Buyer Uncertainty about Seller Capacity: Causes, Consequences, and a Partial Solution

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Abstract

Employers in an online labor market often pursue workers with little capacity to take on more work. The pursuit of low-capacity workers is consequential, as these workers are more likely to reject employer inquires, causing a reduction in the probability a job opening is ultimately filled. In an attempt to shift more employer attention to workers with greater capacity, the market-designing platform introduced a new signaling feature into the market. It was effective, in that when a worker signaled having high capacity, he or she received more invitations from employers, rejected a smaller fraction of those invitations, quoted a lower price to do the work, and was more likely to be hired. A back-of-the-envelope calculation suggests the signaling feature alone could increase market surplus by as much as 6%, both by increasing the number of matches formed and by helping to allocate projects to workers with lower costs.

1 Introduction

In some markets, buyers propose transactions to sellers, and if the pursued seller has no capacity—or at least no capacity at a price the buyer is willing to pay—the buyers' efforts are wasted. An unsuccessful pursuit may be consequential to whether a “match” is ever made, depending on how hard it is for buyers to find substitute sellers. A potential remedy to this problem might be for a market designer to encourage buyers to pursue higher capacity sellers. The market designer might do this by providing buyers with timely, accurate, and fine-grained information about the capacity of individual sellers. This kind of informational intervention would be hard to implement in conventional markets—which may explain

*All code is, or will be, available at http://john-joseph-horton.com/. This paper appeared as an extended abstract at the 2014 ACM Conference on Economics and Computation. Thanks to Eduardo Azevedo, Peter Coles, Panos Ipeirotis, Joe Golden, Ramesh Johari, Amanda Pallais, Richard Zeckhauser, and especially Andrey Fradkin for helpful comments and suggestions. Thanks to the participants at the market design seminar at the Wharton School and to the Economics of Digitization NBER Summer Institute participants for helpful comments and suggestion. I am sincerely grateful to many team members from the platform used in this study for their encouragement, ideas and assistance in this project.
why this kind of information is rare—but would be relatively easy to implement in online marketplaces, which possess information systems to collect, process, and present market information.\footnote{In online contexts where platforms can convey capacity information, they do: Airbnb now shows up-to-date host calendars; ManuscriptCentral (the platform many scholarly journals use to handle the peer-review process) shows a reviewer’s outstanding reviews to the assigning editor; Facebook shows individual relationship statuses; Uber matches passengers to drivers that currently have no passengers (or will have no passengers momentarily). Thanks to an anonymous reviewer for some of these other examples of platform responses to capacity uncertainty.}

This paper explores the phenomenon of buyers pursuing sellers in the context of an online labor market. It also reports the results of an informational intervention designed to improve the recruiting and matching process. In this market, employers (i.e., buyers) posting job openings frequently pursue workers (i.e., sellers) by “inviting” them to apply to their job openings, just as employers recruit candidates in conventional labor markets.\footnote{I use the words “employer” and “worker” to be consistent with the extant literature rather than as a comment on the legal nature of the contractual relationships created on these platforms.} A worker can “accept” the invitation and apply to the associated job opening, or, for any number of reasons, reject it. The most commonly cited reason for rejecting an invitation is insufficient capacity. These rejections appear to be consequential, as the associated job opening is much less likely to be filled, even though spurned employers can invite other workers, or hire from among the non-recruited “organic” applicants their job openings receive.

Despite worker claims about capacity being important—and the correlation between rejections and job openings going unfilled—it is far from clear whether there is actually a problem. Perhaps the negative relationship between a rejection and a match being formed is not causal, and instead reflects heterogeneity in the desirability of the associated job opening. Even if capacity does matter, an employer might be well-aware that his or her preferred worker has little capacity, but simply has a strong preference for that worker relative to the next best option. For the platform to successfully intervene, (1) there should be a causal relationship between recruiting success and match formation, and (2) employers must also find it useful to condition on platform-provided capacity information. Exploring these issues is the focus of this paper.

There are three main empirical portions to the paper: (1) a panel analysis exploring the relationship between worker capacity and invitation acceptance, (2) an instrumental variables analysis of how consequential rejections are to match formation, and (3) an analysis of two different platform interventions designed to reduce employer uncertainty about worker capacity.
To begin, I establish that busier workers receive more invitations, but are also less likely to accept an employer's invitation. However, as busier workers are likely to be better workers, the attributes of the worker are likely confounds—busier workers could also be pickier workers. To address this concern, I construct a panel dataset and then run regressions that include both worker- and time-specific fixed effects. Using this “within worker” approach, I find that when a worker gets more invitations, his or her acceptance rate goes down. As such, from an employer's perspective, the probability that a recruiting invitation to a particular worker is accepted varies based on time-varying factors that the employer likely cannot observe or condition upon, such as the number of invitations from other employers. If employers could condition on additional information about capacity, they might make different—and perhaps better—decisions about which workers to recruit.

Turning to the question of whether rejections are actually consequential, I first show that rejections are highly correlated with the associated job opening going unfilled. This relationship persists even with the inclusion of both worker- and employer-specific fixed effects, ruling out some of the more obvious selection stories that could explain the relationship. To establish that this relationship is in fact causal, I use an instrumental variables analysis that takes advantage of some unique institutional features of the marketplace. I find that a rejection causes a reduction in the probability that the opening is filled. This causal relationship suggests that reducing rejections could increase the quantity of matches formed in the marketplace. A rejection also causes employers to interview and hire more non-recruited applicants; there is some evidence that spurned employers also engage in more recruiting. However, these employer adaptations are not sufficient to offset the overall negative effect of a rejection on whether a job opening is filled.

With the goal of reducing the number of rejected invitations, the platform created new features to give employers more information about the capacity of workers. The platform added “responsiveness metrics” to worker profiles, which reported the historical fraction of invitations the worker accepted, and how quickly he or she provided a response to invitations, on average. In aggregate, this feature seemingly encouraged a “quick no” from workers who previously would have simply not responded, without increasing the number of accepted invitations. The more interesting—and more consequential—intervention was the introduction of a signaling mechanism that allowed workers to publicly state their
Exploiting within-worker changes in the capacity signal being sent, I find that when workers signal they have more capacity, they (1) get more invitations from employers, (2) are more likely to accept an invitation, (3) quote a lower hourly rate to perform the work, and (4) are more likely to be hired. Interestingly, the bidding and hiring results imply that some workers with little capacity shade up their bids rather than simply reject an invitation outright. This suggests that capacity uncertainty not only leads to job openings going unfilled, but also raises costs. In short, capacity uncertainty causes both a quantity and a price effect in the market. If the price effect is due to workers completing projects when they have higher costs, a back-of-the-envelope calculation suggests that employer uncertainty reduces surplus by as much as 3%. If we combine the causal estimates of the effects of a rejection on match formation with the estimates from the signaling feature introduction on acceptance rates, the loss in surplus from unfilled openings could be an additional 3%. Of course, these estimates rely on some strong assumptions, which I will discuss.

This paper adds to the growing literature on the design and functioning of online marketplaces. The main contributions of this paper are documenting an important market failure, quantifying its importance, and exploring potential remedies. Given the generality of the conditions that cause the failure—supply constrained sellers with imperfectly observable capacity—the problem is likely to be commonplace. This paper shows the problem is remediable in part, at least in markets where substantial market design powers exist, as in the case of computer-mediated markets.

2 Related work

There is a large literature on online marketplaces, online IT service marketplaces and a burgeoning literature specifically on online labor markets. Much of this work has, naturally, focused on information, as the defining characteristics of these online markets are that trading partners are usually strangers and goods cannot be directly inspected (Resnick et al., 2006). Dimoka et al. (2012) make an important conceptual distinction about whether the lack of information is about the product or the seller. In labor markets—or markets for services more generally—the two concepts are not so clearly distinct: a “bad” seller can by chance offer a great product, but a “bad” worker or service provider almost by definition
produces bad work. The tight coupling of the seller and the “product”—and all the complications this coupling creates—is why the study of IT service markets is conceptually distinct from online markets generally.

The literature on IT service markets focuses largely on the determinants of match formation as mediated by either bidding (as in the case of procurement auctions) or as mediated by marketplace reputations. For example, Snir and Hitt (2003) explore entry into the reverse auctions run by buyers and identifies a market failure: excess bidding, as would-be sellers do not internalize the costs of bid evaluation. Yoganarasimhan (2013) studies IT firms bidding for projects and explores how the dynamic nature of job-filling could lead to erroneous inferences about seller reputations if analyzed as a static estimation problem. In both of these examples, the focus is on sellers pursuing buyers, in which case seller capacity constraints are not directly relevant, as only sellers with capacity bother to pursue buyers. Further, even if the analysis did focus on buyers pursuing sellers, if the sellers are actual firms rather than individual workers, capacity constraints are presumably less important.

In existing online labor markets, there is a mix of sellers that are individual workers and sellers that are true firms. There is also a mix of buyers proposing fixed-price and hourly projects, which lead both to different bidding dynamics and very different work relationships (see Bajari and Tadelis (2001) on this distinction). There is also a mix of buyers pursuing sellers and sellers pursuing buyers. Further complicating things, both kinds of activity often occur simultaneously for the same job opening, with buyers both recruiting workers to apply to their jobs and evaluating unsolicited “organic” applications.

Given the diversity of the methods parties use to form matches in online labor markets, most of the research has focused on some particular aspect of the market to answer a research question rather than offer a general theory of online labor markets. For example, Pallais (2014) shows via a field experiment that past worker experience in online labor markets is an excellent predictor of being hired for subsequent work on the platform. Stanton and Thomas (2016) uses data from an online labor market to show that agencies (which act as quasi-firms) help workers find jobs and break into the marketplace. Agrawal et al. (2016) investigate what factors matter to employers in making selections from an applicant pool and present some evidence of statistical discrimination. Hong and Pavlou (2015) provide a detailed look at how differences in time-zone, language and cultural factors affect prices in online labor markets. This
paper fits this pattern of focusing on some aspect of the market, but it also takes a more design-based view.

As online marketplaces can be readily changed through changes in software, they are remarkably amenable to being designed. To date, research taking a “market design” view on platforms has largely focused on price structure and levels, often in the context of competition between platforms, e.g., Armstrong (2006), Rochet and Tirole (2003), Rochet and Tirole (2006) and Parker and Van Alstyne (2005). Although price structure and levels are undoubtedly important, these decisions are generally made once or a small number of times, before the platform has received “traction.” In contrast, the firm continually makes decisions that are consequential to the formation of matches, such as through algorithmic recommendations (Horton, 2017), or the ranking of search results and the generation of choice sets (Halaburda and Piskorski, 2010; Casadesus-Masanell and Halaburda, 2014).

There is a growing recognition in the literature of the importance of the platform in shaping who matches with whom, even in decentralized settings. Tadelis and Zettelmeyer (2015) show that information disclosures by the platform can raise revenue at both the low end and high end of a used car market, mainly by helping buyers and workers sort, thereby thickening the market. Motivated by this finding, Lewis and Wang (2013) develop a model of the platform deciding how much to invest in search technology. Horton and Johari (2013) show that buyers will readily reveal their “type” with regards to quality preferences in anticipation of the workers sorting, even though this revelation allows workers to charge them a substantial premium. Arnosti et al. (2014) explores “stockout” and congestion in a dynamic matching market and finds that application quotas can improve market efficiency.

Also in this “design” vein, Allon et al. (2012) presents a theoretical model of the platform’s choice about facilitating communication among platform participants, and the effects their decision has on efficiency. Goes and Lin (2012) examine the effects of a platform introducing paid certifications and, later, costly certifications. While the goal is partly to test a theory about information revelation, the paper also speaks to the platform’s decision-making regarding signals that might reduce information asymmetries. This current paper also considers the platform’s role in creating new signaling opportunities.

The most closely related paper to this one is Fradkin (2014), in which he shows in the context of Airbnb that over 70% of buyer inquiries do not lead to a match. Decomposing the reasons, Fradkin shows...
that screening by hosts explains half of the rejections, but the other half is explained by guests pursuing unavailable property listings—essentially the same market problem explored in this paper. Given the qualitative similarity in results despite such different settings, it seems likely that the phenomenon explored in this paper is commonplace in matching markets where buyers pursue capacity-constrained sellers whose at-that-moment capacity is not common knowledge.

3 Empirical context

In online labor markets, firms hire workers to perform tasks that can be done remotely, such as computer programming, graphic design, data entry, research, and writing. Markets differ in their scope and focus, but common services provided by platforms include publishing job listings, hosting user profile pages, arbitrating disputes, certifying worker skills, and maintaining reputation systems.

The online labor market used for this analysis is one of the largest, with over $1 billion in lifetime transaction volume. The platform focuses primarily on hourly contracts performed by independent workers, or “freelancers.” Hours-worked are measured with a proprietary tracking software that workers install on their computers. The tracking software essentially serves as a digital punch clock that allows for remote monitoring of employees. This monitoring makes hourly contracts, and hence employment-like relationships, possible. This in turn makes the platform’s marketplace more like a traditional labor market than project-based online marketplaces where contracts are usually arm’s-length and fixed price. With this individual worker focus, the capacity of a worker is more important than in marketplaces where the supply side is composed of large firms.

On the platform used in this study, would-be employers write job descriptions, self-categorize the nature of the work and required skills, and then post the job openings to the platform’s website. Workers learn about job openings primarily via electronic searches. Workers submit applications, which include a wage bid (for hourly jobs) or a total project bid (for fixed-price jobs), and a cover letter. In addition to worker-initiated applications, employers can also search worker profiles and invite workers to apply to their job openings; I will discuss this alternative channel of initial connection in more detail below, as recruiting is the central topic of this paper.

The platform used in this study is not the only marketplace for online work, or work more gener-
ally. As such, one might worry that every job opening we see on this platform is simultaneously posted on several other online labor market sites and in the conventional labor market. To assess this "multi-homing" question, the platform hired a market research firm, which in turn surveyed 6,192 randomly selected employers from the platform. When asked about what they would have done with their most recent project if the platform were not available, only 15% of employers responded that they would have made a local hire. Platform employers report that they are generally deciding among (1) getting the work done online, (2) doing the work themselves, and (3) not having the work done at all. The survey also found that 83% of employers said that they listed their last job opening only on the platform in question, and not on a competitor platform. The survey evidence suggests that online and offline hiring are only very weak substitutes, and that multi-homing of job openings is relatively rare (see Agrawal et al. (2015) for more on these points).

### 3.1 Employer recruiting

As in conventional labor markets, on the platform employers may choose to actively recruit candidates to apply for their jobs. These recruiting invitations are not job offers, but rather invitations to apply to the employer's already-posted job opening. Recruiting is common on the platform—about half of employers send at least one recruiting invitation.

Employer recruiting on the platform begins with the employer searching for some skill or attribute they are looking for in candidates. Employers search for workers using a search-engine like interface (see Appendix A for screenshots of the interfaces discussed in this section). As such, the ordering of search results is consequential. The search results were historically ordered by a weighted combination of attributes employers care about, such as on-platform experience and feedback scores. However, as it became clear that worker invitation responsiveness mattered to match formation, a measure of “eagerness” was also added to the weighting formula, with workers recently applying to jobs (hence revealing their availability) getting more weight. These early attempts at conveying worker capacity proved, however, to be a less than satisfactory solution, as there were some reports of workers applying to jobs they were not interested in simply to appear more eager and hence appear higher in search results.

Once an employer finds an worker they are interested in, they can click on a button to invite that
worker to apply for their job opening. The employer can also “click through” to the worker’s full profile before inviting them. The full profile has more information about the worker, such as their full disaggregated work history (rather than just summaries, such as the total hours worked on the platform).

When the employer clicks “contact” they are brought to a new “invite” interface. The “message” text box is pre-populated with a short written request for the worker to apply, which the employer is free to customize. From the worker perspective, invitations appear as messages in an inbox of sorts. For each invitation, the worker can see the date and time the invitation was sent, the title of the associated job, and the employer that sent the invitation, as well as the employer’s message. By clicking the title of the job, the worker can learn more about both the job opening and the employer.

When workers turn down a recruiting invitation, they may give a reason from a list of reasons, or write their own. Using all responses from November of 2013, the most common reason selected is “Too busy on other projects”, at 48%. The next most common is “Not interested in the project” at 29%. All other reasons get less than 10%. This data—as with all data used in the paper—was shared directly by the platform. If we take these worker responses at face value, worker capacity is important, but there is also evidence of substantial discretion, with invited workers conditioning their response decisions on the attributes of the job opening. If an invitation is accepted, the invited worker applies and the employer eventually evaluates applicants. If the employer ultimately makes a hire, the platform intermediates the relationship.

3.2 What do employers know about worker capacity when they recruit?

Employers want to recruit workers that are likely to accept their recruiting invitations. As such, we would expect employers to try to infer worker capacity. However, in the earlier days of the platform, employers had little to work with: employers could not easily observe how many other recruiting invitations a worker had received, nor the response to those invitations. However, employers did have some imperfect proxies for capacity, in that they could observe the cumulative hours-worked by that worker for each of the worker’s projects. From this, the employer could try to estimate how many hours the worker was working per week. However, there was, and still is, substantial individual heterogeneity in hours-worked per week—some workers work full-time, while others work only a few hours per-week—and so
it is unlikely that employers could infer much about capacity.³

More recently, the platform has introduced a number of features to make worker responsiveness and proxies for capacity available to employers, some of which I will discuss in Section 6. One change not discussed is that employers can now also see the relative difference between their own timezone and that of the worker, in hours, to help them gauge whether they will get a quick response to an invitation.

4 Empirics of employer recruiting and the worker response

In this section, using a large dataset of recruiting invitations, I show that a worker's probability of accepting a recruiting invitation declines in the number of other invitations received during the same time period. Using time variation in how heavily a worker is recruited, I present evidence that the negative relationship is not driven by selection but rather that getting more invitations causes the worker to be pickier about which projects to accept. Although I lack an experiment, I use various approaches to rule out alternative, non-causal explanations. The importance of this finding is that if workers have time-varying capacity, then the platform has some justification for trying to “balance” recruiting invitations across workers.

4.1 Data description

I collected a sample of all recruiting invitations sent by employers from January 1st, 2010 until January 1st, 2013. I then restricted the sample to invitations to openings that were public, meaning all workers could see the opening and apply. I also removed any invitations where the recruited worker and employer had interacted previously, such as through a past employment relationship, a previous recruiting invitation, or a completed application by that worker to one of the employer's previous job openings. The motivation for this restriction is to remove any invitation that was, in some sense, pre-arranged.⁴ I also eliminated invitations by employers sending 10 or more invitations for their job opening, as these “mass

³ An emerging stylized fact in computer-mediated labor markets is that when workers are free to choose how many hours to work, there is substantial heterogeneity in the realized number compared to most traditional employment relationships. See Hall and Krueger (2016) on this point in the context of the market for Uber drivers in the US.

⁴ Gefen and Carmel (2008) also looks at an IT marketplace and finds that buyers show a strong preference for firms/workers that they have worked with in the past. This is certainly true on the platform, and it is more evidence towards the importance of information in forming matches: presumably part of the preference for previous contacts is that there is far more information available to both sides.
invite” cases are not bona fide recruiting attempts, but are more akin to spam. These restrictions leave 1,247,379 usable recruiting invitations sent to 240,878 distinct workers by 68,255 distinct employers. The gross invitation acceptance rate for the sample is 40.1%.

I collapsed the sample of invitations to create a worker-week panel. I can do this because for each invitation, I observe the precise time it was sent, to the millisecond. The panel has 1,011,380 worker-week observations. For each week, I observe the number of hours worked, the number of invitations received, and the number of invitations accepted. As my focus is on changes in the acceptance rate, the panel only includes worker-week observations in which at least one invitation was received.

Table 1: Summary statistics on weekly invitation panels (n = 1,011,380)

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of invites received / week</td>
<td>2.096</td>
<td>6.780</td>
<td>1</td>
<td>1,061</td>
</tr>
<tr>
<td>Number of invites accepted / week</td>
<td>0.495</td>
<td>0.631</td>
<td>0</td>
<td>15</td>
</tr>
<tr>
<td>Fraction accepted (accepted invites)/(invites)</td>
<td>0.354</td>
<td>0.445</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Fraction accepted (1 + accepted invites)/(2 + invites)</td>
<td>0.467</td>
<td>0.171</td>
<td>0.023</td>
<td>0.933</td>
</tr>
<tr>
<td>Any hours worked that week?</td>
<td>0.210</td>
<td>0.407</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Exactly one invite?</td>
<td>0.695</td>
<td>0.460</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Notes: This table reports summary statistics for an unbalanced weekly panel of workers. The data is from January 1st, 2010 through January 1st, 2013. There are 240,878 distinct workers in the panel. A worker only has an observation for a week if they received at least one invitation that week.

Summary statistics for the panel are reported in Table 1. Note that there is substantial heterogeneity in the weekly number of invitations received by a worker. Although the mean number of invitations is a little more than two, almost 70% of the worker-week observations are weeks in which the worker received exactly one invitation. The maximum number of invitations received is over a thousand, though even triple digit numbers of invitations is extraordinarily rare; the 99.9th percentile is only 73 invitations. Consistent with workers having limited capacity, the maximum number of accepted invitations is only 15. We can also see that during many of the worker-week observations, the worker in question worked no hours on the platform. These workers might be on vacation or simply have no work to do, but some have presumably left the platform. Their inclusion in the sample presumable biases downward the acceptance rate compared to what it would be if the sample only consisted of still-active workers.

The average acceptance rate over all worker-weeks is about 35%. As it will be useful to have an in-
individual estimate of acceptance probability strictly in \((0, 1)\), I also report \((1 + A)/(2 + I)\), where \(I\) is the number of invitations received and \(A\) is the number accepted. This monotonic transformation gives an acceptance fraction that is slightly larger, as expected given that the untransformed acceptance rate is less than 1/2.\(^5\)

### 4.2 Where do employers send their invitations?

Not apparent from Table 1 is the extent to which employers focus on recruiting the busiest workers. Using the panel data described above, the top facet of Figure 1 shows the mean count of per-week invitations by the number of hours-worked per week (split into 20 evenly spaced percentile bins). The sample is restricted to workers working at least one hour in the week in question. The count of applications received is strongly increasing in hours-worked per week, and invitations are concentrated in the right tail. As such, many invitations go to workers who are unlikely to have the capacity to take on more work. The data bears out this intuition, in that the bottom facet of Figure 1 plots the average acceptance rate by the same hours-worked bins, showing that the busiest workers also have the lowest acceptance rates. Acceptance rates go from above 30% for the workers with the fewest hours-worked to below 10% for workers with the most hours-worked.

The pattern in Figure 1 does not imply that employers are mistaken in their recruiting decisions, as the busiest workers might still be the most attractive workers to pursue, even with their lower acceptance probability. However, if we see that a worker's acceptance probability fluctuates over time in response to how much capacity they have, then it is likely that employers are not fully conditioning on worker capacity, at least in a thick market with many alternative workers. In a nutshell, if there is within-worker variation in the acceptance rate that can be explained by within-worker variation in proxies for capacity, it undercuts the notion that employers are doing the best they can do already.\(^6\) As a proxy for changes in capacity, I use changes in the number of invitations received in a week. The idea is that a worker with

\(^5\) From a Bayesian perspective, the transformed acceptance rate is the posterior of the acceptance rate when the prior on the acceptance rate is an uninformative uniform distribution.

\(^6\) An analogy might make this point clearer. If we see someone pay more for a Lexus than a Honda Civic, we do not conclude they are making a mistake. Similarly, if we see them buy a car after the price rises, we do not conclude they made a mistake—they might not have needed the car before the price increase. However, if we see them buy a specific make, model, year and so on of a car that is also for sale at the same time at a 20% lower price, then we have some evidence they might be making a mistake, and the most likely mistake is that they do not know about the lower price available elsewhere. Our worker- and time-specific fixed effects are essentially showing us that the third situation is what is transpiring.
limited capacity receiving many invitations will have to accept a smaller percentage, whereas a worker without limited capacity could “scale up” and accept the same fraction. An advantage of using invitations received as a proxy is that this quantity is not under the control of the worker (as is the case for hours-worked), and thus changes in that quantity are more plausibly exogenous from the worker’s perspective.

Before presenting within-worker estimates, I first present a cross-sectional regression of the log of the transformed weekly acceptance rate on the weekly invitation count. Column (1) of Table 2 reports a pooled OLS estimate of

$$\log p_{it} = \alpha I_{it} + \text{WEEK}_t + \epsilon_{it},$$

where $p_{it}$ is the transformed acceptance rate for worker $i$ in week $t$, $I_{it}$ is that worker’s invitation count, and $\text{WEEK}_t$ is a week-specific effect.\footnote{One empirical concern is that because the count of invitations appears on both the left- and right-hand sides of the regression, the estimates are subject to attenuation bias. However, because of the computer-mediated nature of the platform, the count of invitations and whether or not they are accepted is measured without error, making this concern unfounded.} There is a strong negative relationship between the number of invi-
tations received and the acceptance probability. In terms of magnitude, a worker going from receiving 10 invitations per week to 20 invitations per week would have an acceptance rate that is about 4.6% lower.\(^8\) Note that as the regression includes week-specific fixed effects, the relationship cannot be explained by changes in the platform or general market conditions.\(^9\)

Table 2: Association between weekly invitation acceptance rates and the number of recruiting invitations received that week

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Invitations/week</td>
<td>-0.007***</td>
<td>-0.006***</td>
<td>-0.005***</td>
</tr>
<tr>
<td>Worker FE</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Week FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Worker-Month FE</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>1,011,380</td>
<td>1,011,380</td>
<td>1,011,380</td>
</tr>
<tr>
<td>R(^2)</td>
<td>0.021</td>
<td>0.393</td>
<td>0.808</td>
</tr>
<tr>
<td>Adjusted R(^2)</td>
<td>0.021</td>
<td>0.203</td>
<td>0.228</td>
</tr>
<tr>
<td>Residual Std. Error</td>
<td>0.369 (df = 1011169)</td>
<td>0.333 (df = 770292)</td>
<td>0.327 (df = 250939)</td>
</tr>
</tbody>
</table>

Notes: This table reports regressions where the dependent variable is the worker’s transformed weekly invitation acceptance probability. See Section 4.1 for a description of the sample. In Column (1), only week fixed effects are included. In Column (2), worker-specific and week-specific fixed-effects are included. In Column (3), worker-month specific and week-specific fixed effects are included. Standard errors are clustered the level of the individual worker. Significance indicators: \(p \leq 0.05: *, p \leq 0.01: **\) and \(p \leq .001: ***\).

Now I turn to the within-worker estimates of how invitation counts affect response rates. Column (2) of Table 2 reports an estimate of Equation 1, but with the inclusion of a worker-specific fixed effect. The negative relationship between invitations and the acceptance rate is still highly significant and close in magnitude to the Column (1) estimate. In short, when a worker gets more invitations, he or she is pickier about which invitations to accept.

Despite the persistent negative relationship between invitations received and acceptance probability, even when using only within-worker variation, workers and markets are not static. Even if worker attributes are not changing quickly, perceived worker attributes could be—say through better or worse...
feedback scores. To address these concerns, I cannot control for worker-week—this fixed effect would absorb all the variation in weekly invitation counts. However, I can include worker-month fixed effects, but still use a weekly panel.

Column (3) of Table 2 reports an estimation of Equation 1, but with the inclusion of worker-month fixed effects. There is still a strong negative relationship between the number of invitations received and the acceptance rate of those invitations. The magnitude of the effect is only somewhat closer to zero, compared to the Columns (1) and (2) regression estimates, and the difference in the estimates is far from conventionally significant. To find a spurious relationship with the presence of worker-month fixed effects, demand and perceived worker productivity would have to be (implausibly) fluctuating within the week, but not within the month.

Although highly significant, the size of the reduction in invitation response rates is fairly small, consistent with workers supplying labor elastically. For a market that focuses on relatively short-term tasks and has a work-force with many people working part-time, a high elasticity is perhaps unsurprising. Farronato and Cullen (2015)—looking at TaskRabbit, a market with similar task sizes and relationship durations—also find that workers have very high labor supply elasticities.

A high labor supply elasticity would seemingly undercut the notion that conditioning on worker capacity is important, as even “busy” workers would readily scale up to meet additional demand. However, there are several counter-arguments to consider. First, accepting an invitation simply means applying, and so a capacity-constrained worker can respond by applying but with a very high price. Indeed, later in this paper, I show that some workers with low stated capacity still applied when recruited, but they raised their wage bids. Even if a worker is offered a contract, they do not necessarily have to agree to the contract or complete the work—they have a job offer, which is useful, even if not pursued. It is also important not to confuse average effects—which weight all workers in the sample equally—with the elasticity of workers that are actually receiving most of the invitations, which is highly skewed towards workers already working many hours per week, as we saw in Figure 1.

The results from the worker panel analysis strongly suggest that workers become pickier when they have many projects to choose from. If projects could be “stored” the average market-wide acceptance

---

10 This is somewhat unlikely, as workers receiving invitations are already likely to have nearly perfect reputation scores (Horton and Golden, 2015). Demand for certain skills might also be changing over time.
rate could be increased by cross-leveling invitations “within” a worker. And so long as not all workers are busy at the same time, it also seems likely that cross-leveling “between” workers is desirable. However, the expected benefit from improving the invitation acceptance rate depends on how consequential invitation rejections are to match formation.

5 Recruiting success and match formation

In this section, I first show that when an employer sends an invitation and it is rejected, the associated job opening is much less likely to be filled. This correlation cannot be interpreted as causal, but I also show that with both worker- and employer-specific fixed effects, the negative relationship persists, undercutting the most obvious selection-driven explanation. To show that the relationship is in fact causal, I conduct an instrumental variables analysis.

5.1 Data used to estimate the effects of rejected invitations on match formation

I constructed a sample of 57,250 recruiting invitations. The time period covered by the sample was 2011 through 2013, inclusive, which is the same time period used for the panel analysis.\(^{11}\) The sample is not the universe of all invitations, but rather it is a selected sample that meets several geographic, job-opening, and time-based restrictions. I will discuss these restrictions in detail, but the motivation for all restrictions is to create a sample where the conditions for causal inference can be met. The restrictions will make more sense when I discuss the instrument, but first I will simply describe the sample.

The sample was restricted to invitations sent by US-based employers to workers residing in Bangladesh, India, Philippines, Russia and Ukraine.\(^{12}\) These are the major non-US worker countries on the platform, with the UK excluded. I excluded the UK because the close cultural and linguistic ties make it more likely that US-based employers would consider the local time in the worker’s country when sending their invitations. This conditioning would violate the exclusion restriction assumption, which I will discuss later when I explain the instrumental variable. I further restricted the sample to invitations by employ-

\(^{11}\) Prior to 2011, there are some database-related complexities in tracking who was invited to a job opening that can be avoided by restricting the sample. As the marketplace was considerably smaller then, left-truncating the data is not important in terms of the sample size.

\(^{12}\) I only include jobs that were open to all applicants, both recruited and organic (i.e., “private” jobs for which a worker needed to be invited to apply were excluded).
ers that sent one and only one “early” invitation for their opening, which I define as being sent within the first hour after posting the opening. This “early” restriction allows me to look at later compensatory recruiting by employers as a response to having their invitations rejected.

Among US employers doing any recruiting at all, the fraction sending a single early invitation is about 30%. This is also the most common number to send, conditional upon sending any. I restrict the sample to job openings with a single early invitation, in part, to simplify the analysis and interpretation. However, the main reason to use the single invitation scenario is that that employers sending multiple invitations are likely doing so precisely because they are concerned that some or all of their invitations will be rejected—and this probability of rejection might be high precisely because of the capacity uncertainty problem this analysis is trying to investigate. As such, the single invitation context offers the best scenario to understand whether rejections are, per se, consequential.

Table 3: Summary statistics for employer recruiting invitations (n = 57,250)

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Job opening filled?</td>
<td>0.446</td>
<td>0.497</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Invitation accepted?</td>
<td>0.545</td>
<td>0.498</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Hour invitation sent (PT)</td>
<td>12.900</td>
<td>7.426</td>
<td>0</td>
<td>23</td>
</tr>
<tr>
<td>Value of the instrumental variable</td>
<td>0.040</td>
<td>0.017</td>
<td>0.008</td>
<td>0.077</td>
</tr>
</tbody>
</table>

Notes: This table reports summary statistics for the data set used in the instrumental variables analysis. The sample consists of recruiting invitations by a sample of employers and the ultimate outcome for that associated job post. See Section 5.1 for the full description of the dataset.

The final sample of 57,250 invitations were sent by 40,971 distinct employers to 24,282 distinct workers. Table 3 contains the summary statistics for the dataset. The gross acceptance rate for this sample is about 55%, meaning a fairly large fraction of invitations are turned down. This is higher than in the panel, which could reflect that employers sending a single invitation are more confident that their invitation will be accepted. Note that the probability that a job opening is filled is less than 50%, meaning that there is plenty of “room” to increase the number of matches. Also note that the average invitation hour (on a 24 hour clock) is 12.90, or about 1pm PT, 4pm ET, consistent with the sample being restricted to US-based employers that keep customary US business hours. This concentration of recruiting activity

13 The figure is with respect to all public job openings posted before 2014.
during the middle of US work day will be important when explaining the identification strategy.

5.2 Correlation between invitation acceptance and match formation

Consider an employer, \( j \), sending a single recruiting invitation to their preferred worker \( i \). Let \( a_{ij} = 1 \) if the worker accepts the invitation and applies, and \( a_{ij} = 0 \) if he or she declines or ignores the invitation. Using the sample of invitations, Column (1), Table 4 reports an OLS estimate of

\[
\Pr[Y_j > 0] = \beta_0 + \beta_1 a_{ij} + \epsilon_{ij},
\]

where \( Y_j \) is the amount of money spent by the employer on workers hired to that opening.\(^{14}\) Standard errors in each regression of Table 4 are clustered at the level of the worker.

We can see in Column (1) that an accepted invitation is strongly associated with the job opening being filled, with an effect of more than 15 percentage points. However, this regression clearly cannot be interpreted causally: firms proposing poorly described, low-value projects are presumably more likely to be rejected, and less likely to be filled by some other worker; firms that require highly sought-after skills are also more likely to be turned down; firms with unobserved off-line arrangements with the worker always fill their jobs and have a nearly 100% accept rate, and so on. Essentially any job opening, employer or worker characteristic that is correlated with the probability that the job opening will be filled would bias the OLS estimate.

I can address some of these worker or employer omitted variable concerns by exploiting the matched worker/employer nature of the invitation data. Column (2) of Table 4 shows the results from a regression

\[
\Pr[Y_j > 0] = \beta_0 + \beta_1 a_{ij} + \gamma_i + \delta_j + \epsilon_{ij},
\]

where \( \gamma_i \) and \( \delta_j \) are worker- and employer-specific fixed effects, respectively. With the inclusion of these controls, the association between invitation acceptance and match-formation does not disappear—on the contrary, it is now above 20%, though the estimate is now less precise.

\(^{14}\) I use money spent as an indication of match formation because it is a revealed preference measure, whereas simply stating an intention to work with someone is only a stated preference, and may not necessarily imply an economic relationship was formed.
Table 4: Association between a worker accepting an employer’s recruiting invitation and whether that employer fills his or her opening

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Job opening filled, (1[Y_j &gt; 0])</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Workers accepts invitation, (a_{ij} = 1)</td>
<td>0.163***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.357***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
</tr>
<tr>
<td>Worker and Firm FEs?</td>
<td>No</td>
</tr>
<tr>
<td>Observations</td>
<td>57,250</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.027</td>
</tr>
<tr>
<td>Adjusted (R^2)</td>
<td>0.027</td>
</tr>
<tr>
<td>Residual Std. Error</td>
<td>0.490 (\text{(df = 57248)})</td>
</tr>
</tbody>
</table>

**Notes:** This table reports regressions where the outcome variable is an indicator for whether an employer filled his or her opening. The dataset consists of a sample of recruiting invitations described in Section 5.1. The key independent variable is whether the recruiter worker “accepted” the invitation by applying to the employer’s opening. In Column (1), no controls are included, whereas in Column (2) worker- and employer-specific fixed effects are included. Standard errors in each regression are clustered at the level of the individual worker. Significance indicators: \(p \leq 0.05 : *, \ p \leq 0.01 : ** \) and \(p \leq .001 : ***\).
Although the double employer and worker fixed effect approach does nothing to deal with omitted variables at the level of the job opening—or time-changing attributes of the worker and employer—it does rule out selection explanations that depend solely on the identity of the invited worker and employer. In short, it rules out the possibility that workers simply turn down “bad” employers who are unlikely to fill their job openings, or naive employers who invite workers with no capacity. Next I turn to an approach that can deal with job-specific attributes and time-changing worker/employer characteristics. However, before doing so, it is useful to first consider why rejections might be consequential to match formation.

Firms presumably recruit to improve their eventual pool of applicants. Following a recruiting invitation rejection, this applicant pool is “missing” the recruited worker. Without this recruited worker, the firm’s payoff from making a hire might be negative, and so they may choose to hire no one at all. Horton (2017) demonstrates this argument in the opposite direction, showing that an increase in the size of the applicant pool increases the probability a job opening is filled. A natural question, however, is why, in a large and presumably thick market, does the rejected employer not simply recruit someone else? Or barring that, why not simply recruit more workers ex ante as a precaution?

Recruiting is costly, so it is no puzzle why some firms invite only a single applicant, or even none at all, despite the possibility of rejection. But stopping a search following a rejection cannot be explained solely by costly recruiting—it was also costly to send the initial recruiting invitation. One possibility is that after a rejection, the firm might infer that recruiting another candidate will be costlier. Given that most employers post a job opening and then recruit candidates in a single session, starting another search session after a rejection might have a higher fixed cost than the original recruiting session. After a rejection, the employer might also infer that their project is less desirable, lowering the returns to additional recruiting.

5.3 Instrumental variable construction

To estimate the causal effect of a recruiting acceptance, ideally the platform would, at random, turn some invitation acceptances into rejections. For a number of reasons this approach is infeasible. However, the platform offers a natural experiment that approximates this hypothetical, providing an instrumental
variable for \( a_{ij} \). The instrument requires some explanation, but the core idea is that the relative time of day in which a worker receives a recruiting invitation has a strong effect on their probability of accepting that invitation, and yet there is no evidence that employers take this relationship into account when deciding which workers to invite.

As noted earlier, most employers on the platform are from the US. They post job openings and send invitations during customary US business hours (recall Table 3). Workers are distributed around the globe, and so the local time an invitation is received varies, depending on when it is sent and to which worker. Although workers adapt to the US-centric rhythm of the market, this adaptation is only partial, with most workers still keeping their home country work hours, more or less. As such, the variation in the local time of an invitation leads to variation in whether a worker happens to be online when an invitation arrives.

Why does the local time when an invitation is received matter? One might imagine that since the recruited worker will eventually come online and see the invitation, a few hours of difference cannot matter to the decision of whether to apply. However, this is empirically not the case. The reason is interesting, and has an economic basis. Because workers are uncertain about when and how an employer will evaluate candidates, all else equal, it is better to apply sooner rather than later. To see this, first suppose the employer will consider applications “in batch” after some amount of elapsed time. As long as the worker is in the batch, they will be considered. This would seemingly undercut the urgency of applying, but if workers do not know when the batch will be processed, applying earlier increases their chance of being considered. The longer the expected time until processing, the weaker the incentive to apply early, but the incentive does not go away. The incentive to apply early also exists if employers monitor the “flow” of applicants, hiring the first one above their reservation utility—now the worker wants to apply before anyone better than them applies.\(^{15}\)

Because of the urgency created by worker uncertainty about the employer’s evaluation process, job openings get all the applicants they will ever receive quite quickly. The modal applicant in some categories of work comes less than 24 hours after posting (see Horton (2017) on this point). The upshot

\(^{15}\) This same argument explains why it would be difficult to show empirically that early applicants are more likely to be hired. When employers monitor the flow of applicants, hiring the first above their reservation value, it is worthwhile from the worker’s perspective to apply sooner rather than later. However, now, the worker hired is always the last one that applied!
of this incentive for speed is that a worker that receives an invitation when they happen to be online is more likely to respond immediately and apply; a worker that receives an invitation when they are offline is more likely to not apply at all, as they will only learn about the opportunity some number of hours or days in the future, when the value of applying has diminished. This difference in the probability of applying, caused by time-zone differences, is the identification strategy.

To construct this instrument, I need an estimate of the probability that a worker from a particular country is online at a particular hour. A perfect indicator that a particular worker is online and using the platform at a given time is that they sent an application at that time; job applications are invariably sent by workers who are awake and using the platform. The top panel of Figure 2 shows the distribution of applications sent in each of the 24 hours of the day, as measured in the Pacific timezone (PT), for the top platform worker countries, namely Bangladesh, India, Philippines, Russia, Ukraine and the United Kingdom. The data for this figure is pooled over the entire history of platform job applications through March 10th, 2015.\(^{16}\)

In this top panel, the lines are quite jumbled and interwoven with each other, but when we shift the data so that the fraction of applications is reported in each worker's local time, the pattern becomes quite clear: all workers show the same basic activity cycle, with on-site activity reaching a peak around 2pm or 3pm (14:00 on the 24 hour clock) and then trailing off in the evening, reaching a trough at around 5am. Figure 2 illustrates that despite the global nature of the market, workers "keep" their home country hours. As such, when an invitation is sent to a worker, the probability that worker is online at that moment and using the platform varies, and so his or her probability of applying varies, giving us a first stage for a two stage least squares estimation (2SLS).

To give an example of how the instrument is calculated, suppose an employer in New York City posts a web design job at 2pm local time on March 12th. If she were to invite a worker from Manila, the invitation would arrive at 2am; if the invited worker was in Moscow, it would arrive at 9pm; if Bangalore, then

\(^{16}\)While it may be tempting to reduce the sample of applications to a smaller window covering the period of the IV analysis, this would likely be a bad trade in the bias/variance trade-off. The goal in constructing the instrument is to get the most accurate possible estimate of a worker's propensity to be online and thus respond to an invitation based on the time of day. For some worker/hour bins, the data is sparse and restricting the sample makes the problem worse. Restricting the sample might seemingly reduce bias—suppose the propensity to be online has changed over time—but as we are trying to capture something that is a general feature of workers in that country (i.e., their patterns of work and sleep), I doubt the bias reduction would be great, while the cost in increased sampling variation would be large.
11pm. If we use Figure 2 as a proxy for the probability of whether a worker from a particular country is online at a particular hour, then in descending order of being online, we have Russia, India and then the Philippines. Of course, we might have a Filipino night owl and a Russian early riser with an 8pm bed time, but on average, we would expect the employer to catch more Russians online than Filipinos.

The precise measure I use for the instrument comes directly from Figure 2: the instrumental variable associated with the acceptance decision for an invitation made by an employer at hour $h$ (24 hour clock) to a worker from country $l$ is the fraction of all job applications by workers from country $l$ sent at hour $h$ (in the employer's time zone). For example, an invitation by our hypothetical NYC-based employer sent at 2pm local time would be received by a worker in the Philippines at 2am; of all applications sent by Filipino workers on the platform, a little bit less than 3% are sent during that 2am-3am period. This 3% value would be the instrument for acceptance for this particular observation. If the Filipino worker had instead received the invitation at 10am local time (which is the peak of activity), the instrument value...
would be nearly 6%. Note that each worker from the same country has the same instrument value for a
given invitation hour.

Following Angrist and Pischke (2008), I formulate the IV estimation problem as a 2SLS regression
using the linear probability model. Given that our interest is in marginal effects rather than prediction—
and that our sample is already highly selected to have the “right” properties vis-a-vis the IV—the sim-
plicity of using the linear probability model in this case makes it advantageous over an IV probit or logit
model, particularly since I will also report a regression with employer-specific fixed effects.

A worker \( i \) is invited to a job opening, \( j \). Let \( l(i) \) index the worker’s country. This invitation occurs
at hour \( H(i, j) \) in the worker’s timezone, but at hour \( H(i, j) + \Delta TZ(l(i), j) \) in PT, where \( \Delta TZ(l(i), j) \) is the
offset. Let \( z_{H(i, j), l(i)} \) be the value of the instrument, which depends on the local arrival hour and the
country of the worker. The two stages are:

\[
a_{ij} = \gamma_0 + \gamma_1 z_{H(i, j), l(i)} + \gamma_{\text{TIME}} H(i, j) + \gamma_{\text{LOC}} l(i) + \xi_{ij} \quad (\text{IV First stage})
\]

\[
1[Y_{ij} > 0] = \beta_0 + \beta_1 a_{ij} + \beta_{\text{TIME}} H(i, j) + \beta_{\text{LOC}} l(i) + \epsilon_{ij} \quad (\text{IV Second stage}),
\]

where \( \beta_{\text{TIME}} \) and \( \gamma_{\text{TIME}} \) are fixed effects for the hour that the invitation was sent (in PT) and \( \beta_{\text{LOC}} \) and \( \gamma_{\text{LOC}} \)
are fixed effects for the invited-worker country.

The exclusion restriction assumption is the following: conditional upon the hour of day and the
country of the invited worker, the instrument is independent of whether the job opening fills or not. With
the inclusion of country- and hour-specific fixed effects, this exclusion restriction assumption would
still hold even if employers that recruit at different times differ systematically from each other (at an
hour level of granularity), or if employers have worker country preferences that are correlated with the
probability of the job being filled. What would violate the exclusion restriction assumption is if some
employers send their invitations to workers they think are more likely to respond quickly because they
are online, based on the invited worker’s country. Other non-country signals of capacity that employers
could condition on do not invalidate the instrument. This conditioning-on-the-IV hypothesis is some-
what testable, and I will present evidence below that employers do not learn to invite workers with higher
values of the instrument. However, I will first present the 2SLS results.
5.4 Instrumental variables estimates of the effects of recruited worker invitation acceptance on match formation

In Column (1), Table 5, the first stage for the instrumental variable regression is shown (Equation 4), with the dependent variable being the invitation acceptance indicator, regressed on the instrument. In this regression—and all regressions in the table—standard errors are clustered at the level of the individual worker. The F-statistic for the first stage regression is 78.99, which implies a very strong instrument (Bound et al., 1995).

Note that although the coefficient on the instrument is highly significant, the effect is not absolutely large: the range of the instrument (from maximum to minimum value) is only about 0.07 and so the first stage coefficient means that from peak to trough, acceptance probabilities only vary by about 5 percentage points. This strong-but-not-large characterization is useful for my purposes, as the larger the effect, the less plausible it is that employers do not learn to condition on the instrument directly, which would violate the exclusion restriction.

In Column (2) of Table 5, the 2SLS estimate shows that a worker acceptance causes an increase in whether any worker was hired at all. Presumably, this effect is largely driven by the firm hiring the invited worker if he or she accepts, but not hiring anyone else if the worker rejects. The 2SLS effect is substantially larger than the OLS estimate, though as expected, the 2SLS estimate is considerably less precise; the 95% CI for the 2SLS estimate overlaps the 95% CI for the OLS estimate.

Although the IV is valid even with job- or employer-specific omitted variables, we can control for the identity of the inviting employer. Column (3) reports the same regression as in Column (2), but with employer-specific fixed effects. The point estimate is similar to the Column (2) estimate, but the estimate is far less precise, which is to be expected given that many of the employers only send one invitation, leaving much less identifying variation.

The direction of the OLS bias relative to the 2SLS estimate, assuming it is not due to sampling variation, offers some insight into the nature of the recruiting process. If the main source of omitted variables bias was job-specific attributes, we would expect the OLS estimate to overstate the true effect of an acceptance. For example, if invitations to “better” job openings are more likely to be accepted, and these better job openings are inherently more likely to be filled, the 2SLS estimate of the effect of an acceptance
Table 5: Effect of an invitation acceptance on the probability a job opening is filled

<table>
<thead>
<tr>
<th></th>
<th>Accepted $a_{ij} = 1$</th>
<th>1[$Y_j &gt; 0$]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1st Stage</td>
<td>2SLS</td>
</tr>
<tr>
<td>Instrument, $z_{ij}$</td>
<td>1.400***</td>
<td>0.673***</td>
</tr>
<tr>
<td></td>
<td>(0.165)</td>
<td>(0.132)</td>
</tr>
<tr>
<td>Invite Accepted, $a_j = 1$</td>
<td>0.577***</td>
<td>0.034</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.083)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.577***</td>
<td>0.034</td>
</tr>
<tr>
<td>Employer FE?</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Observations</td>
<td>57,250</td>
<td>57,250</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.037</td>
<td>−0.218</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.037</td>
<td>−0.218</td>
</tr>
<tr>
<td>Residual Std. Error</td>
<td>0.489 (df = 57221)</td>
<td>0.549 (df = 57221)</td>
</tr>
</tbody>
</table>

Notes: This table reports the results of an IV analysis of the effects of a recruited worker accepting an employer’s recruiting invitation on the probability that the job opening is filled. Column (1) is the first stage of the 2SLS regression and Column (2) is the 2SLS estimate without employer fixed effects, while Column (3) includes employer fixed effects. $Y_j$ is the amount of money spent against the opening and $a_{ij}$ is an indicator for whether the invited worker $i$ accepted the invitation. The instrument $z_{ij}$ is the fraction of applications from $i$’s country that are sent at the hour when the actual recruiting invitation was sent. This instrument is essentially a country-level proxy for the probability that the invited worker was online when they were invited to apply. Significance indicators: $p \leq 0.05: *, p \leq 0.01: **$ and $p \leq .001: ***$. 

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would be closer to zero (and actually be zero if the OLS result was purely due to selection).

If the main source of omitted variables bias was worker-specific attributes, the relative size of the 2SLS estimate would depend on whether those worker-specific attributes made a hire more or less likely, conditional upon an acceptance. For example, suppose invitations are sent to “better” workers who are less likely to accept because they have relatively less capacity—but that if they do accept, these better workers are more likely to be hired, as the employer feels fortunate to get such a good applicant. In this case, the acceptances induced by the instrument would come from relatively better workers, making it more likely that the job opening will be filled. This scenario is consistent with the Table 5 finding that the 2SLS effect from an acceptance is larger than the OLS estimate.

5.5 Effects of invitation acceptances on other outcomes

In addition to whether a hire is made, I can also examine whether the employer interviewed any non-invited applicants, hired some other worker, or engaged in compensatory recruiting following a rejection or acceptance decision. Detecting changes in these other outcomes potentially increases our confidence in the validity of the instrumental variables approach.

Table 6: Effects of an invitation being accepted on organic candidate interviewing and hiring, as well as compensatory recruiting

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Non-recruit interviewed?</th>
<th>Non-recruit hired?</th>
<th>“Late” recruiting?</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2SLS</td>
<td>2SLS</td>
<td></td>
</tr>
<tr>
<td>Invite Accepted, ( a_i = 1 )</td>
<td>-0.595***</td>
<td>-0.239**</td>
<td>-0.135</td>
</tr>
<tr>
<td></td>
<td>(0.133)</td>
<td>(0.105)</td>
<td>(0.095)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.857***</td>
<td>0.385***</td>
<td>0.256***</td>
</tr>
<tr>
<td></td>
<td>(0.084)</td>
<td>(0.066)</td>
<td>(0.060)</td>
</tr>
<tr>
<td>Observations</td>
<td>57,250</td>
<td>57,250</td>
<td>57,250</td>
</tr>
<tr>
<td>Adjusted R(^2)</td>
<td>-0.209</td>
<td>0.014</td>
<td>-0.030</td>
</tr>
<tr>
<td>Residual Std. Error (df = 57221)</td>
<td>0.550</td>
<td>0.430</td>
<td>0.394</td>
</tr>
</tbody>
</table>

Notes: This table reports the results of 2SLS regressions of the effects of a recruited worker accepting an employer’s recruiting invitation on the probability the employer interviews any non-recruited organic applicants, in Column (1), or hires such a worker, in Column (2). In Column (3), the outcome is whether the employer engages in “late” recruiting, defined as recruiting 24 hours after the initial invitations. All regressions are 2SLS regressions using the “fraction of applications” instrument. Significance indicators: \( p \leq 0.05 : \ast, p \leq 0.01 : \ast\ast \) and \( p \leq .001 : \ast\ast\ast \).
Column (1) of Table 6 reports a 2SLS regression where the outcome is whether the employer interviewed any non-recruited, organic applicants. We can see that when an invited worker accepts, the employer is far less likely to interview any organic applicants. This is consistent with the recruited worker being the employer’s first choice and organic applicants serving as less preferred alternatives. Further making this point, in Column (2) the outcome is whether the employer hired a non-recruited applicant. As expected, the effect is negative, and highly significant. In Column (3), the outcome is whether the employer sent any “late” recruiting invitations i.e., those sent an hour or more after the posting of the job opening. As the sign on the coefficient is negative, there is some evidence of compensatory recruiting. However, the effect is imprecisely estimated and not conventionally significant.

The results from Table 6 show that when rejected, employers adjust in comprehensible ways: they rely on organic applicants and (perhaps) recruit again. However, a rejection still lowers hiring overall, as we saw in Table 5, and so the employers adjustments’ are not fully effective in making up for the initial rejection.

5.6 Testing the exclusion restriction

As the 2SLS model is exactly identified, I have no statistical test for the validity of the instrument. However, I can test whether employers learn to invite more-likely-to-be-awake workers over time, as they post more job openings. If employers are learning, then the exclusion restriction would be invalid. However, a caveat is that even if there is no evidence of learning, it does not prove the exclusion restriction is met—perhaps all employers already “know” what to do, however implausible that may be, given how small the effect is. That caveat aside, Column (1) of Table 7 reports a regression of the instrument on the log of $\text{PRIORINVITES}_{jt}$, the employer’s count of previous invitations by that employer in the sample at time $t$:

$$z_{jt} = \beta \cdot \log(\text{PRIORINVITES}_{jt}) + \delta_j + h_{jt} + \epsilon_{jt},$$

(6)

where $\delta_j$ is an employer-specific fixed effect, $h_{jt}$ is a fixed effect for the hour the invitation was sent, and $z_{jt}$ is the instrument value. The sample is the same sample as used in the instrumental variables analysis.
We can see from the Column (1) regression that the coefficient on the prior invitations measure is essentially a precisely estimated zero, with the “wrong” sign, implying there is no evidence that employers learn to seek out workers with higher values of the instrument. In Column (2), I report the same regression as in Column (1), but instead use the count of prior invitations, while in Column (3) I add a squared prior invitations term. In both regressions, the same result holds—there is no evidence employers learn to invite “awake” workers. This result does not prove the exclusion restriction holds, but it is suggestive that it holds.

Table 7: Association between employer prior recruiting experience and the instrument value for the invited worker

<table>
<thead>
<tr>
<th></th>
<th>Value of instrument for invited worker:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Log PRIORINVITES</td>
<td>−0.00004</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
</tr>
<tr>
<td>PRIORINVITES</td>
<td>−0.00002</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
</tr>
<tr>
<td>PRIORINVITES²</td>
<td>0.00000</td>
</tr>
<tr>
<td>Employer Effect</td>
<td>Yes</td>
</tr>
<tr>
<td>Hour-of-day Effect</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>57,250</td>
</tr>
<tr>
<td>R²</td>
<td>0.850</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.471</td>
</tr>
<tr>
<td>Residual Std. Error</td>
<td>0.012 (df = 16255)</td>
</tr>
</tbody>
</table>

Notes: This table reports regressions where the dependent variable is the value of the invited worker’s instrument. All regressions include both hour-of-day and employer fixed effects. The key independent variable is the count of invitations the employer made prior to the current invitation, and various transformations of this variable. Standard errors are clustered the level of the individual employer. Significance indicators: $p \leq 0.05 : *$, $p \leq 0.01 : **$ and $p \leq .001 : ***$.

6 Platform remedies to the worker capacity problem

In response to earlier versions of this analysis, the platform took steps to give recruiting employers more information about worker capacity. First, the platform began reporting each worker’s “responsiveness
metrics” on his or her profile. These metrics showed how long a worker took to respond to invitations, and the fraction of invitations he or she accepted. The goal of the feature was to enable employers to make better choices, but also to give workers an incentive to respond— and respond more quickly—to invitations. Second, the platform created a new signaling mechanism that allowed workers to publicly declare their capacity on their profiles. The hope for the feature was that workers would change their signal as their actual capacity waxed and waned, and that employers in turn would condition on this signal when deciding which workers to invite.

6.1 Showing would-be employers individual worker responsiveness metrics

The new “responsiveness metrics” feature was introduced market-wide, non-experimentally. Figure 3 shows several by-week market-level time series on worker responsiveness. The series are the weekly response, acceptance and rejection rates for all invitations. The sample is restricted to invitations sent by employers sending 10 or fewer invitations per opening. The vertical line at 0 indicates the week the responsiveness metrics were added to worker profiles.

Following the introduction of the feature, the response rate—the fraction of invitations receiving any
response from the worker—rose, going from about 60% to about 75%. However, these additional responses came mostly in the form of rejections: the rejection rate rose, going from about 12% to 25%. The acceptance rate appears to decline slightly following the introduction of the feature. As the denominator for this fraction is the total number of invitations, the acceptance rate should not have fallen if the only effect of the feature was to cause some otherwise-ignored invitations to get a response. If not a statistical artefact, this drop is puzzling, though perhaps it could reflect an overall increase invitations, with these marginal invitations being less likely to be accepted.

A natural question is whether employers conditioned directly on the responsiveness metrics when deciding which workers to invite. Although this analysis is possible in principle, the responsiveness metrics, being averages, change slowly, and by small amounts. This makes the variation in worker metrics less than ideal for studying employer behavior. A more direct way to study employer conditioning comes from the capacity signaling feature the platform introduced.

### 6.2 Worker-reported capacity signal

The capacity signaling feature allowed workers to put one of three messages on their profile about their “availability”: (1) “More than 30 hrs/week,” (2) “Less than 30 hrs/week,” (3) “As Needed - Open to Offers.” The settings were presented in order in the interface to imply that the third option would signal the least amount of capacity. However, as it is somewhat ambiguous as to the relative implied capacity of (2) versus (3), I turn the signal data into a binary indicator for signaling (1), the highest capacity, which I label “Full Time.” For conciseness, I refer to the other two signals as “Part Time” and “As Needed,” respectively. Workers were free to change the setting whenever they wished, but were prompted to do so after events the platform inferred were likely to indicate a change in capacity.

I use changes in worker status settings to obtain within-worker estimate of the effects of the displayed signal on the recruiting process and outcome. Although these changes are, of course, not as good as randomly assigned, from the perspective of the recruiting employer, they are likely viewed as exogenous changes in workers perceived attributes. As far as I am aware, the platform did not use the availability settings made by worker's to determine ranking results in search.

Changes in worker behavior are not “caused” by the signal—our interest is in whether the change in a signal is associated with a change in behavior consistent with

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17 As far as I am aware, the platform did not use the availability settings made by worker's to determine ranking results in search.
the worker truthfully reporting a change in their capacity.

6.3 Data construction and description

For each worker, I observe when they changed his or her signal. From these changes, I construct worker “windows” of time in which his or her signal was unchanged. I use data from April 24, 2014 to May 27, 2016, which gives me 482,723 windows of at least a day in length, for 369,519 distinct workers. However, only 49,378 of these workers actually changed their signal at least once. I only use windows that are at least a day in length, as shorter windows are likely to be workers experimenting with the feature. The most common status window type is “Full Time,” which makes up 73% of all windows, whereas only 16% and 11% of windows are “Part Time” and “As Needed,” respectively.\(^{18}\)

6.4 Effects of the worker capacity signal

The first question of interest is whether employers conditioned their recruiting decisions on the signal observed. Using worker windows as the unit of observation, I regress a measure of employer recruiting intensity on the “Full Time” indicator. The outcome measure is \(\text{INVITESPERQTR}_{iw}\), which is the count of invitations received by worker \(i\) in their window \(w\), divided by the duration of the window (measured in quarters of a year). The regression is

\[
\text{INVITESPERQTR}_{iw} = \beta \cdot \text{FULLTIME}_{iw} + \gamma_i + \text{WEEK}_{t(i,w)} + \epsilon_{iw},
\]

where \(\text{FULLTIME}_{iw}\) is the “Full Time” indicator, \(\gamma_i\) is a workers-specific fixed effect, and \(\text{WEEK}_{t(w,j)}\) is fixed effect for the week the window began.

The leftmost panel of Figure 4, labeled “Invites/quarter,” reports estimates of the effects of the “Full Time” signal. Three estimates are reported, using regressions with: (1) both week and worker fixed effects, labeled “Week + Worker FE,” and corresponding to Equation 7, (2) week fixed effects only, labeled “Week FE,” (3) with neither worker- nor time-specific fixed effects, labeled “No Controls.” For each regression, I use the same sample, which consists of the observations from workers with at least one signal

\(^{18}\) The feature was introduced earlier, but the platform made several changes to the language of the status settings and the user interface for making status changes. After April 24, 2014 the design stabilized and was available to 100% of workers.
Figure 4: Effects of a worker sending a high capacity signal, or “Full Time,” signal

Notes: This figure plots shows a collection of regression estimates of the effects of a worker setting a high capacity signal to the marketplace. For each set of outcomes, three regression results are presented: from left to right, (1) a regression with week and worker specific fixed effects, (2) regression with no controls, and (3) a regression with week fixed effects. In each panel, the reported value is the coefficient on the “Full Time” status indicator. A 95% CI is shown, with standard errors clustered at the worker level.

Change after initially setting their status. For each point estimate, a 95% confidence interval is shown, with standard errors calculated by clustering at the level of the individual worker. In the interests of space, all regression results are presented graphically in Figure 4.

In the “Worker + Week FE” regression, we can see that a worker switching to the “Full Time” status received about 2 more invitations per quarter. This coefficient is identified only from workers changing their status, eliminating concerns that certain kinds of workers likely to give the “Full Time” signal also receive more invitations. In fact, the “Week FE” and “No Controls” regressions show that a worker with a “Full Time” setting received approximately one fewer invitation per quarter. These cross-sectional regressions are simply showing that relatively busier workers get more invitations and are also more likely to signal low capacity.

I now turn to the question of how workers responded to invitations. For this analysis, I switch to using individual invitations as the unit of analysis, with invitations labeled with the signal the worker was giving when receiving that invitation.19

In the “Worker responds” panel of Figure 4, regression results are reported where the outcome is

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19 Given the prior evidence for how little employer effects seem to matter, I do not include an employer-specific fixed effect. I also want to avoid the resulting loss in precision (ala Column (3) in Table 5).
whether a worker responded (i.e., did not just ignore the invitation). From the “Worker + Week FE” regression, we can see that workers are less likely to ignore an invitation when giving the “Full Time” signal, though the effect is small—it is only about a 1.2 percentage point increase. However, the earlier “responsiveness metrics” feature introduction might have left little room for improvement on this outcome. Again illustrating the importance of the within-worker approach, the “Week FE” and “No Controls” estimates actually show a lower response rate associated with a “Full Time” signal. This is puzzling, as those signaling a “Full Time” status would presumably be most interested in taking on more work. One possibility is that since “Full Time” is such a common setting, this regression is picking up inactive workers who have left the platform and do not check their invitation inbox, but left their signal set at “Full Time.”

In the “Worker applies” panel of Figure 4 regressions, results are reported where the outcome is whether the worker actually applied, with the sample restricted to invitations where the worker responded. All three regressions show a strong positive effect, meaning that workers signaling a “Full Time” status were more likely to apply. However, the “No Controls” and “Week FE” regressions show considerably larger effects than the “Worker + Week FE” regression; the “within” estimate is about half the size of the two “between” estimates. One possibility is that those workers that found it worthwhile to change their signal are pickier about projects, as the “Worker + Week FE” estimate comes workers that get a large enough volume of invitations that reducing the volume is attractive. Indeed, workers that used all three signal types over the period covered by the data received about 7 times more invitations per unit of time than those only using one signal type—even though the workers using all three signals were necessarily signaling low capacity at least some of the time.

When the worker applies, they submit an hourly wage bid. The panel labeled “Log wage bid” of Figure 4 reports regressions where the outcome is the log wage bid, with the sample restricted to invitations where the invited worker applied. In all three regressions, workers propose a lower hourly rate when they have given the “Full Time” signal. The “Worker + Week FE” estimate implies workers bid about 2.5% lower. This “discount” is smaller than what is found in the “No Controls” and “Week FE” regressions, which is, again, consistent with those workers using the feature being in greater demand (and hence having higher wage rates).
The rightmost panel of Figure 4, labeled “Worker hired,” reports regressions where the outcome is an indicator for whether the applying worker was hired. The sample is restricted to workers that applied in response to the invitation. In the “Worker + Week FE” regression, we can see that the applying worker is about 3 percentage points more likely to be hired. Given that these same workers bid about 2.5% less (from the log wage bid panel), this increase in hiring probability is unsurprising.

6.5 Discussion of capacity signaling feature

The capacity signaling feature—despite having zero marginal cost to the platform—had several welcome effects. The within-worker estimates show that when a worker switches to giving the “Full Time” signal, they: (1) get more invitations, (2) they respond to a higher fraction of invitations, and (3) they accept a higher fraction of those they respond to, (4) they bid less, and (5) are hired more frequently.

That these improvements were possible strongly suggests that employers were not fully informed about worker capacity before the feature was introduced. All the evidence suggests workers used the feature to signal truthfully, as their behavior is consistent with what they publicly signaled. However, an important caveat—but also an implied opportunity—is that most workers did not change their status once it was set. It is unclear whether this was because they truly had no change in their capacity, or because they were reluctant to reveal their true capacity.

The signaling feature makes clear that high capacity workers tend to be in relatively low demand. We can see this with the often stark differences between the within-worker estimates and the between-worker estimates. An implication of this pattern is that if employers with more information are encouraged to pursue higher capacity workers, they are also more likely to pursue relatively less experienced workers, perhaps with good equity consequences for the marketplaces, ala Pallais (2014).

The capacity signaling feature results allow us to make some ballpark calculations about the likely efficiency effects of capacity uncertainty. In terms of price, in a competitive market, the nearly 3% discount offered by workers when they have more capacity implies that their costs are 3% lower, which means at least a 3% higher social surplus—it could be even more as hours-worked is endogenous with respect to the offered wage. However, an important caveat is that some work is already done by workers with lots of capacity just by chance, so the realized improvement would be lower than 3%, even if all work could
be done by workers with high capacity. In terms of quantity, if we take the approximately 6% increase in acceptance rates by high capacity workers times the approximately 60% increase in fill rate from an acceptance from the IV analysis, we get about a 3.5% increase in quantity of transactions. If these marginal job openings generate as much surplus as the average job opening, then this 3.5% figure would be the increase. However, an important caveat is that many invitations already go to high capacity workers, and furthermore, the IV estimates comes from a sample of employers sending a single invitation (making it likely an over-estimate of the effects of an acceptance).

7 Conclusion

The central conclusion of the paper is that employer uncertainty about worker capacity affects the market studied. Furthermore, the ways it affects the market are likely to be viewed as adverse by an efficiency-minded market designer. The paper also shows that even relatively simple market design interventions by the platform can at least partially remedy the problem.

Although the intervention discussed here was effective, it is not a fully satisfactory solution. For one, workers had fairly weak incentives to use the signaling mechanism, and uptake was concentrated among a small number workers, albeit those most likely to receive invitations. If the platform wanted to take a stronger hand, it could do more than simply provide signals. It would be possible, for example, to prevent the worker from receiving new invitations until all older invitations have been processed.\(^{20}\) Or workers could have some non-monetary visibility or search-result prominence “budget” they could allocate dynamically, creating an opportunity cost to claiming full capacity.

If the platform was open to using money, it could have workers pay to appear higher in search results. Only high capacity workers would pay, and the platform could collect additional revenue. However, this method places a high burden on workers to manage their advertising “campaign,” and it could potentially undermine the overall level of trust in the platform’s actions if organic and paid results were not strongly delineated.

An alternative approach that puts less burden on workers would be for the platform to fit predictive models of capacity, and then adjust search rankings in accordance with the platform’s objectives. Some-

\(^{20}\) Thanks to Randall Lewis for this suggestion.
what ironically, the common industrial practice of fairly static “best-to-worst” search rankings would tend to exacerbate the problems identified in this paper, as the most frequently shown worker is also likely to be capacity constrained (ironically, by the very fact that they appear so often). This machine learning approach places a high burden on the platform, and to the extent workers know their own capacity, a worker-revealing mechanism is probably superior. However, different approaches could be complementary, with the worker-provided signal being just one input into the platform's decision about how “visibility” on the platform is allocated to workers.

References


Halaburda, Hanna and Mikolaj Piskorski, “When should a platform give people fewer choices and charge more for them?,” Antitrust Chronicle, 2010, 7.


Figure 5: Search results interface presented to an employer

Find Freelancers

Figure 5 shows the worker search results displayed for a query of “python,” a popular programming language. Figure 6 shows the interface employer use when inviting a worker to apply for a job opening. Figure 7 shows the interface shown to workers receiving a recruiting invitation from an employer. To “accept” the invitation, they go to the same job application interface as organic applicants.

A Interfaces

Notes: This figure is a screenshot of the platform search interface take on February 9th, 2015 for the query “python,” a popular computer programming language.
Figure 6: Employer interface for contacting a worker with an invitation to apply to a job opening

**Invite**

**Freelancer**
Mila Rahalevich
Python/Django developer - Freelancer

**Message**
Hello!
I’d like to invite you to apply to my job. Please review the job post and apply if you’re available.

Choose a Job
- Choose existing job: R Programmer
- Create a new job post

Job Description
I am looking for an R programmer with experience in ggplot2 and git. You will assist with data exploration and visualization. My projects tend to be quite open-ended and exploratory—I might ask you to re-create an analysis from a paper, write some R code to import a strangely formatted dataset or create some visualizations.

Send Invitation Cancel

**Notes:** This figure shows the view for an employer inviting a worker to a job opening.

Figure 7: Recruiting invitation “inbox” on the platform presented to workers

**Invitations to Interview (1)**

<table>
<thead>
<tr>
<th>Received</th>
<th>Job</th>
<th>Client</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oct 27</td>
<td>Level 2 Software Support Engineer - Systems Engineer (283672429)</td>
<td>gTeam FZ LLC</td>
</tr>
</tbody>
</table>

**Notes:** This figure shows the invitation “inbox” presented to a worker. Note that it shows the date the invitation was received, the title of the associated job and the client [employer] that send the invitation. By clicking the title of the job, the worker can learn more about both the job opening and the employer.