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Skill Spanning in the Online Labor Market: A Double-Edged Sword?

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Abstract

Freelancers in online labor markets often display many skills in their profiles to increase their chances of being hired. However, such behavior may lead to the skills they display straddling multiple categories, that is, "skill spanning." In this paper, we extend the concept of category spanning into online labor markets in the form of skill spanning and empirically examine (1) how freelancers' skill spanning affects employers' hiring decisions for two different types of jobs (low- and high-skill jobs, respectively), and (2) how freelancers' skill matching moderates the effects of skill spanning on employers' hiring decisions. Based on a unique dataset of 12,428 high-skill jobs and 19,875 low-skill jobs on a leading online labor platform, we find that freelancers' skill spanning has different impacts on employers' hiring decisions for these two job types. Specifically, for high-skill jobs, freelancers' skill spanning reduces their likelihood of winning contracts; however, for low-skill jobs, freelancers' skill spanning and their probabilities of winning contracts demonstrate an inverse U-shape relationship. Furthermore, freelancers' skill matching can moderate the negative effects of skill spanning for high-skill jobs but not for low-skill jobs. Our findings provide guidelines for different stakeholders in online labor markets, including freelancers and platform owners.

Keywords: Online Labor Markets, Skill Spanning, Skill Matching, Job Type

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1 Introduction

Online labor markets (OLMs) represent an emerging e-marketplace that typically offers short-term contracts rather than long-term employment. This "nonstandard employment" arrangement in labor markets flattens market hierarchies by allowing individuals to provide services directly to employers and allowing firms or organizations to seek solutions from freelancers worldwide (Kanat et al., 2018). Many platforms, such as oDesk, Elance, and Freelancer have emerged to match employers with on-demand service providers. According to Manyika et al. (2015), online labor markets are projected to provide 72 million full-time-equivalent positions by 2025. However, compared to the tangible hiring process of offline counterparts, employers face certain hiring risks in OLMs.

In OLMs, it is difficult for employers to monitor the actual time and effort that freelancers invest in their jobs (Hong & Pavlou, 2017) because employers and freelancers are typically geographically separated in OLMs and the globalization of platforms produces time and language differences between the two parties (Gefen & Carmel, 2008; Ghani et al., 2014; Hong & Pavlou, 2017; Kim, 2009; Scholz & Haas, 2011). Hence, information provided in freelancers' profiles as well as their past transaction records is an important information source for employers making hiring decisions.

In this paper, we investigate how freelancers' skill information affects employers' hiring decisions. Freelancers may choose to display as many skills as possible in their profiles because they need to match with at least one of the skills required by the employer in order to bid on a project; furthermore, freelancers with more skills have a higher likelihood of being hired, as shown in previous literature (Kokkodis & Ipeirotis, 2014; Kokkodis et al., 2015). However, this means that the skills listed in freelancers' profiles may span multiple categories—i.e., category spanning.

Category spanning refers to organizations or people engaging in several activities that comprise distinct cognitive sets (Paolella & Durand, 2016)—for example, a company's operations crossing established industry boundaries or a chef combining dishes from different cuisine styles. Category spanning has been identified as contributing to the social and economic disadvantages of producers or organizations in a variety of industries (Zuckerman, 1999), including restaurants (Kovács & Hannan, 2010; Kovács & Johnson, 2014), e-Bay auctions (Hsu et al., 2009), cuisine (Rao et al., 2003), wineries (Negro et al., 2011; Negro & Leung, 2013), films (Hsu et al., 2009; Hsu et al., 2012), and so on. Studies have attributed these disadvantages to the vague identities of category spanners because such products or producers are perceived as being difficult to situate, understand, or evaluate (Hsu, 2006; Negro & Leung, 2013; Rao et al., 2005; Zuckerman, 1999). Despite penalties for category spanning in different industries, its impact on freelancers in online labor market remains unclear, given that freelancers often apply for different types of jobs.

Existing findings on category spanning may not completely apply to employers' evaluation of freelancers' skill spanning in online labor markets. Rather than providing products in physical markets, freelancers in OLMs provide services that often deal with complex issues, and freelancers with a narrow focus may not be capable of handling sophisticated cases. Thus, employers may differ in how they prioritize offerings in online labor markets. Moreover, there are different types of jobs in OLMs, and employers may have different requirements for freelancers' skills when selecting freelancers for different types of jobs. For example, for complex and challenging jobs (high-skill jobs) such as software development, the required skills are usually acquired through formal education and training. Because freelancers must devote much energy and time to mastering such skills, skill spanning may undermine employers' trust in freelancers' capabilities. For simple and undemanding jobs (low-skill jobs), however, such as data entry, the required skills are usually easily acquired. Thus, employers might consider skill spanning freelancers versatile or multitalented.

To offer a more context-specific understanding of the impact of skill spanning in online labor markets, this paper makes the following incremental contribution: First, previous research on category spanning has not measured the demand for and/or requirements of producers/products, and have typically assumed that consumer evaluations are based on whether producers/products violate category conformity. However, recent research has found that consumers place greater emphasis on the demand for a product rather than its typicality (Durand & Paolella, 2013; Paolella & Durand, 2016). Hence, it would be worthwhile to consider the actual needs or requirements of consumers when examining the effects of category spanning. Second, we do not divide skills into insular categories because the boundaries between different skills are fuzzy. The transferability of knowledge makes some skills similar, meaning that offering such skills together may not cause uncertainty for employers evaluating a freelancer. Also, employers may consider freelancers that offer skills that are more advanced than the job requires to be more competent. In our setting of online labor platforms, employers publish their skill requirements for posted jobs. These required skills can be understood as employers' requirements for freelancers, thus making it possible to examine how skill spanning affects employers' hiring decisions, especially for different types of jobs. Thus, we formulate the following research questions to guide the analysis process:

RQ1a: How does the degree of freelancers' skill spanning affect employers' hiring decisions in online labor markets?

RQ1b: Is this effect the same for employers seeking low-skill vs. high-skill jobs? If not, how is it different?

Furthermore, freelancers' "skill matching," i.e., how closely a freelancer's skills match an employer's job requirements, may influence the effect of skill spanning on hiring decisions. As mentioned above, employers might list several required skills when posting a project, which can be interpreted as the employer's demands/requirements. Job candidates meet these demands to different degrees. We thus consider the moderating effect of freelancers' skill matching because whether freelancers' skills match the project requirements may affect employers' perceived fit uncertainty (Hong & Pavlou, 2014), and thus affect employers' willingness to offer a contract (Kokkodis & Ipeirotis, 2014). Therefore, when evaluating freelancers' capabilities, employers are very likely to consider both freelancers' skill spanning and their skill matching and consider the tradeoff between these two aspects of their skills. Hence, in this paper, we take these two factors into account to investigate the moderating effects of freelancers' skill matching on skill spanning. Does freelancers' skill matching mitigate or reinforce the effect of skill spanning? We thus ask:

RQ2: How does freelancers' skill matching affect the relationship between skill spanning and employers' hiring decisions for low- and high-skill jobs, respectively?

To answer these research questions, we constructed our dataset from a leading online labor platform—Freelancer.com, where we were able to observe employers' hiring decisions and freelancers' profiles. Our final data is presented in the form of a panel data structure because our observations are at the bid level and, for each job, employers face multiple bids from different freelancers. Using our dataset of 32,303 jobs with 843,235 bids from 252,285 freelancers, we found that (1) For high-skill jobs, freelancers' skill spanning negatively affects their probability of winning a contract, whereas for low-skill jobs, the relationship between skill spanning and freelancers' probability of winning a contract forms an inverse U-shape. (2) When freelancers completely meet employers' skill requirements, the negative impact of skill spanning for high-skill jobs is attenuated but it has no moderating effect on skill spanning for low-skill jobs.

This paper makes several contributions. First, we contribute to the OLM literature by extending the concept of category spanning to examine the impact of freelancers' skill spanning on employers' hiring decisions. More specifically, we categorize jobs as either low-skill or high-skill jobs, finding that freelancers' skill spanning has different impacts on employers' hiring decisions for these two different job types. Second, we expand the literature on category spanning by considering employers' actual requirements for freelancers. Instead of adopting the conventional notion that evaluations of producers are based on how well they fit within a category, our paper suggests that employers' assessment of freelancers' skill spanning is based on whether they fit requirements or match specific situations. Third, our study makes an initial attempt to address the fuzziness of category boundaries. In this paper, to measure freelancers' degree of skill spanning, we calculated the accumulated distances of skills in different categories, instead of using the platform's predefined skill categories.

The remainder of this paper is organized as follows. Section 2 reviews the literature on category spanning and online labor markets. The empirical setting, description of our data, and estimation models are detailed in Section 3. We then present results from our empirical analysis and the robustness check in Section 4 and conclude by discussing contributions and implications in Section 5.

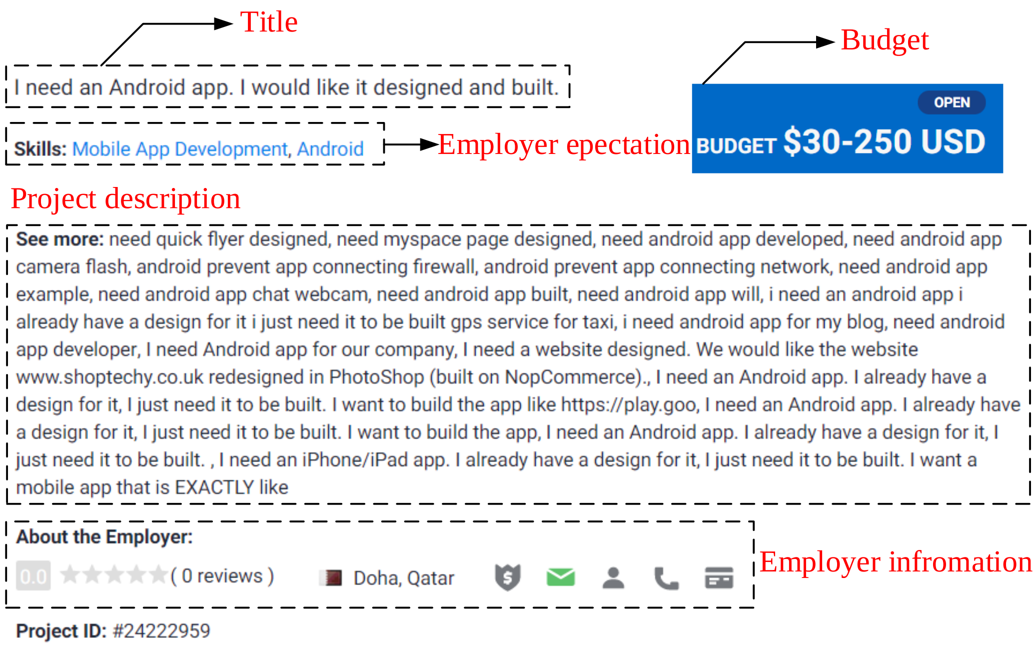
2 Theoretical Background and Hypotheses Development

2.1 Online Labor Markets

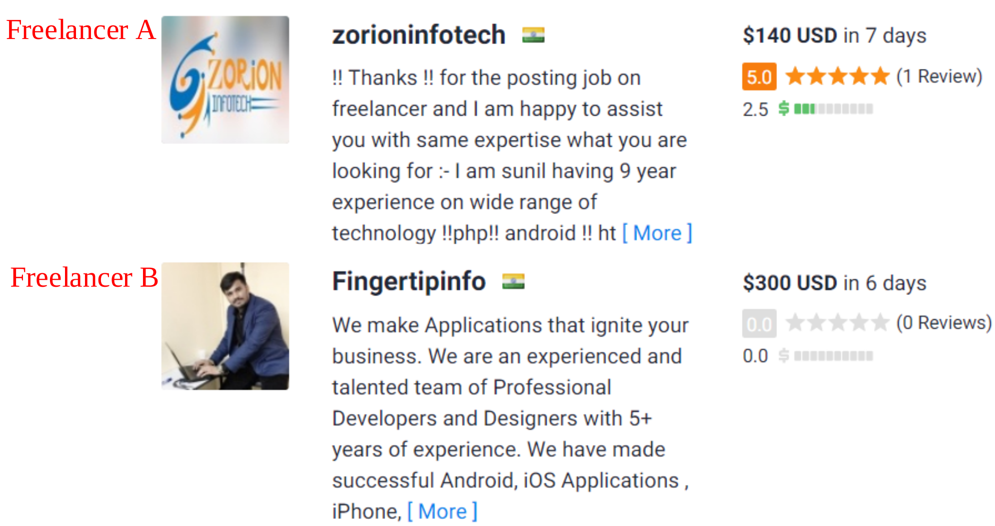
Online labor markets serve as intermediaries bringing together employers and freelancers from all over the world. In online labor markets, an employer first posts tasks on the platform, including budget, detailed description of the job, required skills, etc. Then, freelancers can submit quotes and lead times during the open bid period. Figures 1(a) and 1(b) illustrate a posted job and the freelancers bidding for the job, respectively. After the open bid period ends, the employer evaluates all bids and selects one freelancer to complete the task, based on the submitted quotes as well as information from freelancers' profiles (reputation, past feedback, certification, skills offered, and so on).

Previous literature on online labor markets has largely focused on investigating factors that influence employers' hiring decisions (Chan & Wang, 2017; Hong & Pavlou, 2017; Leung, 2017; Lin et al., 2016; Pallais & Sands, 2016). Employers can access information about freelancers through their profiles, their past transaction records, and the feedback provided by previous employers (if any). For example, Chan and Wang (2017) found evidence that employers exhibit a positive hiring bias in favor of female workers while such bias diminishes as employers gain more hiring experience on the platform. Hong and Pavlou (2017) showed employers' aversion to freelancers from countries with language, time zone, and cultural differences, and their preference for freelancers from countries with high IT development levels. Regarding the impact of reputation systems, Kokkodis and Ipeirotis (2015) showed that freelancers' category-specific reputation scores and feedback are more accurate for predicting future performance.

In this study, we extend the concept of category spanning to the online labor market to investigate how freelancers' skill spanning affects employers' hiring decisions. Existing research has demonstrated that freelancers enjoy a higher probability of being selected if the skills they offer match more closely with employers' requirements (Kokkodis & Ipeirotis, 2014; Kokkodis et al., 2015). Listing multiple skills in profiles can increase freelancers' chances of matching with more projects. Does this imply that freelancers should list as many skills as possible in their profiles in order to increase the chance of matching? Little is known about how skill spanning behavior affects freelancers' probability of winning bids, and this paper aims to fill this research gap.



(a) Screenshot of a released job.



(b) Screenshot of freelancers bidding for a job.

Figure 1. Screenshots of Platform Operation

2.2 Category Spanning

Categories are sociocognitive partitions that set market boundaries and represent the social agreements of market participants (Negro et al., 2011; Negro & Leung, 2013). Categories indicate market participants' shared understanding and perceptions of the defining values of certain types of objects. For example, painting is separated into genres such as impressionism or minimalism (Fine, 2006); films are classified into action, adventure, sci-fi, etc. (Hsu, 2006); and restaurants are clustered by cuisine styles such as Mexican, Indian, Chinese, etc. (Kovács & Johnson, 2014). In each case, people's categorical beliefs follow consistent schemas that tell what appropriately lies within the boundaries of a category (Hsu et al., 2009).

However, objects or producers do not always fit neatly into accepted categories. For instance, Hsu (2006) found that 94.3% of feature films are classified into more than two genres by critics and only 5.7% are categorized by a single genre. Objects classified into multiple categories often exhibit atypical values of features belonging to multiple categories and do not fit perfectly in any single category; such objects are called category spanners.

Previous research has examined the impact of category spanning on market performance but the findings have been inconclusive. Some studies have found that category spanners (who are associated with multiple categories) have social and economic disadvantages in various industries (Hsu, 2006; Hsu et al., 2009; Negro et al., 2010; Zuckerman, 1999). For instance, Rao et al. (2005) suggested that critics give lower evaluations to chefs who combine classical and nouvelle cuisines. Zuckerman (1999) showed that companies that straddle industries often cause confusion and are more difficult for stock analysts to evaluate. As a result, such companies are more likely to be undervalued or ignored by analysts. Hsu (2006) found that films targeting multiple genres often lead to perceptions of poor fit with any single genre and are found less appealing by their audiences. Similarly, Ferguson and Hasan (2013) found that government employees in the Indian Administrative Service benefit less from job rotations that expose them to a broader set of experiences and benefit more from specialized positions that signal specific expertise.

However, previous research has also identified positive effects of category spanning and potential disadvantages associated with focused, specialized profiles. Paolella and Durand's (2016) research on corporate legal services concluded that clients tend to value category spanners positively, especially when their categorical combination is inclusive. Zuckerman et al. (2003) found that while film actors benefit from specializing in a film genre early in their careers, such specialization can result in long-term career disadvantages because of typecasting and may thus limit opportunities in other genres. Merluzzi and Phillips (2016) found disadvantages for MBAs with focused profiles in investment banking.

Two reasons may explain the mixed findings on the effects of category spanning. First, existing research usually ignores the fact that consumers with different demands may have different expectations. Most previous literature is based on the premise that consumers' evaluations are based on how well products correspond to their given categories (Negro et al., 2011; Negro & Leung, 2013). Accordingly, any category spanning would be understood as ab indicator of a misfit, which would, in turn, have negative impacts on performance. However, what matters to consumers is not whether products straddle categories, but the extent to which products fit their requirements or match the current situation.

Second, while prior research often regards categories as separate, the boundaries of categories are often difficult to sharply delineate or define. Categories often "spill over" into one another and have vague, blurry boundaries (Zerubavel, 2009). For instance, a film might be labeled as both horror and sci-fi because it combines features of these two themes. Similarly, music styles are also difficult to clearly demarcate. For example, Jazz and Blues elements can appear in the same piece of music. Such fuzziness can lead to disagreements about audience's consensus on the schema-relevant features. Further, prior research has shown that the demarcation of categories affects the impact of category spanning (Kovács & Hannan, 2010, 2015). Kovács and Hannan (2010) argued that spanning categories with fuzzy boundaries does not cause much confusion for consumers and that penalties for category spanning in such cases are slight. However, consumers tend to devalue products when category spanning involves high-contrast categories because it makes the products difficult to understand or evaluate.

As such, we argue that when investigating the effect of category spanning in online labor markets, it is necessary to consider and specify the expectations of different consumers. In our context of online labor markets, freelancers' skill spanning may have different impacts on employers, given different types of jobs. Figure 2 summarizes the research framework. For high-skill jobs (such as software development), which are usually complex and involve problem solving, employers will be more cautious when evaluating freelancers' competency. High-skill jobs are associated with higher shirking risks (even for freelancers with verifiable work histories) (Leung, 2014) because the complexity and technical expertise required for such jobs make it more difficult for employers to understand the details of the task, giving freelancers greater opportunities to cut corners. In this case, employers may be more conservative when evaluating freelancers and may apply prejudices from traditional labor markets, in which systematic and focused career progression is always preferred (Barley et al., 1989). Skill spanning freelancers may increase employers' uncertainty regarding their service quality because skills take a lot of time and effort to acquire. Therefore, ambidexterity may mean that the freelancer is not particularly specialized in any area and may also suggest a lack of professional commitment (Good & Michel, 2013; Holmqvist, 2004). Hence, for high-skill jobs, employers may have less trust in the abilities of skill-spanning freelances, which would thus reduce their likelihood of winning bids.

For low-skill jobs (such as data entry), employers may evaluate freelancers' skill spanning differently. Previous literature has shown that the consumers (in our context, employers) have no general or unconditional preference for products (i.e., freelancers' skills) focused on a single category (Lamont, 2012; Zuckerman & Rao, 2004). What matters is the value offered by the product, which eventually translates into consumers' willingness to pay for it.

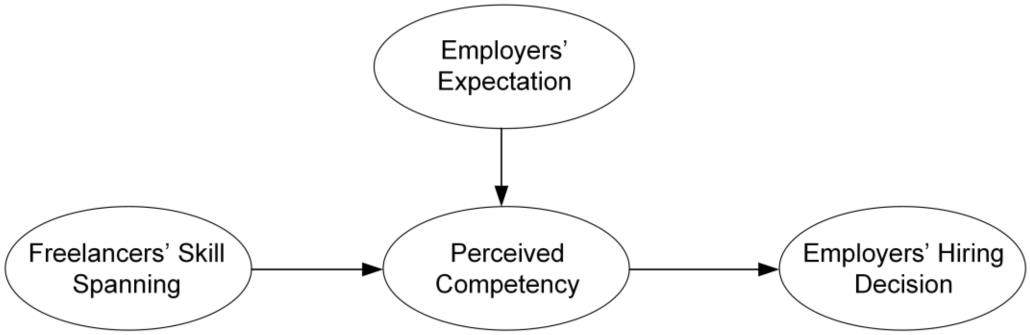


Figure 2. Effect of Freelancer's Skill Spanning on Employer's Hiring Decision

Paolella and Durand's (2016) analysis of the corporate law market showed that when corporate legal services involve multiple practice areas or cases, clients are more likely to choose generalist law firms. In online labor markets, in particular, low-skill jobs typically involve multifarious cases (i.e., employers' demands are complex and require more sophisticated sets of services). Versatile freelancers are thus more likely to be able to handle these complex tasks. In this case, skill spanning may be valued to a certain degree, although excessive skill spanning may induce suspicion from employers. For employers offering high-skill jobs, freelancers advertising highly disparate skills may cause the employer to experience uncertainty regarding the freelancer's commitment and expertise, making them less likely to be hired. Thus, we propose the following hypotheses:

H1a: For high-skill jobs, freelancers' skill spanning and employers' hiring decisions are negatively related.

H1b: For low-skill jobs, freelancers' skill spanning and employers' hiring decisions demonstrate an inverse U-shape relationship.

We argue that the effect of skill spanning on employers' hiring decisions is attenuated by freelancers' skills matching both types of jobs because fit with project requirements may affect employers' perceived fit uncertainty (Hong & Pavlou, 2014). In online labor markets, where employers typically do not hold face-to-face interviews with freelancers to ensure their competency, it is difficult for employers to infer freelancers' undisclosed skills or competencies. The skill set listed by freelancers is one main information source for employers. For both high-skill and low-skill jobs, freelancers' skill matching can help alleviate employers' perceived uncertainty regarding their fit with the project. In this case, skills that match the project well can help to mitigate employers' concerns about the freelancer's competency, even if they engage in skill spanning. As such, the impact of skill spanning on employers' hiring decisions is weaker for freelancers with a higher level of skill matching. We thus posit:

H2: The effect of skill spanning on employers' hiring decisions is attenuated by freelancers' skill matching for both high-skill and low-skill jobs.

3 Methodology

3.1 Data

Our dataset is from one of the largest online labor market platforms—www.freelancer.com, which had 39,567,039 registered users and posted 16,726,583 jobs as of November 2019. We developed an automated agent to collect data from Freelancer.com and the time span of our data sample is from May 2011 to October 2018. To examine the impact of skill spanning on freelancers posting skills in different job categories, we included two job categories in our sample: the *Mobile Phones & Computing* category, which contained 12,428 projects, and the *Data Entry & Admin* category, which contained 19,875 projects. We believe that most jobs in the *Mobile Phones & Computing* category were high-skill jobs because these jobs usually require that freelancers had formal education and training as well as the ability to solve problems, whereas jobs in the *Data Entry & Admin* category were expected to be low-skill jobs because these jobs require only limited computer literacy and are repetitive in nature. The final dataset contained 35,733 jobs with 843,235 bids from 252,285 freelancers. 3,430 jobs were excluded because these jobs were closed without any freelancers being selected.

3.2 Dependent Variables

In our context, employers' final hiring decisions reflect how they evaluate freelancers who bid on their projects. Therefore, our dependent variable $Selection_{ij}$ is a dichotomous variable with a value of 1 if freelancer i was selected by employer j, and 0 if a freelancer was not selected.

3.3 Independent Variables

Our main independent variable of interest was the degree of skill spanning in a freelancer's profile. Previous literature on the measurement of category spanning has certain limitations; the degree of category spanning is either treated as a binary variable (Hsu et al., 2009) or each category is treated equally without considering the similarity or distance between categories[1] (Negro & Leung, 2013). We propose an improved measurement based on the following three aspects.

First, categories do not always have clearly defined boundaries; therefore skills do not always fall neatly into a single category (Negro & Leung, 2013). It is worth noting that the freelancer.com platform divides all skill labels into just 13 categories. For instance, *Javascript, SQL,* and *Software Architecture* belong to the *Websites, IT & Software* category, while *App Store Optimization* and *Mobile App Development* belong to the *Mobile Phones & Computing* category. In our datasets, skills that are grouped into the same category by the platform may not always be that closely related, whereas some skills from different categories may have a high degree of similarity. To illustrate, based on the platform's predefined categories, Freelancer A with skill labels *SQL* and *Data Mining* would have a higher degree of skill spanning than Freelancer B with skill labels *SQL* and *Javascript* because the former two skills are from two categories but the latter two are from the same category. Yet these three skills are all actually closely related, both in terms of the necessary learning process and consumers' perception. Therefore, to address the issue of fuzzy boundaries between categories, we did not use the platform's predefined categories to measure freelancers' degree of skill spanning.

Second, considering only the number of categories that a freelancer is involved in and treating each category equally is too imprecise and rough. For example, a freelancer with two distant skill labels is probably more atypical than a freelancer with multiple but closely related skill labels. Thus, instead of weighing each skill label equally, we used the distance between skills, which depends on the similarity between the skills. Since the similarity of two skills can be reflected by their co-occurrence tendencies (Kovács & Hannan, 2015; Rao et al., 2005), we define the similarity of skills in Equation (1): Leung (2014) used a similar idea to measure freelancers' order of accumulated experiences and examine the impact of freelancers' past job histories on employers' decisions in online labor markets.

$$Similarity(Skill_a, Skill_b) \stackrel{def}{=} \begin{cases} Prob(Skill_a \mid Skill_b) = \dfrac{|Skill_a \cap Skill_b|}{\# Skill_b} \\ Prob(Skill_b \mid Skill_a) = \dfrac{|Skill_a \cap Skill_b|}{\# Skill_a} \end{cases} \quad (1)$$

Here, $|Skill_a \cap Skill_b|$ represents the number of times $Skill_a$ and $Skill_b$ appear simultaneously in freelancers' profiles. The variable $\#Skill_b$ (or $\#Skill_a$) denotes the number of times $Skill_b$ (or $Skill_a$) is listed in freelancers' skill sets. Note that, the similarity between two skills is asymmetric. As illustrated in Figure 3, the distance between $Skill_a$ and $Skill_b$ is greater when we treat $Skill_a$ as a focal skill than when $Skill_b$ is treated as a focal skill because highly advanced skills are judged as being more relevant than less advanced skills. for example, people who master *Data Mining* are very likely to have also mastered *Data Entry* but the reverse is unlikely to be true. Thus, as shown in Equation 2, we can obtain an asymmetric similarity matrix of all skills on the platform with a diagonal of one.

$$Simlarity\ Matrix = \begin{array}{c} \\ Skill_a \\ Skill_b \\ Skill_c \\ \vdots \\ \vdots \\ Skill_x \end{array} \begin{array}{c} \begin{array}{ccccc} Skill_a & Skill_b & Skill_c & \cdots & Skill_x \end{array} \\ \begin{bmatrix} 1 & P(Skill_a \mid Skill_b) & P(Skill_a \mid Skill_c) & \cdots & P(Skill_a \mid Skill_x) \\ P(Skill_b \mid Skill_a) & 1 & P(Skill_b \mid Skill_c) & \cdots & P(Skill_b \mid Skill_x) \\ P(Skill_c \mid Skill_a) & P(Skill_c \mid Skill_b) & 1 & \cdots & P(Skill_c \mid Skill_x) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ P(Skill_x \mid Skill_a) & P(Skill_x \mid Skill_b) & P(Skill_x \mid Skill_c) & \cdots & 1 \end{bmatrix} \end{array}$$

Equation (2)

[1] For example, if a winery produced wines of two styles, its degree of style spanning would be $0.5 = 1 - \left[\left(\frac{1}{2}\right)^2 + \left(\frac{1}{2}\right)^2\right]$. By analogy, the style spanning will be $\frac{2}{3} = 1 - \left[\left(\frac{1}{3}\right)^2 + \left(\frac{1}{3}\right)^2 + \left(\frac{1}{3}\right)^2\right]$, if the winery produced wines of three styles.

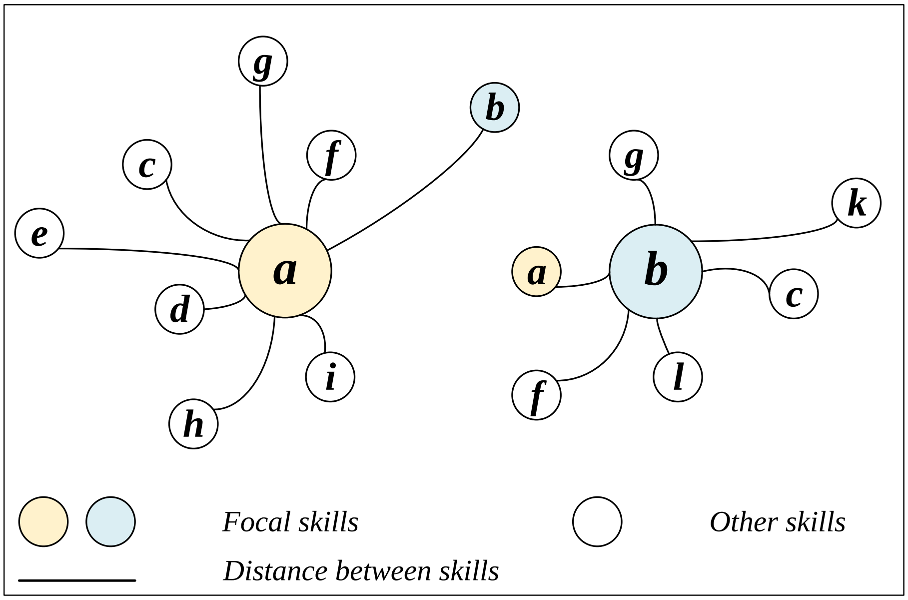


Figure 3. Illustration of the Distance Asymmetry between Skills

We calculate the *similarity matrix* by traversing the profiles of 1,600,374 users on the platform. This large amount of data ensures that the cognition or belief that two skills are relevant or distant is shared by users on the platform. Finally, the *similarity matrix* is a square matrix of 1218 skills. Since distance and relevance are inversely related (Shepard, 1987; Tversky, 1977), in Equation (3), we measure the distance between two skills as 1 minus the similarity between the two skills:

$$Distance(Skill_a, Skill_b) = 1 - Similarity(Skill_a, Skill_b) \quad (2)$$

Accordingly, the distance between skills is between 0 and 1 and is also asymmetric. The distance is close to 0 if the concurrent frequency of two skills in freelancers' profiles is high. Conversely, the distance is close to 1 when two skills rarely occur simultaneously in freelancers' profiles.

Third, we took the consumers' (i.e., employers') expectations regarding the skill requirements for a project into account. Previous literature has found that the expectations of the consumer affect the impact of category spanning (Hsu et al., 2009; Negro & Leung, 2013). However, in the absence of specific information, the default expectation of the consumer does not differ across products (i.e., skills). In our context, the employers' perceived degree of skill spanning varies in relation to projects with different skill requirements. For example, an employer who requires a logo design skill set and an employer who requires a data mining skill will set perceive the degree of skill spanning differently for a freelancer who is tagged with *Graphic Design* and *2D Animation*. In this paper, we incorporate employers' expectations regarding different projects when measuring a freelancer's degree of skill spanning.

Specifically, we used the skill requirements listed in the project descriptions as proxies for employers' expectations for freelancers (as shown in Figure 4). Employer j's expectations regarding freelancers' skills can be expressed as a vector as follows:

$$\boldsymbol{Expectation}_j = \{expectation_j(Skill_a), \ldots\ldots, expectation_j(Skill_x)\}$$

$$expectation_j(Skill_x) = \begin{cases} 1 & if\ skill\ x\ is\ required\ by\ employer\ j; \\ 0 & otherwise. \end{cases} \quad (4)$$

Based on the expectations of employer j, the corresponding nonconformity caused by displaying a certain skill k can be expressed as

$$Total\ Distance(Skill_k)_j = \sum_{x \in K} Distance\ (Skill_x | Skill_k) \cdot expectation_j(Skill_x), \quad (3)$$

where K denotes the number of skill labels on the platform.

Next, to calculate the freelancer's degree of skill spanning, we define freelancer i's skill set $\boldsymbol{L}(\boldsymbol{i}) = \{l_a(i), \ldots\ldots l_x(i)\}$ as Equation (4):

$$l_k(i) = \begin{cases} 1 & if\ skill\ k\ is\ tagged\ by\ freelancer\ i; \\ 0 & otherwise. \end{cases} \quad (4)$$

In this case, freelancer i's degree of skill spanning after incorporating the expectations of employer j can be expressed as Equation (7). Note that we added the term $(1 - expectation_j(Skill_x))$ because we assume that the nonconformity caused by employers' expected skills is 0. We normalized the variable by dividing its maximum value so that freelancers' skill spanning is bounded between 0 and 1.

$$Spanning_{ij} = \sum_{x \in K} l_x(i) \cdot Total\ Distance(Skill_x)_j \cdot (1 - expectation_j(Skill_x)) \quad (7)$$

The other key independent variable was skill matching, which is captured by a continuous variable to account for how well freelancers' skills match the ones required by a given job. Specifically, for each applicant, we counted the number of skills in the freelancer's skill set that matched the employer's requirements and then divided it by the total number of required skills. To examine the robustness of our findings, we repeated all our analyses by replacing this continuous variable with a binary variable; these results are reported in Appendix B.

3.4 Control Variables

The *reputation* of a freelancer is a reputation score graded by prior employers. The reputation system in online labor markets is designed to alleviate employers' risks regarding adverse hiring decisions caused by the information asymmetry between freelancers and employers (Hong & Pavlou, 2017). The extant literature (Hong & Pavlou, 2017; Kim, 2009; Kokkodis & Ipeirotis, 2013b; Lin et al., 2016; Moreno & Terwiesch, 2014; Yoganarasimhan, 2013) has demonstrated the direct or moderating effects of reputation scores on employers' selections.

Lead time is the length of time (measured by day) a freelancer expects it will take to deliver the task. Freelancers are required to submit their lead time with their bid. Kim (2009) demonstrated that clients perceive that a shorter lead time will reduce production costs by clients and thus is associated with a higher probability of winning a contract.

Time difference controls the time zone differences between employers and freelancers. The efficiency of communication, negotiation, and coordination between employers and freelancers is influenced by the time difference. Therefore, employers tend to choose freelancers with a smaller time zone difference (Hong & Pavlou, 2017).

Experience controls the number of reviews a freelancer has accumulated on the platform. Online labor markets record freelancers' transaction histories. We normalized experience by using a freelancer's experience ranking in the target project instead of the absolute number of reviews.

Bidding price was included to represent the quotes submitted by freelancers. Previous literature in online labor markets has shown abundant evidence that lower bids are associated with higher probabilities of winning a contract (Kim, 2009; Scholz & Haas, 2011). Similarly, we normalized freelancers' bidding price in the same way that we normalized experience to address heterogeneity among projects.

Hourly wage is self-reported by freelancers and shown on their profile page. It could signal the freelancer's quality to employers (Chan & Wang, 2017; Hong & Pavlou, 2017) and is thus controlled for in our model.

#Recommendation is captured by the number of recommendations that freelancers have received from prior employers. This factor may reflect freelancers' service quality and prior employers' satisfaction with previous projects.

#Certification is the number of certifications a freelancer holds. Because of the lack of face-to-face interviews and internships, freelancers may list certifications to prove their ability or service quality to potential employers in online labor markets (Goes & Lin, 2012).

Num_exams is measured by the number of standardized exams passed on the platform. *Rehire rate* is provided by the platform to indicate the rate at which a freelancer is rehired by prior employers. Freelancers with higher rehire rates are typically considered to be high quality and easy to work with on this platform. Descriptive statistics of the variables are presented in Table 1, and the associated correlations are presented in Table 2.

3.5 Empirical Model

In our analysis, freelancers' bidding results are not independent of each other but clustered by project—that is, the winner (or winners) of a specific contract are determined within the project. Freelancer *i* wins a contract only if they offer higher utility than other freelancers in the same project. Therefore, the probability of winning for freelancer *i* in project *k* can be represented by Equation (8):

$$P_{ik} = P(U_{ik} > U_{hk}), h = 1, \dots, M_k, \tag{8}$$

where $U_{ik} = X^{\prime} \beta + \varphi_i + \eta_k + \varepsilon_{ik}$ represents the random utility offered by freelancer *i*, and M_k is the number of freelancers in the project k. $X^{\prime}$ is a vector of independent control variables and β is the vector of corresponding parameter estimates. Variables φ_i and η_k denote project-level and employer-level fixed effects, respectively, and ε_{ik} is introduced as a random error term to capture unobserved features.

We adopted a conditional logistic regression to address the nonindependence of bidding results as mentioned above. This method is often used to understand how utility-optimizing consumers make choices among a set of products with varying characteristics (Chan & Wang, 2017; Guadagni & Little, 1983). In our context, employers can be understood as consumers who make a decision from a set of freelancers. We used the "clogit" command in STATA 14 to conduct the analysis, and this regression method can control for the project-level and employer-level fixed effects. In this case, φ_i and η_k are excluded in the regression stage. All results are based on the robust standard errors clustered at the project level.

Table 1. Descriptive Statistics

Variable	Mean	Std. dev.	Min	Max
Selection	0.042	0.201	0	1
Experience	0.520	0.272	0.011	1
Lead time	7.000	10.222	0	100
Bidding price	0.519	0.280	0.005	1
Reputation	2.827	2.410	0	5
Skill match	0.700	0.458	0	1
Skill spanning	0.33	0.048	0	0.997
Time difference	6.041	4.163	0	12
Hourly wage	21.653	19.927	1	1000
#Recommendation	8.852	18.121	0	602
#Certification	2.144	2.939	0	43
Num_exams	0.719	1.038	0	23
Rehire rate	0.157	0.124	0	1

Table 2. Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) *Selection*	1												
(2) *Experience*	0.193	1											
(3) *Lead time*	-0.045	-0.029	1										
(4) *Bidding price*	-0.035	0.006	0.049	1									
(5) *Reputation*	0.165	0.780	-0.039	-0.036	1								
(6) *Skill match*	0.041	0.229	-0.045	-0.020	0.202	1							
(7) *Skill spanning*	0.040	0.282	0.028	0.031	0.282	0	1						
(8) *Time difference*	-0.005	0.035	-0.013	-0.006	0.080	0.056	0.018	1					
(9) Hourly wage	-0.029	0.094	-0.010	0.049	0.122	0.074	0.041	0.087	1				
(10) #Recommendation	0.006	0.258	0.115	0.048	0.190	0.120	0.282	0.069	0.126	1			
(11) # Certification	0.011	0.214	0.143	0.059	0.220	0.137	0.272	00.67	0.182	0.277	1		
(12) Num_exams	0.004	0.026	0.115	0.066	0.095	0.033	0.153	0.038	0.004	0.105	0.130	1	
(13) Rehire rate	0.099	0.222	0.088	0.056	0.330	0.122	0.074	0.036	0.064	0.069	0.191	0.068	1

4 Results

4.1 Main Effects of Skill Spanning for Low- and High-Skill Jobs

The conditional logistic regression is used for parameter estimation and the results of low- and high-skill jobs are reported in Table 3 and Table 4, respectively. The model is significant at the 0.001 level according to the Wald $\chi 2$ test statistic, and the explanatory variables explained 0.211 and 0.140 of the variances, respectively, according to McFadden's pseudo R^2.

In each type of job, we started by including only the linear form of skill spanning in Model 1 and then adding the quadratic term of skill spanning in Model 2. For jobs in the *Data Entry & Admin* category (low-skill jobs), the linear term of skill spanning is not significant in Model 1 ($p < 0.005$), while the coefficients of skill spanning and its squared term are both significant in Model 2 ($p < 0.005$). For jobs in the *Mobile Phones & Computing* category (high-skill jobs), the linear term of skill spanning is negative and significant in both models (Model 1: $p < 0.001$; Model 2: $p < 0.005$), while the quadratic term is not statistically significant. The above results imply that for low-skill jobs, freelancers' degree of skill spanning and employers' hiring decisions exhibit a nonlinear inverted U-shape relationship. For low-skill jobs, skill spanning can increase freelancers' probability of winning up to a point, after which it reduces freelancers' probability of winning. However, for high-skill jobs, a higher degree of skill spanning always reduces freelancers' likelihood of being selected. Numerically, one standard deviation increase of skill spanning reduces a freelancer's chances of winning the contract by approximately 4.58% ($[100 \cdot (e^{-0.976*0.048} - 1)]\%$=-4.58%). Thus, based on the sign and significance of the estimates, we find support for H1a and H1b.

Table 3. Regression Results for Low-Skill Jobs

	Data Entry & Admin	
	Model 1	**Model 2**
Skill spanning	**-0.133(0.147)**	**1.566**(0.503)**
Skill spanning^2		**-6.023**(1.982)**
Skill match	0.125***(0.0119)	0.119***(0.0152)
Control variables		
Reputation	0.655***(0.00923)	0.652***(0.00995)
Lead time	0.00977***(0.00237)	0.00958***(0.00245)
Time difference	-0.0281***(0.00330)	-0.0283***(0.00329)
Experience	1.566***(0.0331)	1.570***(0.0323)
Bidding price	-1.812***(0.0421)	-1.805***(0.0421)
Hourly wage	-0.00792***(0.000548)	-0.00863***(0.000551)
#Recommendation	0.00540*** (0.0133)	0.00545***(0.0129)
#Certification	0.166***(0.00797)	0.163***(0.00798)
Num_exams	0.115*(0.0432)	0.108**(0.0338)
Rehire rate	1.252**(0.402)	1.184***(0.313)
Project-fixed effects	√	√
Observations	553,042	553,042
No. of projects	19,875	19,875
Log-likelihood	-43389.405	-43377.805
Pseudo R^2	0.211	0.212
AIC	86802.81	86781.61
BIC	86934.65	86924.43

Note: Standard errors clustered at the project level are reported in parentheses. ***$p < 0.001$, **$p < 0.005$, *$p < 0.01$

Table 4. Regression Results for High-Skill Jobs

	Mobile Phones & Computing	
	Model 1	**Model 2**
Skill spanning	**-0.976***(0.189)**	**-0.875**(0.307)**
Skill spanning^2		**-0.289(0.882)**
Skill match	0.134***(0.0271)	0.134***(0.0271)
Control variables		
Reputation	0.233***(0.00957)	0.233***(0.00957)
Lead time	0.00972***(0.00184)	0.00971***(0.00184)
Time difference	-0.0576***(0.00515)	-0.0577***(0.00515)
Experience	1.002***(0.0490)	1.001***(0.0490)
Bidding price	-2.347***(0.0435)	-2.348***(0.0435)
Hourly wage	-0.00331***(0.000346)	-0.00332***(0.000346)
#Recommendation	0.0911***(0.0162)	0.0929***(0.0165)
#Certification	0.0269***(0.00361)	0.0269***(0.00362)
Num_exams	0.0993**(0.0322)	0.0995**(0.0312)
Rehire rate	2.183***(0.0702)	2.184***(0.0703)
Project-fixed effects	√	√
Observations	219,166	219,166
No. of projects	12,428	12,428
Log-likelihood	-25622.983	-25622.929
Pseudo R^2	0.140	0.140
AIC	51270.0	51271.9
BIC	51393.1	51405.3

Note: Standard errors clustered at the project level are reported in parentheses. ***$p < 0.001$, **$p < 0.005$, *$p < 0.01$

To explicitly demonstrate how freelancers' degree of skill spanning affects employers' hiring decisions for low-skill jobs, we first visualize the marginal effects of skill spanning in Figure 4. This supplementary model-free analysis is necessary because for binary models (in our case, the conditional logit model), the direct relationship between an explanatory variable and the dependent variable is not given by the explanatory variable's model coefficient but instead by the variable's marginal effect, which varies with the value of all model variables (Wiersema & Bowen, 2009). Thus, we fix all other variables at means and plot the marginal effects of skill spanning with a 95% confidence interval (dashed gray lines) in Figure 5. We excluded freelancers whose degree of skill spanning was greater than 0.7 because such freelancers only accounted for 0.01% of our dataset. For freelancers with a low degree of skill spanning, the marginal effect is positive with a 95% confidence interval; however, as the degree of skill spanning increases, the marginal effect becomes significantly negative. Moreover, almost none of the confidence intervals of the marginal effects (except the values near the turning point) cross 0, which demonstrates the robustness of our results.

Second, we plot the effect of freelancers' skill spanning on the predicted probability of winning with a 95% confidence interval in Figure 6. As the degree of skill spanning increases, the likelihood of being selected by an employer slightly increases before it goes down. Figure 5(b) shows more detail of this ascending part of the curve. It shows that the turning point of skill spanning on freelancers' probability of winning is approximately 0.12. In summary, both the marginal effects and the predicted probability of winning illustrate that there is an inverse U-shape relationship between a freelancer's degree of skill spanning and the likelihood of winning contracts for low-skill jobs.

4.2 Interaction of Freelancer's Skill Matching and Skill Spanning

We proceed to examine the role of freelancers' skill matching (how closely a freelancer's skills match the ones required for a job) in moderating the effect of skill spanning on freelancers' probabilities of winning a contract. The results in Table 5 are also obtained by using the conditional logit regression, which can fix the invariant project-level and employer-level attributes. The key estimates of models for high-skill and low-skill jobs are reported in Model 1 and Model 2 of Table 5, respectively. Based on the sign and significance of the estimates, we find partial support for H2. For high-skill jobs, the direct effects of skill spanning and freelancers' skill matching are consistent in signs with the main effects model reported in Table 4.

The sign of the interaction term in Model 1 indicates that the negative linear relationship between freelancers' degree of skill spanning and employers' hiring decisions is attenuated by the freelancer's skill matching ($\beta = 2.051, p < 0.001$). Specifically, we give a model-free explanation for the moderating role of freelancers' skill matching in Figure 7. As a robustness check, we set freelancers' skill matching as a binary variable with a value of 1 if the freelancer completely satisfies an employer's skill requirements, and 0 if the freelancer partially satisfies an employer's requirements. We reran the models with this alternative measure and report the regression results in Table B1 and Table B2 (see Appendix B for the results). Then, we plotted the effects of skill spanning for freelancers whose skills completely matched the job requirements and for those whose skills partially matched the requirements, respectively.

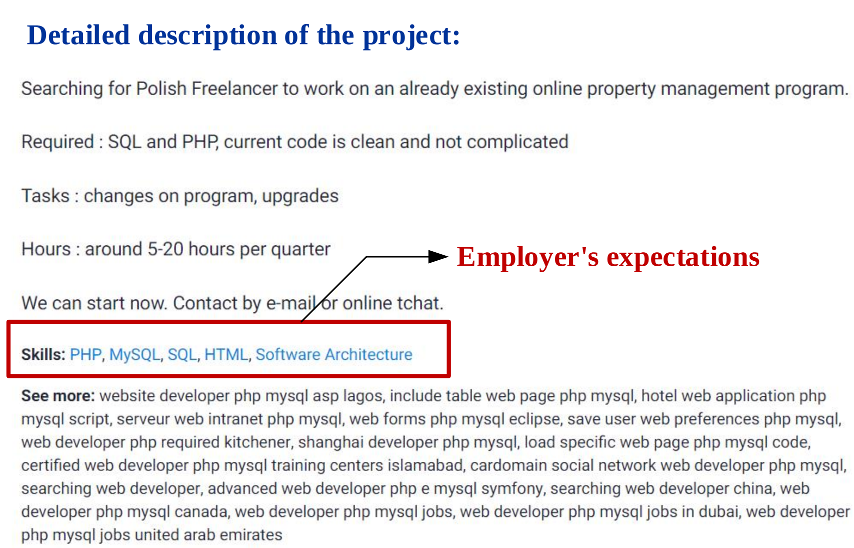


Figure 4. Illustration of Employers' Expectations for a Project

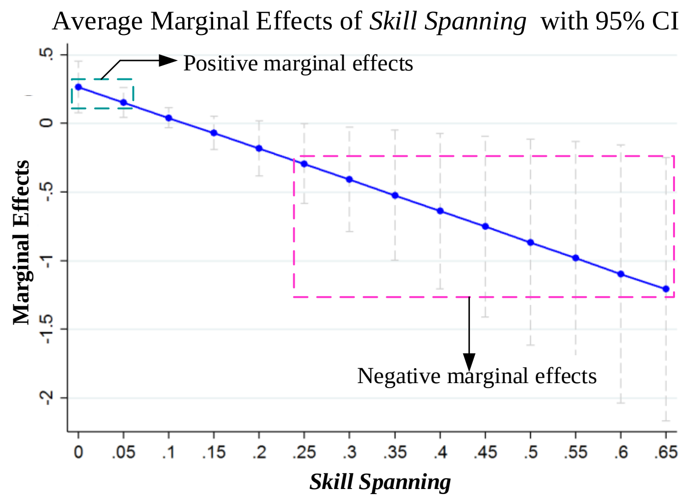
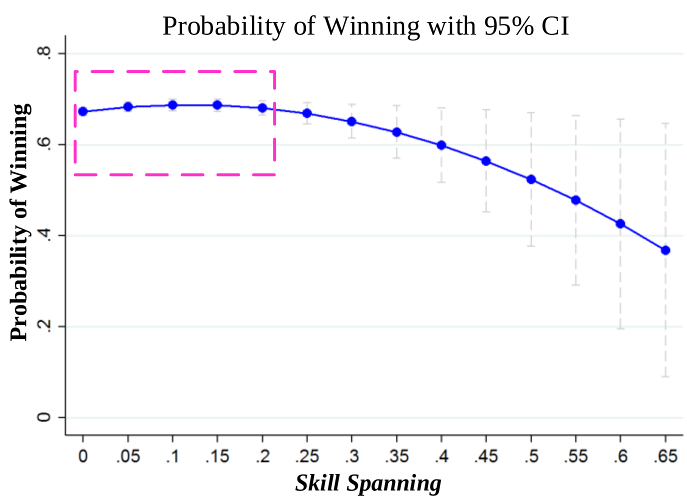
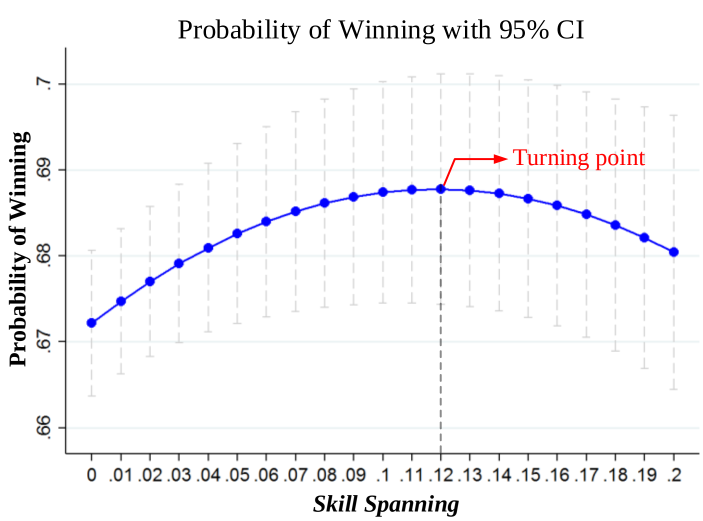


Figure 5. Marginal Effect of Freelancer's Degree of Skill Spanning for Low-Skill Jobs



(a) Plot of skill spanning on probability of winning



(b) Zoomed plot of skill spanning on probability of winning

Note: The probabilities of winning reported in this graph are margins estimated using a conditional logit regression.

Figure 6. The Effect of Freelancer's Degree of Skill Spanning on Probability of Winning for Low-Skill Jobs

Table 5. Interaction of Freelancer's Skill Match and Skill Spanning

	High-skill jobs Model 1	Low-skill jobs Model 2
Skill spanning	**-2.867***(0.696)**	**2.743**(0.964)**
Skill spanning^2		**-8.359**(2.707)**
Skill match	0.0690**(0.0215)	0.174***(0.0382)
Skill match × skill spanning	**2.051***(0.604)**	**-1.534(1.354)**
Skill match × skill spanning^2		**0.484(6.603)**
Control variables		
Reputation	0.234***(0.00959)	0.421***(0.00941)
Lead time	0.00966***(0.00184)	0.00894***(0.00259)
Time difference	-0.0576***(0.00515)	-0.0293***(0.00347)
Experience	0.998***(0.0490)	1.572***(0.0495)
Bidding price	-2.345***(0.0435)	-1.677***(0.0321)
Hourly wage	-0.00330***(0.000344)	-0.00292***(0.000204)
#Recommendation	0.0995***(0.0174)	0.00298***(0.000218)
#Certification	0.0271***(0.00362)	0.0603***(0.00287)
Num_exams	0.0888*(0.0323)	0.0648*(0.0241)
Rehire rate	2.183***(0.0701)	1.063***(0.0653)
Project-fixed effects	√	√
Observations	219,166	553,042
No. of projects	12,428	19,875
Log-likelihood	-25617.741	-43375.037
Pseudo R^2	0.141	0.212
AIC	51261.5	86780.1
BIC	51394.9	86944.9
Note: Standard errors clustered at the project level are reported in parentheses. $^{***}p < 0.001$, $^{**}p < 0.005$, $^{*}p < 0.01$.		

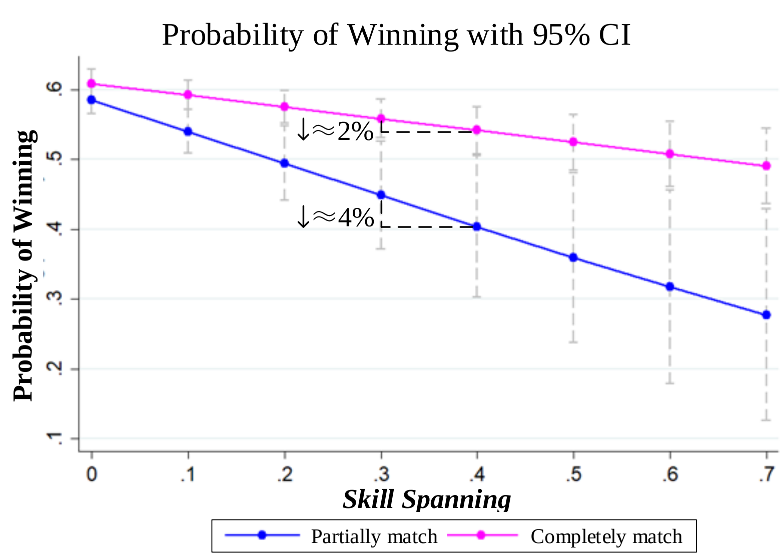


Figure 7. The Interaction of Skill Spanning and Skill Matching for High-Skill Jobs

In Figure 6, the flatter slope for freelancers who satisfy all the requirements suggests that the negative impact of skill spanning on the probability of winning a contract is weakened by freelancers' degree of skill matching. To illustrate, when all other variables are fixed at mean levels, with an increase of 0.1 in freelancers' degree of skill spanning, the probability of winning a contract decreases by approximately 4% for freelancers whose skills partially match with job requirements; the probability of winning, however, only decreases by 2% for those whose skills completely match the job requirements. This implies that, compared to freelancers who completely satisfy skill requirements, those who partially satisfy skill requirements are more severely affected by their degree of skill spanning.

For low-skill jobs, Model 2 in Table 5 includes the interaction terms between skill spanning and skill match (*Skill spanning* × *Skill match*), and skill spanning squared and skill match (*Skill spanning*^{2} × *Skill match*). Based on Model 2, the coefficients associated with the linear and squared terms are again positively and negatively significant, respectively, which confirms the inverted U-shape relationship between skill spanning and employers' hiring decisions. However, neither interaction term is statistically significant. These empirical results suggest that the inverted U-shape relationship between freelancers' degree of skill spanning and employers' hiring decisions is not affected by freelancers' skill matching for low-skill jobs.

4.3 Robustness Check

In this section, we report a set of additional analyses to evaluate the robustness of our key findings. Specially, we report (1) the generalization to other job categories, (2) generalized propensity score matching (GPSM) approach to avoid the endogeneity caused by freelancers' selection of projects, (3) linear probability models, and (4) alternative measure for skill spanning using word embedding. These additional analyses indicate that the results from our main analyses are robust.

4.3.1 Generalization to Other Job Categories

To examine the generalizability of our findings, we extend our analysis to other two job categories on the platform: *Sales & Marketing* and *Websites, IT & Software*, representing low-skill and high-skill jobs in our main analysis, respectively. We extracted 9,611 jobs from the *Sales & Marketing* category and 189,005 jobs from the *Websites, IT & Software* category. The same estimation approach in the main analysis was used in this robustness check. The estimation results in *Sales & Marketing* (low-skill jobs) and *Websites, IT & Software* (high-skill jobs) are reported in Table B3 and B4 respectively in Appendix B. The results for these two additional job categories are consistent with our findings in the main analysis: skill spanning negatively affects employers' hiring decisions for high-skill jobs but exhibits an inverted U-shape relationship for low-skill jobs.

4.3.2 Endogeneity of Freelancers' Selection

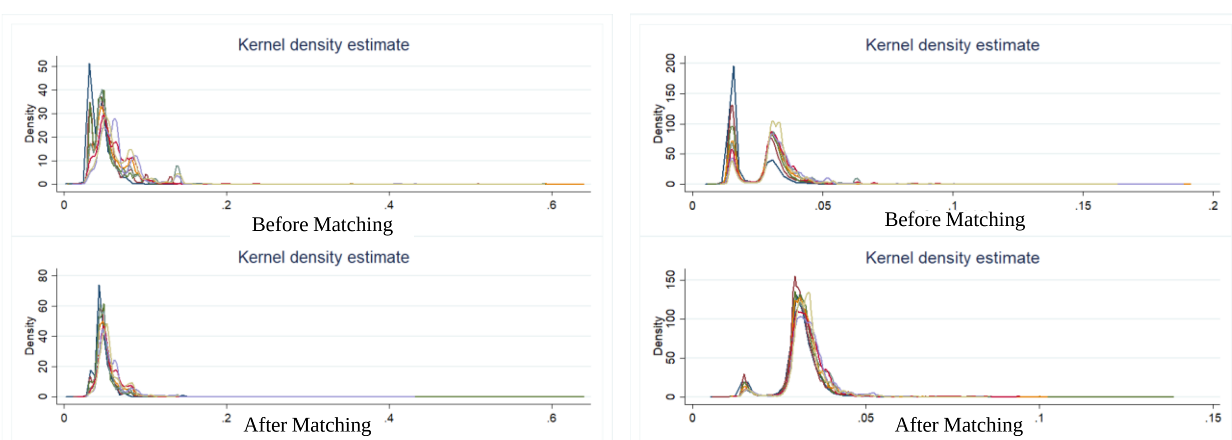
Although we included a large set of freelancer attributes as control variables and the conditional logit model helps us to control for the unobserved project as well as employer effects in the main analysis, selection bias issues caused by freelancers' selection of projects may still exist. This selection bias could cause projects to attract systematically different populations of freelancers. For example, if all or most of the freelancers in a project have very focused skill sets (less skill spanning), the employer's selection may not be driven by the freelancer's level of skill spanning but by other characteristics. To solve this issue, we adopted the generalized propensity score matching (GPSM) approach to ensure that each freelancer in a project was contrasted with a comparable individual with different levels of skill spanning. This matching strategy helped us remove projects that did not contain comparable freelancers with different levels of skill spanning, thereby reducing the estimation bias generated by the systematic differences across projects.

The original propensity score was developed to estimate the causal effects of a binary treatment; however, in many observational studies, the treatment may not be binary or even categorical. Generalized propensity score matching (GPSM) can deal with continuous treatment issues and has been used in prior research involving, for example, the relationship between the time served in prison and offenders' odds of recidivism (Meade et al., 2013) and the effect of teenagers' exposure to antidrug media campaigns on intentions of drug use (Zanutto et al., 2005). We employed GPSM in this study because the treatment is freelancers' degree of skill spanning, which is a continuous variable. To implement this matching strategy, we used the "gpscore2" command in STATA14 to calculate the generalized propensity score of each freelancer based on the covariates.[2] Then, we located comparable freelancers with different levels of skill spanning using a caliper size of 0.001. To assess whether the matching procedure was successful, we performed a balance check by visualizing the distributions of generalized propensity scores of freelancers' different levels of skill spanning before and after matching. Figure 8 shows that the generalized propensity score distribution of freelancers becomes more similar after matching. The results of the GPSM analysis presented in Tables B5 and B6 in Appendix B confirm our findings in the main analysis.

[2] We used freelancers' experience, hourly wage, recommendations, certifications, number of exams, rehire rate, and reputation as covariates to match freelancers with different levels of skill spanning.

Table 6. Linear Probability Model Results for High-Skill Jobs

	High-skill jobs	
	Model 1	**Model 2**
Skill spanning	-0.0480***(0.00649)	-0.0670***(0.0138)
Skill match	0.00606***(0.00117)	0.00517***(0.00143)
Skill match × Skill spanning		0.0217**(0.00710)
Control variables		
Reputation	0.00772***(0.000307)	0.00773***(0.000307)
Lead time	0.000657***(0.0000643)	0.000655***(0.0000643)
Time difference	-0.00288***(0.000216)	-0.00288***(0.000216)
Experience	0.0396***(0.00236)	0.0396***(0.00236)
Bidding price	-0.116***(0.00208)	-0.116***(0.00208)
Hourly wage	-0.000294***(0.0000329)	-0.000294***(0.0000329)
#Recommendation	0.0000708***(0.0000221)	0.0000720***(0.0000221)
#Certification	0.00117***(0.000171)	0.00117***(0.000171)
Num_exams	0.000150(0.000454)	0.000154(0.000454)
Rehire rate	0.141***(0.00474)	0.142***(0.00474)
Constant	0.0402***(0.00183)	0.0409***(0.00192)
Project-fixed effects	Yes	Yes
Employer fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Observations	219,166	219,166
R^2	0.1262	0.1263
RMSE	0.2222	0.2222
Note: ***p < 0.001, **p < 0.005, *p < 0.01		



More-skilled Jobs ***Less-skilled Jobs***

Note: Since our treatment is a continuous variable (*skill spanning*), we use lines with different colors to represent the kernel density distribution of generalized *p*-score. For the sake of figure clarity, we only plot the generalized *p*-score distribution of eight levels of treatment values.

Figure 8. Generalized *P*-Score Distribution of Different Levels of Skill Spanning before and after Matching

4.3.3 Linear Probability Models

To confirm the robustness of our findings, we report the estimation results from a linear probability model (LPM) in this section. The linear probability models provide an alternative that is easier to interpret than logit and probit models, especially for interaction terms (Greenwood & Agarwal, 2016; Kanat et al., 2018). Although there are consistency and biases issues in the linear probability model estimates (Horrace & Oaxaca, 2006), it is well known that with large sample sizes such as ours, the results are qualitatively identical across models (Gordon et al., 1994). We fixed the project effects, employer effects, and the release time of the project by applying the "reghdfe" command in STATA14. Table 6 and Table 7 report the results of linear probability models for high-skill and low-skill jobs, respectively. Because of the different assumptions of the two models, a direct comparison between the conditional logistic regression results and LPM results was not viable. However, it is evident that the results of the linear probability model are consistent with the main analysis in terms of the signs of the key variables.

4.3.4 Alternative Measure for Skill Spanning: Using Word Embedding

Inspired by Kokkodis (2019), in this section, we use *word embedding* to measure freelancers' skill spanning in order to test the robustness of our estimations across alternative measures. Word embedding (W2V) is a natural language processing method in machine learning that can project vocabularies into multidimensional vectors. In our context, we first used the skill requirements of more than 1.5 million employers as the training set to obtain the vectors of skill vocabularies because employers often require multiple similar skills. With our massive amount of data to train the model, we ensured that semantically similar words appeared close to each other in the mapping space. The similarity between two skills can be obtained by calculating the cosine value of the corresponding vectors. As suggested by Kokkodis (2019), we used the average of the similarities in a skill set to measure freelancers' skill spanning. Like Kokkodis (2019), we also negated this similarity result to avoid confusion so that higher values represented greater freelancer skill spanning. This new variable was distributed between -1 and 1, with a mean of -0.177. We reran the regression for low-skill and high-skill jobs with the alternative measure of skill spanning. Tables 8 and 9 report the corresponding results. As expected, these results are qualitatively the same as those from our main analysis. Note that the coefficient of skill spanning for low-skill jobs is negative. This makes sense because this alternative measure is mostly distributed below 0; thus, the turning point should be to the left side of the x-axis.

Table 7. Linear Probability Model Results for Low-Skill Jobs

	Low-skill Jobs	
	Model 1	**Model 2**
Skill spanning	$0.0884^{***}(0.0161)$	$0.0966^{***}(0.0220)$
Skill spanning²	$-0.0111^{**}(0.00379)$	$-0.0193^{*}(0.00713)$
Skill match	$0.00531^{**}(0.001709)$	$0.00361^{**}(0.00101)$
Skill match × Skill spanning		0.0125(0.0278)
Skill match × Skill spanning²		-0.0837(0.0728)
Control variables		
Reputation	$0.00444^{***}(0.000227)$	$0.00444^{***}(0.000228)$
Lead time	$0.0000820^{*}(0.0000303)$	$0.0000820^{*}(0.0000303)$
Time difference	$-0.000919^{***}(0.0000925)$	$-0.000920^{***}(0.0000925)$
Experience	$0.0722^{***}(0.00219)$	$0.0721^{***}(0.00221)$
Bidding price	$-0.0471^{***}(0.000945)$	$-0.0471^{***}(0.000945)$
Hourly wage	$-0.000108^{***}(0.00000934)$	$-0.000108^{***}(0.00000934)$
#Recommendation	$0.000231^{***}(0.0000180)$	$0.000231^{***}(0.0000180)$
#Certification	$0.00181^{***}(0.000166)$	$0.00181^{***}(0.000166)$
Num_exams	$0.00331^{***}(0.000172)$	$0.00331^{***}(0.000172)$
Rehire rate	$0.0338^{***}(0.00218)$	$0.0338^{***}(0.00218)$
Constant	$0.00686^{***}(0.00103)$	$0.00699^{***}(0.00110)$
Project-fixed effects	Yes	Yes

Employer fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Observations	553,042	553,042
R^2	0.1079	0.1079
RMSE	0.1850	0.1850
Note: ***p < 0.001, **p < 0.005, *p < 0.01		

Table 8. Using Word Embedding to Measure Skill Spanning (high-skill jobs)

	High-skill Jobs	
	Model 1	**Model 2**
Skill spanning	-0.532***(0.0832)	-0.545***(0.110)
Skill match	0.141***(0.0273)	0.146***(0.0396)
Skill match × Skill spanning		0.0296*(0.0166)
Control variables		
Reputation	0.234***(0.00965)	0.234***(0.00965)
Lead time	0.00989***(0.00186)	0.00988***(0.00186)
Time difference	-0.0579***(0.00516)	-0.0579***(0.00516)
Experience	1.011***(0.0497)	1.010***(0.0497)
Bidding price	-2.360***(0.0439)	-2.360***(0.0439)
Hourly wage	-0.00314***(0.000334)	-0.00314***(0.000334)
#Recommendation	0.00186**(0.000568)	0.00187**(0.000571)
#Certification	0.0239***(0.00363)	0.0239***(0.00364)
Num_exams	0.00960(0.0112)	0.00955(0.0112)
Rehire rate	2.173***(0.0707)	2.173***(0.0709)
Project-fixed effects	√	√
Observations	219,166	219,166
No. of projects	12,428	12,428
Log-likelihood	-25089.546	-25089.53
Pseudo R^2	0.143	0.143
AIC	50203.1	50205.1
BIC	50325.9	50338.1
Note: Standard errors clustered at the project level are reported in parentheses. ***p < 0.001, **p < 0.005, *p < 0.01		

Table 9. Using Word Embedding to Measure Skill Spanning (low-skill jobs)

	Low-skill Jobs	
	Model 1	**Model 2**
Skill spanning	-0.651***(0.185)	-0.719**(0.243)
Skill spanning^2	-1.451***(0.347)	-1.397***(0.402)
Skill match	0.118***(0.0233)	0.134**(0.0421)
Skill match × Skill spanning		0.0694(0.411)
Skill match × Skill spanning^2		-0.122(0.685)
Control variables		
Reputation	0.422***(0.00950)	0.422***(0.00950)
Lead time	0.00940***(0.00261)	0.00940***(0.00261)

Time difference	-0.0303***(0.00355)	-0.0303***(0.00355)
Experience	1.591***(0.0497)	1.590***(0.0497)
Bidding price	-1.680***(0.0327)	-1.680***(0.0327)
Hourly wage	-0.00295***(0.000211)	-0.00295***(0.000211)
#Recommendation	0.00294***(0.000218)	0.00294***(0.000218)
#Certification	0.0583***(0.00887)	0.0583***(0.00887)
Num_exams	0.0605***(0.00287)	0.0604***(0.00288)
Rehire rate	1.026***(0.0660)	1.026***(0.0661)
Project-fixed effects	√	√
Observations	553,042	553,042
No. of projects	19,875	19,875
Log-likelihood	-41953.48	-41953.233
Pseudo R^2	0.200	0.200
AIC	83933.0	83936.5
BIC	84075.2	84100.6

Note: Standard errors clustered at the project level are reported in parentheses.***$p < 0.001$, **$p < 0.005$, *$p < 0.01$

5 Discussion

5.1 Key Findings

In this paper, we explore whether and how freelancers' skill spanning affects employers' hiring decisions in online labor markets and also examine how skill spanning affects employers seeking to hire freelancers for low-skill and high-skill jobs, respectively. Moreover, we also investigate how freelancers' skill matching (how closely a freelancer's skills match the ones required by a jobs) moderates the effects of skill spanning on employers' hiring decisions.

First, we found that freelancers' skill spanning influenced employers' hiring decisions and that such effects exhibited different patterns for low-skill and high-skill jobs. For high-skill jobs, an increase in a freelancer's degree of skill spanning reduced their likelihood of winning a contract. However, for low-skill jobs, freelancers' skill spanning and the probability of winning a contract exhibit an inverse U-shape relationship—that is, a certain degree of spanning can increase the probability of being hired but, after a turning point, further increases in spanning reduce the probability of being hired. Since high-skill jobs are usually complex and require high levels of technical skill, typically acquired through intensive training and effort, employers may have more uncertainty about the service quality provided by skill spanners compared to specialists who list specific skills, particularly since they generally do not conduct in-person interviews on such platforms. In contrast, on online labor platforms, low-skill jobs are likely to involve a haphazard combination of miscellaneous tasks. Therefore, for low-skill jobs a certain extent of skill spanning may be considered an asset. However, our results show this is true only up to a point—even for low-skill jobs, too much skill spanning reduces the likelihood of freelancers winning job contracts.

Second, our empirical results suggest that freelancers' skill matching can moderate the negative effects of skill spanning for high-skill jobs but has no moderating effect for low-skill jobs. One possible explanation is that for high-skill jobs, specific abilities are absolutely necessary; if freelancers' do not explicitly list them, employers will not be able to form appropriate expectations about their capabilities. In such cases, satisfying all of a job's requirements can reduce employers' concerns about freelancers' fit for the job and thus can attenuate the negative effects of skill spanning on high-skill jobs. In contrast, for low-skill jobs (Gonzaga & Guanziroli, 2019), whether or not freelancers satisfy all the required skills required is less important, as employers are paying more for time than for specific skills.

5.2 Contributions and Implications for Theory and Practice

This study offers several contributions: First, our study contributes to the OLM literature by using the concept of category spanning to explain how freelancers' skill spanning affects employers' hiring decisions. Although a growing number of studies in economic sociology and organization theory have demonstrated the effects of category spanning in a variety of market situations (Hsu, 2006; Negro & Leung, 2013; Rao et al., 2005; Zuckerman, 1999), much less is known about how employers in online labor markets consider freelancers' skill spanning when making hiring decisions. By extending the concept of category spanning to the online labor context, our study takes a novel approach to examining freelancers' skill spanning by investigating this effect with two different types of jobs (low- and high-skill jobs), respectively, thereby offering a new explanation of how and why category spanning affects producers' market performance.

Second, our study contributes to the research on category spanning in two ways. Existing literature has found that category boundaries are fuzzy and not all objects fall neatly into single categories (Negro & Leung, 2013). We address this problem by blurring the boundaries of categories. More specifically, we calculate the degree of skill spanning using the accumulated distances of freelancers' skills instead of first classifying those skills into categories. Furthermore, previous work on category spanning builds on the premise that consumers' perceptions of product spanning are based on whether the product conforms to a category (Negro et al., 2011; Negro & Leung, 2013). In this paper, we propose measuring the consumers' (i.e., employers') expectations according to their actual demands, that is, the posted required skills. This allows our study to more precisely examine the impact of skill spanning in online labor markets.

Finally, we offer practical implications for different stakeholders in online labor markets: freelancers and platform owners. Our findings provide guidance to freelancers on how to properly configure their skills on their profile pages. Specifically, according to our findings, for high-skill jobs, freelancers are devalued by skill spanning; for low-skill jobs, freelancers may benefit from a certain degree of skill spanning, but too much skill spanning may reduce freelancers' probability of winning a contract. This means that freelancers should modulate the skills they list on their profile page based on the types of jobs they are seeking. For instance, freelancers applying for high-skill jobs should build their image as a specialist by emphasizing specific skills. However, freelancers who are mainly applying for low-skill jobs can portray themselves as generalists. However, they should avoid listing too many skills in their profiles. Moreover, our findings imply that for high-skill jobs, skill spanners who satisfy all the requirements of an employer have an advantage over spanners who do not. However, whether all the requirements are met does not affect employers' evaluation of skill spanners for low-skill jobs.

Our findings also provide practical guidance to online labor platform owners on how to better design platform-based functions and advise freelancers about how to configure profiles in order to increase their probability of winning a contract. For instance, platforms can analyze freelancers' profile data and past jobs to find associations between these skills. Such information could be provided to freelancers as a value-added service.

5.3 Limitations and Future Research

This study is not without limitations. First, our study takes into account employers' expectations for different jobs when investigating the effects of skill spanning. We believe that there may be differences between primary and secondary requirements—that is, for a certain job, employers may care more about some skills than others. Future research could extend our research by analyzing employers' detailed job descriptions to distinguish between primary and secondary skill requirements.

Second, this paper uses data from one single online market. However, our paper provides a new way of measuring skill spanning, which considers the distance and relevance between different skills by using the word embedding method. This could be adopted by future research on other markets to measure other spanning behavior.

Third, this study is based on secondhand data which was obtained by a self-developed crawler. We used limited controls for freelancer attributes, such as gender, education background, and offline working experience. Future research could explore this direction by combining other approaches such as surveys or interviews for a more comprehensive empirical analysis of freelancers' skill spanning.

Lastly, this paper focuses on how freelancers' skill spanning affects employers' decisions for different jobs, namely high-skill and low-skill jobs. In practice, these online job contracts could be either fixed-price contracts or hourly contracts. Future research could study how the choice of contract type may affect the employers' evaluation of freelancers' skill spanning.

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Appendix A

Table A1. Related Research on Category Spanning and Key Findings.

Year	Related works	Research setting	Key findings
2005	Rao et al. (2005)	French gastronomy	Explain the causes and consequences of boundary erosion.
2006	Hsu (2006)	US feature films	Highlight the role of audiences' perceptions in the trade-offs of different niche strategies.
2010	Kovács & Hannan (2010)	Online-review website	The effect of category spanning depends on the fuzziness of the categories.
2012	Hsu et al. (2012)	US feature films	Ambiguous category schemas encourage category-spanning products and innovating through category spanning has exceptional performance advantages.
2013	Ferguson & Hasan (2013)	Indian Administrative Service	Government employees benefit less from job rotations that exposed them to a broader set of experiences but benefit more from specialized positions that signaled specific expertise.
2014	Kovács & Johnson (2014)	Online restaurant reviews	Directly test and contrast consumer-side argument and the producer-side argument. High-quality organizations can benefit from being atypical.
2015	Bowers (2015)	Diamond solitaire rings on eBay auctions	Expectations that are inherent in the full member of a category can impact market outcomes even when categorical boundaries are respected.
2015	Kovács & Hannan (2015)	Online reviews of restaurants and books	Introduce novel measures to categorical distance. Consequences of category spanning are more severe when the categories spanned are distant and have high contrast.
2016	Paolella & Durand (2016)	Corporate legal services	The effects of category spanning are contingent on clients' theory of value.
2017	Keuschnigg & Wimmer (2017)	US feature films	Negative effects of category spanning are far from universal, manifesting only in certain circumstances (culturally distant combined genres; released to a stable and highly institutionalized market and offers lack familiarity).
2019	Goldenstein et al. (2019)	Metal bands	Category spanning has a nonlinear effect on new ventures' risk of failure. Venture's age and the category's density moderate the effect of category spanning.

Appendix B

We use a binary variable to represent freelancers' matching with the job skill requirements. Specifically, freelancers' skill match is 1 if the freelancer completely satisfies the employer's skill requirements, and 0 if they partially satisfy the employer's requirements. The results for low-skill jobs and high-skill jobs are reported in Table B1 and Table B2, respectively. Tables B3 and B4 show the regression results based on the robustness check in Section 4.3.1, which aims to examine the generalization of the findings to other categories. Table B3 reports the results of *Websites, IT & Software* (high-skill jobs) and Table B4 reports the results of *Sales & Marketing* (low-skill jobs). Tables B5 and B6 show the regression results of high-skill and low-skill jobs based on the robustness check in Section 4.3.2, which seeks to determine the endogeneity of freelancers' selection of projects.

Table B1. Regression Results for Low-Skill Jobs (using a binary measure for freelancer's skill match)

	Low-skill jobs	
	Model 1	**Model 2**
Skill spanning	**1.553**(0.721)**	**1.475**(0.705)**
Skill spanning^2	**-8.147*(3.452)**	**-7.679**(3.331)**
Skill match	0.139***(0.0311)	0.125**(0.0519)
Skill match × Skill spanning		**0.574(1.699)**
Skill match × Skill spanning^2		**-4.650(11.07)**
Control variables		
Reputation	0.421***(0.00941)	0.421***(0.00942)
Lead time	0.00894***(0.00259)	0.00893***(0.00259)
Time difference	-0.0292***(0.00347)	-0.0292***(0.00347)
Experience	1.577***(0.0493)	1.577***(0.0496)
Bidding price	-1.676***(0.0321)	-1.676***(0.0321)
Hourly wage	-0.00296***(0.000207)	-0.00296***(0.000207)
#Recommendation	0.00298***(0.000219)	0.00298***(0.000219)
#Certification	0.0601***(0.00287)	0.0601***(0.00287)
Num_exams	0.0649***(0.00888)	0.0650***(0.00888)
Rehire rate	1.067***(0.0653)	1.067***(0.0653)
Project-fixed effects	√	√
Observations	553,042	553,042
No. of projects	19,875	19,875
Log-likelihood	-43365.16	-43365.029
Pseudo R^2	0.200	0.201
AIC	86756.3	86760.1
BIC	86899.1	86924.8
Note: Standard errors clustered at the project level are reported in parentheses. ***p < 0.001, **p < 0.005, *p < 0.01		

Table B2. Regression Results for High-Skill Jobs (using a binary measure for freelancer's skill match)

	High-skill Jobs	
	Model 1	**Model 2**
Skill spanning	**-1.002***(0.190)**	**-1.747***(0.287)**
Skill match	0.261***(0.0390)	0.389***(0.0533)
Skill match × Skill spanning		**5.155***(1.375)**
Control variables		

Reputation	0.233***(0.00957)	0.234***(0.00958)
Lead time	0.00969***(0.00184)	0.00959***(0.00184)
Time difference	-0.0573***(0.00516)	-0.0572***(0.00516)
Experience	0.984***(0.0490)	0.979***(0.0491)
Bidding price	-2.345***(0.0435)	-2.343***(0.0435)
Hourly wage	-0.00331***(0.000347)	-0.00328***(0.000344)
#Recommendation	0.0796***(0.0173)	0.0890*** (0.0192)
#Certification	0.0271***(0.00362)	0.0275***(0.00362)
Num_exams	0.0954*(0.0506)	0.0787*(0.0451)
Rehire rate	2.176***(0.0702)	2.175***(0.0701)
Project-fixed effects	√	√
Observations	219,166	219,166
No. of projects	12,428	12,428
Log-likelihood	-25612.377	-25603.529
Pseudo R^2	0.141	0.141
AIC	51248.8	51233.1
BIC	51371.9	51366.5
Note: Standard errors clustered at the project level are reported in parentheses. $^{***}p < 0.001$, $^{**}p < 0.005$, $^{*}p < 0.01$		

Table B3. Regression Results for Jobs from Websites, IT & Software Category (high-skill jobs)

	Websites, IT, & Software	
	Model 1	**Model 2**
Skill spanning	-1.763***(0.0779)	-1.862***(0.0592)
Skill match	0.458***(0.0177)	0.469***(0.0176)
Skill match × Skill spanning		2.719***(0.703)
Control variables		
Reputation	0.326***(0.00318)	0.326***(0.00318)
Lead time	-0.00580***(0.000904)	-0.00575***(0.000904)
Time difference	-0.0435***(0.00314)	-0.0435***(0.00314)
Experience	1.738***(0.0132)	1.740***(0.0132)
Bidding price	-1.852***(0.0240)	-1.852***(0.0240)
Hourly wage	-0.00316***(0.000317)	-0.00316***(0.000317)
#Recommendation	0.00725***(0.000906)	0.00725***(0.000906)
#Certification	0.0579***(0.00304)	0.0579***(0.00304)
Num_exams	0.0449*(0.0164)	0.0450*(0.0164)
Rehire rate	1.177***(0.0536)	1.177***(0.0536)
Project-fixed effects	√	√
Observations	2,196,961	2,196,961
No. of projects	189,005	189,005
Log-likelihood	-295403.82	-295390.45
Pseudo R^2	0.168	0.168
AIC	520930.7	520904.9
BIC	520994.2	520972.4
Note: Standard errors clustered at the project level are reported in parentheses. $^{***}p < 0.001$, $^{**}p < 0.005$, $^{*}p < 0.01$		

Table B4. Regression Results for Jobs from Sales & Marketing Category (low-skill jobs)

	Sales & Marketing	
	Model 1	**Model 2**
Skill spanning	1.652**(0.544)	-2.808***(0.768)
Skill spanning^2	-4.974*(1.772)	3.368*(1.237)
Skill match	0.115***(0.0347)	0.126***(0.0343)
Skill match × Skill spanning		4.657(3.314)
Skill match × Skill spanning^2		-1.77(4.115)
Control variables		
Reputation	0.273***(0.0130)	0.274***(0.0130)
Lead time	-0.0147***(0.00201)	-0.0148***(0.00201)
Time difference	-0.0565***(0.00727)	-0.0567***(0.00726)
Experience	1.079***(0.0788)	1.083***(0.0788)
Bidding price	-1.188***(0.0568)	-1.186***(0.0568)
Hourly wage	-0.00298***(0.000617)	-0.00295***(0.000619)
#Recommendation	0.0154***(0.00202)	0.0191***(0.00202)
#Certification	0.0663***(0.00514)	0.0647***(0.00516)
Num_exams	0.0390***(0.0111)	0.0394***(0.0110)
Rehire rate	1.616***(0.133)	1.628***(0.133)
Project-fixed effects	√	√
Observations	61,713	61,713
No. of projects	9,611	9,611
Log-likelihood	-10591.556	-10583.609
Pseudo R^2	0.169	0.170
AIC	21209.1	21197.2
BIC	21325.6	21331.6
Note: Standard errors clustered at the project level are reported in parentheses. ***p < 0.001, **p < 0.005, *p < 0.01		

Table B5. Matching Results for High-Skill Jobs

	High-skill Jobs	
	Model 1	**Model 2**
Skill spanning	**-1.440***(0.244)**	**-3.126***(0.754)**
Skill match	0.134***(0.0279)	0.0737**(0.0260)
Skill match × skill spanning		**1.888**(0.608)**
Control variables		
Reputation	0.213***(0.00992)	0.213***(0.00993)
Lead time	0.0135***(0.00188)	0.0134***(0.00188)
Time difference	-0.0546***(0.00519)	-0.0546***(0.00519)
Experience	0.898***(0.0533)	0.896***(0.0533)
Bidding price	-2.371***(0.0456)	-2.369***(0.0456)
Hourly wage	-0.00972***(0.000671)	-0.00964***(0.000672)
#Recommendation	0.0850*(0.03181)	0.0717*(0.02612)
#Certification	0.0436***(0.00510)	0.0443***(0.00510)
Num_exams	0.0371***(0.0103)	0.0359***(0.0103)
Rehire rate	2.208***(0.0759)	2.210***(0.0758)

Project-fixed effects	√	√
Observations	154,410	154,410
No. of projects	10,238	10,238
Log-likelihood	-21959.056	-21955.314
Pseudo R^2	0.143	0.143
AIC	43942.1	43936.6
BIC	44061.5	44065.9
Note: Standard errors clustered at the project level are reported in parentheses. ***p < 0.001, **p < 0.005, *p < 0.0		

Table B6. Matching Results for Low-Skill Jobs

	Low-skill jobs	
	Model 1	**Model 2**
Skill spanning	**1.418**(0.451)**	**2.460**(0.789)**
Skill spanning^2	**-7.843**(2.386)**	**-7.374**(2.562)**
Skill match	0.137***(0.0232)	0.176***(0.0376)
Skill match × Skill spanning		**-1.255(1.292)**
Skill match × Skill spanning^2		**-0.469(6.065)**
Control variables		
Reputation	0.416***(0.00951)	0.416***(0.00952)
Lead time	0.00940***(0.00256)	0.00938***(0.00256)
Time difference	-0.0280***(0.00348)	-0.0280***(0.00348)
Experience	1.558***(0.0497)	1.562***(0.0499)
Bidding price	-1.671***(0.0323)	-1.673***(0.0323)
Hourly wage	-0.00383***(0.000189)	-0.00383***(0.000189)
#Recommendation	0.0297***(0.00220)	0.0297***(0.00220)
#Certification	0.0691***(0.00320)	0.0693***(0.00320)
Num_exams	0.0652***(0.00909)	0.0653***(0.00909)
Rehire rate	1.049***(0.0665)	1.047***(0.0666)
Project-fixed effects	√	√
Observations	411,927	411,927
No. of projects	12,123	12,123
Log-likelihood	-42446.315	-42443.917
Pseudo R^2	0.191	0.191
AIC	84918.6	84917.8
BIC	85060.7	85081.8
Note: Standard errors clustered at the project level are reported in parentheses. ***p < 0.001, **p < 0.005, *p < 0.01		

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