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Just DM Me (Politely): Direct Messaging, Politeness, and Hiring Outcomes in Online Labor Markets

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Abstract. This study examines the role of text-based direct messaging systems in online labor markets, which provide a communication channel between workers and employers, adding a personal touch to the exchange of online labor. We propose the effect of workers' use of the direct messaging system on employers' hiring decisions and conceptualize the information role of direct messaging. To empirically evaluate the information role of the direct messaging system, we leverage data on the direct messaging activities between workers and employers across more than 470,000 job applications on a leading online labor market. We report evidence that direct messaging with a prospective employer increases a worker's probability of being hired by 8.9%. However, the degree to which workers benefit from direct messaging is heterogeneous, and the effect amplifies for workers approaching employers from a position of disadvantage (lacking tenure or fit with the job) and attenuates as more workers attempt to message the same prospective employer. The effects also depend on message content. In particular, we find that the benefits of direct messaging for workers depend a great deal on the politeness of the workers, and this "politeness effect" depends on several contextual factors. The beneficial effects are amplified for lower-status workers (i.e., workers lacking tenure and job fit) and workers who share a common language with the employer. At the same time, the beneficial effects weaken in the presence of typographical errors. These findings provide important insights into when and what to message to achieve favorable hiring outcomes in online employment settings.

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1. Introduction

Online labor markets, defined as digital platforms that enable employment of on-demand workers,[1] have thrived in the last decade, attracting significant attention from both practitioners and researchers. The value of these markets to workers and employers stems from the access they provide to a large pool of geographically dispersed, semianonymous virtual transaction partners. Additionally, during this particular time with a pandemic that led to a trend of work from home, online labor markets are more popular than ever. However, because of the lack of formal interactive screening processes (e.g., face-to-face job interviews), which are common in offline labor markets, employers in online labor markets must contend with a great deal of uncertainty about the workers' qualification and fitness for the job (Autor 2001, Hendricks et al. 2003, Pallais 2014). Online labor markets commonly employ several policies, procedures, or mechanisms in an effort to alleviate information asymmetry, including online reputation systems (Dellarocas 2003), worker monitoring systems (Liang et al. 2016), dispute resolution services (Burtch et al. 2019), and direct messaging systems (the focus of this work).

Most online labor markets now incorporate direct messaging systems that provide a channel of communication between the worker and the employer. Typically, workers have the option to initiate communication with the prospective employer via direct messaging systems, as they submit a job application. However, it is unclear whether, when, how, and to what extent workers' use of the direct messaging system affects their employment outcomes. On the one hand, initiating direct messaging with a prospective employer enables workers to connect with the employer directly and to convey a variety of pertinent information, such as workers' level of interest in and availability to complete the posted job. In turn, direct messages may enable workers place their skills and experience in context. On the other hand, employers may discount the messages entirely, treating them merely as "cheap talk," and they may even glean negative information from message content. For example, a worker may unintentionally reveal a piece of information that leaves employers with particular impressions about the worker, which may dissuade the employer from offering the job, such as employing a tone that does not sit well with the employer (e.g., being perceived as impolite). Given the impersonal nature of the digitally mediated online labor markets, social aspects of the initial messaging have the potential to play an important role, as employers seek to ascertain whether the worker will be easy to work with, after contracted. Therefore, we expect workers' politeness in their direct messaging to be particularly important in landing a job. Bearing this in mind, we formally investigate the following research questions. What is the effect of initiating direct messaging with a prospective employer on a worker's probability of being hired? How does the effect vary across workers? Does a worker's politeness (as reflected in the messaging text) associate with hiring probability? Additionally, how does the effect vary across workers?

To answer these questions, we analyze a proprietary data set from a leading online labor market that includes three key pieces of information: the occurrence of precontract direct messaging (whether a worker initiated a message, timestamps, and the textual content of messages); the set of workers who applied for a given job; and the employer's choice of worker for each given job. Our analyses first show that a worker's use of direct messaging has a positive and significant effect on the worker's probability of being hired, even after accounting for self-selection. Specifically, our instrumental variable estimations indicate that on average, direct messaging increases the probability of a worker being hired by 8.9%. Additionally, this effect is corroborated with a recursive bivariate probit model that explicitly accounts for the endogenous structure of the messaging decision. Further, we show that the benefits of direct messaging are heterogeneous, being larger for newer workers, as well as workers whose profile information indicates they are a poorer fit for the posted job. Further, we observe that the benefits of direct messaging decrease when a larger percentage of competing workers also elects to message the employer for the same job.

Second, we examine the influence of the message content that workers employ in their direct messaging efforts, with a particular focus on politeness, one specific impression the workers leave on the employer. We analyze the relationship between hiring outcomes and the politeness measures of the workers' initial messages, extracted using a combination of text mining, human labeling, and machine learning techniques. We find that workers' use of text reflecting their politeness associates positively with a hiring outcome. Notably, this politeness effect is heterogeneous, such that workers approaching employers from a position of disadvantage (e.g., lacking tenure or job fit) are more likely to benefit from politeness, whereas the effects of politeness are weaker when employers and job applicants do not share a common language and when workers' messages contain more typographical errors.

Our work makes two important contributions to the literature. First, we extend prior work on the role of direct messaging in online platforms, which thus far has focused primarily on retail settings (Ou et al. 2014, Lv et al. 2018, Tan et al. 2019), to the context of online employment, which is increasingly important in the digital economy. We document several moderating conditions that bound the effects of direct messaging in the online labor market context. These findings contribute to the literature on the cold-start problem in online platforms (Pallais 2014). New workers and workers whose profiles do not fit well with posted job descriptions can use direct messaging to potentially contextualize their past and off-platform work experience, therefore partially alleviating the entry barriers associated with the cold-start problem. Related to this, our work contributes more broadly to an emerging stream of research on hiring decisions in online labor markets (Moreno and Terwiesch 2014, Hong and Pavlou 2017, Lin et al. 2018). We have identified a previously unconsidered factor of workers' initiation of direct messaging that has a substantial impact on employers' hiring decisions, beyond wage, reputation, and distances, which have received much of the focus in prior literature.

Second, we provide what is to our knowledge a first consideration of the role of textual content in direct messaging. In doing so, we consider that direct messaging in online labor markets is likely to influence transaction outcomes through the impressions that messages leave with employers. We focus specifically on the construct of politeness to find its positive association with hiring outcomes as well as several important moderators of this politeness effect. By exploring the effects worker politeness, we extend the reference literature to the online employment context. We consider that worker-employer communication around online job search bears many differences from traditional offline job interviews. Online labor markets suffer from asynchronous communication exchange and a lack of social cues. The impersonal nature of these online platforms will likely lead employers to be concerned about workers' willingness to manage a smooth work process (Hong and Pavlou 2017) (i.e., how easy they are to work with, suggesting relatively higher potential returns to workers' politeness).

2. Theoretical Overview

2.1. Direct Messaging in Online Platforms

Online platforms facilitate semianonymous transactions among geographically dispersed individuals and thus, are characterized by significant information asymmetry. In any online platform, it is crucial that market operators take steps to mitigate information asymmetry and uncertainty (Dimoka et al. 2012, Einav et al. 2016). Uncertainty for employers is problematic because it can lead them to employ heuristics and exhibit biases in decision making. Platforms employ a combination of features and policies to reduce uncertainty, with perhaps the best-known example being the online reputation system (e.g., Dellarocas 2003, Moreno and Terwiesch 2014). Unfortunately, online reputation systems work effectively only when workers have previously completed work on the platform (Pallais 2014) and when the nature of a posted project falls within the worker's relevant expertise (Kokkodis and Ipeirotis 2015). Therefore, solely relying on reputation systems to make hiring decisions can lead to inefficient hiring and the exclusion of well-qualified candidates who simply have yet to establish a reputation.

Direct messaging communication features within online peer-to-peer platforms provide an avenue by which participants can provide information by directly reaching out to their potential transaction partners. The information systems literature has recently begun to examine the effects of buyer-seller communication in recent years. Of particular relevance to our study is the paper by Ou et al. (2014), who draw on survey data to show that communications on Taobao (an online e-commerce platform in China) can build swift trust between buyers and sellers, which in turn, impacts sellers' intention to purchase. Similarly, using archival data, Lv et al. (2018) and Tan et al. (2019) demonstrate that live chat between a buyer and a seller on Taobao has a positive effect on a buyer's purchase decisions.

It is notable that the prior literature dealing with direct messaging systems has thus far focused primarily on markets for the sale of goods. Online labor markets differ from typical e-commerce markets in a number of important ways. The transaction involves the exchange of services that are more involved than the delivery of goods (Hong and Pavlou 2017). Social factors are likely to play a greater role, given the ongoing communication that is typically required between the worker and the employer to satisfactorily complete a job. Additionally, whereas prior studies of direct messaging systems typically consider buyers' initiation of conversations with sellers (e.g., Lv et al. 2018, Tan et al. 2019), this pattern is reversed in online labor markets, with sellers (workers) typically initiating conversations with the employers (e.g., Dranove and Jin 2010). This distinction is important because it reflects differences in the nature of information asymmetry between these two types of markets. In typical e-commerce settings, buyers bear the majority of risk in taking possession of the product from the seller. In contrast, in online labor markets, risk is distributed to a greater degree between both parties. Further, whereas messaging systems are used primarily for the purposes of acquiring additional product information or price negotiation in e-commerce settings, they may serve a greater, more nuanced role in online labor markets, as employers may seek to ascertain whether the worker will be easy to work with, after contracted. In this vein, we seek to explore the effects of perceptual characteristics of the message content that workers transmit to potential employers (i.e., the impressions that workers may leave on employers, particularly the workers' politeness). To the best of our knowledge, our work is the first to offer a systematic examination of the role of direct messaging in the online employment setting.

2.2. Direct and Heterogeneous Effects of Messaging Initiation

Message content aside, workers' decisions to initiate direct messaging with a prospective employer have the potential to reduce that employer's uncertainty and thus, the potential to facilitate a positive hiring outcome. Any direct messaging that a worker initiates has the potential to indicate that the worker is particularly interested in the job and would have available bandwidth to take on new work at that point in time. Horton (2019) argues that employers' lack of insight into worker bandwidth can lead to wasted time and effort; a worker who applies for the job and is subsequently selected may ultimately turn down the position because of a lack of availability. Given such importance, employers would perceive workers who initiate direct messaging to have a higher capacity both because they have the slack resources to conduct these conversations and because they are actively seeking to increase their utilization rate.[2] Bearing this in mind, we expect direct messaging initiation to positively affect hiring probability.

The extent to which initiating direct messaging may reduce employer uncertainty is likely to be heterogeneous. In particular, at least two aspects of a worker may moderate the relationship between direct messaging and the hiring outcome: worker tenure and worker-job fit. For new workers, a key disadvantage is that they suffer from the cold-start problem (Pallais 2014); direct messaging may enable workers to provide additional information about their off-platform work experience that may alleviate the employers' uncertainty. Therefore, we expect that newer workers will benefit disproportionally from direct messaging. When it comes to workers seeking jobs that are not clearly aligned with their profile, direct messaging may enable a worker to contextualize his or her background or to provide additional details of relevant work experience. Therefore, again, we might expect workers whose profile information does not align as well with the job descriptions to benefit disproportionally from direct messaging.

Finally, information overload may occur on the employer's part (Jacoby 1984), such that, for a given job posting, when there is a large number of workers messaging the employer, it becomes less likely that the employer will be able to extract useful information. Therefore, we expect that an increasing number of workers initiating direct messaging for a given job posting will attenuate any benefits of direct messaging.

2.3. Direct and Heterogeneous Effects of Messaging Politeness

When it comes to the perceptual characteristics of message text in the online employment context, it is natural to draw on prior work in computational linguistics and social computing on the role of politeness. First, the prior literature has documented the general benefits of politeness in online social discourse. For example, politely framed questions in knowledge-exchange communities are more likely to receive answers (Lee et al. 2019), and polite answers in said communities are more likely to be selected as best (Burke and Kraut 2008, Lee et al. 2019). Further, requests for help are also more likely to be fulfilled, and fulfilled attentively, when posed politely (August and Reinecke 2019, Hu et al. 2019). Also, polite candidates are more likely to be elected Wikipedia editors (Danescu-Niculescu-Mizil et al. 2013). However, there is also suggestion that the effects of politeness are context dependent. Past work has found that politeness may in fact backfire in some situations. For example, although politeness may help low-status community members gain favor, it may be penalized when employed by high-status members (Wang 2020). When negotiators are polite, they have been shown to obtain poorer outcomes because their initial offers are less likely to be accepted (Jeong et al. 2019). Also, finally, politeness in email communication has been found to result in perceptions of deference and low status and thus, attributions of incapability (Jessmer and Anderson 2001).

Online labor markets bear unique characteristics of specific relevance to the workers' politeness in their initial interaction with the employer. First, relative to offline employment settings, online labor markets facilitate semianonymous transactions and afford fewer social cues (Huang et al. 2020). The impersonal nature of these markets makes it is difficult for the employers to assess how easy the workers will smoothly collaborate with the employer over the course of the project. Second, online labor markets facilitate on-demand work transactions, in which there is no formal organizational structure between the employer and the worker to ensure work performance, and further, the employer and the workers typically need to collaborate to complete the job (Hong and Pavlou 2017). Being perceived as a polite worker eases employers' concerns over the possibility of an unpleasant experience in working together on a project and thus, is desirable in the online labor market context.

This politeness effect, however, is likely heterogeneous. First, prior work has found that low-status members of online communities are more likely to exhibit politeness (Althoff et al. 2014), and to benefit systematically more from politeness, in terms of gaining attention, reply, and compliance with requests (Wang 2020). Accordingly, we expect that workers approaching employers from a position of disadvantage (e.g., lacking tenure or job fit) should be more likely to benefit from politeness in their messages. Second, what constitutes "polite" differs between cultures (Ogiermann 2009, House 2012, Haugh and Chang 2015, Luijkx et al. 2020). As such, the effects of politeness may vary between employer-applicant dyads, depending on whether they share a common language, which is a key component of culture that is relevant in communication. Notably, past work suggests that the negative effects of being impolite in business communications are mitigated by the presence of a plausible rationale or justification for mistakes (e.g., grammatical errors when sending from a mobile phone) (Carr and Stefaniak 2012). Accordingly, we expect that whereas politeness is readily interpreted when employers and job applicants share a common language, impoliteness/politeness may play a weaker role in crosscultural or interlingual exchanges, as employers may pay less attention to etiquette and soft signals, if they are cognizant of differing linguistic and cultural norms. Third, recruiters make inferences about applicants based on the presence of typographical errors. For example, some work has observed that recruiters interpret such sloppiness as evidence of impoliteness toward or disrespect for the recipient (Jessmer and Anderson 2001, Martin-Lacroux 2017). Therefore, we expect that in online labor markets, workers will benefit less from politeness when their messages contain more typographical errors because the impoliteness conveyed by those errors may contradict the politeness in message content.

3. Data and Models

3.1. Study Context

Of late, online labor markets have attracted significant attention from information systems researchers (e.g., Kokkodis and Ipeirotis 2015, Chan and Wang 2017, Lin et al. 2018, Horton 2019). An online labor market is a web-based platform that follows a reverse, buyer-determined auction mechanism for on-demand skilled labor, such as software development, design, and data entry (Asker and Cantillon 2010, Hong et al. 2016). To conduct this study, we obtained access to a proprietary database from our corporate partner, a leading platform in this space that connects workers and employers from around the world. We describe a typical hiring process on the platform as follows: An employer first posts a job to the platform, specifying the estimated budget and a description of the job. Interested workers submit a job application, specifying their prices for completing the job. The worker has an option to send a direct message to the potential employer (not publicly observable), when submitting the application. After receiving the applications, the employer evaluates the workers and makes a hiring decision.

The data we obtained pertain to jobs posted between January 1, 2010 and May 31, 2010 that resulted in an employment contract. Our sample excludes trial jobs, deleted jobs, and jobs where the application was restricted to gold members, as well as jobs flagged to be spam by the platform. We construct our estimation sample as a panel of worker-job pairs. Each observation incorporates associated applicant (worker) information, including time-invariant (e.g., country of origin, etc.) and time-variant (e.g., the total number of reviews, tenure, etc.) characteristics, as well as associated employer information. We exclude job applications that were ultimately retracted before the time of contracting; note that these comprise a small portion of the original sample, and their inclusion does not influence our results.

A unique feature of our data set is that we observe the worker-employer communication history at the keystroke level. Each message exchange is tied to a particular job posting. We observe the raw text of each message, the identity of the transmitting party, and that of the receiving party. For each worker-job pair, we divide the communication records between the worker and the employer into pre- and postcontract communications, based on the timing of the employer awarding a contract. Our analyses squarely focus on precontract communication because postcontract communication, by definition, cannot have an effect on employer hiring decisions and is beyond the scope of this research. Based on features of our data, we consider multiple identification strategies that enable us to quantify the impact of precontract worker-initiated direct messages on the hiring outcomes.

3.2. Measures for the Key Variables

We carefully constructed the data set, which involves multiple steps. First, to investigate whether and when direct messaging benefits workers' chances of being hired, we introduce measures capturing the hiring outcome, the messaging decision, moderating variables that characterize the worker-job pair, and finally, a set of control variables related to the worker and the application. Second, to address self-selection concerns around the messaging decision, we propose two sets of instrumental variables and explain why they are valid, both conceptually and empirically. Third, and last, to understand how the politeness of messages affects the hiring outcomes, we draw on text mining, human labeling, and machine learning to construct a measure for politeness. Cognizant that textual measures are undefined in those cases where workers did not initiate a direct message, we take steps to accommodate those nonexistent values, and the validity of our imputation approach is demonstrated with an analytical proof and a series of simulations reported in Online Appendix A. We define our key measures and provide a definition for each variable in Table 1, and we provide corresponding descriptive statistics for the variables in Table 2.

3.2.1. Direct Messaging Initiation and Moderators. To study how workers' initiation of direct messages with a prospective employer affects their hiring outcomes, we introduce our focal variable, an indicator of whether the worker initiated a message to the employer (*workerMessage*), and our outcome of interest, an indicator of whether the worker was ultimately hired (*hired*). We also introduce a series of moderators to capture the boundaries and contingencies under which messaging will be beneficial to workers, including worker tenure, a measure of worker-job fit, and the volume of competing bidders who initiated a message to the same employer. Finally, we include a number of controls that may affect the hiring outcome, including the reputation volume of the worker, the sequence and amount of the bid, and the similarity (language and distance) between the worker and the employer. Specifically, we construct all time-variant variables at the time of each job application. We calculate the tenure of each worker at the time of job application, measured in number of months since registering. We also calculate a textual similarity measure of workers' fit with the posted job. Following Hong and Pavlou (2017), we construct the term frequency-inverse document frequency (TF-IDF) matrices using the corpus of all the worker profile descriptions and job descriptions, and we then calculate cosine similarities between the vector representations of the worker profile text and the job description text for each worker-job pair. We do not consider job- or employer-level characteristics in our analyses because these are broadly subsumed by our inclusion of job-level fixed effects.

3.2.2. Instrumental Variables. The first instrument we consider is whether the message initiated by the worker in his or her most recent prior job application, if any, was read by the relevant employer. Whether the last direct message was read by that prior employer is likely to be driven by factors related to the prior employer or job, rather than factors related to the worker. This is particularly true after we condition upon worker-level characteristics that are likely to have influenced the worker's intention to message that prior job's employer. For example, the message sent to the prior employer

Table 1. Summary of Variable Descriptions

Variable descriptions
Dependent variable
• Hired measures whether the worker's job application resulted in a job offer
Focal variables
• Worker initiation of direct messaging (*workerMessage*) measures whether the worker initiated a private message with the employer in the precontract stage
• Politeness represents the politeness based on text mining of the first message sent by the worker
Other variables
• Bid amount (log(*bidAmount*)) is the amount of payment in dollars the worker requested in the job application (or bid)
• Bid sequence (log(*bidSequence*)) represents the sequence of the focal worker's application, among all applications for the same job
• Reputation volume (log(*reviews*)) measures the number of reviews the worker has received from the employers on completed jobs, at the time of each job application
• Tenure (log(*tenure*)) measures the number of months the worker has been registered on the platform, at the time of each job application
• Insignia (*hasInsignia*) measures whether the worker has any platform awarded insignia; for example, workers may be awarded a Hypertext Preprocessor (PHP) expert insignia if their scores are very high in the PHP examination
• Examination (*hasExam*) measures whether the worker has passed any platform-hosted examinations (e.g., English level 1)
• Language similarity (*simLanguage*) measures the similarity between ideal English and the common spoken language in the worker's country of residence, based on the language database in Centre d'Études Prospectives et d'Informations Internationales (CEPII) (Melitz and Toubal 2014)
• Spatial distance (log(*distance*)) measures the distance between the employer and the worker based on the longitudes and latitudes of their locations
• Worker-job fit (*workerJobFit*) measures the workers' fit with the posted job; specifically, it is measured by the vocabulary similarity between the worker's profile and the job's description
• Initiated bidders (log(*iniBidders*)) represents the number of workers who initiated a message while bidding for a project
• Typographical errors (*pctTypos*) are based on PyEnchant and pyspellchecker, which measure the percentage of typographical errors the worker made in the private messages he or she sent to the employer
• Message word count (log(*words*)) measures the word count in the first message sent by the worker
Instrumental variables
• Worker last message read (*lastMsgRead*) measures whether the worker's last initiated message was read by the employer (coded as zero if not initiated or not read)
• Submission weekday (*subWeekday*) measures the day of the week (Monday to Sunday) when the worker submits the bid for the job using six dummy variables

might be left unread simply because the employer forgot to check incoming messages or because the employer's inbox was swamped. Even if the employer did notice the message, only very limited information (i.e., worker identification and a preview of the first few words in the message; a screenshot is in Online Appendix B) is available to the employer before deciding to read it. A worker identification is unlikely to affect the employer's decision to read, given that 99% of job

Table 2. Descriptive Statistics of Key Variables

Variable	Mean	Standard deviation	Min	Max
hired	0.07	0.26	0.00	1.00
workerMessage	0.60	0.49	0.00	1.00
politeness	3.76	0.29	1.91	4.70
log(*words*)	4.21	0.84	0.69	9.40
pctTypos	0.03	0.03	0.00	1.00
log(*bidAmount*)	4.69	1.15	0.00	13.82
log(*bidSequence*)	2.38	1.12	0.00	5.63
log(*reviews*)	1.56	1.89	0.00	7.23
log(*tenure*)	2.15	1.35	0.00	4.36
log(*distance*)	7.83	2.26	0.00	9.42
workerJobFit	0.07	0.08	0.00	0.87
simLanguage	0.28	0.27	0.00	0.98
hasInsignia	0.34	0.48	0.00	1.00
hasExam	0.12	0.32	0.00	1.00
log(*iniBidders*)	2.68	1.06	0.00	4.71
lastMsgRead	0.51	0.50	0.00	1.00

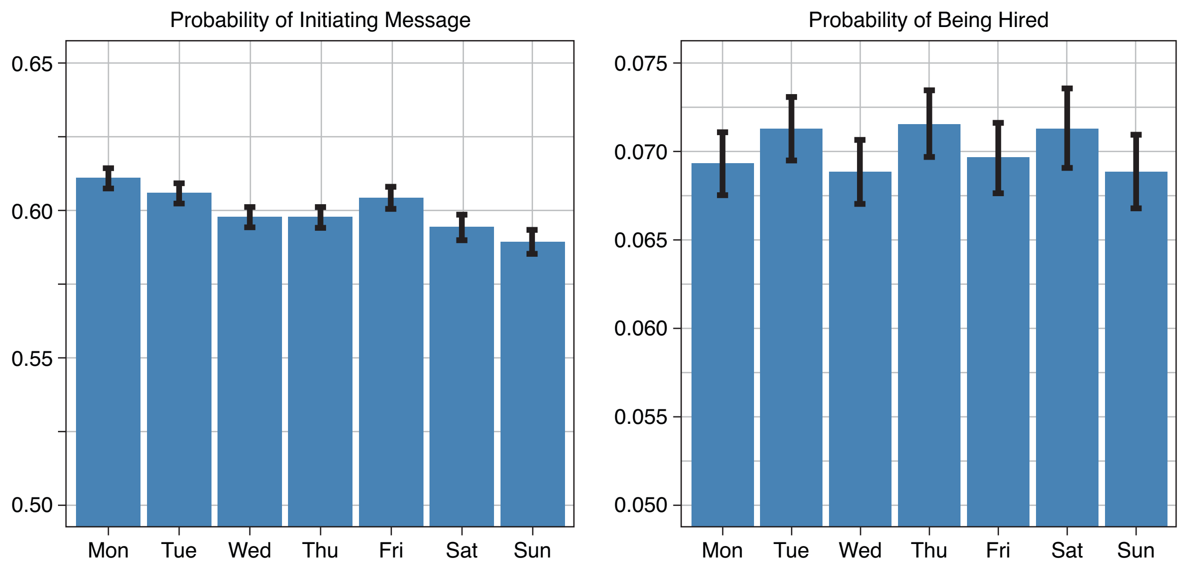
applications in our data were submitted by workers who had never worked for the employers before.

The second set of instruments we consider is the day of week when the worker submitted the job. The day of week may affect workers' decisions on whether to message. For example, workers might be less likely to initiate messages on weekends when employers are likely to be unresponsive. On the other hand, it is *unlikely* for an employer to decide whether to hire the worker based on which day the worker submitted the application. Figure 1 provides model-free evidence on how the average probability to initiate a message and to be hired varies across the different days of week. The model-free evidence is consistent with our expectation. The probability to initiate a message is markedly lower on weekends (error bars indicate 95% confidence intervals), whereas the probability to be hired does not significantly differ across different days of week. We conducted analysis of variance tests, which suggest that the probability to initiate a message varies significantly across days of a week ($p < 0.001$) but not the probability to be hired ($p = 0.16$).

3.2.3. Politeness Measure. To assess the impact of worker politeness on hiring outcome, for each worker who initiated a message to the employer, we extract the textual content of the opening line (first message) sent by the worker. We focus on the first message because the content of the workers' subsequent messages depends on the responses from the employers, if any. Any finding on the impact of the content of the first message can provide insights into the role of first impression in job applications.

To measure politeness, we begin by drawing on third-party coders to evaluate message text and report their perceptions. In our data, we have 358,225 unique first messages. We follow the prior work to execute

Figure 1. (Color online) Model-Free Evidence on Impact of Day of Week of Job Application



the annotation task (Voigt et al. 2017, Lee et al. 2019). We invited coders from Amazon Mechanical Turk to label their perceived politeness of the workers for a random sample of 6,000 messages. We then trained a machine learning model to predict the resulting labels, such that politeness scores could be automatically derived for the remainder of our full sample.

To ensure the quality of responses, the labeling task was only made accessible to Turkers (coders) who resided in the United States and who had completed at least 500 Human Intelligence Tasks (HITs) with an approval rate of higher than 98%. We limited labelers to U.S. Turkers because the official language of the platform is English, and most employers on the platform are from the United States. Online Appendix C provides the details of the labeling task, including the instructions that were provided to coders. For each message, we invited nine coders to rate the extent to which they agreed that the worker sending the message seemed polite, on a Likert-type scale of one to five (strongly disagree to strongly agree, respectively). To further ensure label quality and reliability, we dropped responses supplied by the 10% of coders whose ratings deviated most from the label averages. From the remaining sample, we retain observations with at least six coders. Ultimately, we are left with 5,010 messages. Note that the findings from the associated analyses are consistent if we retain these observations, as well as if we instead remove the 20% of coders whose ratings exhibited greatest deviation from the average.

Using the average value of coder responses, we employ eXtreme Gradient Boosting (XGBoost) to train a machine learning model to predict this continuous value of worker politeness.[3] In training the XGBoost Regressor, we employ TF-IDF weighted unigram, bigram, and trigram tokens; the number of words appearing in a message; the number of characters; the number of typographical errors;[4] dozens of politeness features extracted using the *R* package "politeness" (e.g., latent features derived based on the presence of words and phrases related to greetings, goodbyes, gratitude, and positive and negative emotions);[5] and a few extra features (e.g., the number of Uniform Resource Locators [URLs] in the message and whether the message included a signature, a price, or contact information). The hyperparameters employed in the XGBoost Regressor model were tuned via grid search, in tandem with 10-fold crossvalidation. The root mean squared error of the predictions was 0.126, when we withhold 20% of data for validation. The corresponding mean absolute percentage error was 7.8%. We train our final prediction model using all 5,010 messages. Online Appendix D provides the coded politeness scores for sample messages.

3.2.4. Accommodating Undefined Textual Variables (Absence of Direct Messaging). In 40% of job applications, the worker did not message the employer while bidding for the job. For these applications, the text variables are undefined because no text has been transmitted to the employer. This situation is notably different from the conventional missing value problem because the values are in fact nonexistent, rather than simply being unobserved (Allison 2010). In these 40% of job applications, our text variables cannot possibly have any causal effect on the hiring outcome, although they may affect the hiring outcome in the remaining 60% of job applications. As conceptually explained by Allison (2010) and as we demonstrate by analytical proof and simulations in Online Appendix A, the effect of message content on hiring outcomes can be estimated using an interaction approach or an equivalent imputation approach. Specifically, we regress the hiring decision directly over the interaction of *workerMessage* with each text variable (e.g., *workerMessage* × *politeness*). With the effect of politeness automatically switched off if no message was initiated, the interaction term will capture the main effect of politeness on hiring outcome. One caveat with this interaction approach is that the main effect of *workerMessage* will be interpreted as the effect of messaging when all the text variables equal zero, an unrealistic baseline in that the politeness never takes on a value of zero. To ensure that the main effect has roughly the same interpretation as the average treatment effect, we use the imputation approach discussed in Online Appendix A instead. Specifically, we impute values for our text variables in those 40% of applications where they are undefined, inserting the mean values from those 60% of applications where we did observe direct messaging activities. We then regress the hiring outcome directly over the imputed text variables.

This imputation approach follows the recommendations of Allison (2010) for handling observations of values that do not exist (e.g., the average age of kids for one with no kid). As Allison (2010) points out, this approach does *not* lead to bias or inconsistency when variables are undefined as opposed to standard missingness. Note that our approach is also preferable to simply removing the observations where our text measures are undefined because doing so would limit our analysis to a sample of workers who self-selected to message and hence, result in biased estimates. In contrast, when we use the imputation approach, the bias resulting from the endogenous messaging decision can be addressed with instruments for the messaging decision (see Online Appendix A for a series of simulation results). In the imputation approach, the main effects of our text variables can still be interpreted as their effects on the hiring outcome, whereas the main effect of *workerMessage* can be interpreted as the effect of messaging when a message with average content is sent.

Lastly, for the sake of comprehensive consideration, we also report regression results (Online Appendix G) for the subsample of observations where job applications did involve direct messaging (i.e., the subsample where our text measures are defined), and the results are consistent with the imputation approach.

3.3. Models

Following the prior literature on employer preferences in online labor markets (Ghani et al. 2014, Hong and Pavlou 2017), we estimate a linear probability model (LPM) to analyze hiring outcomes. Primarily, the LPM is preferred in this analysis because of the associated ease of interpreting interaction effects, which are not readily interpretable in nonlinear models.

To alleviate the concern that hiring outcomes are jointly determined across workers for any given job, we include a job-level fixed effect, which accounts for any observed or unobserved time-invariant, job-specific characteristic that may affect the hiring decision. Let w, j, and e index workers, jobs, and employers, respectively. We use α_j to capture the job-level fixed effects, which also subsume employer-level fixed effects as the employer of each job is unique. Our model specifications also control for observable worker characteristics that vary across bids because of the progression over time.

Equation (1) represents our baseline model, wherein we seek to establish the average effect of direct messaging on hiring probability. This is our most parsimonious specification, in which the coefficient (β_1) associated with the focal independent variable, *workerMessage*, quantifies the effect of worker-initiated private messaging on the hiring outcome:

$$\begin{aligned} Hired_{w,j} = {} & \beta_1 \times workerMessage_{w,j} \\ & + \beta_2 \times \log(reviews_{w,j}) \\ & + \beta_3 \times \log(tenure_{w,j}) \\ & + \beta_4 \times \log(spatialDistance_{w,e}) \\ & + \beta_5 \times \log(bidAmount_{w,j}) \\ & + \beta_6 \times \log(bidSequence_{w,j}) \\ & + \beta_7 \times hasInsignia_w + \beta_8 \times hasExam_w \\ & + \beta_9 \times simLanguage_w \\ & + \beta_{10} \times workerJobFit_{w,j} + \alpha_j + e_{w,j}. \end{aligned} \tag{1}$$

It is notable that the worker's decision to initiate communication is subject to self-selection and is thus potentially endogenous. In an effort to alleviate this concern, we instrument the focal variable, *workerMessage*, with the two instrumental variables discussed in Section 3.2 (i.e., *lastMsgRead* and *subWeekday* dummies) and estimate the parameters in Equation (1) using the two-stage least squares (2SLS) method. Note that the instrumental variable (IV) estimates produced by other estimation methods (e.g., limited information maximum likelihood) are highly consistent and available upon request:

$$\begin{aligned} workerMessage_{w,j} = 1(&\alpha_0 + \alpha_1 \times \log(reviews_{w,j}) \\ &+ \alpha_2 \times \log(tenure_{w,j}) \\ &+ \alpha_3 \times \log(spatialDistance_{w,e}) \\ &+ \alpha_4 \times \log(bidAmount_{w,j}) \\ &+ \alpha_5 \times \log(bidSequence_{w,j}) \\ &+ \alpha_6 \times hasInsignia_w \\ &+ \alpha_7 \times hasExam_w \\ &+ \alpha_8 \times simLanguage_w \\ &+ \alpha_9 \times workerJobFit_{w,j} + u_{w,j} > 0) \end{aligned} \tag{2a}$$

$$\begin{aligned} Hired_{w,j} = 1(&\beta_0 + \beta_1 \times workerMessage_{w,j} \\ &+ \beta_2 \times \log(reviews_{w,j}) + \beta_3 \times \log(tenure_{w,j}) \\ &+ \beta_4 \times \log(spatialDistance_{w,e}) \\ &+ \beta_5 \times \log(bidAmount_{w,j}) \\ &+ \beta_6 \times \log(bidSequence_{w,j}) \\ &+ \beta_7 \times hasInsignia_w + \beta_8 \times hasExam_w \\ &+ \beta_9 \times simLanguage_w \\ &+ \beta_{10} \times workerJobFit_{w,j} + v_{w,j} > 0) \end{aligned} \tag{2b}$$

$$\begin{pmatrix} u_{w,j} \\ v_{w,j} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right).$$

Further, we consider an alternative empirical strategy that achieves identification by functional forms (Li et al. 2019), instead of relying on the validity of the instruments. Specifically, as shown in Equations (2a) and (2b), we use a recursive bivariate probit model to explicitly model the endogeneity structure of the messaging decision. In this model, both the messaging and hiring decisions are determined by a probit model, and the error terms of the two models are assumed to be bivariate normally distributed. The model is recursive in the sense that the hiring decision depends on the messaging decision. The correlation parameter captures the relationship between the confounders that affect the messaging decision of the worker and the hiring decision of the employer. Additionally, this model can be identified without instruments (Greene 2012, p. 746; Li et al. 2019).

We primarily focus on the results produced by the IV models, and we report the (consistent) results from the recursive bivariate probit model to explain the differences in the effect sizes of the *workerMessage* variable in the ordinary least squares versus the two-stage least squares in Online Appendix G. To examine heterogeneity in these effects, we subsequently consider the interactions of *workerMessage* with a subset of the worker features, including worker tenure and worker job fit.

When we explore the effect of message content, namely politeness, we incorporate the politeness measure and its interactions with the various contextual moderators we discussed in the prior section. These moderators include (i) worker tenure, (ii) worker-job fit, (iii) whether the worker and potential employer share a common language, and iv) the presence of typographical errors. We introduce these moderators individually, before estimating a model incorporating all of them jointly, as in Equation (3):

$$\begin{aligned} Hired_{w,j} = &\beta_1 \times workerMessage_{w,j} \\ &+ \beta_2 \times \log(reviews_{w,j}) + \beta_3 \times \log(tenure_{w,j}) \\ &+ \beta_4 \times \log(spatialDistance_{w,e}) \\ &+ \beta_5 \times \log(bidAmount_{w,j}) \\ &+ \beta_6 \times \log(bidSequence_{w,j}) \\ &+ \beta_7 \times hasInsignia_w + \beta_8 \times hasExam_w \\ &+ \beta_9 \times simLanguage_w + \beta_{10} \times workerJobFit_{w,j} \\ &+ \beta_{11} \times \log(words_{w,j}) + \beta_{12} \times pctTypos_{w,j} \\ &+ \beta_{13} \times politeness_{\mathrm{w},j} \\ &+ \beta_{14} \times politeness_{w,j} \times \log(tenure_{w,j}) \\ &+ \beta_{15} \times politeness_{w,j} \times workerJobFit_{w,j} \\ &+ \beta_{16} \times politeness_{w,j} \times simLanguage_w \\ &+ \beta_{17} \times politeness_{w,j} \times pctTypos_{w,j} + \alpha_j + e_{w,j}. \end{aligned} \tag{3}$$

4. Results

4.1. Main Effect of Messaging

We use the panel data two-stage least squares model to estimate the effect of message initiation on hiring outcomes. We consider three models to estimate the main effect of direct messaging, as summarized in Table 3. In the first model, we control for job-level fixed effects, worker-level characteristics, and worker-job–level characteristics, as noted, but we do not consider the endogeneity of message initiation. In the second model, we use the variable *lastMsgRead* as an instrument for *workerMessage* and perform 2SLS estimation. The weak identification statistic is larger than the 10% maximal IV size threshold (i.e., 16.38), suggesting that this instrument is rather strong (Stock and Yogo 2002). In the third model, we instrument *workerMessage* with both *lastMsgRead* and *subWeekday* dummies. As reported in column (3), the weak identification statistic continues to be larger than the 10% maximal IV size threshold (i.e., 31.50) when these two sets of instruments are used at the same time. More importantly, the overidentification test (Hansen *J* statistic) suggests that the null hypothesis that the instruments are valid cannot be rejected (p = 0.232), which provides further confidence about the validity of the instruments.

One concern with the validity of *lastMsgRead* as an instrument is that it depends on whether the worker initiated a message in his or her last job application, which might be correlated with the unobserved confounders affecting his or her probability to be hired. To address this concern, we further consider a model in which we explicitly control for whether the worker sent a message in the last job application (*lastWorkerMessage*). The results are summarized in column (4) in Table 3.

Table 3. Main and Heterogenous Effects of Direct Messaging

	(1) OLS Hired	(2) 2SLS Hired	(3) 2SLS Hired	(4) 2SLS Hired	(5) 2SLS Hired	(6) 2SLS Hired
log(*reviews*)	0.019***	0.017***	0.017***	0.016***	0.018***	0.018***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(*tenure*)	−0.002***	−0.006***	−0.006***	−0.002***	−0.001	−0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)
log(*distance*)	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(*bidAmount*)	−0.051***	−0.049***	−0.049***	−0.048***	−0.049***	−0.050***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(*bidSequence*)	0.003***	0.007***	0.007***	0.012***	0.007***	0.008***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
hasInsignia	0.013***	0.007***	0.008***	0.006***	0.007***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
hasExam	0.008***	0.008***	0.008***	0.007***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
simLanguage	0.032***	0.033***	0.033***	0.032***	0.033***	0.032***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
workerJobFit	0.079***	0.051***	0.051***	0.022**	0.138***	0.079***
	(0.005)	(0.006)	(0.006)	(0.008)	(0.020)	(0.006)
lastWorkerMessage				−0.084***		
				(0.012)		
workerMessage	0.024***	0.089***	0.089***	0.220***	0.080***	0.664***
	(0.001)	(0.004)	(0.004)	(0.023)	(0.006)	(0.020)
workerMessage × log(*tenure*)					−0.009**	
					(0.004)	
workerMessage × *workerJobFit*					−0.129***	
					(0.031)	
workerMessage × log(*iniBidders*)						−0.202***
						(0.006)
Observations	472,801	472,801	472,801	472,801	472,801	472,801
R^2	0.037	—	—	—	—	—
Job FE	Yes	Yes	Yes	Yes	Yes	Yes
Jobs	29,999	29,999	29,999	29,999	29,999	29,999
Weak identification statistic	—	20,779	2,976	125.1	170.7	555.2
Hansen *J* (overidentification) statistic	—	—	8.09	10.67	20.40	11.42
Overidentification test p-value	—	—	0.232	0.099	0.311	0.494

Notes. Robust standard errors clustered by jobs are in parentheses. The first model does not use any instrument. The second model uses *lastMsgRead* as an instrument, whereas the third model uses *lastMsgRead* and *subWeekday* as instruments. The fourth model further controls for the messaging decision of the worker in his or her last job application. The first-stage results of 2SLS models in columns (2)–(4) are reported in Online Appendix E. The fifth and sixth models extend the third model by including interaction terms. FE, fixed effect; OLS, ordinary least squares.

$^{**}p < 0.01$; $^{***}p < 0.001$.

Overall, we observe a positive effect of workers' direct messaging on the probability of being hired. Additionally, further, the main effect of *workerMessage* becomes larger after accounting for the endogeneity of *workerMessage*, which suggests that there are unobserved confounders leading to an understated estimate of the benefits of direct messaging.[6] One speculation is that systematically higher rates of direct messaging by low-quality workers would yield exactly this pattern, given low-quality workers should also be systematically less likely to be hired. This speculation of adverse selection is consistent with the negative *association* between *lastWorkerMessage* and hiring decision in column (4) in Table 3. To better understand the nature of the endogeneity, in our additional robustness checks reported in Online Appendix G, we further explore the relationship between the unobserved confounders affecting the messaging and hiring decisions using the recursive bivariate probit model, as formulated in Equations (2a) and (2b). We find that the unobserved factors influencing messaging decision and hiring outcome are negatively correlated, lending support to the speculated adverse selection.

After establishing the main causal effects of direct messaging on workers' probability of being hired, we next examine heterogeneity over a subset of worker characteristics and competitive intensity. We again use the instrumental variable approach. To address the endogeneity of the interaction terms, we follow the approach discussed in Wooldridge (2010), including the interaction of the instruments with the respective moderator variables (log(*tenure*), *workerJobFit*, and log(*iniBidders*)) as additional instrumental variables. Based on column (5) of Table 3, we can see that the positive effect of worker direct messaging is stronger for new workers (i.e., those who registered recently) and for workers whose platform profile indicates a poorer fit with the posted job. Lastly, we check if there is information overload in direct messaging from the employer's perspective. Based on column (6) of Table 3, we observe that the positive effect of direct messaging decreases when more workers initiate direct messaging with the employer. This result suggests that information overload does exist.

4.2. Main and Heterogeneous Effects of Politeness

Having considered the general effects of direct messaging, we now turn our attention to the message content and message politeness in particular. We used the imputation approach as discussed in Section 3.1 and Online Appendix A to estimate the effect of message content on hiring outcomes. Table 4 contains the regression results based on multiple model specifications, including a specification that considers the interaction between politeness and our various contextual moderators. Several interesting findings emerge from this analysis.

First, we observe a consistent, positive effect of politeness in workers' direct messaging content on hiring probability. Second, considering politeness moderators, we see several interesting patterns. In particular, we find that politeness is significantly more beneficial when workers approach employers from a position of disadvantage (i.e., lacking tenure or job fit). We also find that politeness is more important when workers share a common language with the employer. Finally, we find that the benefits of politeness are weakened by the presence of typographical errors. Considering the direct effects of other content-based variables, namely message length and typographical errors, we find that longer messages are positively associated with hiring, whereas spelling errors are negatively associated with hiring.

5. Discussion

5.1. Key Findings

We have examined the role of the direct messaging system in employers' hiring decisions in an online labor market. After demonstrating evidence that message initiation significantly increases the probability of being hired, we proceed to explore worker-level heterogeneity in the benefits of direct messaging. We demonstrate that direct messaging is more beneficial for workers who are newly registered on the platform, as well as workers whose profile information does not match well with the job description. We further show that, as more workers initiate direct messaging with the same potential employer, the benefits of direct messaging decrease, consistent with an information overload mechanism. Finally, we examine the textual content communicated by a worker and associate the extracted textual features (conveyed impressions of politeness, in addition to length and spelling errors) with the worker's hiring probability. We find worker politeness to associate positively with the hiring outcome, and this politeness effect is amplified for workers who approach the employer from a position of disadvantage (lacking tenure and job fit) and who share the same language with the employer; however, it is attenuated when there is a larger percentage of typographical errors in the worker initiated message.

5.2. Contributions to the Literature

Our work makes several important contributions to the literature. First, by examining workers' direct messaging with employers, this paper builds on related prior research on the role of communication in online retail environments (Ou et al. 2014, Lv et al. 2018, Tan et al. 2019) into the context of online work, which is of increasing importance to society. We build on past research, considering not only contextual moderators on the effect of direct messaging, such as worker tenure and the similarity between worker profile and job

Table 4. Direct and Heterogeneous Effects of Politeness on Hiring Outcome

Variables	(1) Hired	(2) Hired	(3) Hired	(4) Hired	(5) Hired	(6) Hired	(7) Hired
log(*reviews*)	0.017*** (0.000)	0.017*** (0.000)	0.017*** (0.000)	0.017*** (0.000)	0.017*** (0.000)	0.017*** (0.000)	0.017*** (0.000)
log(*tenure*)	−0.006*** (0.000)	−0.006*** (0.000)	−0.006*** (0.000)	−0.006*** (0.000)	−0.006*** (0.000)	−0.006*** (0.000)	−0.006*** (0.000)
log(*distance*)	−0.003*** (0.000)	−0.003*** (0.000)	−0.003*** (0.000)	−0.003*** (0.000)	−0.003*** (0.000)	−0.003*** (0.000)	−0.003*** (0.000)
log(*bidAmount*)	−0.049*** (0.001)	−0.049*** (0.001)	−0.049*** (0.001)	−0.049*** (0.001)	−0.049*** (0.001)	−0.049*** (0.001)	−0.049*** (0.001)
log(*bidSequence*)	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)
hasInsignia	0.008*** (0.001)	0.008*** (0.001)	0.008*** (0.001)	0.007*** (0.001)	0.008*** (0.001)	0.008*** (0.001)	0.007*** (0.001)
hasExam	0.008*** (0.002)	0.008*** (0.002)	0.008*** (0.002)	0.008*** (0.002)	0.008*** (0.002)	0.008*** (0.002)	0.008*** (0.002)
simLanguage	0.031*** (0.002)	0.031*** (0.002)	0.031*** (0.002)	0.031*** (0.002)	0.031*** (0.002)	0.031*** (0.002)	0.031*** (0.002)
workerJobFit	0.049*** (0.006)	0.049*** (0.006)	0.048*** (0.006)	0.050*** (0.006)	0.049*** (0.006)	0.049*** (0.006)	0.049*** (0.006)
log(*words*)	0.003*** (0.001)	0.002** (0.001)	0.003*** (0.001)	0.002** (0.001)	0.002** (0.001)	0.002** (0.001)	0.003*** (0.001)
pctTypos	−0.189*** (0.012)	−0.187*** (0.012)	−0.189*** (0.012)	−0.188*** (0.012)	−0.187*** (0.012)	−0.230*** (0.014)	−0.227*** (0.014)
workerMessage	0.088*** (0.004)	0.088*** (0.004)	0.087*** (0.004)	0.088*** (0.004)	0.087*** (0.004)	0.087*** (0.004)	0.087*** (0.004)
politeness		0.004* (0.002)	0.006** (0.002)	0.005* (0.002)	−0.003 (0.002)	0.009*** (0.002)	0.005* (0.002)
politeness × log(*tenure*)			−0.014*** (0.001)				−0.013*** (0.001)
politeness × *workerJobFit*				−0.070*** (0.014)			−0.044** (0.014)
politeness × *simLanguage*					0.024*** (0.005)		0.016*** (0.005)
politeness × *pctTypos*						−0.170*** (0.025)	−0.148*** (0.025)
Observations	472,801	472,801	472,801	472,801	472,801	472,801	472,801
Job FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jobs	29,999	29,999	29,999	29,999	29,999	29,999	29,999
Weak identification statistic	2,988	2,984	3,008	2,984	2,981	2,985	3,003
Hansen *J* (overidentification) statistic	7.648	7.675	7.590	7.656	7.744	7.697	7.649
Overidentification test *p*-value	0.265	0.263	0.270	0.264	0.257	0.261	0.265

Notes. Robust standard errors clustered by jobs are in parentheses. Politeness and its moderators are demeaned to ease the interpretation of interactions. All the models use *lastMsgRead* and *subWeekday* as instruments. The substantive findings from the recursive bivariate probit model are similar. When we remove the top 20%, instead of 10%, unreliable coders while measuring politeness, the results are consistent (see Online Appendix F). FE, fixed effect.

$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

descriptions, but also, message content. With our findings, this study contributes to the literature on the cold-start problem related to platform experience (Ghani et al. 2014, Pallais 2014), as the direct messaging system allows new workers and workers whose profile does not fit well with posted job descriptions to potentially contextualize their work experience and skills as they initiate conversations with the employers. These findings suggest that the entry barriers and inefficiency typically associated with the cold-start problem can be partially addressed by offering direct messaging features and encouraging market participants to leverage them during the job application process. This work also contributes more generally to an emerging stream of research on hiring decisions in online labor markets (Moreno and Terwiesch 2014, Agrawal et al. 2016, Burbano 2016, Lin et al. 2018), which provide millions of jobs for gig workers and are an important part of the gig economy workplace. We have identified workers' direct messaging with potential employers and several linguistic features that are significant yet understudied factors with a substantial effect on employers' hiring choices, beyond factors such as wage, reputation, language, certification, and spatial distance.

Second, our study reports a first exploration of how the textual content of direct messages, namely politeness, may influence employment outcomes. Beyond objective aspects of message content, such as communication volume (length) and quality (spelling mistakes), we focus on the efficacy of workers' politeness as a key construct, and we identify when and for whom politeness plays a particularly important role in online job search. These findings contribute more generally to the extant literature on the importance of communication in online employment (Morand and Ocker 2003, Hong and Pavlou 2017). Online labor markets suffer from asynchronous communication exchange and a lack of social cues. The findings suggest that in the context of online employment, as workers engage in direct messaging and seek to make a positive impression on employers, it is important to convey soft signals, perhaps indicative of functional quality (i.e., indications of the worker's ability to work smoothly in collaboration with the employer). Similarly, the findings extend prior literature on politeness in traditional job interviews to an online employment setting. Politeness, as an important element of impression management, has been studied previously by a number of scholars in the area of personnel psychology and human resources, typically in offline contexts (Cheng et al. 2014). Our work extends that prior literature to the online employment setting, operationalizing and evaluating the role of politeness reflected in the content of textual messages sent to the employer.

5.3. Contribution to Practice

This study provides a number of actionable insights for both workers and operators of online labor markets. Our findings suggest that the nearly 40% of all instances wherein workers fail to reach out to employers constitute a sizeable opportunity to increase workers' chances of employment. However, messaging can be counterproductive if not used properly. Most notably, our findings suggest that it would be particularly helpful to reach out to employers if a worker is new to the platform, if the job does not clearly match to the worker's profile, if the worker has a solid grasp of English, and when the volume of competition for the job is not extreme. Our findings suggest that, as workers reach out to prospective employers, they should ensure that they use a polite tone with the employer to showcase that they are easy to work with, particularly for workers who are new share a common language with the employer. Finally, on the platform side, our findings suggest that platform operators might benefit from encouraging direct interaction between employers and workers prior to hiring decisions, especially when information asymmetry is likely to result in hiring biases and cold-start problems, such as when the workers are new to the platform. Thus, in addition to supplying the system, platforms might actively advocate their use, through the provision of guidelines, and coach workers on effective communication strategies. Finally, our work suggests that platform operators may benefit from incorporating integrated spelling and grammar assistance tools into their direct messaging systems.

5.4. Limitations

This study of course has a few limitations, which we believe constitute opportunities for future research. The first limitation is that we are unable to account for the endogenous nature of textual content that workers incorporate into their messages. Conceivably, workers who exhibit a higher rate of typographical errors may be systematically weaker in their presentation in other, unobserved, respects (e.g., their choice of profile photo), which can lead to spurious associations between textual features and hiring probability. Nevertheless, an experiment involving the randomized incorporation of textual content features within employee messaging attempts to employers is quite challenging to implement. That said, future work might seek to adapt prior job interview laboratory experiments to the online environment to accomplish this. Second, our objective here has been to establish the baseline effects of direct messaging and to understand, in particular, the effects of politeness in message content. We leave more advanced analyses of textual content for future work, wherein scholars might employ, for example, topic modeling techniques to identify subjects of discussion that workers should or should not broach to employers in the precontracting stage.

6. Conclusion

We analyze a large-scale archival data set from a leading online labor market to understand the impact of direct messaging system usage on worker hiring outcomes in the online employment setting. As the digital economy grows, more and more offline activities are mediated by online platforms. These platforms allow semianonymous transactions among individuals who do not know each other in the offline world. Our study provides a first attempt at understanding the extent to which a direct messaging system influences hiring behavior in online labor markets, and it is our hope that this work will set the stage for more research on the role of direct messaging systems in online job search, employment contracting, and other contexts.

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Endnotes
[1] We use the terminology of "employers," "workers," "jobs," and "applications" in this paper, which are interchangeable with other terminology that appears in the literature. For example, employers are sometimes referred to as buyers or clients, workers are sometimes referred to as bidders or freelancers, jobs are sometimes referred to as projects, and applications are sometimes referred to as bids.

[2] Note that the decision to engage in direct messaging may confound our estimation of messaging's effect on hiring outcomes. For example, if low-quality workers are systematically more likely to engage in direct messaging, this selection effect would confound the relationship between messaging and hiring outcomes, given that worker quality will influence hiring outcomes through other causal paths. Accordingly, when conducting our analysis, it will be important to account for such selection effects.

[3] XGBoost is an implementation of gradient-boosted decision trees that excels in both speed and performance (Chen and Guestrin 2016). As a fairly new algorithm, it has already won 10 data science competitions on Kaggle. See https://xgboost.readthedocs.io/en/latest/python/python_api.html and https://github.com/dmlc/xgboost/tree/master/demo#machine-learning-challenge-winning-solutions.

[4] In addition to PyEnchant (https://pypi.org/project/pyenchant/), we further consider pyspellchecker (https://pypi.org/project/pyspellchecker/), another popular package to detect typographical errors.

[5] See https://cran.r-project.org/web/packages/politeness/vignettes/politeness.html.

[6] It should also be noted that, because an employer may not read every message, the estimated effect of sending a message is likely to be lower than the effect of having a message read by an employer. We thank an anonymous reviewer for this observation.

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