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Online Freelance Marketplaces**

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Communication in the Gig Economy: Buying and Selling in Online Freelance Marketplaces

Abstract

The proliferating gig economy relies on online freelance marketplaces, which support relatively anonymous interactions by text-based messages. Informational asymmetries thus arise that can lead to exchange uncertainties between buyers and freelancers. Conventional marketing thought recommends reducing such uncertainty. However, uncertainty reduction and uncertainty management theories indicate that buyers and freelancers might benefit more from balancing, rather than reducing, uncertainty, such as by strategically adhering to or deviating from common communication principles. With dyadic analyses of calls for bids and bids from a leading online freelance marketplace, this study reveals that buyers attract more bids from freelancers when they provide moderate degrees of task information and concreteness, avoid sharing personal information, and limit the affective intensity of their communication. Freelancers' bid success and price premiums increase when they mimic the degree of task information and affective intensity exhibited by buyers. However, mimicking a lack of personal information and concreteness reduces freelancers' success, so freelancers should always be more concrete and offer more personal information than buyers do. These contingent perspectives offer insights into buyer–seller communication in two-sided online marketplaces; they clarify that despite, or sometimes due to, communication uncertainty, both sides can achieve success in the online gig economy.

Keywords: online freelance marketplaces, gig economy, multi-sided platforms, business-to-business exchange, uncertainty management, text analysis

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3 Online freelance marketplaces, such as Upwork, Fiverr, and PeoplePerHour, have already
4 prompted massive transformations in business-to-business (B2B) markets (Constantinides,
5 Henfridsson, and Parker 2018; Zhou et al. 2021). In particular, they allow buyers to post gigs, or
6 short-term service projects, which initiate reverse auctions in which interested freelance workers
7 submit bids to offer their services (Jap 2007). In these digital environments, buyers and
8 freelancers often devote rather limited time and attention to detailed assessments and instead
9 make choices on the basis of rational value expectations or prices (Ba and Pavlou 2002; Rajdeep
10 et al. 2015). In addition, online freelance marketplaces suffer information asymmetries, because
11 they rely on text-based messages, which can create uncertainty and hinder the exchange (Hong,
12 Wang, and Pavlou 2016; Srivastava and Chandra 2018). Imagine a buyer wants to hire a
13 freelancer to optimize its pet website's search rankings, so it posts a call for bids, requesting
14 "someone for an SEO job." In response, Freelancer A might vaguely promise, "I have plenty of
15 experience writing content that users find interesting to improve the quality and quantity of your
16 traffic," whereas Freelancer B more concretely states, "I have four years of experience writing
17 articles and blogs that engage users and are SEO friendly. For example, I could focus on interest
18 pieces like the everyday lives of pets." The buyer and the freelancers' communication create
19 different degrees of uncertainty; likely impacting who applies and who gets hired.
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42 Uncertainty regarding communication can lead to various negative outcomes on both sides,
43 including high rates (more than 50%) of service gigs that go unfulfilled (Horton 2019),
44 diminished bid success, or less-than-optimal pricing for freelancers (Ba and Pavlou 2002). Yet in
45 general, parties to B2B exchanges also leverage uncertainty in their communication strategically
46 to achieve more effective outcomes, such as when negotiators conceal information (Putman and
47 Jones 1982) or ambiguous contracts help reduce litigation concerns and increase cooperation
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3 (Zheng et al. 2020). Buyers and freelancers on online freelance marketplaces engage in a form of
4 B2B exchange, so we propose that they similarly might balance their communication efforts by
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6 reducing and increasing uncertainty strategically to maximize their exchange success. In our
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8 previous example, by staying vague and without any specific direction from the buyer,
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12 Freelancer A might be trying to keep multiple options open and avoid overpromising outcomes.
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15 In addition to fundamental questions regarding how to manage uncertainty in B2B
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17 exchanges (Lawrence et al. 2019; Palmatier, Dant, and Grewal 2007), we seek to address the role
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19 of communication in such exchanges (Berger et al. 2020; Rajdeep et al. 2015; see also Web
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21 Appendices A and B). We integrate uncertainty reduction theory (Berger and Calabrese 1975)
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23 and uncertainty management theory (Brashers 2001) to predict that, in online freelance markets,
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25 various strategies for reducing and increasing the ability of message recipients to anticipate
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27 message senders' meaning and actions can benefit the exchange (Bradac 2001). Using Grice's
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29 (1975) communication principles, we argue that greater provision of task and personal
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31 information might reduce uncertainty in service exchanges (Ma and Dubé 2011) but also could
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33 relate to information overload or disagreements (Eisenberg and Witten 1987; Jones, Ravid, and
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35 Rafaeli 2004). Presenting information in a more concrete (cf. abstract) manner or with greater
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37 affective intensity also can reduce uncertainty (Grice 1975; Hamilton and Hunter 1998; Packard
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39 and Berger 2020). But again, too much concreteness or affective intensity might lead to
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41 restrictive communication that hinders exchanges (Eisenberg and Witten 1987; Hosman 2002).
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47 We apply this theoretical reasoning to exchanges in online freelance marketplaces, in
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49 which buyers post calls for bids to attract as many freelancers as possible to apply (Horton
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51 2019). These buyers face a trade-off, between reducing uncertainty for freelancers (e.g., provide
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53 more information, use less ambiguity) and still efficiently granting them sufficient interpretative
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3 freedom. Theorists concur that principles for using relevant information or unambiguously often
4 get deliberately flouted in conversation, such as to save face (Goffman 2008) or please a
5 counterpart (Khosarvzadeh and Sadehvandi 2011). If different communication strategies might
6 entice more freelancers to bid, we could establish optimal designs for the calls for bids.
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12 In response to those calls for bids, freelancers write and submit their bids. In doing so,
13 these freelancers also must manage uncertainty. Thus, they might benefit from matching or
14 mimicking the communication approach adopted by the prospective buyer that issued the call
15 (Verbeke, Dietz, and Verwaal 2011). Communicative mimicry can evoke similarity perceptions,
16 which tend to increase receivers' sense of rapport and reduce their uncertainty (Soliz and Giles
17 2014). Research on adaptive selling recommends matching the buyer's communication (e.g.,
18 McFarland, Challagalla, and Shervani 2006; Singh, Marinova, and Singh 2020). Yet in some
19 situations, deviations also may be beneficial (Afifi and Burgoon 2000), so we consider a more
20 nuanced distinction, related to the level at which the similarity occurs. Furthermore, if
21 freelancers compete on price, they may become enmeshed in a self-defeating value trap (Hong,
22 Wang, and Pavlou 2016; Sridhar and Mittal 2020): They win more bids but earn less revenue.
23 Strategically mimicking or deviating from a buyer's communication might provide a viable
24 means to win more gigs without being trapped. We accordingly suggest how freelancers should
25 calibrate their bid formulations to improve their bid success and achieve a price premium.
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44 Using a unique, large-scale data set of calls for bids and bids, obtained from a leading
45 online freelance marketplace, along with a series of multilevel models that account for
46 endogeneity, we establish three main contributions. First, we determine the effects of buyers'
47 strategic communication in two-sided online marketplaces (Berger et al. 2020). Rather than
48 uncritically recommending that communication should always be informative and unambiguous,
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3 we specify the diminishing, even adverse consequences that can result if buyers relay too much
4 task or personal information in a very concrete, intense manner. Second, in an extension of
5 research into adaptive selling (McFarland, Challagalla, and Shervani 2006; Verbeke, Dietz, and
6 Verwaal 2011), we reveal how freelancers' dyadic communicative mimicry affects bid success.
7 Mimicry effects are contingent on the communicative aspect and the buyer's relative uses of
8 each aspect. As we show, mimicking buyers in terms of the provision of task information and use
9 of affective intensity increases bid success. In contrast, we find that freelancers should always
10 offer more personal information and be more concrete in their bid formulations than buyers' calls
11 for bids are. Third, we offer insights into how freelancers can avoid predatory pricing
12 (Constantinides, Henfridsson, and Parker 2018) and escape a value trap (Sridhar and Mittal
13 2020). By strategically managing uncertainty according to the information communicated, and
14 the manner they use to do so, they can earn price premiums.

30 **Online Freelance Marketplace Exchanges**

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33 Online freelance marketplaces that feature reverse auctions rely on a three-stage process
34 (Hong, Wang, and Pavlou 2016; Jap 2007). First, in seeking a suitable freelancer, a buyer
35 describes a gig or short-term service project in a call for bids. Second, multiple freelancers apply,
36 by formulating and submitting bids that describe themselves, the service offering, and the price
37 requested. Third, the buyer compares the bids and selects a freelancer to complete the gig. The
38 outcome of each stage defines exchange success. That is, buyers' success results from a large
39 pool of viable freelance offers; a higher number of bids increase the chances of finding a suitable
40 freelancer for the gig (Horton 2017, 2019). Freelancers' success depends on whether their bids
41 are chosen, preferably at a price premium (Hong and Pavlou 2017; Constantinides, Henfridsson,
42 and Parker 2018). In this context, a price premium is the monetary amount in excess of the
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3 buyer's original payment offer (i.e., expected price; Grewal, Monroe, and Krishnan 1998; Singh
4 and Sirdeshmukh 2000). Buyers might pay a premium beyond their original payment offer for
5 various reasons, including their willingness or "need to compensate the seller for reducing
6 transaction risks" (Ba and Pavlou 2002, p. 248). In competitive online markets, freelancers also
7 might encounter value traps, such that they wind up selling more of their services at a lower price
8 (Ba and Pavlou 2002; Sridhar and Mittal 2020). In this sense, freelancers' success depends on
9 winning the bid but also earning price premiums (or avoiding discounts). Unlike traditional B2B
10 exchanges, buyers' and freelancers' success hinge on textual communication (Constantinides,
11 Henfridsson, and Parker 2018; Horton 2019). Comparing theories on uncertainty and the role of
12 communication in producing or reducing it, we delineate how both buyers and freelancers may
13 best strike a balance between providing more information and reducing ambiguity versus
14 preserving some uncertainty and maintaining interpretative flexibility.

30 **Conceptual Background**

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33 Uncertainty reduction theory (Berger and Calabrese 1975) and uncertainty management
34 theory (Brashers 2001) draw on a central tenet of information theory (Shannon and Weaver
35 1949), namely, that communication, information, and uncertainty are inextricably linked. Thus,
36 uncertainty is inherent to any interaction. Goffman (1959) suggests uncertainty depends on the
37 ability to draw inferences from provided information content and the manner in which it is
38 provided. Whereas uncertainty reduction theory predicts how communication can reduce
39 uncertainty, uncertainty management theory examines how people cope with uncertainty, which
40 may include efforts to increase uncertainty to attain beneficial outcomes (Bradac 2001). Our
41 conceptual development relies on these fundamental principles.

Communication Principles in Online Freelance Marketplaces

In online freelance marketplaces, buyers and freelancers depend on one another; all else being equal, they want their mutual exchange to succeed. In such interactions, Grice (1975) suggests that four generalized cooperative communication principles (or maxims) apply. Three principles refer to what should be said: the quantity of information (“give as much information as is required, and no more than is required”), its quality (“do not say what is false or that for which you lack adequate evidence”), and its relevance. Then the fourth principle, manner (be clear and avoid ambiguity), pertains to “how what is said is to be said” (Grice 1975, p. 46). In our study context, neither a buyer nor a freelancer can know upfront whether the other party might be lying, so truthfulness would have to be assumed prior to the exchange. We also highlight that information does not have to be “correct” to influence uncertainty perceptions (Brashers 2001). Therefore, among the four maxims, we focus on the quantity of relevant information that buyers and freelancers offer and the manner in which they present it.

Uncertainty Implications of Communication Principles

Communication outcomes are fundamentally uncertain (Berger and Calabrese 1975). When people vary their use of communication principles (Grice 1975), they create conversational implications, such that message recipients must infer what speakers are trying to imply with their wording. Accordingly, the (un)certainty that buyers and freelancers encounter while making inferences should depend on the degree to which call for bids and bids provide relevant information in an unambiguous manner, though the meaning of relevant information varies by context. In line with prior research (e.g., Berger et al. 2020), we define this degree as the proportion of specific lexical terms used, relative to the total number of words in a message.

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3 More information reduces uncertainty (Berger and Calabrese 1975) and increases
4 receivers' perceptions of its value (Weiss, Lurie, and MacInnis 2008). In service exchanges, the
5 parties seek information about the task and the person who will complete it (Ma and Dubé 2011).
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7 A greater degree of task information should reduce uncertainty about functional service aspects
8 (Ma and Dubé 2011). By self-disclosing greater degrees of personal information, a sender also
9 provides a receiver with more information about the self (Derlega, Harris, and Chaikin 1973). In
10 line with the quantity principle (Grice 1975), sparse provision of relevant task and personal
11 information would make it difficult for the receiver to anticipate outcomes or distinguish among
12 options, thus creating uncertainty (Engelhardt, Bailey, and Ferreira 2006).
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15 Regarding the principle of manner (Grice 1975), greater degrees of concreteness and
16 affective intensity should reduce ambiguity and enhance clarity. Concrete terms describe
17 something in a perceptible, precise, specific, or clear manner (Brysbaert, Warriner, and
18 Kuperman 2014; Larrimore et al. 2011; Packard and Berger 2020). A greater degree of
19 concreteness reduces ambiguity because it makes it easier for receivers to perceive or recognize
20 what it is that the message sender is implying (Brysbaert, Warriner, and Kuperman 2014;
21 Hamilton and Hunter 1998; Packard and Berger 2020). Affective intensity instead reflects the
22 proportion of affective terms included in a message (Hamilton, Hunter, and Burgoon 1990).
23 More affective terms, as a proportion of the total word count, produces a greater degree of
24 affective intensity, which increases receivers' ability to make evaluative judgments (Hamilton
25 and Hunter 1998; Hosman 2002).¹ We provide examples of these principles in table 1.
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51 ¹ Task and personal information, concreteness, and affective intensity do not comprise an exhaustive list of all the
52 lexical elements that might define relevant information content and communication manners. Various extensions are
53 thus available for further research. However, we note the primacy of these elements in previous research and
54 therefore prioritize them for this initial effort to establish how the communication principles relate to uncertainty
55 perceptions and exchange outcomes in online freelance marketplaces.
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[please insert Table 1 here]

Reducing and Maintaining Uncertainty in Communication Exchanges

Cross-disciplinary research provides ample evidence that conversational partners generally prefer to reduce uncertainty (Berger 2011). In B2B relationships, reducing uncertainty increases exchange effectiveness (Heide and Weiss 1995; Lawrence et al. 2019; Palmatier, Dant, and Grewal 2007). In online, freelance, relatively anonymous marketplaces specifically, the required coordination and dependence by rational buyers and freelancers may increase their need for information and clarity (Constantinides, Henfridsson, and Parker 2018; Hong, Wang, and Pavlou 2016). Thus for example, reputation cues commonly appear in online freelance markets, as a way to reduce uncertainty and facilitate exchanges (Hong, Wang, and Pavlou 2016). More broadly, reducing uncertainty by adhering to Grice's (1975) principles in dyadic, buyer–freelancer communications may boost exchange success.

However, people experience uncertainty differently and do not always prefer to reduce it (Bradac 2001). Instead, according to uncertainty management theory (Brasher 2001), strategic communication choices that might not minimize uncertainty, and even cultivate it, can be effective and lead to better outcomes for consumers (Humphreys, Isaac, and Wang 2020), organizations (Eisenberg and Witten 1987; Homburg, Klarmann, and Staritz 2012), and interorganizational governance (Zheng et al. 2020). For example, Humphreys et al. (2020) find that a lack of concreteness aids consumers' initial online searches, because such vague queries return a greater variety of search results. In collective bargaining settings, seasoned negotiators use concealment and ambiguity to enhance the likelihood of agreement (Putnam and Jones 1982). In B2B exchanges, parties can use less information and more ambiguity strategically to accomplish specific goals (Bayer, Tuli, and Skiera 2017; Zheng et al. 2020). Even if such efforts

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3 are not universally favored, uncertainty-cultivating communication provides benefits by allowing
4 for multiple, simultaneous meanings, as understood by different receivers (Eisenberg and Witten
5 1987). Moreover, communication theorists concur that people sometimes deliberately flout or
6 violate Grice's (1975) conversation principles, such as when they intentionally maintain
7 uncertainty to save face (Goffman 2008) or please a counterpart (Khosarvizadeh and Sadehvandi
8 2011). Subverting the principles is not necessarily less cooperative; furthermore, the purpose of
9 communication is not always to be as informative and clear as possible. Arguably, cooperative
10 principles encourage reasonable adherence, not compulsion. Thus, strategically allowing
11 recipients to develop a broader range of possible interpretations, by maintaining some level of
12 uncertainty, might facilitate buyer–freelancer exchanges.

26 **Research Propositions**

28 ***Managing Freelancers' Uncertainty in Calls for Bids***

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31 Freelancers choose whether to offer their services in response to a buyer's call for bids.
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33 The number of freelancers who choose to do so is consequential for the buyer, because more bids
34 implies a greater likelihood of finding a suitable service provider (Horton 2019). Managing
35 freelancers' uncertainty through relevant information provision and the manner of
36 communication in the calls for bids should influence freelancers' decisions to apply.
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42 *Relevant information.* In calls for bids, buyers can vary the degree of task and personal
43 information included in the description of the gig. If freelancers evaluate this information
44 favorably, they develop more positive dispositions and are more likely to apply (Singh,
45 Marina, and Singh 2020). As prior research establishes, more information enhances
46 communication outcomes in business settings, by reducing uncertainty. For example, studying
47 web forums, Weiss, Lurie, and MacInnis (2008) indicate that the breadth of information provided
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3 by a sender affects receivers' objective judgments of the value of that information. Larrimore et
4 al. (2011) find that greater degrees of monetary information increase peer-to-peer lending, and
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7 Joshi (2009) shows that more task information increases the time and commitment sellers
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10 allocate to a buyer. Greater degrees of personal information also reduce uncertainty, increase
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12 trust (Ma et al. 2017), and enhance performance on crowdsourcing platforms (Pollock, Lutgens,
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14 and Pillar 2019). Such self-disclosure can strengthen ongoing buyer–seller relations too (Crosby,
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16 Evans, and Cowles 1990). In contrast, a greater proportion of non-relevant information (i.e.,
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18 lesser degree of relevant information) increases uncertainty (Brashers 2001). Because greater
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20 degrees of task and personal information in calls for bids help reduce freelancers' uncertainty,
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25 freelancers who believe they qualify should be more willing to submit bids.

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27 Excessive relevant information may be ineffective however, even if it reduces
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freelancers' uncertainty. That is, if buyers provide excessive details about the task, the gig may
appear too restrictive or prescriptive (Eisenberg and Witten 1987), which might not appeal to
freelancers. For example, leaving detailed information out of contracts (Ghosh and John 2005) or
negotiations (Putman and Jones 1982) represents a tactic to improve exchange performance. In a
downsizing context, a greater degree of information provision can increase uncertainty and
negative reactions (Homburg, Klarmann, and Staritz 2012). For freelancers, excessive
information can feel overwhelming and limit their motivation, opportunity, or ability to process
the information and submit bids (Jones, Ravid, and Rafaeli 2004). A buyer that self-discloses a
lot of personal information also might appear less attractive as a prospective business contact
(Collins and Miller 1994). Because extensive self-disclosures are unusual in initial B2B online
exchanges (Koponen and Rytsy 2020), they might be perceived as inappropriate (Moon 2000).

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3 In summary, we argue that moderate degrees of task and personal information in calls for
4 bids relate to more bids by freelancers. Buyers who provide greater degrees of task and personal
5 information should attract more bids, but beyond a moderate degree (i.e., very dense provision of
6 relevant information), providing still greater degrees of task and personal information may
7 decrease the number of bids. We thus propose a curvilinear relationship.
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14 **P₁**: Extremely sparse and extremely dense degrees of (a) task and (b) personal
15 information in calls for bids yield fewer freelance bids than do moderate degrees.
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18 *Communication manner.* In calls for bids, buyers can vary the concreteness and affective
19 intensity with which they describe the gig. Researchers disagree about whether more or less
20 ambiguous communication leads to more efficacious speech (Bradac 2001; Eisenberg and Witten
21 1987; Hosman 2002), but in an online freelance marketplace, we posit that buyers must reduce
22 ambiguity to at least some extent, by being more concrete and intense. Greater concreteness and
23 affective intensity can be more efficient, because recipients can process the information with less
24 time and effort (Hosman 2002, Packard and Berger 2020). Their use also tend to be more
25 persuasive, memorable, and accessible than communication that uses predominantly abstract or
26 unemotional wording (Hosman 2002; Hamilton and Hunter 1998). In other settings, greater
27 concreteness increases consumer satisfaction with employee interactions and purchase likelihood
28 (Packard and Berger 2020). Greater degrees of intensity, achieved through proportionally more
29 affective words, provide accessible, diagnostic signals to customers (Ludwig et al. 2013). As a
30 form of inspirational appeals, they can sway business partners' decisions too (Singh, Marinova,
31 and Singh 2020). Finally, greater concreteness and affective intensity provide heuristic cues, so
32 freelancers can take mental shortcuts, which makes them more likely to bid (Hosman 2002).
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52 However, if the calls for bids appear too concrete or too intense, the task might appear
53 narrow which reduces the appeal of performing the gig (Hosman 2002). Williams (1980) finds
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3 that greater vagueness (cf. less concreteness) can enhance judgments of a speaker's character,
4 message acceptance, and recall. Moreover, some research asserts that reducing uncertainty with
5 more concrete formulations is ineffective (Brashers 2001; Eisenberg and Witten 1987), so
6 managers instead should embrace strategic ambiguity to allow for interpretative freedom
7 (Keleman 2000). In contracts, unexpected specificity even increases ex ante costs (Mooi and
8 Ghosh 2010). Greater task ambiguity instead can lower costs, as well as reduce the risk of
9 litigation and enhance cooperation in B2B exchanges (Zheng et al. 2020). Greater degrees of
10 concrete terms in communications with investors also can have adverse effects (Pan et al. 2018),
11 and excessive degrees of positive affective words diminish the impact of customer reviews
12 (Ludwig et al. 2013). Thus, we predict a stylistic trade-off: Overly ambiguous calls for bids,
13 lacking any concreteness or affective intensity, may undercut buyers' success in attracting
14 freelancers, but some degree of ambiguity (i.e., avoiding overly concrete, affectively intense
15 communication) can allow for divergent interpretations to coexist. Thus, moderate degrees of
16 concreteness and affective intensity may be most effective in encouraging freelancers to bid.

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35 **P₂**: Extremely sparse and extremely dense degrees of (a) concreteness and (b) affective
36 intensity in calls for bids yield fewer freelance bids than do moderate degrees.

37 38 39 ***Managing Buyers' Uncertainty in Bids***

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41 Buyers also face uncertainty when deciding whom to hire and how much to pay (Ba and
42 Pavlou 2002; Constantinides, Henfridsson, and Parker 2018). By managing these uncertainties
43 through their bids, freelancers can affect their chances of winning bids and their price premiums.
44 To establish relevant predictions, we integrate Grice's (1975) communication principles with
45 uncertainty research, such that we anticipate that a greater provision of relevant information,
46 communicated with greater concreteness and affective intensity, allows buyers to draw
47 inferences from freelancers' bids with more certainty. Beyond these communication principles,
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3 Berger and Calabrese (1975) suggest that perceived similarity to a message sender reduces
4 receivers' uncertainty. Thus, both purchase likelihood and buyers' willingness to pay a price
5 premium might be influenced by freelancers' adherence to certain communication principles, as
6 well as by their communicative similarity to the buyer.
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12 *Winning bids.* In other exchange contexts, research has established that greater degrees of
13 service or personal information (Liu et al. 2015, Packard, Moore, and McFarran 2018) that
14 service employees relay, improve customers' intentions to purchase. Willingness to purchase
15 also increases if employees use greater concreteness in online service chats (Packard and Berger
16 2020) or greater degrees of affective words in their emails (Singh, Marinova, and Singh 2020).
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24 However, the dense provision of relevant information in a bid risks information overload
25 (Jones, Ravid, and Rafaeli 2004), and being overly concrete or intense might signal a restrictive,
26 narrow approach to the gig (Hosman 2002). Our reasoning here parallels that for the buyers' call
27 for bids formulations. We thus similarly predict that moderate degrees of task and personal
28 information, provided in a moderately unambiguous manner (i.e., moderate degrees of
29 concreteness and affective intensity), enhance freelancers' chances of winning the gig.
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38 Yet preferences for uncertainty also might be situational and dispositional (Brashers 2001),
39 as reflected in buyers' own communicative choices (Holtgraves 1997). Specifically, calls for bids
40 can reveal buyers' expectations and preferences for communication behaviors. For example,
41 buyers might like to get to know freelancers or prefer to keep their business relationships
42 impersonal. The extent to which they disclose their own personal information in calls for bids
43 should signal these preferences. An ambiguous bid offered in response to an ambiguous call for
44 bids might lead the buyer to conclude that the freelancer is tactful, sensitive, and non-coercive
45 (Brown and Levinson 1987). Adaptive communications also raise perceptions of credibility,
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3 common social identity, approval, and trust (Ludwig et al. 2013; Soliz and Giles 2014), as well
4 as similarity perceptions, which in turn reduce uncertainty (Berger and Calabrese 1975). Crafting
5 responses that mimic the buyer's communication is a common personal selling recommendation
6 (Verbeke, Dietz and Verwaal 2011). As Singh, Marinova, and Singh (2020) show, when sellers
7 mimic buyers' communicative manner, it increases buyers' attention. Accordingly, freelancers
8 who mimic a buyer's communication content and manner might improve their exchange success.
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11 In some situations, though, deviating from buyers' communication may be more beneficial
12 (Afifi and Burgoon 2000). Even in studies that note the performance benefits of adaption,
13 researchers highlight the importance of the degree of adaptivity (e.g., degree to which sales
14 behaviors adjust for each customer during the interaction; Verbeke, Dietz, and Verwaal 2011).
15 Similarly, studies of communication accommodation investigate the degree of accommodation
16 used (Soliz and Giles 2014). Extending these insights, the outcomes of adaptation likely depend
17 on communication levels (e.g., very informative vs. not informative); in keeping with uncertainty
18 reduction theory, we expect that buyers are less likely to hire freelancers whose bids offer sparse
19 information and are very ambiguous, even if the call for bids has these characteristics.
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38 **P₃**: When the degrees of (a) task and (b) personal information, (c) concreteness, and (d)
39 affective intensity provided by the buyer are at least moderate (sparse), freelancers can
40 increase (decrease) their chances of bid success by mimicking buyers' communication.
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43 *Achieving price premiums.* Buyers' uncertainty about a freelancer should influence their
44 willingness to pay a price premium (Ba and Pavlou 2002). Although there are many reasons for
45 price variations (Grewal, Monroe, and Krishnan 1998), in online freelance marketplaces, buyers
46 compensate (penalize) freelancers for reducing (increasing) their transaction uncertainty by
47 deciding to accept a price above (below) their original payment offer (Ba and Pavlou 2002). In
48 line with Rao and Monroe (1996), freelancers' greater provision of relevant task and personal
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3 information in a more concrete and intense manner in bids likely reduces buyers' information
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5 asymmetry and exchange-specific risks. Therefore, buyers who want to transact with high
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7 certainty may render a price premium for such bids (Liu et al. 2015).
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10 The degree to which freelancers mimic buyers' communication also may influence the
11 price premium. For example, Mullins, Agnihotri, and Hall (2020) find that adaptive approaches
12 for different customers help salespeople increase those customers' willingness to pay a price
13 premium. However, in line with our arguments regarding bid success, we expect that the positive
14 influence of mimicry depends on the specific level of the communication element that the buyer
15 uses. This reasoning aligns conceptually with the communication principles (Grice 1975), the
16 recommendation that uncertainty should be carefully managed (Bradac 2001), and the benefits of
17 mimicry identified in studies of communication accommodation (Soliz and Giles 2014) and
18 adaptive selling (Verbeke, Dietz, and Verwaal 2011). However, we know of no studies that
19 consider price premium implications of communicative trade-offs between reducing buyers'
20 uncertainty and adapting to buyers' communication. In addition, we are not aware of any
21 research that considers the possible negative effects when sellers mimic buyers who provide
22 lesser task and personal information, are less concrete, or sparsely use affective intensity.
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40 Buyers who want to transact with high certainty might render a price premium to
41 freelancers who reduce their uncertainty by providing greater degrees of relevant information, in
42 a more concrete and intense manner. But if buyers perceive that these provisions of relevant
43 information, degrees of concreteness, and intensity surpass their own reasonable level, they
44 might feel overloaded or restricted and thus be unwilling to pay a premium. We thus predict that
45 buyers offer a price premium to freelancers who provide degrees of relevant information,
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concreteness, and affective intensity similar (but never too sparse) to their own communication manner, because only these bids help reduce buyers' exchange risks.

P₄: When the degrees of (a) task and (b) personal information, (c) concreteness, and (d) affective intensity provided by the buyer are at least moderate (sparse), freelancers can increase (decrease) their chances of earning a price premium by mimicking the communication of the buyer.

Figure 1 presents the propositions, including predictions about the success of buyers' calls for bids (i.e., number of freelancers attracted, at Stage 2 of the bidding process) and the success of freelancers' bids (i.e., chances of winning and obtaining a price premium, Stage 3).

[please insert Figure 1 here]

Field Study of an Online Freelance Marketplace

Setting and Sample

We conducted a large-scale field study with a proprietary data set of calls for bids and corresponding bids, posted on a leading, global online freelance marketplace. The hosts seven freelance service submarkets: (1) design, (2) writing & translation, (3) video, photo, & audio, (4) business support, (5) social media, sales, & marketing, (6) software & mobile development, and (7) web development. As Figure 1 illustrates, the bidding process follows a sequential, sealed-bid reverse auction format, and it concludes when the buyer chooses one winning bid (Hong, Wang, and Pavlou 2016; Jap 2007). We use text data from 343,796 calls for bids issued by 49,081 buyers (restricted to those who posted at least two gigs) to predict buyers' call for bids success, 2,327,216 bids submitted by 34,851 freelancers (restricted to those who submitted at least two bids) to predict freelancers' bid success, and 148,158 bids submitted by 30,851 freelancers (restricted to those who won and for which the payment was disclosed) to predict freelancers' price premium. Our multilevel approach requires more than one observation (call for bid or bid) in each level 2 unit (buyer or freelancer); otherwise, level 2 and level 1 variance might be

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3 confounded (Snijders and Bosker 2011). Web Appendix C summarizes the definitions and
4 operationalizations and Web Appendix J the descriptive statistics and correlations.
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7 ***Measurement of Constructs***

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10 The number of freelancers who submit bids to offer their services provides the measure of
11 the *success of buyers' call for bids*. More submitted bids increase the probability that buyers can
12 find an appropriate freelancer, whereas failing to find a suitable match is time consuming and
13 costly, because it requires further searches and delays the project (Horton 2017, 2019). We
14 measure *freelancers' bid success* as a binary indicator of whether (1) or not (0) the freelancer is
15 chosen by the buyer and wins the bid (Hong and Pavlou 2017). For *freelancers' price premium*,
16 we gauge the percentage by which the accepted bid price for the project exceeds (or falls short
17 of) the buyer's original payment offered (i.e., benchmark price; Farris et al. 2010). This
18 operationalization accounts for the difference between the final price a buyer pays and the
19 original price she offered (i.e. what the buyer expected to pay) (Singh and Sirdeshmukh 2000).
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33 To capture the independent communication variables, we mined the text of each call for
34 bid and each bid. For the preprocessing and extraction steps, we used the R package Quanteda
35 (Benoit et al. 2018), as well as a combination of newly developed and prevalidated text mining
36 dictionaries. For the degree of *task information* in each text, we inductively sourced a list of
37 context-specific task descriptor words. To start, we acquired all 34,851 freelancers' service skill
38 tags (Berger et al. 2020; for an illustration, see Web Appendix D), which freelancers list in their
39 profiles to describe the service tasks they offer (e.g., “developer,” “illustrator”). After removing
40 stop words and duplicates, two coders reviewed the remaining word list, deleted any misspelled
41 words, and removed terms that did not describe a service (e.g., “great,” “reliable”). Using
42 Quanteda (Benoit et al. 2108), we stemmed the remaining words, leaving 1,912 unique word
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3 stems that describe service tasks. We mined each call for bids and bid and summed word
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5 occurrences reflecting the new task dictionary. By dividing this sum by total words, we obtain a
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7 measure of the degree (ratio) of task information in each text. When people self-disclose
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9 *personal information*, they use singular, first-person pronouns. In line with previous research
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11 (e.g., Pennebaker and Stone 2003), we measure the degree of personal information as the ratio of
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13 first-person singular pronoun words (e.g., “I,” “me”) to the total words in each text. To determine
14
15 the degree of communication *concreteness*, we mined each text for Brysbaert, Warriner, and
16
17 Kuperman’s (2014) list of generally known English lemmas that indicate whether a concept
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19 denoted by a term refers to a perceptible entity. Following their operationalization, we include all
20
21 terms that receive a rating of 3 or greater on their bipolar, 5-point abstract-to-concrete rating
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23 scale.² That is, terms that score 3 or higher refer to relatively more specific objects, materials,
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25 people, processes, or relationships. We again divide the sum of the concrete terms by the total
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27 words in each text. Finally, the ratio of emotion-laden words (e.g., “problematic,” “easy”;
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29 Hamilton and Hunter 1998; Hosman 2002) determines *affective intensity*. From the LIWC affect
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31 dictionary, we obtain a list of affect words, which we sum for each text (Pennebaker et al. 2015),
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33 then divide by the total word count to obtain the degree of affective intensity.
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40 ***Pilot Studies***

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42 *Validity of text-mined measures.* To ensure the validity of our text-mined communication
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44 measures, we asked two coders to classify the texts of a random subsample of 100 calls for bids
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46 ($M_{\text{length}} = 129$ words) and 100 bids ($M_{\text{length}} = 102$ words). The coders indicated if considerable
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48 task information, personal information, concreteness, and affective intensity were present in each
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54 ² More stringent term lists, using cut-off levels at 3.5 or 4, strongly correlate ($r > .60$, $p < .01$) with the list that uses
55 3 as a cut-off.
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3 text(1); or not (0). Comparing the coders' classifications with our text-mined classification
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5 revealed substantial agreement, for both calls for bids (.73 to .94) and bids (.66 to .88)
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7 (Krippendorff 2013). The average F1 measure is sufficiently high for both bids (.79 to .95) and
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9 calls for bids (.80 to .95), as we detail in Web Appendix F.

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12 *Experimental evidence of uncertainty reduction.* To establish the internal validity of the
13
14 chosen communication aspects on receivers' uncertainty perceptions, we conducted a series of
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16 experimental pilot studies. We use single-factor, within-subject designs for (1) task information,
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18 (2) personal information, (3) concreteness, and (4) affective intensity. For each pilot study,
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20 between 50 and 53 U.S. consumers, with a mean age of 37.6 years (50% women), were recruited
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22 from Amazon MTurk (for details, see Web Appendix G). In line with previous research (e.g.,
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24 Hamilton and Hunter 1998; Larrimore et al. 2011; Ma et al. 2017; Packard and Berger 2020), we
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26 find that greater use of all four communication aspects in bids significantly reduces buyers'
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28 uncertainty perceptions and affects their hiring intentions.
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32 33 ***Predicting the Success of Buyers' Calls for Bids***

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35 *Model-free evidence.* In Web Appendix H, we summarize the model-free findings. The
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37 mean-level comparison indicates that calls for bids with significantly greater degrees of task
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39 information and concreteness, as well as significantly lower degrees of personal information and
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41 affective intensity, receive more freelance bids than does an average call for bids ($M = 5$).
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45 *Econometric model and identification.* The success of calls for bids reflects a count
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47 variable. Noting the overdispersion in the data ($p < .001$), we use a negative binomial model
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49 instead of a Poisson model. Furthermore, calls for bids are nested within buyers, and thus the call
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51 for bids and number of freelancers who offer their service might be interdependent. The
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53 significant between-group variance ($p < .001$) and $ICC_{(1)}$ of .27 suggests a multilevel structure.
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We thus specify a multilevel model with a random intercept to control for time-invariant unobserved differences between buyers (e.g., education, country, gender) that could relate to differences in their success, using the following base equation:

$$(1) \quad \text{CALSUC}_{ij} = y_{00} + y_{01}BTASK_{ij} + y_{02}BPERS_{ij} + y_{03}BCONC_{ij} + y_{04}BINTE_{ij} + y_{05}BTASK_{SQij} + y_{06}BPERS_{SQij} + y_{07}BCONC_{SQij} + y_{08}BINTE_{SQij} + \mu_{0j} + \varepsilon_{ij},$$

where CALSUC_{ij} is the success of a call for bids i ($i = 1, \dots, 343,796$) issued by buyer j ($j = 1, \dots, 49,081$), $BTASK_{ij}$ is buyer task information, $BPERS_{ij}$ indicates buyer personal information, $BCONC_{ij}$ is buyer concreteness, and $BINTE_{ij}$ refers to buyer affective intensity in the call for bids. In turn, $BTASK_{SQij}$ is buyer task information squared, $BPERS_{SQij}$ is buyer personal information squared, $BCONC_{SQij}$ is buyer concreteness squared, and $BINTE_{SQij}$ is buyer affective intensity squared. Finally, μ_{0j} is the random intercept, and ε_{ij} is the error term.

Some empirical challenges inhibit a robust model identification, which we address in several ways. To account for observed heterogeneity, we incorporate covariates that might influence how many freelancers respond to a particular call for bids. First, in line with extant text mining studies (Berger et al. 2020), we control for the word count in each call for bids. Second, as a reputation cue, we measure buyer experience as the number of projects a buyer has commissioned previously on the platform, prior to posting the focal call for bids (Hong and Pavlou 2017). Third, a higher payment offer may attract more freelancers (Horton 2019), so we determine the payment offered by the buyer in U.S. dollars, multiplied by an undisclosed index for anonymity. For non-disclosed payments, we use a dummy, but we replace missing values with a grand mean to retain the observations. Fourth, we measure project duration; longer projects attract more freelancers (Horton 2019). A dummy variable indicates if the project is slated to last more (1) or less than a month (0). Fifth, more buyers demanding freelance services

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3 at the same time creates a relative shortage of freelancers (Horton 2019). To account for an
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5 excess supply of freelancers, we take the sum of all active freelancers in the specific submarket
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7 of the call for bids, divided by the sum of all calls for bids posted around the same time (± 31
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9 days) in the same submarket. Sixth, the marketplace grew over time, so we included fixed effects
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11 for the year of the call for bids. Seventh, we include fixed effects for the seven submarkets, since
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13 submarkets that feature more complex projects have fewer qualified freelancers.
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17 Beyond these observed covariates, buyers' bid formulations might vary by project
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19 characteristics unobservable to us. To the extent that these unobserved project characteristics
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21 influence both the buyers' communication strategies and buyer outcomes, the estimated
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23 parameters might be biased. Therefore, we concatenated all service skill tags from the service
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25 profile of each freelancer who submitted a bid in response to a specific call. Then, to uncover the
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27 latent mixture of project types, we applied a latent dirichlet allocation model to the project-
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29 specific skill tags (e.g., Berger et al. 2020; see Web Appendix I). We include the resulting 12
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31 latent project characteristics as fixed effects to account for unobserved heterogeneity.
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35 Buyers also make their communication decisions strategically, in learned anticipation of a
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37 larger number of bids or other factors, potentially unobservable to us. This strategic behavior
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39 could make communication approaches endogenous (Kanuri, Chen, and Sridhar 2018). Because
40
41 our data do not contain valid, strong instruments for buyers' communication, we adopt Park and
42
43 Gupta's (2012) approach and use Gaussian copulas to model the correlation between each buyer
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45 communication $BCOM_{ij}^{1-4}$ and the error term. We add regressors to Equation 1, such that
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49 (2)
$$\widetilde{BCOM}_{ij}^{1-4} = \Phi^{-1}[H(BCOM_{ij}^{1-4})],$$

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52 where Φ^{-1} is the inverse of the normal cumulative distribution function, and $[H(BCOM_{ij}^{1-4})]$
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54 represents the empirical distribution functions of the four buyer communication approaches. The
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3 endogenous regressors must be non-normally distributed for identification (Park and Gupta
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5 2012), which Shapiro–Wilks tests confirm (all $p < .001$). The updated equation to predict buyers'
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7 call for bids success, after correcting for endogeneity, thus is:
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9

$$(3 \text{ } CALSUC_{ij} = y_{00} + y_{01}BTASK_{ij} + y_{02}BPERS_{ij} + y_{03}BCONC_{ij} + y_{04}BINTE_{ij} + y_{05}BTASl$$

$$) \quad + y_{06}BPERS_SQ_{ij} + y_{07}BCONC_SQ_{ij} + y_{08}BINTE_SQ_{ij} + y_{09-14}CON_{ij}^{1-6}$$

$$+ y_{15-20}YEAR_{ij}^{1-6} + y_{21-26}SUBM_{ij}^{1-6} + y_{27-37}PROJ_{ij}^{1-11} + y_{38-41}B\overline{COM}$$

$$_{ij}^{1-4} + \mu_{0j} + \varepsilon_{ij},$$

17 where CON_{ij}^{1-5} is the vector of control variables, $YEAR_{ij}^{1-6}$ are year effects, $SUBM_{ij}^{1-6}$ are
18
19 submarket effects, $PROJ_{ij}^{1-11}$ are latent project clusters, and $B\overline{COM}_{ij}^{1-4}$ are Gaussian copulas.
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22 We used a robust estimator to account for correlated and clustered standard errors.
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25 *Results and discussion.* The maximum variance inflation factor is 2.11, indicating no
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27 potential threat of multicollinearity. Table 2 contains the results of a main-effects model and the
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29 full model, and Figure 2 displays the curvilinear effects from the full model. We have proposed
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31 that extremely sparse and extremely dense degrees of relevant information, concreteness, and
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33 affective intensity in calls for bids yield fewer freelance bids than moderate degrees of these
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35 communication elements. In line with our expectations, we find a positive linear effect (.152, $p <$
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37 .01) and negative squared effect for task information (-.026, $p < .01$), as displayed in Figure 2,
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39 Panel A. Moderate levels of the use of task information (50%: .222, $p < .01$) yield better results
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41 than sparse (10%: -.426, $p < .01$) and dense (90%: -.495, $p < .01$) uses. Furthermore, we find a
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43 positive linear effect (.052, $p < .01$) and negative squared effect for concreteness (-.080, $p < .01$)
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45 (Figure 2, Panel C). Moderate use (50%: .078, $p < .01$) yields better results than sparse use (10%:
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47 -.092, $p < .01$) or dense use (90%: -.251, $p < .01$) of concreteness. Contrary to our expectation,
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49 we find a negative linear effect (-.190, $p < .01$) and a positive squared effect (.032, $p < .01$) of
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51 personal information (Figure 2, Panel B). We also find a negative linear effect (-.084, $p < .01$)
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3 and a non-significant squared effect (.001, *ns*) of affective intensity (Figure 2, Panel D). Thus, it
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5 appears that any provision of personal information or greater use of affective intensity by the
6
7 buyer is always ineffective. As a possible explanation, we note that in B2B online conversations,
8
9 self-disclosure and emotions may be valued only after business relations have been established,
10
11 not at the moment they form (Koponen and Rytsy 2020). Most of the exchanges in our data are
12
13 between strangers, rather than repeat exchanges, so buyers may more appropriately avoid
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15 personal details and appear rational rather than emotive.
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18
19 To entice more freelancers to bid, buyers should keep their calls for bids brief ($-.027, p <$
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21 $.01$ for word count), which emphasizes the need for careful formulations. Higher payment offers
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23 ($.168, p < .01$), longer project durations ($.117, p < .01$), and an excess supply of freelancers ($.606,$
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25 $p < .01$) all increase the number of bids. Notably, the number of projects a buyer previously has
26
27 commissioned relates negatively to the number of freelance who bid ($-.033, p < .01$). These
28
29 experienced buyers might have established relations with specific freelancers, which reduces
30
31 other freelancers' chances, so they refrain from bidding (Lanzolla and Frankort 2016).
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35 [please insert Table 2 and Figure 2 here]
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37

38 ***Predicting Freelancers' Bid Success***

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40 *Model-free evidence.* Bids that offer greater task information, concreteness, and affective
41
42 intensity and less personal information are more successful in winning projects. Among bids that
43
44 won, the mean-level comparisons indicate nonlinear effects of mimicry. That is, successful
45
46 freelancers mimic buyers' use of task information, personal information, and concreteness
47
48 closely. If a buyer uses very sparse or very dense degrees of these communication aspects, the
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50 winning freelancers deviate more, indicating a nonlinear impact of mimicry. We do not find
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52 evidence of this mimicry relationship for affective intensity (see Web Appendix H).
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3 *Measurement of similarity.* Previous studies often operationalize communication similarity
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5 as the absolute difference between two measures (e.g., Ludwig et al. 2013; Soliz and Giles
6
7 2014), but this approach suffers some implicit constraints (Edwards and Parry 1993). In
8
9 particular, difference scores suggest that one party's communication increases at the same
10
11 magnitude as the other's decreases; they also ignore the level of communication at which relative
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13 mimicry occurs. As a preferable alternative, we use polynomial regression, which allows for
14
15 simultaneous testing of similarity and dissimilarity effects on bid success, at different levels of
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17 freelancers' and buyers' uses of the four communication aspects. In their study of positive and
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19 negative emotional tone convergence, Gooty et al. (2019) also use polynomial regression to
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21 explore the nuanced effects of convergence in leader–follower relationships on leader–member
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23 exchange quality. A simple regression model, capturing absolute deviation, cannot
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25 simultaneously assess the degree of task information by the buyer and the potential nonlinear
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27 effects of task information mimicry by the freelancer. So, we undertake polynomial regression
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29 with response surface analyses for each communication aspect to capture the extent to which
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31 freelancers mimic a prospective buyer's provision of relevant information and communication
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33 manner. We detail this polynomial modeling approach that lead to Equation 4 and the calculation
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35 of all polynomial terms, using task information as an example, in Web Appendix E.
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42 *Econometric model and identification.* We test freelancers' trade-off between adding more
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44 uncertainty-reducing communication versus mimicking the buyer's communication in a
45
46 polynomial regression model that includes linear terms, quadratic terms, and interactions. In the
47
48 multilevel base equation to predict freelancers' bid success ($ICC_{(1)} = .09, p < .001$),
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50

51 (4 $BIDSUC_{kl}$
52)
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$$= y_{00} + y_{01-04}FCOM_{kl}^{1-4} + y_{05-08}BCOM_{kl}^{1-4} + y_{09-12}FCOM_SQ_{kl}^{1-4} + y_{13-16}FCOM_{kl}^{1-4} \times BCOM_{kl}^{1-4} + y_{17-20}BCOM_SQ_{kl}^{1-4} + \mu_{0l} + \varepsilon_{kl}$$

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$BIDSUC_{kl}$ is the success of bid k ($k = 1, \dots, 2,327,216$) by freelancer l ($l = 1, \dots, 34,851$),
 $FCOM_{kl}^{1-4}$ are the four freelancer communication aspects, $BCOM_{kl}^{1-4}$ indicate the four buyer
communication aspects, $FCOM_SQ_{kl}^{1-4}$ are freelancer communication squared, $(FCOM_{kl}^{1-4} \times$
 $BCOM_{kl}^{1-4})$ are interactions of freelancer and buyer communication aspects, $BCOM_SQ_{kl}^{1-4}$ are
buyer communication squared, μ_{0l} is the random intercept, and ε_{kl} is the error term.

We incorporate several covariates that might influence freelancers' bid success. As in the
buyer model, we control for word count, project payment, project duration, and excess supply of
active freelancers. We also include fixed effects for years, submarkets, and latent project
characteristics. We account for the number of projects the freelancer completed prior to
submitting the focal bid as a reputation cue that might determine bid success (Hong and Pavlou
2017). Freelancer rating is an average five-point satisfaction rating that a freelancer has received
for all completed projects. To retain observations of unrated freelancers, we include a dummy for
observations without star ratings and replace the missing values with a grand mean rating.

Several additional controls relate to whether a bid is successful. First, following prior
research, we assess linguistic style matching (LSM), or the similarity between each bid and the
respective call for bids, across nine function word categories (Ludwig et al. 2013). Second, we
account for any previous relationship, such that the freelancer completed at least one project for
the same buyer prior to the specific call for bids (Hong and Pavlou 2017). Third, freelancers
submit a bid price that may differ from the payment offered by the buyer; a higher bid price may
reduce the likelihood of bid success (Hong and Pavlou 2017). We measure each bid price as a
ratio, between the asking price and the average indexed bid price requested by all competing
freelancers for the same call for bids. Fourth, the longer it takes freelancers to submit a bid, the
lower their chances of success (Hong, Wang, and Pavlou 2016). We measure time-to-bid as the

number of days between the posting of the call for bids and the bid submission. A dummy variable also indicates if the bid was submitted late (1) or on time (0); though some buyers might accept bids submitted after the auction expiration date, late bids are less likely to succeed (Horton 2019). Fifth, competition for a specific call for bid should impact each bid's success chances, so we control for the number of bids for the same call (Hong, Wang, and Pavlou 2016).

Similar to buyers, freelancers make communication decisions strategically in anticipation of higher bid success or other, unobservable factors. Thus, freelancer communication is potentially endogenous, and we again use Gaussian copulas (Shapiro–Wilks tests: all $p < .001$).

The updated equation to predict freelancers' bid success is as follows:

$$(5 \text{ } BIDSUC_{kl} = y_{00} + y_{01-04}FCOM_{kl}^{1-4} + y_{05-08}BCOM_{kl}^{1-4} + y_{09-12}FCOM_SQ_{kl}^{1-4} + y_{13-16}(FCOM_{kl}^{1-4} \times BCOM_{kl}^{1-4}) + y_{17-20}BCOM_SQ_{kl}^{1-4} + y_{21-33}CON_{kl}^{1-13} + y_{34}YEAR_{kl}^{1-6} + y_{40-45}SUBM_{kl}^{1-6} + y_{46-56}PROJ_{kl}^{1-11} + y_{57-60}FCOM_{kl}^{1-4} + y_{61-64}BCOM_{kl}^{1-4} + \mu_{0l} + \varepsilon_{kl})$$

where CON_{kl}^{1-14} is the vector of control variables, $YEAR_{kl}^{1-6}$ are year effects, $SUBM_{kl}^{1-6}$ are submarket effects, $PROJ_{kl}^{1-11}$ are latent project clusters, $FCOM_{kl}^{1-4}$ are Gaussian copulas for bid text, and $BCOM_{kl}^{1-4}$ are Gaussian copulas for calls for bids text.

Results and discussion. The maximum variance inflation factor is 3.86, indicating no threat of multicollinearity. Table 3 contains the results of the freelancer bid success models, Web Appendix K summarizes the response surface coefficients, and Figure 3 displays these coefficients on three-dimensional surfaces, reflecting relationships among freelancer communication, buyer communication, and bid success. We also highlight the misfit line used to explore the trade-off between exceeding and falling short of buyers' communication levels.

We have proposed that when the degree of relevant information, concreteness, and affective intensity provided by the buyer is at least moderately dense (sparse), freelancers can

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3 increase (decrease) their chances of bid success by mimicking the buyer's communication. The
4 surface-level tests along the plotted misfit line (Web Appendix K) display negative curvatures
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6 for task information ($-.020, p < .01$), personal information ($-.007, p < .01$), concreteness ($-.011, p$
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8 $< .01$), and affective intensity ($-.020, p < .01$). These results indicate that mimicking the buyer's
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10 communication increases bid success (see Web Appendix L for further clarification).
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15 In line with our proposition, we qualify this effect for sparse degrees of task and personal
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17 information, concreteness, and affective intensity provided by the buyer in Web Appendix M. If
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19 we were to find positive slope coefficients at lower levels, it would suggest that freelancers can
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21 increase their chances of bid success by exceeding, rather than mimicking the buyer's
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23 communication. This prediction holds for personal information ($.020, p < .01$) and concreteness
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25 ($.024, p < .01$), according to the slopes at low levels of buyer communication. But contrary to our
26
27 expectations, we find negative effects for the slopes of task information ($-.008, p < .01$) and
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29 affective intensity ($-.030, p < .01$) at low levels of buyer communication. Therefore, freelancers
30
31 should always mimic the degree of task information and affective intensity provided by the
32
33 buyer. For these two communication aspects, the tenets of communication accommodation
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35 theory (Soliz and Giles 2014) and adaptive selling (Verbecke et al. 2011) hold: Mimicking the
36
37 buyer is always better. To increase their chances of bid success further, freelancers also must
38
39 keep their bids concise ($-.021, p < .01$ for word count). Reputation cues (experience: $.002, p <$
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41 $.01$; rating: $.010, p < .01$) increase freelancers' chances of bid success, as do linguistic style
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43 matching ($.051, p < .01$), previous business relations with the buyer ($.078, p < .01$), lower bid
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45 prices ($-.006, p < .01$), timely (cf. late) bid submissions ($-.004, p < .01$), lack of competition ($-$
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47 $.251, p < .01$), and reduced supply of freelancers ($-.042, p < .01$).
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53 [please insert Table 3 and Figure 3 here]
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Predicting Freelancers' Price Premium

Model-free evidence. Bids with significantly more task information, personal information, and concreteness and significantly less affective intensity achieve greater price premiums than an average bid (M = 14% discount). Moreover, 96% of freelancers completed projects without any price premium, indicating the prevalence of value traps. The bids that achieved price premiums mimicked those buyers that made moderate use of task information, concreteness, and affective intensity closely, yet they deviated from buyers that made very sparse or very dense use of them. For personal information, we find a distinctive, positive, linear relationship for mimicry; successful freelancers mimicked buyers that supplied a lot of personal details but deviated if buyers supplied very little or moderate degrees of personal information (Web Appendix H).

Econometric model and identification. The price premium analysis is restricted to bids that win and buyers that disclose their payment offer upfront. Thus, our estimates may be biased by self-selection by buyers, in terms of which bid they choose and whether they disclose payments. Therefore, we employ a two-stage selection model. In the first stage, we estimate a choice model, with the availability of the necessary data as a binary dependent variable (i.e., bid was won, and payment was disclosed). From this model, we compute the inverse Mills ratio to account for the potential selection bias (probit model in Web Appendix N) and include this correction term in the final model estimation. To identify second-stage parameters, there needs to be one term in first-stage equation that is unrelated to the error term in the freelance price premium equation. We thus included the dummy that indicates if the bid was submitted late only in the first-stage equation because this term explains buyers' choice of the bid but we do not expect it to be conceptually related with the eventual price premium. Thus, we believe that this term satisfies both relevance and exogeneity requirements. The updated equation of our

multilevel model ($ICC_{(1)} = .13, p < .001$) is as follows:

$$\begin{aligned}
 (6 \text{) } \text{PREMIUM}_{kl} = & y_{00} + y_{01-04}FCOM_{kl}^{1-4} + y_{05-08}BCOM_{kl}^{1-4} + y_{09-12}FCOM_SQ_{kl}^{1-4} \\
 & + y_{13-16}(FCOM_{kl}^{1-4} \times BCOM_{kl}^{1-4}) + y_{17-20}BCOM_SQ_{kl}^{1-4} + y_{21-31}CON_k^1 \\
 & + y_{32-37}YEAR_{kl}^{1-6} + y_{39-43}SUBM_{kl}^{1-6} + y_{44-54}PROJ_{kl}^{1-11} + y_{55-58}FCOM_{kl}^{1-4} \\
 & + y_{59-62}BCOM_{kl}^{1-4} + y_{63}IMR_{kl} + \mu_{0l} + \varepsilon_{kl},
 \end{aligned}$$

where $PREMIUM_{kl}$ is the price premium of bid k ($k = 1, \dots, 148,158$) offered by freelancer l ($l = 1, \dots, 30,851$), and IMR_{kl} is the correction term.

Results and discussion. The maximum variance inflation factor is 2.74, indicating no threat of multicollinearity. Table 4 contains the results of the freelancer price premium models, Web Appendix K details the response surface coefficients, and Figure 3 displays the surfaces.

We have proposed that when the degree of relevant information and communication manner provided by the buyer is at least moderately high (low), freelancers can increase (decrease) their chances of earning a price premium by mimicking this communication. Web Appendix O displays the misfit lines on two-dimensional planes. In line with our expectations, the surface-level tests along the plotted misfit line show a negative curvature for task information ($-.023, p < .01$), concreteness ($-.007, p < .01$), and affective intensity ($-.008, p < .01$), such that mimicking the buyer's communication increases bid success. Yet for personal information, we find a positive curvature ($.003, p < .05$), which implies freelancers should always offer more personal information than the buyer. For these B2B services, the provider and the service are inseparable, which may lead buyers to place more value on personal information about freelancers, even if their own provision of personal details in the calls for bids is sparse.

At low levels of relevant information and communication manner established by the buyer (Web Appendix P), a positive slope would suggest that freelancers can increase their chances of earning a price premium by exceeding rather than mimicking the buyer. We find support for this

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2
3 prediction in the slope of personal information (.027, $p < .01$) at low levels of buyer personal
4 information. However, negative effects emerge from the slopes of task information (-.016, $p <$
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prediction in the slope of personal information (.027, $p < .01$) at low levels of buyer personal information. However, negative effects emerge from the slopes of task information (-.016, $p < .01$) and affective intensity (-.012, $p < .01$), and we find a non-significant effect for concreteness (.002, *ns*). Mimicking the buyer's task information and affective intensity is always better, in line with accommodation theory and adaptive selling (Soliz and Giles 2014; Verbecke et al. 2011).

Freelancers also increase their price premiums by avoiding lengthy bids (-.014, $p < .01$). Although platform reputation cues (experience and rating) can boost freelancers' chances of bid success, they do not determine the final price buyers pay. The skew in the ratings, toward very high scores, may limit their ability to help prospective buyers determine an appropriate price (Kokkodis and Iperiotis 2016). Linguistic style matching (.023, $p < .01$), a previous relationship with the prospective buyer (.056, $p < .01$), submitting early in the bid process (.009, $p < .01$), and reduced competition (-.015, $p < .01$) all increase buyers' acceptance of a price premium.

[please insert Table 4 here]

General Discussion

Across disciplines, substantial research has tried to identify success determinants in online freelance marketplaces (e.g., Horton 2019; Srivastava and Chandra 2018). For example, studies of B2B exchanges and two-sided marketplaces emphasize communication (see Web Appendix A). But at the specific word level, we lack insights into the optimal information or manner of communication (Berger et al. 2020). With this initial investigation of how buyers' and freelancers' success might be enhanced by appropriately managing the other party's uncertainty, we postulate, in line with uncertainty reduction (Berger and Calabrese 1975) and uncertainty management (Brashers 2001) theories, that communication that is not completely informative and clear still may be effective. Accordingly, we investigate how buyers' communication can

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2
3 attract freelance bids and freelancers' communication can determine their bid success and price
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5 most effectively, and the results offer both theoretical and practical implications.
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8 ***Theoretical Contributions***

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10 First, we advance research on how buyers' communication determines their ability to
11 attract freelancers. Drawing on prior communication research, we identify communication
12 principles that critically relate to receivers' uncertainty, such as relevant task and personal
13 information and the relative concreteness and affective intensity with which this information is
14 communicated (Giles 1975; Bradac 2001). To entice more freelancers to bid, buyers should
15 carefully formulate their calls for bids to keep them brief. Freelancers' information processing
16 motivation, time, skills, and proficiency likely are limited, so buyers must choose their wording
17 carefully and select among different effective communicative aspects. They can attract a larger
18 pool of bids if they provide moderate degrees of task information in a moderately concrete
19 manner. Offering too little of these features leaves freelancers with too much uncertainty; dense
20 information provision or being very concrete is too restrictive. If buyers provide greater degrees
21 of personal information or express greater affective intensity in their calls for bids, it reduces the
22 number of service offers they receive. This finding contrasts with uncertainty reduction theory
23 (Berger and Calabrese 1975) and B2B research that suggests self-disclosure strengthens buyer-
24 seller cooperativeness (Joshi 2009). However, instead of ongoing B2B relationships, our study
25 refers mostly to initial interactions between strangers (in 98% of cases, the freelancer had never
26 worked for the prospective buyer). Evidence obtained from buyer-seller online chats similarly
27 suggests that self-disclosure and emotive expressions are valued only in existing B2B
28 relationships, not in new ones (Koponen and Rytty 2020). Overall, we offer empirical support
29 for communication theorists' suggestions that common communication principles can be
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3 purposefully flouted to achieve better conversation outcomes (Goffman 2008).
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5 Second, freelancers must keep their bids concise. They too face a trade-off between
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7 reducing the buyer's uncertainty and offering overly dense information. In line with research on
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9 communication accommodation (Soliz and Giles 2014) and adaptive selling (Verbeke, Dietz and
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11 Verwaal 2011), we show that freelancers can improve their bid success by mimicking the
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13 prospective buyer's communication. Adding to these research streams, we introduce a
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15 contingency perspective that reveals that the efficacy of mimicry depends on the degree to which
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17 buyers use specific communication elements. In line with accommodation theory and adaptive
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19 selling, bid success always improves when freelancers mimic buyers' provision of task
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21 information and use of affective intensity. But in line with uncertainty reduction theory (Berger
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23 and Calabrese 1975) and expectancy violations (Afifi and Burgoon 2000), when buyers supply
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25 little personal information and are less concrete, freelancers can increase their chances of bid
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27 success by diverging and providing more personal information and concreteness.
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33 Third, freelancers often struggle to avoid value traps, in which they sell more of their
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35 services for less (Sridhar and Mittal 2020). Rational buyer expectations should allow high-
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37 quality freelancers to charge price premiums (Rao and Monroe 1996), but the quality of
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39 freelance services is unobservable prior to purchase, and rational buyers might refuse to pay any
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41 price premium if they are uncertain and suspect hidden information (Dimoka et al. 2012).
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43 Therefore, to achieve premiums, freelancers should offer short, appropriately formulated bids.
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45 Buyers are more willing to pay a premium to freelancers who mimic their provision of task
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47 information, concreteness, and affective intensity, in line with communication accommodation
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49 theory (Soliz and Giles 2014) and adaptive selling research (Verbeke, Dietz, and Verwaal 2011).
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51 However, similar to the findings for bid success, freelancers should offer more, rather than
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3 mimic, buyers' provision of personal information. In most service settings, a "bad" seller might
4 provide a great product by chance; almost by definition though, a bad freelancer produces bad
5 service (Horton 2019). This tight coupling between the freelancer and service quality represents
6 a conceptual distinction of our study, which accordingly shows that buyers' willingness to pay a
7 premium increases with more personal information issued by the freelancer.
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14 ***Practical Implications***

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17 The findings offer actionable insights for the millions of buyers and freelancers working in
18 online freelance marketplaces, the value of which are predicted to reach \$2.7 trillion by 2025
19 (Manyika et al. 2015). In detail, being informative and unambiguous may be a common
20 assumption, but it is not an imperative, nor does it always lead to success.
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26 *Implications for buyers.* Although 59% of U.S. companies use a flexible workforce to
27 some degree, more than one-third of contracted projects are never completed (Hong and Shao
28 2021). To attract freelancers, buyers should keep their calls for bids succinct. Beyond that
29 recommendation, we offer several tips for formulating calls for bids in Table 5. In detail, a task
30 description with a moderate amount of information helps freelancers anticipate the task, without
31 overloading them with details. Due to the relative anonymity of online freelance marketplaces,
32 buyers might assume that freelancers will need to know who they are, but instead, we find that
33 the less buyers describe themselves (to focus on describing the task), the better the outcomes.
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Relatable and imaginable, rather than abstract, descriptions of the project help freelancers grasp the requirements. However, being excessively concrete becomes prescriptive, which deters freelancers. Using emotion words makes the content of a call for bids relatively more intense. Such intensity can remove ambiguity and make opinions quickly accessible, but we find that calls for bids are more effective if they are formulated relatively impassively; enthusiastic project

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3 descriptions seemingly might raise freelancers' suspicion that the project is too good to be true.
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5 Offering a higher payment might attract a larger pool of freelance bids, as do long- rather than
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7 short-term gigs. Finally, more freelancers bid when there are less calls for bids in the subsector.
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10 *Implications for freelancers.* Freelancers are not necessarily natural marketers, but their bid
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12 formulations determine their marketability. Existing online reputation systems provide some
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14 assistance, but they also create entry barriers to new freelancers who first must earn good overall
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16 ratings (Constantinides, Henfridsson, and Parker 2018). Fortunately, winning gigs and achieving
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18 price premiums also depends on freelancers' communication. Table 5 includes advice to help
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20 freelancers formulate more successful bids and avoid the value trap. In line with the mantra of
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22 adaptive selling, the call for bids provides a starting point, such that mimicking the buyer's task
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24 information and affective intensity increases freelancers' success—even if they provide few task
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26 details or seem very impassive. But freelancers should always offer personal information and be
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28 concrete. Even if a buyer does not provide personal information or the call is relatively abstract,
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30 freelancers' chances of success and price premiums increase if their bids contain more personal
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32 information and are at least somewhat concrete. The strongest predictor of bid success is a
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34 preexisting buyer relationship, so more broadly, freelancers should grow their buyer relations.
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40 [please insert Table 5 here]
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42 ***Limitations and Directions for Further Research*** 43

44 In examining theoretically grounded communicative aspects, we offer novel insights into
45
46 how to manage uncertainty in buyer–freelancer exchanges. Intriguingly, we find that
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48 communication approaches that do not aim to minimize uncertainty can be effective. Continued
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50 research should investigate this notion further and develop additional insights into the exchange
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52 implications of linguistic choices in B2B but also business-to-consumer and consumer-to-
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3 consumer communication on multi-sided platforms (Luo et al. 2021). For example, affiliative
4 (Pennebaker et al. 2015) or collaborative terms might affect uncertainty and influence exchanges
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6 too. Arguably, the personal characteristics of buyers and freelancers (e.g., gender, education,
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8 experience), channel choices (Lawrence et al. 2019), different sources of uncertainty (Heide and
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10 Weiss 1995), perceived risks (Grewal, Gotlieb, and Marmorstein 1994), and spatial distances
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12 between buyers and freelancers also might moderate the efficacy of communication aspects, so
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14 additional research should specify their influences. For example, if buyers lack the expertise to
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16 specify what they want, they might benefit from more ambiguous calls for bids (Humphreys et
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18 al. 2020). Perhaps buyers' communication or alternative factors which we cannot account for
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20 (e.g. underestimation of the amount of work required to fulfil the task), influence the final price
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22 they pay too. Efforts to specify these additional effects also might address some of our more
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24 controversial findings, such as the evidence that the number of previously commissioned projects
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26 by a buyer relates negatively to the number of freelancers who bid. We posit that experienced
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28 buyers might prefer freelancers whom they have hired in the past (Lanzolla and Frankort 2016),
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30 but they also might have incurred switching costs or dependencies (Heide and Weiss 1995).
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32 Methodologically, we estimated all the models sequentially; buyers' calls for bids and their
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34 success occur prior to freelancers' bids and their success. But an equilibrium approach that
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36 estimates these models simultaneously at the bid level could reflect an alternative way to think
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38 about the data structure. The concreteness word list we use (Brysbaert et al. 2014) may require
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40 further refinement too, to differentiate specific concreteness levels among the set of concrete
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42 words. Finally, the anonymity and speed of exchanges in online freelance marketplaces may
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44 make communication particularly important; a comparative analysis of the influence of
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46 uncertainty management efforts across different B2B contexts, beyond these marketplaces, could
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offer interesting insights, especially if uncertainty avoidance is a central goal.

Peer Review Version

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Table 1. Communication Elements, Links to Uncertainty, and Examples

Communication Element	Definition	Link to Uncertainty	Example
Task information	A content element of communication; in service exchanges, it is conveyed through functional, duty terms (Ma and Dubé 2011). The proportion of task terms to the total number of words in a message defines the degree of task information.	Greater (lesser) degrees of task information decrease (increase) uncertainty	Sparse degree of task information: “I saw your <u>project</u> description and I would like to work for you. I have plenty experience in different settings where I have <u>written content</u> which users find interesting.” Dense degree of task information: “I saw your <u>project</u> description and would like to <u>write the content</u> for your <u>website</u> . I have experience in <u>writing articles, blogs & E-books</u> which is user engaging and <u>SEO</u> friendly as well.”
Personal information	A content element of communication that is conveyed through self-disclosing terms (Derlega, Harris, and Chaikin 1973). The proportion of self-disclosing terms to the total number of words in a message defines the degree of personal information.	Greater (lesser) degrees of personal information decrease (increase) uncertainty	Sparse degree of personal information: “Saw your project description and would like to write the content for your site. <u>I</u> have experience in writing articles, blogs & E-books which is user engaging and SEO friendly as well.” Dense degree of personal information: “ <u>I</u> saw your project description and <u>I</u> would like to write the content for your site. <u>I</u> have 12 years of work experience in copy writing for articles, blogs & E-books. <u>I</u> have a Master’s in Journalism and have worked fulltime for companies like Adobe.”
Concreteness	A manner element of communication, conveyed by terms that are perceptible, precise, or specific (Packard and Berger 2020; Brysbaert, Warriner, and Kuperman 2014). The proportion of concrete terms to the total number of words in a message defines the degree of concreteness.	Greater (lesser) degrees of concreteness decrease (increase) uncertainty	Sparse degree of concreteness: “I noticed your project description and I would like to do work on it. I have plenty of experience in scripting <u>text</u> , which is engaging, compelling, and SEO friendly.” Dense degree of concreteness: “ <u>I</u> saw your <u>posted</u> project description on <u>Upwork</u> , and I would like to <u>write the contents</u> for your <u>website</u> . I have a lot of experience in <u>article</u> and weblog <u>writing</u> in an <u>SEO</u> friendly <u>fashion</u> .”
Affective intensity	A manner element of communication that is conveyed through affective terms (Hamilton and Hunter 1998). The proportion of affective terms to the total number of words in a message defines the degree of affective intensity.	Greater (lesser) degrees of intensity decrease (increase) uncertainty	Sparse degree of affective intensity: “I saw your project description and I can write the required content for your site. I have plenty of experience in writing articles, blogs & E-books which is user engaging and SEO <u>friendly</u> as well.” Dense degree of affective intensity: “ <u>I</u> <u>liked</u> your project description and would be <u>happy</u> to write the content for your site. I have <u>great</u> experience in writing articles, blogs & E-books which is user engaging and <u>SEO</u> <u>friendly</u> as well.”

Table 2. Predicting the Success of Buyers' Calls for Bids

	Model 1: Main Effects			Model 2: Full Model		
	β	SE	95% CI	β	SE	95% CI
Buyer Communication						
Task information	.123**	.003	.117, .128	.152**	.003	.146, .159
Personal information	-.149**	.004	-.157, -.141	-.190**	.004	-.199, -.181
Concreteness	.040**	.003	.035, .045	.052**	.003	.046, .057
Affective intensity	-.098**	.007	-.112, -.085	-.084**	.008	-.100, -.068
Buyer Communication Squared						
Task information squared				-.026**	.001	-.028, -.024
Personal information squared				.032**	.002	.029, .035
Concreteness squared				-.008**	.001	-.011, -.007
Affective intensity squared				.001	.001	-.001, .004
Controls						
Word count	-.025**	.003	-.031, -.019	-.027**	.003	-.033, -.021
Buyer experience	-.033**	.007	-.046, -.020	-.033**	.007	-.046, -.020
Project payment	.170**	.005	.159, .181	.168**	.005	.158, .179
Payment not disclosed	.073**	.005	.063, .083	.071**	.005	.061, .081
Project duration	.116**	.003	.110, .122	.117**	.003	.111, .123
Excess supply of freelancers	.614**	.004	.606, .622	.606**	.004	.598, .613
Fixed Effects						
Years			included			included
Submarkets			included			included
Unobserved Heterogeneity						
Project characteristics			included			included
Endogeneity Corrections						
Gaussian copulas			included			included
Buyers						49,081
Call for bids						343,796

** $p < .01$, * $p < .05$. Standardized results. Significance is based on two-tailed tests.

Notes: The dependent variable is the count of all bids received. The sample includes all projects listed by buyers with at least two projects to which at least one freelancer submitted a bid. Effects for years, submarkets, project characteristics, and Gaussian copulas are detailed in Web Appendix Q.

Table 3. Predicting Freelancers' Bid Success

	Model 3: Freelancer Communication			Model 4: Full Model		
	β	SE	95% CI	β	SE	95% CI
Freelancer Communication						
y ₀₁ : Task information	.014**	.001	.013, .015	.015**	.001	.014, .016
y ₀₂ : Personal information	.018**	.001	.016, .019	.017**	.001	.016, .017
y ₀₃ : Concreteness	.030**	.001	.029, .031	.031**	.001	.030, .032
y ₀₄ : Affective intensity	.001	.001	-.001, .003	.000	.001	-.002, .001
Buyer Communication						
y ₀₅ : Task information				-.009**	.000	-.009, -.008
y ₀₆ : Personal information				-.017**	.000	-.018, -.017
y ₀₇ : Concreteness				-.008**	.000	-.009, -.008
y ₀₈ : Affective intensity				.001**	.000	.001, .002
Freelancer Communication Squared						
y ₀₉ : Task information squared	-.006**	.000	-.006, -.005	-.006**	.000	-.007, -.006
y ₁₀ : Personal information squared	-.005**	.000	-.005, -.004	-.005**	.000	-.005, -.004
y ₁₁ : Concreteness squared	-.006**	.000	-.007, -.006	-.007**	.000	-.007, -.007
y ₁₂ : Affective intensity squared	.000**	.000	.000, .001	.000**	.000	.000, .001
Freelancer-Buyer Interactions						
y ₁₃ : Task information interaction				.015**	.000	.015, .016
y ₁₄ : Personal information interaction				-.002**	.000	-.002, -.001
y ₁₅ : Concreteness interaction				.005**	.000	.004, .005
y ₁₆ : Affective intensity interaction				.020**	.000	.020, .021
Buyer Communication Squared						
y ₁₇ : Task information squared				.001**	.000	.001, .002
y ₁₈ : Personal information squared				-.004**	.000	-.005, -.004
y ₁₉ : Concreteness squared				.001**	.000	.001, .001
y ₂₀ : Affective intensity squared				.000*	.000	.000, .000
Controls						
Word count	-.022**	.001	-.024, -.021	-.021**	.001	-.022, -.020
Linguistic style matching	.051**	.001	.048, .053	.051**	.001	.048, .053
Freelancer experience	.002**	.001	.001, .003	.002**	.001	.001, .003
Freelancer rating	.010**	.001	.009, .010	.010**	.001	.009, .010
Project payment	-.001**	.000	-.001, -.001	-.001**	.000	-.001, -.001
Payment not disclosed	-.028**	.000	-.029, -.028	-.029**	.000	-.030, -.028
Previous relationship	.078**	.001	.076, .081	.078**	.001	.075, .080
Bid price	-.006**	.000	-.006, -.006	-.006**	.000	-.007, -.006
Time-to-bid	.001	.000	.000, .001	.001	.000	.000, .001
Late submission	-.005**	.000	-.005, -.004	-.004**	.000	-.005, -.004
Competition	-.251**	.007	-.265, -.238	-.251**	.007	-.264, -.238
Excess supply of freelancers	-.044**	.000	-.045, -.043	-.042**	.000	-.043, -.042
Fixed Effects						
Years			included			included
Submarkets			included			included
Unobserved Heterogeneity						
Project characteristics			included			included
Endogeneity Corrections						
Gaussian copulas			included			included
Freelancers						34,851
Bids						2,327,216

** $p < .01$, * $p < .05$. Standardized results. Significance is based on two-tailed tests.

Notes: The dependent variable is whether the freelancer is chosen and wins the bidding process. The sample includes all bids by freelancers with at least one winning and at least one losing bid. Effects for years, submarkets, project characteristics, and Gaussian copulas are detailed in Web Appendix Q.

Table 4. Predicting Freelancers' Price Premium

	Model 5: Freelancer Communication			Model 6: Full Model		
	β	SE	95% CI	β	SE	95% CI
Freelancer Communication						
y ₀₁ : Task information	.023**	.002	.020, .026	.022**	.002	.019, .025
y ₀₂ : Personal information	.021**	.002	.017, .025	.021**	.002	.017, .026
y ₀₃ : Concreteness	.006**	.001	.004, .007	.005**	.001	.003, .007
y ₀₄ : Affective intensity	.004	.003	-.002, .010	.003	.003	-.003, .009
Buyer Communication						
y ₀₅ : Task information				.003*	.001	.001, .005
y ₀₆ : Personal information				-.016**	.002	-.019, -.012
y ₀₇ : Concreteness				-.004**	.001	-.006, -.002
y ₀₈ : Affective intensity				-.001	.002	-.005, .003
Freelancer Communication Squared						
y ₀₉ : Task information squared	-.001	.001	-.002, .000	-.001	.001	-.002, .001
y ₁₀ : Personal information squared	-.004**	.001	-.006, -.002	-.004**	.001	-.006, -.002
y ₁₁ : Concreteness squared	-.003**	.001	-.004, -.002	-.003**	.001	-.005, -.002
y ₁₂ : Affective intensity squared	.000	.000	-.001, .000	.000	.000	-.001, .000
Freelancer-Buyer Interactions						
y ₁₃ : Task information interaction				.025**	.003	.024, .027
y ₁₄ : Personal information interaction				-.004**	.001	-.005, -.002
y ₁₅ : Concreteness interaction				.002**	.000	.001, .002
y ₁₆ : Affective intensity interaction				.010**	.003	.008, .012
Buyer Communication Squared						
y ₁₇ : Task information squared				.003**	.001	.001, .004
y ₁₈ : Personal information squared				.003**	.001	.002, .005
y ₁₉ : Concreteness squared				-.002**	.001	-.004, -.001
y ₂₀ : Affective intensity squared				.002**	.001	.000, .003
Controls						
Word count	-.014**	.002	-.018, -.011	-.014**	.002	-.018, -.011
Linguistic style matching	.022**	.004	.013, .030	.023**	.004	.015, .032
Freelancer experience	-.001	.001	-.004, .001	-.001	.001	-.004, .001
Freelancer rating	-.001	.001	-.003, .001	-.001	.001	-.003, .001
Project payment	-.029**	.010	-.049, -.009	-.029**	.010	-.049, -.009
Previous relationship	.057**	.001	.054, .059	.056**	.001	.054, .059
Time-to-bid	.009**	.001	.007, .012	.009**	.001	.006, .011
Competition	-.015**	.002	-.019, -.011	-.015**	.002	-.019, -.011
Excess supply of freelancers	-.001	.001	-.002, .001	-.001	.001	-.002, .001
Fixed Effects						
Years			included			included
Submarkets			included			included
Unobserved Heterogeneity						
Project characteristics			included			included
Endogeneity Corrections						
Gaussian copulas			included			included
Sample-Selection Correction						
Inverse mills ratio	-.016**	.002	-.020, -.012	-.016**	.002	-.020, -.012
Freelancers						30,851
Bids						148,158

** $p < .01$, * $p < .05$. Standardized results. Significance is based on two-tailed tests.

Notes: The dependent variable is price premium for the chosen bid. The sample includes all winning bids for which the payment was disclosed. Effects for years, submarkets, project characteristics, and Gaussian copulas are detailed in Web Append

Table 5. Buying and Selling Services in Online Freelance Marketplaces

How to formulate calls for bids to attract freelancers?			
	<i>Bad practice excerpt</i>	<i>Good practice excerpt</i>	<i>Lift in bids</i>
<i>Specify tasks and skills</i>	“I need a website to showcase the full range of my fitness workouts.”	“I need a website designer who can design a WordPress website using a WordPress premium theme.”	From 18% to 29% task terms, resulting in 5% more bids
<i>Avoid personal information</i>	“I have been creating my own classes for almost 10 years now ... clients tend to especially love my classes on strength and flexibility. Now I need help setting up my website.”	“I am a Fitness Trainer and need help with building my website to showcase my mixed services and home workouts.”	From 9% to 4% personal terms, resulting in 4% more bids
<i>Be moderately concrete</i>	“I require a professional who is savvy in configuring a stylish website employing a premium theme.”	“You should have got very good creative skills but know how to design for web and also know how to include calls to actions within a good design.”	From 21% to 26% concrete terms, resulting in 1% more bids
<i>Avoid being affectively intense</i>	“I have created a fantastic theme but you should be confident and eager about WordPress and help optimize.”	“The theme and examples will be provided, but you should also know about WordPress and optimize.”	From 11% to 4% affective terms, resulting in 4% more bids
How to formulate successful bids and achieve price premiums?			
	<i>Bad practice excerpt</i>	<i>Good practice excerpt</i>	<i>Lift in bid success</i>
<i>Mimic task description</i>	“Dear Sir, would love to work for you...”	“Hi Gary, I am happy to help you with your fitness website development and design...”	From 16% to 25% task terms, resulting in 7% higher bid success and 8% higher price premium
<i>Exceed buyers who supply little personal information</i>	“I am an enthusiastic designer and expert in Web development...”	“I am a WordPress Freelancer with 15 years of work experience...”	From 6% to 8% personal terms, resulting in 3% higher bid success and 4% higher price premium
<i>Exceed buyers who are not concrete</i>	“I have great skills and plenty of fantastic experience in creating relevant websites...”	“I have worked on several similar projects, designing websites using a WordPress including premium themes and I can deliver to a tight schedule...”	From 24% to 30% concrete terms, resulting in 7% higher bid success (but no effect on price premium)
<i>Mimic the buyer’s affective intensity</i>	“The content will be creative and fun, attractive, and thoughtful...”	“Website content that I produce will be creative and include original designs...”	From 18% to 6% affective terms resulting in 11% higher bid success and 7% higher price premium

Notes: Web Appendix S provides the full call for bids and bids examples which we used for calculating the degrees of each communicative principle and the corresponding expected lift success. We used the “good practice” call for bids example to devise the bad and good examples for the corresponding freelance bid.

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Figure 1. Bidding Process and Conceptual Framework

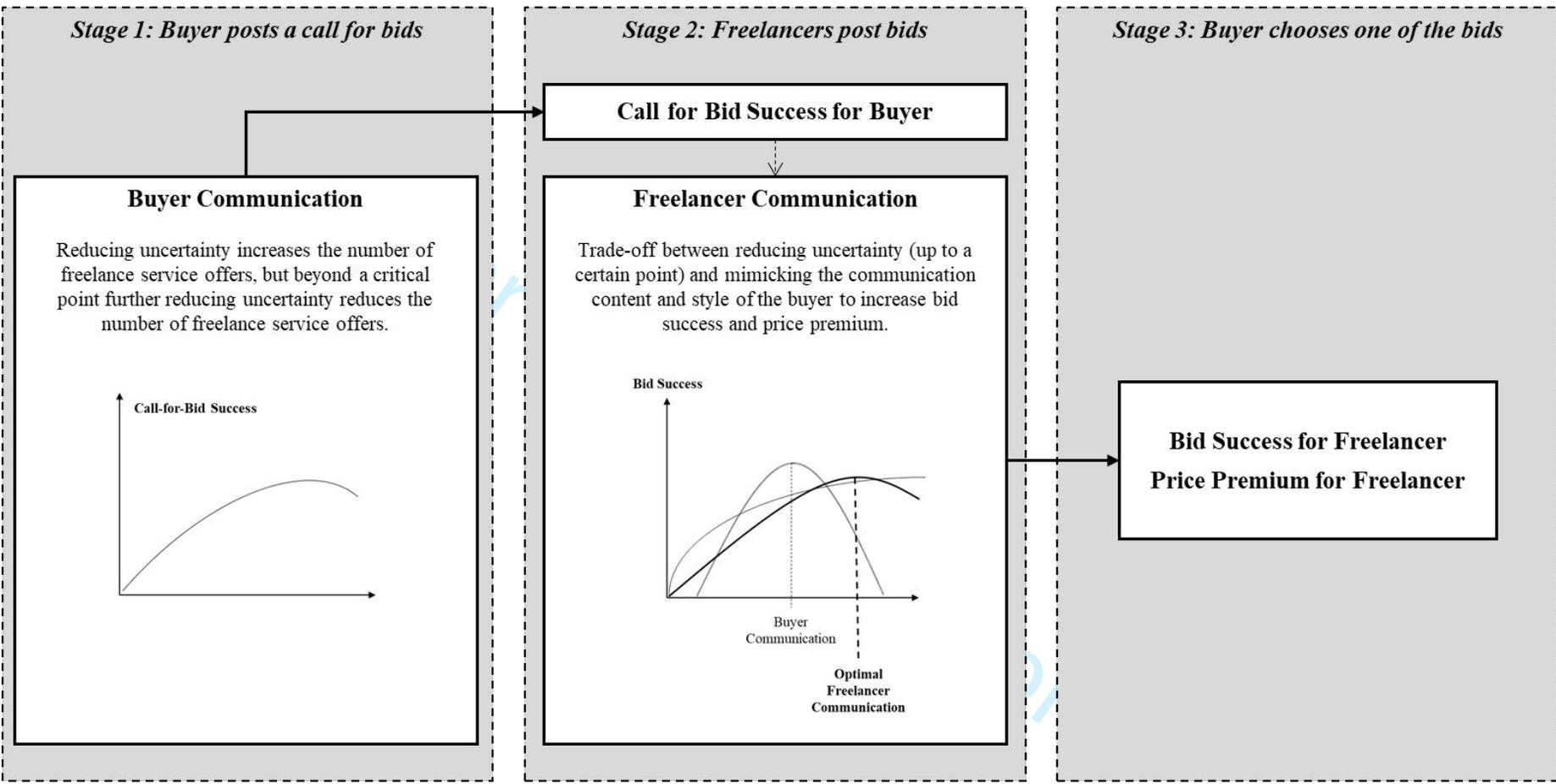
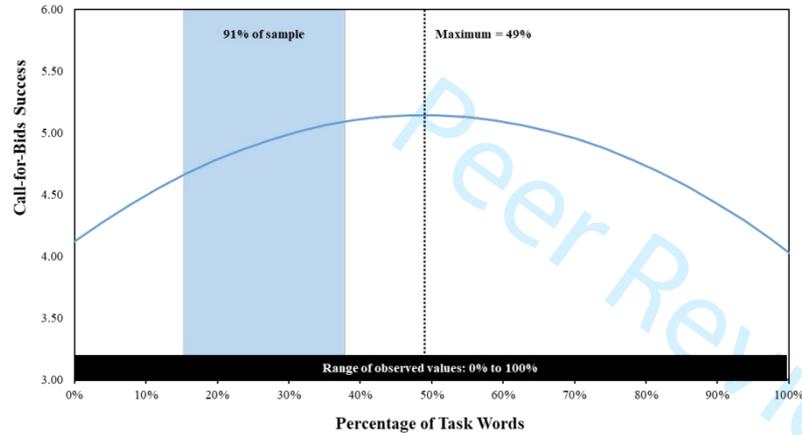


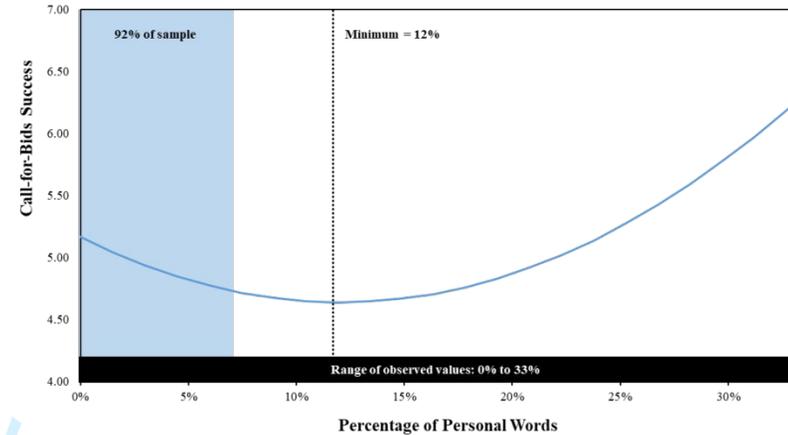
Figure 2. Effect of Buyers' Communication on Calls for Bids Success

Results are based on Table 2, Model 2: Predicting the Success of Buyers' Calls for Bids

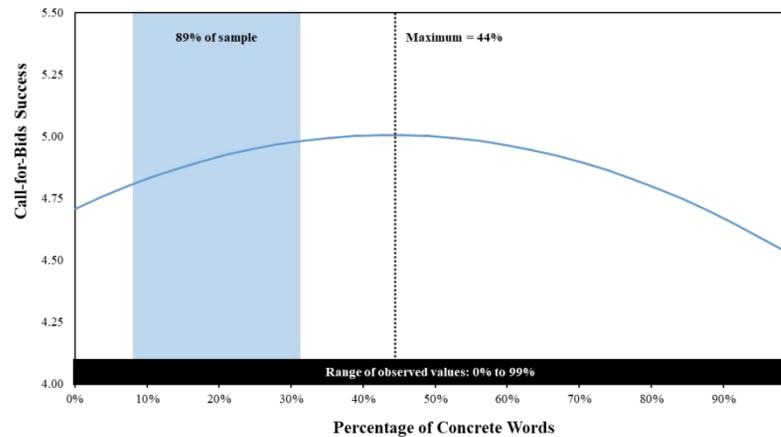
A. Effect of Task Information



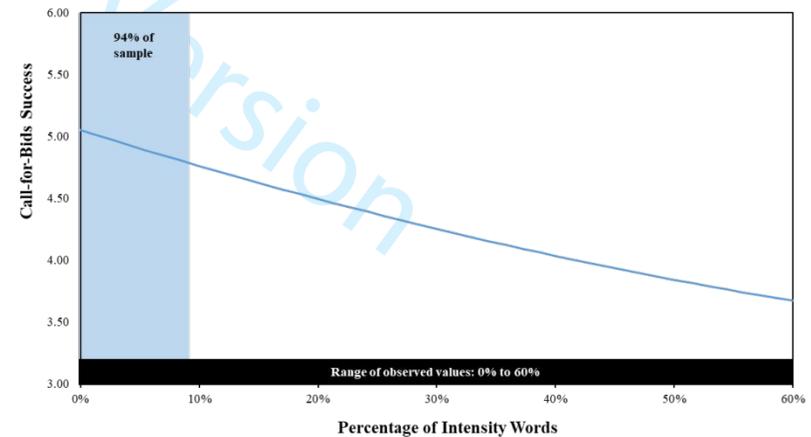
B. Effect of Personal Information



C. Effect of Concreteness



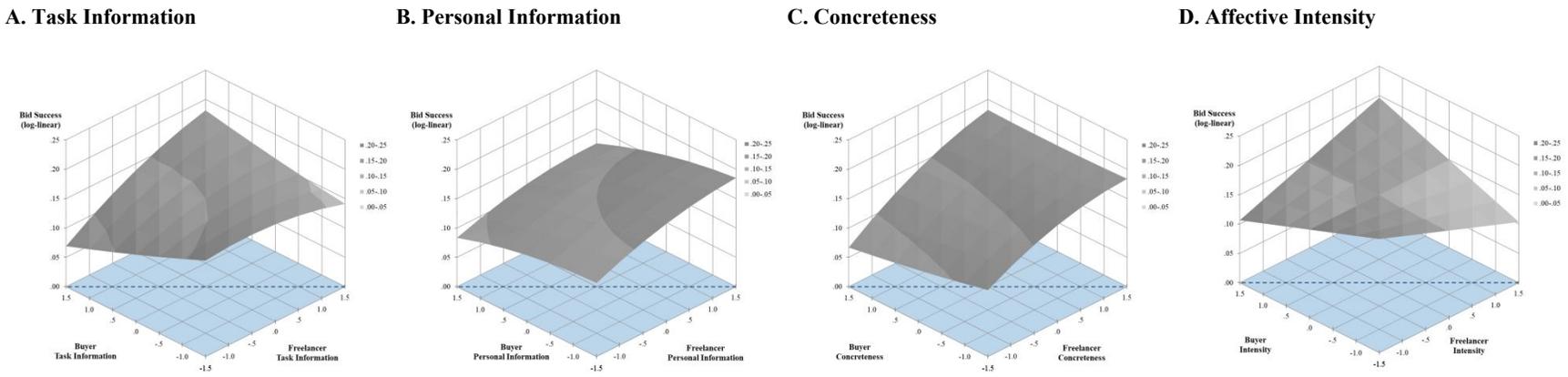
D. Effect of Affective intensity



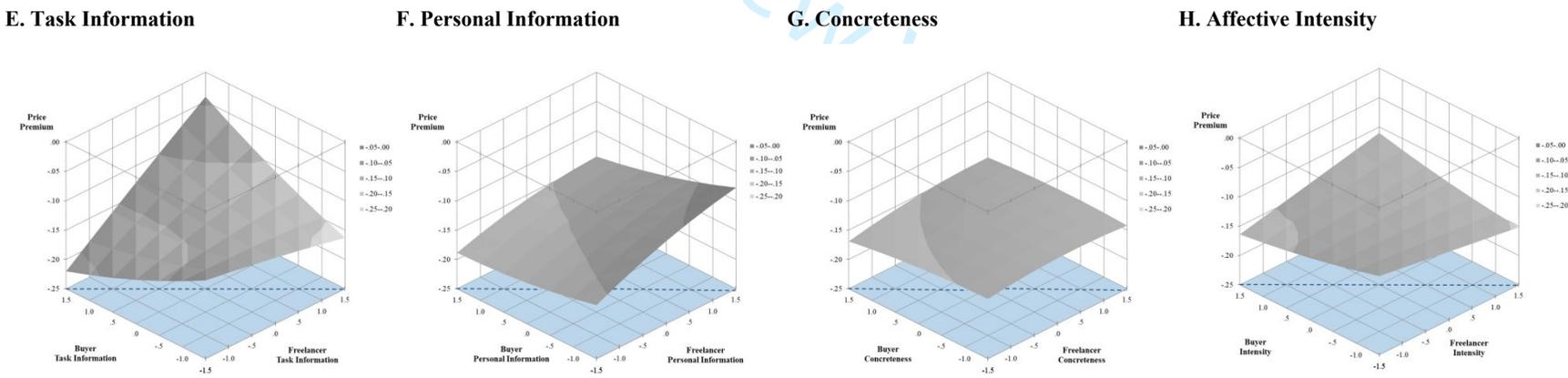
Note: The blue area includes all values within ± 1.5 SD from the mean.

Figure 3. Response Surfaces for Bid Success and Price Premium

Results are based on Table 3, Model 4: Predicting Freelancers' Bid Success



Results are based on Table 4, Model 6: Predicting Freelancers' Price Premium



Notes: We detail the response surfaces in the Web Appendix. Web Appendix L displays similarity and dissimilarity effects for bid success, Web Appendix M displays simple slope analyses of low vs. high levels of buyers' communication for bid success, Web Appendix O displays similarity and dissimilarity effects for price premium, Web Appendix P displays simple slope analyses of low vs. high levels of buyers' communication for price premium.

WEB APPENDIX

Communication in the Gig Economy: Buying and Selling in Online Freelance Marketplaces

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"These materials have been supplied by the authors to aid in the
understanding of their paper. The AMA is sharing these materials at the
request of the authors."

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WA#A: Main Empirical Marketing Studies on B2B Communication Aspects

Authors	Context	Communication	Dependent Variables	Communication Aspects	Data Source
Agnihotri, Rapp, and Trainor (2009)	Offline	Seller → Buyer	Buyers' satisfaction (P)	Timeliness and relevance of communication (P)	Survey
Ahearne, Jelinek, and Jones (2007)	Offline	Seller → Buyer	Buyers' satisfaction (P)	Efficacy of communication (P)	Survey
Anderson and Narus (1990)	Offline	Buyer → Seller Seller → Buyer	Sellers' cooperation (P) Buyers' cooperation and trust (P)	Efficacy of communication (P)	Survey
Anderson, Lodish, and Weitz (1987)	Offline	Buyer → Seller	Sellers' time allocated to buyer (B)	Frequency of positive feedback, formality and detail in communication (P)	Survey
Bialaszewski and Giallourakis (1985)	Offline	Buyer → Seller	Sellers' trust in buyer (P)	Efficacy of communication (P)	Survey
Cannon and Homburg (2001)	Offline	Seller → Buyer	Buyers' transaction costs (P)	Frequency and amount of communication (P)	Survey
Comstock and Higgins (1997)	Offline	Seller → Buyer	Buyer's satisfaction (P)	Cooperativeness, apprehensiveness, socialness and competitiveness in communication (P)	Survey
Dion and Notarantonio (1992)	Offline	Seller → Buyer	Sellers' performance (B)	Contentious, open, dramatic, precise, relaxed, friendly, dominant, attentive, animated and impressionistic communication (P)	Survey and experiment
Guiltan, Rejab, and Rodgers (1980)	Offline	Seller → Buyer	Buyers' coordination (P)	Efficacy of communication (P)	Survey
Homburg et al. (2002)	Offline	Seller → Buyer	Buyers' satisfaction (P)	Frequency of information sharing (P)	Survey
Homburg, Giering, and Menon (2003)	Offline	Seller → Buyer	Buyers' satisfaction (P) and loyalty (P)	Frequency of communication (P)	Survey
Homburg, Muller, and Klarmann (2011)	Offline	Seller → Buyer	Buyers' loyalty (P)	Task and interaction orientation in communication (P)	Survey
Hossain and Chonko (2018)	Offline	Seller → Buyer	Buyers' loyalty (P) and performance (P)	Frequency and formality of communication (P)	Survey
Hung and Lin (2013)	Offline	Seller → Buyer	Buyers' satisfaction (P)	Regularity, timeliness and quality of communication (P)	Survey
Jaramillo and Grisaffe (2009)	Offline	Seller → Buyer	Sellers' sales performance (B)	Seller's customer orientation and adaptive selling (P)	Survey and objective data
Joshi (2009)	Offline	Buyer → Seller	Sellers' knowledge (P), commitment (P), and performance (P)	Frequency, formality, reciprocity, rationality in communication (P)	Survey
Kozlenkova et al. (2017)	Online	Seller → Buyer	Buyer's relationship formation (B)	Bilateral communication (B) Number of interactions (B)	Objective data

Kumar and Venkatesan (2005)	Online & Offline	Buyer → Seller Seller → Buyer	Revenue, Share of Wallet, Past Customer Value, Likelihood of Staying Active (B)	Number of times the customer contacted the supplier via the internet vs. offline (B)	Objective data
Lawrence et al. (2019)	Online & Offline	Seller → Buyer	Sales revenue (B)	Number of interpersonal contact between customer and salesperson (B)	Survey and objective data
McFarland, Challagalla, and Shervani (2006)	Offline	Seller → Buyer	Sellers' performance (P)	Task, self and interaction orientation in communication (P)	Survey
Mohr and Sohi 1995	Offline	Seller → Buyer	Buyers' satisfaction (P)	Amount, frequency, adequate, timely, accurate, complete and credible communication (P)	Survey
Mohr, Fisher, and Nevin 1996	Offline	Seller → Buyer	Buyers' satisfaction and commitment (P)	Frequency, bidirectionality, formality and noncoercive of communication (P)	Survey
Authors	Context	Communication	Dependent Variables	Communication Aspects	Data Source
Morgan and Hunt (1994)	Offline	Seller → Buyer	Buyers' trust, commitment, uncertainty, cooperation (P)	Efficacy and timeliness of communication (P)	Survey
Murphy and Sashi (2018)	Offline	Seller → Buyer	Buyers' satisfaction with seller (P)	Frequency, rationality and reciprocity in communication (P)	Survey
Palmatier, Dant, and Grewal (2007)	Offline	Buyer → Seller Seller → Buyer	Buyers' commitment, trust, interdependence, opportunism, investments, norms (P)	Timeliness, completeness and accuracy in communication (P)	Survey
Palmatier et al. (2006)	Offline	Seller → Buyer	Buyers' commitment, trust, satisfaction, relational quality (P)	Amount, frequency and the quality of communication (P)	Meta-analysis
Román and Martín (2008)	Offline	Seller → Buyer	Sales volume, perceived service quality and buyer satisfaction (P)	Call frequency in the supplier-customer relationship (B) Call frequency (B)	Survey and objective data
Schmitz et al. (2020)	Online & Offline	Seller → Buyer	Sales (B)	Personal communication vs. phone communication (B)	Objective data
Singh, Marinova and Singh (2020)	Online	Seller → Buyer	Buyer attention (P) and sales (B)	Recommendations, promises, assertiveness, info sharing via emails (B)	Objective data
Zhang, Netzer, and Ansari (2014)	Online & Offline	Buyer → Seller	Bid probability (B) and Accept probability (B)	Direct order vs. quote request (B)	Objective data
<i>This study</i>	<i>Online</i>	<i>Buyer → Seller Seller → Buyer</i>	<i>Call for bid success and bid success (B), uncertainty reduction (P)</i>	<i>Degree of task information, personal information, concreteness, affective intensity, and mimicry in communication</i>	<i>Objective data and experiment</i>

Note: Measures are classified into perceptions (P), intentions (I), and behaviors (B). Objective data comprises behavioral and communication data as naturally observed, surveys can be both cross-sectional and longitudinal.

WA#B: Main Studies Using Automated Text-Analysis to Investigate Communication

Authors	Context: Text Type	Type of Flow	DVs	Independent and Moderating Variables	
		C = Consumer B = Business	Perception (P) Intentions (I) Behavior (B)	Main Communication Aspects	Uncertainty Reduction Aspects
Barasch and Berger (2014)	<i>Informational:</i> customer reviews, WOM	C → C	Self-presentation in language (B)	Self- versus other-orientation in communication	no
Herhausen et al. (2019)	<i>Informational:</i> WOM	C → C	Virality consumer posts (B)	Emotions and emotional arousal in communication	no
Homburg, Ehm and Artz (2015)	<i>Informational:</i> WOM and company reaction	C → C B → C	Consumer sentiment (P)	Relative firm engagement in consumer communication	no
Kim and Kumar (2018)	<i>Transactional:</i> direct marketing	B → C	Customer purchase behavior (B)	Economic and relational content in communication	no
Kronrod and Danziger (2013)	<i>Informational:</i> customer reviews, advertisements	C → C B → C	Consumer product, review-, advertisement attitude (P), and product choice (B)	Figurative versus literal communication	no
Ludwig et al. (2013)	<i>Informational:</i> customer reviews	C → C	Online retail site conversion rates (B)	Affect in- and linguistic style of communication	no
Ma, Sun and Kekre (2015)	<i>Informational:</i> WOM	C → C B → C	Relationship state (P), voice (B), friends' influence on communication (B)	Complaints versus compliments	no
Moon and Kamakura (2017)	<i>Informational:</i> customer reviews	C → C	Product position (P) and features (P) on perceptual map	Writing style of reviewer	no
Nguyen and Chaudhuri (2019)	<i>Transactional:</i> product (pre-) announcements, WOM	C → C B → C	Consumer online engagement (B) and aggregated product sales (B)	Positive sentiment, content richness,	no
Pitt, Mulvey and Kietzmann (2018)	<i>Informational:</i> customer reviews	C → C	Consumer sentiments (P)	Emotions in communication	no
Rocklage and Fazio (2015)	<i>Informational:</i> customer reviews	C → C	Consumer intention to share message (I)	Emotions and emotional extremity in communication	no
Sonnier, McAlister and Rutz (2011)	<i>Transactional:</i> WOM	C → C	Aggregated product sales (B)	Sentiment in communication	no
Timoshenko and Hauser (2019)	<i>Informational:</i> customer reviews	C → C	Customer needs (P)	Informative versus non-informative content in communication	no

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Van Laer et al. (2018)	<i>Informational:</i> customer reviews	C → C	Consumer review helpfulness (B)	Narrativity of communication	no													
Villarroel Ordenes et al. (2018)	<i>Informational:</i> WOM	C → C	Consumer sharing and liking of message (B)	Intentions in communication (i.e., assertive, expressive, or directive)	no													
Villarroel Ordenes et al. (2017)	<i>Informational:</i> customer reviews	C → C	Consumer sentiment (P)	Sentiment in communication	no													
Yin, Bond and Zhang (2017)	<i>Informational:</i> customer reviews	C → C	Consumer review helpfulness (P)	Emotions and emotional arousal in communication	no													
Zhang, Moe and Schweidel (2017)	<i>Informational:</i> WOM	C → C	Consumer rebroadcasting of messages (B)	Content of message	no													

Authors	Context: Text Type	Type of Flow	DVs	Independent and Moderating Variables	
		C = Consumer B = Business	Perception (P) Intentions (I) Behavior (B)	Main Communication Aspects	Uncertainty Reduction Aspects
Packard and Berger (2020)	<i>Informational:</i> customer service phone calls and email	B → C	Satisfaction (P), Willing to purchase (I), and Purchase (B)	Concreteness	yes
Packard, More and McFerran (2018)	<i>Informational:</i> customer queries, company answers	C → B B → C	Consumer purchase (B)	Customer orientation in communication	no
Singh, Marinova and Singh (2020)	<i>Transactional:</i> Email	B → B	Buyer attention (P) and sales (B)	Recommendations, promises, assertiveness, info sharing via emails	no
<i>This study</i>	<i>Transactional:</i> <i>Call for bids and Bids</i>	<i>B ↔ B</i>	<i>Number of bids (B), Winning bid (B), Price Premium (B)</i>	<i>Communication strategies to manage uncertainty</i>	<i>yes</i>

WA#C: Definitions, Representative Articles, and Operationalizations of All Measures

Construct	Definition	Representative Articles	Operationalization
<i>Dependent Variables</i>			
Call For Bid Success	The number of freelancers who submit a bid application	Horton (2019)	The number of freelancers who submit a bid to the call for bids.
Bid Success	Whether or not the freelancer's bid is successful	Hong and Pavlou (2017)	Whether (1) or not (0) a freelancer was chosen by the buyer and thus wins the bidding process.
Price Premium	The monetary amount in excess of the buyer's original payment offer for a certain freelance service project	Singh and Sirdeshmukh (2000)	The percentage by which the final (accepted) bid price for the project exceeds (or falls short of) the buyer's original payment offered (her benchmark price)
<i>Communication Content</i>			
Task Information	Task information is a content element of communication, that, in the service exchange context, is conveyed through lexical terms on functional service duties (Ma and Dubé 2011)	N.A.	Proportion of context specific task descriptor words (using freelancers' service skill tags which list key words freelancers use to describe the service tasks they offer (e.g., "Python Developer", "Designer", "Illustrator")) to total words in the message.
	The proportion of lexical task terms to the total number of words in a message, defines the degree of task information (Bradac, Hopper, and Weimann 1989; Berger et al. 2020).		
Personal Information	Personal information is a content element of communication, that is conveyed through lexical self-disclosing terms about the self (Derlega, Harris, and Chaikin 1973)	Pennebaker and Stone (2001)	Proportion of first-person singular pronouns (e.g., "I", "me") to total words in the message (using the "I" LIWC dictionary; Tausczik and Pennebaker 2010).
	The proportion of lexical self-terms to the total number of words in a message, defines the degree of personal information (Bradac, Hopper, and Weimann, 1989; Berger et al. 2020).		

Construct	Definition	Representative Articles	Operationalization
<i>Communication Style</i>			
Concreteness	Concreteness is a manner element of communication, that is conveyed through lexical terms which are perceptible, precise, or specific (Packard and Berger 2020; Brysbaert, Warriner, and Kuperman 2014)	Brysbaert et al. (2014)	Proportion of concrete words to total words in the message (using all the relatively concrete lemmas ($\Rightarrow 3$) in the dictionary by Brysbaert et al. 2014).
	The proportion of lexical concrete terms to the total number of words in a message, defines the degree of concreteness (Bradac, Hopper, and Weimann, 1989; Berger et al. 2020).		
Affective Intensity	Affective intensity is a manner element of communication, that is conveyed through lexical terms which are affective (Hamilton and Hunter 1998)	Hamilton and Hunter (1998)	Proportion of affect words (e.g. “problematic”, “great”, “easy”) to total words in the message (using the “affect” LIWC dictionary; Tausczik and Pennebaker 2010).
	The proportion of lexical emotional terms to the total number of words in a message, defines the degree of intensity (Bradac, Hopper, and Weimann, 1989; Berger et al. 2020).		
<i>Controls for buyers' Call for bids Success</i>			
Word Count	The extent to which a text provides information	Herhausen et al. (2019)	Sum of words in a text.
Buyer Experience	The number of projects a buyer already had purchased on the platform prior to posting the focal project description	Hong and Pavlou (2017)	The number of projects a buyer had already purchased on the platform prior to posting the focal call for bids.
Project Payment	The buyer's initial payment offered for the service.	Ostrom and Iacobucci (1995)	The actual dollar value offered by the buyer in her call for bids, multiplied by an undisclosed index for anonymity purposes.

Construct	Definition	Representative Articles	Operationalization
Payment not Disclosed	The buyer did not disclose a payment offer upfront	Horton and Johari (2018)	Coded (1) if the buyer indicated a payment offer upfront along with the call for bids (1), or not (0).
Project Duration	The buyer's expected project duration.	Horton (2019)	An indicator for a project's duration that was specified by the buyer in her project description at t ₋₁ to last either more (1) or less than a month (0).
Excess Supply of Freelancers	The relative amount of supply (in freelancers) to the amount of projects available in any given sub-market	Horton (2019)	Number of active freelancers (all freelancers in the specific submarket, who will submit at least one bid in the future), divided by the number of buyers who post call for bids around the same time (± 31 days) and in the same submarket
<i>Additional Controls for Freelancers' Bid Success</i>			
Linguistic style matching (LSM)	The extent to which two texts match in function word use	Ludwig et al. (2013)	The degree of LSM across each function word category in a freelancer's bid to a buyer's call for bids. By aggregating all nine LSM scores with equal weights, we obtain an LSM score bound between 0 and 1, and scores closer to 1 reflect greater degree of communication style matching between the freelancer and buyer.
Freelancer Experience	The number of projects the freelancer already completed	Hong and Pavlou (2017)	The number of projects the freelancer already completed prior to submitting her bid to the focal call for bids.
Freelancer Rating	The average five-point quality rating the freelancer received from all previous projects	Hong and Pavlou (2017)	The average five-point quality rating the freelancer received from all previous projects (with 5 indicating highest quality).
Previous relationship	Whether the exchange relation was a repeat- or a first-time business interactions	Hong and Pavlou (2017)	Coded (1) if the freelancer had completed a project with the specific buyer before and (0) if not.
Bid Price	The relative asking price by the freelancer	Hong and Pavlou (2017)	The percentage by which the actual dollar value asked for by the freelancer in her bid (multiplied by an undisclosed index for anonymity purposes) exceeds (or falls short of) the average asking price of all competing bids for the same project.
Time-to-bid	Duration it took for the freelancer to submit her bid	Dalya and Nath (2005)	Time in days it took the freelancer to submit her bid (time-to-bid), following the call for bids
Late submission	Whether the bid was submitted late	N.A.	Whether the bid was submitted late (1) or on time (0).
Competition	How many freelancers were applying for the same call for bids	Horton (2019)	The number of freelancers who applied for the same call for bids.

WA#D: Illustrative Figure of Freelancer Profile



Name: Jennifer S.

Rating: 4.5 out of 5 stars

Number of Projects completed: 17

Skills: Keynote Microsoft PowerPoint Presentation Data Visualization

Infographics Copywriting

Peer Review Version

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WA#E: Response Surface Methodology

Our measures of communication mimicry are based on the constraints placed within the polynomial model using the freelancer's and buyer's communication aspects. Earlier studies have examined communication mimicry using a difference score approach (e.g., Ludwig et al. 2013; Soliz and Giles 2014). However, given the conceptual and methodological problems it creates, Edwards and Parry (1993) recommend the polynomial technique as an effective alternative that can avoid the limitations of the difference score approach. An increasing number of studies have used the polynomial technique to explore such topics as perceptual differences and (mis)fit (e.g., Mullins et al. 2015; Menguc et al. 2016). For instance, by using polynomial regression with response surface analysis we are able to test predictions as to how bid success and service price premium may change when freelancers' of mimic different levels of buyers' task information. One of the benefits of polynomial regression is that the effect of mimicking on an outcome is treated as a three-dimensional surface, simultaneously relating the degree of mimicry as well as the freelancer's and buyer's communication levels to the respective outcomes (i.e., bid success and price premium). These graphs allow us to examine the precise nature of mimicry relationships (e.g., Harris, Anseel, and Lievens 2008) and study at which level of communication mimicry by the freelancer towards the buyer is beneficial or aversive.

In polynomial modeling, the dependent variable is estimated by entering five polynomial terms into the equation. For example, we estimated bid success against a freelancer's task information (FTASK), buyer's task information (BTASK), and the three higher-order effects (i.e., $FTASK^2$, $FTASK \times BTASK$, and $BTASK^2$) that are created as product terms of FTASK and BTASK in Table 3, Model 4. We standardized all communication variables because means and standard deviations are comparable across freelancers and buyers (Shanock et al. 2010). Yet

the estimated coefficients that relate to the effect of each polynomial term on bid success individually are not directly employed to test any proposition. Rather, the estimated coefficient for each polynomial term is used to compute the slope and curvature along the fit and misfit lines, which is also known as response surface analysis. Using Edwards and Parry's (1993) formula, we computed the slopes and curvatures along the fit (FTASK = BTASK) and misfit (FTASK = - BTASK) lines as fit slope (FTASK + BTASK) and fit curvature (FTASK² + FTASK × BTASK + BTASK²) and misfit slope (FTASK - BTASK) and misfit curvature (FTASK² - FTASK × BTASK + BTASK²). Because of the nested nature of our data (i.e., multiple bids from each freelancer), we took a multilevel, random coefficients approach to the polynomial modeling technique (e.g., Jansen and Kristof-Brown 2005). As a result, we employed multilevel path analysis to estimate the model's proposed relationships simultaneously. Thus, the relationship between freelancer's task information, buyer's task information, and bid success in Table 3, Model 4 can be written as:

$$(WA1) \quad BIDSUC_{kl} = y_{00} + y_{01}FTASK_{kl} + y_{05}BTASK_{kl} + y_{09}FTASK_SQ_{kl} + y_{13}(FTASK_{kl} \times BTASK_{kl}) + y_{17}BTASK_SQ_{kl} + \mu_{0l} + \varepsilon_{kl},$$

where $BIDSUC_{kl}$ is the success of bid k from freelancer l, $FTASK_{kl}$ is freelancer task information, $BTASK_{kl}$ is buyer task information, $FTASK_SQ_{kl}$ is freelancer task information squared, $(FTASK_{kl} \times BTASK_{kl})$ is the interaction term between freelancer and buyer task information, $BTASK_SQ_{kl}$ is buyer task information squared, μ_{0l} is the random intercept, and ε_{kl} is the error term. We stated that mimicking buyers' task information should increase freelancers' bid success. To test whether bid success varies for misfit in task information, we define the polynomial regression with FTASK = - BTASK. Substituting FTASK = - BTASK in equation WA1, the misfit line can be written as:

$$(WA2) \quad BIDSUC_{kl} = y_{00} + (y_{01} - y_{05})FTASK_{kl} + (y_{09} - y_{13} + y_{17})FTASK_SQq_{kl} + \mu_{0l} + \varepsilon_{kl},$$

where the misfit line slope ($y_{01} - y_{05}$) represents the linear effect of freelancer task information that are greater than buyer task information. When the effect is positive, bid success increases as freelancer task information grows greater than buyer task information, but decreases as freelancer task information decreases further below buyer task information. The misfit line curvature ($y_{09} - y_{13} + y_{17}$) represents the non-linear effect of misfit in task information on bid success. When this effect is positive (i.e., u-shaped), bid success will be at a minimum at perfect fit and increase with misfit when freelancer task information either under- or overestimates buyer task information. Conversely, when the effect is negative (i.e., inverted u-shaped), bid success will be maximized at perfect fit, and decrease as freelancer task information either under- or overestimates buyer task information.

We further qualified this effect and proposed that when freelancers mimic buyers' who provide little task information, their chance of bid success decrease. Thus, in this situation it would be beneficial for the freelancer to provide more task information regardless of the buyer. To test this, we inspect the slope of FTASK when BTASK is at -1.5 standard deviations below the mean:

$$(WA3) \quad BIDSUC_{kl} = y_{00} + y_{01}FTASK_{kl} - (1.5 SD \times y_{13}(FTASK_{kl} \times BTASK_{kl})) + \mu_{0l} + \varepsilon_{kl},$$

where a positive effect would indicate that providing more task information is better for the freelancer. Summarizing the explanations above, assessing the response surface allows a novel and quantitative description of the three-dimensional relationships between freelancer's task information, buyer's task information, and bid success (as well as price premium).

WA#F: Manual Validity Checks of Text Analysis Approach

To ensure the validity of the text analysis, two expert coders were used to classify the texts of a random subsample of 100 call for bids (with a mean of 129 words) and 100 bids (with a subsample mean of 125 words). For each text the coders indicated whether they agreed (coded 1) that “The buyer/freelancer presents a lot of information related to the service task” (adapted from Venkatesh, Kohli, and Zaltman 1995). “The buyer/freelancer writes about her/himself for fairly long period” (Wheless 1976), “The buyer’s call for bids/ freelancer’s bid text is extremely concrete” (Krishnan, Biswas, and Netemeyer 2006), “The buyer’s call for bids/ freelancer’s bid text feels very emotional (Hamilton and Stewart 1993)

After practicing on five example call-for bids and bids, the coders classified the sampled texts, and we compared their classification with the automated text analysis. Between the coders and the automated text analysis, generally substantial agreement levels were achieved ($.71 < a < .87$ for the call for bids and $.82 < a < .92$, for the bids; Krippendorff 2013). Following our automatic text mining approach, we classified those bids that contained above average degrees of (1) task information, (2) personal information, (3) concreteness and (4) affective intensity as (1) and below average degrees as (0). Averages for call for bids and bids are shown in Web Appendix J. In those cases where the coders agreed, on average, substantial agreement levels were achieved between the agreed coder classification and the classification using the automated text analysis ($.73 < a < .94$ for the call for bids and $.66 < a < .88$, for the bids; Krippendorff 2013).

Following Berger et al. (2020) we then calculated *precision*, *recall*, and the *F1-Measure* (see Table WA E1). Overall our results demonstrate the accuracy of our text mined measures.

Table WA F1. Krippendorff's Alpha, Precision, Recall, and F-Measure

Text-Mined Measures	Krippendorff's α between coders (bids / calls for bids)	Krippendorff's α between coders and automated measurement (bids / calls for bids)	Precision (bids / calls for bids)	Recall (bids / calls for bids)	F-Measure (bids / calls for bids)
<i>Communication Content</i>					
Task Information	.86 / .83	.86 / .85	.89 / .87	.93 / .93	.91 / .90
Personal Information	.92 / .87	.88 / .94	1.00 / .91	.89 / 1.00	.95 / .95
<i>Communication Style</i>					
Concreteness	.82 / .87	.66 / .73	1.00 / .67	.66 / 1.00	.79 / .80
Affective Intensity	.89 / .71	.88 / .88	.96 / 1.00	.89 / .80	.92 / .89
Mean	.88 / .82	.82 / .85	.96 / .86	.84 / .93	.89 / .89

Note. *Precision* (true positives / (true positives + false positives)) is the count of correct class predictions by the text mining approach that actually belong to the positive class (correct was what the human coders agreed on), *recall* (true positives / (true positives + false negatives)) quantifies the number of positive class predictions made by the text mining approach out of all positive classifications made by the human coders, and the *F1-Measure* is the harmonic mean of the levels of recall and precision ($2 * \text{Precision} * \text{Recall} / (\text{Precision} + \text{Recall})$).

Table WF2. Human Coder Correlations for Bids

	1	2	3	4	5	6	7	8	9	10	11	12
1. Task information Coder 1												
2. Task information Coder 2	.82											
3. Task information PC	.82	.73										
4. Personal information Coder 1	-.12	-.17	-.10									
5. Personal information Coder 2	-.13	-.13	-.11	.87								
6. Personal information PC	-.05	-.10	-.03	.92	.84							
7. Concreteness Coder 1	.12	.03	.06	-.07	-.18	-.10						
8. Concreteness Coder 2	.14	.05	.13	-.12	-.19	-.16	.87					
9. Concreteness PC	.15	.10	.12	-.08	-.15	-.07	.75	.66				
10. Affective intensity Coder 1	-.17	-.07	-.16	.19	.19	.20	-.07	-.15	-.02			
11. Affective intensity Coder 2	-.01	-.01	.00	.25	.24	.26	-.10	-.17	-.04	.72		
12. Affective intensity PC	-.17	-.17	-.16	.30	.29	.31	-.07	-.15	-.02	.79	.72	

Note. N=100. Coder 1 and 2 refers to the two human coders for this validation study and "PC" is the classification by the text mining approach.

Table F3. Human Coder Correlations for Calls for Bids

	1	2	3	4	5	6	7	8	9	10	11	12
1. Task information Coder 1												
2. Task information Coder 2	.86											
3. Task information PC	.86	.77										
4. Personal information Coder 1	-.18	-.13	-.14									
5. Personal information Coder 2	-.16	-.16	-.17	.92								
6. Personal information PC	-.17	-.13	-.13	.89	.84							
7. Concreteness Coder 1	.10	.14	.08	-.42	-.45	-.45						
8. Concreteness Coder 2	.17	.22	.16	-.48	-.47	-.57	.82					
9. Concreteness PC	.14	.18	.10	-.37	-.37	-.40	.64	.63				
10. Affective intensity Coder 1	-.22	-.18	-.20	.10	.12	.16	-.16	-.16	-.11			
11. Affective intensity Coder 2	-.20	-.20	-.18	.14	.16	.16	-.19	-.18	-.12	.90		
12. Affective intensity PC	-.24	-.14	-.21	.08	.09	.13	-.13	-.13	-.13	.88	.82	

Note. N=100. Coder 1 and 2 refers to the two human coders for this validation study and "PC" is the classification by the text mining approach.

WA#G: Experimental Evidence of Uncertainty Reduction

We use single-factor, within-subject designs for each of the four communication aspects. Across the studies, between 50 and 53 U.S. consumers, with a mean age of 37.6 years (50% women), were recruited from Amazon Mechanical Turk. Confidentiality was assured, and participants were told to imagine hiring someone to write content for their website on Upwork (a global freelancing website). To qualify to participate, respondents had to be native English speakers and sufficient online freelance marketplace experience (i.e., a minimum of 1,000 submitted task on MTurk). Moreover, on a scale from 1 = “do not agree” to 7 = “fully agree”, they scored on average 5.89 regarding the statement “I have experience working as a freelancer on online platforms”. An instructional manipulation check excluded two to four participants from each study. Following the introduction, participants were randomly allocated to one of four communication aspects (i.e., task information, personal information, concreteness, and affective intensity), then exposed in random order to two different bids from two different freelancers, using strategies that reflected the greater or lesser degree version of the focal condition, such that it was at least one standard deviation different from the value obtained in the field study (e.g., for example the mean difference of personal information between our high- and low condition is 4.32%, (2.50% vs. 6.82%) as determined using our text mining approach. We provide an example of the stimuli in Figure G1; the text for all stimuli is in Table G2.

After reading the stimuli, participants indicated their hiring intentions for each bid and chose one of the two bids, using a seven-point semantic differential scale (1 = “definitely bid A” to 4 = “indifferent” to 7 = “definitely bid B”), where bid A and bid B feature the greater and lesser use of the respective communication aspect, assigned randomly. Next, we asked participants to rate each bid according to the level of uncertainty related to the freelancer who

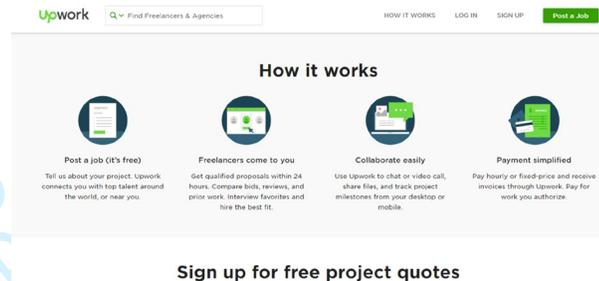
1
2
3 submitted the bid with a measure from Grewal, Gotlieb, and Marmorstein 1994; “How confident
4 are you that the freelancer will perform well?”, “How certain are you that the freelancer will
5 work satisfactory?”, “Do you feel that the freelancer will perform as requested?”, $\alpha = .93$). We
6 used the questions from the manual validity check reported in Web Appendix F as manipulation
7 checks. Table G3 provides all means and standard deviations.

8
9
10 All the text manipulations were successful, and the simple contrasts and participants’
11 choices are in line with our expectations (see Table G4). They indicated greater hiring intentions
12 for bids that contained more task information ($M_{\text{high}} = 5.44$, $M_{\text{low}} = 4.28$, $t(51) = 3.84$, $p < .01$),
13 more personal information ($M_{\text{high}} = 5.28$, $M_{\text{low}} = 4.00$; $t(49) = 6.96$, $p < .01$), more concreteness
14 ($M_{\text{high}} = 5.23$, $M_{\text{low}} = 4.06$; $t(52) = 4.11$, $p < .01$), and more affective intensity ($M_{\text{high}} = 5.55$, M_{low}
15 $= 4.49$; $t(50) = 3.58$, $p < .01$). We then applied mediation procedures to the within-subjects
16 designs (Montoya and Hayes 2017) and the MEMORE macro to test for the mediating role of
17 uncertainty reduction between the communication strategies and hiring intentions. The greater
18 versus lesser use of each communication aspect in each study predicts uncertainty reduction (β s
19 between .76 and 1.35, all $p < .01$). In turn, uncertainty reduction significantly predicts hiring
20 intention (β s between .84 and 1.21, all $p < .01$), and 5,000 bootstrap samples reveal indirect
21 effects of greater versus lesser uses of each communication aspect on hiring intentions, through
22 uncertainty reduction (β s between .82 and 1.32, all 95% confidence intervals range from .43 to
23 1.83).

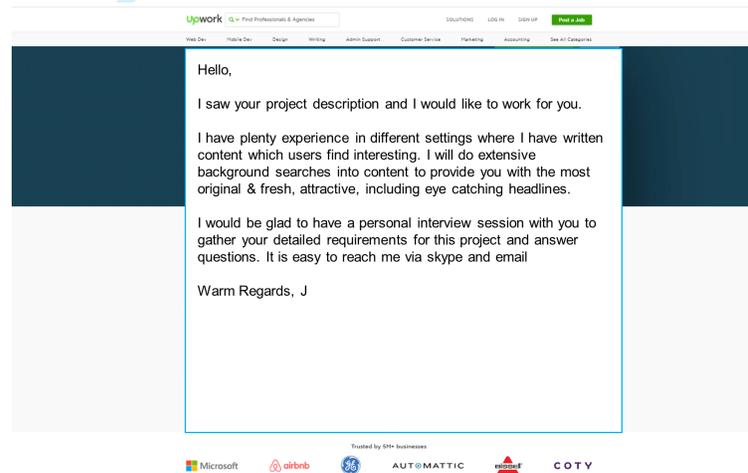
Figure WA G1. Sample Stimuli

Study Context

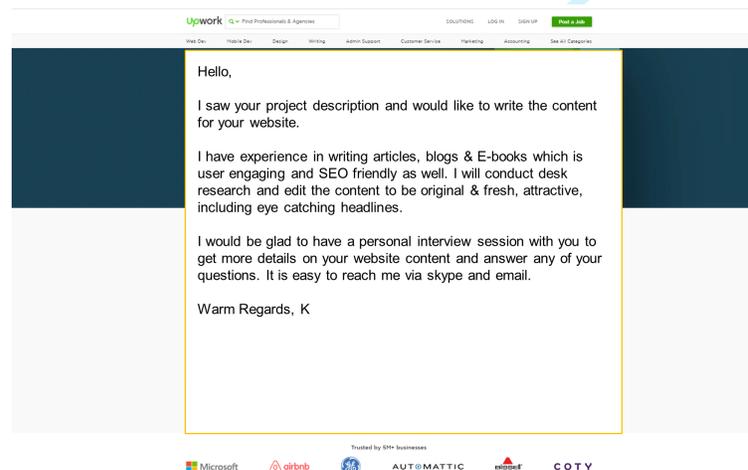
Imagine you want to hire someone to write content for your website. Thus, you visit Upwork — the largest global freelancing website to hire a freelancer. In the following, you will read two different bids from two different freelancers. We will ask you to rate each bid and to choose one of the two bids.



Low Task Information Bid



High Task Information Bid



Note: We randomized the order of the bids in all experimental studies.

Table WA G2. Text for All Stimuli

	A: Task Information	D: Personal Information	C: Concreteness	D: Affective Intensity
Low Bid Condition	I saw your project description and I would like to work for you. I have plenty experience in different settings where I have written content which users find interesting. I will do extensive background searches into content to provide you with the most original & fresh, attractive, including eye catching headlines. I would be glad to have a personal interview session with you to gather your detailed requirements for this project and answer questions. It is easy to reach me via skype and email	Saw your project description and would like to write the content for your site. Have experience in writing articles, blogs & E-books which is user engaging and SEO friendly as well. Content provided by me will be original & fresh, attractive, including eye catching headlines, fully researched and relevant. Would be glad to have a personal interview session with you to gather your detailed requirements and answer any of your questions. It is easy to reach me via skype and email.	I noticed your project description and I would like to do work on it. I have plenty of experience in scripting text, which is engaging, compelling, and SEO friendly. I can write ideal content and optimize your existing ones. Content provided by me will be spiriting, attractive, with striking headlines, researched and relevant. I would be glad to have a personal interview with you to gather requirements and answer queries. It is easy to get in touch with me via various communication channels.	I saw your project description and I can write the required content for your site. I have plenty of experience in writing articles, blogs & E-books which is user engaging and SEO friendly as well. Content provided by me will be original, including eye catching headlines, fully researched and relevant. Let us have a personal interview session to gather your detailed requirements and answer any questions. Reach me via skype and email.
High Bid Condition	I saw your project description and would like to write the content for your website. I have experience in writing articles, blogs & E-books which is user engaging and SEO friendly as well. I will conduct desk research and edit the content to be original & fresh, attractive, including eye catching headlines. I would be glad to have a personal interview session with you to get more details on your website content and answer any of your questions. It is easy to reach me via skype and email.	I saw your project description and would like to write the content for your site. I have 12 years of work experience in copy writing for articles, blogs & E-books. I focus on SEO friendly content as well. I have a Master's in Journalism from the University of Melbourne and have worked fulltime for companies like Adobe. I would be glad to have a call with you to gather your detailed requirements and answer any of your questions. It is easy to reach me via skype and email.	I saw your posted project description on Upwork, and I would like to write the contents for your website. I have a lot of experience in article and weblog writing in an SEO friendly fashion. I can provide a lot of new content and optimize the all the current content on your site. The content I add to your site will invite, be crisp and flash headlines. If you like we can have a kick off call to answer any question you have? It is easy to reach me via skype and email.	I liked your project description and would be happy to write the content for your site. I have great experience in writing articles, blogs & E-books which is user engaging and SEO friendly as well. Content provided by me will be original & fresh, attractive, including eye catching headlines, fully researched and relevant. I would be delighted to have a kick off call and answer any questions. It is easy to reach me via skype and email.
Text Mining Results	Task information: $M_{low}= 19.28\%$ vs. $M_{high}=25.29\%$	Personal information: $M_{low}=2.50\%$ vs. $M_{high}=6.82\%$	Concreteness: $M_{low}= 22.10\%$ vs. $M_{high}=43.33\%$	Affective intensity: $M_{low}= 6.94\%$ vs. $M_{high}=11.84\%$

Table WA G3. Means and Standard Deviations

A: Task Information					
	Low Task Information		High Task Information		Effect Size
	Mean	SD	Mean	SD	
MC: Task Information	4.28	1.57	5.33	1.27	.52
Mediator: Risk Reduction	4.59	1.47	5.43	1.28	.43
DV: Hiring Intention	4.35	1.63	5.44	1.21	.54
B: Personal Information					
	Low Personal Information		High Personal Information		Effect Size
	Mean	SD	Mean	SD	
MC: Personal Information	4.78	1.13	5.73	.95	.64
Mediator: Risk Reduction	4.33	1.53	5.67	1.15	.70
DV: Hiring Intention	4.00	1.46	5.82	1.26	.95
C: Concreteness					
	Low Concreteness		High Concreteness		Effect Size
	Mean	SD	Mean	SD	
MC: Concreteness	4.50	1.30	5.50	1.28	.54
Mediator: Risk Reduction	4.57	1.27	5.30	1.47	.38
DV: Hiring Intention	4.06	1.51	5.23	1.58	.54
D: Affective Intensity					
	Low Affective Intensity		High Affective Intensity		Effect Size
	Mean	SD	Mean	SD	
MC: Affective Intensity	5.08	1.14	5.96	.90	.61
Mediator: Risk Reduction	4.74	1.26	5.50	1.17	.44
DV: Hiring Intention	4.49	1.47	5.55	1.29	.54

Note: MC = Manipulation Check, DV = Dependent Variable.

Table WA G4. Results in the Pilot Studies

	A: Task Information	B: Personal Information	C: Concreteness	D: Affective Intensity
Participants	52 U.S. consumers, mean age 38.4 years, 38% women (the instructional manipulation check excluded four participants)	50 U.S. consumers, mean age 41.9 years, 49% women (the instructional manipulation check excluded two participants)	53 U.S. consumers, mean age 36.7 years, 43% women (the instructional manipulation check excluded three participants)	51 U.S. consumers, mean age 40.4 years, 47% women (the instructional manipulation check excluded four participants)
Manipulation measure	Amount of task information (Sicilia and Ruiz 2010)	Self-disclosure scale (Wheless 1976)	Level of concreteness (Krishnan, Biswas, and Netemeyer 2006)	Valence of information exchanged (Adjei, Noble, and Noble 2010)
Manipulation check	Manipulated successfully ($M_{high} = 5.33$, $M_{low} = 4.28$; $t(51) = 3.84$, $p < .01$).	Manipulated successfully ($M_{high} = 5.73$, $M_{low} = 4.78$; $t(49) = 5.24$, $p < .01$).	Manipulated successfully ($M_{high} = 5.50$, $M_{low} = 4.50$; $t(52) = 4.71$, $p < .01$).	Manipulated successfully ($M_{high} = 5.96$, $M_{low} = 5.08$; $t(50) = 4.54$, $p < .01$).
Paired sample results	High vs. low task information significantly predicts hiring intention ($M_{high} = 5.44$, $M_{low} = 4.35$; $t(51) = 4.03$, $p < .01$)	High vs. low personal information significantly predicts hiring intention ($M_{high} = 5.28$, $M_{low} = 4.00$; $t(49) = 6.96$, $p < .01$)	High vs. low concreteness significantly predicts hiring intention ($M_{high} = 5.23$, $M_{low} = 4.06$; $t(52) = 4.11$, $p < .01$)	High vs. low affective intensity significantly predicts hiring intention ($M_{high} = 5.55$, $M_{low} = 4.49$; $t(50) = 3.58$, $p < .01$)
Open choice results	81% choose the high task information amount bid	90% choose the high personal information bid	68% choose the high concreteness bid	75% choose the high intensity bid
Mediation results	<ul style="list-style-type: none"> ▪ High vs. low task information significantly predicts risk reduction ($\beta = 1.09$, $p < .01$) ▪ Risk reduction significantly predicts hiring intention ($\beta = .84$, $p < .01$) ▪ There is an indirect effect of high vs. low task information on hiring intention through risk reduction ($\beta = .82$, 95% CI .43 to 1.25). 	<ul style="list-style-type: none"> ▪ High vs. low personal information significantly predicts risk reduction ($\beta = 1.35$, $p < .01$) ▪ Risk reduction significantly predicts hiring intention ($\beta = .98$, $p < .01$) ▪ There is an indirect effect of high vs. low personal information on hiring intention through risk reduction ($\beta = 1.32$, 95% CI .89 to 1.83). 	<ul style="list-style-type: none"> ▪ High vs. low concreteness significantly predicts risk reduction ($\beta = .93$, $p < .01$) ▪ Risk reduction significantly predicts hiring intention ($\beta = .92$, $p < .01$) ▪ There is an indirect effect of high vs. low concreteness on hiring intention through risk reduction ($\beta = .85$, 95% CI .37 to 1.52). 	<ul style="list-style-type: none"> ▪ High vs. low affective intensity significantly predicts risk reduction ($\beta = .76$, $p < .01$) ▪ Risk reduction significantly predicts hiring intention ($\beta = 1.21$, $p < .01$) ▪ There is an indirect effect of high vs. low affective intensity on hiring intention through risk reduction ($\beta = .91$, 95% CI .42 to 1.40).

Note: CI = confidence interval.

WA#H: Model Free Evidence

Table H1. Model Free Evidence for Call for Bids' Success and Use of Communication Elements

Number of Bids	Task Information		Personal Information		Concreteness		Affective Intensity	
	≤ 5	> 5	≤ 5	> 5	≤ 5	> 5	≤ 5	> 5
Mean	.256	.278	.033	.028	.197	.227	.046	.036
SD	.076	.083	.029	.033	.073	.062	.030	.027
t-test	-108.59		63.47		262.50		134.42	
P-value	p<.001		p<.001		p<.001		p<.001	

Note: We chose a cut off of 5 bids submitted, which is the mean number of bids submitted to call-for-bids across all 644,397 call for bids (403,262 call for bids received 5 bids or less; 241,135 call for bids received more than 5 bids).

Table H2. Model Free Evidence for Bids' Success and Use of Communication Elements

Bid Outcome	Task Information		Personal Information		Concreteness		Affective Intensity	
	Lost	Won	Lost	Won	Lost	Won	Lost	Won
Mean	.281	.302	.050	.047	.170	.184	.045	.047
SD	.202	.204	.044	.056	.094	.097	.051	.075
t-test	-66.88		42.75		-95.61		-24.08	
P-value	p<.001		p<.001		p<.001		p<.001	

Note: We split bids between those who won and those that lost across all 5,167,787 bids (4,712,990 bids were unsuccessful; 454,797 bids were successful).

Table H3. Model Free Evidence for Bids' Success and Mimicry of Communication Elements

Buyer's use of communication element	Task Information			Personal Information			Concreteness			Affective Intensity		
	Low degree	Moderate degree	High degree	Low degree	Moderate degree	High degree	Low degree	Moderate degree	High degree	Low degree	Moderate degree	High degree
Mean Mimicry by Freelancer	.446	.759	.617	.349	.443	.423	.505	.798	.724	.443	.446	.438
SD	.335	.196	.247	.476	.290	.383	.361	.268	.227	.499	.381	.380
Relation	∩			∩			∩			no relation		

Note: Here, we only considered bids that won. We split the bids between those which replied to a buyer that used (1) a low degree (<10% of range of observed values), (2) moderate degree (45%-55% of range of observed values), and (3) high degree (>90% of range of observed values), of the respective communicative element (i.e., task information,

personal information, concreteness, or affective intensity) across all 5,167,787 bids (4,712,990 bids were unsuccessful; 454,797 bids were successful). We calculated the difference between each bid's (b) use of each respective communication element (C) and the respective call for bids' (cfb) use of the same communication element (C) using the same formula as Ludwig et al. (2013) when they calculated the linguistic style match. Specifically Mimicry of $C_b = 1 - [(C_b - C_{cfb}) / (C_b + C_{cfb} + 0.0001)]$. The resulting similarity score is bounded by 0 and 1 for each bid, higher numbers represented greater similarity (or mimicry) by the freelancer towards the buyer's use of the respective communication element. We split the reporting of the average differences for all bids which were submitted in response to (1) call for bids that used the communication element to a less degree, (2) moderate degree, and (3) great degree.

Table WA H4. Model Free Evidence for Price Premium

Price Premium	Task Information		Personal Information		Concreteness		Affective Intensity	
	No	Yes	No	Yes	No	Yes	No	Yes
Mean	.224	.248	.064	.069	.183	.200	.048	.042
SD	.140	.193	.051	.064	.094	.077	.064	.075
t-test	-12.05		-7.015		-13.65		6.78	
P-value	$p < .001$		$p < .001$		$p < .001$		$p < .001$	

Note: We split bids between those with a price below the asking price ("discount") and those above the asking price ("premium"; 45,841 bids were below and 6,207 bids were above, the rest matched the asking price).

Table WA H5. Model Free Evidence for Bids' Price Premium and Mimicry of Communication Elements

Buyer's use of communication element	Task Information			Personal Information			Concreteness			Affective Intensity		
	Low degree	Moderate degree	High degree	Low degree	Moderate degree	High degree	Low degree	Moderate degree	High degree	Low degree	Moderate degree	High degree
Mean Mimicry by Freelancer	.722	.812	.703	.261	.398	.508	.521	.745	.613	.267	.591	.505
SD	.344	.201	.212	.438	.299	.347	.329	.327	.283	.442	.351	.328
Relation	∩			/			∩			∩		

Note: Here, we only considered bids that received a price premium. We split the bids between those which replied to a buyer that used (1) a low degree (<10% of range of observed values), (2) moderate degree (45%-55% of range of observed values), and (3) high degree (>90% of range of observed values), of the respective communicative element (i.e. task information, personal information, concreteness, or affective intensity). 45,841 bids were below and 6,207 bids were above, the rest matched the asking price. We calculated the difference between each bid's (b) use of each respective communication element (C) and the respective call for bids' (cfb) use of the same communication element (C) using the same formula as Ludwig et al. (2013) when they calculated the linguistic style match. Specifically Mimicry of $C_b = 1 - [(C_b - C_{cfb}) / (C_b + C_{cfb} + 0.0001)]$. The resulting similarity score is bounded by 0 and 1 for each bid, higher numbers represented greater similarity (or mimicry) by the freelancer towards the buyer's use of the respective communication element. We split the reporting of the average differences for all bids which were submitted in response to (1) call for bids that used the communication element to a less degree, (2) moderate degree, and (3) great degree.

WA#I: Latent Dirichlet Allocation to Account for Project Characteristics

To account for potential project specifics which may (partly) explain the call-for bids or bids formulations and success, we used latent Dirichlet allocation (LDA; Blei 2012). LDA measures word co-occurrence across texts (e.g., keywords in freelancers' profile service descriptors), identifies latent topics, and the probability of each word appearing in a given topic.

To approximate the kind of project, we therefore used the skill keywords in freelancers service profile descriptors instead (see illustrative figure in Web Appendix D, the skill keywords are listed in Point 4). Specifically, any number of freelancers can apply to the same project. Overall, our reduced data comprises 343,796 unique projects. For each project, we concatenated all service skill tags keywords in from each applying freelancers' service profile who submitted a bid to the specific call for bids. These combined profile descriptor words were then processed using the R-package Quanteda (Benoit et al. 2018) to first remove punctuation, symbols, and English stopwords. Second, we stemmed the words. Third, we detected bigram collocations, such as "graphic design", and treat these as single tokens. We then formed a document-feature matrix from the tokens, and trimmed this to remove any terms that occurred fewer than 10 times, or in less than .001 percent of all documents. Following best practice (Blei 2012), we ran the structural topic model for $K = 1$ to 20 topics. Fit measures (i.e., held-out likelihood, semantic coherence, residuals, and lower bound) revealed the best fit at $K = 12$, so we fitted the $K = 12$ topic model. We then estimated topic proportions per project, resulting in a vector of 12 control variables capturing the proportion of the applying freelancers' keyword service descriptors pertaining to each of the 12 latent topics extracted, see Table II. We include a control for each of the 12 topic proportions to account for the project type.

Table WA II. Latent Project Characteristics derived from the LDA

Topic	Top Word Stem Examples
1	seo, sale, social media
2	writer, editor, copywrit*
3	consult*, manag*, analyst*
4	translat*, proofread*, content writer
5	artist, 3d, video editor
6	web design, websit*, website design
7	illustr*, programm*, architect*
8	php, wordpress, html
9	web develop*, communic*, ui
10	account, support, project manag*
11	photograph, video, audio
12	data entr*, administr*, office

WA#J: Descriptive Statistics and Correlations

Table WA J1. Descriptive Statistics and Correlations for Call for Bid Success

	1	2	3	4	5	6	7	8	9	10	11
1. Call for bids success											
2. Task information	.11										
3. Personal information	-.07	-.08									
4. Concreteness	.14	-.07	-.04								
5. Affective intensity	-.11	-.14	.02	-.13							
6. Word count	-.09	-.23	-.20	-.02	.07						
7. Buyer experience	-.08	.01	-.01	-.02	.01	.02					
8. Project payment	.13	.02	-.07	.03	-.04	.06	-.02				
9. Payment not disclosed	.22	.00	.02	.10	-.06	-.13	-.06	-.10			
10. Project duration	.47	.12	-.06	.21	-.16	-.18	-.08	.14	.37		
10. Excess supply of freelancers	.21	.09	.05	.08	-.13	-.18	-.07	.07	.12	.23	
Mean	4.92	.26	.03	.20	.04	125.60	11.18	57.58	.15	.33	7.25
SD	8.37	.08	.03	.07	.03	93.57	20.00	230.32	.35	.47	2.27

Note: Observations = 343,796.

*Please note that there is a non-disclosure agreement in place for the secondary data restricting the disclosure of confidential information.

Table WA J2. Descriptive Statistics and Correlations for Bid Success

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	
1. Bid success																						
2. Freelancer task information	.03																					
3. Freelancer personal information	-.02	-.39																				
4. Freelancer concreteness	.04	-.44	.18																			
5. Freelancer affective intensity	.01	-.17	.10	.09																		
6. Buyer task information	-.04	.05	.01	-.01	.01																	
7. Buyer personal information	.03	-.01	.02	.00	.01	-.11																
8. Buyer concreteness	-.06	-.06	.03	.10	.01	-.08	-.04															
9. Buyer affective intensity	.02	.01	-.01	.00	.05	-.12	.04	-.10														
10. Word count	-.11	-.22	-.03	.26	.01	.00	-.04	.05	.01													
11. Linguistic style matching	.10	.46	-.25	-.49	-.10	.04	-.04	-.08	.00	-.41												
12. Freelancer experience	.11	-.01	-.02	.03	.01	.03	.00	-.02	.01	.00	.01											
13. Freelancer rating	.02	-.01	.01	.04	-.01	-.01	.00	.01	.00	.00	-.02	.11										
14. Project payment	-.03	-.04	-.01	.03	.00	.00	-.05	.00	.00	.08	-.06	-.01	-.01									
15. Payment not disclosed	-.06	-.04	.01	.03	-.01	.00	.04	.02	.00	.05	-.05	.05	.02	-.11								
16. Previous relationship	.36	.00	.01	.02	.01	-.01	.01	-.03	.01	-.06	.06	.11	.02	-.01	-.02							
17. Bid price	-.01	-.03	-.02	.03	.00	-.01	.00	.00	.00	.05	-.03	.06	.03	.01	-.03	.01						
18. Time-to-bid	-.01	.01	.00	-.01	-.02	-.01	-.02	.00	.01	.00	.02	-.10	.00	.03	.00	.03	.00					
19. Late submission	-.16	.02	-.05	-.01	.01	.01	.00	.01	.00	.04	-.03	-.03	-.01	.01	.00	-.26	-.01	-.01				
20. Competition	-.21	.02	.01	-.01	.00	.06	-.03	.01	.00	.05	-.04	-.05	.01	.10	-.07	-.09	-.02	.03	.02			
21. Excess supply of freelancers	-.06	.03	-.02	-.01	-.01	-.01	-.02	.05	-.04	.03	-.01	-.12	.00	.03	-.04	-.03	-.01	-.02	.01	.16		
Mean	.08	.28	.05	.17	.05	.28	.03	.23	.04	96.23	.48	6.02	4.53	233.58	.32	.02	-.07	1.57	1.00	22.96	8.28	
SD	.27	.20	.05	.09	.05	.08	.03	.06	.03	111.79	.22	8.28	.63	1402.62	.47	.13	.59	4.31	.06	20.58	2.17	

Note: Observations = 2,327,216.

*Please note that there is a non-disclosure agreement in place for the secondary data restricting the disclosure of confidential information.

Table WA J3. Descriptive Statistics and Correlations for Price Premium

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	
1. Price premium																				
2. Freelancer task information	.25																			
3. Freelancer personal information	-.20	-.48																		
4. Freelancer concreteness	-.10	-.21	.03																	
5. Freelancer affective intensity	.00	-.06	-.07	-.05																
6. Buyer task information	.00	.09	.02	-.06	.01															
7. Buyer personal information	.10	.08	-.04	-.01	-.02	-.09														
8. Buyer concreteness	-.13	-.14	.09	.32	.00	-.10	-.06													
9. Buyer affective intensity	.06	.06	-.06	-.04	.11	-.10	.03	-.12												
10. Word count	-.27	-.27	.11	.18	-.01	-.02	-.09	.15	-.04											
11. Linguistic style matching	.27	.42	-.25	-.28	-.01	-.06	.01	-.18	.09	-.49										
12. Freelancer experience	.13	.09	-.11	-.03	.02	.00	.01	-.06	.05	-.11	.14									
13. Freelancer rating	-.03	-.05	.05	.04	-.01	-.01	-.02	.04	-.03	.04	-.05	.10								
14. Project payment	-.21	-.09	.05	.05	.00	.00	-.08	.05	-.03	.15	-.11	-.03	.02							
15. Previous relationship	.05	-.01	.02	-.02	.02	.04	.00	-.04	.00	-.15	.09	.13	.06	-.01						
16. Time-to-bid	-.08	-.11	.18	.02	-.04	.00	-.04	.03	-.01	.00	-.01	-.03	.02	.06	.13					
17. Late submission	.00	.09	-.15	.01	.03	-.01	.02	.00	.01	.06	-.02	-.03	-.04	-.02	-.23	-.04				
18. Competition	-.24	-.16	.20	.05	-.03	.04	-.12	.12	-.05	.22	-.18	-.09	.05	.13	-.05	.17	-.13			
19. Excess supply of freelancers	-.19	-.06	.08	.05	.00	.02	-.02	.10	-.08	.13	-.14	-.16	.05	.07	-.03	.02	.01	.16		
Mean	-.13	.32	.04	.18	.05	.27	.03	.21	.04	51.20	.57	9.07	4.57	96.25	.18	1.14	.97	7.36	7.79	
SD	.26	.21	.05	.10	.08	.08	.03	.07	.03	86.14	.23	10.50	.57	328.12	.38	3.71	.18	10.72	2.23	

Note: Observations = 148,158.

*Please note that there is a non-disclosure agreement in place for the secondary data restricting the disclosure of confidential information.

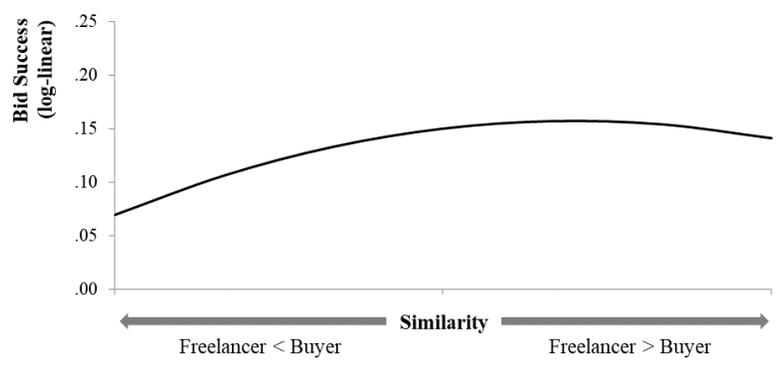
WA#K: Response Surface Coefficients

	Model 4: Bid Success			Model 6: Price Premium		
	β	SE	95% CI	β	SE	95% CI
Task Information						
Fit line slope ($y_{01} + y_{05}$)	.006**	.001	.005, .008	.025**	.002	.021, .028
Fit line curvature ($y_{09} + y_{13} + y_{17}$)	.010**	.001	-.009, .011	.027**	.002	.025, .029
Misfit line slope ($y_{01} - y_{05}$)	.023**	.001	.022, .025	.019**	.002	.015, .023
Misfit line curvature ($y_{09} - y_{13} + y_{17}$)	-.020**	.000	-.021, -.019	-.023**	.001	-.025, -.021
Slope at low level of buyer's task information ($y_{01} - 1.5 SDy_{13}$)	-.008**	.001	-.009, -.007	-.016**	-.003	-.017, -.015
Slope at high level of buyer's task information ($y_{01} + 1.5 SDy_{13}$)	.038**	.001	.037, .040	.060**	.007	.055, .066
Personal Information						
Fit line slope ($y_{02} + y_{06}$)	.000	.001	-.001, .001	.006*	.003	.003, .009
Fit line curvature ($y_{10} + y_{14} + y_{17}$)	-.011**	.000	-.012, -.01	-.004*	.002	-.007, -.001
Misfit line slope ($y_{02} - y_{06}$)	-.035**	.001	.033, .037	.037	.003	.032, .042
Misfit line curvature ($y_{10} - y_{14} + y_{17}$)	-.007**	.000	-.006, -.008	.003*	.002	.008, .014
Slope at low level of buyer's personal information ($y_{02} - 1.5 SDy_{14}$)	.020**	.001	.019, .020	.027**	.001	.025, .029
Slope at high level of buyer's personal information ($y_{02} + 1.5 SDy_{14}$)	.014**	.001	.013, .016	.015**	.004	.009, .023
Concreteness						
Fit line slope ($y_{03} + y_{07}$)	.023**	.001	.022, .024	.001	.001	-.006, .008
Fit line curvature ($y_{11} + y_{15} + y_{19}$)	-.001**	.000	-.001, .000	-.002**	.001	-.004, -.001
Misfit line slope ($y_{03} - y_{07}$)	.040**	.001	.038, .041	.009**	.003	.007, .011
Misfit line curvature ($y_{11} - y_{15} + y_{19}$)	-.011**	.000	-.011, -.010	-.007**	.003	-.009, -.005
Slope at low level of buyer's concreteness ($y_{03} - 1.5 SDy_{15}$)	.024**	.001	.024, .025	.002	.002	-.002, .004
Slope at high level of buyer's concreteness ($y_{03} + 1.5 SDy_{15}$)	.039**	.001	.036, .041	.008	.001	-.005, .019
Affective Intensity						
Fit line slope ($y_{04} + y_{08}$)	.001	.001	-.001, .003	.002	.003	-.004, .009
Fit line curvature ($y_{12} + y_{16} + y_{20}$)	.020**	.000	.020, .021	.012**	.001	.011, .013
Misfit line slope ($y_{04} - y_{08}$)	-.002	.001	-.003, .000	.004	.004	-.003, .011
Misfit line curvature ($y_{12} - y_{16} + y_{20}$)	-.020**	.000	-.021, -.020	-.008**	.001	-.01, -.006
Slope at low level of buyer's intensity ($y_{04} - 1.5 SDy_{16}$)	-.030**	.001	-.031, -.030	-.012**	.002	-.015, -.009
Slope at high level of buyer's intensity ($y_{04} + 1.5 SDy_{16}$)	.030**	.001	.028, .032	.018**	.005	.009, .027

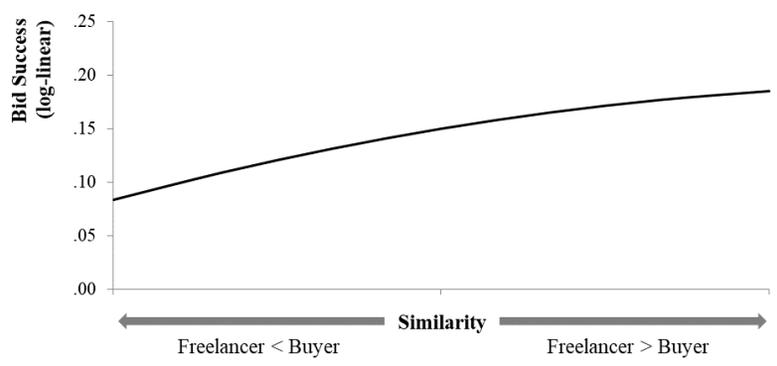
** $p < .01$, * $p < .05$. Significance is based on two-tailed tests.

WA#L: Effect of Matching the Buyers' Communication on Bid Success

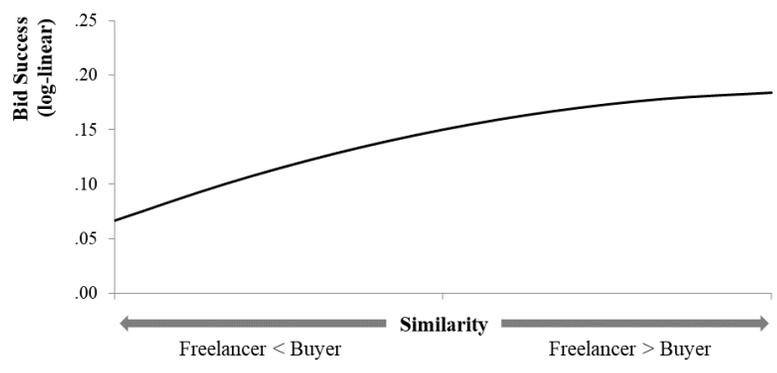
A. Similarity and Dissimilarity of Task Information



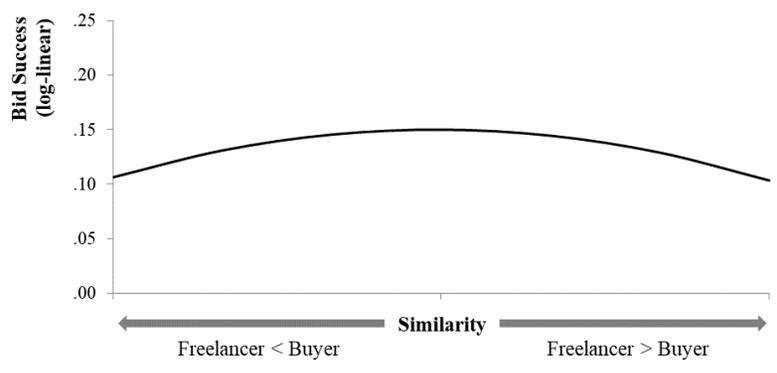
B. Similarity and Dissimilarity of Personal Information



C. Similarity and Dissimilarity of Concreteness

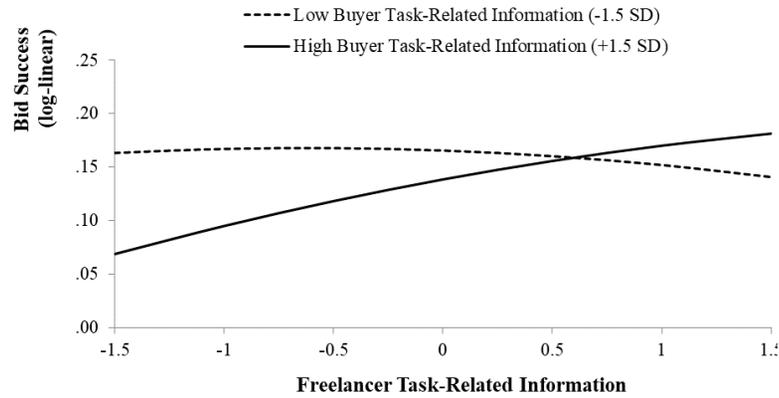


D. Similarity and Dissimilarity of Affective Intensity

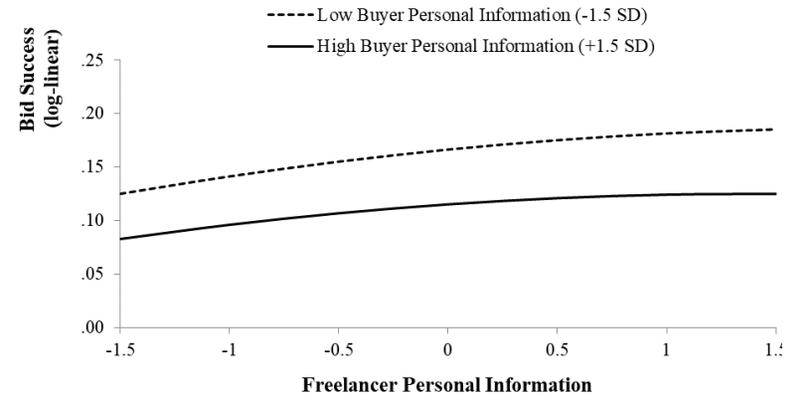


WA#M: Low vs. High Levels of Buyers' Communication and Bid Success

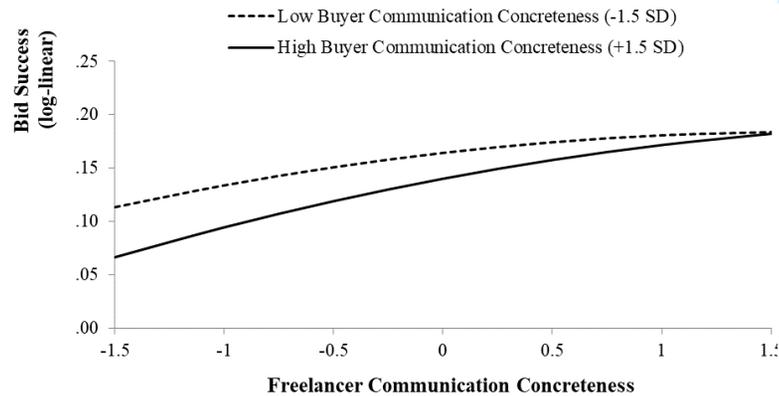
A. Low and High Levels of Buyers' Task Information



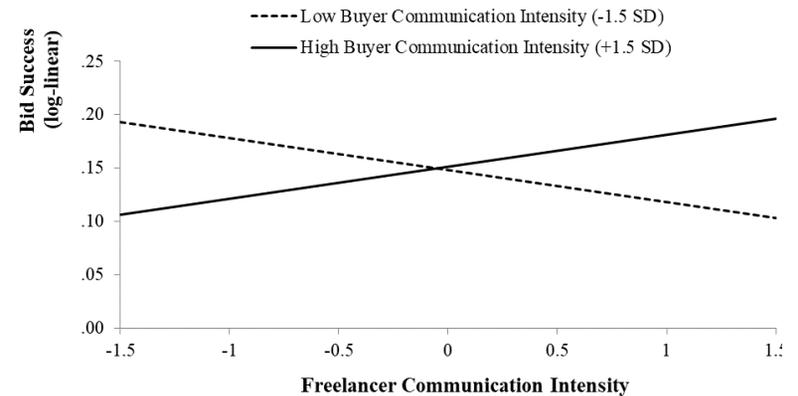
B. Low and High Levels of Buyers' Personal Information



C. Low and High Levels of Buyers' Concreteness



D. Low and High Levels of Buyers' Affective Intensity



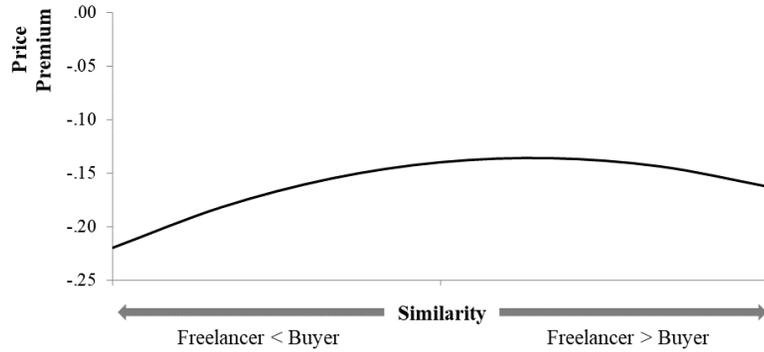
WA#N: Results for the Selection Model

	Selection Model		
	β	SE	95% CI
Freelancer Communication			
Task information	.270**	.006	.258, .282
Personal information	.228**	.005	.219, .238
Concreteness	.425**	.004	.417, .433
Affective intensity	-.018*	.008	-.034, -.002
Buyer Communication			
Task information	.002	.004	-.006, .010
Personal information	-.377**	.006	-.389, -.365
Concreteness	-.165**	.004	-.173, -.158
Affective intensity	.027**	.004	.019, .034
Freelancer Communication Squared			
Task information squared	-.092**	.002	-.096, -.088
Personal information squared	-.045**	.002	-.048, -.042
Concreteness squared	-.158**	.004	-.166, -.150
Affective intensity squared	.005**	.001	.004, .006
Freelancer-Buyer Interactions			
Task information interaction	.055**	.003	-.033, -.026
Personal information interaction	-.042**	.003	.100, .112
Concreteness interaction	.131**	.004	-.011, -.003
Affective intensity interaction	.020**	.002	-.007, -.002
Buyer Communication Squared			
Task information squared	-.029**	.002	.049, .061
Personal information squared	.106**	.003	-.049, -.036
Concreteness squared	-.007**	.002	.122, .139
Affective intensity squared	-.004**	.001	.016, .024
Controls			
Word count	-.381**	.007	-.395, -.367
Linguistic style matching	.750**	.014	.722, .777
Freelancer experience	.149**	.003	.143, .154
Freelancer rating	.052**	.003	.046, .058
Project payment	-.008*	.003	-.014, -.001
Previous relationship	.308**	.002	.304, .312
Bid price	-.120**	.003	-.125, -.114
Time-to-bid	-.111**	.004	-.119, -.103
Late submission	-.142**	.007	-.157, -.128
Competition	-.321**	.038	-.396, -.247
Excess supply of freelancers	.089**	.005	.080, .099
Fixed Effects			
Year		included	
Submarkets		included	
Unobserved Heterogeneity			
Project characteristics		included	
Endogeneity Corrections			
Gaussian copulas		included	
Freelancers		34,851	
Bids		2,327,216	

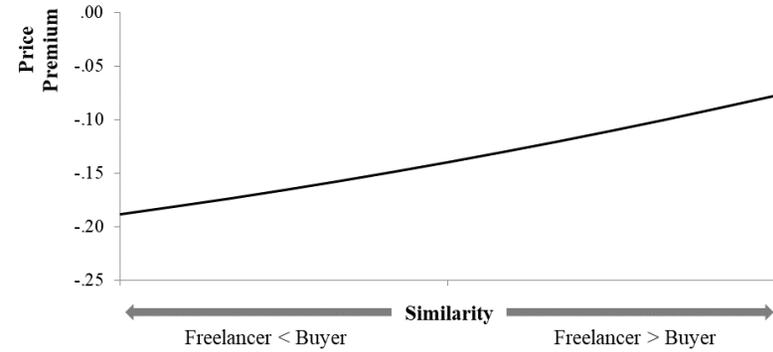
** $p < .01$, * $p < .05$. Significance is based on two-tailed tests. All variance inflation factors < 3.86 .

WA#O: Effect of Matching the Buyers' Communication on Price Premium

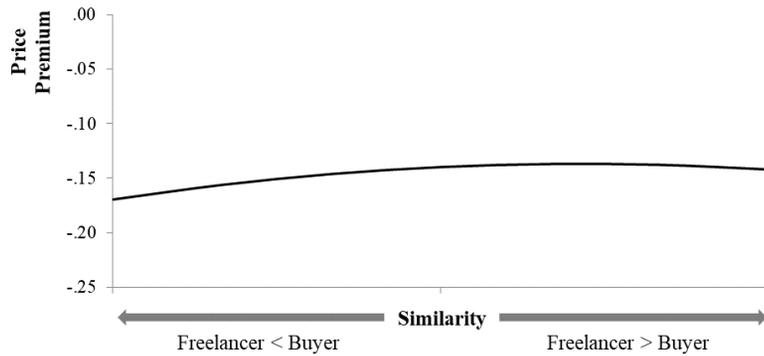
A. Similarity and Dissimilarity of Task Information



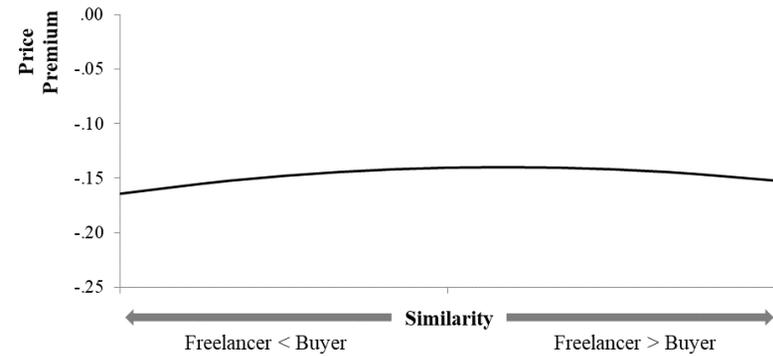
B. Similarity and Dissimilarity of Personal Information



C. Similarity and Dissimilarity of Concreteness

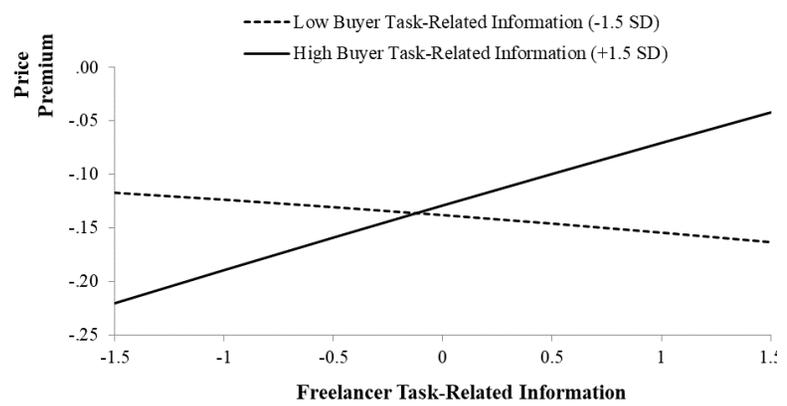


D. Similarity and Dissimilarity of Affective Intensity

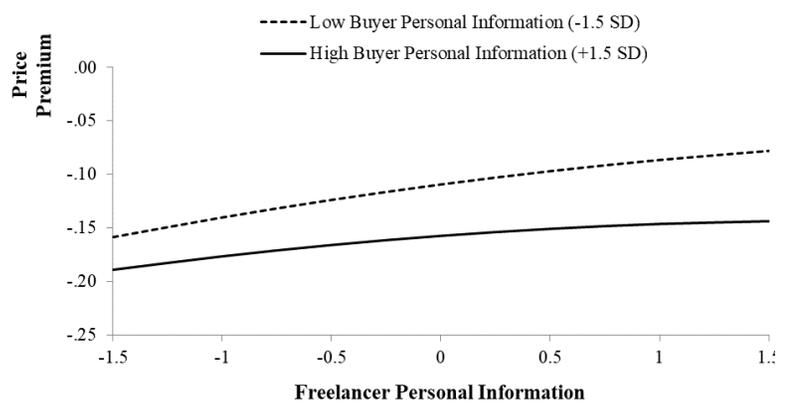


WA#P: Low vs. High Levels of Buyers' Communication and Price Premium

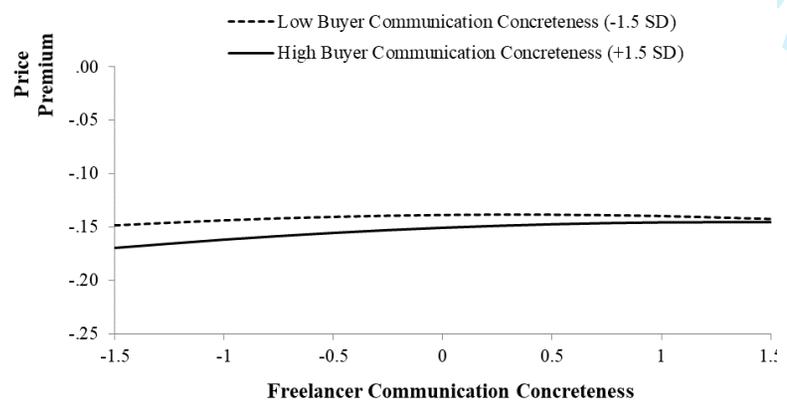
A. Low and High Levels of Buyers' Task Information



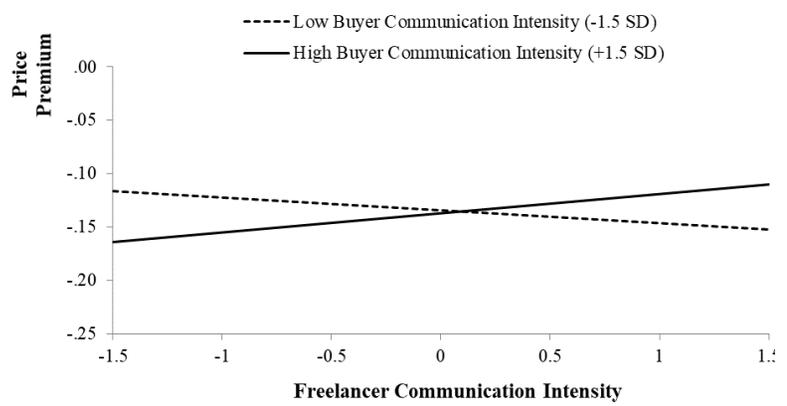
B. Low and High Levels of Buyers' Personal Information



C. Low and High Levels of Buyers' Concreteness



D. Low and High Levels of Buyers' Affective Intensity



WA#Q: Additional Effects for All Analyses

Table WA Q1. Additional Effects for Buyers' Call for bids Success

	Model 1: Main Effects			Model 2: Full Model		
	β	SE	95% CI	β	SE	95% CI
Years						
Year 2009	-.025	.262	-.538, .489	-.020	.264	-.537, .496
Year 2010	.174**	.038	.099, .248	.166**	.038	.091, .240
Year 2011	.121**	.022	.077, .165	.116**	.022	.072, .160
Year 2012	.288**	.014	.260, .316	.285**	.014	.258, .313
Year 2013	.078**	.008	.062, .094	.079**	.008	.063, .095
Year 2014	.043**	.006	.030, .055	.042**	.006	.030, .055
Submarkets						
Design	.115**	.011	.092, .137	.126**	.011	.104, .148
Writing & translation	.206**	.013	.181, .231	.211**	.013	.185, .236
Video, photo, & audio	.088**	.019	.050, .125	.107**	.019	.069, .144
Business support	.154**	.012	.129, .178	.162**	.012	.137, .186
Software & mobile development	-.078**	.016	-.109, -.047	-.072**	.016	-.103, -.041
Web development	-.091**	.018	-.126, -.056	-.083**	.018	-.118, -.048
Effects of Project Characteristics						
Skills "seo, sale, social media"	-.358**	.015	-.387, -.329	-.358**	.015	-.387, -.329
Skills "writer, editor, copywrit"	-.437**	.015	-.467, -.407	-.439**	.015	-.468, -.409
Skills "consult*, manag*, analyst*"	-.691**	.021	-.732, -.651	-.694**	.021	-.734, -.654
Skills "artist, 3d, video editor"	-.574**	.017	-.607, -.541	-.567**	.017	-.599, -.534
Skills "web design, websit*, website design"	-.558**	.015	-.587, -.529	-.560**	.015	-.589, -.531
Skills "illustr*, programm*, architect*"	-.543**	.015	-.573, -.514	-.547**	.015	-.576, -.517
Skills "php, wordpress, html"	-.221**	.030	-.281, -.162	-.219**	.030	-.279, -.160
Skills "web develop*, communic*, ui"	-.274**	.014	-.302, -.246	-.282**	.014	-.310, -.254
Skills "account, support, project manag*"	-.571**	.035	-.640, -.502	-.570**	.035	-.638, -.502
Skills "photograph, video, audio"	-.658**	.016	-.689, -.627	-.659**	.016	-.689, -.628
Skills "data entr*, administr*, office"	-.304**	.031	-.366, -.243	-.299**	.031	-.360, -.237
Effects of Gaussian Copulas						
Buyer task information	.126**	.004	.119, .134	.123**	.004	.115, .130
Buyer personal information	.117**	.003	.111, .123	.115**	.003	.109, .121
Buyer concreteness	-.021**	.005	-.031, -.012	-.029**	.005	-.038, -.019
Buyer intensity	.062**	.008	.047, .077	.053**	.008	.037, .069
Buyers				49,081		
Call for bids				343,796		

** $p < .01$, * $p < .05$. Significance is based on two-tailed tests. All variance inflation factors < 2.11 .

Notes: We omitted year = 2008, submarket = "social media, sales, & marketing", and project characteristics = "translat*, proofread*, content writer". The dependent variable is the count of all bids received; the sample includes all projects listed by buyers with at least two projects to which at least one freelancer submitted a bid.

Table WA Q2. Additional Effects for Freelancers' Bid Success

	Model 3: Freelancer Communication			Model 4: Full Model		
	β	SE	95% CI	β	SE	95% CI
Years						
Year 2009	.026**	.000	.025, .026	.025**	.000	.025, .026
Year 2010	.002	.004	-.007, .010	-.001	.004	-.010, .007
Year 2011	-.003	.002	-.007, .001	-.005*	.002	-.008, -.001
Year 2012	-.007**	.002	-.010, -.003	-.008**	.002	-.011, -.005
Year 2013	-.015**	.001	-.017, -.012	-.016**	.001	-.019, -.014
Year 2014	-.005**	.001	-.007, -.003	-.007**	.001	-.009, -.005
Submarkets						
Design	-.006**	.001	-.007, -.004	-.006**	.001	-.007, -.004
Writing & translation	-.050**	.003	-.055, -.045	-.049**	.003	-.054, -.044
Video, photo, & audio	-.042**	.003	-.047, -.037	-.042**	.003	-.047, -.037
Business support	-.040**	.004	-.047, -.033	-.041**	.003	-.047, -.034
Software & mobile development	-.031**	.002	-.035, -.027	-.033**	.002	-.037, -.028
Web development	-.024**	.002	-.029, -.020	-.024**	.002	-.029, -.020
Effects of Project Characteristics						
Skills "seo, sale, social media"	-.022**	.002	-.027, -.017	-.023**	.002	-.028, -.018
Skills "writer, editor, copywrit*"	-.016**	.002	-.019, -.012	-.016**	.002	-.019, -.012
Skills "consult*, manag*, analyst*"	-.003	.002	-.006, .001	-.002	.002	-.005, .002
Skills "artist, 3d, video editor"	.014**	.003	.009, .020	.015**	.003	.010, .020
Skills "web design, websit*, website design"	.027**	.002	.023, .032	.026**	.002	.022, .031
Skills "illustr*, programm*, architect*"	.007**	.002	.003, .011	.008**	.002	.004, .011
Skills "php, wordpress, html"	.011**	.002	.007, .015	.013**	.002	.009, .017
Skills "web develop*, communic*, ui"	-.007**	.002	-.011, -.003	-.006	.002	-.011, -.002
Skills "account, support, project manag*"	-.021**	.002	-.025, -.018	-.019**	.002	-.022, -.016
Skills "photograph, video, audio"	.006	.003	-.001, .012	.006	.003	-.001, .012
Skills "data entr*, administr*, office"	.023**	.002	.018, .027	.023**	.002	.019, .028
Effects of Gaussian Copulas						
Freelancer task information	-.013**	.003	-.019, -.008	-.013**	.003	-.019, -.008
Freelancer personal information	-.031**	.001	-.033, -.029	-.029**	.001	-.031, -.027
Freelancer concreteness	.008**	.001	.006, .009	.007**	.001	.006, .009
Freelancer intensity	.010**	.000	.009, .011	.010**	.000	.009, .010
Buyer task information				-.005**	.001	-.007, -.003
Buyer personal information				.005**	.000	.004, .005
Buyer concreteness				-.007**	.000	-.008, -.007
Buyer intensity				-.007**	.000	-.008, -.007
Freelancers						34,851
Bids						2,327,216

** $p < .01$, * $p < .05$. Significance is based on two-tailed tests. All variance inflation factors < 3.86 .

Notes: We omitted year = 2008, submarket = "social media, sales, & marketing", and project characteristics = "translat*, proofread*, content writer". The dependent variable is whether the freelancer is chosen and wins the bidding process; the sample includes all bids by freelancers with at least one winning and at least one losing bid.

Table WA Q3. Additional Effects for Freelancers' Price Premium

	Model 5: Freelancer Communication			Model 6: Full Model		
	β	SE	95% CI	β	SE	95% CI
Years						
Year 2009	-.012**	.002	-.016, -.009	-.012**	.002	-.015, -.009
Year 2010	-.027**	.002	-.030, -.023	-.026**	.002	-.029, -.022
Year 2011	-.020**	.002	-.023, -.017	-.020**	.002	-.023, -.017
Year 2012	-.021**	.001	-.024, -.018	-.021**	.001	-.023, -.018
Year 2013	-.007**	.001	-.009, -.004	-.007**	.001	-.009, -.004
Year 2014	.000	.002	-.005, .005	.000	.002	-.005, .004
Submarkets						
Design	.007**	.002	.003, .011	.0073*	.002	.004, .011
Writing & translation	-.002	.001	-.005, .000	-.002	.001	-.005, .000
Video, photo, & audio	.008**	.002	.004, .012	.007**	.002	.004, .011
Business support	-.004	.003	-.009, .001	-.004	.003	-.009, .001
Software & mobile development	-.002	.003	-.007, .003	-.002	.003	-.007, .003
Web development	-.003*	.002	-.006, .000	-.003*	.002	-.006, .000
Effects of Project Characteristics						
Skills "seo, sale, social media"	-.006**	.002	-.009, -.002	-.006**	.002	-.009, -.002
Skills "writer, editor, copywrit*"	-.003**	.001	-.006, -.001	-.003**	.001	-.006, -.001
Skills "consult*, manag*, analyst*"	-.003	.002	-.006, .001	-.003	.002	-.006, .000
Skills "artist, 3d, video editor"	-.011**	.002	-.015, -.007	-.012**	.002	-.016, -.008
Skills "web design, websit*, website design"	-.008**	.002	-.012, -.004	-.008**	.002	-.012, -.005
Skills "illustr*, programm*, architect*"	-.003*	.001	-.005, .000	-.003*	.001	-.005, .000
Skills "php, wordpress, html"	-.018**	.002	-.022, -.013	-.018**	.002	-.023, -.014
Skills "web develop*, communic*, ui"	.000	.001	-.003, .002	-.001	.001	-.003, .002
Skills "account, support, project manag*"	-.004**	.001	-.007, -.001	-.004	.001	-.007, -.001
Skills "photograph, video, audio"	-.002	.001	-.004, .001	-.002	.001	-.004, .001
Skills "data entr*, administr*, office"	-.003	.004	-.011, .006	-.004	.004	-.013, .004
Effects of Gaussian Copulas						
Freelancer task information	.009**	.002	.005, .012	.009**	.002	.005, .012
Freelancer personal information	.003**	.001	.001, .005	.003**	.001	.001, .005
Freelancer concreteness	-.015**	.003	-.020, -.010	-.014**	.003	-.019, -.009
Freelancer intensity	-.014**	.001	-.016, -.011	-.014**	.001	-.017, -.011
Buyer task information				-.001	.002	-.004, .003
Buyer personal information				.002	.001	-.001, .004
Buyer concreteness				.005**	.002	.002, .008
Buyer intensity				-.036**	.003	-.042, -.030
Freelancers						30,851
Bids						148,158

** $p < .01$, * $p < .05$. Significance is based on two-tailed tests. All variance inflation factors < 2.74 .

Notes: We omitted year = 2008, submarket = "social media, sales, & marketing", and project characteristics = "translat*, proofread*, content writer". The dependent variable is price premium for the chosen bid; the sample includes all winning bids where the payment was disclosed.

WA#R: Robustness Test: Predicting Freelancers' Bid Success

	Model 7: Freelancer Communication			Model 8: Full Model		
	β	SE	95% CI	β	SE	95% CI
Freelancer Communication						
y ₀₁ : Task information	.014**	.001	.013, .015	.016**	.001	.015, .017
y ₀₂ : Personal information	.018**	.001	.017, .019	.017**	.001	.016, .018
y ₀₃ : Concreteness	.028**	.000	.028, .028	.029**	.000	.029, .029
y ₀₄ : Affective intensity	.003**	.001	.002, .004	.001	.001	.000, .002
Buyer Communication						
y ₀₅ : Task information				-.009**	.000	-.009, -.009
y ₀₆ : Personal information				-.016**	.000	-.016, -.016
y ₀₇ : Concreteness				-.008**	.000	-.008, -.008
y ₀₈ : Affective intensity				.001**	.000	.001, .001
Freelancer Communication Squared						
y ₀₉ : Task information squared	-.006**	.000	-.006, -.006	-.006**	.000	-.006, -.006
y ₁₀ : Personal information squared	-.004**	.000	-.004, -.004	-.004**	.000	-.004, -.004
y ₁₁ : Concreteness squared	-.006**	.000	-.006, -.006	-.006**	.000	-.006, -.006
y ₁₂ : Affective intensity squared	.000**	.000	.000, 0.00	.000**	.000	.000, .000
Freelancer-Buyer Interactions						
y ₁₃ : Task information interaction				.002**	.000	.002, .002
y ₁₄ : Personal information interaction				-.001**	.000	-.001, -.001
y ₁₅ : Concreteness interaction				.005**	.000	.005, .005
y ₁₆ : Intensity interaction				.002**	.000	.002, .002
Buyer Communication Squared						
y ₁₇ : Task information squared				.000**	.000	.000, .000
y ₁₈ : Personal information squared				-.004**	.000	-.004, -.004
y ₁₉ : Concreteness squared				.001**	.000	.001, .001
y ₂₀ : Affective intensity squared				.000**	.000	.000, .000
Controls						
Word count	-.020**	.001	-.021, -.019	-.020**	.001	-.021, -.019
Linguistic style matching	.022**	.001	.021, .023	.023**	.001	.022, .024
Freelancer experience	.003**	.001	.002, .004	.003**	.001	.002, .004
Freelancer rating	.002**	.000	.002, .002	.002**	.000	.002, .002
Project payment	-.001**	.000	-.001, -.001	-.063**	.001	-.064, -.062
Payment not disclosed	-.027**	.000	-.027, -.027	-.001**	.000	-.001, -.001
Previous relationship	.077**	.001	.076, .078	-.027**	.000	-.027, -.027
Bid price	-.006**	.000	-.006, -.006	.076**	.001	.075, .077
Time-to-bid	.000	.000	.000, .000	-.006**	.000	-.006, -.006
Late submission	-.005**	.000	-.005, -.005	-.004**	.000	-.004, -.004
Competition	-.252**	.007	-.259, -.245	-.252**	.007	-.259, -.245
Excess supply of freelancers	-.040**	.000	-.04, -.04	-.039**	.000	-.039, -.039
Fixed Effects						
Years			included			included
Submarkets			included			included
Unobserved Heterogeneity						
Project characteristics			included			included
Endogeneity Corrections						
Gaussian copulas			included			included
Freelancers						114,455
Bids						2,530,111

** $p < .01$, * $p < .05$. Significance is based on two-tailed tests. Notes: The dependent variable is whether the freelancer is chosen and wins the bidding process. The sample includes all bids by freelancers with at least one bid.

WA#S: Illustrative Examples of Bad and Good Practice Calls for Bids and Bids

Good practice call for bids

(specific on tasks and skills, avoid personal information, moderately concrete, avoid being affectively intense)

Hi, I am a Fitness Trainer and need help with building my website to showcase my mixed services and home workouts. I need a website designer who can design a WordPress website using a WordPress premium theme. The theme and examples will be provided, but you should also know about WordPress and optimize. You should have got very good creative skills but know how to design for web and also know how to include calls to actions within a good design. The website should be complete within 2 weeks. Please see the suggested payment and state your asking price for the entire project not per hour. Looking forward to hearing from you. Gary

Bad practice call for bids

(not specific on tasks and skills)

Hi, need a website to showcase the full range of my fitness workouts. Job is 14 days, looking forward to your bid.

Bad practice call for bids

(too much personal information)

Hi, I am a Fitness Trainer with a lot of experience running workouts. I have been creating my own classes for almost 10 years now. Clients tend to especially love my classes on strength and flexibility. Now I need help setting up my website to showcase my services and home workouts. I need a website designer who can design a WordPress website using a WordPress premium theme. The theme and examples will be provided, but you should also know about WordPress and optimize. You should have got very good creative skills but know how to design for web and also know how to include calls to actions within a good design. The website should be complete within 2 weeks. Please see the suggested payment and state your asking price for the entire project not per hour. Looking forward to hearing from you. Gary

Bad practice call for bids

(not concrete enough)

Hi, I provide certified, all-rounder fitness exercises and I seek help with establishing my interactive website. I require a professional who is savvy in configuring a stylish website employing a premium theme. I will impart the exposition but you should be cognizant about WordPress and reinvigorate. You should have got very good creative skills but know how to design for web and also know how to include calls to actions within a good design. The website should be complete within 2 weeks. Please see the suggested payment and state your asking price for the entire project not per hour. Looking forward to hearing from you. Gary

Bad practice call for bids

(too affectively intense)

Hi, I am a super enthusiastic Fitness Trainer and need help with building an outstanding website to showcase my excellent services and home workouts. I need an open-minded website designer who is excited about designing a WordPress website using a WordPress premium theme. I have created a fantastic theme but you should be confident and eager about WordPress and help optimize. You should have got very good creative skills but know how to design for web and also know how to include calls to actions within a good design. The website should be complete within 2 weeks. Please see the suggested payment and state your asking price for the entire project not per hour. Looking forward to hearing from you. Gary

Good practice bid (directed to the good practice call for bids)

(mimic task description, exceed little provision of personal information, exceed concreteness, mimic affective intensity)

Hi Gary, I am happy to help you with your fitness website development and design.

I am a WordPress Freelancer with 15 years of work experience. I have worked on several similar projects, designing websites using a WordPress including premium themes and I can deliver to a tight schedule.

Website content that I produce will be creative and include original designs.

If you choose me for your website project, I would be very happy to discuss this further and get started for you as soon as possible. Thanks! Peter

Bad practice bid (directed to the good practice call for bids)

(less specific on tasks and skills, less personal information, less concrete, exceeding affective intensity)

Dear Sir, would love to work for you. I have great skills and plenty of fantastic experience in creating relevant websites. I am an enthusiastic designer and expert in Web development. The content will be creative and fun, attractive, and thoughtful. If you award me the project, I'd be very happy to discuss this further and get started for you as soon as possible. Thanks! Peter

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