**Failed Searches: How the choice set of job applicants
affects an employer's likelihood of making an offer***

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ABSTRACT

Most accounts of hiring focus on understanding why a particular job candidate was chosen and do not examine hiring as an outcome for the employer. I suggest that a focus on developing a better understanding of failed searches, job openings which end unfilled, is a valuable, yet understudied, piece of the hiring puzzle. I do so here by highlighting the effect of an employer's choice set on whether a job offer is extended to any candidate. In particular, I hypothesize that the categorical overlap among the candidates who apply affects the likelihood of an offer being extended. Because a hiring decision is one an employer seeks to maximize, comparisons are effortful. The less overlap in the background of job candidates', the more difficult it is to compare them, the less likely any decision will be made. To support my contention that this is driven by cognitive effort, I further predict that choice set commensurability issues are less salient for jobs which are more urgent; suggesting variation in satisficing and maximizing motivations. Finally, commensurability is more challenging for employers with greater categorical fluency because differences among candidates are further exacerbated by the employer's more nuanced expectations. I demonstrate support for my contentions with data from Elance, an online market for freelancing services.

KEYWORDS

Labor market matching, Hiring, Categories, Choice set, Commensuration, Freelancing

What accounts for failed labor market searches? Most hiring research focuses on understanding *which* candidate was eventually employed and does not address the reasons *whether* an employer made any offer of employment. For example, the hiring literature has implicated employers as the cause of differential hiring outcomes of employees (Baron and Bielby 1980) but has yet to delve into how employers themselves react to hiring. In this vein of work, scholars have accounted for discriminatory hiring and promotion practices which affect members of certain racial groups (Castilla 2008) or gender (Fernandez-Mateo 2009, Fernandez and Weinberg 1997, Peterson and Saporta 2004). While work by Beckman and Phillips (2005) more squarely implicate the employer's clients in assisting us in understanding the possible pressures employer's face in hiring on the outcome of women lawyers' rates of promotion – work has yet to delve into the limitations employer's face in hiring. In short, little light has been shed on the constraints employers may face in coming to a decision to hire which is ultimately the outcome of interest for labor market scholars.

To investigate this question, I begin by conceptualizing the hiring decision as one made by employers regarding a pool of applicants for a particular position. Choices are made on a panel of applicants, among which one or more may be chosen. This detailed characterization of the hiring process as being sensitive to the list of applicants available underlies the theories of labor queues (Reskin and Roos 1990), which inherently suggests, though at an aggregate level, that the composition of available candidates necessarily affects an employers' decision as to whom they hire. Yet research to date has left unexamined the micro-mechanisms which underlie such theories. More generally, the 'black box' of hiring has obscured the actions of the applicants and employers at the hiring interface to scholars, among which are questions regarding what occurs when employers make their hiring decisions and what factors affect those decisions.

Here, I focus our attention on the choice set an employer is faced with, which has been demonstrated to implicate outcomes in many other domains. Take, for example, evidence which demonstrates how ones choice set drastically alters ones preferences and eventual decision (Denrell and Le Mens 2007, Iyengar and Lepper 2000). Or, more broadly, the work that demonstrates how structures

constrain choice in markets: such as the sequential arrival of options (Mogilner, Shiv, and Iyengar 2012) and work demonstrating the geographic limitations to search (Sorenson and Stuart 2001). Most recently, Bowers (2014) identified how the comparison set affects judgments of equity analysts.

Questions regarding whether any job candidate is hired or not can be more generally portrayed as being one of market efficiency. Economic sociologists suggest that categories are one social mechanism which facilitates market transactions (Hsu 2006, Hannan, Polos, and Carroll 2007, Hsu et al 2009, c.f. Fleischer 2009). Because individuals naturally lump and separate (Zerubavel, 1997) items into recognizable groupings, buyers in markets use these socially understandable categorical identities to identify appropriate sellers (or their products). For example, recognized movie genres (e.g. drama, comedy, horror) assist audiences in making sense and sorting between films to see (Hsu 2006), winemakers are divided by the traditional or modern techniques they utilize (Negro, Hannan, and Rao 2011), and restaurants are organized and evaluated by their types of cuisines (e.g. Chinese, Italian, French) (Kovacs and Hannan 2014). Categorical boundaries, which circumscribe similar social objects and exclude dissimilar ones, ease the process of identification and commensuration (Espeland and Stevens 1998) of those otherwise unorganized social actors. The existence of classificatory systems should therefore facilitate market transactions by assisting buyers in eliminating those applicants who do not obviously fall into the prevailing categorical distinctions. This is used to explain why French chefs which incorporate competing cuisine styles garner lower Michelin star ratings (Rao et al 2005), software companies which incorporate ambiguous products lose consumer appeal (Pontikes 2012), and restaurants which do not hew to the expectations of their cuisine style are rated lower by the general public (Kovacs and Johnson 2014). For review, see Hannan (2010).

I animate the link between choice set and buyer assessments in this article by leveraging the category paradigm and ask: How does the categorical affiliation of items in a choice set affect the evaluation process of buyers? By categorical similarity I refer to the extent with which the items under consideration exhibit the same or different categorical affiliations. I demonstrate the importance of this perspective by using it to explain the outcomes of a hiring decision. In particular, I proceed from the

belief that a hiring decision is one where the employer will generally wish to maximize (versus satisfice) on the outcome by attempting to choose the best candidate from the slate who apply. An implication of my conceptualization is that frictions in labor markets affects the pool of applicants, and that job searches vary by which applicants eventually apply. A set of applicants with less categorical overlap of past experiences makes it difficult for an employer to identify a 'best' candidate – these searches are more likely to end in failure. However, to the extent that the urgency of a job leads to less maximizing behavior, we expect commensurability issues to be less of an issue. Finally, experience with the categorical schema, termed fluency (Hsu et al 2009) should act to exacerbate this effect, as cross-category comparisons magnify the nuanced differences more fluent employers will recognize.

Problematizing this phenomenon affords us theoretical purchase. Specifically, this paper sheds light on the decision making process of employers – the relatively neglected role of this two-sided market. The structural or cognitive constraints employers face figure heavily into the theoretical accounts of discrimination, yet most of these investigations portray observations of differential hiring outcomes as the result of biased employer actions. However, hiring is a result of the interaction between employees and employers, thereby muddying the theoretical clarity of conclusions drawn from merely the outcomes. Without further visibility into the detailed mechanisms which underlie a hiring decision, scholars are left to theorize on mere observable outcomes. For example, a decision not to hire can either be attributed to the applicants or the employers – but scholars will not know which mechanisms affect which side of the two-sided market without further investigation. In a related vein, economists have more recently concerned themselves with the possible 'frictions' that may persist in a labor market (Mortensen 1986, 1988). Their recent revelation of the importance of this 'black box' of hiring (Petrongolo and Pissarides 2001) allows scholars to better understand potential inefficiencies in labor marketing matching in general (Diamond 1981). In short, a more detailed understanding of the challenges employer's face is merited.

One reason scholars have yet to investigate this issue is the tremendous difficulty in gathering data on the individual job searches a firm performs. However, the particular setting under examination here, an online market for project based work (Elance.com), affords us this luxury. Here freelancers bid

on jobs posted by employers of temporary labor. Empirically, this is a particularly apt setting to study how the choice set of job candidates affects employer decisions for several reasons. First, the nature of the context affords an analyst multiple opportunities to observe an employment process as multiple jobs are posted with multiple bids by a variety of freelancers. The setting also tracks all past experiences (on the website) of each freelancer, allowing me the rare opportunity to account for the past experiences of all job candidates. Lastly, a limitation to most work on employment, and indeed categories and markets more generally, is the lack of observability into the choice set that an audience member is faced with. Here, the complete list of applicants for each job is visible, and indeed, is the focus on this article.

CATEGORIES, CONTEXT, AND COMMENSURATION IN LABOR MARKETS

Categories pervade social life by helping us lump and separate objects into discernable groups (Zerbuval 1997). Categories are socially recognized groupings of like-objects, and serve to circumscribe similar items and exclude dissimilar ones (Rosch 1973, Hannan, Pólos, and Carroll 2007). This parallels our universal inclination to partition an assortment of complex items or objects into manageable and socially understood classificatory clusters, reducing the requirement that we see each instance anew (Fiske and Taylor 1991; Murphy 2004). For example, firms are divided into industry groups (Zuckerman 1999), films are identified by genres (Hsu 2006), software companies are partitioned by their software functions (Pontikes 2012), and restaurants are identified by cuisine type (Kovacs and Hannan 2014). Because categories usefully group like-objects, people become familiar with what to expect of an object that is categorized in a certain way. Identification with a category leads those expected characteristics to be applied to that object by outside observers. So when faced with a choice as to what movie to watch, audiences can rely on default assumptions as to what characteristics a movie will have given what genre it has identified itself with. If a moviegoer wants to see a funny movie, she will expect to find that in a film identified as a comedy.

In essence, sociologists that study market behavior have expanded on previously identified race or gender categories to include other socially consequential distinctions among actors. For example, in

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labor markets, one's past experiences are often identified and separated into categorical distinctions as well. Instead of experiences being described in detail, job applicants submit resumes or CVs which summarize past accomplishments. Past experiences that are classified helps us easily understand what a potential employee is capable of. For example, in the labor market for feature films, the genres of films in which an actor has worked in serves to convey the breadth (or lack thereof) of their experiences (Zuckerman et al 2003). Categorization, in this case, usefully solves the problem of comprehension because the alternative to using simple and recognized classifications would be for job candidates to include detailed descriptions of their past work experiences which would require extensive effort by a potential employer to understand. Instead, work experiences that are categorized by firm or industry (as a past employer's name would indicate), function or role (as past titles would imply), or even by particular skills (such as functions) makes it easier for an employer to understand what a candidate is capable of.

One function that categories serve in labor markets is to demarcate items into similar groups (Zuckerman et al 2003, Ferguson and Hasan 2013). Employers see experiences labeled in identical categories as comparable. Experiences in different categories are more difficult to compare because they hold little similarity to one another (Leung 2014). These classificatory distinctions are useful in labor markets because categorized experiences act as a proxy for understanding the abilities a candidate possesses. Because categories serve to circumscribe similar tasks and exclude dissimilar ones, as a first order approximation, ones experience in a particular category demonstrates facility with that category and also likely implies inability in another, possibly incompatible one. Zuckerman and his colleagues (2003) investigation of typecasting in the feature film industry showed that those actors who had worked previously in a particular genre were most likely to secure future work in that same genre. This was because lacking any other quantifiable measure of ability, the casting directors had to rely predominantly on an actor's past experiences to evaluate their future ability. Therefore, the best guarantee of success in one film genre would be previously demonstrated success in that genre.

To the extent that categories serve to usefully partition "actual" differences in tasks they encompass (that acting in a horror movie requires different skills than acting in a comedy), then we

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should expect the translation of experiences across categories to be problematic. As is the case in the feature film industry, casting directors were seldom convinced that experience in one movie genre was easily transportable to another (Zuckerman et al 2003). This was because they were unsure as to how the skills from one film would be able to satisfy the demands of a role in another genre. For example, in order to successfully act in a comedy, it is reasonable to assume that the actor needs to be funny. However, it would be unclear how the ability to be funny would help the actor succeed in a horror movie, where presumably, they would have to be skilled at acting frightened. An implication of this is also that job candidates who attempt to string together a highly incompatible sequence of experiences will also be penalized (Leung 2014) because it represents an erratic career trajectory. More general examples where spanning incurs penalties include movies that span genres (Hsu 2006), eBay sellers who list items across multiple product categories (Hsu et al 2009), wines from winemakers who transgress modern and traditional styles (Negro and Leung 2013), those seeking personal loans from groups with disparate purposes (Leung and Sharkey 2014), software companies who produce products in several categories (Pontikes 2012), and restaurants that combine elements from several cuisines (Kovacs and Hannan 2014).

This paper reorients the discussion to focus on how categories influence how buyers engage in purposeful evaluation of potential candidates. Comparisons between options are ultimately cognitive processes based in judgments of similarity (Tversky 1977). In order to make comparisons, decision makers attempt to align items on the basis of the similarity that they exhibit with a category exemplar (Smith and Medin 1981), to one another (Markman and Genter 1996), or to some past experience (Smith and Osherson 1989). That is, we compare the choices we have with one another and attempt to identify the best choice. This comparison process can either be complicated or eased by how similar the objects under consideration are with one another. The more characteristics a set of options share with one another, the more similar they will be to one another. Take the example of deciding among several of commodity-like products, such as a pound of nails with identical properties, i.e. they are the same size, material, shape. If they merely vary by price, then this decision would be one of "alignable differences" (Markman and Gentner 1996). That is, all the characteristics among the items under consideration exhibit

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high commonality. In which case, the comparison is then relatively straightforward. One only needs to decide how much they are willing to pay. However, hiring decisions are rarely this simplistic. I expand on this below.

A HIRING DECISION

Consider a hiring decision. Skills that are required for success at a job may not always be clear or easily discernable. For example, the hiring of a new junior faculty colleague is fraught with complexity. Often there is very little guidance beyond a general preference for a particular discipline or area of study that would qualify a candidate. In addition, there are a myriad of skills that may determine success of a junior faculty – be it research ability, teaching acumen, or their camaraderie. Here, the employer is limited by the pool of candidates that they are able to observe, namely those that apply. These situations are considered "constructive choice" situations (Tversky and Simonson 1993, Bettman et al 1998). That is, instead of an employer having absolute confidence in knowing what they want *a priori*, they will have to rely on the choice set presented to them and then attempt to form preferences among this group (Iyengar et al 2006).

Evaluating candidates for a hiring decision could be approached in one of two ways – to satisfice or to maximize (Simon 1955, Schwartz et al 2002). Under a satisficing paradigm, the objective could be for an employer to identify the first candidate which minimally meets the objective they are seeking. In these situations, decision making is relatively straightforward. As long as any candidate meets the minimally identified requirements of the task, one of them is likely to be chosen. While this simplistic decision making heuristic may be applicable to some hiring decisions, it is reasonable to instead believe that as opposed to merely satisficing and choosing a candidate who meets our minimal expectations an employer will be more likely to attempt to maximize this decision's outcome. This is because a job candidate is someone that an employer needs to trust as the cost of hiring isn't trivial and poor decisions will have large and possibly far reaching consequences. In comparison, consider the decision to choose a bar of soap. The cost of a bar of soap is relatively inexpensive compared to a choice to hire, the variation

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in performance of a bar of soap will likely have less impact on our well-being (not only because it's likely a small part of our routine, but also because there's less variation in its ability to clean something), finally, if a poor decision was made regarding the soap, then we could easily switch to a different brand. On the other hand, the decision to hire someone differs dramatically. It likely is more costly, a longer term investment, and poor hiring decisions are very risky. Here, a decision maker will likely seek out the ideal candidate, as opposed to merely one that is adequate. To do so, all options in a choice set need to be examined.

In these situations, when presented with an increasingly divergent candidate pool, it will be more difficult to simply maximize on a single attribute. Indeed, there will be a challenge to even identifying the appropriate attributes to consider. As described above, the simple, 1st stage decision would be to find those applicants with relevant experiences and satisfice by choosing any of them. But in situations where the experiences of job applicants vary in how similar they are to one another or how relevant their experiences are to the task at hand – comparison becomes more difficult. Take a situation where the candidates all demonstrate appropriate past experiences, yet, they differ in their other, additional, experiences. As in the case of hiring a sociologist, all candidates with PhD training as sociologists should be qualified. Beyond this, however, the candidates may vary widely in their research interests or their teaching styles.

In the particular case of a labor market hiring decision, because differently categorized experiences are treated by employers as likely incompatible, disparately categorized past experiences of applicants to a job make it hard for an ideal candidate to be identified. This is because differently categorize experiences will be seen as incompatible because their attributes do not line up with one another. The disparate backgrounds of different candidates will thereby increase the cognitive effort involved in evaluation (Gourville and Soman 2005). For example, it is difficult to compare experiences in qualitative research to experiences in quantitative research. The standards for quality are different, the questions that can be answered differ, and the project time frames and the training required vary tremendously as well. So cross category comparisons of past experiences becomes cognitively

challenging. This is why decision makers face more inherent conflict when attempting to make decisions which require increasing numbers of tradeoffs (Tversky and Shafir 1992). Two alternatives, which vary along incomparable dimensions, may suggest that they would have different advantages and disadvantages. So the qualitative researcher I introduced above may be more apt to delve deeply into a phenomenon or setting whereas a quantitative researcher may be more able to identify causal linkages. This leads to conflict in a decision maker's mind because tradeoffs have to be made regardless of the choice (Gourville and Soman 2005). In addition, when motivated to find the best alternative, we will likely regret the choices we don't make (Iyengar and Lepper 2000) making it even harder to decide.

Categorical differences in a choice set should therefore affect the decision to hire at all. The effort required to perform a thorough evaluation is not trivial so avoidance from difficult and hard to reconcile choices is often a reasonable defensive mechanism (Festinger 1962). Certainly, in situations where it is hard to identify an obviously superior alternative, not making a choice is often the preferred alternative (Tversky and Sharif 1992). In a hiring decision, one could choose not to hire anyone at all and perhaps repost the job. So in situations where there is less overlap in the past categorized experiences of applicants in a choice set, we should expect there to be a lower likelihood any is chosen at all. Formally,

> *Hypothesis 1:* The less category overlap in experiences there is between job candidates in
> a choice set, the less likely an employer will choose any of them.

The argument above hinges on the fact that an employer will most likely take a maximizing perspective to their employee search. While on average we believe this to be the case, moderators which alter how likely an employer is to seek to maximize their hiring choice should commensurately alter the effect of the overlap of the job candidates on employer decisions to hire. For example, satisficing is generally portrayed as a quicker method by which to make a decision. To the extent employers may vary in how urgent a job is needed to be filled, they would also vary in the amount of time they would have to evaluating the candidates. Without the luxury of time to be spent in considering the multiple choices one could decide among, a simpler method of decision making may be employed. If this were the case, to the

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extent the cognitive mechanisms I'm suggesting are operating, then we should expect to see that the effect of job candidate overlap in past experiences on the likelihood of making a hiring decision to be attenuated by the urgency of the job itself.

Hypothesis 2: The effect of category overlap on employer choice to hire anyone will be attenuated by a satisficing approach to decision making.

Because we believe that the variation in the time taken to make a decision as well as the likelihood of a decision being made at all arises because cross category comparisons are difficult to make, then a better understanding of what the categories entail should alter this effect. I refer to this as fluency (Hsu et al 2009), whereby a market participant has increased facility with the categorical schema that can be accessed and utilized. Yet, the effect of familiarity with the characteristics of each category on cross category comparisons is uncertain. On one hand, consider the example of a naïve 1st year PhD student, who is introduced to academic literature for the first time. Their understanding as to which publications are academically rigorous versus those that are less so will likely be poorly developed. This is due, in part, to their experience in the field. As they become more savvy consumers, gained through reading and engagement with the research - the students should gain a better understanding as to what elements of an article will be considered academically rigorous and which are less so.

On the other hand, developing increased awareness of a categorical schema may lead an employer to actually see more distinctions among the various categorical offerings, that familiarity breeds differentiation (McClelland and Chappell 1998). This is because increased nuances between categories are more recognizable as one becomes more familiar with them. Take, for example, the hiring of a junior faculty member again. While the differences between those applicants with sociological training and economic training are likely to be recognized by even the most naïve employer, more experienced faculty will likely begin to consider the nuances between a qualitative and a quantitative sociologist or between those that study demography from those that study organizations. Cognitively, an in-depth understanding

of the various categories leads to increased recognition of the potential differences that could exist beyond the generally accepted category structure. The more familiar with the items under consideration, the more the differences come to the fore (Murnane and Shiffrin 1991). This should serve to exacerbate the difficulty in choosing an employee as a function of the myriad of applicant background. Formally,

> *Hypothesis 3:* The effect of category overlap on employer choice to hire anyone will be exacerbated as an employer gains greater fluency across categories.

AN ONLINE LABOR MARKET

Following a similar trend in tangible product markets, labor market hiring has begun to move online. The recent proliferation of online "crowd-sourced" labor markets that mediate employers and employees, such as Monster or Career Builder; or ones that specialize in temporary contract labor, such as oDesk or Elance exemplify this change. Elance.com, the site under study here, is the oldest firm in this arena and acts as a virtual marketplace where buyers of a broad range of business services find and hire independent professionals on a contract basis to work remotely. Freelancers (bidders) bid on projects that employers post to the website. See Figure 1 for a sample job listing. There are currently over 100,000 jobs posted each month and over 2 million freelancers located worldwide on the website. Since founding in late 1999, cumulative transactions worth over $1 Billion have been completed on the website with an average job value of over $600 in 2014.

[Insert Figure 1 about here]

As a necessity, given the volume of transactions, Elance.com job listings are organized into job categories that represent conventionally recognized divisions of tasks. Examples include "Website Programming", "Administrative Assistance", "Translation Services", and "Logo Design." (See Appendix for complete list.) In offline markets, staffing agents often mediate the relationship between a contractor and their employers by assisting the freelancer in tailoring their past experiences to best fit a job. To the

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extent that job categories lead to beliefs by employers of a particular candidate's suitability to that task, then a candidate who is able to craft a resume that demonstrates relevant experience and progress will be advantaged in securing subsequent work. So contractors and their staffing agents often modify and frame a freelancer's past experiences to convey relevance (Barley and Kunda 2004, Osnowitz 2010) with the hope that past jobs or skills that match what an employer is seeking will increase the likelihood their freelancer will be hired.

Once a job is listed, freelancers bid on it. Bids include the stated price but the lowest bidder is not automatically chosen. See Figure 2 for a list of bids by freelancers. Employers receive approximately eight bids on average for each job they post. A buyer can choose to hire whomever they wish. In order to choose, a buyer will have the opportunity to look closer at each freelancer's background information.

[Insert Figure 2 about here]

In contrast, online markets often capture and display all of a seller's previous transactions. Elance is no different. A freelancer's history of past completed jobs on the website is visible and identified by their job category. See Figure 3 for an example of a freelancer's profile. A freelancer's list of jobs then poses as their online career and is immutable when displayed to employers. In making a decision, buyers have access to this online profile. Freelancers are able to work in any job category they wish, so they can accumulate disparate experiences. The bidding concludes within a timeframe established by the buyer, generally within a week, whereupon a buyer may decide to choose a winning bidder to perform the task. Note from Figure 3 that each job completed by the freelancer is listed with the category the work occurred in, which further highlights the distinctions between job types.

[Insert Figure 3 about here]

DATA AND METHODS

I received a download from Elance of their operational database, which included all job posting details, all freelancer past histories, and, most crucially, the bidders for each of the jobs posted from their inception in December, 1999 to April, 2008. In this timeframe, there were 301,740 job postings by 174,466 unique employers across all the job categories. These job postings received 3,961,856 bids from 30,626 unique freelancers. The average freelancer, therefore, made 129.4 bids, with a standard deviation of 625.8.

Dependent Variables

The likelihood of a job posting closing with a winner being picked by the buyer is my dependent variable of interest. Once a pre-determined number of days is up, a buyer much choose a freelancer to complete the project. However, approximately 50% of transactions end without a bidder being chosen. Specifically, of the 301,740 jobs posted in my dataset, 153,014 (50.7%) of them ended with a freelancer being chosen to complete the job. Exchange does not occur in these instances. I coded those posting which closed with a winner =1, otherwise 0.

Independent Variables

My main independent variable of interest is the amount of overlap among the past job experiences of all the applicants to each job posting. Here we are attempting to calculate the similarity of a set of past experiences. I use the Jaccard index as a measure of job category overlap between all bidders for a job. For example, if freelancer 1 worked in categories A, B, C, and D while freelancer 2 worked in categories A, C, and E – then the measure of their overlap in past experiences would be 2/5, or .4. With more than 2 bidders, the overlap measure was calculated between all (pairs of) bidders for each job and then averaged. Specifically, overlap among bidders for each job is taken as the average overlap between each pair of bidders, with the overlap of each dyad calculated as the intersection of their individual categorical past

experiences (as a count of identical categories) divided by the union of their past category experiences (the count of total categories). Formally,

$$Bidder\ Overlap_k = \frac{\sum_{i=2}^{n} \sum_{j=1}^{i-1} Jaccard_{i,j}}{\binom{n}{2}},$$

$$Jaccard_{i,j} = \frac{(i \cap j)}{(i \cup j)}$$

Where the Bidder overlap of job k is defined as the average Jaccard overlap that each pair of different bidders i and j have with one another in past categories of jobs they have completed before posting their bid. Note, we do not include the overlap of identical candidates (i.e. Jaccard Overlap$_{i,i}$). This measure can range from 0 to 1, with 0 meaning none of the bidders had any past experiences in common and 1 meaning all bidders had the exact same past experiences.

[Insert Figure 4 about here]

Figure 4 plots the histogram of the Bidder Overlap measure of all jobs – partitioned by those that ended with a freelancer being chosen versus none being chosen. There are two aspects of note from the diagram. First, that the measure of bidder overlap is Gaussian in distribution, with a well identifiable mean and standard deviation. Second, the bidder overlap measure for any job posting ranged from 0.03 to 1 with a mean of 0.39 and a standard deviation of 0.14 while for jobs that ended with a winner being chosen, the mean increases to 0.41. As depicted by Figure 4, we can see there is a slight shift in the two distributions, where the jobs which ended with a winner were more prevalent than those which didn't end with a winner on the right-hand side tail. Jobs which ended with no winner being chosen were over-represented on the left side of the diagram. This is suggestive of my main contention, though certainly more thorough analyses are necessary.

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Control Variables

I attempted to control for a variety of factors which may hinder identification of my mechanism at the level of the job, the employer, as well as the set of freelancers bidding. At the level of the job, the most obvious alternative explanation is the complexity of the job. The more complex the job, the greater variety of freelancers may be inclined to bid on it because complexity may suggest a greater variety of skills may be applicable to the task. This could subsequently also affect the difficulty in choosing a bidder because a complex job will require more deliberation than a simple one. In order to control for this potential endogeneity problem I included two control variables. First, the average cost of all the bids received should serve as an indicator, at least from the perspective of the freelancers, of how complex the job is. I also include a measure of how urgent the job is. I measure this by first calculating the number of days an employer designated to complete their job, then assigning those jobs which were below the median in number of days as 'urgent' while those above as 'non-urgent'. The median budgeting time for a job was ~7 days. Second, from the employer's perspective, I also included a count of the words in the job description that they post. This should capture the effort expended in explaining the task and the details the employer thought necessary to include – yet another measure of the complexity of the task.

In addition to these controls for endogeneity of a job's inherent complexity, I also included controls at the level of the freelancers bidding. Specifically, I included the average experience of all the bidders in the focal job category they are bidding on – measured by the average number of jobs completed in the focal category. Recall that if employers merely choose according to experience in the focal bidding category, this measure should increase the likelihood a freelancer will be chosen as well as the speed at which this will occur. Relatedly, the greater this measure, the greater likelihood of increased overlap of the bidders as well. I also included the total number of bids the job received, as that may also delay a decision by making the decision more difficult. Finally, I also included variables at the level of the employer as well. Specifically, I include the experience the buyer had in that category (number of times they have bought in the focal category in the past) and the number of different categories the buyer has purchased jobs in. These variables are updated each time a freelancer or employer completes a job and is

lagged to capture their last, most recent, experience. Summary statistics and correlations are presented in Tables 1 and 2 below.

[Insert Tables 1 and 2 about here]

MODELS AND RESULTS

Because the dependent variable of interest, whether a winner was picked or not, was dichotomous in nature, a logistic regression seemed most appropriate. However, because of the interactions necessary to test hypotheses two and three, I ran and reported results of Linear Probability Models. I note that all results hold with Logistic Regression specifications as well. I included a Fixed-Effects specification clustered on employers as well as job category to rule out time-invariant heterogeneity between people as well as the different types of jobs posted on this website. Table 3 below reports the results. Model 1 includes only the control variables which generally behave as expected. Overall employer experience reduces the chances they will hire a freelancer after posting a job, perhaps because they post so often. However, the increased experience an employer has with the specific job category under consideration increase their likelihood of choosing to hire. Fluency, as measured by an employer's breadth of categorical experiences decreases their likelihood of hiring. Complexity of the job, as measured by the number of words in the job posting, increases the likelihood of someone being hired. Though this may seem counter-intuitive, the measure may also be picking up how serious an employer is since these results are estimated within a particular job category, the inherent heterogeneity of the complexity of the jobs is mostly controlled for. The larger the job and the greater the variation in the bods received, the less likely someone will be hired. Finally, both increased experience between the employer and applicants as well as the increased experiences the bidders have with the focal job category increases the likelihood a winner will be chosen. Urgent jobs also are more likely to result in a hire.

[Insert Table 3 about here]

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Model 2 includes the independent variable of interest, bidder category overlap. Results support my first hypothesis - that the greater overlap in job experiences all bidders have, the more likely a buyer will pick a winner among them. Specifically, a one standard deviation increase in overlap in bidder categorical experience above the mean (holding all other variables constant at their means) will increase the likelihood a buyer will pick a winner by ~4% (0.33 x 0.13 = 0.04%). To test my second hypothesis, I include the interaction of bidder overlap with urgency in Model 3. As predicted, the effect of overlap on the increased likelihood that a winner will be chosen is dampened when the employer is in a hurry to complete their job, as reflected by the negative and significant coefficient of this interaction (β=-0.2154, $p<0.001$).

Visually, I plot the marginal effect of increased overlap and likelihood of making an offer as a function of the urgency of the job in Figure 5 below where the horizontal axis is the overlap of bidder experiences and the vertical axis is the point estimate of the likelihood of a job ending with someone being hired. First note that the likelihood of purchase is higher overall for those more urgent jobs, the upper line, compared to the lower one, which are less urgent jobs. Note also that the main effect of overlap still persists, that both lines are increasing as overlap increases. However, more germane to my argument, the effect of increasing overlap in the past experienced of the bidders is much less pronounced, that is the slope is lessened, on those more urgent jobs. Therefore, in support of hypothesis two, employers that are merely satisficing are less prone to commensuration issues that when they have the luxury of maximizing on their decision.

[Insert Figure 5 about here]

Model 4 tests my third hypothesis by including an interaction between the fluency of a buyer's categorical understanding and the category overlap of the bidders. Here, results support my contention that as a buyer gains greater breadth of experience, the increasing overlap of bidders actually decreases the likelihood that the employer will make an offer, exemplified by the negative and significant (β=-

0.0335, p<0.05). I illustrate the marginal effects in Figure 6 below. Specifically, note that the main effect of overlap continues to persist, with the likelihood of hire increasing across all levels of fluency and as overlap increases. However, note for lower levels of fluency, (upper line) that as overlap increases, the decision to hire increases in likelihood at a greater rate than for those with higher levels of fluency (lower line). Note the lack of a difference in effect on the very low end of bidder overlap, which suggests to me that these situations suggest pools of candidates that are too different to even warrant an extended examination into their differences. However, the differences become much more distinct on the high end of the overlap spectrum, which I contend is a function of the fact that highly fluent employers of the categorical schema will still see nuances in differences among job applicants which may nominally seems identical.

[Insert Figure 6 about here]

Additional Considerations

As an additional analysis to triangulate my story, I investigated the effect of bidder category overlap on the price a buyer eventually chose to pay for the service. If my contention that increased overlap makes comparison between bidders easier, then we should expect to see that the price paid for such a listing would be lower as well. To the extent that increased overlap between bidders makes it easier for a buyer to choose among them because their past experiences are more alignable, then their basis of competition should orient on price. In short - lower differentiation between bidders should reduce competition to one over price because there's little else to differentiate them. Their experiences become more commoditized. This suggests that I should find that increased overlap between bidders to decrease the price a buyer pays for their services.

To test this, I rank ordered all bids for each job by price from 1 to 'n', where 'n' equaled the total number of bids received for that job. The lower the rank, the lower priced the bid. For each job, I then noted the eventual rank of the winning bid – i.e. if the winning bid picked was the lowest priced one, then it would be recorded as a 1, the second lowest price bid picked was coded a 2, etc. Note, I didn't use the

actual mean deviated price paid because there is tremendous heterogeneity between the costs of the jobs on the website, ranging from $50 for a logo design to several thousand for website programming services. I then estimated the effect of overlap in bidder experiences on this outcome. Because the dependent variable here is basically a count variable (1, 2, 3 etc), I utilized a negative binomial model (fixed-effects by buyer and job category). Results are reported below in Table 4.

[Insert Table 4 about here]

Results demonstrate a negative and significant effect of the overlap of bidders' past experiences on the eventual rank of the price paid for the job. That is as overlap of experience between bidders for a job increases, the buyer is more likely to choose bids that are lower priced. This is consistent with my contention that increased overlap between bidders makes them seem more similar and therefore easier to compare. As these dimensions of differences are eliminated (i.e. past experiences) competition then hinges on price. Note also that I did not use an absolute price as a dependent variable because, as simple economic theory would dictate, increased competition in the form of past job category overlap, will also drive the overall average price of the bids down as well. Hence, my results which examine the within job rank of the eventual winner is insensitive to this between job heterogeneity.

Additional concerns regarding the endogeneity of my results could arise if employers who are more desperate to hire are also more prone to getting a narrower range of applicants. For example, perhaps those most serious employers are also the ones which are better at attracting more focused freelancers, thereby leading to the observed correlation. While my fixed-effects specification by employer should have solved some time-invariant heterogeneity concerns, one can still vary in seriousness between jobs, which my inclusion of job posting word count attempted to capture. Despite this, an idea test would be for me to somehow demonstrate that an exogenous shock which affected the overlap of freelancers applying leads to the expected observed outcome. I was fortunate enough to identify one.

Recall for each job, an employer is required to write a description of the task. Not surprisingly, these can vary tremendously on their level of detail and, commensurately, on their ability to draw a focused set of applicants. At one point in their history, Elance had market makers in place whose responsibility was to review each job posting to ensure their quality and suitability for the category it was posted then to identify particularly suitable freelancers for those jobs. Kohler and Applegate's (2000) Elance case states "…market makers would contact the buyer and suggest changes to the posting to ensure consistency of categorization and clarity of descriptions" (Kohler and Applegate 2000: 4). In essence, these market makers assisted employers in articulating their needs and ensured the appropriate freelancers would understand and therefore bid on the job. Eventually, this function was eliminated, leaving employer with no assistance in drawing appropriate freelancers to their job. Given this, we should expect to see that job postings that were reviewed by these market makers will garner more focused bids than those not reviewed by them. In short, the timing, before and after this change, could be used as an instrument to proxy for the commensurability of job applicants.

[Insert Figure 7 about here]

Figure 7 above plots the average overlap of all jobs posted within a 30-day moving window over my observation window. The vertical dashed line identifies the period where the company switched from using market markers. Note the difference in average overlap of freelancers bidding on jobs in the time period prior to the elimination of these 'market makers' with afterwards. As expected, overlap among bidders was higher beforehand. Statistically, I estimated the likelihood of a job closing with a winner as a function of the job being posted before versus after this cutover. I limited my window of observation to one year before and one year after the change – in an attempt to reduce effects of time. In addition to job category fixed-effects, I included employer fixed-effects, to ensure that later entering buyers don't affect results. Results, not reported for brevity, support my contention that jobs posted after the elimination of market makers were significantly less likely to close than those posted before. This suggests that the

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exogenous change in how focused a group of bidders an employer received affected the likelihood of their decision to hire or not.

Finally, as an additional check on my story that the observed reduction in the likelihood of hiring is due to the cognitive difficulty in commensuration among a set of bidders with low categorical overlap, I also investigate whether the same overlap variable induces employers to spend more time deciding on which applicant to hire, conditional on hiring. Note, this subsets my data into only those jobs which end with a freelancer receiving a job. In analyses unreported for brevity, I find that of those jobs which ended with a winner being picked, jobs which attracted bidders with more overlap were likely to be awarded quicker (in days) than those with less overlap.

DISCUSSION

In this paper, I reorient the question in employment and labor market studies by examining the outcome of job searches for the employer. Specifically, I've asked, what causes job searches to fail? Hiring and recruiting can be costly, yet there is very little theoretical work which examines these effects on the employer. Because an employer will want to maximize (as opposed to satisfice) the decision to hire, they are more likely to hire a freelancer (and spent less time deciding), if the applicants had more similar past experiences. Evidence also demonstrated that the difficulty in commensuration was exacerbated by the categorical fluency of the employer. Finally, the urgency of the job was found to ameliorate the commensuration difficulties faced by employers because they simply had less time to make a decision on who to hire.

It is notable that this paper further unpacked the mechanisms which occur at the hiring interface – which are currently still considered a 'black box' to scholars of employment and labor markets. Specifically, I have conceptualized hiring as a decision to be made among a panel, or choice set, of applicants – which I feel is a much more realistic view of hiring. This lies in contrast to previous studies which examine the set of all applicants an organization may have received over a period of time – then identifying who was or wasn't extended an offer. The benefit of this more nuanced view that I present is

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realized when taking into account the underlying assumptions of labor market queues (Reskin and Roos 1990) as well as theories which take into account the interactions between job candidates and their employers, but with only visibility into the final outcome of the hiring decision.

More generally, a particularly interesting tension that is highlighted by this paper is how a seller's motives to differentiate themselves from others appear to be at odds with facilitating the comparisons by a buyer. From a seller perspective, categorical coherence merely results in their inclusion into a short-listed set of viable options (Zuckerman et al 2003). Yet, after this 1st stage, it is suggested that a strategically advantageous position for a seller is to differentiate themselves from others within the choice set – thereby assisting them in standing out from the crowd. They therefore straddle an 'optimally distinct' position (Brewer 1991). However, to the extent my theories are operating, this encouragement that seller's attempt to distance themselves from one another, particularly in the second stage, results in a buyer suffering the consequences of increased difficulty in candidate comparisons, thereby reducing market efficiency in terms of transaction closure. Seller motivated actions to differentiate lead to buyer difficulties in making a decision.

This paper also re-addresses the literature on niche overlap (Dobrev, Kim, and Hannan 2001, Hannan and Freeman 1989) by focusing the discussion on the outcome of the audience. While past scholarly research examined the effect of niche crowding on organizational mortality, this paper instead suggests how niche crowding can ironically increase market functioning by easing comparison processes. The past literature on niche overlap identified the increased competitive pressure that is felt by organizations when they enter a niche in increasing numbers. Quite simply put, increased entry into a niche means there are more firms that compete against each other for limited resources in that niche. Interestingly, this paper would suggest that having firms with more niche (or categorical) overlap would actually facilitate transactions. While not an outcome which favors an individual organization, increased niche overlap may benefit market functioning overall.

By highlighting the importance of the choice set an employer is faced with, this paper also raises the concern as to whether a single-sided perspective of what is inherently a two-sided market is

warranted. For example, past studies of labor markets which have utilized a two-stage market model and categories (Zuckerman et al 2003) have proposed that candidates with more focused identities are preferred over those with less coherent backgrounds. However, without an understand as to the mechanisms which drive candidates to choose which jobs they apply to, we are, at best, left with a partial understanding of the phenomenon. To the extent that the choice set available to an employer influences their eventual decision, future work should consider more carefully the antecedents to candidate application in two-sided labor markets (Fernandez and Sosa 2005).

There are at least three potential extensions initiated by this study. This paper's findings suggest a potentially fruitful avenue for future research is to examine within employer variation, perhaps over time. For example, we can ask, do employers "learn" to hire? That is, given the finding that more experienced employers make decisions differently from less experienced ones – does this also imply that the decisions are better as well? Theories of statistical discrimination (Becker 1957) should suggest that an employer who has experience hiring may learn from whom they have hired in the past and usefully incorporate this knowledge into future hires. Yet, taste-based discrimination models would imply that there will be no change to how one hires, regardless of their experience. Empirical settings, such as this website, allow us to follow the history of an employer's choices and thereby potentially elucidating us on issues such as these.

Second, and related, an interesting extension could be to understand just how the use of categories evolves and is learned over time. For example, future work could examine how the effect of being faced with a divergent labor pool results in a feedback loop to the buyer. If a job posting for a position garnered widely divergent applicants, we could expect that a buyer learn from this a perhaps re-evaluate either how they worded the job posting, or whether they have been myopic in past job searches. This learning process should eventually increase the overall efficiency of labor market functioning. To the extent that job categories and needed skills remain fixed, an employer could improve the way they seek and recruit candidates to apply.

Third, a closer examination as to how market transactions are further influenced because of categorical divisions in reporting of past experiences could be fruitful as well. For example, are there systematic differences in which buyer eventually gets picked given a divergent pool of applicants? Past research would suggest that specialist freelancers would be more attractive, as they are likely to possess the abilities to successfully perform a task. However, perhaps those freelancers with more variation in their past experiences (generalists) will seem more attractive to a buyer if they are faced with widely divergent bidders. To the extent that a buyer faced with a disparate group of bidders may re-evaluate what they originally thought they needed, they may be less sure of a precise skill and instead prefer someone with broader experiences.

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FIGURE 1
JOB POSTING

Scraping data from a website

IT & Programming > Other IT & Programming

Job Status: Selecting Candidate | Budget: Less than $500

Posted: Sat, Nov 23, 2013 | Fixed Price Job

Location: Anywhere | Elance Escrow Protection

Start: Immediately | W9 Not Required

My Team (1) | 6 invited

Hi there,

I need someone to scrape data from a website and provide the data and the code used to me. The code should be in Python or Perl.

Specifically, I need the following four datafields scraped from the metacritic.com website, for only the movies.

- Movie Title
- Production Company
- Release Date
- Home Release Date

I have attached a sample screenshot of the page from which this data will come from. Note, I've circled the fields I would need scraped.

Webpage: http://www.metacritic.com/movie/the-worlds-end/details

Title: The World's End
Production: Relativity Media
Release Date: Aug 23, 2013
Home Release Date: Nov 19, 2013

FIGURE 2
SAMPLE OF BIDS RECEIVED

Kalpesh Tawde ☆
🇮🇳 India | Rate: $15/hr | IT & Programming [2] | 27 jobs | $3,618 Earnings | ★★★★★ 4.9 | Portfolio

Rate Proposal ○○○○○

$300.00
Delivery within 3 days

Expand Proposal ▼

⊖ Hide   **Select**

B. D. ☆
🇷🇴 Romania | Rate: $15/hr | IT & Programming [3] | 8 jobs | $2,888 Earnings | ★★★★★ 4.8 | Portfolio

Rate Proposal ○○○○○

$273.97
Delivery within 1 week

Expand Proposal ▼

⊖ Hide   **Select**

Malik Khan ✓ ☆
🇧🇩 Bangladesh | Rate: $15/hr | IT & Programming [2] | 0 jobs | $0 Earnings | ☆☆☆☆☆ 0.0 | Portfolio

Rate Proposal ○○○○○

$219.18
Delivery within 2 weeks

Expand Proposal ▼

⊖ Hide   **Select**

Salman Tariq Mirza ☆
🇨🇦 Canada | Rate: $14/hr | IT & Programming [1] | 0 jobs | $0 Earnings | ☆☆☆☆☆ 0.0 | Portfolio

Rate Proposal ○○○○○

$219.18
Delivery within 3 days

Expand Proposal ▼

⊖ Hide   **Select**

Liu H. ☆
🇨🇳 China | Rate: $20/hr | IT & Programming [8] | 56 jobs | $6,648 Earnings | ★★★★★ 5.0 | Portfolio

Rate Proposal ●●●●●

$200.00
Delivery within 1 week

Expand Proposal ▼

AWARDED

FIGURE 3
FREELANCER PROFILE PAGE

Liu H.
Python

Hire Me »

China | Shaoguan, Guangdong | 7:15 am Local Time

Overview

Minimum Hourly Rate $20

I'm skilled in Web Scraping, Data Mining, Automatically, Networking, etc. Happy to help you. Thanks.

Read More »

Job History

Private Job
Dec 6, 2014 | Data Analysis | Private | Working

Private Job
Dec 6, 2014 | Web Programming | Private | Completed | ★★★★★ 5.0

Private Job
Nov 27, 2014 | Database Development | Private | Completed | ★★★★★ 5.0

Private Job
Nov 19, 2014 | Database Development | Private | Completed | ★★★★★ 5.0

View All »

My Snapshot

All Categories ▾

12 months | Lifetime

Jobs	56	Total
	58	Milestones
	88	Hours
Reviews	48	★★★★★ 5.0
	99%	Recommend
Clients	14	Total
	43%	Repeat
Earnings	Private	Total
	Private	Per Client

Identity

Username	liuhz
Type	Individual 👤
Member Since	April 2013
Elance URL	http://liuhz.elance.com
Verifications	$ ☎ 🌐 0

TABLE 1
SUMMARY STATISTICS
(N = 167,299)

Variable	Mean	Std. Dev.	Min	Max
Winner Picked = 1	0.562	0.496	0	1
Total Number of Bids	12.009	11.199	0	123
Overall Employer Experience (logged)	1.179	1.172	0	7.277
Employer's Category Experience (logged)	0.241	0.690	0	7.226
Number of Different Category Purchases (logged)	1.098	0.786	0	3.713
Word Count of Listing Description (logged)	4.464	1.372	0	6.716
Average of All Bids (logged)	5.355	1.818	0	13.342
Standard Deviation of All Bid Amounts (logged)	4.614	2.067	0	13.790
Previously Worked with Employer (Flag)	0.075	0.264	0	1
Maximum Bidder Experience in Category (logged)	2.877	1.570	0	7.365
Urgent Job = 1	0.554	0.496	0	1
Category Overlap of Bidders	0.342	0.131	0	1

TABLE 2

CORRELATIONS

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1)	Winner Picked = 1	1										
2)	Total Number of Bids	0.110	1									
3)	Overall Employer Experience (logged)	0.052	-0.046	1								
4)	Employer's Category Experience (logged)	0.105	-0.035	0.544	1							
5)	Number of Different Category Purchases (logged)	0.053	-0.029	0.866	0.247	1						
6)	Word Count of Listing Description (logged)	0.269	0.245	0.232	0.088	0.315	1					
7)	Average of All Bids (logged)	0.143	0.295	0.163	0.032	0.258	0.743	1				
8)	Standard Deviation of All Bid Amounts (logged)	0.048	0.300	0.106	-0.021	0.196	0.581	0.868	1			
9)	Previously Worked with Employer (Flag)	0.196	0.006	0.258	0.375	0.145	0.038	0.025	-0.012	1		
10)	Maximum Bidder Experience in Category (logged)	0.240	0.441	0.127	0.130	0.154	0.423	0.409	0.337	0.096	1	
11)	Urgent Job = 1	0.411	-0.005	0.073	0.032	0.122	0.225	0.109	0.001	0.107	0.168	1
12)	Category Overlap of Bidders	0.280	0.233	0.182	0.145	0.218	0.627	0.578	0.417	0.098	0.346	0.243

FIGURE 4
HISTOGRAM OF JACCARD OVERLAP FOR ALL JOBS, 1999-2008
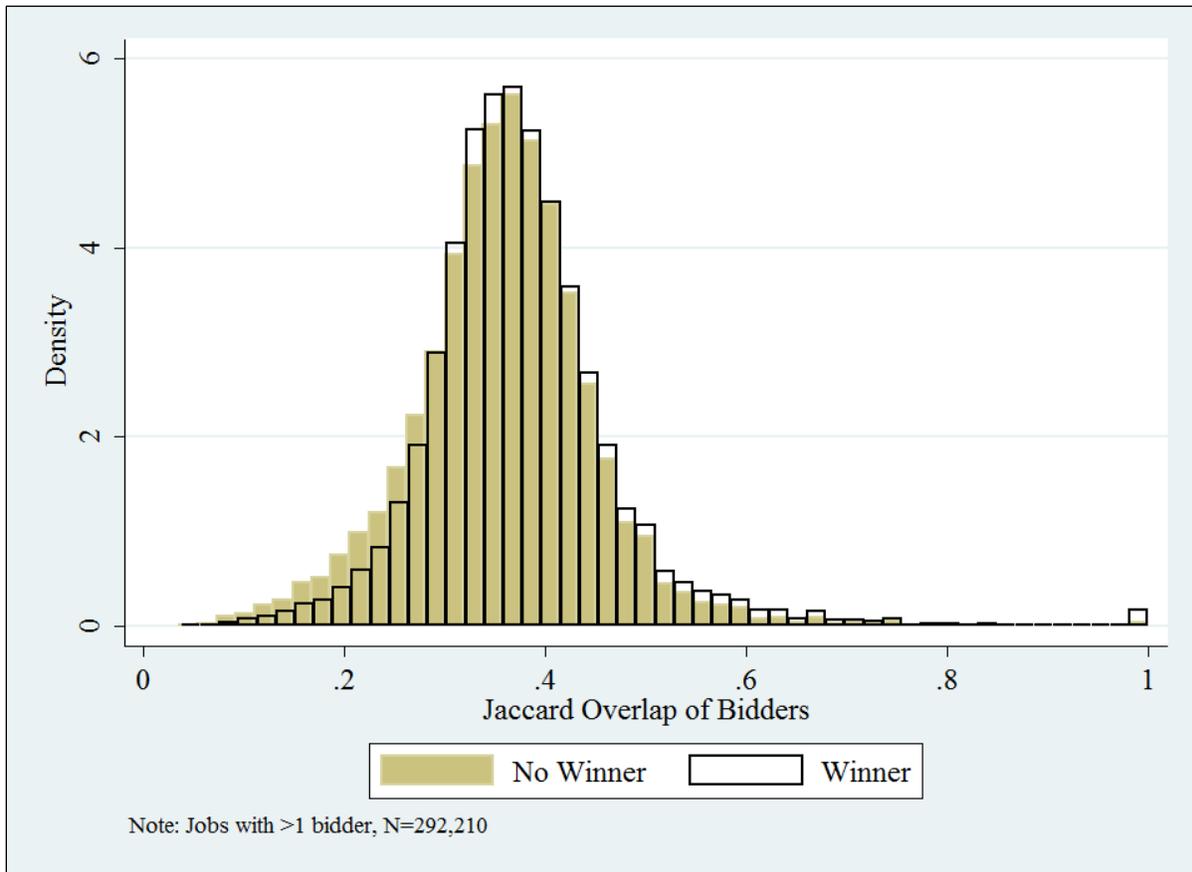(by Jobs with and without winners chosen)

TABLE 3
LIKELIHOOD OF LISTING RESULTING IN A WINNER BEING PICKED
(Fixed-Effects LPMs, Grouped by Employer and Job Category)

	(1)	(2)	(3)	(4)	(5)
Total Number of Bids	-0.0002	-0.0003*	-0.0003*	-0.0003*	-0.0003**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Overall Employer Experience (logged)	-0.0749***	-0.0739***	-0.0738***	-0.0740***	-0.0739***
	(0.0033)	(0.0033)	(0.0033)	(0.0033)	(0.0033)
Employer's Category Experience (logged)	0.0264***	0.0247***	0.0246***	0.0250***	0.0248***
	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Number of Different Category Purchases (logged)	-0.0327***	-0.0310***	-0.0309***	-0.0186*	-0.0198**
	(0.0044)	(0.0044)	(0.0044)	(0.0072)	(0.0072)
Word Count of Listing Description (logged)	0.0269***	0.0264***	0.0263***	0.0263***	0.0262***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Average of All Bids (logged)	-0.0255***	-0.0277***	-0.0277***	-0.0277***	-0.0278***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Standard Deviation of All Bid Amounts (logged)	-0.0085***	-0.0068***	-0.0069***	-0.0068***	-0.0069***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Previously Worked with Employer (Flag)	0.2246***	0.2224***	0.2228***	0.2225***	0.2229***
	(0.0046)	(0.0045)	(0.0045)	(0.0045)	(0.0045)
Maximum Bidder Experience in Category (logged)	0.0290***	0.0319***	0.0316***	0.0319***	0.0316***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Urgent Job	0.2939***	0.2909***	0.3694***	0.2909***	0.3690***
	(0.0026)	(0.0026)	(0.0091)	(0.0026)	(0.0091)
Category Overlap of Bidders		0.3272***	0.4672***	0.3706***	0.5057***
		(0.0125)	(0.0199)	(0.0236)	(0.0280)
Overlap X Urgent			-0.2154***		-0.2143***
			(0.0238)		(0.0238)
Overlap X Fluency				-0.0335*	-0.0303*
				(0.0155)	(0.0145)
Constant	-0.0288	-0.0243	-0.0252	-0.0243	-0.0252
	(0.0732)	(0.0730)	(0.0730)	(0.0730)	(0.0730)
Groups	19114	19114	19114	19114	19114
Min	2	2	2	2	2
Mean	8.8	8.8	8.8	8.8	8.8
Max	11249	11249	11249	11249	11249
Observations	167296	167296	167296	167296	167296

Notes: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

FIGURE 5
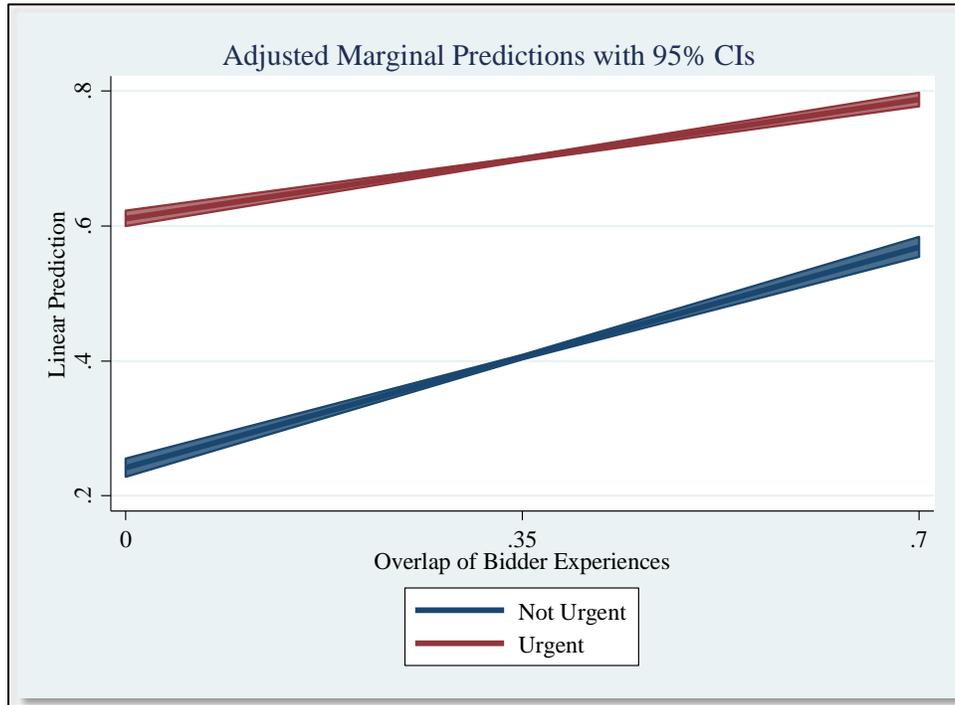**MARGINAL EFFECTS OF OVERLAP AND URGENCY ON LIKELIHOOD OF WINNER BEING PICKED**

Adjusted Marginal Predictions with 95% CIs

FIGURE 6
MARGINAL EFFECTS OF OVERLAP AND FLUENCY ON LIKELIHOOD OF WINNER BEING PICKED

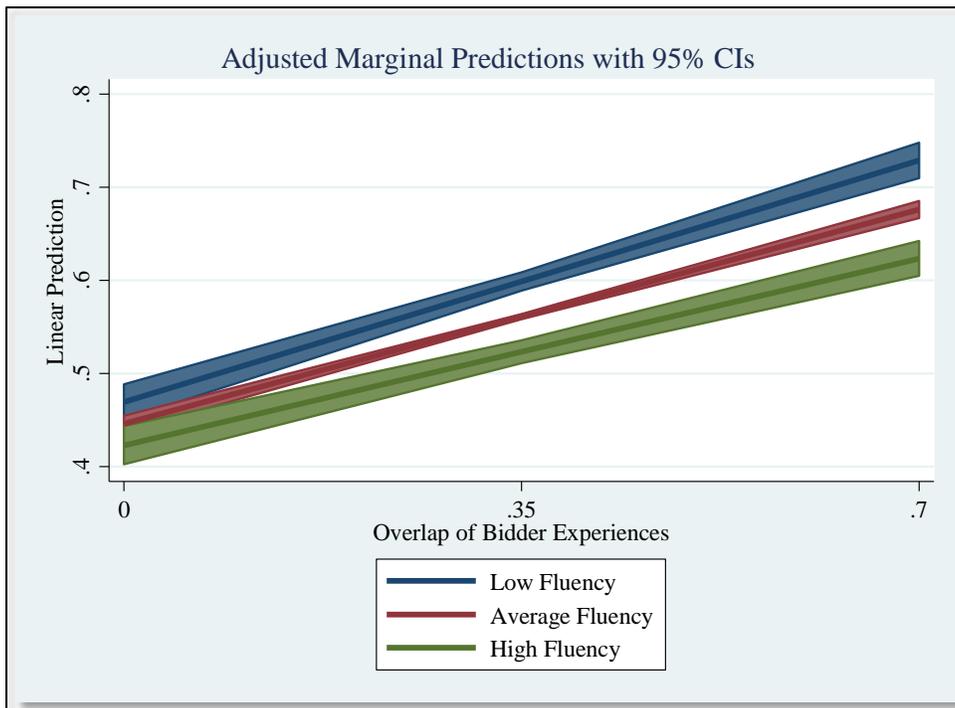Adjusted Marginal Predictions with 95% CIs

TABLE 4
ORDINAL RANK (BY COST) OF THE BID EVENTUALLY CHOSEN
(Fixed-Effects Negative Binomial Estimation Grouped by Buyer)

(Lower rank means lower priced bid)

	(1)	(2)
Average of All Bids (logged)	-0.0071***	-0.0037**
	(0.0012)	(0.0012)
Standard Deviation of All Bid Amounts (logged)	0.0335***	0.0311***
	(0.0008)	(0.0008)
Total Number of Bids	0.0216***	0.0217***
	(0.0000)	(0.0000)
Buyer's Category Experience	0.0014	-0.0005
	(0.0027)	(0.0007)
Number of Different Category Purchases....................	-0.0030*	0.0003
	(0.0014)	(0.0014)
Word Count of Listing Description (logged)..............	-0.0032***	-0.0023**
	(0.0009)	(0.0009)
Previously Worked with Buyer (Flag)........................	-0.0051**	-0.0044*
	(0.0021)	(0.0021)
Category Overlap of Bidders		-0.3360***
		(0.0094)
Constant..	-.06493	0.0222
	(.03633)	(0.0364)
Observations...	1960871	1960871
Groups..	57106	57106
Min:	2	2
Mean:	34.3	34.3
Max:	4057	4057
Log-Likelihood	-6424785.8	-6424149.6
Chi²	322646.90	323641.50

*Notes: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

FIGURE 7
30-DAY SPELLS OF AVERAGE BIDDER OVERLAP

Discontinuous Variation in Average Bidder Overlap
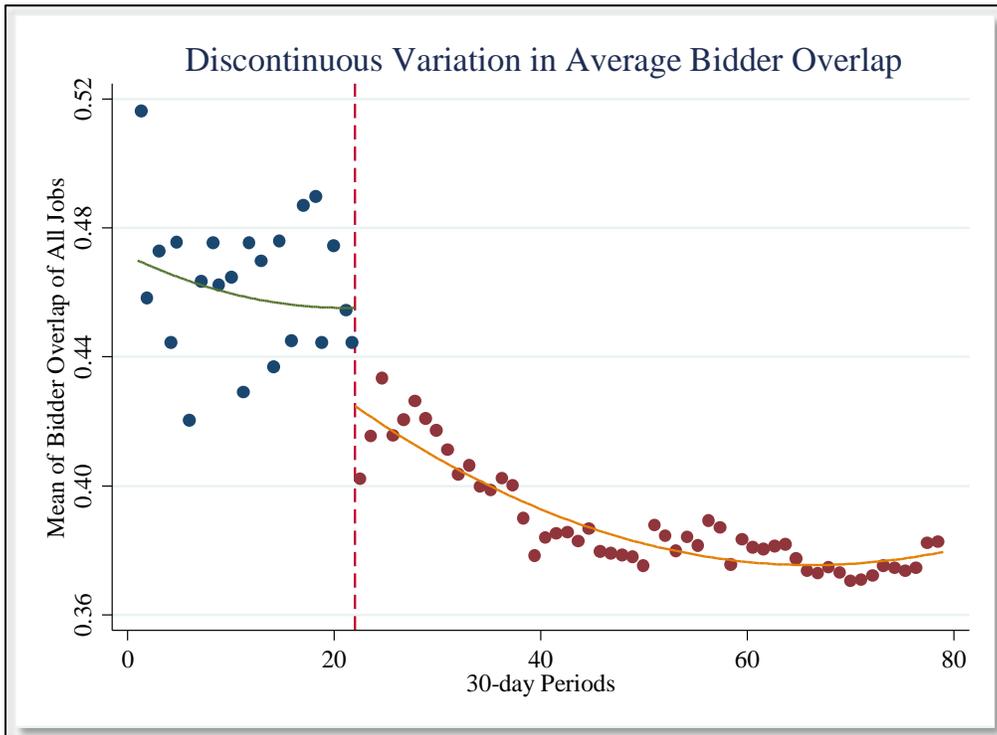
APPENDIX A

ADMIN SUPPORT
Bulk Mailing
Customer Response
Data Entry
Event Planning
Fact Checking
Mailing List Development
Office Management
Other - Administrative Support
Presentation Formatting
Research
Transcription
Travel Planning
Virtual Assistant
Word Processing

DESIGN AND MULTIMEDIA
3D Graphics
Animation
Banner Ads
Brochures
Card Design
Cartoons and Comics
Catalogs
CD and DVD Covers
Commercials
Corporate Identity Kit
Digital Image Editing
Direct Mail
Displays and Signage
Emails and Newsletters
Embedded Video/Audio
Graphic Design
Illustration
Label and Package Design
Logos
Menu Design
Music
Other - Design
Other - Multimedia Services
Page and Book Design
Photography and Editing
Podcasts
Presentation Design
Print Ads
Radio Ads and Jingles
Report Design
Sketch Art
Stationery Design
Videography and Editing
Viral Videos
Voice Talent

ENGINEERING AND MANUFACTURING
Architecture
CAD
Civil and Structural
Contract Manufacturing
Electrical
Industrial Design
Interior Design
Mechanical
Other - Architecture and Engineering

FINANCE AND MANAGEMENT
Accounting and Bookkeeping
Billing and Collections
Budgeting and Forecasting
Cost Analysis and Reduction
Financial Planning
Financial Reporting
HR Policies and Plans
Management Consulting
Other - Management and Finance
Outsourcing Consulting
Process Improvement
Stock Option Plans
Supply Chain Management
Tax

LEGAL
Bankruptcy
Business and Corporate
Contracts
Criminal
Family
Immigration
Incorporation
Landlord and Tenant
Litigation
Negligence
Other - Legal
Patent, Copyright and Trademarks
Personal Injury
Real Estate
Tax Law
Wills, Trusts and Estates

SALES AND MARKETING
Advertising
Branding
Business Plans
Business Skills
Business Software
Competitive Analysis
Corporate Training
Diversity Training
Email and Direct Marketing
Grassroots Marketing
Lead Generation
Management Training
Market Research and Surveys
Marketing and Sales Consulting
Marketing Collateral
Marketing Plans
Media Buying and Planning
Media Training
Other - Sales and Marketing
Other - Training and Development
Policies and Manuals
Pricing
Product Research
Programming Languages
Project Management
Promotions
Public Relations
Retailing
Sales Presentations
Sales Training
Search and Online Marketing
Technical Training
Telemarketing
Tradeshows and Events

WEB AND PROGRAMMING
Application Development
Blogs
Database Development
Ecommerce Website
Enterprise Systems
Flash Animation
Handhelds and PDAs
HTML Emails
Network Administration
Online Forms
Other - Programming
Other - Website Development
Project Management
Quality Assurance
Scripts and Utilities
Security
SEO and SEM
Simple Website
System Administration
Technical Support
Usability Design
Web Design
Web Programming
Website QA
Wireless

WRITING AND TRANSLATION
Test Writing
Academic Writing
Article Writing
Children's Writing
Copywriting
Creative Writing
E-books and Blogs
Editing and Proofreading
Ghost Writing
Grant Writing
Newsletters
Other - Writing Services
Press Releases
Report Writing
Resumes and Cover Letters
Sales Writing
Speeches
Technical Writing
Translation
User Guides and Manuals
Web Content