New entrants, Incumbents, and the Search for Knowledge: The Role of Job Title Ambiguity in the U.S. Information and Communication Technology Industry, 2004–2014

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Abstract

New entrants and incumbent firms rely on new knowledge to innovate and compete in the market. One way to acquire new knowledge is through the recruitment of new employees from competitors, a phenomenon popularly known as "poaching." Digital labor platforms are widely used by firms for this aim. We argue that job titles represent the first and most visible public source of information about knowledge workers and thus play a key role in navigating the vast spectrum of competencies available in digital platforms. Our analyses of the career trajectories of 11,644 knowledge workers in the United States between 2004 and 2014 suggest that increases in the ambiguity of a job title claimed by an employee are negatively associated with the likelihood of the employee being hired by a new employer. This finding appears stronger in the case of transitions to incumbent firms rather than new entrants. In the concluding section of the paper, we take stock of the various analyses presented and reflect on the potential role of job titles in the strategic management of human capital.

Keywords: Job titles; Categorization theory; New entrant and incumbent firms; LinkedIn.

INTRODUCTION

"In a hot job market, especially in sectors where the number of jobs exceeds the number of skilled workers, there's a high probability that other organizations are trying to poach your employees. Not just your superstars. Everyone." (Markman, 2022)

The challenge of acquiring knowledge for survival and innovation involves both new entrants and incumbent firms (Agarwal et al., 2004; Dencker et al., 2009; Klepper, 2007). For instance, Apple "poached" DJ Zane Lowe from BBC Radio 1 when they launched a new online radio service. In that knowledge embodied in human capital is one of the most relevant sources of competitive advantage (Castanios & Helfat, 1994; Coff & Kryscynski, 2011), also incumbents compete to acquire and extend their knowledge pool by poaching employees from competitors (Song et al., 2003). The competition for acquiring knowledge is particularly severe when it relates to engineers, scientists, and inventors (Tzabbar, 2009). For instance, Microsoft approached engineers to poach from Adobe and Google by using a food truck parked at lunchtime near the headquarters (Boudreau, 2014).

Digital labor market platforms such as LinkedIn made poaching much easier and a widespread tool for companies compared to a covert food truck mobilized at competitors' headquarters (Caers & Castelyns, 2011; Tambe, Ye, & Cappelli, 2020). Ample evidence suggests that intermediaries use LinkedIn to support the poaching efforts of incumbent firms and new entrants (e.g., Ollington et al., 2013; Zide et al., 2014), particularly when scouting information and communication technology (ICT) workers (Pinho et al., 2019). Primary data from job hunters and experimental evidence confirm that LinkedIn profile information is used by recruiters for shaping the pool of candidates to poach (Koivunen et al., 2019; Zide, 2015).

Nevertheless, recruiters who aim to poach knowledge workers from incumbents are exposed to substantial information asymmetries. An enormous array of candidates is available on digital labor platforms; thus, recruiters are likely to resort to cognitive shortcuts to guide their search for further information (e.g., Kovacs et al., 2021). In this paper, we claim that job titles may be leveraged for this purpose. Recruiters indeed use job titles as a meaningful public source of information to select poaching targets and infer knowledge workers' human capital (Koivunen et al., 2019). For example, the job title "senior software engineer" implies that the worker is mostly engaged in technical rather than management tasks but is likely to coordinate a team of subordinates.

This work addresses the following research question: "How do job titles affect knowledge workers' outward mobility in digital labor markets?" We focus on outward mobility because, in labor markets such as ICT, there is an established "war for talent" (Gardner, 2005) and poaching is common and widespread. Regarding job titles, we specifically focus on their ambiguity. To explain the influence of job title ambiguity, we borrow from categorization theory (Hannan et al., 2019) and highlight how ambiguity is likely to prompt multiple and potentially inconsistent meanings (Hannan et al., 2019; Zuckerman, 1999; Zunino et al., 2019). Workers who hold job titles with multiple meanings, however, are exposed to a greater set of potential recruiters and market opportunities. Consequently, our goal is first to explore the consequences of job title ambiguity for knowledge workers' mobility, then differentiate the influence of this ambiguity on mobility for entrants and incumbents due to divergent degrees of industry knowledge.

To address this question, we created a unique longitudinal dataset using data from public LinkedIn accounts and the U.S. Patent and Trademark Office (USPTO) to build the employment histories, job titles and patenting records of 11,644 knowledge workers with a Ph.D. degree employed between 2004 and 2014 by 168 U.S. incumbent firms operating in the ICT industry. To compute the ambiguity of job titles, we resorted to topic modeling algorithms (Corritore et al., 2020; DiMaggio et al., 2013; Yan et al., 2013).

Our results show that the ambiguity of an inventor's job title is negatively associated with the likelihood that the employee will be hired by a new employer. To identify the likely mechanism behind this finding, we explore its sensitivity to alternative explanations such as social networks and ambiguity within the employer. Our results suggest that the extent to which the ambiguity of job titles affects outward mobility varies between new entrants and incumbent firms. We find that the influence of job title ambiguity is stronger for mobility to incumbents than for mobility to entrants. Our study informs several fields of literature and contributes to refining our understanding of the challenges faced by new entrants and incumbent firms when acquiring knowledge in hot labor markets.

THEORETICAL BACKGROUND

Poaching and Social Evaluation

In industries where human capital is the main source of competitive advantage (Castanias & Helfat, 1991), there is more demand than supply of skilled workers, and labor markets tend to be hot (Gardner, 2005; Markman, 2014). In these contexts, organizations heavily rely on poaching workers from competitors, and outward mobility is mostly generated by recruiters who actively seek candidates to fill new or vacant positions[1] (Rao & Drazin, 2002; Tambe et al., 2020). We define recruiters as individuals who act on behalf of an organization to poach a candidate. This definition encompasses recruiters who are either from new entrants or incumbent firms. Similarly, we define candidates as knowledge workers who are employed in a firm and are at risk of being poached. This definition is agnostic about whether those workers actively search for a new employer.

Digital labor markets decreased the barriers to poaching and created a tradeoff. On the one hand, the availability of online information about the resume of knowledge workers

[1] Although there is a lack of precise quantitative evidence, evidence is seen of the economic significance of poaching in the ICT industry. In 2011, an antitrust case (United States vs. Adobe et al.) led to a judgement where six employers (Adobe, Apple, Google, Intuit, Pixar, LucasFilms) were found guilty of forging no-poaching agreements to solicit employees between 2005 and 2009.

allows them to reach a broader labor market more easily. The phenomenon is so widespread that nearly every organization uses digital labor platforms to construct their recruiting pool (Pinho et al. 2019; Zide et al. 2014). LinkedIn is widely used for recruitment purposes (e.g., Ollington et al., 2013; Zide et al., 2014) and is favored over other social media (Caers & Castelyns, 2011), particularly for ICT workers (Pinho et al., 2019). On the other hand, such an abundance of information exposes recruiters to the problem of the riches: recruiters face higher levels of information overload, without necessarily a decrease in labor market information asymmetries (Mawdsley & Somaya, 2015).

To navigate this tradeoff and make inferences about candidates' knowledge and fit to the task, recruiters are likely to use categories as cognitive infrastructures that guide their search for additional information (for a similar example among patent examiners see e.g. Kovacs et al., 2021). Job titles serve this purpose because "communicate the knowledge, skills, abilities, and other characteristics that employees who hold the job are likely to possess" (Grant, Berg, & Cable, 2014), and they represent one of the most effective ways to convey this information also to external stakeholders.

In view of the copious amount of information available on digital platforms, we claim that recruiters who need to infer the possible tasks that a potential candidate can perform will navigate through the available options by constructing their consideration set via job titles' searches. Our claim is backed by research that suggests that the role of job titles is particularly salient for recruiters who use online platforms for recruitment purposes (Koivunen et al., 2019) and insert keywords in return of a list of candidates fitting those keywords. The powerful role of keywords in the exclusion and inclusion of relevant candidates on online platforms is well-known among professionals who recognize that “your profile isn’t going anywhere if you’re not showing up in a recruiter’s LinkedIn search.”[2]

The Role of Job Title Ambiguity

In developing our argument, we start from the premise that job titles differ in their ability to communicate the tasks carried out by a worker to external stakeholders. This difference among job titles is nicely described by the concept of ambiguity. The premise of our reasoning is that in the presence of information asymmetries and cognitive overload, the ambiguity of a job title complicates the interpretation of the tasks currently carried out by a worker. Hannan and his colleagues (2019) claim that evaluators find an object ambiguous when it is hard for them to make sense of its underlying components. We build on this reasoning, we claim that recruiters first evaluate workers using job titles to construct their consideration set (Koivunen et al., 2019), and that participation in such a consideration set significantly affects a worker’s chances of mobility to a new employer.

Job titles can be ambiguous for three reasons. First, they may be too generic. Take for example a recruiter who is looking for a “software engineer.” When a candidate has a job title that is too generic, such as “engineer,” it is hard to make sense of the tasks and responsibilities of a worker: they could be related to software engineering, to mechanical engineering, or to civil engineering. Second, job titles can refer to unique task combinations. For instance, the job title “software engineer and consultant” is ambiguous to recruiters because it is harder to make sense of which concept associate the worker with. The job title evokes tasks related both to software engineering and consulting. Such a job title is more likely to appear in searches for software engineers but also consultants, however it is unclear the main set of tasks that the worker is able to perform. Third, the job title can be self-reflective and derived from workers’

[2] See: https://www.themuse.com/advice/3-smart-ways-to-attract-recruiters-to-your-linkedin-profile?utm_source=linkedin&utm_medium=social&utm_campaign=jobsearch_march2020&utm_content=advice accessed on February 22 2023

interaction with the organization (Grant et al., 2014; Rousseau et al., 2006). Some of these self-reflective job titles may relate more to the worker's identity rather than the related tasks, for example, the job title "coding artist." Such job titles tend to be rarer and potentially less informative, but also with a chance of standing out.

This job title ambiguity may influence mobility in opposing ways though. On the one hand, workers with ambiguous job titles, especially when containing multiple meanings are more likely to appear in recruiters' searches and thus to be poached. On the other hand, the difficulty in associating a worker to a well-bounded set of tasks makes workers with ambiguous job titles harder to evaluate and thus makes them less likely to move. In this paper, we aim to evaluate the association between job title ambiguity and outward mobility. We further contend that these results may be conditional on the mobility destination since entrants may have different sensitivity than incumbents when they evaluate job titles due to different recruitment techniques or industry knowledge. We explore this trade-off via several analyses involving mobility to incumbent or entrant firms as well as different industries.

DATA AND METHOD

Setting

For this research, we focus on a sample of U.S. firms operating in the information and communications technology (ICT) industry from 2004, when LinkedIn reached 1 million users, to 2014. The ICT industry is ideal for addressing our research question for several reasons. First, the ICT industry is an industry where human capital is a key factor for competitive advantage. For this reason, it is an industry where the practice of screening and recruiting candidates directly from competitors, what we labeled as employee poaching, is particularly prevalent (Tambe, Ye, & Cappelli, 2020). Second, the ICT industry is characterized by higher degrees of job title heterogeneity. There is no regulation that imposes certain job titles (Cohen, 2013), and job titles tend to be abundant where there is a large share of technical and managerial positions (Baron & Bielby, 1986). Third, by focusing only on one industry, we can rule out the possibility of what we measure as ambiguity in job titles being the mechanical result of ambiguity across industries. Fourth, the ICT industry regularly employs professional online platforms, such as LinkedIn, to attract and recruit new talent, including through employee poaching (Koch et al., 2018; Koivunen et al., 2019). Finally, ICT is a knowledge-intensive industry (Almeida et al. 2002) in which the environment encourages employees to patent (Hall & MacGarvie, 2010), and patenting activities provide a reliable source of data to estimate employee productivity (Dietz & Bozeman, 2005). The vast number of employees with public LinkedIn accounts and patents thus facilitates the collection of reliable data on career histories, as well as several dimensions of employees' general and specific human capital.

Sample of U.S. firms and knowledge workers

We started the data collection by identifying the firms operating in ICT hardware. Specifically, using the Organisation for Economic Co-operation and Development (2002) definition of ICT hardware, we found the largest public firms having either their primary or the secondary activity related to "office computing and accounting machines" (three-digit standard industrial code [SIC] 357), "communications equipment and electronic components" (three-digit SIC 365, 366, 367), or "measuring and controlling devices" (three-digit SIC 382). In this list, 172 U.S. corporations accounted for about 80% of sales in the U.S. North American hardware market from 2004 to 2014. This list includes 122 firms with primary activity in the hardware sector, and 46 firms with secondary activity in the same sector. These 46 firms have primary activity in the software industry and are diversifying entrants in the hardware industry. Therefore, we focus on these 168 firms in this work.

We used LinkedIn profiles[3] and patenting activities reported by the United States Patent and Trademark Office (USPTO) to identify engineers and scientists who worked and patented for any of the 168 firms on our list. In the first stage, using USPTO patent data, we identified 197,216 inventors who reported a listed firm as an assignee on at least one of their patents since the firm's incorporation. Following that, to obtain a clean list of inventors employed by listed firms, in the second stage we identified and selected those who had a public LinkedIn profile that reported a listed firm as one of their employers during their working career by matching data points on the person's name, geographical location, and employment/patenting dates at that firm from the two data sources. Limiting this list to inventors with a LinkedIn profile and USPTO records and those employed by a listed firm during our study period (2004–2014), we successfully matched 92,875 firm employees. Finally, for our main analyses, we restricted this list to 11,644 knowledge workers who hold a doctoral degree to rule out alternative explanations related to individual sources of heterogeneity.[4]

Our methodological approach in selecting corporate inventors with doctoral education allows to rule out a possible competing explanation that ambiguity in job titles reflects more generalist human capital. By selecting for occupation-specific human capital (operationalized as inventors with a doctoral degree), the relationship between job titles and unobserved human capital generality becomes less worrisome. We followed analogous arguments to focus solely on inventors as knowledge workers.

First, inventors are valuable sources of human capital in an organization, and their outward mobility can challenge the productivity and the competitive advantage of the firms they work for. Second, choosing inventors allows us to control for time-variant individual

[3] The data were collected in between 2015 and 2016 through an approved application to the LinkedIn Vetted API access program.
[4] We retrieved this information from inventors' LinkedIn profiles.

productivity in terms of patents and their quality. Third, a focus on inventors mitigates measurement errors regarding employment history because we can triangulate our data with patent data, thus increasing data reliability.

The LinkedIn setting is particularly desirable for this study because of its relevance for both employers and employees. LinkedIn is the main hub for recruitment from the external labor market for the ICT industry and more generally. The platform recognizes the value of job titles: every year it posts the trending categories of job titles and lists them among the key elements for a recruitment strategy.[5] Recruiters resort to online platforms when they need to fill a position, and their search entails the use of job titles.[6] Thus, workers may want to modify their job titles to signal their skills, increase their reach in the job market, and negotiate higher salaries.

The use of LinkedIn data leads to a reasonable assumption regarding job demand and offers. Job titles on LinkedIn are self-reported, and employees can customize them.[7] In that employers tend to monitor their workers' self-reported job titles, limit their modifications, or negotiate them for external use,[8] the margins for customization are limited. To validate this assumption, we collected data from all H1B applications by the employers in our sample. Each H1B application includes the job title that the employer assigns to the worker. We compared the distribution of job title features of job titles in the H1B data with the distribution of self-reported job titles for H1B workers in our LinkedIn sample. The comparison, reported in Table A1 in Appendix, shows that workers tend to customize their job titles but only slightly.

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[5] https://www.techrepublic.com/article/linkedin-names-the-hottest-jobs-for-2021/, accessed on October 11, 2021.
[6] https://business.linkedin.com/content/dam/me/business/en-us/marketing-solutions/resources/pdfs/linkedin-targeting-playbook-v4.pdf, accessed on October 11, 2021.
[7] https://www.fastcompany.com/90254129/this-is-the-easiest-way-to-make-your-linkedin-profile-stand-out, accessed on October 11, 2021.
[8] https://www.collage.co/magazine/hr-advice-employee-lying-on-linkedin/, https://www.linkedin.com/pulse/job-title-dilemma-accuracy-vs-consistency-cristina-taboada, accessed on October 11, 2021.

The use of LinkedIn data has some limitations, however. Not all employees join the platform and report information on their career history publicly on LinkedIn, and these employees may differ systematically from those who do in their use of human capital and mobility preferences. Our sampling of inventors with a Ph.D. degree mitigates this concern by focusing on a selection of employees with similar levels and types of human capital and propensities for mobility (Tzabbar, Cirillo, & Breschi, 2021).

To ensure our sampling strategy is not biased against less mobile and less productive employees, we tested the quality of our match between LinkedIn and USPTO data considering cases in which a firm's inventors reported their patents in their LinkedIn profiles. Using this subset, we determined that our matching algorithm had a rate of false positive matches (Type 1 error) of less than 3%, meaning that it correctly assigned a LinkedIn profile to an inventor in more than 97% of cases. Furthermore, using patent data, we leveraged differences between inventors matched to LinkedIn profiles and those who were not matched to LinkedIn profiles. This test shows that inventors with a LinkedIn profile do not differ systematically from inventors without a LinkedIn profile regarding patent productivity (i.e., number of patents successfully applied for at the USPTO) and interfirm mobility (i.e., number of mobility events detected in assignee data). This result corroborates our choice of focusing our analyses on inventors.

Variables

We consolidated the LinkedIn data and inventors' patent records per year. For an observation window, we selected the period corresponding to inventors' careers at any of the 168 firms with 2004 and 2014 as left and right censoring years, respectively. We divided the inventor observations by year and balanced them to update the covariates. Our final dataset includes 83,282 inventor-year observations. For each inventor year included in our sample, we measured the following variables (see Table 1 for a detailed description of each measure and data sources).

[Insert Table 1 here]

Dependent variable. Prior studies on individual mobility have generally confounded different typologies and destinations of mobility (Tzabbar et al., 2021). Our goal, however, is to see how much job titles affect the hiring of knowledge workers by incumbent and new firms. To help explore this point, we built several dependent variables that distinguish between mobility to another employer and mobility to new entrants, as well as in relation to the industry of destination.

Our main dependent variable, (interfirm) *mobility*, is a binary indicator set to 1 in year *t* when the focal inventor leaves the firm to join another employer in *t + 1*, and 0 otherwise. If the LinkedIn profile of an inventor shows two consecutive jobs, first with one firm and then with a different firm, where the time gap is no more than one year, we presume the inventor left the first firm in the starting year of the record. Following this criterion, we identified 4,774 inventors in our data who left their current employer to join another employer (*mobility)* during the timeframe of this study. Of these, 2,446 inventors joined other incumbents (such as a firm operating in the same primary industry of the previous employer—either hardware or software), and 971 inventors joined industry entrants.

We further distinguished between 379 diversifying entrants (if the current employer has its primary activity in hardware, then the new employer has its primary activity in software and its secondary activity in hardware, and vice versa) and 592 de novo entrants (if the new employer is a private, single business company entering the primary industry of the previous employer). The remaining 1,357 inventors joined firms operating in other industries (i.e., outside the primary industry of the previous employer). For further analyses, we also coded cases of co-mobility (Marx & Timmermans, 2017). Of the 4,774 mobility events, 3,619 inventors moved alone to a new employer, 1,155 inventors moved to the same new employer with at least one coworker, and 709 inventors moved to the same new employer with at least two coworkers.

Independent variable. To measure our main independent variable, *job title ambiguity*, we followed Hannan and colleagues (2019) and resorted to the following entropy index[9]:

$$ambiguity = -\sum_{k=1}^{K} p_k \log(p_k) \quad (1)$$

Where k is an arbitrary number of concepts. As we do not have a predefined number of categories, we inferred them from job titles in our sample using a topic modeling algorithm. Conventional topic modeling algorithms such as latent Dirichlet allocation (Scwharz, 2018) tend to perform well when the text to process is long, for instance, when one uses it on article abstracts (Cirillo, Tzabbar, & Seo, 2020) or emails (Corritore et al., 2019). However, they tend to underperform with short texts, such as job titles. Therefore, we opted for a biterm topic modeling algorithm (BTM) (Cheng et al., 2014; Yan et al., 2013), which was designed to process tweets and can apply to other short texts.[10] In the model, each title is viewed as a mix of various latent topics, or categories, and each topic uses only a small set of biterms, or pairwise combinations of words.

The BTM learns topics through short texts by directly modeling the generation of all possible pairwise combinations of words (i.e., co-occurrence patterns) in the overall corpus (i.e., the job title). That is, the BTM considers the whole corpus as a mixture of topics, where each biterm is drawn from a topic independently. For example, in the job title “senior software engineer,” there are three biterms: “senior software,” “senior engineer,” and “software engineer.” The BTM procedure thus uses the co-occurrence of such observed biterms to infer

[9] For a robustness check (unreported), we also compute ambiguity as the inverse of the Herfindahl index.
[10] We checked the robustness of our approach by also using an LDA algorithm to model the latent topics in the set of job titles appearing in a worker’s entire career. This alternative topic modeling solution helps alleviate the problem of word sparsity in the case of short job titles. The results obtained from those analyses (unreported) appear aligned with the main findings of this paper.

the “hidden structure” of latent topics—job categories—within the set of job titles in the industry. The procedure requires us to define the number of latent topics we expect to find ex ante. For this study, we limited the search to five topics in the job titles, which produced a set of topics that were meaningful both statistically and semantically.[11]

Figure 1 reports an example of the five topics estimated by the algorithm. The strongest association is around the word “engineer.” Other notable terms include “manager,” “staff” (as in the job title member of technical staff), “architect,” and “design.” To consider various trends in the emergence and decline of topics in the industry, we used the job titles in our dataset from $t - 5$ to $t - 1$ as a training set to train for job titles in year t. The algorithm estimates a probability distribution that each job title belongs to each of the topics. These probabilities are used to compute the ambiguity variable via the entropy index (Hannan et al., 2019).

[Insert Figure 1 about here]

This index captures well the various instances of ambiguity discussed above. For instance, the job title “engineer” scores high in ambiguity: as there are no other words, the job title falls into any topic where the word “engineer” is predictive. Similarly, the job title “software engineer and consultant” scores high in ambiguity because the biterm “software engineer” would be predictive of one topic, whereas any word combination with “consultant” would be predictive of another topic more associated to management. Finally, the third instance of “code artist” would be equally high in ambiguity because “code artist” would rarely fall into any given topic. Table 2 shows other examples of job titles by ambiguity and different job title length.

[Insert Table 2 here]

[11] We found consistent results with 10, 20, 50, and 100 topics.

Control Variables. We control for a host of variables that might affect an inventor's propensity to be poached by other employers. Prior research suggests that inventors' experience and capabilities increase their opportunities to obtain a new job and their motivation to leave their current employer (Hoisl, 2007). To account for these explanations, we controlled for the number of an inventor's *prior patents*, the *impact* of the inventor's patents (i.e., yearly mean of forward citations the inventor's prior patents received), the inventor's *specialization* (i.e., a Herfindahl index of the distribution of the inventor's prior patents across USPTO classifications), the inventor's prior firm mobility (i.e., number of different employers in their prior career history), and the inventor's tenure in the firm, *firm tenure* (i.e., the number of years from recruitment to the focal year). We also assumed that the longer an inventor occupies a certain job title, the greater the probability of a career change, and thus of interfirm mobility. Therefore, as an alternative tenure measure, we computed the number of years the worker occupied a position with a given job title at the firm, *job tenure*, which allows us to ensure that ambiguity does not relate to senior positions that tend to be occupied for longer.

Some job titles vary in their degree of familiarity among recruiters; therefore, we controlled for the frequency of each focal job title in the industry, *job title frequency* (i.e., the number of inventors holding the same job title within our sample). In addition, we controlled for the *number of positions* occupied by a worker in their career span (Leung, 2014). These controls ensure that ambiguity does not confound the effect of unobserved career trajectories.

We also acknowledge that the propensity to change employers might vary by gender and immigration status. To identify each inventor's gender, we matched our list of employees' names with the IBM InfoSphere Global Name Management© database (Breschi, Lissoni, & Miguelez, 2017). Thus, we used a dummy variable to control for a *female* inventor in the sample. To identify an inventor's immigration status, we took advantage of the geography data in the career and education records in LinkedIn profiles to identify whether the inventor moved from a foreign country to the United States for a new employment position. Thus, we used a time-variant dummy variable to identify whether the inventor had entered the United States less than six years prior to the focal year. This procedure was designed to reflect the extent to which the inventor was likely to be employed with an *H1B visa*.

In addition to individual-level variables, we also recognize that firms may create deterrence against employee poaching by competitors and prevent the outward mobility of human capital by establishing a reputation for litigiousness regarding their intellectual property (Ganco, Ziedonis, & Agarwal, 2014). Thus, we included a control on the number of patent *litigations* an inventor's employer initiated during the past five years. We then recognized that leading firms in the industry may be more subject to employee poaching than follower firms. Thus, we controlled for the number of the *employer's patents* successfully applied for during the past five years to account for this effect. We also included a control for the nature of the industry of the employer, with a binary indicator that takes the value of one if the employer is in the *software industry*.

Finally, we included a variety of fixed effects. First, we controlled for year fixed effects to account for the ebb and flow of this labor market over the years included in our observation window. Second, in robustness specifications, we also controlled for time-invariant employer factors through employer fixed effects to rule out alternative explanations about unobserved firm-level factors (Baron & Bielby, 1986).

Statistical Approach

Given that the mobility events occur in continuous time, but we observe them only at a discrete time (annually), we estimate a complementary log-logistic (cloglog) hazard function to derive the predicted hazard of an inventor's move to another employer (Fontana & Nesta, 2010; Tzabbar et al., 2021). The hazard rate function for inventor i at time $t + 1$ takes the proportional hazard form $\theta_{it} = \theta_0(t) \bullet X'_{it}\beta$, where $\theta_0(t)$ is the baseline hazard function, and X_{it} is a series of time-varying covariates summarizing observed differences across inventors. The discrete time formulation of the hazard of a move to another employer for inventor *i* in year *t* results from the complementary log-logistic function

$$h_t(X_{it}) = 1 - exp\{-exp(X'_{it}\beta + \theta(t))\} \quad (2)$$

where $\theta(t)$ is the baseline hazard function related to the hazard rate $h_t(X_{it})$ of a move to another employer in year *t*.

To assess robustness, we also model the various types of mobility under investigation in our paper through a linear probability model. The model allows us to include fixed effects to parse out time-invariant unobserved characteristics.

$$Mobility_{it} = \alpha + \mathrm{B}\boldsymbol{X}_{it} + \gamma * ambiguity_{it} + \tau_t + \pi_{it} + \eta_{it} \quad (3)$$

The vector *X* includes time-varying control variables; τ and π are a set of dummies for year and employer fixed effects, respectively; and the coefficient γ captures the within-subject correlation between interfirm mobility and job title ambiguity. Across all the analyses of this paper, the standard errors reported in the tables were clustered at the individual level.

FINDINGS

Descriptive Results

Table 3 reports the descriptive and correlation statistics. The variance inflation factors (VIFs) are less than 10, and the mean VIF is 1.77, indicating that multicollinearity is not a concern in our dataset.

[Insert Table 3 here]

On average, the workers included in our sample held a job title for about eight years. The average mobility rate is 5.7% per employee/year. Remember that these statistics concern a sample of inventors with doctorate education. The job title—*principal scientist*—with the mean value of 0.67 appears 480 times in our sample and it is common among 70 single knowledge workers. Table 3 highlights a negative correlation between a job title's ambiguity and its frequency in the industry: job titles that are rarer tend to be more ambiguous, which represents a useful sanity check for our measure.

Main effect of Job Title Ambiguity on Employee Mobility Outcomes

Table 4 presents the estimates of the association between job title ambiguity and the hazard rate of moving to any new employment relative to staying at the current employer (Columns 1–3). The coefficient of job title ambiguity is associated with a decrease in the probability of mobility to another employer ($p < 0.001$, Column 2).[12] In particular, a one standard deviation increase in job title ambiguity is associated with about a 20% lower likelihood of mobility ($[e^{-0.211*(0.666+0.399)} - 1] \times 100 = -20.13\%$) relative to staying at the current employer.

To illustrate the effects of job title ambiguity, we selected a representative job title for each quartile. A job title representative of low ambiguity (1st quartile) is "research staff member," whereas one of high ambiguity (4th quartile) is "research staff member, network analytics and network technologies." For each job title, we estimated the predicted probability of a worker's mobility to another employer. That probability for the job title in the 1st quartile is 5.6%. For increasingly ambiguous job titles, the probability decreases consistently. In the 4th quartile, the probability of mobility to another employer is 5.2%, a drop of 0.4 percentage points that corresponds to a relative decrease of 7.14% per employee/year.

[Insert Table 4 here]

Moreover, as the algorithm to measure job title ambiguity does not distinguish the head noun of a job title (e.g., engineer) from modifiers (e.g., software) and seniority terms

[12] To corroborate those results, we ran several other robustness checks, which we report in the Appendix. First, we ran the complementary log-log model by controlling for employer (see Table A2, Column 1, in the Appendix) and state fixed effects (see Table A2, Column 2, in the Appendix). We then reran the topic modeling algorithm to measure job title ambiguity using 10, 20, 50, and 100 topics (see Table A3 in the Appendix, Columns 1–4). In both cases, the results remain robust across various specifications, thus confirming the prior estimates.

(e.g., senior), we ran a further check to exclude the possibility that job title ambiguity is primarily driven by the effect of seniority or hierarchy on mobility. For each job title, thus counted the number of head nouns (such as "engineer"), modifiers (such as "research"), and seniority terms (such as "executive"), and we tested their influence on mobility outcomes (see Zunino et al., 2019). The results obtained from this procedure (shown in Table A3 in Appendix, Columns 5) confirm that using more than a head noun in a job title is associated with a lower probability of mobility. Additionally, the number of seniority terms is negatively associated with interfirm mobility, as expected. Conversely, the higher the number of modifiers, the higher the likelihood of interfirm mobility.

Two additional analyses were directed at validating the mechanism of information asymmetries against another competing explanation. First, as a further test, we also explored the association between job title ambiguity and the hazard rate of co-mobility (Columns 4 and 5 of Table 4). The idea is that when employees move with coworkers to another firm, the recruiter may hold more private information that transcends individual job titles, for example, via the coworkers' social network. Columns 3–5 show that compared with solitary moves ($[e^{-0.197*(0.666+0.399)} - 1] \times 100 = -18.93\%$), $p < 0.001$, Column 3), the negative association between job title ambiguity and mobility to another employer loses statistical significance when an employee leaves with at least one other colleague ($[e^{-0.175*(0.666+0.399)} - 1] \times 100 = -17.00\%$, $p < 0.05$, Column 4), up to become statistically insignificant when the move involves two colleagues or more ($[e^{-0.064*(0.666+0.399)} - 1] \times 100 = -6.59\%$, $p > 0.1$, Column 5). Second, job title ambiguity may be negatively associated with mobility because it represents a manifestation of improved fit between worker and employer (Rousseau et al., 2006). In Table A4 of the Appendix, we computed another variant of our job title ambiguity measure with a BTM algorithm that considers only the job titles observed at the current employer as the training set. This variable identifies job title ambiguity *within the firm*, in contrast to the previous measurement of job title ambiguity *within the industry*. If our main results were driven by employees' idiosyncratic deals of workers with their current employers, we would expect job title ambiguity within firms to exhibit a statistically significant negative effect on mobility. The comparison between the estimates obtained from the two measures refutes this explanation.

Taken together, these results provide robust evidence for the following finding.

Finding 1. *Job title ambiguity is associated with a lower likelihood of an employee moving to another employer relative to staying at their current employer.*

Job Titles and Incumbent Firms versus New Entrants

In the next analysis, we unpack the influence of job titles across destination firms. We report our results in Table 5. In particular, we compare incumbents (Column 1) with new entrants (Column 2), which we further divide into diversifying (Column 3) and de novo entrants (Column 4). The effect of mobility when involving firms from other industries is also explored (Column 5).

We observe that the coefficient of job title ambiguity for mobility to incumbents is negative, statistically significant, and its size is comparable to the predictions in the main model of Table 4 ($[e^{-0.220*(0.666+0.399)} - 1] \times 100 = -20.88\%$, $p < 0.0001$, Column 1). The sign of the influence of job title ambiguity on the mobility of entrants is negative but smaller in size and statistically insignificant ($[e^{-0.123*(0.666+0.399)} - 1] \times 100 = -12.27\%$, $p > 0.1$, Column 2). Although insignificant, the sign of the coefficient is positive for diversifying entrants ($[e^{-0.057*(0.666+0.399)} - 1] \times 100 = -5.89\%$, $p > 0.1$, Column 3) and negative for de novo entrants ($[e^{-0.078*(0.666+0.399)} - 1] \times 100 = -7.97\%$, $p > 0.1$, Column 4). Additionally, the strength of the association between ambiguity and mobility to other industries is weaker than the case of mobility to incumbents ($[e^{-0.170*(0.666+0.399)} - 1] \times 100 = -16.56\%$, Column 5).

[Insert Table 5 about here]

The results of these additional analyses suggest that the negative influence of job title ambiguity is stronger for mobility toward incumbents than to new entrants or firms active in other industries. Two possible reasons may explain these findings. On the one hand, in line with categorization theory, job titles may be most established and used among incumbent firms since incumbents firms possess higher degrees of industry knowledge (Kovacs et al., 2021; Zuckerman, 1999); on the other hand, new entrants and firms from other industries may resort to different poaching methods that involve, for example, the exploitation of social networks.

In sum, these analyses point to the following finding.

Finding 2. *Job title ambiguity is associated with a lower likelihood of a move to new employers particularly when these employers are incumbent firms of the same industry.*

Sensitivity Analysis

In this section, we corroborate the robustness of our results by using linear regression. We use a linear probability model where we estimate the probability of interfirm mobility with the same set of controls of the main estimation and add employer fixed effects in every specification.

We report the main results in Table 6. In Column 1, we report the results of our main analysis. Compared to the baseline of a 5.74% probability of moving per employee/year, a standard deviation increase in job title ambiguity is associated with a 1.15% decrease in the probability of moving, which amounts to a 20% relative decrease. In Columns 2 and 3, we compare mobility to incumbents and entrants. For incumbents, the coefficient is negative and statistically significant ($p < 0.001$). Compared to the baseline 2.98% probability of moving to an incumbent, a standard deviation increase in job title ambiguity is associated with a 0.60%

decrease in the probability of moving, which amounts to a 20% relative decrease. For entrants, the coefficient is negative but loses statistical significance ($p > 0.05$). Compared to the baseline 1.16% probability of moving to an entrant, a standard deviation increase in job title ambiguity is associated with a 0.3% decrease in the probability of moving, which amounts to a 25% relative decrease. The negative effect of job title ambiguity on the likelihood of moving to an incumbent is also statistically stronger than that on the likelihood of moving to an entrant ($p = 0.0179$, two-sided Wald test). Then, we unpack the mobility of diversifying firms in Column 4 and de novo entrants in Column 5. The negative correlation between job title ambiguity and mobility appears larger for diversifying than de novo entrants, but such difference is not statistically significant ($p = 0.7914$, two-sided Wald test, not shown here). Compared to them, the negative effect of job title ambiguity on the likelihood of moving to an incumbent is also statistically stronger ($p = 0.0011$ and $p = 0.0019$, two-sided Wald test, respectively).

[Insert Table 6 about here]

DISCUSSION AND CONCLUSION

Knowledge workers' mobility represents a widely known source of new knowledge acquisition for firms (Agarwal et al., 2004; Klepper, 2007). In this paper, we explored the influence of job title ambiguity on knowledge workers' mobility by leveraging data obtained from a digital platform. We develop our argument from the insight that recruiters use digital platforms when they form a consideration set (Zide, 2015) and resort to keywords to guide their search (e.g., Kovacs et al., 2021). In this respect, job titles offer a meaningful public source of information to select poaching targets (Koivunen et al., 2019). Our findings suggest that job title ambiguity predicts less interfirm mobility of knowledge workers. The results of our analyses inform the following contributions.

Job Titles and Knowledge Acquisition

Our findings showed that knowledge workers whose job titles were more ambiguous tended to be less likely to be poached by other employers. These results are strongest for mobility to industry incumbents. Taken together, our analysis suggests that the negative correlation between job title ambiguity and mobility might be driven by the cognitive challenges that recruiters face in evaluating those job titles due to information asymmetries. We read the various results across incumbents and new entrants as suggesting that the effects of job title ambiguity on mobility are contingent on the degree of familiarity and socialization of the relevant actors.

The trend of results emerging from our analyses is consistent with the insight that job titles may act as cognitive anchors, much like any category label does (*Finding 1*). Recruiters must construct their consideration set to poach knowledge workers in the context of online platforms where valuable information is scarce and the risk of information overload is substantial (Granqvist et al., 2013; Weick, 1995).

To confront such complexity, recruiters use keywords as cognitive shortcuts to guide their searches (Kovacs et al., 2021). Job titles whose keywords fail to comply with expectations, we claim, lead to social discounts similar to those shown in category research, particularly concerning the exclusion of a candidate from the consideration set of evaluators (Zuckerman, 1999). Interestingly, this finding runs counter to the popular notion of "keyword stuffing" of job titles on LinkedIn profiles to increase the probability of being offered new opportunities.

The heterogeneous effect of job ambiguity across evaluators bears important implications for industry entrants. New entrants as well as lateral entrants tend to be less sensitive to job title ambiguity than industry incumbents (*Finding 2*). This result does not align with the claim that new entrants as well as employers from other industries may use job titles as a substitute for obtaining industry knowledge. If that were the case, job titles' ambiguity would be associated more strongly with mobility to new entrants or employers from other industries. As we observe the opposite, we offer two interpretations: on the one hand, industry entrants may systematically resort to different recruitment techniques, for example via private networks; on the other hand, industry entrants as well as employers from other industries may lack industry knowledge to make sense of job titles.

Job Titles and Knowledge Retention

A further implication of our findings is that recruiters shy away from knowledge workers with ambiguous job titles (*Finding 1*). This suggests that job titles may not only shape workers' self-perception and compensating differentials among them (Baron & Bielby, 1986, Grant et al., 2014) but also affect the perceptions of workers made by external evaluators (Anteby et al., 2016).

This result provides a novel and different insight into human capital theory (Coff & Raffiee, 2015). While extant research has suggested that workers' own perceptions matter the most for interfirm mobility (Raffiee & Coff, 2016), our findings support a complementary view in which external stakeholders' perceptions—such as those of recruiters—shape the potential for interfirm mobility. In contexts characterized by a scarce supply of workers and high degrees of poaching like the one studied here—that is, in contexts of "wars for talents" (Gardner, 2005; Tambe et al., 2020)— job title ambiguity may act as a meaningful way to reduce the poaching of workers from other employers. In turn, firms may decide to strategically leverage ambiguous job titles to increase the odds of retention of valuable human capital and the knowledge associated with it (Campbell et al., 2012). A small caveat to this conclusion comes from Finding 2, which points to a stronger relationship between job title ambiguity and mobility for incumbents rather than entrants. While job titles may serve as a buffer against incumbent firms, they may be less effective against the poaching attempts of entrants or employers active in other industries.

Conclusion

This study illustrates a fresh perspective on information flows in external labor markets. Our analyses rule out a set of alternative explanations that could explain the relationship between job title ambiguity and knowledge workers' mobility. Notwithstanding the robustness of our results, it is fair to recognize that they hold under a few boundary conditions. First, our study focused on job titles that workers with specialized human capital chose to display on a professional social network. Future research could expand on this condition by studying the difference between job titles employers assign and those workers report, as well as their consequences for the employers and the worker's mobility for a broader set of workers with more generalized human capital. Second, our study relied on topic modeling algorithms to aggregate job titles into categories. These models impose the choice of the number of topics ex ante. While we showed that the results are not particularly sensitive to the number of topics, we assumed a stable structure over time. Future research could ease this assumption and investigate, similarly to category labels and technological evolution (Grodal et al., 2015; Zunino et al., 2019), how certain job titles emerge and fall out of use. Third, our study focused on a job market where poaching is particularly salient (Tambe et al., 2020). Under these conditions, external mechanisms of recruiters' evaluations naturally dominate internal negotiations between workers and their current employers. Future research may address this boundary condition and study under which specific contingencies ambiguous job titles may influence mobility because of internal rather than external factors. Fourth, as we are unable to observe the different recruiting techniques—common to other studies using secondary data—we could only speculate on the mechanisms underlying the significant differences that we observe between mobility to incumbent and entrants. Future research could identify a favorable setting to address this limitation with novel data sources.

While we consider the present effort as just an initial empirical attempt at assessing the role of job titles for interfirm mobility, we remain hopeful that our work contributes to introducing a new perspective on strategic human capital that will spark new ideas among scholars from different fields.

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Table 1. Descriptions of the Main Measures and Data Sources

Variable	Measure	Data Source
1. *Mobility to another employer* $_{t+1}$	1{employee leaves to join another firm in year *t+1*}; 0 otherwise.	LinkedIn
1.a. *Incumbent* $_{t+1}$	1{employee leaves to join another firm in year *t+1*, with the new employer operating in the same primary industry of the previous employer}; 0 otherwise.	LinkedIn
1.b. *Entrant* $_{t+1}$	1{employee leaves to join another firm, which is an industry entrant, in year *t+1*}; 0 otherwise.	LinkedIn
1.b.1. *Diversifying* $_{t+1}$	1{employee leaves to join another firm in year *t+1*, with the new employer operating a secondary business in the same primary industry of the previous employer}; 0 otherwise.	LinkedIn
1.b.2. *De Novo* $_{t+1}$	1{employee leaves to join another firm in year *t+1*, with the new employer being a private, single business firm that entered the primary industry of the previous employer}; 0 otherwise.	LinkedIn
2. *Job title ambiguity* $_{[t-4,\ t]}$	Entropy measure of the probability of employee's job title belonging to each of the 5 topics (biterm topic modeling)	LinkedIn
3. ln(*Time* $_t$)	ln(1 + # years since inventor's first patent with the firm until year *t*)	LinkedIn
4. ln(*Job title length* $_t$)	ln(1 + # of characters in the job title)	LinkedIn
5. ln(*Job title frequency* $_t$)	ln(1 + # employees in our sample who report the same job title of the focal employee (included) in year *t*)	LinkedIn
6. ln(*Prior patents* $_{[t-4,\ t]}$)	ln(1 + # employee's patents granted by USPTO until year *t*)	USPTO
7. *Impact* $_{[t-4,\ t]}$	Mean of forward citations to employee's patents.	USPTO
8. *Specialization* $_{[t-4,\ t]}$	Complement to one of an Herfindahl index of the distribution of inventor's prior patents across USPC classes.	USPTO
9. *Firm tenure* $_t$	Inventor's tenure at the firm in year *t*.	LinkedIn
10. *Job tenure* $_t$	Inventor's tenure at the firm in the focal job position (i.e., current job title) in year *t*.	LinkedIn
11. *Number of positions* $_t$	# job titles held by the focal employee from the beginning of the career until year *t*.	LinkedIn
12. *Prior mobility* $_t$	# employers the employee had before the current employer at year *t*.	LinkedIn
13. *Gender(female)*	1{female}; 0{male}.	IBM InfoSphere
14. *H1B visa* $_t$	1{employee entered the United States with an employment position less than six years prior year t}; 0 otherwise.	LinkedIn
15. ln(*litigations* $_{[t-4,\ t]}$)	ln(# patent litigations the current employer initiated in [*t-4*, *t*] as either plaintiff or defendant)	Thompson
16. ln(*employer's patents* $_{[t-4,\ t]}$)	ln(# patents the current employer successfully applied for in [*t-4*, *t*] at USPTO)	USPTO
17. ln(*Job title frequency in state* $_t$)	ln(Share of positions with same job title in a given state in year *t*)	LinkedIn
18. *Software*	1{employer's primary SIC code is Software}; 0 otherwise.	Compustat

Table 2. Examples of Job Titles by Ambiguity

Ambiguity **Number of words**	**1 SD below mean**	**Mean**	**1 SD above mean**
1	Physicist	Researcher	Director
2	Research scientist	Staff engineer	Senior manager
3	Senior software engineer	Senior program manager	Senior engineer manager
4	Integrated circuit design engineer	Senior staff software engineer	Security technical solution manager

Table 3. Descriptive Statistics and Correlations

Variable	1	1.a	1.b	1.b.1	1.b.2	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. *Mobility to another employer* $_{t+1}$																						
1.a. *Incumbent*	0.71																					
1.b. *Entrant*	0.44	−0.02																				
1.b.1. *Diversifying*	0.27	−0.01	0.62																			
1.b.2. *De Novo*	0.34	−0.01	0.78	−0.01																		
2. *Job title ambiguity* $_{[t-4,\ t]}$	0.00	0.00	−0.01	0.00	−0.01																	
3. ln(*Time* $_t$)	0.00	0.00	−0.01	0.00	−0.02	0.07																
4. ln(*job title length t*)	0.00	0.00	0.00	0.00	0.00	0.27	0.05															
5. ln(*job title frequency* $_t$)	−0.03	−0.03	0.00	0.00	0.00	−0.41	−0.01	−0.5														
6. ln(*prior patents* $_{[t-4,\ t]}$)	−0.04	−0.02	−0.02	0.00	−0.02	−0.02	0.02	−0.03	0.09													
7. ln(*impact* $_{[t-4,\ t]}$)	−0.01	0.00	0.00	0.00	0.00	−0.04	−0.07	−0.03	0.09	0.6												
8. *Specialization* $_{[t-4,\ t]}$	−0.03	−0.02	−0.01	0.00	−0.01	−0.02	−0.02	−0.03	0.08	0.54	0.28											
9. *Firm tenure* $_t$	−0.03	−0.02	−0.03	−0.01	−0.03	0.03	0.71	0.01	0.00	0.00	−0.09	−0.04										
10. *Job tenure* $_t$	−0.01	0.00	−0.02	0.00	−0.02	−0.04	0.51	−0.07	0.14	0.04	−0.03	0.00	0.66									
11. *Number of positions* $_t$	0.02	0.01	0.02	0.01	0.02	0.13	0.02	0.17	−0.25	−0.14	−0.13	−0.09	−0.01	−0.31								
12. *Prior mobility* $_t$	0.04	0.03	0.02	0.01	0.03	0.04	−0.31	0.02	−0.06	−0.11	−0.08	−0.08	−0.27	−0.19	0.53							
13. *Gender(female)*	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	−0.03	−0.01	−0.01	−0.01	−0.03	0.01	−0.01						
14. *H1B visa* $_t$	0.01	0.00	0.00	0.00	0.00	−0.05	−0.26	−0.05	0.04	−0.02	0.01	0.01	−0.27	−0.19	−0.12	−0.09	0.01					
15. ln(*litigations* $_{[t-4,\ t]}$)	0.01	0.00	0.01	0.03	−0.01	0.05	0.13	0.03	−0.02	−0.07	−0.12	−0.02	0.08	0.05	0.06	0.01	0.00	−0.02				
16. ln(*employer's patents* $_{[t-4,\ t]}$)	−0.05	−0.05	−0.01	0.00	−0.02	−0.04	0.13	0.00	0.11	0.15	0.02	0.13	0.18	0.11	−0.06	−0.16	0.05	0.03	0.33			
17. ln(*Job title frequency in state* $_t$)	−0.03	−0.03	−0.01	−0.01	−0.01	−0.3	0.02	−0.29	0.68	0.05	0.04	0.04	0.04	0.12	−0.14	−0.07	0.01	−0.06	−0.01	0.12		
18. *Software*	−0.03	−0.04	0.03	0.01	0.03	−0.13	0.00	−0.02	0.13	0.05	0.04	0.05	0.07	0.03	−0.01	−0.07	0.05	0.04	−0.28	0.38	0.13	
Mean	0.06	0.03	0.01	0.01	0.01	0.67	1.62	3.18	4.01	1.41	1.49	0.34	8.32	5.14	1.74	0.21	0.12	0.27	1.52	8.08	−5.65	0.40
Standard Deviation	0.23	0.17	0.11	0.07	0.08	0.40	0.75	0.52	2.33	1.08	1.11	0.33	6.93	5.91	1.20	0.47	0.32	0.45	1.38	1.72	1.62	0.49
Minimum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.69	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	−7.82	0.00
Maximum	1.00	1.00	1.00	1.00	1.00	1.61	2.71	4.61	8.32	6.25	5.98	1.00	57.00	45.00	13.00	4.00	1.00	1.00	5.55	10.27	0.00	1.00

Note. N = 83,282. All correlations above |.01| are significant at $p < 0.001$.

Table 4. Complementary Log-Log Regressions: The Hazards of Employees' Exit

Exit by	***Mobility to another employer*** $_{t+1}$				
			(solo)	*(with at least one colleague)*	*(with at least two colleagues)*
	1	2	3	4	5
Job title ambiguity $_{[t-4,\, t]}$		−0.211***	−0.197***	−0.175*	−0.064
		(0.036)	(0.041)	(0.070)	(0.084)
ln(*time* $_t$)	0.268***	0.273***	0.239***	0.398***	0.546***
	(0.032)	(0.032)	(0.036)	(0.068)	(0.091)
ln(*job title length* $_t$)	−0.128***	−0.106**	−0.119**	−0.065	−0.080
	(0.033)	(0.033)	(0.037)	(0.068)	(0.087)
ln(*job title frequency* $_t$)	−0.078***	−0.086***	−0.093***	−0.059*	−0.065*
	(0.011)	(0.011)	(0.013)	(0.023)	(0.029)
ln(*prior patents* $_{[t-4,\, t]}$)	−0.127***	−0.124***	−0.170***	0.013	0.032
	(0.021)	(0.021)	(0.024)	(0.043)	(0.054)
ln(*impact* $_{[t-4,\, t]}$)	0.070***	0.070***	0.064***	0.096**	0.064
	(0.016)	(0.016)	(0.019)	(0.033)	(0.042)
Specialization $_{[t-4,\, t]}$	−0.092†	−0.089†	−0.040	−0.260*	−0.347*
	(0.052)	(0.052)	(0.058)	(0.114)	(0.149)
Firm tenure $_t$	−0.059***	−0.059***	−0.063***	−0.048***	−0.044***
	(0.005)	(0.005)	(0.006)	(0.009)	(0.011)
Job tenure $_t$	0.032***	0.032***	0.032***	0.030***	0.036***
	(0.005)	(0.005)	(0.005)	(0.008)	(0.010)
Number of positions $_t$	0.034*	0.034*	0.017	0.082**	0.124***
	(0.017)	(0.017)	(0.020)	(0.030)	(0.036)
Prior mobility $_t$	0.102*	0.105**	0.166***	−0.096	−0.211†
	(0.040)	(0.040)	(0.045)	(0.082)	(0.117)
Gender (female)	−0.033	−0.030	−0.019	−0.057	−0.061
	(0.048)	(0.048)	(0.055)	(0.096)	(0.123)
H1B visa $_t$	0.073*	0.070*	0.049	0.134†	0.100
	(0.035)	(0.035)	(0.040)	(0.069)	(0.091)
ln(*litigations* $_{[t-4,\, t]}$)	0.073***	0.072***	0.026†	0.205***	0.215***
	(0.013)	(0.013)	(0.015)	(0.024)	(0.028)
ln(*employer's patents* $_{[t-4,\, t]}$)	−0.105***	−0.103***	−0.107***	−0.079***	−0.093***
	(0.009)	(0.010)	(0.010)	(0.020)	(0.024)
ln(*Job title frequency in state* $_t$)	−0.016	−0.018	−0.007	−0.053*	−0.050
	(0.013)	(0.013)	(0.015)	(0.026)	(0.032)
Software	0.032	0.014	−0.085*	0.307***	0.334***
	(0.035)	(0.036)	(0.041)	(0.070)	(0.084)
Job topics FE	*included*	*included*	*included*	*included*	*included*
Observations	83,282	83,282	83,282	83,282	83,282
Log Likelihood	−17,890.4	−17,877.2	−14,515.5	−5,881.8	−3,865.7

Note. Robust standard errors (in parentheses) clustered by employee; FE, fixed effect.
*** $p < .001$; ** $p < .01$; * $p < .05$; † $p < .1$.

Table 5. Complementary Log-Log Regressions: The Hazards of Employees' Exit

Exit by	***Mobility to another employer*** $_{t+1}$				
	to incumbent	*to entrant*	*to diversifying entrant*	*to de novo entrant*	*to other industries*
	1	2	3	4	5
Job title ambiguity $_{[t-4,\ t]}$	−0.200***	−0.123	−0.057	−0.078	−0.170*
	(0.056)	(0.092)	(0.160)	(0.112)	(0.078)
ln(*time* $_{t}$)	0.374***	0.277***	0.252*	0.329**	0.122*
	(0.045)	(0.075)	(0.115)	(0.102)	(0.057)
ln(*job title length* $_{t}$)	−0.174***	−0.062	−0.084	−0.047	−0.011
	(0.046)	(0.073)	(0.110)	(0.099)	(0.059)
ln(*job title frequency* $_{t}$)	−0.102***	−0.007	−0.010	−0.006	−0.102***
	(0.016)	(0.026)	(0.040)	(0.033)	(0.021)
ln(*prior patents* $_{[t-4,\ t]}$)	−0.096**	−0.142**	−0.014	−0.235***	−0.151***
	(0.029)	(0.046)	(0.072)	(0.061)	(0.040)
ln(*impact* $_{[t-4,\ t]}$)	0.074***	0.109**	0.082	0.133**	0.031
	(0.022)	(0.034)	(0.059)	(0.041)	(0.031)
Specialization $_{[t-4,\ t]}$	−0.137†	0.031	0.002	0.038	−0.094
	(0.073)	(0.110)	(0.181)	(0.139)	(0.096)
Firm tenure $_{t}$	−0.065***	−0.078***	−0.080***	−0.080***	−0.036***
	(0.007)	(0.013)	(0.019)	(0.018)	(0.009)
Job tenure $_{t}$	0.035***	0.013	0.048**	−0.016	0.035***
	(0.006)	(0.010)	(0.016)	(0.014)	(0.008)
Number of positions $_{t}$	0.013	0.073*	0.137**	0.031	0.033
	(0.024)	(0.034)	(0.051)	(0.046)	(0.031
Prior mobility $_{t}$	0.171**	0.070	−0.149	0.190†	0.017
	(0.054)	(0.083)	(0.141)	(0.102)	(0.079)
Gender (female)	−0.032	0.005	0.180	−0.113	−0.051
	(0.066)	(0.100)	(0.155)	(0.133)	(0.088)
H1B visa $_{t}$	0.075	−0.062	−0.033	−0.079	0.143*
	(0.048)	(0.075)	(0.120)	(0.097)	(0.066)
ln(*litigations* $_{[t-4,\ t]}$)	0.041*	0.150***	0.411***	−0.038	0.067**
	(0.018)	(0.028)	(0.044)	(0.035)	(0.024)
ln(*employer's patents* $_{[t-4,\ t]}$)	−0.119***	−0.094***	−0.110***	−0.076***	−0.063***
	(0.014)	(0.016)	(0.032)	(0.018)	(0.018)
ln(*Job title frequency in state* $_{t}$)	−0.026	−0.106***	−0.116*	−0.097*	0.047*
	(0.018)	(0.031)	(0.049)	(0.039)	(0.023)
Software	−0.250***	0.745***	0.726***	0.811***	−0.112
	(0.052)	(0.071)	(0.125)	(0.088)	(0.070)
Job topics FE	*included*	*included*	*included*	*included*	*included*
Observations	83,282	83,282	83,282	83,282	83,282
Log Likelihood	−10,717.0	−5,075.5	−2,288.8	−3,328.6	−6,815.7

Note. Robust standard errors (in parentheses) clustered by employee; FE, fixed effect.
*** $p < .001$; ** $p < .01$; * $p < .05$; † $p < .1$.

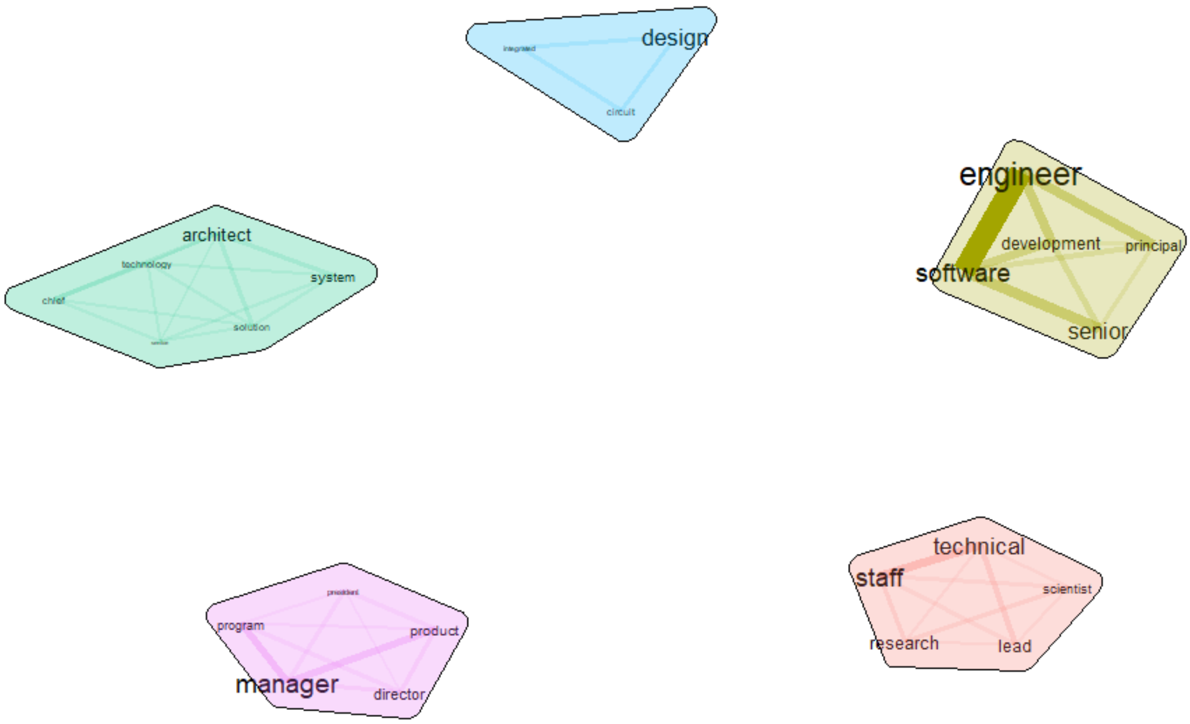
Table 6. Linear Regressions with Multiple Level Fixed Effects

Exit by	*Mobility to another employer* $_{t+1}$				
	to any new employer	*to incumbent*	*to entrant*	*to diversifying entrant*	*to de novo entrant*
	1	2	3	4	5
Job title ambiguity $_{[t-4,\,t]}$	−0.011***	−0.006***	−0.003*	−0.002*	−0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
ln(*time* $_t$)	−0.005**	−0.004**	−0.000	−0.000	−0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
ln(*job title length* $_t$)	−0.003***	−0.002***	−0.000	−0.000	−0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
ln(*job title frequency* $_t$)	−0.006***	−0.003**	−0.001	0.000	−0.001**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
ln(*prior patents* $_{[t-4,\,t]}$)	0.006***	0.003***	0.001*	0.000	0.001*
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
ln(*impact* $_{[t-4,\,t]}$)	−0.005†	−0.004†	0.000	0.000	0.000
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Specialization $_{[t-4,\,t]}$	−0.002***	−0.001***	−0.000***	−0.000***	−0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm tenure $_t$	0.001***	0.001***	0.000*	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Job tenure $_t$	0.002*	0.001	0.001*	0.000	0.001)
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Number of positions $_t$	0.002	0.001	0.001	0.000	0.000
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Prior mobility $_t$	−0.000	0.000	0.001	0.001	−0.000
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Gender (female)	0.000	−0.000	−0.001	−0.000	−0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
H1B visa $_t$	0.007***	0.003***	0.003***	0.002***	0.001*
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
ln(*litigations* $_{[t-4,\,t]}$)	−0.003	−0.002	−0.002	−0.004**	0.002***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
ln(*employer's patents* $_{[t-4,\,t]}$)	−0.002*	−0.001*	−0.001**	−0.001**	−0.001†
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
ln(*Job title frequency in state* $_t$)	−0.011***	−0.006***	−0.003*	−0.002*	−0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Job topics FE	*included*	*included*	*included*	*included*	*included*
Employer FE	*included*	*included*	*included*	*included*	*included*
Year FE	*included*	*included*	*included*	*included*	*included*
Observations	83,277	83,277	83,277	83,277	83,277
Log Likelihood	4,495.7	30,877.2	68,419.1	107,405.7	88,658.8

Wald Tests on coefficient differences across models	***p*-values**
Model 2 vs. Model 3	
Job title ambiguity $_{[t-4,\,t]}$ [mobility to incumbent] − *Job title ambiguity* $_{[t-4,\,t]}$ [mobility to entrant] = 0	0.0179
Model 2 vs. Model 4	
Job title ambiguity $_{[t-4,\,t]}$ [mobility to incumbent] − *Job title ambiguity* $_{[t-4,\,t]}$ [mobility to diversifying entrant] = 0	0.0011
Model 2 vs. Model 5	
Job title ambiguity $_{[t-4,\,t]}$ [mobility to incumbent] − *Job title ambiguity* $_{[t-4,\,t]}$ [mobility to de novo entrant] = 0	0.0019

Note. Robust standard errors (in parentheses) clustered by employee; FE, fixed effect.
*** $p < .001$; ** $p < .01$; * $p < .05$; † $p < .1$.

Figure 1. Topic Distribution. 5 topics solution, 2009—2014



APPENDIX

Table A1. Comparison between H1B data and LinkedIn data (conditional on being H1B)

	Head noun		**Modifiers**		**Seniority**	
	H1B	LinkedIn	H1B	LinkedIn	H1B	LinkedIn
1th percentile	0	0	0	0	0	0
5th percentile	0	0	0	0	0	0
10th percentile	1	1	0	0	0	0
25th percentile	1	1	1	1	0	0
50th percentile	1	1	1	1	0	0
75th percentile	1	1	2	2	0	1
90th percentile	1	2	2	2	1	1
95th percentile	2	2	2	3	1	1
99th percentile	3	3	3	4	1	2
Mean	1.01	1.15	1.30	1.31	0.15	0.40
S.D.	0.42	0.54	0.81	0.97	0.37	0.55
Variance	0.18	0.29	0.66	0.95	0.14	0.30
N	4,789,644	22,818	4,789,644	22,818	4,789,644	22,818

Table A2. Robustness Check: Complementary Log-Log Regressions by Controlling for Employer and State Fixed Effects

Exit by	***Mobility to another employer*** $_{t+1}$	
	1	2
Job title ambiguity $_{[t-4,\,t]}$	−0.183***	−0.210***
	(0.042)	(0.042)
ln(*time* $_t$)	0.238***	0.316***
	(0.033)	(0.032)
ln(*job title length* $_t$)	−0.095**	−0.128***
	(0.033)	(0.034)
ln(*job title frequency* $_t$)	−0.062***	−0.181***
	(0.012)	(0.018)
ln(*prior patents* $_{[t-4,\,t]}$)	−0.125***	−0.119***
	(0.022)	(0.021)
ln(*impact* $_{[t-4,\,t]}$)	0.101***	0.055***
	(0.018)	(0.016)
Specialization $_{[t-4,\,t]}$	−0.087†	−0.076
	(0.053)	(0.052)
Firm tenure $_t$	−0.065***	−0.054***
	(0.005)	(0.005)
Job tenure $_t$	0.032***	0.034***
	(0.005)	(0.005)
Number of positions $_t$	0.032†	0.024
	(0.018)	(0.017)
Prior mobility $_t$	0.047	0.091*
	(0.043)	(0.041)
Gender (female)	−0.003	−0.031
	(0.048)	(0.048)
H1B visa $_t$	0.028	0.064†
	(0.035)	(0.038)
ln(*litigations* $_{[t-4,\,t]}$)	0.112***	0.093***
	(0.021)	(0.013)
ln(*employer's patents* $_{[t-4,\,t]}$)	0.030	−0.097***
	(0.033)	(0.010)
ln(*Job title frequency in state* $_t$)	−0.026†	0.171***
	(0.014)	(0.027)
Job topics FE	*included*	*included*
Employer FE	*included*	*included*
Year FE	*included*	*included*
Observations	83,099	83,230
Log Likelihood	−17,279.3	−17,650.7

Note. Robust standard errors (in parentheses) clustered by employee; FE, fixed effect.
*** $p < .001$; ** $p < .01$; * $p < .05$; † $p < .1$.

Table A3. Robustness Check: Alternative Operationalizations of Job Title Ambiguity. Complementary Log-Log Regressions: The Hazards of Employees' Exit

Exit by	***Mobility to another employer*** $_{t+1}$				
	1	2	3	4	5
Job title ambiguity (10 topics) $_{[t-4,\,t]}$	−0.188***				
	(0.033)				
Job title ambiguity (20 topics) $_{[t-4,\,t]}$		−0.189***			
		(0.028)			
Job title ambiguity (50 topics) $_{[t-4,\,t]}$			−0.111***		
			(0.024)		
Job title ambiguity (100 topics) $_{[t-4,\,t]}$				−0.093***	
				(0.022)	
Number of head nouns					−0.109***
					(0.031)
Number of modifiers					0.087***
					(0.016)
Number of seniority terms					−0.084**
					(0.026)
All controls	*included*	*included*	*included*	*included*	*included*
Observations	83,282	83,282	83,282	83,282	83,282
Log Likelihood	−17,890.4	−17,877.2	−14,515.5	−5,881.8	−3,865.7

Note. Robust standard errors (in parentheses) clustered by employee.
*** $p < .001$; ** $p < .01$; * $p < .05$.

Table A4. Intra-firm Job Title Ambiguity

Exit by	***Mobility to another employer*** $_{t+1}$
	(All)
	1
Job title ambiguity $_{[t-4,\,t]}$	−0.226***
(within industry) $_{[t-4,\,t]}$	(0.034)
Job title ambiguity $_{[t-4,\,t]}$	0.063*
(within firm) $_{[t-4,\,t]}$	(0.032)
All controls	*included*
Job topics and year FEs	*included*
Observations	83,282
Log Likelihood	−17,904.0

Note. Robust standard errors (in parentheses) clustered by employee; FE, fixed effect.
*** $p < .001$; ** $p < .01$; * $p < .05$.