Assortative Matching in Mergers: Evidence from Skill Demand

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Abstract

Using job skill requirements from the near universe of online job postings, we show that similar hiring strategies for job skills increase the likelihood of mergers among firms, consistent with assortative matching (i.e., Rhodes-Kropf and Robinson, 2008). Moreover, a firm is more likely to become a target if (1) its skill requirements become more similar to the top skill requirements of its potential acquirer, and (2) it is seeking to hire relatively experienced employees. Following the merger, the combined firm continues hiring in skills that are similar between the two firms. We show that lower search frictions and integration costs lead to increased assortative matching in mergers, consistent with prior theories. Mergers induced by similar skill demand experience more synergies, which largely accrue to the acquirer.

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1. Introduction and Literature Review

In 2016, Walmart purchased Jet.com for $3.3 billion, in the largest e-commerce acquisition ever (Mac, 2016). Walmart CEO Doug McMillon noted that due to the deal, "Walmart.com will grow faster, the seamless shopping experience we're pursuing will happen quicker, and we'll enable the Jet brand to be even more successful in a shorter period of time… Our customers will win. It's another jolt of entrepreneurial spirit being injected into Walmart."[1] At the time, Walmart was struggling to grow its online sales business, which accounted for just 3% of its total revenue (about $15 billion). The deal anticipated benefits from combining, including in Walmart's ability to compete with Amazon.com. In 2020, Walmart announced plans to discontinue Jet.com and phase out the brand; Walmart's CEO credited the deal with helping Walmart launch new initiatives including curbside pickup, home delivery, and new types of products. In the *Harvard Business Review*, Schrage (2018) notes the view that the deal has paid off, in bringing on unique talent. Indeed, the founder of Jet.com continued leading Walmart's U.S. E-commerce business; in the fiscal year ending in January 2022, Walmart's ecommerce sales had grown to about $73 billion (out of $568 billion total sales).[2]

Rhodes-Kropf and Robinson (2008) develop a theory of mergers and discuss the notion of assortative matching in mergers, in that like buys like. Their approach extends the property rights theory of the firm (Grossman and Hart, 1986; Hart and Moore, 1990; Hart, 1995). Their assortative matching theory suggests that asset complementarities are an important motive for mergers. By examining firms' existing assets, prior literature provides empirical support to this assortative matching theory by documenting that firms are more likely to merge if they have similar products

[1] See the details on Walmart's website: https://corporate.walmart.com/newsroom/2016/08/08/walmart-agrees-to-acquire-jet-com-one-of-the-fastest-growing-e-commerce-companies-in-the-u-s.
[2] See Walmart's 10-K filing for fiscal year 2021: https://www.sec.gov/Archives/edgar/data/104169/000010416922000012/wmt-20220131.htm.

(Hoberg and Phillips, 2010) or labor force structure/characteristics (Lee, et al., 2018; Lagaras 2021). However, as recognized in Rhodes-Kropf and Robinson (2008), their model does not address how asset complementarities should be evaluated; they indicate that "developing new empirical tests along these lines may shed better light on the motives for merger activity by more fully articulating the ways in which firms search for appropriate partners." In particular, the theory does not state whether asset complementarities should be defined using a firm's existing assets (which result from the firm's previous investments) or its recent demand for assets (which reflect the firm's current growth strategy). These two definitions can be quite different if the firm's growth strategy is different from the past. To the extent that a merger itself is an active decision by the merging firms, it is reasonable to expect the merger to be particularly associated with the firm's strategic decisions.

To measure firms' recent demand for assets, we focus on their human capital investments. Given the view of human capital as arguably firms' most valuable asset (Zingales, 2000), mergers are a unique setting to examine the role of human capital on assortative matching. We use detailed information on skills demanded for firms' new employees and examine how the demanded skills are associated with firms' merger decisions. If assortative matching applies to recent demand for skills, firms with similar areas of focus in hiring would be more likely to merge. To the extent that skill demand reflects a firm's growth strategy, such a merger is likely to accelerate this growth and the associated merger synergies are likely to be greater. However, due to the complexity of integrating two firms after a merger, recent demand for human capital might not be substantial enough to incentivize a merger. Also, firms hiring employees with dissimilar skills could arguably complement each other, as one firm's set of expertise/focus could offer benefits to the other firm's different strengths (Beaumont et al., 2022).

In our paper, we use detailed skill-level data from Burning Glass Technologies (BGT) of recruiting postings for new employees and examine how the demanded skills are associated with firms' merger decisions.[3] Our data covers the near universe of online job posts placed by firms. We wish to note two key features of using BGT data for the question of assortative matching around M&A. First, BGT data provides a forward-looking perspective of human capital—firms' labor skill demand. Second, BGT data provides granular firm-level information on human capital—the detailed skills that are required of firms' labor forces.

We begin by showing that firms with similar job skills are more likely to merge, consistent with assortative matching. We find that a one standard deviation increase in our skill demand similarity measure is associated with a 6%-7% increase in the possibility of a merger. This effect is economically meaningful, and comparable to the magnitude associated with a one standard deviation increase in a firm's total assets. Our results remain robust to controlling for other measures of relatedness between firms (including industry characteristics, deal integration type, industry similarity, and geographic distance), indicating that our measure of skill demand similarity reflect a novel determinant of mergers and that its effects cannot be explained by other aspects of relatedness between firms.

To understand whether the evolution of skill demand influences merger occurrence, we examine changes in firms' hiring focus. We find that, controlling for firms' skill demand similarity in the past, firms that become more similar in skill demand are more likely to merge, indicating the importance of recent skill demand evolution in merger decisions. Our evidence shows that a firm is more likely to become a target if it experiences substantial growth in skill demand that are

[3] Some other recent papers that use BGT to assess workforce composition include Bloom, Hasan, Kalyani, Lerner, and Tahoun (2020), Gao, Merkley, Pacelli, and Schroeder (2020), Campello, Gao, and Xu (2021), Tambe (2021), Darendeli, Law, and Shen (2022), Haslag, Sensoy, and White (2022), and Babina, Fedyk, He, and Hodson (2023).

the focus of the acquirer; we find that a one standard deviation increase in skill demand that matches the top skill requirements of the acquirer is associated with a 25% increase in the likelihood of being acquired.

We next document that the seniority of posted jobs influences the role of skill demand similarity in the merger decisions. For deals induced by similar employee skills, a firm is more (less) likely to become a target (acquirer) if it is also hiring talent with more experience. This evidence is consistent with the crucial role of organizational skills in determining whether firms build on existing human capital or acquire human capital through an acquisition (Beaumont, Hebert, and Lyonnet (2022)).

We show the role of search frictions in enabling assortative matching for mergers induced by human capital. This provides empirical support for Rhodes-Kropf and Robinson (2008). Firms' human capital characteristics can reduce search frictions in their area of expertise and can also mitigate other known search frictions, including for deals between firms in unrelated industries or that are geographically distant.

We continue our study by examining the combined firm skills demanded following the deal. It is unclear ex ante if human capital driven acquisitions serve as substitutes or complements for the skills brought into the combined firm. From one perspective, it is plausible that a merged firm does not have as pressing a need to hire employees with skills comparable to those that are newly added the firm due to the acquisition. Conversely, and consistent with the merger being driven by the areas of hiring focus by each of the two firms, it is possible that the combined firm would seek to continue hiring employees with skills along the dimension of the pre-deal similarity between the two firms. We find support for the latter argument. Our results are thus consistent with the two firms converging pre-merger (by their hiring activity), and thus the combined firm reflecting the two firms' areas of focus.

Lastly, we examine the announcement returns, the results of which indicate that the mergers that are driven by skill demand similarity create more synergies: A one standard deviation increase in the similarity of demanded skills is associated with increased returns of 1%, compared to an average cumulative abnormal return (CAR) of 3.2% in our sample. Our evidence suggests that the returns attributable to mergers induced by skill-similarity accrue to the acquirer, consistent with predictions from prior literature that the acquirer would experience the gains associated with human capital driven acquisitions.

Our study contributes primarily to three areas of the literature. First, we contribute to the broader literature on the role of similarity on merger decisions, including aspects such as technology (Bena and Li, 2014), culture (Ahern, Daminelli, and Fracassi, 2015; Bereskin, Byun, Officer, and Oh, 2018), products (Hoberg and Phillips 2010), and political partisanship (Duchin, Farroukh, Harford, and Patel, 2023). Our focus on skill demand similarity reflects firms' focus as it relates to desired changes in their human capital, Moreover, our approach enables us to analyze how firms realize associated synergies and how their human capital considerations change following the merger. This helps us understand the mechanism for the synergies associated with firm similarity: When firms with similar skill demand merge, the combined firm hires relatively *more* among similar skills, consistent with the merged firm being able to grow in its area of focus.[4]

Second, we contribute to studies examining the effects of human capital on firm performance. For example, some studies examine how firms' investment decisions reflect their

[4] In contrast, many of the synergies from the occupational similarity of existing employees would be associated with cost reductions. Consequently, examining the occupational similarity of existing employees, and the skill set associated with recruiting postings reflect substantially distinct determinants of merger decisions and outcomes.

ability to grow necessary human capital (Ouimet and Zarutskie (2020); Beaumont, Hebert, and Lyonnet (2022); Ma, Ouimet, and Simintzi (2022)). Other studies (i.e., Bai, Jin, and Serfling (2021)) examine the role of management practices around M&A. Babina, Ma, Ouimet, and Zarutskie (2022) present evidence consistent with lower-quality workers being selected into new firms. Bernstein, Townsend, and Xu (2023) and reduced talent flow to startups following downturns. Chen, Halford, Hsu, and Lin (2020) examine the role of personal bankruptcy laws on corporate risk-taking. Lakkis (2022) examines how human capital considerations affect the timing of firms' IPOs. We add to the literature by showing the role of certain demanded skills around mergers.

Finally, we contribute to the literature examining human capital around mergers. Ouimet and Zarutskie (2020), Chen, Gao, and Ma (2021), and Chen, Hshieh, and Zhang (2023) show that acquiring target firm employees is an important consideration in many mergers. Beaumont et al. (2022) shows that a firm's decision to achieve diversification through acquisition is related to its human capital. Agrawal and Tambe (2019) document that job search activity for employees of M&A targets tend to increase prior to a takeover announcement. Lee et al. (2018) and Lagaras (2021) show that firms' labor force structure or characteristics influence merger decisions. Lagaras (2021) and Gehrke et al. (2022) show that there is substantial labor restructuring in the target firm post-merger.[5] Abramova (2022) examines the role of shocks to labor supply for auditors on merger activity among audit firms. We add to the above literature by examining a new aspect of firms' human capital—skills demanded for new employees—and documenting that firms that demand similar human capital are more likely to merge and continue to pursue the same area of focus in hiring activities post-merger.

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[5] We recognize the potential role of local labor protections and unions, as discussed in studies such as John, Knyazeva, and Knyazeva (2015), Dessaint, Golubov, and Volpin (2017), and Tian and Wang (2021).

2. Empirical Design and Data

2.1 Job Posting Data and Skill Demand Similarity

We begin by defining our measure of human capital demand similarity (*Skill Demand Similarity*) using data from BGT. BGT data is from online job postings of U.S. employers from 2010 through 2020 and provides details regarding individual job positions at the firm level such as the location, industry, job title, and—most importantly for the purposes of our study—detailed skill requirements for the position. BGT's database includes over 40,000 online job boards and firm websites, and then standardizes job ads to facilitate analysis. BGT's job posting data of over one billion records contains detailed skill requirements, pulled from the text of online job ads.

Between 2010 and 2020, BGT data include 16,121 unique skills, which are directly scripted from job ads.[6] Similar skills are subsequently classified using BGT's proprietary taxonomy and review by subject-matter experts into broader "skill clusters"; there are 658 skill clusters. At the broadest level, clusters are organized into cluster families, which approximately resemble career classification, such as health care or finance. There are 29 cluster families. After matching with Compustat (and before defining our sample of actual and pseudo merger deals), there are 51.5 million job postings and 41,885 firm-years of data.

We match BGT data to the firm level. We focus on skill clusters to analyze firms' skill demand. We apply principal component analysis (PCA) to extract principal components of skill clusters that are informative while still reducing dimensionality. Other studies with a focus on certain skills or skill clusters tend to focus on particular measures—for example, Gao et al. (2020) use job postings from the "Finance" skill cluster family or "Internal Controls" skill in their analysis

[6] As discussed by Burning Glass (2019), the three skill types are classified either as baseline (e.g., creativity or problem-solving), technical (e.g., software development), and software (e.g., SQL).

of firms' demand for financial skills.; Babina et al. (2023) focus on AI-related skills to understand firms' AI investment. For our research question, we believe it is necessary to examine all skill clusters in which the firm is hiring in order to identify the overall similarity in demanded human capital skills.

We compute skill demand similarity between two firms in three steps. First, for each firm-year observation, we calculate the skill demand percentage, which is the number of job positions for each skill cluster over the total number of job postings by the firm in that year. This skill demand percentage measures the relative importance of the skill cluster for the firm in that year.

Next, we use the skill demand percentage to generate principal components. There are 658 skill clusters, but certain types of skills are potentially of low information in terms of reflecting firms' human capital demands. Therefore, applying principal component analysis allows us to further reduce the dimensionality of our analysis while including only the linear combination of highly informative skills that distinguish one firm from another. We notice that the resulting principal components give no components with an eigenvalue greater than one and thus keep the components with eigenvalues that are in the top quartile (i.e., the top 165 principal components) for a balanced approach between preserving information and removing noise.

In the final step, using these 165 principal components, we calculate *Skill Demand Similarity* as:

$$\textit{Skill Demand Similarity} = \frac{H_i H_j'}{\sqrt{(H_i H_i')(H_j H_j')}}, \quad (1)$$

where H is the vector of the top 165 principal components.

2.2 Empirical Methods

As discussed in our introduction, our research question is whether skill demand is associated with deal occurrence, in that firms seeking to hire employees with similar types of skills are likely to see a benefit of merging, as their skill demands reflect convergence between the two firms. Indeed, although there is broad evidence of assortative matching in employee skills, there are also plausible reasons that one might not expect this to occur. For example, in many cases firms might prefer to recruit the skill set aligned with their particular needs directly, as opposed to acquiring another firm and dealing with the associated challenges. This would especially be the case as our measure examines firms' current hiring needs, as opposed to the existing workforce. Moreover, it is reasonable to expect that firms would benefit from combining differing areas of expertise. Consequently, it is not immediately clear whether skill demands should be associated at all with merger occurrence (and if so, whether the effect would be positive or negative).

To test the role of skill demand similarity on whether a deal occurs, we follow prior literature (e.g., Bena and Li, 2014; Bereskin et al., 2018) and estimate the likelihood of mergers by generating pseudo acquirers and targets for each merger in our sample. We adopt OLS regressions and assign the variable *Actual Deal* with a value of one to indicate an actual deal, and with a value of zero to indicate a pseudo deal. Our test follows the regression setup:

$$Actual\ Deal_i = \beta_0 + \beta_1 Skill\ Demand\ Similarity_i + \boldsymbol{Controls_i} \cdot \boldsymbol{\gamma} + \varepsilon_i, \qquad (1)$$

where *Controls* indicate control variables and fixed effects. Our focus is on β_1. If β_1 is significant, we would conclude that *Skill Demand Similarity* contributes to M&A decisions. In our baseline specifications, we include size, market-to-book ratio, leverage, cash holdings and sales growth for both the acquirer and the target as our control variables. Following Lee, Mauer and Xu (2018), we include year fixed effects in our models.[7]

A related aspect is whether and how the evolution of skill demand of a firm pair affects their merger decision. To this end, we study the role of changes in hiring skills desired by the firm, and whether those changes are more aligned with the skills demanded by the merger partner. We thus construct Δ*Skill Demand Similarity* as the three-year change in *Skill Demand Similarity.* This approach examines the role of the two firms becoming more similar, with respect to their demanded skills. We thus run the following regression:

$$\begin{aligned} Actual\ Deal_i = \beta_0 &+ \beta_1 \Delta Skill\ Demand\ Similarity_{i,t-1,t-4} \\ &+ \beta_2 Skill\ Demand\ Similarity_{i,t-4} + \boldsymbol{Controls_i} \cdot \boldsymbol{\gamma} + \varepsilon_i, \qquad (2) \end{aligned}$$

where we focus on interpreting β_1 to estimate the effects of the acquirer and target becoming more similar in the leadup to the merger.

We extend this analysis by examining whether the effects are driven by the acquirer's or target's changes in skill demands. To examine this matter we calculate the percentage of the overlapped skill clusters between the acquirer's (target's) top increased skill demand and the target's (acquirer's) top skill demand. In other words, we measure the change in the acquirer's (target's) hiring characteristics to the target's (acquirer's) existing hiring strategy. We report our results based on the changes between years *t-1* and *t-3* for the top 20 and top 50 skill clusters, where *t* is the merger announcement year. We then regress the merger outcome on the interaction measures of the acquirer and the target's skill demands along with other control variables. Consequently, our regression appears as follows:

[7] For robustness, we also examine specifications with industry-year fixed effects and without fixed effects. In unreported results, we implement probit regressions with the response variable being an indicator variable for an actual deal, and the results are consistent.

$$Actual\ Deal_i = \beta_0 + \beta_1 Acquirer\ Skill\ Evolution_i +$$

$$\beta_3 Target\ Skill\ Evolution_i + \boldsymbol{Controls_i} \cdot \boldsymbol{\gamma} + \varepsilon_i, \qquad (3)$$

where β_1 captures the marginal effect of the acquirer's skill demand changes towards the target's skill demand and β_2 captures the marginal effect of the target's skill demand changes towards the acquirer's skill demand.

Next, we investigate the job experience requirements and its influence of the merger outcome. First, we calculate the three-year average of the job experience requirements with the average number of years of job experience required by each job postings at the firm level. We refer to this variable as *Acquirer Experience* and *Target Experience*, representing the job experience level in which the firm is hiring. We split *Skill Demand Similarity* at the median level to examine whether the effect of *Job Experience* is concentrated in mergers characterized by high or low levels of *Skill Demand* Similarity. Consequently, we regress the merger outcome on job seniority and other control variables, as follows:

$$\begin{aligned} Actual\ Deal_i = \beta_0 &+ \beta_1 High\ Skill\ Demand\ Similarity_i \times Acquirer\ Experience_i \\ &+ \beta_2 High\ Skill\ Demand\ Similarity_i \times Target\ Experience_i \\ &+ \beta_3 Low\ Skill\ Demand\ Similarity_i \times Acquirer\ Experience_i \\ &+ \beta_4 Low\ Skill\ Demand\ Similarity_i \times Target\ Experience_i \\ &+ \beta_5 High\ Skill\ Demand\ Similarity_i + \boldsymbol{Controls_i} \cdot \boldsymbol{\gamma} + \varepsilon_i. \qquad (4) \end{aligned}$$

We next conduct channel and robustness tests, to explore and rule out potential drivers of the effect captured by our skill demand similarity measure. As prior studies show the role of search frictions on limiting assortative matching in mergers, we consider this effect, as well as other effects consistent with reduced integration challenges. At the firm-level, we examine the role of acquirer's and target's diversity of demanded skills (to measure the complexity of their hiring needs), the acquirer's and target's capital intensity (to estimate the effects of search costs and potential ease of integration), and whether the acquirer and target are in the technology industry (to estimate whether our effect is concentrated in technology firms or applies to a broader cross-section of firms). We also examine the cross-sectional results for certain merger-pair characteristics, including the geographic distance between the two firms, the relative size, and whether the merger is same-industry or a conglomerate merger. Consequently, we run the following regression:

$$
\begin{aligned}
Actual\ Merger_i = \beta_0 + \beta_1 Skill\ Demand\ Similarity_i \times Merger\ Characteristics_i \\
+ \beta_2 Skill\ Demand\ Similarity_i + \beta_3 Merger\ Characteristics_i + \\
\boldsymbol{Controls_i} \cdot \boldsymbol{\gamma} + \varepsilon_i, \qquad (5)
\end{aligned}
$$

where we focus on interpreting β_1 to estimate the marginal effects of skill demand similarity on merger decisions conditional merger characteristics.

Another benefit of our approach and data is that we can investigate firms' hiring decisions following the merger—this can identify whether the influence from *Skill Demand Similarity* is strategic, to identify if the merger-induced acquisition of skills serves as a complement or a substitute to the combined firm's subsequent recruiting along that dimension.

We thus define *Post-Deal Hiring Demand* for acquirers based on their skill demand one year before and one year after their acquisitions using the same definition of *Skill Demand Similarity* as in (1) but changing our calculation to focus on the similarity of the combined firm with the acquirer (or target) between $t-1$ and $t+1$, where t is the M&A year.

We thus define: $Post\text{-}Deal\ Hiring\ Demand_{i,t} = \frac{H_{i,t+1}H_{i,t-1}^{'}}{\sqrt{(H_{i,t+1}H_{i,t+1}^{'})(H_{i,t-1}H_{i,t-1}^{'})}}$, where $H_{i,t}$ is the vector of top 165 principal component scores of firm i in year t. Using this definition, we examine the effects of skill demand similarity on *Post-Deal Hiring Demand* for the acquirers themselves and between the acquirers and the targets, to examine how a merger associated with similar skills affects the changes in recruiting (in those skills) for the combined firm, by running the following regression:

$$Post\text{-}Deal\ Hiring\ Demand_i = \beta_0 + \beta_1 Skill\ Demand\ Similarity_i + \boldsymbol{Controls_i} \cdot \boldsymbol{\gamma} + \varepsilon_i, \tag{6}$$

where our focus is on β_1. A positive value of β_1 is consistent with a merger induced by skill demands resulting in accelerating growth in those skills following the merger. In contrast, a negative value of β_1 would reflect the merger satisfying the acquiring firm's desired skills (and potentially restructure the combined workforce, as discussed in Lagaras (2021) and Gehrke et al. (2022))—thus enabling the combined firm to reduce hiring along that dimension.

Consistent with the benefits of the deal occurrence, we examine the magnitude of the stock market's reaction to deal announcement. We expect that if these deals are more profitable, the announcement return would be positive (consistent with expected synergies). We calculate the cumulative abnormal returns (CAR) surrounding each firm-pair's announcement. We report the results for the centered 5-day window. Our estimation window is 120 days, and we estimate until 15 days prior to the announcement.

The regression takes the following form, where our focus is also on the coefficient of *Skill Demand Similarity*.

$$CAR_i[-2,+2] = \beta_0 + \beta_1 Skill\ Demand\ Similarity_i + \boldsymbol{Controls} \cdot \boldsymbol{\gamma} + \varepsilon_i. \tag{7}$$

We separately examine the CAR of acquirers and targets to evaluate the ultimate effects of *Skill Demand Similarity*, and how the associated synergies are distributed between acquirer and target.

2.3 Sample Construction and Data

For each deal we match the acquirer and target with five pseudo acquirers and five pseudo targets, as is typical in the literature. Our main analysis involves five different data sets. Merger information is from Securities Data Company (SDC) Platinum database. We collect the Input and Output Account Use Table of 2012 from the Bureau of Economic Analysis (BEA) to calculate Fan and Goyal's (2006) vertical relatedness score. We obtain segment data from the Compustat segment database so that the relatedness score is based on granular industry classifications. We obtain financial variables from the Compustat Fundamental database. Lastly, we obtain job position skill demand data from Burning Glass, which includes the details of the required skills from 2010 to 2020.[8] We also use CRSP to calculate our returns.

We require the mergers to be associated with a deal resulting in more than 50% ownership after the transaction. We focus on US firms and require firms to have total assets greater than zero and not missing the control variables included in our sample. Finally, we exclude deals where the merging firms are not in the Burning Glass database in the year prior to the merger. Similarly, we require the pseudo deal pairs to be in the Burning Glass database to be considered in the matching process.

With the sample of firms that exist in the Compustat Fundamental database, the Compustat Segment database, and Burning Glass, we define firm-segment pairs using the GVKEY-segment identity. For the business segment, we identify firms' segments using their 4-digit NAICS code. We obtain about 11,750,000 firm-segment combination pairs, excluding those of the same GVKEY-segment identity. With the exhaustive list of potential firm-segment pairs, we assign the firm-segment pairs Fan and Goyal's (2006) vertical relatedness. We calculate the relatedness score

[8] We also use other data sources for other robustness specifications, including Product Market Relatedness from Hoberg and Phillips (2010, 2016) and Human Capital Relatedness from Lee, Mauer and Xu (2018) using data from the Occupational Employment Statistics (OES) of the Bureau of Labor Statistics (BLS).

using the IO Account Use Table from the BEA and merge the score into our firm-segment pair data. Then, we keep the highest score such that the data is aggregated to the firm level, from which we initiate the matching process.

Our matching approach follows from Lee et al. (2018) and we base our matching process on the similarity scores, including the vertical relatedness described above and Product Market Relatedness from Hoberg and Phillips (2010, 2016). We also consider several aspects to identify potential deals that are similar to the actual deals, including the market-to-book ratio, cash holdings, leverage, number of segments, and sales growth. We first identify the merger type (horizontal, vertical, and conglomerate mergers) between the unconditionally matched pairs. We define firm pairs with a vertical relatedness score greater than 1% as a vertical merger. Firm-pairs with the same 4-digit NAICS industry and with a vertical relatedness score less than or equal to 1% are defined as horizontal mergers. A firm pair with different 4-digit NAICS and a vertical relatedness score greater than 1% is classified as a conglomerate merger. For each actual pair we require the candidate pseudo pairs to have the same type of relatedness as that of the actual pair.

We use sequential filtering to retain the most similar pseudo pairs. For each of the actual pairs we rank the candidate pseudo pairs from the last step according to the Product Market Relatedness between the actual acquirer and the candidate pseudo acquirers, and the Product Market Relatedness between the actual target and the candidate pseudo targets. We keep the top ten pairs of acquirer matches and the top ten pairs of target matches, totaling 100 candidate pseudo deals. This step restricts our sample to include only real-pseudo acquirers (and targets) that are in the same product market.

Next, we match firms based on their financial characteristics, as is typical in the literature. Based on the 100 candidate pseudo deals, we select 20 pairs, 10 pairs, and 5 pairs sequentially according to the Euclidian distance based on the number of segments, the total assets, and the market-to-book ratios, respectively. Ultimately, we match each actual deal with five pseudo deals. Using this matched sample we construct our main measure, *Skill Demand Similarity*, through Euclidean distance using results from dimension reduction based on the original 658 skill clusters, as described in Section 2.1.

Our final sample of actual deals includes 318 observations, while our full sample includes 1,908 observations (of which 1,590 are pseudo deals). We use the full sample to test the influence of *Skill Demand Similarity* on the occurrence of a merger and the actual deals to test the return implications.

We provide our sample statistics in Table 1. Panel A provides the sample statistics for the actual deals, and panel B provides corresponding sample statistics for the combined sample with matched pseudo deals. Among our sample of actual deals, we note that the mean value of *Skill Demand Similarity* is 0.36, reflecting positive similarity in skill demands. The first quartile of *Skill Demand Similarity* is 0.14, and third quartile is 0.55. We also provide sample statistics for variables used in the paper, including the size of the merging firms, market-to-book, leverage, cash, sales growth, and number of segments. All variables used in our tests are defined in Appendix A.

In robustness tests we control for the nature of the merger (whether it is a vertical, horizontal, or conglomerate merger), and product market relatedness (Hoberg and Phillips (2010, 2016)). Prior research is consistent with product market relatedness affecting merger occurrence and outcomes, although we recognize that the measure is meaningfully distinct from *Skill Demand Similarity* (given the latter's focus on firm's human capital inputs as opposed to the former's focus on product market outputs). Similarly, we control for the merger type, and note that 61% of sample mergers are vertical (i.e., vertical relatedness greater than 1%), 21% of sample mergers are horizontal (same industry and vertical relatedness less than 1%), and 18% of sample mergers are conglomerate mergers (different industries and vertical relatedness less than 1%).

3. Results

3.1 Deal occurrence

In Table 2, we provide our baseline result, demonstrating that *Skill Demand Similarity* is positively associated with occurrence of a merger. In particular, the coefficient ranges from 0.22 (in a specification with year and industry fixed effects) to 0.25 (in a specification without fixed effects). In other words, a one standard deviation increase in *Skill Demand Similarity* will increase the possibility of a merger by 6%-7%, comparable to the economic effect of a one standard deviation increase in the acquirer's total assets. The coefficient from our specifications change very little depending on the use of fixed-effects. Additionally, the coefficient of *Skill Demand Similarity* is consistently significant at better than the one per cent level.

By comparison, Lee et al. (2018) find that a one standard deviation increase in industry-level relatedness increases the probability of a merger by 8%. This comparison highlights the importance of our empirical question and the corresponding measure of human capital complementarities in understanding M&A decisions. We note that our measure is (a) computed at the firm level (as opposed to industry), and (b) reflects the *focus* of hiring (i.e., the "flow" of labor) as opposed to the total workforce (i.e., "stock"). Both of these differences make for a meaningfully distinct setting, reflecting each firm's labor market focus.

In Table 3, we provide robustness results when including other relatedness measures, given potential concerns for whether the effect of *Skill Demand Similarity* can be subsumed by other measures that capture similarities between acquirers and targets.

First, in model (1) we include Lee et al.'s measure of *Human Capital Relatedness*, as discussed above. Our results remain economically and statistically comparable, even when including that measure (*Skill Demand Similarity* remains significant at the 1% level, and its coefficient increases from 0.22 in Table 2 to 0.26 in model (1) of Table 3).

Another potentially important aspect of similarity between firms is the product market relatedness. It is plausible that the effect of *Skill Demand Similarity* can be explained by similar product markets offered by the firm; consequently, we add *Product Market Relatedness* (Hoberg and Phillips (2010, 2016)) in our model. We find that *Skill Demand Similarity* remains of comparable economic and statistical significance (the coefficient remains 0.22 even when controlling for *Product Market Relatedness*). Interestingly, *Product Market Relatedness* is statistically insignificant, suggesting that potential effects of similar product markets on merger occurrence would be subsumed by these firms having similar human capital needs. This is not surprising; our measure is based on granular details of hiring demands. Considering the relation between production and employee skills it is reasonable that a granular skill similarity measure would absorb product market effects.

We control for merger type (*Vertical* and *Horizontal* in (3), and *Same Industry* in (4)) to study whether our results remain robust to controlling for deal-type. Our definition of *Vertical* and *Horizontal* follow from Fan and Goyal (2006); we show that the effects of *Skill Demand Similarity* are distinct from industry-level characteristics of the merger pair (in fact, *Vertical* and *Horizontal* are statistically insignificant whereas *Skill Demand Similarity* remains of comparable economic and statistical significance to its value in Table 2). We explore the incremental role of deal type in greater detail in Table 7.

Finally, another important measure is the geographic distance between firms: It is plausible for firms' skill similarity to be consistent with a closer geographic distance (*Geographic Distance*), with associated implications for the nature of the merger. As expected, *Skill Demand Similarity* remains positive and significant even when controlling for the geographic distance (*Geographic Distance* is negative and significant, as expected). We include all of the robustness variables in model (6), and results remain comparable. Throughout Table 3, our other coefficients remain mostly consistent with expectations.

3.2 Pre-deal human capital considerations

Next, in Panel A of Table 4 we examine the effects of changes in *Skill Demand Similarity*. Rather than use the value from the year prior to the merger (*t-1*), we lag by an additional three years (*t-4*) and separately examine the change in *Skill Demand Similarity* over this time period. This examines whether our results are robust to the overall change in similarity, regardless of whether the changes are driven by the acquirer's or target's changes. We show that Δ*Skill Demand Similarity* is positive and significant, and that a one standard deviation change is associated with a 14% change in deal occurrence. In this panel, *Skill Demand Similarity* remains positive and significant.

In Panel B of Table 4, we examine whether the effects of changes in the acquirer's or target's needs for particular skills. Specifically, we examine the skills that experience the highest growth for a firm compared to prior years and compare this change with its merger partner's top skills over the same period. Based on this comparison, we analyze the extent that a firm's skill demand converges to that of its merger partner. We focus on the growth in the top 20 (top 50) skills demanded by the firm compared to the top 20 (top 50) demanded skills of its merger partner.

Consistently, we show that when a firm experiences higher growth in demand for skills that are the top demanded skills of the acquirer, they are more likely to be acquired. For example, for a one-standard deviation in the change in *Target Skill Evolution (Top 20)* and *Target Skill Evolution (Top 50)* the merger is 7% (10%) more likely to occur.

This result is consistent with acquiring a target firm to access its human capital, also known as "acqui-hiring" (Coyle and Polsky, 2013). In columns (3) and (6) we show that the effect of the *Target Skill Evolution* remains robust even when controlling for the acquirer's changes (*Acquirer Skill Evolution*).

As expected, the acquirer's skill changes (*Acquirer Skill Evolution (Top 20)* and *Acquirer Skill Evolution (Top 50)*) is generally insignificant (it is only significantly positive in (4)); this result is reasonable. Although an increase in skill similarity, all else being equal, would make a merger more likely to occur (to the extent that *Skill Demand Similarity* would increase), when driven by *Acquirer Skill Evolution* it could be offset by the acquirer's decision to grow organically ("build") instead of by acquiring ("buy").

We continue our analysis of the pre-merger hiring characteristics in Table 5, by examining the role of the required years of experience for both acquirers and targets. Greater years of experience requirements can proxy for the quality of the human capital investment.

Our hypothesis is that targets with more experienced employees are more likely to be acquired (consistent with acqui-hiring). Similarly, acquirers with more senior employees are less likely to acquire, as there is generally less of a need to engage in acqui-hiring when the firm has a high-quality and experienced workforce. Our results support these hypotheses. These results are consistent with Beaumont, Hebert, and Lyonnet (2022), who discuss the role of organizational skills required to build on existing human capital (more experienced employees would thus reflect firms with greater organizational skills and growing future investment in human capital—acquirers with more senior employees would thus generally have the organizational capital to grow without acquisitions). Drawing on our example from Walmart at the beginning of this paper, Walmart was likely attracted to the target firm due to the quality/seniority of its employees, compared to the Walmart employees in that space.[9]

Moreover, our results can be understood in light of the role of search frictions on assortative matching: A target that hires relatively senior employees would generally have less information asymmetries in its hiring, and thus make for a more appealing target. Moreover, an acquirer with a more senior workforce would be less attracted to such a target, given employees' likely objections with respect to integration issues and redundancies (when hiring a firm with more senior employees).

3.3 Cross-sectional tests: Search frictions and integration costs

In this subsection, we examine additional characteristics of mergers induced by *Skill Demand Similarity*, as well as additional robustness tests. In model (1) of Table 6, we examine the role of the *Acquirer Diverse Skill Demand* and *Target Diverse Skill Demand*. We define the acquirer's or target's *Diverse Skill Demand* as an indicator variable if the number of skills demanded in the firm-year are greater than or equal to the industry-adjusted median. We rerun our specifications from Table 2 with *Acquirer Diverse Skill Demand* and *Target Diverse Skill Demand*, as well as *Skill Demand Similarity* × *Acquirer Diverse Skill Demand* and *Skill Demand Similarity* × *Target Diverse Skill Demand.*

[9] Indeed, Souza (2016) notes that Marc Lore of Jet.com became the CEO of Walmart Global eCommerce, and his arrival coincided with the departure of senior leadership from Walmart's eCommerce division (as well as appointments of executives from Jet.com).

As expected, *Skill Demand Similarity* remains positive and significant in this specification. Additionally, we find that *Skill Demand Similarity* × *Acquirer Diverse Skill Demand* is positive and significant, with a magnitude almost three that of *Skill Demand Similarity*. This indicates that the effect of *Skill Demand Similarity* is amplified among mergers where the acquirer's demanded skills are complex. This would be expected, as firms recruiting in similar complex skills would have fewer search frictions, and thus more likely to experience a merger induced by *Skill Demand Similarity*. The interaction term *Skill Demand Similarity* × *Target Diverse Skill Demand* is insignificant, implying that the benefits of having a workforce with wide-ranging expertise is offset to the extent that there could be greater complexity and search frictions.

In model (2), we examine the role of the acquirer's or target's capital-intensity. We define *Capital Intensive Acquirer* (*Capital Intensive Target*) as one for mergers where the ratio of assets to sales is greater than the sample median, and zero otherwise. Despite the additional terms, *Skill Demand Similarity* remains positive and significant throughout. Additionally, we do not find evidence that the effects are only concentrated in deals with capital-intensive firms, as might be expected given the reduced search frictions for capital-intensive (compared to labor-intensive) firms.

Finally, another potential concern is whether our results are driven only by technology-induced mergers. Given the importance of human capital to technology firms, it is plausible that our results are only relevant to technology-related mergers. In model (3), we address this issue by interacting *Skill Demand Similarity* with indicator variables for *Tech Acquirer* and *Tech Target*, where *Tech* firms are defined by the Fama and French 12 Industry classification. Consistently, we find that whereas *Skill Demand Similarity* remains positive and significant across all specifications, the interaction terms of *Skill Demand Similarity* with either *Tech Acquirer* or *Tech Target* are insignificant. This indicates that the effect of *Skill Demand Similarity* on merger occurrence is not driven by technology firms.

3.4 Role of additional merger-pair characteristics

In Table 7, we conduct several robustness tests to examine if the effect of *Skill Demand Similarity* on mergers varies with merger-pair characteristics.

First, in model (1) we examine the role of geographic distance of the merger pair, and note that more geographically distant firms would generally be less likely to merge, due to integration challenges and search frictions. As expected, *Log(Geographic Distance)* is negative and significant. However, consistent with similar human capital demands mitigating these search frictions, we find that this the effect is offset for firms with similar skill demands—the interaction term *Skill Demand Similarity* × *Log(Geographic Distance)* is positive and significant.

In model (2), we follow in like manner by examining an interaction term of *Skill Demand Similarity* with *High Relative Size* (defined as one for mergers where the ratio of the acquirer's to target's market value of assets is greater than the sample median, and zero otherwise). We find that the effects of *Skill Demand Similarity* are substantially magnified in the presence of deals where the acquirer is significantly larger than the target. This is consistent with the acquirer being more capable of integrating the target, and likely having expertise along the dimensions of the target.

Next, we examine the role of within-industry mergers. In model (3) we introduce an indicator variable for *Same Industry* (defined by the 2-digit SIC code), and the interaction term of *Skill Demand Similarity* × *Same Industry*. Even when controlling for the interaction term *Skill Demand Similarity* × *Same Industry*, we find that *Skill Demand Similarity* remains positive and significant, consistent with our earlier analysis. Moreover, the interaction term is *negative* and significant, suggesting that the effect of *Skill Demand Similarity* reduces the occurrence of an inter-industry merger. This result is consistent with earlier results from Fulghieri and Sevilir (2011) and Lee et al. (2018).

Fulghieri and Sevilir (2011) suggest a theory in which that mergers of product market competitors reduce labor competition (and thus workers' incentives), resulting in reduced innovation. They also show that the combined firm will not generally reduce the workforce, as the firm would value coinsurance associated with employees' complementary skills. Consequently, they suggest that product market competitors can find it optimal to remain as standalone firms, despite potential benefits from reducing product market competition and employee wages. Lee et al. (2018) provide empirical results consistent with Fulghieri and Sevilir (2011).

We examine Lee et al.'s insights in greater detail in model (4) by examining the role of conglomerate mergers (using the definition of *Conglomerate* from Fan and Goyal (2006) and Lee, Mauer, and Xu (2018)). Evidence from Lee et al. (2018), among others, would imply that the effect of *Skill Demand Similarity* would be especially important when the acquirer is purchasing a target outside of its main product market.

Our results are consistent with the notion that human capital considerations make mergers less likely for horizontal and vertical mergers, potentially due to employees' concerns of reduced outside options or workforce reductions in a merged firm (Fulghieri and Sevilir, 2011; Lee et al., 2018). These considerations would generally not be present to the same extent for conglomerate mergers. This evidence is also consistent with the notion that human capital is an important driver for diversifying mergers (Tate and Yang 2016).

3.5 Post-deal labor market implications

We next examine how the acquisition affects the demand for skills of the combined firm. As we discussed in our introduction, it is unclear whether an acquisition motivated by *Skill Demand Similarity* would be associated with an increase in hiring along that dimension (for example, if the acquisition enables the combined firm to accelerate growth in the two firms' areas of focus) or reduces associated hiring (for example, if the firms' demanded skills are addressed due to scale and redundancies).

We examine this issue in Table 8, where the dependent variable is the similarity in human capital demand between the merged entity in the year after the merger compared to the acquirer in the year prior to the merger (*Post-Deal Hiring Demand*, as defined in Section 2.1.1). We show that following deals with high levels of *Skill Demand Similarity*, the acquirer is *more* likely to hire in like manner compared to prior to the merger: In Table 8, *Skill Demand Similarity* remains positive and significant across all specifications. Moreover, the effects are economically significant: A one standard deviation increase in *Skill Demand Similarity* is associated with a 10.6% increase in *Post-Deal Hiring Demand* when compared to the acquirer in the year prior to the merger and a 20.3% increase in *Post-Deal Hiring Demand* when compared to the target in the year prior to the merger.

Our finding is intriguing as it is consistent with a *Skill Demand Similarity*-driven acquisition reflecting the two firms naturally converging—and this convergence continuing to occur in the focused areas of human capital following the deal. In this respect, the skills gained in the merger are arguably complementary to continued growth in those skills of the combined firm. Our result contrasts with Lee et al. (2018)—demonstrating the difference between focusing on existing human capital (as in their paper) and the changes in firms' demanded human capital (as in our paper). Our results thus highlighting the unique information reflected in firms' recent demand for their human capital.

In the event that *Skill Demand Similarity* was negative, the evidence would have been consistent with skill-similarity satisfying immediate hiring needs (and thus enabling the combined firm to hire in different dimensions following the deal). Consequently, Table 8 provides an intriguing result in the broader literature of human capital acquisitions, in that it suggests that these deals are driven by firms' longer-term needs to grow in certain areas.

3.6 Market value implications

Finally, we evaluate whether *Skill Demand Similarity* is associated with improved deal announcement returns. This would be expected if *Skill Demand Similarity* is a meaningful driver of merger-related synergies. Additionally, previous research suggests that the synergies associated with human-capital related acquisitions would generally accrue to acquirers rather than targets (we discuss this in greater detail later in this section). In Table 9, we analyze the five-day cumulative abnormal returns of the acquirers, targets, and the capitalization-weighted average, respectively. CARs are calculated for each observation based on the market model with the CRSP value-weighted index as the benchmark return.

In column (1), we show that acquirer CARs are positive and significant. Given the standard deviation of 0.28 a one standard deviation increase in *Skill Demand Similarity* results in an increase in the acquirer's CAR by 1%. The gain from the CAR around the announcement accrues to the acquirers; targets do not significantly benefit from the abnormal returns associated with the deal, as we show in column (2). Finally, we show that the effect holds for the average firm, in that the coefficient of *Skill Demand Similarity* on the combined CAR is 0.0368, which is comparable to the acquirer CAR.

Our finding that the benefit of the similarity accrues largely to the acquirers is consistent with the notion that acquirers can capture the benefits of the human capital driven acquisition. We view this finding as consistent with Shleifer and Summers (1988) and Shleifer and Vishny (1988). To the extent that the majority of the literature suggests that mergers are followed by labor force restructuring or compensation declines (see, for example, John, Knyazeva and Knyazeva (2015), Dessaint, Golubov and Volpin (2017), Babenko, Du and Tserlukevich (2021), Lagaras (2021), and He and le Maire (2022)), we believe it is reasonable that the synergies created accrue largely to the acquiring firms.

Indeed, Ma, Ouimet, and Simintzi (2022) show that target establishments tend to spend more on technology following mergers; they suggest that this occurs due to acquirers being able to employ technology more efficiently, the effects of target financial constraints limiting pre-merger investment, and agency conflicts (for example, if entrenched managers of the target firm are unwilling to displace employees). Consequently, we suggest that it is reasonable to expect acquirers to obtain most of these expected synergies if they are the party uniquely able to create value from the deal.

4. Conclusion

One of the crucial determinants of merger decisions is the ability of the acquirer to obtain the target's employees. Consequently, we study the role of the similarity in the employee skills demanded by the acquirer and target, and how this similarity affects merger occurrence and success. Our study contributes to the literature by using the near universe of firms' online job postings to gauge which skills are the focus of firms' job postings.

Our results are consistent with assortative matching affecting merger decisions along the dimension of which employee skills are preferred by the merging firms. We show that the similarity in firms' preferred skills is associated with increases in the likelihood of merging, with an economic magnitude consistent with equivalent increases in firms' size. Consistent with acquisitions being driven by the acquirer's desire to hire certain employees, we show that targets with hiring focus that become more similar to their merger-partner are more likely to be acquired. Moreover, consistent with employee quality being an important determinant of whether firms choose to grow through acquisitions or through hiring, we show that firms hiring more experienced employees are more likely to be acquired. Cross-sectional tests confirm that our results are robust to controlling for the diversity of skills demanded by the firms, their capital intensity, and apply to firms both inside and outside the technology industry. Our results confirm prior studies suggesting the crucial role of reduced search frictions in enabling assortative matching.

We contribute to the literature examining post-deal human capital decisions in showing that the combined firm continues to seek employees with the skills that it shared with the target firm. This is consistent with the evidence that the acquisition enables the acquirer to accelerate growth in its area of focus. Finally, we show that mergers induced by similarity in demanded skills are associated with larger expected synergies. Consistent with the extant literature and the notion of acquirers possessing greater ability to extract synergies, announcement returns are concentrated among acquiring firms.

Our study makes a meaningful contribution to the evidence of the extent of assortative matching in mergers, by examining the role of firms' similarity in sought-after employee skills.

Moreover, our evidence suggests that mergers induced by these skills are associated with superior expected synergies and accelerated growth enabled by these employee skills.

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Table 1: S**ummary Statistics**

This table reports the summary statistics of our main variables. Panel A reports the summary statistics for the actual pairs, which are the firms observed in the ground truth M&A deals. Panel B reports the summary statistics for all pairs including five matched pairs for each actual pair.

Panel A: Actual Pairs

	N	Mean	StdDev	Q1	Median	Q3
Skill Demand Similarity	318	0.36	0.26	0.14	0.36	0.55
Acquirer characteristics						
Acquirer Size	318	8.92	1.76	7.80	8.93	10.05
Acquirer M/B	318	9.79	113.61	1.50	2.27	3.55
Acquirer Leverage	318	0.21	0.17	0.06	0.19	0.32
Acquirer Cash	318	0.14	0.15	0.03	0.09	0.19
Acquirer Sales Growth	318	0.12	0.22	0.01	0.07	0.18
Target characteristics						
Target Size	318	6.91	1.79	5.68	6.92	8.24
Target M/B	318	5.02	24.67	1.21	1.92	3.26
Target Leverage	318	0.17	0.19	0.00	0.10	0.29
Target Cash	318	0.20	0.23	0.03	0.11	0.30
Target Sales Growth	318	0.10	0.25	-0.03	0.06	0.19
Pair characteristics						
Product Market Relatedness	318	0.05	0.08	0.00	0.01	0.09
Human Capital Relatedness	318	0.70	0.38	0.36	1.00	1.00
Vertical	318	0.61	0.49	0.00	1.00	1.00
Horizontal	318	0.21	0.41	0.00	0.00	0.00
Conglomerate	318	0.18	0.39	0.00	0.00	0.00
Log(Geographic Distance)	248	5.62	2.41	4.99	6.35	7.21
Same Industry	318	0.73	0.44	0.00	1.00	1.00
Acquirer Change to Target (Top 20)	318	0.16	0.13	0.00	0.15	0.25
Acquirer Change to Target (Top 50)	318	0.22	0.15	0.08	0.26	0.34
Target Change to Acquirer (Top 20)	318	0.16	0.15	0.00	0.20	0.25
Target Change to Acquirer (Top 50)	318	0.20	0.17	0.00	0.22	0.34
Acquirer Diverse Skills	318	0.66	0.47	0.00	1.00	1.00
Target Diverse Skills	318	0.41	0.49	0.00	0.00	1.00
Capital Intensive Acquirer	318	0.54	0.50	0.00	1.00	1.00
Capital Intensive Target	318	0.53	0.50	0.00	1.00	1.00
Relative Size	318	35.44	160.90	2.40	5.81	16.75
TSDS Acquirer (t+1) vs Acquirer (t-1)	288	0.72	0.27	0.60	0.83	0.92
TSDS Acquirer (t+1) vs Target (t-1)	288	0.42	0.28	0.18	0.42	0.65
Returns						
Acquirer CAR (-2,+2)	250	0.00	0.07	-0.04	0.00	0.03
Target CAR (-2,+2)	244	0.29	0.33	0.10	0.21	0.37
Combined CAR (-2,+2)	239	0.03	0.07	-0.01	0.02	0.07

Panel B: All Pairs

	N	Mean	StdDev	Q1	Median	Q3
Skill Demand Similarity	1908	0.23	0.28	0.01	0.17	0.42
Acquirer characteristics						
Acquirer Size	1908	8.10	1.86	6.82	8.06	9.37
Acquirer M/B	1908	4.00	46.61	1.32	1.85	3.12
Acquirer Leverage	1908	0.18	0.17	0.03	0.14	0.29
Acquirer Cash	1908	0.16	0.19	0.03	0.08	0.21
Acquirer Sales Growth	1908	0.11	0.23	-0.01	0.07	0.17
Target characteristics						
Target Size	1908	7.09	1.59	6.10	7.21	8.14
Target M/B	1908	2.93	10.31	1.27	1.92	3.07
Target Leverage	1908	0.16	0.16	0.01	0.13	0.27
Target Cash	1908	0.20	0.23	0.03	0.10	0.28
Target Sales Growth	1908	0.10	0.26	-0.02	0.07	0.17
Pair characteristics						
Product Market Relatedness	1908	0.05	0.08	0.00	0.00	0.08
Human Capital Relatedness	1908	0.68	0.38	0.31	0.99	1.00
Vertical	1908	0.61	0.49	0.00	1.00	1.00
Horizontal	1908	0.21	0.41	0.00	0.00	0.00
Conglomerate	1908	0.18	0.39	0.00	0.00	0.00
Log(Geographic Distance)	1661	6.27	1.91	5.77	6.61	7.39
Same Industry	1908	0.49	0.50	0.00	0.00	1.00
Return Correlation	819	0.34	0.25	0.17	0.33	0.52
Acquirer Skill Evolution (Top 20)	1908	0.15	0.13	0.00	0.15	0.25
Acquirer Skill Evolution (Top 50)	1908	0.19	0.15	0.02	0.20	0.30
Target Skill Evolution (Top 20)	1908	0.14	0.13	0.00	0.10	0.25
Target Skill Evolution (Top 50)	1908	0.17	0.15	0.00	0.16	0.30
Acquirer Experience	1168	2.82	1.41	1.76	2.79	3.64
Target Experience	1226	2.79	1.34	1.79	2.85	3.57
ΔSkill Demand Similarity	394	-0.05	0.31	-0.19	-0.02	0.14
Acquirer Diverse Skills	1908	0.50	0.50	0.00	1.00	1.00
Target Diverse Skills	1908	0.50	0.50	0.00	1.00	1.00
Capital Intensive Acquirer	1908	0.50	0.50	0.00	0.50	1.00
Capital Intensive Target	1908	0.50	0.50	0.00	0.50	1.00
Tech Acquirer	1908	0.26	0.44	0.00	0.00	1.00
Tech Target	1908	0.21	0.41	0.00	0.00	0.00
Relative Size	1908	29.66	256.20	0.71	2.25	10.05

Table 2: Skill Demand Similarity and Merger Occurrence

This table reports OLS regression results on the effect of *Skill Demand Similarity* on merger occurrence. The dependent variable is equal to one if the observation is an actual merger deal, and zero otherwise. All control variables are defined in the Appendix. We note the models where we include two sets of industry fixed effects (one set for the acquirers and the other set for the targets) and year fixed effects. T-statistics with deal-clustered standard errors are included in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Skill Demand Similarity	0.2472***	0.2479***	0.2238***	0.2243***
	(8.18)	(8.14)	(6.69)	(6.63)
Acquirer characteristics				
Acquirer Size	0.0434***	0.0442***	0.0497***	0.0513***
	(9.20)	(9.21)	(9.12)	(9.27)
Acquirer M/B	0.0003***	0.0003***	0.0003***	0.0003***
	(10.00)	(9.64)	(7.01)	(6.59)
Acquirer Leverage	0.0237	0.0229	-0.0184	-0.0299
	(0.41)	(0.39)	(-0.25)	(-0.40)
Acquirer Cash	0.0433	0.0425	0.0011	0.0102
	(0.87)	(0.83)	(0.02)	(0.17)
Acquirer Sales Growth	0.0895**	0.0865*	0.1022**	0.0956**
	(2.04)	(1.91)	(2.19)	(1.99)
Target characteristics				
Target Size	-0.0351***	-0.0353***	-0.0318***	-0.0323***
	(-5.85)	(-5.81)	(-5.03)	(-5.07)
Target M/B	0.0026***	0.0025***	0.0025***	0.0024***
	(2.84)	(2.84)	(2.83)	(2.77)
Target Leverage	0.0739	0.0773	0.0811	0.0739
	(1.37)	(1.41)	(1.22)	(1.09)
Target Cash	-0.1108**	-0.1118**	-0.0886	-0.0944*
	(-2.56)	(-2.52)	(-1.63)	(-1.72)
Target Sales Growth	-0.0448	-0.0467	-0.0359	-0.0383
	(-1.43)	(-1.49)	(-1.12)	(-1.19)
Year FE	No	Yes	No	Yes
Acquirer and target industry FE	No	No	Yes	Yes
N	1,908	1,908	1,908	1,908
Adj. R^2	9.3%	9.0%	10.9%	10.7%

Table 3: Robustness to Additional Relatedness Measures

This table provides robustness results to Table 2 (OLS regression results on the effect of *Skill Demand Similarity* on merger occurrence) when controlling for additional relatedness measures. The dependent variable is equal to one if the observation is an actual merger deal, and zero otherwise. *Human Capital Relatedness* is as defined in Lee, Mauer, and Xu (2018). *Product Market Relatedness* is as defined in Hoberg and Phillips (2010, 2016). *Vertical* is an indicator variable equal to one if the merger's vertical relatedness score is greater than 1%, using Fan and Goyal's (2006) approach. *Horizontal* is an indicator variable equal to one if the merger's vertical relatedness score is less than 1% and the merging firms are in the same industry, using Fan and Goyal's (2006) approach. *Same Industry* is an indicator variable equal to one if the two firms have the same 2-digit SIC, and zero otherwise. *Log(Geographic Distance)* is the logged distance between the headquarters of the two firms, in miles. All models include the additional explanatory variables that we used in Table 2: *Acquirer Size*, *Acquirer M/B*, *Acquirer Leverage*, *Acquirer Cash*, *Acquirer Sales Growth*, *Target Size*, *Target M/B*, *Target Leverage*, *Target Cash*, and *Target Sales Growth*. All control variables are defined in the Appendix. We include two sets of industry fixed effects (one set for the acquirers and the other set for the targets) and year fixed effects. T-statistics with deal-clustered standard errors are included in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Skill Demand Similarity	0.2579***	0.2249***	0.2232***	0.2570***	0.1232***	0.2248***
	(6.87)	(6.30)	(6.37)	(6.64)	(3.18)	(4.87)
Human Capital Relatedness	-0.0764***					-0.1374***
	(-2.69)					(-4.50)
Product Market Relatedness		-0.0121				-0.2985*
		(-0.09)				(-1.67)
Vertical			0.0125			-0.0107
			(0.68)			(-0.48)
Horizontal			0.0051			-0.0174
			(0.23)			(-0.61)
Same Industry				0.1416***		0.1721***
				(5.95)		(6.10)
Log(Geographic Distance)					-0.0178**	-0.0146**
					(-2.55)	(-2.10)
Additional control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Acquirer and Target Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1908	1908	1908	1908	1661	1661
Adj. R^2	11.0%	10.6%	10.6%	12.8%	12.5%	15.4%

Table 4: Effects of the Evolution of Skill Demand Similarity

This table provides robustness results to Table 2 (OLS regression results on the effect of *Skill Demand Similarity* on merger occurrence) when controlling for the effects of changes in *Skill Demand Similarity* (Panel A) and the role of changes in skills demanded (Panel B). The dependent variable is equal to one if the observation is an actual merger deal, and zero otherwise. Δ*Skill Demand Similarity* is the change in *Skill Demand Similarity* over the three years prior to the merger announcement year. *Acquirer Skill Evolution Top 20 (Top50)* is the percentage of overlap between the acquirer's top 20 (top 50) increasing skill demands and the top 20 (top 50) skill demands of the target, as defined by skill clusters, over the three years prior to the merger announcement year. *Target Skill Evolution Top 20 (Top-50)* is the percentage of overlap between the target's top 20 (top 50) increasing skill demands and the top 20 (top 50) skill demands of the acquirer, as defined by skill clusters, over the three years prior to the merger announcement year. All control variables are defined in the Appendix. We note the models where we include two sets of industry fixed effects (one set for the acquirers and the other set for the targets) and year fixed effects. T-statistics with deal-clustered standard errors are included in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Change in Skill Demand Similarity

	(1)	(2)	(3)	(4)
ΔSkill Demand Similarity	0.1905***	0.1737***	0.1730**	0.1685**
	(3.21)	(2.77)	(2.58)	(2.37)
Skill Demand Similarity$_{t-4}$	0.3367***	0.3523***	0.2798***	0.2880***
	(4.74)	(4.82)	(3.62)	(3.62)
Acquirer characteristics				
Acquirer Size	0.0993***	0.1007***	0.1070***	0.1080***
	(7.59)	(7.57)	(7.89)	(7.77)
Acquirer M/B	0.0001***	0.0001**	0.0000	-0.0000
	(2.70)	(2.51)	(0.01)	(-0.27)
Acquirer Leverage	-0.1512	-0.1436	-0.1406	-0.1469
	(-1.15)	(-1.08)	(-0.87)	(-0.91)
Acquirer Cash	0.0485	0.0323	-0.0258	-0.0207
	(0.32)	(0.21)	(-0.14)	(-0.11)
Acquirer Sales Growth	0.1570	0.1497	0.1542	0.1488
	(1.65)	(1.52)	(1.60)	(1.49)
Target characteristics				
Target Size	-0.0965***	-0.0977***	-0.0927***	-0.0943***
	(-6.22)	(-6.12)	(-5.69)	(-5.67)
Target M/B	0.0006*	0.0006*	0.0005	0.0005
	(1.83)	(1.76)	(1.13)	(1.13)
Target Leverage	0.2529**	0.2533*	0.2110	0.1925
	(2.04)	(1.95)	(1.20)	(1.07)
Target Cash	-0.2277*	-0.2301*	-0.2370*	-0.2456*
	(-1.97)	(-1.92)	(-1.71)	(-1.72)
Target Sales Growth	-0.1068	-0.1190	-0.0652	-0.0807
	(-1.22)	(-1.32)	(-0.76)	(-0.91)
Year FE	No	Yes	No	Yes
Acquirer and target industry FE	No	No	Yes	Yes
N	394	394	394	394
Adj. R^2	19.9%	18.8%	21.5%	20.4%

Panel B: Changes in Top Skills for Acquirer or Target

	(1)	(2)	(3)	(4)	(5)	(6)
Acquirer Skill Evolution (Top 20)	0.4639**		0.0441			
	(2.00)		(0.18)			
Target Skill Evolution (Top 20)		0.9369***	0.9184***			
		(4.28)	(3.82)			
Acquirer Skill Evolution (Top 50)				0.5995***		-0.1321
				(2.81)		(-0.49)
Target Skill Evolution (Top 50)					0.9670***	1.0511***
					(4.57)	(3.80)
Skill Demand Similarity$_{t-4}$	-0.0329	-0.0305	-0.0334	-0.0379	-0.0660	-0.0627
	(-0.56)	(-0.50)	(-0.53)	(-0.68)	(-1.07)	(-1.02)
Acquirer characteristics						
Acquirer Size	0.1135***	0.1016***	0.1017***	0.1099***	0.0965***	0.0959***
	(8.33)	(6.90)	(6.90)	(7.85)	(6.35)	(6.30)
Acquirer M/B	0.0000	0.0001	0.0001	0.0000	0.0000	0.0000
	(0.64)	(1.17)	(1.20)	(0.03)	(0.43)	(0.48)
Acquirer Leverage	-0.0710	-0.0863	-0.0869	-0.0326	-0.0194	-0.0218
	(-0.44)	(-0.54)	(-0.54)	(-0.20)	(-0.12)	(-0.13)
Acquirer Cash	0.0029	0.0045	0.0072	0.0243	0.0187	0.0105
	(0.02)	(0.02)	(0.04)	(0.13)	(0.10)	(0.06)
Acquirer Sales Growth	0.1433	0.1636	0.1629	0.1545	0.1851*	0.1867*
	(1.39)	(1.57)	(1.56)	(1.53)	(1.80)	(1.79)
Target characteristics						
Target Size	-0.0970***	-0.0949***	-0.0955***	-0.1025***	-0.1015***	-0.0997***
	(-5.43)	(-5.61)	(-5.50)	(-6.03)	(-6.28)	(-5.99)
Target M/B	0.0003	0.0004	0.0004	0.0004	0.0001	0.0001
	(0.61)	(0.98)	(0.84)	(0.81)	(0.15)	(0.17)
Target Leverage	0.2308	0.2826	0.2824	0.2561	0.3007*	0.2997
	(1.22)	(1.53)	(1.53)	(1.37)	(1.65)	(1.65)
Target Cash	-0.2450*	-0.1607	-0.1618	-0.2494*	-0.2142	-0.2115
	(-1.76)	(-1.15)	(-1.16)	(-1.81)	(-1.53)	(-1.49)
Target Sales Growth	-0.0324	-0.0308	-0.0322	-0.0181	-0.0014	0.0005
	(-0.34)	(-0.34)	(-0.36)	(-0.19)	(-0.02)	(0.01)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Acquirer and target industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	394	394	394	394	394	394
Adj. R^2	15.8%	19.5%	19.3%	16.8%	20.5%	20.3%

Table 5: Effects of Acquirer and Target Job Experience

This table provides robustness results to Table 2 (OLS regression results on the effect of *Skill Demand Similarity* on merger occurrence) when controlling for the role of the years of experience for the acquirer or target. The dependent variable is equal to one if the observation is an actual merger deal, and zero otherwise. *High Skill Demand Similarity* (*Low Skill Demand Similarity*) is an indicator variable equal to one if *Skill Demand Similarity* is above (below) the median value of the sample. *Acquirer Experience* (*Target Experience*) is the mean number of years of experience for the acquirer's (target's) job listings in the three years before the merger year. All control variables are defined in the Appendix. We include two sets of industry fixed effects (one set for the acquirers and the other set for the targets) and year fixed effects. T-statistics with deal-clustered standard errors are included in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
High Skill Demand Similarity × Acquirer Experience	-0.0312**		-0.0410**
	(-2.05)		(-2.21)
High Skill Demand Similarity × Target Experience		0.0352**	0.0424**
		(2.46)	(2.31)
Low Skill Demand Similarity × Acquirer Experience	-0.0265*		-0.0153
	(-1.71)		(-0.83)
Low Skill Demand Similarity × Target Experience		0.0161	0.0137
		(1.45)	(0.94)
High Skill Demand Similarity	0.1452**	0.0804	0.1196
	(2.31)	(1.64)	(1.59)
Acquirer characteristics			
Acquirer Size	0.0677***	0.0538***	0.0713***
	(7.55)	(8.11)	(7.17)
Acquirer M/B	0.0002***	0.0002***	0.0002***
	(4.21)	(5.00)	(3.23)
Acquirer Leverage	-0.1252	-0.0303	-0.1304
	(-1.25)	(-0.33)	(-1.14)
Acquirer Cash	0.0644	-0.0893	-0.0635
	(0.71)	(-1.14)	(-0.60)
Acquirer Sales Growth	0.1216*	0.1264**	0.1582**
	(1.90)	(2.12)	(2.12)
Target characteristics			
Target Size	-0.0351***	-0.0425***	-0.0495***
	(-3.79)	(-4.41)	(-4.14)
Target M/B	0.0024**	0.0022**	0.0022**
	(2.44)	(2.39)	(2.30)
Target Leverage	0.0644	0.0315	0.0249
	(0.71)	(0.35)	(0.23)
Target Cash	-0.1024	-0.1513*	-0.1469
	(-1.27)	(-1.92)	(-1.47)
Target Sales Growth	-0.0185	-0.0664	-0.0614
	(-0.44)	(-1.44)	(-1.16)
Year FE	Yes	Yes	Yes
Acquirer and target industry FE	Yes	Yes	Yes
N	1,168	1,226	947
Adj. R^2	12.6%	14.4%	15.6%

Table 6: Additional Cross-Sectional Tests

This table provides additional cross-sectional results following from Table 2 (OLS regression results on the effect of *Skill Demand Similarity* on merger occurrence). The dependent variable is equal to one if the observation is an actual merger deal, and zero otherwise. The new variables that we use in this table are the following: *Acquirer Diverse Skill Demand* (*Target Diverse Skill Demand*), defined as an indicator variable equal to one for firm-years where the acquirer's (target's) SIC 2-digit industry-adjusted number of skills demanded is greater than or equal to the median, and zero otherwise; *Capital Intensive Acquirer* (*Capital Intensive Target*) defined as an indicator variable equal to one if the assets to sales ratio is greater than the acquirer (target) sample average; *Tech Acquirer* (*Tech Target*) is defined as an indicator variable equal to one if the acquirer's (target's) Fama-French 12 Industry is Business Equipment and Software, and zero otherwise. All models include the additional explanatory variables that we used in Table 2: *Acquirer Size*, *Acquirer M/B*, *Acquirer Leverage*, *Acquirer Cash*, *Acquirer Sales Growth*, *Target Size*, *Target M/B*, *Target Leverage*, *Target Cash*, and *Target Sales Growth*. All control variables are defined in the Appendix. We include two sets of industry fixed effects (one set for the acquirers and the other set for the targets) and year fixed effects. T-statistics with deal-clustered standard errors are included in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Skill Demand Similarity	0.2949***		
× Acquirer Diverse Skill Demand	(4.28)		
Skill Demand Similarity	-0.0585		
× Target Diverse Skill Demand	(-0.90)		
Acquirer Diverse Skill Demand	-0.0527**		
	(-2.04)		
Target Diverse Skill Demand	-0.0614***		
	(-2.92)		
Skill Demand Similarity		0.0123	
× Capital Intensive Acquirer		(0.15)	
Skill Demand Similarity		0.0050	
× Capital Intensive Target		(0.06)	
Capital Intensive Acquirer		0.0240	
		(0.93)	
Capital Intensive Target		0.0036	
		(0.17)	
Skill Demand Similarity			-0.0904
× Tech Acquirer			(-0.85)
Skill Demand Similarity			-0.0473
× Tech Target			(-0.44)
Tech Acquirer			-0.0271
			(-0.42)
Tech Target			-0.0622
			(-0.93)
Skill Demand Similarity	0.1127**	0.2160***	0.2610***
	(2.14)	(4.19)	(6.11)
Additional control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Acquirer and target industry FE	Yes	Yes	Yes
N	1,908	1,908	1,908
Adj. R^2	12.2%	10.6%	10.7%

Table 7: Merger-Pair Characteristics and Skill Demand Similarity

This table provides robustness results to Table 2 (OLS regression results on the effect of *Skill Demand Similarity* on merger occurrence) when controlling for additional merger-pair characteristics. The dependent variable is equal to one if the observation is an actual merger deal, and zero otherwise. *Log(Geographic Distance)* is the logged distance between the headquarters of the two firms, in miles. *High Relative Size* is an indicator variable equal to one if the ratio of the acquirer's market value of assets to the target's market value of assets is greater than the sample median, and zero otherwise. *Same Industry* is an indicator variable equal to one if the acquirer and target are from the same SIC 2-digit industry, and zero otherwise. *Conglomerate* is an indicator variable equal to one for conglomerate mergers (following from Fan and Goyal (2006)), when the vertical relatedness score using NAICS is less than 1% and the merging firms are from different industries. All models include the additional explanatory variables that we used in Table 2: *Acquirer Size*, *Acquirer M/B*, *Acquirer Leverage*, *Acquirer Cash*, *Acquirer Sales Growth*, *Target Size*, *Target M/B*, *Target Leverage*, *Target Cash*, and *Target Sales Growth*. All control variables are defined in the Appendix. We include two sets of industry fixed effects (one set for the acquirers and the other set for the targets) and year fixed effects. T-statistics with deal-clustered standard errors are included in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Skill Demand Similarity	0.0455***			
× Log(Geographic Distance)	(4.68)			
Log(Geographic Distance)	-0.0416***			
	(-5.30)			
Skill Demand Similarity		0.3150***		
× High Relative Size		(4.62)		
High Relative Size		0.0472		
		(1.62)		
Skill Demand Similarity			-0.2029***	
× Same Industry			(-2.78)	
Same Industry			0.1836***	
			(7.15)	
Skill Demand Similarity				0.1861***
× Conglomerate				(5.08)
Conglomerate				0.2066**
				(2.23)
Skill Demand Similarity	-0.0177	0.0998***	0.2509***	-0.0478**
	(-0.25)	(3.13)	(4.10)	(-2.20)
Additional control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Acquirer and target industry FE	Yes	Yes	Yes	Yes
N	1,661	1,908	1,908	1,908
Adj. R^2	13.4%	13.2%	13.2%	10.9%

Table 8: Post-Deal Hiring Demand

We report the regression results examining the effects of *Skill Demand Similarity* on *Post-Deal Hiring Demand* between the combined firm and the predecessor firms, reflecting the temporal continuation of human capital demand before and after the merger. In models (1)-(4) we compare the combined firm with the acquirer in the year prior to the merger; in models (5)-(8) we compare the combined firm with the target in the year prior to the merger. All control variables are defined in the Appendix. We note the models where we include two sets of industry fixed effects (one set for the acquirers and the other set for the targets) and year fixed effects. T-statistics with deal-clustered standard errors are included in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Post-Deal Hiring Demand vs. Acquirer **[Combined Firm (t+1) vs Acquirer (t-1)]**				Post-Deal Hiring Demand vs. Target **[Combined Firm (t+1) vs Target (t-1)]**			
Skill Demand Similarity	0.4059***	0.4216***	0.3906***	0.4079***	0.7959***	0.7854***	0.7932***	0.7816***
	(6.56)	(6.73)	(6.76)	(7.01)	(18.26)	(17.63)	(17.44)	(17.03)
Acquirer characteristics								
Acquirer Size	0.0373***	0.0371***	0.0380***	0.0378***	-0.0197**	-0.0212***	-0.0196**	-0.0204**
	(2.92)	(2.91)	(3.04)	(2.96)	(-2.53)	(-2.68)	(-2.37)	(-2.45)
Acquirer M/B	0.0000	0.0000	0.0000	0.0000	-0.0001***	-0.0000**	-0.0001**	-0.0001
	(0.58)	(1.17)	(0.60)	(0.63)	(-3.96)	(-2.26)	(-2.39)	(-1.63)
Acquirer Leverage	0.1952*	0.2437**	0.1980	0.2599**	0.0176	0.0195	0.0097	0.0261
	(1.83)	(2.31)	(1.54)	(2.12)	(0.22)	(0.25)	(0.11)	(0.31)
Acquirer Cash	0.0607	0.1113	0.0304	0.0991	-0.0331	-0.0619	-0.0286	-0.0500
	(0.51)	(0.94)	(0.22)	(0.73)	(-0.40)	(-0.72)	(-0.30)	(-0.50)
Acquirer Sales Growth	-0.0546	-0.0667	-0.0224	-0.0437	-0.0848**	-0.0665	-0.0873*	-0.0726
	(-0.71)	(-0.82)	(-0.28)	(-0.52)	(-1.98)	(-1.47)	(-1.84)	(-1.49)
Target characteristics								
Target Size	-0.0239*	-0.0234*	-0.0159	-0.0172	0.0178*	0.0245**	0.0223**	0.0277***
	(-1.95)	(-1.92)	(-1.20)	(-1.28)	(1.85)	(2.52)	(2.53)	(3.18)
Target M/B	0.0005**	0.0004	0.0005**	0.0005	-0.0002	0.0000	-0.0001	0.0000
	(2.37)	(1.62)	(2.09)	(1.60)	(-0.91)	(0.02)	(-0.67)	(0.12)
Target Leverage	-0.1170	-0.1194	-0.1501	-0.1603	-0.0498	-0.0527	-0.1313*	-0.1164
	(-1.08)	(-1.16)	(-1.21)	(-1.36)	(-0.84)	(-0.85)	(-1.97)	(-1.62)
Target Cash	-0.0285	-0.0497	-0.0403	-0.0677	0.0321	0.0690	0.0358	0.0608
	(-0.29)	(-0.54)	(-0.40)	(-0.69)	(0.53)	(1.10)	(0.55)	(0.88)
Target Sales Growth	-0.0254	-0.0197	0.0072	0.0206	-0.0484	-0.0321	-0.0404	-0.0273
	(-0.49)	(-0.38)	(0.13)	(0.36)	(-1.35)	(-0.90)	(-1.07)	(-0.72)
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Acquirer and target industry FE	No	No	Yes	Yes	No	No	Yes	Yes
N	298	298	298	298	288	288	288	288
Adj. R^2	19.2%	20.7%	18.8%	20.4%	59.3%	61.1%	58.6%	60.5%

Table 9: Cumulative Abnormal Returns

This table reports the regression on the centered 5-day cumulative abnormal return for the acquirer (model (1)), target (model (2)), and the combined firm (model (3)). We include two sets of industry fixed effects, one set for the acquirers and the other set for the targets. We include standalone industry fixed effects based on Fama-French 12 Industries. All control variables are defined in the Appendix. We note the models where we include industry fixed effects (acquirer and target fixed effects in (1) and (2), and acquirer fixed effects in (3)); year fixed effects are included throughout. T-statistics with industry-clustered standard errors (acquirer's industry in (1) and (3), and target's industry in (2)) are included in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	Acquirer CAR	Target CAR	Combined CAR
Skill Demand Similarity	0.0309***	0.0584	0.0368***
	(3.99)	(0.59)	(4.29)
Acquirer characteristics			
Acquirer Size	-0.0031	0.0464	
	(-0.77)	(1.76)	
Acquirer M/B	-0.0011	0.0020	
	(-1.59)	(0.65)	
Acquirer Leverage	0.0282	-0.3616	
	(0.64)	(-1.64)	
Acquirer Cash	-0.0139	-0.3150	
	(-0.40)	(-1.48)	
Acquirer Sales Growth	0.0324**	-0.0333	
	(2.88)	(-1.22)	
Target characteristics			
Target Size	-0.0037	-0.0959***	
	(-0.89)	(-4.02)	
Target M/B	0.0001	-0.0010*	
	(1.39)	(-2.10)	
Target Leverage	0.0150	0.3670***	
	(0.40)	(4.10)	
Target Cash	0.0075	0.3332	
	(0.23)	(1.75)	
Target Sales Growth	-0.0194	-0.1419	
	(-1.39)	(-1.16)	
Combined firm characteristics			
Combined Size			-0.0115***
			(-4.31)
Combined M/B			-0.0018
			(-1.50)
Combined Leverage			0.0549
			(0.71)
Combined Cash			0.0321
			(0.83)
Combined Sales Growth			0.0058
			(0.41)
Year fixed-effects	Yes	Yes	Yes
Acquirer and target industry FE	Both	Both	Acquirer
Industry error cluster	Acquirer	Target	Acquirer
N	250	244	239
Adj. R^2	9.0%	26.1%	21.4%

Appendix

Table A1: Variable Definitions

Panel A: Main Test Variables

Variable	*Definition*
Deal characteristics	
Deal	A merger where the acquirer owns less than 50% of the target firm prior to the bid and is seeking to own more than 50% of the target firm after the bid.
Skill Demand Similarity	Similarity between firms *i* and *j* is calculated as $\frac{H_i H_j'}{\sqrt{(H_i H_i')(H_j H_j')}}$ where the vector $H_{i,t} = (H_{i1,t}, H_{i2,t}, \cdots, H_{iS,t})$ denotes the top contributing principal components of firm *i*'s skill clusters in recruiting postings that occur in year *t*. We select the components of eigenvalues greater than the 3rd quartile of those of all 658 principal components and end up with 165 principal components for our calculation of skill demand similarity.
Post-Deal Hiring Demand	Equivalent to *Skill Demand Similarity* for the same firm in years t+1 and t-1, where year *t* is the merger year; in other words, $Post\text{-}Deal\ Hiring\ Demand_{i,t} = \frac{H_{i,t+1} H_{i,t-1}'}{\sqrt{(H_{i,t+1} H_{i,t+1}')(H_{j,t-1} H_{j,t-1}')}}$.
CAR	Cumulative abnormal returns in excess of the CRSP value-weighted market index calculated over [-120,-15] window.
Firm Characteristics	
Size	The log of total assets.
M/B	The market-to-book ratio, defined as fiscal year end market capitalization scaled by total equity adjusted for deferred taxes and preferred stock.
Cash	Cash holdings, defined as cash position scaled by total assets.
Leverage	Leverage, defined as long-term debt scaled by total assets.
Sales Growth	One-year percentage change in sales.

Table A1 (Continues)

Panel B: Additional Test Variables

Variable	*Definition*
Acquirer (Target) Diverse Skill Demand	Indicator variable equal to one for firm-years where the industry-adjusted (SIC 2-digit) number of skills demanded is greater than or equal to the median, and zero otherwise.
Acquirer (Target) Experience	Mean number of years of experience for the acquirer's (target's) job listings in the three years prior to the merger announcement year.
Acquirer Skill Evolution Top 20 (Top 50)	The percentage of overlap between the acquirer's top 20 (top 50) increasing skill demands and the target's top 20 (top 50) skill demands, as defined with skill clusters. Changes are measured as the percentage of the skill hiring increase in the three years prior to the announcement year of the merger.
Capital Intensive Acquirer (Target)	An indicator variable equal to one if the ratio of assets to sales is greater than the median value of the sample average, and zero otherwise.
Conglomerate	Indicator variable equal to one for a conglomerate merger, and zero otherwise, following the approach described in Fan and Goyal (2006). A conglomerate merger occurs if the firms are from different industries (using NAICS) and their Fan and Goyal (2006) vertical relatedness is less than 1%.
Geographic Distance	Geographic Distance is calculated as the great circle distance in miles between the headquarters of two firms using the longitudes and the latitudes based on 5-digit zip codes**.** We define the great circle distance between two points on earth as $$3949.99 \times \arccos \left[\begin{matrix} \sin\left(\frac{arctan(1)}{45} \times acquier\ latitude\right) \times \\ \sin\left(\frac{arctan(1)}{45} \times target\ latitude\right) \\ + \\ \cos\left(\frac{arctan(1)}{45} \times acquirer\ latitude\right) \times \\ \cos\left(\frac{arctan(1)}{45} \times target\ latitude\right) \times \\ \cos\left(\begin{matrix} \frac{arctan(1)}{45} \times acquirer\ longitude - \\ \frac{arctan(1)}{45} \times target\ longitude \end{matrix}\right) \end{matrix} \right]$$ And the log scale in miles is applied to the distance calculation.
High Relative Size	Indicator variable based on the ratio between the acquirer's market value of assets and the target's market value of assets. If the firms have a relative size greater than the sample median, we assign a value of one to the firms. Otherwise, we assign a value of zero to the firms.
High (Low) Skill Demand Similarity	Indicator variable with a value of one when the firms have *Skill Demand Similarity* higher (lower) than the median of the sample average; zero otherwise.
Horizontal	Indicator variable equal to one for a horizontal merger, and zero otherwise, following the approach described in Fan and Goyal (2006). A horizontal merger occurs if the firms are from the same industries (using NAICS) and their Fan and Goyal (2006) vertical relatedness is less than 1%.
Human Capital Relatedness	Human Capital Relatedness as defined is Lee, Mauer, and Xu (2018).
Product Market Relatedness	Product Market Relatedness from Hoberg and Phillips (2010, 2016).
Same Industry	Indicator variable equal to one if the merging firms have the same 2-digit SIC code, and zero otherwise.
ΔSkill Demand Similarity	The three-year change in *Skill Demand Similarity* between the two firms.

Target Skill Evolution Top 20 (Top 50)	The percentage of overlap between the target's top 20 (top 50) increasing skill demands and the acquirer's top 20 (top 50) skill demands, as defined with skill clusters. Changes are measured as the percentage of the skill hiring increase in the three years prior to the announcement year of the merger.
Tech Acquirer (Target)	Fama-French 12 Industry classification of computers, software, and electronic equipment.
Vertical	Indicator variable equal to one for a vertical merger, and zero otherwise, following the approach described in Fan and Goyal (2006). A vertical merger occurs if the firms' Fan and Goyal (2006) vertical relatedness is greater than or equal to 1%.