). Since such core knowledge is likely concentrated among the top executives and skilled workers, I use the earnings of the individuals to determine their relative standing in the firm. In particular, I label workers to be high earners if they are 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 by earnings level.

[Insert Table 5 here]

Table 5 presents the results of interacting the acquired worker status with a dummy indicating whether the individual is a high earner. First, it is important to note that the baseline effect of being a high earner is negative and significant, meaning that top earners are less likely to leave. This is consistent with the existing prior literature which attributes the negative link between higher compensation and risk of exiting 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. 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.

5.5 Heterogeneity by Patents and Non-Compete Enforceability

Having established that acquired workers – especially the top earners – are more likely to exit relative to traditional hires, I next assess the sectoral heterogeneity in the effects (1) by whether the target firm possesses a patent, and (2) by the underlying region's degree of non-compete enforceability.

First, I examine how the results vary by whether the target startup owns a patent. On the one hand, employee departures could be higher among patent-owning targets if the acquirer is primarily interested in buying the patent and therefore less inclined to retain the workers. In support of this argument, Cunningham et al. (2017) find in the pharmaceutical setting that only 22% of the inventors from the target firm are retained following an acquisition. On the other hand, employee departures may be lower with patent-owning target firms if the workers are complements to the acquired knowledge. In this case, the acquirer is less likely to dismiss the target employees especially if it decides to preserve and commercialize the purchased patent (Gambardella, Ganco, and Honoré 2014). To test these predictions, 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.

Table 6 presents the heterogeneous effects 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.

[Insert Table 6 here]

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.

Next, I test whether the effect varies by how enforceable non-competes are in the underlying state. Given that acquired employees are typically required to sign new employment contracts with the buyer, I base the degree of non-competes enforceability on the acquiring firm's state laws.[22] To measure the degree of enforceability, I use each state's non-compete enforceability scores computed by Starr (2018). I code the acquisitions as operating in High (Low) non-compete enforceability regimes for states above (below) the median score.

Specifications 4-6 present the results on high versus low non-compete enforceability. Consistent with prior results, the baseline effect shows that acquired workers are generally more likely to leave than regular hires. Furthermore, the interaction effect demonstrates that the departure rates are roughly the same among the two groups. This is not surprising since the original estimates are within-firm effects, meaning that both the acquired workers and regular hires are subject to the same degree of non-compete enforceability. Therefore, while the levels may shift depending on the intensity of non-compete enforceability, the relative difference between the two groups appears to remain stable. Overall, these results serve as a robustness check by rejecting the underlying variation in non-compete enforceability as a potential explanation for the high rates of departure among acquired workers.

5.6 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 managerial 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 suggest that firms can learn to improve their acquisition performance over time (Eisenhardt and Martin 2000). In support of this view, several studies document the importance of organizational learning through prior M&A experience, which positively relates to subsequent performance (Haleblian and Finkelstein 1999; Trichterborn, Knyphausen-Aufsess, and Schweizer 2016). In parallel, acquirers may learn how to enhance their post-acquisition rates of employee retention as they gain experience in acquiring other organizations.

[22] Interviews with lawyers in Massachusetts and California confirmed that acquiring firms generally require the target workers to sign new employment contracts that are enforced under the employer's "law of choice", which is typically based on the acquirer's state.

I empirically test this hypothesis by transitioning to firm-level analyses and focusing on serial acquirers, which account for roughly half of the acquisitions in the sample.[23] In particular, I examine the how the predictability of post-acquisition departure rates by Startup Affinity Score varies as the acquiring firm gains experience with acquiring startups. If the firm accumulates a managerial capability throughout deals, then the link between Startup Affinity Score and post-acquisition departure rate (i.e., raw predictability) should decline as the retention outcome is partly explained away by the acquirer's (unobserved) managerial capability.

[Insert Table 7 here]

Table 7 presents the results from interacting Startup Affinity Score with the acquirer's experience in startup acquisitions. For brevity, the outcome is the proportion of employees leaving the firm within three years following the acquisition. Consistent with prior results, the standalone effect on Startup Affinity Score is positive and statistically significant, meaning that it strongly predicts the rate of employee exits. However, the interaction term is negative and significant. This means that that the positive link between Startup Affinity Score and employee departure rates falls as the acquirer gains more experience. In other words, each additional startup acquisition prior to the focal deal lowers the rate of employee departures by roughly 3%.

A concern with this firm-level analysis is that serial acquirers are fundamentally different from one-time acquirers. For instance, serial acquirers may possess higher (unobservable) managerial quality. To mitigate this concern, Specification 2 includes acquirer firm fixed effects. Therefore, the resulting estimates are within-firm effects, which are more aligned with the learning hypothesis. The interaction effect is consistently negative and statistically significant with a slightly larger point estimate. Taken together, these results suggest that firms learn and thus become more effective in retaining their acquired workers as they accumulate experience in startup acquisitions.

6 Conclusion

While a vast literature in entrepreneurship examines the birth and growth of new enterprises in isolation, several studies have demonstrated a rich interaction between young firms and industry incumbents – whether in a competitive or cooperative context (c.f., Gans and Stern 2003). This study sheds light on a growing trend that dynamically shapes the competitive landscape between nascent and incumbent firms: Startup acquisitions. Among other factors, a common motivation behind buying out startup firms is the desire to bring in superior talent.

This paper provides the first large-scale empirical investigation on the effectiveness of startup acquisitions as a hiring strategy versus conventional hiring. The fundamental takeaway

[23] 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).

is that acquired workers are significantly less likely to be retained in comparison to traditional hires, even after accounting for worker and firm-specific traits that may influence retention outcomes.

Even more intriguing is that these departures can be largely predicted based on information before the acquisition. To show this, I leverage population-level data on career histories and construct a measure of "startup affinity" for each firm based on its pre-acquisition employment patterns. I demonstrate that this measure is systematically related to the degree of employee turnover following an acquisition. When target startups exhibit a strong affinity for entrepreneurial (established) organizations, the resulting employee retention tends to be considerably lower (higher). In line with the proposed narrative of organizational mismatch, these departure effects are even more severe when the target is acquired by a firm with a lower affinity for startups.

In contrast to prior studies that treat match quality as an ex-post object that can be assessed only once the two parties are matched (Jovanovic 1979; O'Reilly et al. 1991), this study contributes to the literature by illustrating that organizational fit can be assessed ex-ante. This takeaway provides important managerial implications, especially for how M&A due diligence is conducted. In practice, buyers can use the prediction tool introduced in this study to pre-diagnose the likelihood of retaining a potential target company's human capital. In turn, a more informed understanding of this dimension can shape not only the decision to (not) acquire a particular organization, but also the pricing and personnel incentives underlying the deal.

At the heart of these empirical results is the lack of choice for the acquired workers: unlike regular hires who choose to join a new employer, acquired workers seldom have a choice in their employer's ownership change. Therefore, precisely because the target employees do not choose their new employer, acquisitions often create poor matches between the target workers and the acquiring firm, resulting in elevated rates of employee turnover. Taken together, the central lesson is that worker choices matter: When workers do not exercise choice amid an organizational change, they may resist the transition by electing to leave the firm.

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.[24] 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. As a first step, an insightful exercise would be to validate this study's Startup Affinity Score against other measures of organizational culture. For instance, Sull et al.'s (2019) machine learning-based scores of firm culture using Glassdoor reviews could be a useful platform.[25] To the extent that it captures the entrepreneurial culture of a firm, Startup Affinity Score likely positively corresponds to similar cultural values on Glassdoor like "agility" and "execution".

An important question for future research 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.

In addition, future research may address the policy implications of startup acquisitions. Given that an important motivation in acquiring a startup in eliminating nascent competitors (Santos and Eisenhardt 2009; Cunningham et al. 2017), there has been a growing discussion of the anti-competitive effects of acquisitions on the entry and survival of young firms. While this study documents the entry of new firms in the same industry following an acquisitions, the net impact of acquisitions on competition remains unclear. Therefore, more work is needed to clarify the competitive dynamics between M&A and subsequent entrepreneurship by the departing workers.

Another avenue is to explore how the acquired technology is integrated and implemented inside the buyer firm. Extending a broad literature on this topic (c.f., Puranam and Srikanth 2007; Bena and Li 2014), a novel topic is the duality of technology and individuals that flow during an acquisition. Although this study documents nuanced effects depending on whether the target firm owns a patent, reflecting the important role of appropriability, 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

[24] Even for startup acquisitions with extremely large valuations, as in the case of Facebook's $19 billion acquisition of WhatsApp in 2014, the non-founding employees experienced much smaller wealth gains compared to founders and early investors. https://blog.wealthfront.com/whatsapp-acquisition-employees/

[25] Sull et al. (2019) compute culture scores by analyzing over 1.2 million text reviews on Glassdoor. https://sloanreview.mit.edu/projects/measuring-culture-in-leading-companies/

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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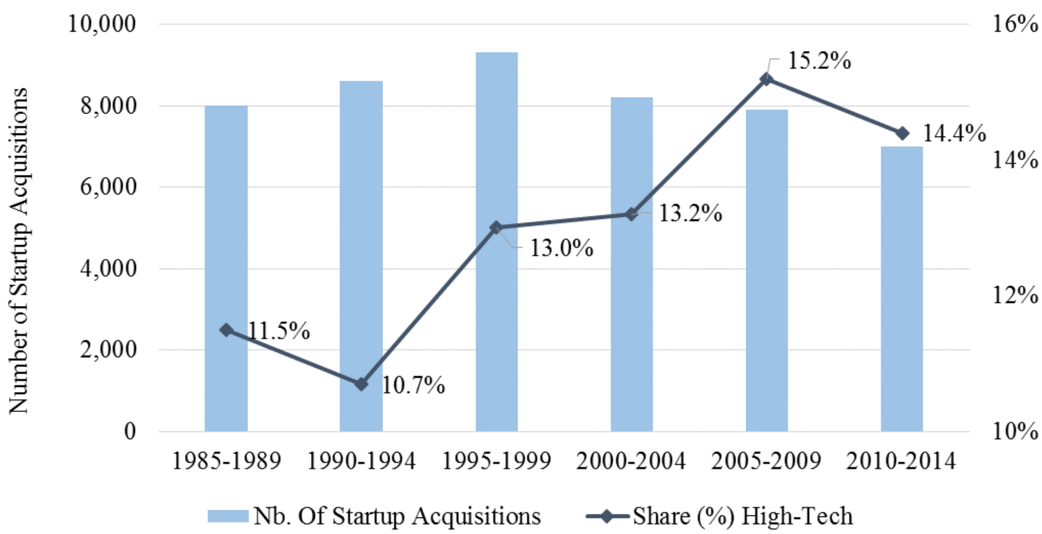
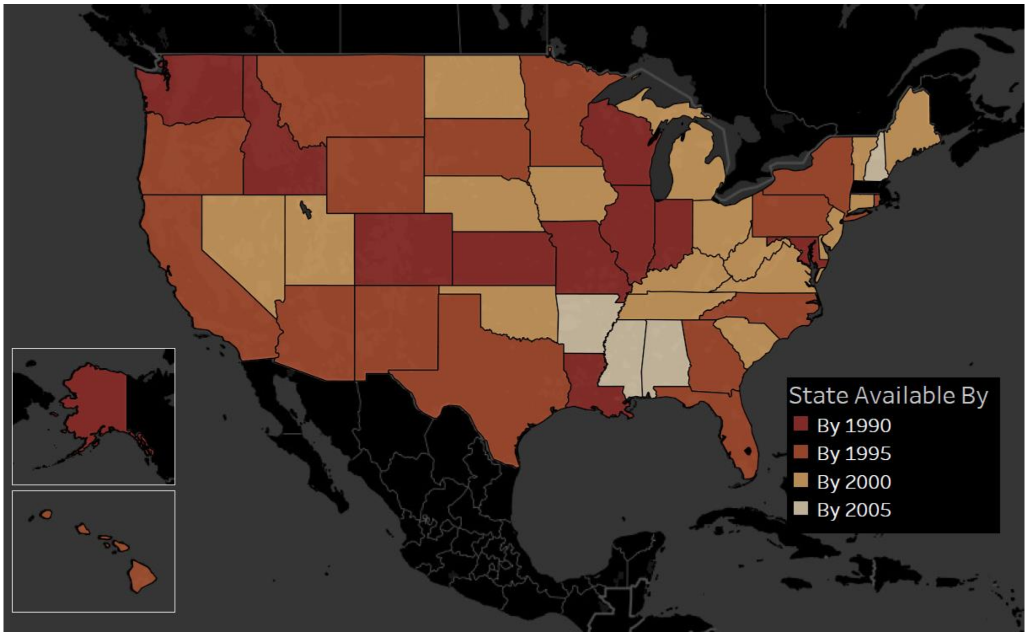
Figures

Figure 1: Time Trends in US Startup Acquisitions



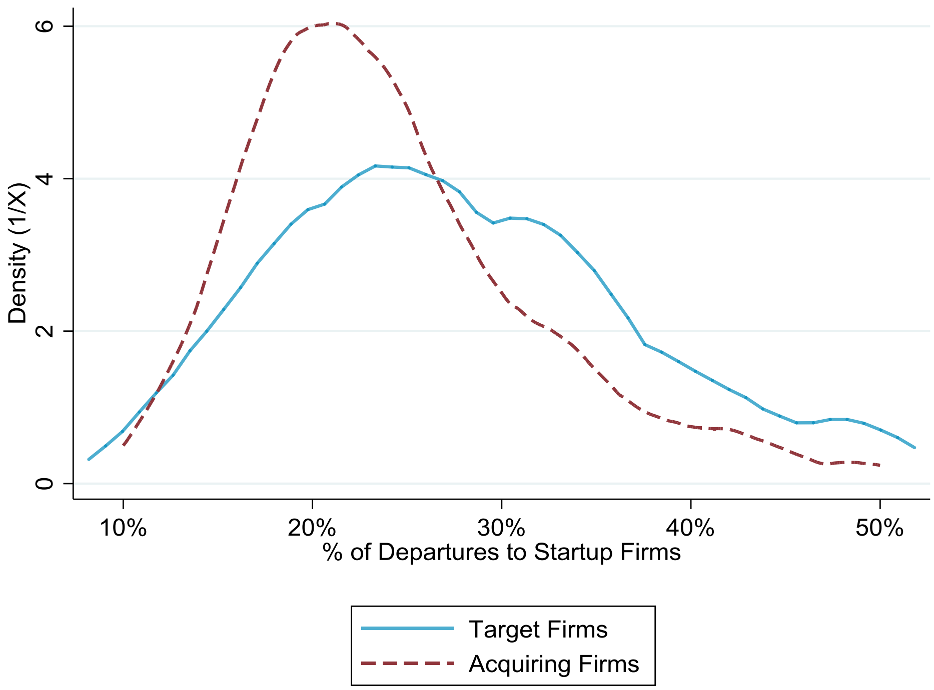
Note: This figure counts the number of times that startups, defined as younger than ten years old, are acquired by existing firms in a given five-year window. Acquisition activity is measured using the author's algorithm based on firm ownership changes in the LBD. Share of high-tech is the percentage 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: Map of US States and Entry Year in LEHD



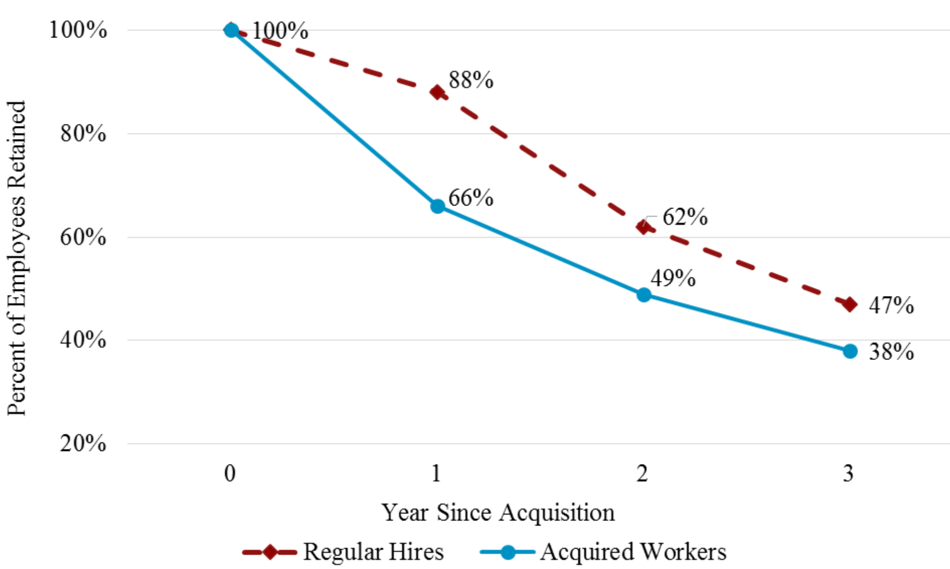
Note: See Vilhuber (2018) for a detailed description of the LEHD. This study uses all available states in the LEHD.

Figure 3: Distribution of Pre-Acquisition Departures to Startups



Note: This figure is the kernel density plot of the firm-level 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.

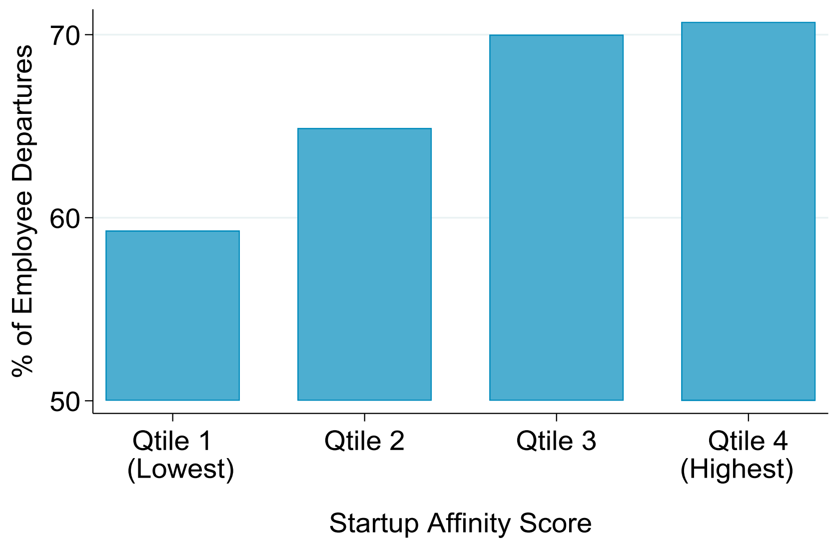
Figure 4: Employee Retention Rates: Acquired Workers vs. Regular Hires



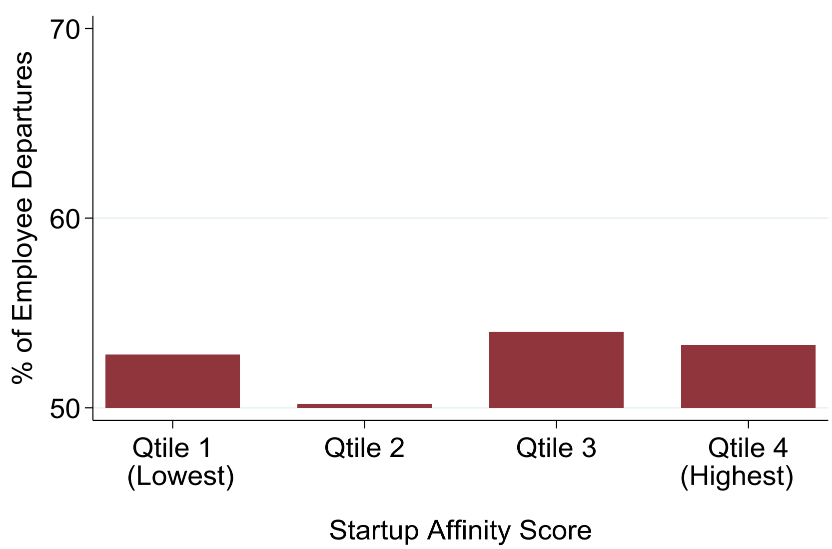
Note: This figure plots the unconditional retention rates. Both acquired workers and regular hires join the acquiring firm in year 0. Employee is retained in year t if she works for the firm for at least a quarter in year t.

Figure 5: Employee Exit Rates by Prior Employer's Startup Affinity Score

Panel A: Target Firms



Panel B: Prior Employers of Regular Hires



Note: These figures plot the unconditional rates of employee departures for acquired workers and regular hires in Panels A and B, respectively. X-axis is the quartile-indicator for the prior employer's share (%) of pre-acquisition worker departures to startups (5 years old or younger). Prior employer for the acquired workers is the target startup. Employee departure in year t equals 1 if she does not receive any wages from the firm in year t.

Tables

Table 1A: Firm-level Summary Statistics

Characteristics	Target Firms (N=3,700) Mean	Median*	SD	Acquirers 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: Effect of Hiring Channel on Employee Departures

	Full Sample			Matched Sample		
	Depart by t+1	Depart by t+2	Depart by t+3	Depart by t+1	Depart by t+2	Depart by t+3
	(1)	(2)	(3)	(4)	(5)	(6)
Acquired Worker	0.2173***	0.1316***	0.0860***	0.2172***	0.1363***	0.0898***
	(0.0130)	(0.0133)	(0.0130)	(0.0147)	(0.0151)	(0.0149)
Mean DV of Regular Hires	0.122	0.376	0.535	0.108	0.350	0.517
Buyer-Target 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	0.1066	0.1150	0.1094	0.1187	0.1117	0.1137

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: Effect of Hiring Channel on Employee Departures by Startup Affinity Score

	Departure by *t+1*	Departure by *t+2*	Departure by *t+3*
	(1)	(2)	(3)
Startup Affinity Score[Q4] × Acquired Worker	0.0978**	0.1239***	0.1167**
	(0.0400)	(0.0438)	(0.0459)
Startup Affinity Score[Q3] × Acquired Worker	0.1061**	0.1213***	0.1037**
	(0.0419)	(0.0434)	(0.0450)
Startup Affinity Score[Q2] × Acquired Worker	0.0412	0.0476	0.0585
	(0.0383)	(0.0420)	(0.0441)
Startup Affinity Score[Q4]	0.0074***	0.0010	-0.0064
	(0.0025)	(0.0040)	(0.0042)
Startup Affinity Score[Q3]	0.0078***	-0.0053	-0.0111**
	(0.0024)	(0.0040)	(0.0046)
Startup Affinity Score[Q2]	0.0012	-0.0088**	-0.0106**
	(0.0021)	(0.0034)	(0.0045)
Acquired Worker	0.1568***	0.0650*	0.0224
	(0.0332)	(0.0374)	(0.0407)
Mean DV of Regular Hires	0.108	0.350	0.517
Matched Workers	YES	YES	YES
Buyer-Target Firm FE	YES	YES	YES
Observations	1,874,000	1,874,000	1,874,000
R-squared	0.1202	0.1127	0.1143

Note: This table is a set of worker-level regressions using OLS. All specifications 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*. Startup Affinity Score[Qn] is a quartile-indicator for the prior employer's share of pre-acquisition worker departures to startups (5 years old or younger); prior employer is the target firm for the treated group, and the preceding job for the control group. Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Effect of Hiring Channel on Employee Departures by Startup Affinity: High vs. Low Organizational Mismatch

	HIGH Organizational Mismatch			**LOW Organizational Mismatch**		
	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)
Startup Affinity Score[Q4] × Acq. Worker	0.1237***	0.1373***	0.1303***	-0.0199	0.0608	0.0316
	(0.0367)	(0.0385)	(0.0500)	(0.0761)	(0.0749)	(0.0741)
Startup Affinity Score[Q3] × Acq. Worker	0.1321***	0.1387***	0.1149**	0.0747	0.0998	0.0960
	(0.0414)	(0.0390)	(0.0498)	(0.0524)	(0.0626)	(0.0619)
Startup Affinity Score[Q2] × Acq. Worker	0.0950**	0.0938**	0.1049**	0.0040	0.0110	0.0183
	(0.0444)	(0.0435)	(0.0520)	(0.0421)	(0.0491)	(0.0518)
Startup Affinity Score[Q4]	0.0092***	0.0057	-0.0041	0.0025	-0.0101*	-0.0123**
	(0.0031)	(0.0051)	(0.0055)	(0.0042)	(0.0055)	(0.0058)
Startup Affinity Score[Q3]	0.0091***	-0.0042	-0.0106*	0.0039	-0.0084*	-0.0133***
	(0.0030)	(0.0053)	(0.0063)	(0.0034)	(0.0050)	(0.0046)
Startup Affinity Score[Q2]	0.0028	-0.0089**	-0.0116*	-0.0023	-0.0090	-0.0092
	(0.0022)	(0.0042)	(0.0061)	(0.0043)	(0.0056)	(0.0056)
Acquired Worker	0.1380***	0.0521*	0.0123	0.1584***	0.0666	0.0246
	(0.0284)	(0.0300)	(0.0448)	(0.0396)	(0.0442)	(0.0474)
Mean DV of Regular Hires	0.108	0.350	0.517	0.108	0.350	0.517
Matched Workers	YES	YES	YES	YES	YES	YES
Buyer-Target Firm FE	YES	YES	YES	YES	YES	YES
Observations	1,245,000	1,245,000	1,245,000	629,000	629,000	629,000
R-squared	0.1187	0.1134	0.1150	0.1238	0.1108	0.1133

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 (0) if the target firm's Startup Affinity Score is higher than (less than or equal to) the buyer's Startup Affinity Score. Depart by *k* equals 1 if the worker does not receive any wages from the firm in year *k*. Startup Affinity Score[Qn] is a quartile-indicator for the prior employer's share of pre-acquisition worker departures to startups (5 years old or younger); prior employer is the target firm for the treated group, and the preceding job for the control group. Standard errors, clustered at the firm level, are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5: High Earners and Employee Departures

	Departure by *t+1* (1)	Departure by *t+2* (2)	Departure by *t+3* (3)
High Earner × Acquired Worker	+	++***	++***
	(.)	(.)	(.)
Acquired Worker	++***	+***	+***
	(.)	(.)	(.)
High Earner	—***	—***	—***
	(.)	(.)	(.)
Matched Workers	YES	YES	YES
Buyer-Target Firm FE	YES	YES	YES
Observations	-	-	-
R-squared	-	-	-

Note: Since these results are not yet disclosed from the US Census, only qualitative results (e.g., direction of estimates and level of statistical significance) are shown. 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 6: Heterogeneous Effects by Sector

Sector	**Patent-Owning Target Firms**			**High Non-Compete Enforeability**		
	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 × Sector	+	+	—	+	+	—
	(.)	(.)	(.)	(.)	(.)	(.)
Acquired Worker	++***	++***	++***	++***	++***	++***
	(.)	(.)	(.)	(.)	(.)	(.)
Matched Workers	YES	YES	YES	YES	YES	YES
Buyer-Target Firm FE	YES	YES	YES	YES	YES	YES
Observations	-	-	-	-	-	-
R-squared	-	-	-	-	-	-

Note: Since these results are not yet disclosed from the US Census, only qualitative results (e.g., direction of estimates and level of statistical significance) are shown. 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. High non-compete enforceability is a binary indicator defined at the level of the acquiring firm's state laws based on Starr 2018. Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Do Serial Acquirers Learn Over Time?

	DV = % Rate of Employee Departures by t+3	
	(1)	(2)
Nb. Prior Deals × Startup Affinity Score	—***	—***
	(.)	(.)
Startup Affinity Score	++***	++***
	(.)	(.)
Constant	-	-
	(.)	(.)
Acquiring Firm FE	NO	YES
Observations	-	-
R-squared	-	-

Note: Since these results are not yet disclosed from the US Census, only qualitative results (e.g., direction of estimates and level of statistical significance) are shown. 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. Startup Affinity is a continuous score between 0 and 1 as described in Section 3.2. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix

List of High-Tech Industries

As discussed in Section 3.1, I follow Hecker (2005) and Goldschlag and Miranda (2016) to label a set of industries as high-tech. More specifically, I identify the NAICS-4 industries with the highest shares of STEM-oriented workers. Table A1 displays the list of high-tech NAICS-4 industries represented among the target startups.

Table A1: List of High-Tech (NAICS-4) Industries

NAICS-4	Industry
2111	Oil and Gas Extraction
3254	Pharmaceutical and Medicine Manufacturing
3341	Computer and Peripheral Equipment Manufacturing
3342	Communications Equipment Manufacturing
3344	Semiconductor and Other Electronic Component Manufacturing
3345	Navigational, Measuring, Electromedical, and Control
3364	Aerospace Product and Parts Manufacturing
5112	Software Publishers
5161	Internet Publishing and Broadcasting
5171	Wired Telecommunications Carriers
5179	Other Telecommunications
5181	Internet Service Providers & Web Search Portals
5182	Data Processing, Hosting, and Related Services
5191	Other Information Services
5413	Architectural, Engineering, and Related Services
5415	Computer Systems Design and Related Services
5417	Scientific R&D Services (including Life Sciences)

Additional Analyses on Startup Affinity Scores

A central concern with interpreting results in Section 5.3 is that *Startup Affinity Score* may be systematically related to other firm characteristics. For instance, it could be the case that small firms tend to exhibit higher post-acquisition turnover as well as high share of pre-acquisition departures to startups. In this case, *Startup Affinity Score* – which is calculated by the share of pre-acquisition departures to startups – would be an endogenous reflection of firm size rather than a measure of affinity for startup employers. To address this concern, I first regress *Startup Affinity Score* on important target startup characteristics including firm size, age, and NAICS-4 industry, and provide empirical support that this measure is not driven by other firm covariates. Furthermore, I use the residuals from the preceding regression to replicate the original results in Section 5.3 that net out the effects from firm characteristics.

Table A2 shows the results from regressing *Startup Affinity Score* on observable characteristics of the target firm. *Startup Affinity Score* is the percent share of pre-acquisition departures to startups, bounded between 0 and 1. All specifications include a fully saturated set of NAICS-4 industry indicators. Specification 1 and 2 demonstrate that the effect of firm age and firm size on *Startup Affinity Score* is statistically indistinguishable from zero. When entered together in Specification 3, the results are consistently zero. These null findings show that *Startup Affinity Score* is not systematically related to firm age, firm size, or industry-specific traits.

Table A2: Predicting Startup Affinity Score

	DV: Startup Affinity Score [0,1]		
	(1)	(2)	(3)
Firm Age	-0.00043		-0.00036
	(0.00118)		(0.00115)
Log Firm Size		-0.00107	-0.00096
		(0.00275)	(0.00270)
Observations	3,400	3,400	3,400
R-squared	0.02600	0.02602	0.02605
Industry (NAICS-4) FE	YES	YES	YES

Note: This table shows a series of firm-level OLS regressions. Startup Affinity Score is a percent share (between 0 and 1) of pre-acquisition departures to startup (5 years old or younger). Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Next, I provide further robustness by using the residuals from Table A2. In particular, I test the impact of *Startup Affinity Score* on acquired employee outcomes, after netting out the portion of *Startup Affinity Score* explained by firm size, age, and industry. Instead of converting *Startup Affinity Score* into quartiles values as done in Table 3, Table A3 uses the raw score for clarity. For brevity, only outcomes using a one-year window are reported; results are consistent with using two- and three-year windows.

Table A3: Employee Outcomes by Startup Affinity Score: Actual vs. Residual Values

Dependent Variable	Departure	Any Spawn	Related Spawn	Departure	Any Spawn	Related Spawn
Time Window	by t+1	by t+1	by t+1	by t+1	by t+1	by t+1
	(1)	(2)	(3)	(4)	(5)	(6)
Startup Affinity Score x Treated	0.3109***	0.0052***	0.0025**			
	(0.0992)	(0.0016)	(0.0011)			
Residual Score x Treated				0.3259***	0.0050***	0.0028**
				(0.1102)	(0.0017)	(0.0012)
Treated	0.1280***	-0.0003	0.0001	0.2145***	0.0012***	0.0008***
	(0.0325)	(0.0004)	(0.0003)	(0.0114)	(0.0002)	(0.0001)
Mean DV of Control Group	**0.105**	**0.0016**	**0.0004**	**0.105**	**0.0016**	**0.0004**
Observations	2,354,000	2,354,000	2,354,000	2,354,000	2,354,000	2,354,000
R-squared	0.1123	0.0035	0.0043	0.1123	0.0035	0.0043
Matched Workers	YES	YES	YES	YES	YES	YES
Buyer-Target Firm FE	YES	YES	YES	YES	YES	YES

Note: This table shows a series of firm-level OLS regressions. Startup Affinity Score is a percent share (between 0 and 1) of pre-acquisition departures to startup (5 years old or younger). Residual scores are calculated for each from Table A1. Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Specifications 1-3 in Table A3 use the original *Startup Affinity Score*. Consistent with Table 3, the interaction between the score and *Treated* indicator are positive and significant. In other words, acquired workers from startups with a high *Startup Affinity Score* are more likely to leave as well as spawn new companies, compared to their counterparts from a firm with a low *Startup Affinity Score*. Specifications 4-6 repeat these regressions, except with using residuals from Table A2. The results are strongly consistent. Therefore, over and above the target firm's size, age, and industry, pre-acquisition departures to startups are a robust predictor of the acquired employees' career outcomes.