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INFORMATION SYSTEMS RESEARCH
Vol. 33, No. 4, December 2022, pp. 1196–1220
ISSN 1047-7047 (print), ISSN 1526-5536 (online)

Managing Congestion in a Matching Market via Demand Information Disclosure

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Received: January 7, 2020
Revised: November 7, 2020; August 23, 2021; January 18, 2022
Accepted: March 31, 2022
Published Online in Articles in Advance: June 29, 2022

https://doi.org/10.1287/isre.2022.1148

Abstract. Congestion is a common issue in digital platform markets, wherein users tend to focus their attention on a subset of popular peers. We examine this issue in the context of online dating, considering the potential efficacy of an informational intervention, namely, the disclosure of peers' recent demand. In doing so, we first note that the benefits of disclosing demand information are not altogether clear in this context, a priori, because dating platforms are distinct from other platforms in several important respects. On the one hand, dating platforms facilitate social relationships, rather than trade in goods and services. Therefore, they operate on different norms and typically lack common levers that platform operators employ to balance supply and demand, such as pricing mechanisms and reputation systems. Dating app users may therefore pay greater attention to the quality implications of peer demand information, worsening congestion. On the other hand, demand information disclosure may be atypically effective at mitigating congestion in a dating context because, in addition to opportunity costs of time and effort, daters also bear fears of social rejection, leading them to shy away from in-demand peers. We evaluate our treatment's efficacy in mitigating congestion and improving matching efficiency, conducting a randomized field experiment at a large mobile dating platform. Our results show that the intervention is particularly effective at improving matching efficiency when presented in tandem with a textual message-framing cue that highlights the capacity implications of the peer demand information. Heterogeneity analyses further indicate that these effects are driven primarily by those users who most contend with congestion in the form of competition, namely, male users and those who rely more heavily upon outbound messages for matches.

History: This paper has been accepted for the *Information Systems Research* Special Section on Market Design and Analytics.
Supplemental Material: The online appendix is available at https://doi.org/10.1287/isre.2022.1148.

Keywords: information disclosure • congestion • matching efficiency • online dating • platform design

1. Introduction

Almost 40% of heterosexual individuals now meet their partners online (Rosenfeld et al. 2019), and the worldwide population of online daters is projected to reach 279.8 million by 2024 (Statista 2019). Online dating platforms play a crucial role in the formation of romantic relationships. The design of these platforms is thus important to consider, given their major implications for society (Bapna et al. 2016).

As is the case with many platforms, successful matchmaking is the primary objective of online dating. However, matching rates in online matching platforms are typically quite low (Zheng et al. 2016). A variety of factors can impede the matching rate, for example, search costs (Li and Netessine 2020) and distrust (Einav et al. 2016), but a central source of matching inefficiency, which we focus upon here, is congestion (Horton 2019, Arnosti et al. 2021). Congestion refers to a concentration of matching requests toward a subset of users (the head of the distribution), reflecting an imbalance of supply and demand. Absent an effective coordinating mechanism, users tend to collectively focus their attention asymmetrically toward popular peers. Because any given user operates under a capacity constraint (at some point they become too "busy" to entertain more inquiries), a great deal of suitors' time and effort may thus be wasted, implying wasted effort in outreach and opportunity costs. Furthermore, the resulting nonresponse may, in turn, lead to feelings of social rejection for many users, and thus dissatisfaction or churn. This is particularly notable, because prior work has found that individuals with fears of social rejection are systematically more likely to seek dates online (Blackhart et al. 2014).

In this work, we explore the congestion-mitigating benefits of an informational intervention, namely, the disclosure of demand information within a prospective peer partner's profile page. We do so via a randomized natural field experiment, conducted in collaboration with a large online dating platform based in China, Summer (https://imsummer.cn/official/; hereafter referred to as our corporate partner). Demand information in this context refers to how many requests a user has received in a certain period, for example, the past 30 days. As we describe in more detail below, the effects of such an intervention are not altogether clear, a priori. Although there is good reason to believe that this sort of intervention may help to mitigate congestion in a dating context, there are also reasons to believe that it may backfire, driving increases in congestion, depending on how the information is interpreted. Accordingly, we go beyond the simple revelation of demand information, exploring more nuanced approaches (i.e., pairing the information with accompanying message-framing cues, and exploring heterogeneity to inform targeted delivery). Formally, we thus seek to address the following questions:

- How does the disclosure of peer demand information affect congestion and matching efficiency in a dating market?
- To what extent can congestion be addressed and matching efficiency be elicited through the inclusion of accompanying message-framing cues or targeted information delivery?

Although congestion is not unique to the dating context,[1] several aspects of online dating platforms distinguish them from other types of matching markets that facilitate trade in goods and services, in ways that may influence the efficacy of congestion-mitigation solutions.[2] Most fundamentally, online dating platforms do not facilitate economic trade; they facilitate relationships. As a result, social norms guide behavior rather than market norms (Heyman and Ariely 2004). Considering it is generally taboo to offer money in exchange for a date, there are no pricing mechanisms to regulate supply and demand on dating platforms. Whereas Uber or Lyft may employ a price surge, and a worker on Freelancer or Upwork may respond to rising demand by increasing their hourly wage, a dating platform and dater have no such option. More generally, because they operate on different norms, dating platforms lack the levers that most platform operators rely on to manage market liquidity, such as reputation systems, dispute resolution, or, as noted, pricing mechanisms. Because daters lack access to the information and guarantees these types of features afford, they have relatively little information on prospective dating partners, beyond peers' self-reported profile information, which is often misrepresented (Hancock et al. 2007).

Absent quality signals or guarantees, any informational intervention a dating platform might deploy will operate in relative isolation, rather than in tandem with other mechanisms. So, although an indication that a peer is "in demand" has the potential to elicit a perception of positive quality in any platform context, in a typical platform setting (economic trade), that information is more likely to be made redundant by other, stronger, more explicit signals or rendered less important by the presence of ex post quality guarantees, for example, dispute resolution or escrow. This distinction is notable because prior work describes how demand information has the potential to drive follow-on demand via observational learning (Banerjee 1992), and other work has demonstrated such effects empirically in several online marketplaces (Sorensen 2007, Tucker and Zhang 2011). Thus, there is the potential that disclosing peer demand information in a dating context may in fact be counterproductive, driving increased congestion.

That said, there is also reason to believe that disclosing demand information would be atypically effective in an online dating context. Recent work has found some congestion-reducing benefits from the introduction of an opt-in feature, wherein workers can self-report their availability (Horton 2019). Furthermore, online dating platforms involve social mechanisms that may amplify a desirable response, most notably a fear of social rejection. Indeed, prior work in offline dating has observed that suitors may be concerned about the potential for nonresponse when making dating requests, referring to this as a fear of social rejection (Huston 1973, Shanteau and Nagy 1979, Stinson et al. 2015). Prior work has also noted that those individuals who bear the greatest fear of social rejection in their dating efforts are systematically more likely to use online dating apps, and recent online dating work has reported evidence that when peer popularity information is available, online daters tend to "shade" their preferences when they encounter a more popular peer, out of an expectation that said peer will not reciprocate interest (Bojd and Yoganarasimhan 2022). Accordingly, daters may respond strongly to the knowledge that a peer is in demand by avoiding them, effectively reducing congestion.

The points above collectively raise competing predictions about the likely effect on congestion and matching efficiency from introducing peer demand information into the platform market. This tension makes it difficult to anticipate the efficacy of such an intervention. Depending on the presence and strength of different mechanisms, we may observe a desirable or undesirable impact on the overall distribution of demand, and matching efficiency in turn. In conducting the experiment, our corporate partner randomly assigned 48,658 users on its platform across four experimental conditions. First and foremost, the study included (i) a control group that received no peer demand information (the user interface (UI) remained unchanged) and (ii) a baseline intervention group, that is, a demand information condition (Demand condition; the UI incorporated the number of requests a prospective peer partner has received from others in the past 30 days, updated in real time). Additionally, the platform included two other experimental conditions that incorporated message-framing cues, intended to shift the salience of a particular signal conveyed by the demand information, namely, the popularity of the peer and the availability of the peer. Thus, the experiment also included (iii) a Demand + Popularity Cue condition (conveying textually, based on the actual peer demand information, that the peer appears to be popular or unpopular), and (iv) a Demand + Capacity Cue condition (conveying textually, based on the actual demand information, that the peer appears to be busy or free).

We document several notable findings. Although we observe little significant effect of our treatments on the total volume of dating requests that users issue toward peers in the market, upon separating the requests into those targeting high-demand and low-demand peers, we observe that the treatment appears to drive systematic shifts in attention over the distribution of peer demand. Specifically, our treatments all drive a decline in attention toward high-demand peers, and we find some evidence that the capacity framed intervention also drives an increase in attention toward low-demand peers.[3] Second, when we examine the effects of our treatments on matching efficiency, we find strong evidence that the capacity framed intervention drives a significant improvement. Although request volumes generally decline, we observe no significant change in match volumes, implying efficiency gains. Third, in our heterogeneity analyses, we explore how the treatment effect varies as a function of subjects' likely sensitivity to congestion, in terms of their own recent demand and gender. We report evidence that the intervention is particularly influential when targeted toward those users who are most congestion sensitive, for example, relatively less popular male users.

Our paper contributes to prior research on platform market design with an eye toward facilitating matching efficiency. Previous studies on the market design of two-sided platforms have explored pricing mechanisms (Arnosti et al. 2021), reputation systems (Benson et al. 2020), and recommendation systems (Ashlagi et al. 2020). Our design, in line with the emerging literature about information disclosure design in matching markets (Tadelis and Zettelmeyer 2015), seeks to build upon prior findings on the value of worker capacity signaling in online labor market contexts (Horton 2019). Our work explores whether and to what extent congestion-reducing benefits may be obtained from revealing peers' demand information in online dating, a rather unique platform context. We show that disclosing demand information can have desirable balancing effects on the demand distribution in dating markets, particularly for certain segments of users and when framed appropriately. Our findings are of clear actionable managerial relevance as well, as they provide actionable implications for the design of dating platforms. In fact, the design we report in this study was ultimately adapted and implemented by the partner platform.

2. Related Literature and Theoretical Background

2.1. Online Dating

With the proliferation of dating platforms and mobile applications, such as eHarmony, Match.com, and OkCupid, the phenomenon of online dating has attracted growing research interest and attention in the information systems discipline (e.g., Finkel et al. 2012, Bapna et al. 2016). Prior literature on online dating can be summarized into three major themes: (i) the value of online dating (e.g., Finkel et al. 2012, Jung et al. 2019, Rosenfeld et al. 2019), (ii) user behavior (e.g., Hitsch et al. 2010a, Whyte et al. 2018, Levy et al. 2019), and (iii) dating platform design (e.g., Rosenfeld 2017, Bojd and Yoganarasimhan 2022).

The first category speaks to the radical changes that dating platforms have driven in dating and romantic relationships (Finkel et al. 2012).[4] The second set of literature primarily seeks to describe and explain individual preferences and behaviors within online dating contexts and associated matching outcomes (e.g., Bruch and Newman 2018, Whyte et al. 2018, Levy et al. 2019).[5] The third and final stream of research explores how platform features, policy choices, or mechanism designs affect individual- and market-level outcomes (e.g., Bapna et al. 2016, Burtch and Ramaprasad 2016, Bojd and Yoganarasimhan 2022). It is this latter stream of work that we contribute to most directly.

For instance, Bapna et al. (2016) examine the impact of an anonymity feature that allows users to view peers' profiles anonymously. The authors show that users receiving this feature explore more profiles yet have fewer matches than their counterparts, because of a breakdown in "weak signaling," that is, conveying implicit interest by visiting a peer's profile and thereby triggering an app notification to the visited peer. Bojd and Yoganarasimhan (2022) leverage archival data from a dating platform to investigate the effect of a dater's recent popularity with peers (conveyed via a star rating) on the contemporaneous demand that user receives. Those authors provide evidence that recent demand associates negatively with present demand, and the authors conclude that this occurs because less popular individuals shade their preferences when they anticipate rejection by a popular other. At the same time, it should be noted that earlier work conducted in a different online dating context found no evidence to suggest that dating users strategically shade their preferences (Hitsch et al. 2010b).

This last work is perhaps the most directly related to our study, so it is worth taking a moment to note the distinctions. First and foremost, it is important to note that the context from which Bojd and Yoganarasimhan (2022) draw their data employs a somewhat unique, synchronous matching mechanism, which precludes a role of capacity or congestion in daters' decision making. In their context, users opt into a synchronous "game" in search of a date. By their very decision to participate, users signal availability. By contrast, on many if not most dating platforms (including the one we study), users encounter peer profiles and request a date in an unsolicited manner, typically lacking clear signals of peer availability. Accordingly, the interpretation of information about recent peer demand can be quite different between the two contexts. And this difference drives our attempts to distinguish between peer availability concerns versus concerns about popular peers' preference for "better" others. We discuss these two mechanisms in our study, and we attempt to distinguish between them via the textual framing manipulations. That we find cleaner effects from the capacity manipulation, one more apparent than a simple demand number manipulation, suggests framing can be important.

Second, Bojd and Yoganarasimhan (2022) do not ultimately study the question of congestion, as we do here. Those authors examine how users react to information on recent peer demand ("stars" in their context), conditional on its presence. Although we report some evidence here that is consistent with their results, that users shade preferences when encountering popular peers, our question and objective are ultimately ones of market design. We ask whether the mere provision of peer demand information is desirable, that is, whether it helps to reduce congestion and improve matching efficiency. As we will demonstrate, providing this information does indeed have desirable effects.

Given the prominence of online dating platforms and the important societal implications, platform design is crucial for improving market efficiency (Bapna et al. 2016). Our study contributes to this stream of work on dating market design by investigating and advancing our understanding of the potential of employing alternative demand information disclosure strategies to reduce congestion and improve matching efficiency.

2.2. Potential Dual Effects of Demand Information Disclosure

The public revelation of peer demand information may have two competing effects on users' interest in pursuing a given peer. On the one hand, revealing demand information may drive follow-on demand, through observational learning (Banerjee 1992). In the context of online dating platforms, the observational learning effect would be undesirable, as it would lead to greater congestion. This possibility extends directly from past studies of online marketplaces for products and services (Sorensen 2007, Tucker and Zhang 2011). As noted earlier, these effects are likely to arise when disclosing popularity information in a dating environment, because daters operate in a noisy environment with very little in the way of information on peer quality. Dating markets, operating on social norms (Heyman and Ariely 2004), lack features like reputation and ratings, or dispute resolution processes. Accordingly, receiving peer demand information, users may latch onto that information, resulting in increased attention toward already popular individuals. This would, in turn, lead to increased congestion.

Nonetheless, there is the potential that revealing demand information may still have the opposite, desired effect, inducing a reallocation of attention away from busy individuals toward others who are more available. This expectation extends from past work in the context of online labor markets (Horton 2019), which found that allowing workers to self-select into revealing their availability led employers to reallocate attention toward more available workers, to avoid wasted time and effort, and the implied opportunity costs.

Indeed, earlier research about offline dating has made observations that indicate the existence of similar capacity concerns in dating, and the perceived likelihood of reciprocation is a predictor of partner pursuit. Notably, the effect of availability information in a dating context may be even more pronounced because such work has also noted that individuals tend to avoid prospective dates who will ignore them not just out of capacity concerns, but also out of a fear of social rejection (Huston 1973, Shanteau and Nagy 1979, Stinson et al. 2015). This is notable, because recent work has also highlighted that those with a greater fear of social rejection may be more likely to employ online, rather than offline dating channels (Blackhart et al. 2014). Moreover, Bojd and Yoganarasimhan (2022) reported evidence that, conditional on peer popularity information being available, users tend to shade their preferences when encountering a popular peer, anticipating that their interest will not be reciprocated.

The above arguments collectively illustrate a theoretical tension and various unique features of dating markets that raise questions about whether the intervention we consider here will yield a desirable response. Given the potential for both mechanisms to be at play, it is important to consider two points: (a) how we may adapt our interventions to encourage attention to one mechanism (capacity concerns) over the other (popularity inferences) and (b) whether certain groups of users are likely to respond in a more desirable manner (i.e., attending to capacity concerns more than popularity).

2.3. Market Design on Information Disclosure

Prior research on market design has often dealt with information disclosure interventions, documenting the efficacy of designing information disclosure in shaping market outcomes, such as the exposure of quality information (e.g., Jin and Leslie 2003, Dimoka et al. 2012), preference information (e.g., Ashlagi et al. 2020), and bidding information (e.g., Bimpikis et al. 2020). Information disclosure is important to a marketplace because, if properly designed, it can mitigate information asymmetry, prevent adverse selection, and improve market efficiency (e.g., Hong et al. 2015, Tadelis and Zettelmeyer 2015).

Our work focuses on the disclosure of demand information in the context of two-sided matching markets, particularly the online dating market. Demand information typically involves a number of users pursuing the same supplier, which signals the supplier's appeal in the market (Salganik et al. 2006, Luo et al. 2014). Although supply information is more or less observable (e.g., the number of available users in the dating market), demand information is especially valuable but typically unobserved (e.g., the number of suitors for a user). Besides, disclosing demand information might lead to observational learning and further reinforce the existing demand trends for suppliers (Zhu and Zhang 2010, Tucker and Zhang 2011). However, one major issue in the two-sided matching market is the capacity constraints of suppliers (Allon et al. 2012, Fradkin 2015); that is, when a supplier faces a high demand, that supplier might have limited bandwidth to meet the additional demand brought in through others' observational learning. In this regard, the disclosure of demand information in a market with capacity constraints plays a nuanced dual role for participants in the market. On the one hand, demand information signals the popularity and the quality of the supplier (Tucker and Zhang 2011). On the other hand, demand information also signals the available capacity of the supplier because the amount of demand negatively correlates with the remaining capacity (Fradkin 2015, Horton 2019).

Previous research offers limited answers on how to design information disclosure to address capacity constraints in two-sided matching markets. For example, Fradkin (2015) found that many guests on Airbnb typically consider a subset of available options and do not know the probability of successful transactions with sellers. Like online dating markets, sellers on Airbnb have limited capacity (Burdett et al. 2001). As a result, when sellers decline searchers' bids for any reason, for instance, capacity concern, the searchers might leave the matching market notwithstanding some remaining potentially good matches. In that scenario, Fradkin (2015) proposed a personalized ranking algorithm in the buyers' search results to reduce search friction and increase matches. Meanwhile, in the online labor market, Horton (2019) demonstrated that when a worker receives more invitations, the worker becomes less likely to accept an additional job offer. The author's suggestion is that allowing the workers to indicate whether they are full time or part time helps partially address the capacity issue, as workers who self-disclose as being a full-time worker will receive and accept more invitations.

Building on the partial solutions that have been considered in related contexts in the prior literature, we explore alternative designs for demand information disclosure features in an online dating market, with which our corporate partner experimented. Specifically, additional experimental manipulations were deployed, over and above a basic demand information disclosure intervention, pairing the peer demand information with accompanying message-framing cues. These cues included both a capacity cue and a popularity cue. Notably, this framing cue approach to exploring competing mechanisms has a great deal of precedent in the literature. By highlighting one aspect of the demand information we provide (capacity) versus another (popularity), we make a given mechanism more prominent, by increasing the salience of a particular aspect to the subject. Multiple prior studies have taken this approach (e.g., Tversky and Kahneman 1981, Roggeveen et al. 2006, Bryan et al. 2011, Huang et al. 2019). For example, Roggeveen et al. (2006, p. 116) examined the effects of comparative advertising on consumer perception. In their experiments, the same information was conveyed with different framings. One manipulation is "[Store Name]'s Magion has superior … to Canon's Sure Shot," whereas the other manipulation is "Canon's Sure Shot has inferior … to [Store Name]'s Magion."

Finally, it is interesting to consider that different users may be more (or less) sensitive to congestion and competition on a dating platform, depending on the extent to which they encounter congestion and competition on the platform. Consider that very popular users face less competition, as they may rely less on outbound requests to obtain dates. And, when they do submit requests, they may be more likely to have their requests accepted. This observation suggests important sources of heterogeneity that we can consider when exploring the effects of our intervention. To begin with, we can directly assess the notion that subjects will be particularly responsive when they are congestion sensitive by examining heterogeneity in relation to a subject's own recent demand from peers. Our expectation here is that popular subjects will be less responsive than unpopular subjects, and they may even respond in an undesirable manner at the extreme, eliciting greater attention toward already popular others. Furthermore, however, we can also explore gender heterogeneity. Females experience a great deal less congestion than males on most dating platforms, in large part because females are greatly outnumbered by males in most cases. A recent industry report estimated that men outnumber women by a ratio of approximately three to one in U.S. online dating contexts, and the percentage of male users is even higher elsewhere, constituting ~85% of users in the United Kingdom, 87% in Spain, and 91% in Italy (Ogury 2019). This gender imbalance is also particularly pronounced in China (Denyer and Gowen 2018), and we see clear evidence of it in our partner platform. Furthermore, males typically send the majority of dating requests in online dating markets (Bapna et al. 2016), and that is also the case in our setting. Accordingly, we would expect the effects of treatments to be significantly more pronounced on male users.

3. Methods

3.1. Research Context

We analyze the data and report the results from a randomized natural field experiment conducted by our corporate partner platform.[6] The platform uses a novel two-sided matching mechanism: Each user lists a number of open-ended questions of interest in the question-and-answer (Q&A) section of his or her profile page.[7] For any user who lands on the profile page of a focal user, those hoping to match with this user need to answer those questions in order to send a matching request. The receiving users then read the submitted answers and determine whether to approve the request. Once matched, the pair can start chatting in the application. Each user can be on the initiating or the receiving end of a matching request. Note that answering the questions can be costly for initiating users, because it takes time and cognitive effort to articulate quality answers that may persuade the target to agree to a match.

3.2. Experimental Design and Procedure

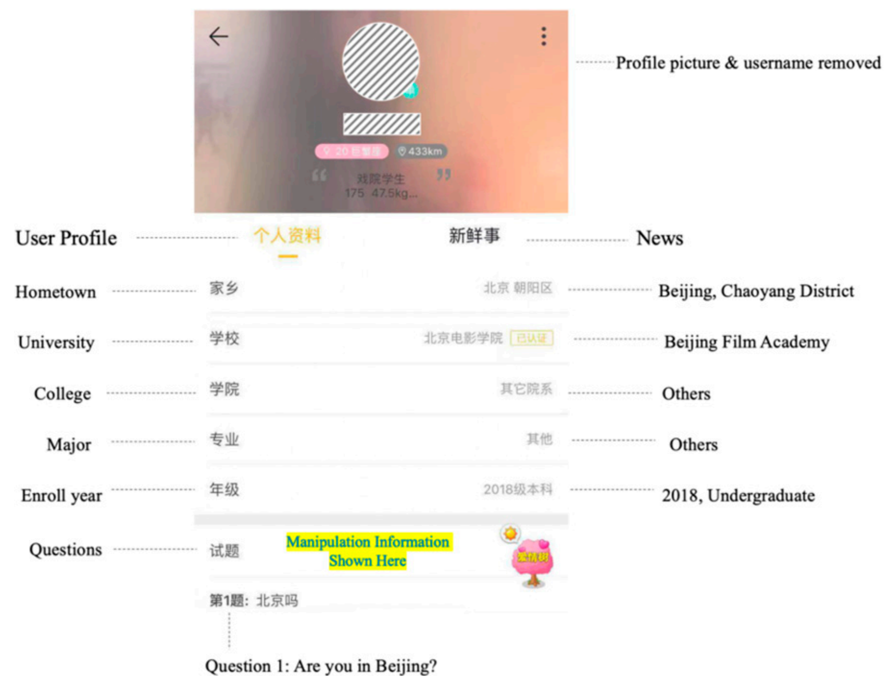
The partner platform employed a user-level, between-subjects design in the experiment, purposefully introducing variation into the user experience, serving alternative UIs that were designed by the corporate partner on Version 3.5.2 of the mobile application. The users of the platform automatically entered the experiment as they updated their mobile application to this version. Each user was randomly assigned into one of the experimental groups and stayed in the corresponding group throughout the experimental period.[8] The experiment continued for a period of two weeks, beginning on September 2 and ending on September 16, 2019.[9]

Figure 1 presents a screenshot of a typical user profile page within the mobile application. When subjects visited peers' profiles, the UI of the profile pages displayed different (manipulated) information, depending on the experimental group a subject was assigned to.[10] Manipulating the UI in this manner ensured the proper delivery and receipt of the treatment, as the information was shown precisely at the time a user decided whether to make a matching request, that is, to answer the listed questions. Building the manipulation into the UI of the application also ensured consistency of presentation and delivery of the treatments.

The field experiment comprised of four experimental groups, including a control group, a demand information group, and two additional treatment groups that received message-framing cues in tandem with the demand information treatment. For the control group, the UI remained the same as in the previous version of the mobile application, and thus the users in this group experienced no change. For the demand information group, peers' profile pages included their recent demand information, shown as the number of matching requests they received in the past 30 days.[11] This information was displayed on top of the Q&A section, next to the "Questions" heading. The number of matching requests was computed and updated in real-time, and prior to the experiment, we tested and verified that the computation for the demand information was efficient and accurate.

Users in the Demand + Popularity Cue condition saw the same information as shown in the Demand condition, except for a framing cue message that primed them to focus on the peer popularity implications of the demand number. Similarly, users in the Demand + Capacity Cue condition observed the same information as the those in the Demand condition in addition to a framing cue that primed them to focus on the peer capacity implications of the demand number. Note that the groups receiving popularity or capacity cues also experienced additional variation in the content of the framing cue text, depending on the actual user demand value. This is because it is impractical to apply the same cues for high-demand and low-demand users. Thus, the capacity cues were varied to state that the peer was "busy handling requests" or "has time to handle requests," respectively,

Figure 1. (Color online) Screenshot of a User Profile Page on the Platform



Notes. This figure presents a screenshot of a sample user's profile page for a subject in the control group, that is, absent manipulation. For the Demand, Demand + Capacity Cue, and Demand + Popularity Cue groups, the manipulation information is shown in the area highlighted. Note that interviews with users and the product team indicated that the position of the treatment information on the UI is conspicuous enough for users to notice and take into account when they make a request decision.

depending on actual demand, to ensure the cue aligned with the peer's actual demand information.

We selected the threshold for high-demand peers (i.e., "popular," "busy") in consultation with the company's product team. We first identified the median number of monthly requests across all active users, a value of nine. Additionally, surveys and interviews indicated that the users of the platform perceived a peer having 10 or more requests in a month to be in high demand. We thus used 9 or 10 requests as the cutoff point for defining high-demand users, and hence the varied texts of the popularity and capacity cue messages for low- versus high-demand peers. We did not manipulate demand information, as we did not want perceptions of artificiality and deception to taint the results of our study. For instance, users may experience cognitive dissonance if they see a highly active and good-looking user that receives a low number of requests, and vice versa. We summarize the manipulation information in each experimental group in Table 1.

We visualize the experimental procedure in Figure 2, which also shows the data generation process. The process begins with a subject visiting a peer's profile page, which displays the UI manipulation per his or her experimental group assignment. Upon viewing the peer profile, the subject decides whether to make a matching request to the peer by answering the questions on the profile page. Then, the subject can return to the dating application's home page and continue exploring other peer profiles, and the peers who received the answers can determine whether to approve the matching requests and start conversations with the initiators. Note that on the app's home page, the app recommends prospective dating partners based on location. Users are shown a scrolling list of user accounts displayed as thumbnails of usernames and profile pictures, and subjects can view a peer's profile by tapping the thumbnail.

Given that subjects in different groups are balanced in their locations (see Online Appendix B for the randomization check), on average, these subjects across the experimental groups are recommended identical peers. Thus, a subject's decision to open a specific profile is orthogonal to the experimental assignment. Furthermore, it is important to clarify that subjects stay in only one experimental condition and receive consistent manipulation across different peer profiles they view throughout the experimental period. For example, for a subject in the Demand + Capacity Cue group, all the user profiles the subject visits would display the treatment information with the number of requests in the past month, in tandem with a capacity cue.

Table 1. Manipulation Information by Experimental Groups

Experimental group	Manipulation information
1. Control	N/A
2. Demand	Received x requests in the past month
3. Demand + Popularity Cue	[High] Received x requests in the past month; this lady (or gentleman) is very popular
	[Low] Received x requests in the past month; this lady (or gentleman) is not picked by many others
4. Demand + Capacity Cue	[High] Received x requests in the past month; this lady (or gentleman) is busy handling requests
	[Low] Received x requests in the past month; this lady (or gentleman) has time to handle requests

Notes. A [High] treatment indicates $x \geq 10$, and a [Low] treatment indicates $x < 10$. The treatment information shown here is the English translation of the original content in Mandarin Chinese. Note that we conducted a series of interviews and two laboratory experiments to verify manipulation effectiveness with the mobile application's users. The results suggest that the treatment information indeed leads to the desired manipulations. We report further details of the interviews and two laboratory experiments in Online Appendix A.

Last, because the context of our study constitutes a networked environment, it is important to consider potential leakage issues (e.g., Aral and Walker 2011, Bapna and Umyarov 2015). To mitigate this possibility, the corporate partner continuously monitored and promptly removed a few posts relating to the UI change on the app's discussion page. Additionally, the geographical locations of users in the platform are relatively sparse, and our experiment involves just 5% of the user population; thus, offline contamination is unlikely. Finally, in Online Appendix E, we examine how users behave across experimental conditions, in the very first peer profile interaction they experience upon entering the experiment, and we demonstrate a consistent set of results, which lends further confidence that our results do not appear subject to substantial interference.

4. Data

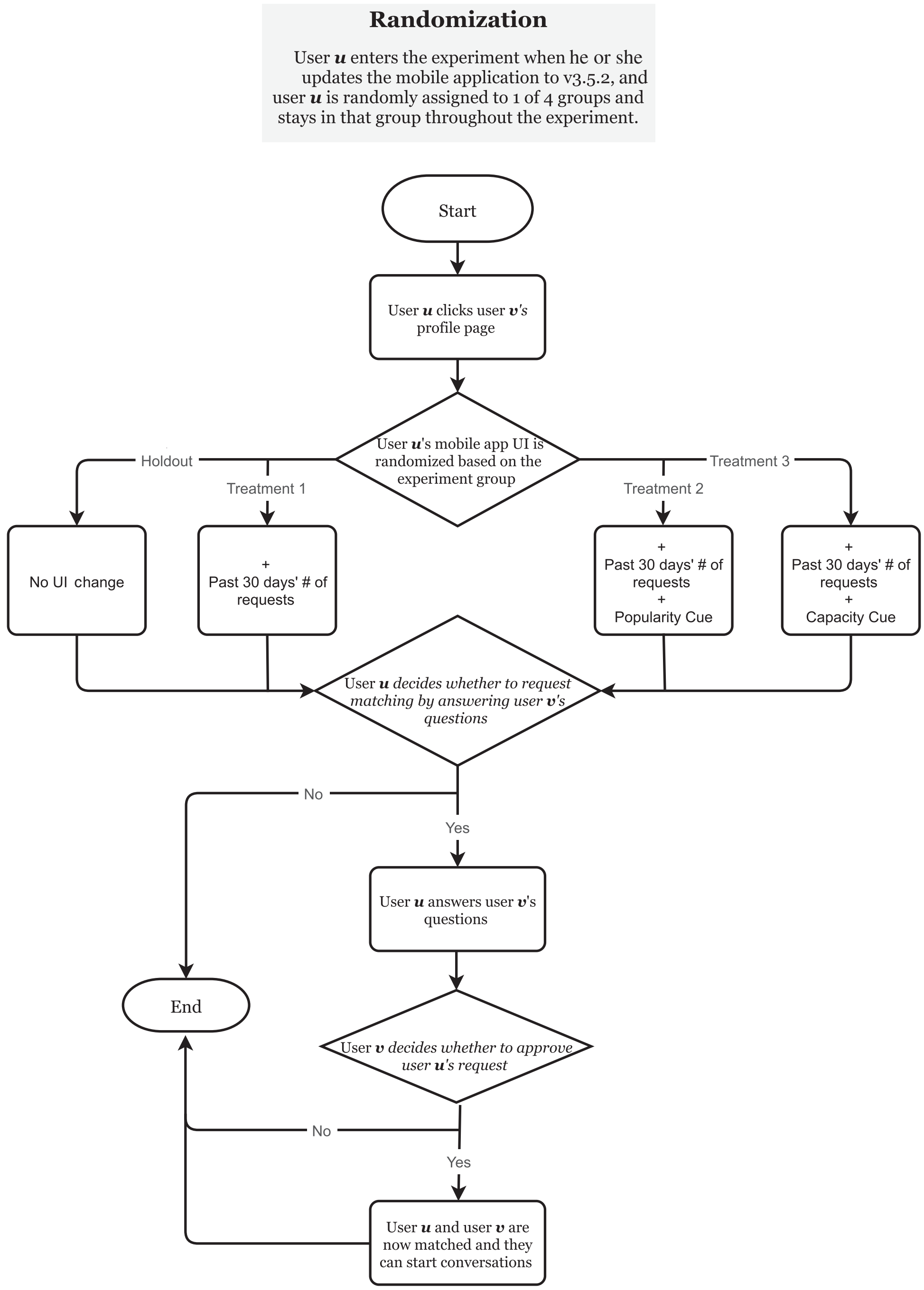
We combined data from multiple sources to perform our analyses. First, we obtained data on users' experimental group assignments from the corporate partner's A/B test system. In addition, we extracted data on observable user information from the platform's transactional database. Furthermore, the corporate partner employs an industry-leading analytics service to store all users' mobile tap-stream events in a cloud data warehouse, allowing us to reliably observe the entire sequence of users' digital footprints and attribute their decisions to those recorded tap events. Similar to clickstream data capturing user-initiated events via mouse clicks, tap-stream data record user interactions with the application's UI through finger taps, which support microlevel observations of the mobile application users' behavioral traces (Zhang et al. 2019), which we leverage not just for the user-level main analyses, but several tap-level analyses that provide additional insights. Last, we retrieved users' conversation counts through the in-app messaging function, from the data warehouse of a third-party vendor. We list each data type and its corresponding source in Table 2.

We first describe the user-level data, which contain the users' demographic and behavioral records aggregated for each subject in the experiment. Table 3 presents the definition and operationalization of the main variables, and Table 4 shows the descriptive statistics of those variables in the user-level data, also broken down by peer demand group. In total, 48,658 subjects entered the field experiment. We observe the subjects' gender and age based on user profile data. Additionally, at the user level, we calculate the number of distinct peer profiles a subject viewed, the number of matching requests a subject made, the number of matching requests that were approved by peers (termed "initial matches"), and the number of successful matches (termed "engaged matches") by a subject with more than two rounds of message exchanges (i.e., equivalent to four messages) during the experimental period.[12] And this measure of engaged matches follows prior work that defined meaningful subsequent communication through message exchanges in online dating (Bapna et al. 2016, Jung et al. 2019).

Moreover, leveraging the tap-stream data, we also observe subjects' responses to the manipulations at a more granular level. Particularly, for each subject's visit to a peer's profile page, we monitor whether the subject submitted a matching request and the numerically displayed level of peer demand. As such, we can leverage the tap-level observations to elaborate on our main analyses, to understand the effects of our treatments on subject requesting behavior at the level of the individual visit, over the distribution of peer demand. We report the tap-level variable definitions in Table 5 and the descriptive statistics of those variables in Table 6.

Before conducting further analyses, we performed balance checks on the observable covariates, across the experimental groups, to assess the efficacy of the randomization procedure. Because the unit of randomization and treatment is a subject, we conducted

Figure 2. Experimental Design and Process



the randomization checks at the user level. We performed mean comparisons of subjects' demographics, prior engagement levels, prior demand levels, and the date they entered the experiment across conditions. We also performed distributional comparisons (Kolmogorov–Smirnov tests) of users' locations, schools, and majors. All pairwise *t*-tests yielded statistical insignificance, implying balance and effective randomization. Thus, we confirmed that the randomization procedure was effective. We report the details of our randomization checks in Online Appendix B.

5. Analyses and Results

5.1. Main Results

Our main analyses focus on the average effects of our interventions on requesting behavior, matching volumes, and, ultimately, matches per request, our

Table 2. Data Sources

Data	Source
Experimental user assignment	A/B test system
User information	Transactional database
Tap-stream events	Event analytics cloud data warehouse
User conversation counts	Data warehouse of a third-party vendor

Note. The data on user information and conversation counts were shared with the author team without personally identifiable information.

measure of matching efficiency. As demonstrated in our experimental design and process (Figure 2), the treatment manipulation is expected to affect each subject's decision about whether to issue a matching request, as well as matching outcomes. Requests and matches can obviously occur numerous times because the subject may visit various peer profiles. We thus perform our analyses primarily at the user level, employing aggregate request and match data over the experiment's two-week period. In later analyses, we examine effects at the visit level, employing observations of individual profile page visits. Our key dependent variables in the user-level analyses are the number of requests submitted by a subject, the number of matches a subject obtains (accepted requests), and the ratio of matches to requests, our measure of efficiency.

Before we proceed, we first confirm that the treatment was delivered correctly. As previously explained, the treatment manipulation manifests solely when a subject visits a peer profile page; that is, subjects across all conditions observe an identical UI design within the app's home landing page prior to entering a peer's profile. As such, our experiment should *not* affect subjects' decisions about which peer profiles to visit; that is, we should *not* observe significant variation in subjects' quantity and composition of viewed peer profiles across the experimental groups. To confirm this, we conducted a placebo check employing our user-level data, estimating whether the treatments impacted subjects' (a) total number of unique profile views and (b) number of unique profile views toward high-demand versus low-demand peers. From these analyses, reported in Online Appendix C, we confirmed that there are no significant differences between experimental groups in terms of profile viewing behavior.

5.1.1. Descriptive Evidence. The manipulated UI information (shown in Table 1) varies by both group *and* peer demand; that is, a subject's matching request behavior is a function of the subject's (a) group assignment and (b) a prospective peer's recent demand (i.e., high versus low). Accordingly, we begin by examining requesting behavior by experimental groups and by peer demand level. In Figure 3, we plot our user-level data, depicting the average number of requests (with 90% confidence intervals (CIs)) submitted by subjects in each experimental condition, toward high-demand versus low-demand peers, upon visiting their profiles. We observe here that users in the control group, absent demand information, exhibit clearly skewed attention toward more popular peers. In contrast, subjects in the demand information condition, who are made able to view peers' demand information, exhibit a reduced number of requests toward high-demand peers.

Additionally, we see some evidence that message-framing cues amplify these effects. Showing demand information in tandem with the popularity cue further reduces subjects' matching requests toward high-demand peers. We see no evidence that the reduction in requests to high-demand peers is compensated by a rise in requests to low-demand peers, under either the demand information intervention alone or the intervention offered in tandem with a popularity cue. However, we do see evidence that demand information intervention leads to a redistribution of attention

Table 3. Variable Descriptions in the User-Level Data

Variable	Description
Treat	A subject's experimental group assignment, which take the following categorical values: 1 = Control, 2 = Demand, 3 = Demand + Popularity Cue, 4 = Demand + Capacity Cue
NumberOfRequests	The number of matching requests that a subject sends in the experiment
InitialMatches	The number of matching requests that a subject sends and are approved
EngagedMatches	The number of initial matches that resulted in more than two rounds of message exchange
ProfileViews	The number of distinct profiles that a subject viewed in the experiment
Gender	A binary variable that measures a subject's gender (0 = male, 1 = female)
Age	A numerical integer that captures a subject's age

Table 4. Descriptive Statistics in the User-Level Data

Variable	Obs.	Mean	Median	Std. dev.	Min	Max
NumberOfRequests	48,658	4.66	0.00	12.71	0	300
NumberOfHighRequests	48,658	2.47	0.00	7.64	0	249
NumberOfLowRequests	48,658	2.19	0.00	6.74	0	171
InitialMatches	48,658	0.96	0.00	2.43	0	101
InitialHighMatches	48,658	0.53	0.00	1.54	0	36
InitialLowMatches	48,658	0.43	0.00	1.36	0	74
EngagedMatches	48,658	0.52	0.00	1.49	0	69
EngagedHighMatches	48,658	0.29	0.00	0.97	0	21
EngagedLowMatches	48,658	0.23	0.00	0.82	0	48
ProfileViews	48,658	35.80	14.00	59.25	1	686
ProfileHighViews	48,658	15.83	5.00	28.98	0	454
ProfileLowViews	48,658	19.97	7.00	37.05	0	659
Female	48,658	0.31	0.00	0.46	0	1
Age	48,658	23.29	23.00	2.60	19	31

Note. Obs., observations; Std. dev., standard deviation.

toward low-demand peers when it is provided in tandem with a capacity cue. In fact, we find that the demand information treatment with a capacity cue message is the only intervention that results in statistically insignificant differences in the number of requests they make to high- versus low-demand peers.

Before proceeding further with more formal regression analyses, it is worth discussing the importance of attentional shifts versus declines for congestion mitigation. In an ideal world, the platform operator would hope to divert the attention toward low-demand peers, rather than lose it altogether. However, even if such reallocation does not take place, there is still value in reducing demand concentration; reducing requests toward high-demand users will, on its own, be quite valuable, for at least two reasons. First, a "popular" user who might otherwise have been overwhelmed by requests they ultimately ignore will obtain a better user experience. Bear in mind that prior dating research has documented negative consequences of choice overload for satisfaction in online dating (D'Angelo and Toma 2017), and an excess number of dating requests will also lead to excess screening costs (Arnosti et al. 2021). Second, the individuals who would otherwise have issued requests to popular peers will now see a reduction in wasted time and effort, and they will also experience less social rejection. The latter is important, as prior research has found that individuals who have a fear of social rejection are systematically more likely to employ online dating rather than date offline (Blackhart et al. 2014), and thus the consequences of being ignored or declined for the user experience may be substantial in this setting. Accordingly, what we will ultimately be most concerned with is the efficiency of matching, generally, rather than the occurrence of matches in particular segments of the peer-demand distribution.

5.1.2. Effects on Requesting Behavior. We report a series of regressions of the form articulated in Equation (1), where the key variables of interest are captured by $Treat_u$, a vector of experimental group dummies, with the control group omitted to serve as the reference condition. In the equation, u indexes subjects. The outcome variable, $NumberOfRequests_u$, thus captures a subject u's total number of matching requests issued. We repeat this regression for requests toward high-demand peers, low-demand peers, and peers in general. Low-demand peers are those who had received <10 requests in the past 30 days, whereas high-demand peers are those who received ≥10 requests in the past 30 days. We report the results of these three analyses in Table 7. Equation (1) is given as follows:

$$NumberOfRequests_u = \boldsymbol{Treat}_u + \epsilon_u. \qquad (1)$$

First, considering the effects on attention toward high-demand peers, we see that all three treatments have a significant negative effect (Table 7, column (1)).

Table 5. Variable Descriptions in the Tap-Level Data

Variable	Description
RequestMatch	Provided a subject, u, lands on a peer v's profile page, whether u submitted a matching request to v by answering the questions (0 = no request, 1 = request)
HighDemandProfile	When a subject u lands on a peer v's profile page, whether v is a high-demand peer or a low-demand peer (0 = low demand, 1 = high demand)

Table 6. Descriptive Statistics in the Tap-Level Data

Variable	Obs.	Mean	Std. dev.	Min	Max
RequestMatch	1,741,890	0.13	0.34	0	1
HighDemandProfile	1,741,890	0.44	0.50	0	1

Note. Obs., observations; Std. dev., standard deviation.

Furthermore, the capacity cue treatment yields the most desirable results, as we also observe a marginally significant *increase* in requests issued toward low-demand peers (β = 0.158, p = 0.06), implying a more uniform allocation of attention over the peer demand distribution, compared with the control group. These effects are practically large in relative terms. For example, the estimated decline in requests issued toward high-demand peers constitutes an approximate 13% decline as compared with the control group, whereas the estimated rise in requests toward low-demand peers represents an approximate 7% increase.

5.1.3. Effects on Matching Efficiency. Having established an effect of our treatments on users' attentional distribution, in terms of requesting behavior, we turn our attention to matching outcomes and matching efficiency. We examine matches operationalized in two ways. We begin by considering initial matches, based on the formal, explicit matching process within the partner dating application, wherein the receiving peer decides to accept a matching request. That is, after a subject, u, initiates the matching request to peer v by answering v's questions, peer v may optionally approve the matching request. An initial match thus results when peer v approves the matching request from subject u.[13] Second, we also consider the number of engaged matches, based on the social interactions (in-app messages) that take place between the requestor and requestee after the initial match occurs (Bapna et al. 2016, Jung et al. 2019).

Leveraging these operationalizations of matching, we begin by exploring two sets of outcomes in the user-level data. We begin by estimating treatment effects on (i) the average total number of matches attained and (ii) the ratio of matches to requests. If our intervention is driving improvements in matching efficiency, we would expect to observe an increase in the fraction of requests that yield a match. Furthermore, having established that our treatments drive a significant decline in total request volumes, for any rise in matches per request to be clearly desirable, we would need to ensure our treatments do not drive significant declines in total match volumes.

We thus estimate the regressions indicated by Equation (2), considering both initial matches per request issued and engaged matches per request issued.

$$NumberOfMatches/Request_u = \boldsymbol{Treat}_u + \epsilon_u. \quad (2)$$

As in our prior analyses, the control group serves as our reference condition. We report the regression results in Table 8. Broadly, we observe improvements in matching efficiency, particularly under our demand treatment paired with the capacity cue framing message. We observe a statistically significant increase in both initial and engaged matches per request in the Demand + Capacity Cue condition, relative to the control group (β = 0.021 and β = 0.010, respectively, with p-values below 0.05 in each case). Presumably, matching rates rise in the Demand + Capacity Cue condition because of the reallocation of attention away from high-demand peers toward low-demand peers; those requests are now more likely to be reciprocated. Collectively, our estimates indicate an ~7%–9% (relative) increase in matching efficiency over the two weeks following the introduction of our intervention, with no statistically significant declines in absolute match volumes.

One caveat here is that our estimation sample in the matches-per-request regression is a selected sample. Our outcome is defined only for subjects who issued at least one matching request in our two-week period of observation. Ignoring this aspect, it is difficult to gauge whether the treatment effects we observe are driven by causal shifts in user behaviors or by systematic differences in behavior among those users who are responsive to the intervention. Intuitively, it seems unlikely that selection can explain our findings, because we have already demonstrated that the users most responsive to our treatments are those who receive lesser interest from peers to begin with, and thus are more dependent upon outbound requests to obtain matches. A selection explanation would require that the users who respond most are also those users who perform best in terms of matching efficiency. In

Figure 3. (Color online) Volume of Matching Requests Issued by Condition and Peer Demand Split

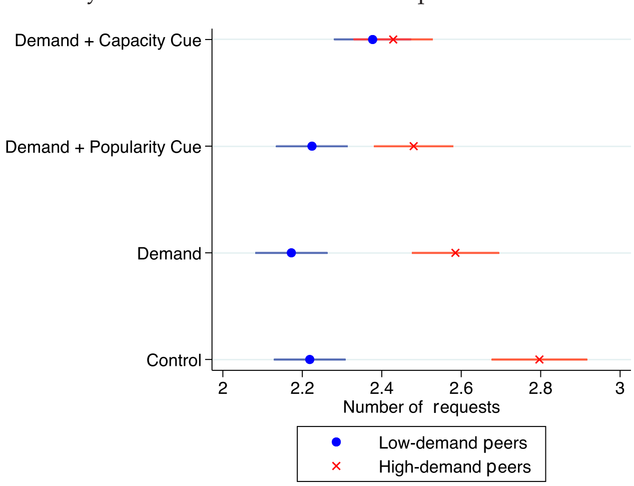


Table 7. Regressions Analysis: Effects on Request Volumes

Variable	(1) OLS (high-demand peers)	(2) OLS (low-demand peers)
Demand	−0.211*	−0.046
	(0.113)	(0.089)
Demand + PopularityCue	−0.317***	0.006
	(0.109)	(0.089)
Demand + CapacityCue	−0.368***	0.158*
	(0.109)	(0.092)
Constant	2.797***	2.219***
	(0.084)	(0.063)
Observations	48,658	48,658
Wald χ^2	4.33	1.81
	(3, 48,654)	(3, 48,654)

Notes. Robust standard errors are in parentheses. OLS, ordinary least squares.
*$p < 0.10$; ***$p < 0.01$.

any case, we address this concern more directly in Online Appendix D, where we conduct balance tests on several observable characteristics of the subjects who enter the regressions, that is, among subjects who issue at least one outbound request during our study period. We find no evidence of systematic differences in observable features. Moreover, when we implement a reweighted regression employing covariate balancing propensity scores (Imai and Ratkovic 2014), we observe even stronger effects, suggesting our results are not a product of selection on treatment.

Finally, we can repeat these regressions, splitting between high- and low-demand peers, to explore whether the improvements in matching efficiency do indeed arise where we would expect. Table 9 reports results of the matches-per-request regressions, broken out by high- and low-demand peers. Here we observe that although the matching efficiency improved for outbound requests to both high- and low-demand peers in terms of initial matches per request, the matching efficiency improvements for engaged matches per request largely come from outcomes related to high-demand peers. This again suggests that the lost requests toward high-demand peers were, by and large, requests that would have been unsuccessful.

5.1.4. Tap-Stream Analysis. We next conduct analyses at the visit level, to evaluate the robustness of our user-level analyses. We begin by reporting regressions analogous to those reported previously for user-level requesting behavior. The data generation process of the tap-level observations is such that a subject u can visit at least one and at most many other peers' profiles on the platform. This process creates a panel data structure wherein each subject possibly has multiple observations that contain a panel of records reflecting their visits to different peer profiles. After a subject taps into a peer's profile, he or she can make a binary decision: (a) request a match by answering the questions or (b) navigate away without requesting a match. Thus, the key outcome variable at the tap level is $RequestMatch_{uvt}$, which measures whether a subject

Table 8. Regressions Analysis: Effect on Matches per Request

Variable	(1) Initial matches/request	(2) Engaged matches/request
Demand	−0.001	0.005
	(0.006)	(0.004)
Demand + PopularityCue	0.008	0.005
	(0.006)	(0.004)
Demand + CapacityCue	0.021***	0.010**
	(0.006)	(0.004)
Constant	0.285***	0.117***
	(0.004)	(0.003)
Observations	21,442	21,442
F-statistic	5.18	1.66
	(3, 21,438)	(3, 21,438)

Note. Robust standard errors are in parentheses.
**$p < 0.05$; ***$p < 0.01$.

Table 9. Regressions Analysis: Effect on Matches per Request by High- vs. Low-Demand Peers

Variable	(1) Initial matches/request (high-demand peers)	(2) Initial matches/request (low-demand peers)	(3) Engaged matches/request (high-demand peers)	(4) Engaged matches/request (low-demand peers)
Demand	0.008	−0.003	0.010**	−0.001
	(0.007)	(0.008)	(0.005)	(0.005)
Demand + PopularityCue	0.016**	0.004	0.011**	−0.0003
	(0.007)	(0.008)	(0.005)	(0.005)
Demand + CapacityCue	0.018**	0.016**	0.012**	0.002
	(0.007)	(0.007)	(0.005)	(0.005)
Constant	0.286***	0.262***	0.100***	0.110***
	(0.005)	(0.005)	(0.003)	(0.004)
Observations	15,017	15,117	15,017	15,117
F-statistic	2.68	2.29	2.54	0.14
	(3, 15,013)	(3, 15,113)	(3, 15,013)	(3, 15,113)

Note. Robust standard errors are in parentheses.
$^{**}p < 0.05$; $^{***}p < 0.01$.

u made a matching request to peer v's profile during visit t (or not).

A notable point with the tap-stream data is that we can also condition upon the visited peer, via a peer fixed effect, φ_{vt}, which helps ensure our estimated effects are driven only by within-peer variation in visit activity from subjects in different experimental conditions. We thus estimate a regression of the form expressed in Equation (3). In Table 10, we observe a very consistent set of results, aligned with those reported previously in Table 7; the pattern of effects is qualitatively similar. Equation (3) is given as follows:

$$RequestMatch_{uvt} = \boldsymbol{Treat}_u + \varphi_{vt} + \epsilon_{uvt}. \tag{3}$$

The tap-stream data also have the benefit of enabling us to estimate the effect of the treatments on subjects' likelihood of initiating a match across the distribution of peer demand, in a flexible manner. That is, rather than employing a dichotomous split (i.e., a cutoff to define high- versus low-demand peers), we can estimate the effect of the treatments on subjects' probability of initiating a match with any given peer, employing a series of dummies to flexibly capture effects across different peer demand values.

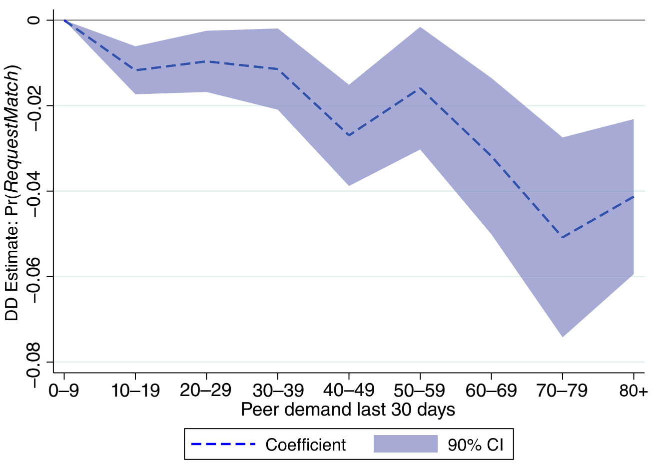
Thus, we next estimate request probability as a function of visited peer v's demand information (represented as a vector of peer demand range dummies, bucketed by ranges of 10, taking 0–9 as the reference range, and aggregating all values ≥80 into a single dummy as well, "80+") at time t. We once again incorporate a peer profile fixed effect, φ_{vt}, and we cluster standard errors by subject and peer profile. As noted previously, the experimental manipulation occurs at the user level, $Treat_u$; hence a subject always observes the same pieces of information when visiting different peer profiles, based on the subject's assigned experiment condition. Equation (4) reflects our estimation:

Table 10. Regressions Analysis: Treatment Effect on Probability of Request (Visit-Level Analysis)

Variable	(1) OLS (high-demand peers)	(2) OLS (low-demand peers)
Demand	−0.009**	0.001
	(0.004)	(0.002)
Demand + PopularityCue	−0.015***	0.003
	(0.004)	(0.002)
Demand + CapacityCue	−0.013***	0.005*
	(0.004)	(0.002)
Constant	0.165***	0.118***
	(0.003)	(0.002)
Observations	767,367	840,550
Peer Fes	Yes	Yes
F-statistic	5.16	1.47
	(3, 31,396)	(3, 43,554)

Notes. Robust standard errors are in parentheses (two-way clustering by subject and peer profile). Some observations were dropped because of singletons under peer profile fixed effects (FEs). OLS, ordinary least squares.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Figure 4. (Color online) Regression Coefficients from Difference-in-Differences (DD) Estimation (Demand + Capacity Cue × Peer Demand Range) and Effect on Probability of Initiating Requests Toward Peers (Standard Errors Clustered by Subject)

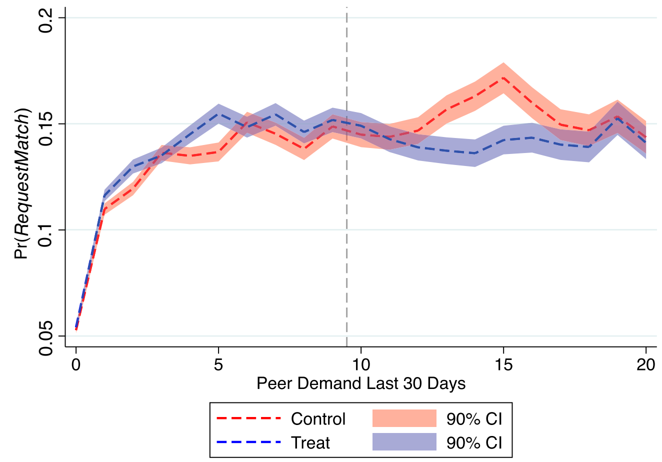


$$RequestMatch_{uvt} = \boldsymbol{Treat_u} \times \sum PeerDemandRange_{vt} + \sum PeerDemandRange_{vt} + \varphi_{vt} + \epsilon_{uvt}. \tag{4}$$

We limit our attention here to the effect of the Demand + Capacity Cue treatment, given that it yields the largest effects in our main analyses. Note, however, that we observe very similar patterns for the Demand treatment alone, indicating that, even without a messaging cue, there is a beneficial, congestion-reducing effect at play. For simplicity, we present the relevant coefficient estimates visually; Figure 4 depicts the difference-in-differences estimates. Consistent with the user-level results, compared with the effect of the treatment on attention allocated toward low-demand peers (peers exhibiting a recent demand between zero and nine), we see that the treatment effect grows significantly more negative as we look at visits to increasingly popular peers.

Another notable point from our user-level analyses is that male subjects, in particular, appeared to shift attention toward low-demand peers under the Demand + Capacity Cue treatment. In that analysis, recall that low- versus high-demand peers were defined based on a median split in the global population for 30-day peer request volumes; in particular, high peer demand is defined as demand with a threshold value of ≥10. Furthermore, recall that our Demand + Capacity Cue condition incorporated a discontinuous shift to the textual message-framing cue above the threshold. If we narrow our attention to focus on the range of peer demand around the cutoff threshold (depicted in Figure 5) for demand values between 0 and 20, and simply plot the mean and 90%

Figure 5. (Color online) Mean and 90% Confidence Intervals of Request by Peer Demand Values 0–20 (Treat = Demand + Capacity Cue)



confidence intervals of the *Request* variable for the control and treatment groups, at each peer demand value, we see the expected demand shift.[14] That is, relative to control subjects, we see that treated subjects exhibited an increased rate of matching request initiations toward peers below the threshold, yet a relatively reduced rate of matching request initiations toward peers above the threshold.

5.2. Heterogeneous Effects

5.2.1. Own-Demand Heterogeneity. We next explore heterogeneity in the effects, with an eye toward understanding mechanisms and informing a targeted delivery strategy. First, we consider whether subjects' responses depend on their own recent demand. Our expectation here is that users will be more responsive to the demand information interventions when they face greater competition and congestion on the platform. By examining heterogeneity in terms of a subject's own recent demand (requests the subject has received in the past 30 days), we can gain greater insight into the role of congestion sensitivity.

We thus estimate a model consistent with Equation (5), which mirrors Equation (1), with the exception that it also incorporates an own-recent-demand moderator. Note that we demean the $OwnDemand_u$ variable, so the main effects of our treatment condition dummies reflect effects on the average user. We once again estimate this model related to requests toward high-demand peers and again toward low-demand peers:

$$NumberOfRequests_u = \boldsymbol{Treat_u} + OwnDemand_u + \boldsymbol{Treat_u} \times OwnDemand_u + \epsilon_u. \tag{5}$$

In Table 11, we observe evidence consistent with our expectations. Users who had received a greater volume of in-bound requests in the 30 days prior were

Table 11. Regressions Analysis: Heterogeneity by Subjects' Own Demand (All Subjects)

Variable	(1) OLS (high-demand peers)	(2) OLS (low-demand peers)
Demand	−0.205*	−0.044
	(0.113)	(0.089)
Demand + PopularityCue	−0.312***	0.007
	(0.108)	(0.089)
Demand + CapacityCue	−0.367***	0.158*
	(0.108)	(0.092)
OwnDemand	−0.057***	−0.017***
	(0.004)	(0.004)
Demand × *OwnDemand*	0.010*	−0.006
	(0.005)	(0.006)
Demand + PopularityCue × *OwnDemand*	0.021***	0.005
	(0.006)	(0.010)
Demand + CapacityCue × *OwnDemand*	0.015***	−0.006
	(0.006)	(0.006)
Constant	2.794***	2.218***
	(0.083)	(0.063)
Observations	48,658	48,658
F-statistic	82.43	12.70
	(7, 48,650)	(7, 48,650)

Notes. Robust standard errors are in parentheses. OLS, ordinary least squares.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

significantly less responsive to the treatments. Moreover, in the extreme case, our estimates indicate that users receiving extremely high levels of inbound demand may even exhibit undesirable responses, shifting greater interest toward high-demand peers.

Next, we repeat this analysis, limiting the regression to male users. We do so because we wish to address the possibility that the own demand moderator is simply proxying for gender, bearing in mind that male users on the partner platform issue the vast majority of dating requests, consistent with observations in past work on dating platforms (Bapna et al. 2016). Repeating the regression solely for male subjects alone, we observe consistent results in Table 12.

5.2.2. Gender Heterogeneity. As alluded to in the prior section, there are potentially important differences between male and female subjects, in terms of the congestion they encounter on dating platforms, and thus in terms of how they may react to our interventions. Male subjects face a great deal more competition on dating platforms, because they typically comprise a larger fraction of the user base, and because they are systematically more likely to issue requests (Bapna et al. 2016). Accordingly, there is good reason to believe that males will be more likely to respond to our treatments, generally.

That said, there are some difficulties that arise in comparing the effects of our treatments between male and female subjects, particularly when it comes to our treatments that involve textual cues conveying capacity or popularity framings. As noted previously, the textual labels displayed to users in the two experimental conditions that incorporated said labels would update dynamically, depending on whether the observed peer's demand value was greater than or equal to 10 at the time a visit took place. This value of 10 was chosen for the design because it was the global median of recent demand observed across active users in the preexperiment period. Presumably, capacity is an objective notion, in that a user is either available for a date or not; thus, a single threshold for all users makes sense.

However, the median peer demand a female user encounters on Summer is much lower than that encountered by males. In fact, the median male prior demand value was ~2. This is important, because we face a tension in any regression analysis we might hope to perform, in terms of how we define the high-demand peer threshold. If we employ the value of 10, we face a difficulty that there are relatively few males that surpass that threshold, implying very few peers will have met the condition. However, if we instead employ a value of 2, we face the difficulty that the analysis is no longer aligned with the design of the experimental treatment.

For this reason, in exploring gender heterogeneity, we limit our attention to gender heterogeneity in the effects of the Demand condition, absent textual labels. Because there is no textual label involved, we are free

Table 12. Regressions Analysis: Heterogeneity by Subjects' Own Demand (Male Subjects)

Variable	(1) OLS (high-demand peers)	(2) OLS (low-demand peers)
Demand	−0.064	0.100
	(0.197)	(0.168)
Demand + PopularityCue	−0.204	0.035
	(0.179)	(0.121)
Demand + CapacityCue	−0.369**	0.288**
	(0.183)	(0.142)
OwnDemand	−0.038**	−0.030**
	(0.016)	(0.014)
Demand × *OwnDemand*	0.061*	0.024
	(0.032)	(0.032)
Demand + PopularityCue × *OwnDemand*	0.079***	−0.004
	(0.026)	(0.018)
Demand + CapacityCue × *OwnDemand*	0.052*	0.020
	(0.029)	(0.024)
Constant	3.777***	2.226***
	(0.124)	(0.089)
Observations	33,750	33,750
F-statistic	3.60	2.64
	(7, 33,742)	(7, 33,742)

Notes. Robust standard errors are in parentheses. OLS, ordinary least squares.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

to employ whatever definition we like for high-demand peers when conducting our regressions. As such, we explore several alternative definitions of the $HighDemandPeer_{vt}$ dummy variable in these regressions, considering values from 1 through 20. Furthermore, we conduct these analyses using visit-level tap-stream data, to mitigate the potential that a lack of significant response among female subjects might be attributable to a lack of statistical power. We estimate linear probability models reflected by Equation (6). We regress an indicator of whether a match was requested onto a high-demand peer dummy, a treatment dummy, and their interaction. Once again, we condition on a peer-profile fixed effect, φ_{vt}:

$$Request_{uvt} = \boldsymbol{Treat}_u + HighDemandPeer_{vt} + \boldsymbol{Treat}_u \times HighDemandPeer_{vt} + \varphi_{vt} + \epsilon_{uvt}. \tag{6}$$

In Table 13, we report the coefficients associated with the $\boldsymbol{Treat}_u \times HighDemandPeer_{vt}$ interaction across all split definitions, contrasting estimates obtained on the subpopulation of males and females. Furthermore, in column (3), we report p-values associated with a test of significant differences between the two coefficients, obtained via the estimation of a three-way interaction model ($\boldsymbol{Treat}_u \times HighDemandPeer_{vt} \times Female_u$).

We observe a statistically significant, negative interaction between the demand information treatment and the high-demand peer dummy for males with nearly every split definition. In contrast, we do not observe a statistically significant effect for females under any split definition. When we examine the significance of the gender heterogeneity via a three-way interaction regression (reporting the p-values associated with the three-way interaction term), we see that the differences between males and females are statistically significant for splits ranging from one through seven. Beyond that point, significance fades, in part because the standard errors associated with female estimates begin to grow larger (which occurs at least in part because there are few male users who exhibit recent peer demand values of such magnitude). It is perhaps notable, however, that all coefficient estimates among females are quite small, and most are positive, whereas those among males are larger and negative. Altogether, these results are consistent with the idea that males, who contend with congestion more often, are also more responsive to demand information.

5.3. Further Analyses

5.3.1. Alternative Explanations. We see clear evidence of the beneficial effect of the Demand + Capacity Cue intervention on congestion. Although our analyses suggest that the treatment effects are particularly influential for subjects who are sensitive to congestion, there are possibly two other mechanisms that

Table 13. Gender Heterogeneity: Demand Information Effect by Gender

	Treat 3 HighDemandProfile		
High ≥ x	Male	Female	Test of coefficient equivalence (p-value)
1	−0.010*** (0.004)	0.006 (0.005)	0.023**
2	−0.010** (0.004)	0.005 (0.005)	0.051*
3	−0.012*** (0.004)	0.004 (0.005)	0.029**
4	−0.011*** (0.004)	0.006 (0.006)	0.037**
5	−0.013*** (0.004)	0.011 (0.007)	0.004***
6	−0.014*** (0.003)	0.011 (0.007)	0.003***
7	−0.010*** (0.003)	0.010 (0.008)	0.056*
8	−0.011*** (0.003)	0.008 (0.009)	0110
9	−0.010*** (0.003)	0.007 (0.010)	0.186
10	−0.011*** (0.003)	0.006 (0.010)	0.206
11	−0.012*** (0.003)	−0.0003 (0.011)	0.329
12	−0.013*** (0.003)	−0.0002 (0.011)	0.341
13	−0.013*** (0.003)	−0.001 (0.012)	0.441
14	−0.012*** (0.003)	0.002 (0.013)	0.425
15	−0.010*** (0.003)	0.005 (0.014)	0.385
16	−0.008** (0.004)	0.007 (0.015)	0.541
17	−0.009** (0.004)	0.012 (0.016)	0.431
18	−0.009** (0.004)	0.014 (0.016)	0.497
19	−0.010*** (0.004)	0.017 (0.017)	0.401
20	−0.010*** (0.004)	0.011 (0.017)	0.586
Observations	610,003	126,850	
Peer FE	Yes	Yes	

Note. Robust standard errors are in parentheses (two-way clustering by subject and peer profile).
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

may contribute to this result. First, by shifting attention toward a larger pool of low-demand peers, our treatment may expose subjects to a more diverse pool of potential matches, among whom subjects may identify better matches. Second, after shifting toward lower-demand peers, subjects may become more confident and put either more or less effort into answering questions, resulting in either a lower or higher chance of receiving matches.

We next explore the potential roles of these two other mechanisms, estimating the effect of our treatments on (i) the diversity of requested peers, operationalized in terms of the variance/dispersion of two key peer characteristics, namely, school attended and age, and (ii) subject effort expended pursuing the match, operationalized in terms of the average number of characters a user writes when responding to peers' questions.

To operationalize the inequality in school (a categorical variable), we consider the approach suggested by Kader and Perry (2007) using the following formula: $Dispersion(School) = 1 - \sum_i \left(\frac{S_i}{N}\right)^2$, where each subject sends requests to N users, with i possible values for schools of those N users. The term S_i represents the number of peers who are from school i and received requests sent by the subject. In other words, $\frac{S_i}{N}$ captures the proportion of peers who are from school i that a subject requested. We model these outcomes as functions of treatment assignment at the user level, shown in Equation (7). Estimation results in Table 14 indicate no significant differences in the diversity of peers targeted by subjects across conditions, or in the effort exerted by subjects in pursuing requests. Equation (7) is given as follows:

$$Diversity_u \mid Effort_u = \boldsymbol{Treat}_u + \epsilon_u. \qquad (7)$$

Given the absence of any effects, we have no evidence that either of these alternative mechanisms contributes to our results. That said, we must acknowledge that we cannot rule out these alternative explanations completely. Of course, the same caveat that was noted earlier applies, about a potentially selected sample, given some users did not initiate any requests during the experimental window. That said, as we have demonstrated in Online Appendix D, we do not observe any systematic differences in subject characteristics across experimental arms.

Table 14. Regressions Analysis: Effects on Request Effort and Dispersion of Requested Peer Characteristics Request

Variable	Var(*Age*)	*Dispersion* (*School*)	Log (*Characters*)
Demand	0.005	−0.498	−0.017*
	(0.004)	(0.870)	(0.010)
Demand + PopularityCue	−0.002	−1.173	−0.005
	(0.004)	(0.794)	(0.010)
Demand + CapacityCue	−0.003	0.062	0.002
	(0.004)	(0.892)	(0.010)
Constant	0.366***	7.257***	3.110***
	(0.003)	(0.624)	(0.007)
Users	42,480	42,480	42,480
F-statistic	1.05	1.10	1.32
	(3, 42,476)	(3, 42,476)	(3, 42,476)

Note. Robust standard errors are in parentheses.
*$p < 0.1$; ***$p < 0.01$.

5.3.2. Examining the Independent Effect of Capacity Cue Text. A natural question arises as to whether the capacity message framings alone are responsible for the strong effects we have observed, or whether those cues only act in concert with the quantitative demand information.[15] Although our partner platform chose not to implement an experimental condition that employed message-framing cues in isolation for practical reasons, we assess this possibility via a local discontinuity regression analysis around the high-low median demand threshold, given this threshold was used as a basis for displaying text indicating whether a user was available or busy. To isolate the local independent effect of the capacity cue message shifting in content, we employ a difference-in-differences regression, which, given the threshold at play, is conceptually similar to a difference-in-discontinuity design (Grembi et al. 2016). We estimate the independent effect of the capacity cue message by limiting our attention to the Demand condition and the Demand + Capacity Cue condition. These conditions are identical, except that the latter received a textual cue about peer availability, which shifted discontinuously in its message with the transition from 9 to 10 peer requests in the prior 30 days.

Equation (8) reflects our simple difference-in-differences regression specification, where *Treat* is equal to one for subjects in the Demand + Capacity Cue condition and is zero for users in the Demand condition. The *HighDemandProfile* dummy denotes a peer's demand level in the profile, with one being in high demand and zero representing in low demand. To minimize potential endogeneity around the peer demand variable, we incorporate peer profile fixed effect, φ_{vt}.

Equation (9) reflects an exploded version of the specification, wherein we replace the *HighDemandProfile* dummy with a vector of *PeerDemand* dummies. In the latter regression, we omit the *PeerDemand* value of zero, treating it as the point of reference. Additionally, as before, we incorporate a peer profile fixed effect, φ_{vt}, which helps to isolate effects that are due solely to variation in the information displayed on a particular peer profile page. The results of our simple difference-in-differences regression, expressed in Equation (8), appear in Table 15. For the sake of brevity, we present the difference-in-differences coefficient estimates from Equation (9) visually, in Figure 6. And Equations (8) and (9) are given as follows:

$$RequestMatch_{uvt} = HighDemandProfile_{vt} + \boldsymbol{Treat}_u \times HighDemandProfile_{vt} + \varphi_{vt} + \epsilon_{uvt}\ , \tag{8}$$

$$RequestMatch_{uvt} = \sum_{1}^{20} PeerDemand_{vt} + \boldsymbol{Treat}_u \times \sum_{1}^{20} PeerDemand_{vt} + \varphi_{vt} + \epsilon_{uvt}\ . \tag{9}$$

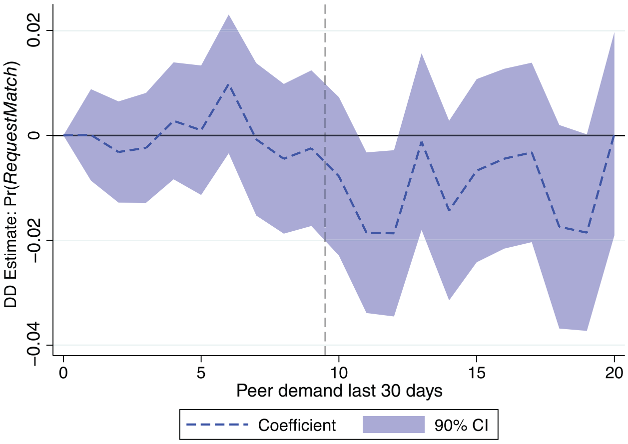
In both cases, our estimates suggest that the dynamic textual component of the Demand + Capacity Cue treatment contributes negatively to the overall treatment effect. Specifically, our simple difference-in-differences results suggest that the propensity of subjects to request a match falls by approximately 1 percentage point ($p < 0.01$) with the transition from a cue of "available" to a cue of "busy." The estimated effect of the Demand + Capacity Cue treatment in Table 10 is perhaps the most comparable estimate, because in that analysis we employ the same tap-level data, and thus condition on a visit, and we also contrast the behavior of subjects toward high- versus low-demand peers. In that estimation, we see a rise of 0.5 percentage points in requesting probability toward low-demand peers, and a decline of 1.3 percentage points in the probability of reaching out to a high-demand peer (an approximate shift of 1.8 percentage points in total). Considering these two estimations in tandem, and comparing them, we might conclude that a large portion of the

Table 15. Contribution of Capacity Cue to Effect of Demand + Capacity Cue

Variable	(1) OLS
Demand + CapacityCue × HighDemandProfile	−0.010***
	(0.004)
Observations	533,937
Peer FEs	Yes
F-statistic	93.75
	(3, 23,169)

Notes. Robust standard errors are in parentheses clustered by peer profile and subject. Tap observations are limited to visits to peers with a recent demand value ≤20. The reference group receives only peer demand information (no capacity cue). OLS, Ordinary least squares; FEs, fixed effects.
***$p < 0.01$.

Figure 6. (Color online) Dynamic Local Difference-in-Differences Analysis of Capacity Cue's Contribution to the Total Effect of Demand + Capacity Cue on the Probability of Initiating Requests Toward Peers



overall treatment effect cannot be attributed solely to the textual cue, and thus likely depends in some way on the demand information number. Although our experimental design does not enable us to completely isolate the independent influence of the textual cue from the demand information, this result at least suggests that the textual cue alone would be unlikely to deliver the magnitude of benefit we observe from the combined treatment. That said, future work is of course needed to determine this with surety.

5.3.3. Considering the Potential for Interference. Given the networked environment in which our experiment was conducted, it is important to consider the potential for interference and spillovers. From a conceptual standpoint, there is reason to believe that interference would not be extreme in our setting. First, our sample comprises just 5% of users on the platform, and those users are in general widely distributed geographically. Second, whereas a typical networked experiment raises concerns of interference due to direct peer interactions, in our case, given that we split our estimations by gender, the potential for interference is weaker.

A large majority (~85%) of matching requests on this platform are issued by male users, consistent with what has been observed in other prior online dating research (Bapna et al. 2016). This observation implies that the potential for a treatment effect to spill over into a peer's requesting behavior is limited, because interference would need to manifest primarily through indirect interactions, for example, shifts in the competition male users face from other males, or shifts in the already limited requesting behavior of females after they begin to be approached (or cease to be approached) by male users. The above having been said, we nonetheless also sought to explore this issue empirically, because it may be the case that female users would exhibit a treatment effect that interference issues are perhaps masking.

To accomplish this, in Online Appendix E, we examine the sensitivity of our results to focusing on only the very first peer interaction a subject exhibited upon entering our experiment. In theory, by considering only the very first peer profile visit, the potential for interference to influence our results is reduced, because these observations took place very early, before peers would have had the opportunity to contaminate behavior. Leveraging our tap-level data and considering only the very first peer profile visit initiated by any given subject, we regress a binary indicator of matching request initiation onto a vector of dummies reflecting a given subject's assigned experimental condition. We examine how the results vary by gender and whether the peer profile is high versus low demand (greater than or equal to 10 peer requests in the prior 30 days or not). The results of those regressions are essentially identical; we observed the same pattern of attentional reallocation. Indeed, we even observe a greater statistical significance of the reallocation of attention toward low-demand peers from the capacity cue intervention. The stability of our results in that narrowed sample suggests our results are not a product of interference.

6. Discussion

We report the results from a large-scale, randomized natural field experiment conducted by an online dating platform. Our corporate partner experimented with alternative interventions in revealing peer demand information to users to understand the efficacy of the interventions in reducing congestion, that is, skewed attention toward a subset of popular users, which is typically beyond the capacity of those users to entertain. The results indicate that disclosing demand information can induce users to reduce platform congestion by reducing their attention toward high-demand peers. Our results further suggest that, framed appropriately, providing peer demand information has the potential to reallocate user attention toward low-demand peers. What is more, our findings demonstrate significant improvements in matching efficiency. Analyses of heterogeneity indicate that these effects manifest most strongly when the intervention is targeted toward users who are congestion sensitive, that is, users who rely to a greater degree upon outbound requests to obtain matches. Furthermore, our results suggest that the effects are particularly pronounced when the intervention is designed with an accompanying message-framing cue that highlights capacity implications of the demand information. Based on these findings, we next discuss the implications of this study for both academic research and industry practice.

6.1. Implications for the Literature

This study contributes to the literature on digital platform design, particularly for two-sided matching markets. Prior work has explored several mechanisms for managing matching efficiency in platforms, often with a focus on pricing (e.g., Arnosti et al. 2021). However, scholars have recently taken interest in the potential of informational interventions for facilitating matching efficiency, particularly in the context of platforms for trade in goods and services (Jin and Leslie 2003, Tadelis and Zettelmeyer 2015, Ashlagi et al. 2020). Online dating is unique in the sense that it operates on a fundamentally different set of norms (Heyman and Ariely 2004), that is, social rather than market. Those differing norms give rise to distinct social mechanisms, for example, fears of social rejection, and they lead to the absence of many conventional levers that platform operators tend to employ to manage their markets, for example, price mechanisms, insurance, reputation systems, and dispute resolution. Social rejection may make individuals more concerned about the potential that they will be ignored. At the same time, absent the typical platform features and mechanisms, daters may react in an unpredictable manner to a new information source that has a quality connotation.

The present study builds on prior work in the information systems literature on information disclosure designs (Hong et al. 2015, Bapna et al. 2016), providing a first experimental consideration of a novel informational intervention (disclosing peer demand information to prospective matching suitors) and applying it within a unique and increasingly important context of online dating. Our work highlights that the effect of disclosing information about peers' likelihood of responding is likely to be dependent upon the receiving individual's experience contending with congestion or competition. That is, users who tend to rely more (less) on outbound (inbound) requests to obtain matches are more likely to be swayed by this information. A related possible reason for nonresponse is that users may be particularly selective in their partner preferences (Fisman et al. 2006). Being particularly resolute, users may ignore the information provided. Unfortunately, we lack data to disentangle whether a weaker response is more likely to be driven by the strength of preferences or experience with competition, but this is something that future work can and should explore. Understanding these distinct mechanisms could have important implications for determining to what extent, for example, an informational intervention of this sort might be more (or less) effective in shaping the behavior of new or younger dating app users (who have yet to experience a great deal of competition).

Our paper also speaks to the literature on observational learning, and specifically its relevance in online dating. First, our paper draws attention to the possible role of peer capacity inferences that users may make, alongside quality inferences (Zhang 2010). Our paper elaborates on the capacity signal of current demand, whereas past literature primarily focuses on the signaling role of demand (e.g., popularity) for quality (Tucker and Zhang 2011, Luo et al. 2014). Though our empirical findings yield no clear evidence that users make quality inferences from demand information in dating markets, we do not rule out the presence of a popularity effect; it may be that capacity concerns consistently countervail quality inferences, despite our inclusion of the message-framing cues.

Notably, our finding that many users respond negatively to higher peer demand is consistent with the findings of other recent work, which reported that historically popular dating users receive lesser contemporaneous interest from peers, on average (Bojd and Yoganarasimhan 2022). A possible explanation for the lack of positive popularity effects in online dating is the dyadic-choice nature of matches. The prior literature on observational learning has typically focused on contexts wherein one party tends to play a fixed role, such as restaurants (Cai et al. 2009), group buying (Luo et al. 2014), and the music market (Salganik et al. 2006), wherein the consumer chooses the product or service. Free from the fear of being rejected, users in those contexts can pick what they want, and will generally seek out options with the best features. In contrast, given human attractions are largely based on subjective fit (Frost et al. 2008), these contextual nuances about online dating may make the role of observational learning (popularity) weaker.

Finally, our work speaks to the broader literature on competitive search and frictions in matching markets. It is common in matching markets for individuals to face difficulty in coordinating their efforts, resulting in inefficient allocations (Petrongolo and Pissarides 2001). Theoretical work suggests that these coordination challenges are likely to arise when a candidate's visible characteristics correlate with the degree of interest they receive from others in the market (Wright et al. 2019). However, such conclusions are predicated on the assumption that competition information is not available to market participants. That assumption need not hold in digital markets, where it is relatively straightforward to surface competition information to users (as we do here). Hitsch et al. (2010a) provide some evidence that matches that result on dating platforms are stable; our work speaks to the efficiency with which those matches arise, by informing users' predictions about whether their solicitations will be reciprocated. Although it is not altogether clear a priori whether the provision of competitive information may drive improved coordination in this setting, we report evidence that, indeed, it does.

6.2. Implications for Practice

Our paper has practical implications for matching market design. The informational interventions we test are effective for addressing congestion, a frequent challenge in two-sided matching platforms. Our estimates indicate no statistically significant change in the absolute number of matches an average user obtains. However, they also demonstrate a statistically significant rise in the number of matches a user obtains per request issued. Specifically, our estimates translate to an ~7% increase in the request conversion rate. Viewed another way, our estimates imply a 6%–7% reduction in "fruitless requests." As the average user issues nearly ~10 requests per month, our results translate to roughly one fewer ignored or rejected matching request, per user, every 1.5 months. When we extrapolate to the quarter million daily active users that this platform hosts, it is clear that this effect translates to a very large reduction in wasted effort and social rejection. Indeed, the value of our intervention is perhaps made most apparent by the fact that, following this field experiment, the corporate partner proceeded to adapt our intervention, to disclose user demand information on an ongoing basis.

Our results have several design implications. The first design implication relates simply to the value of disclosing demand information in two-sided matching platforms. Although demand information has the potential to elicit two countervailing (popularity and capacity) signals, our empirical evidence shows that a congestion-reducing response dominates. The second design implication relates to targeted delivery. We find that users are systematically less responsive to the treatment when they are highly demanded themselves. In fact, our heterogeneity estimations suggest that, in the extreme, some high-demand users respond in an undesirable way to the provision of peer demand information, increasing their attention toward more popular peers. Accordingly, our results suggest that targeted delivery of the peer demand information may be useful. Future work might also consider deploying the demand information as a premium, paid feature, particularly to the user segments that respond to it.

6.3. Limitation and Future Research

Our study has several limitations, which also point to ample opportunities for future research. First, the experimental design did not incorporate a group that received only textual capacity cues (absent demand information) because of practical limitations with the corporate partner. Although we tackle this aspect to some extent by leveraging our tap-level data, to understand the discontinuous effects of priming cues around the capacity (free versus busy) threshold, future work might explore the effects of independent textual cues experimentally. Relatedly, the experiment we consider only focused on designing demand information disclosure interventions. It may be fruitful for future work to explore other information disclosure interventions. For example, it may be interesting to examine the effects of disclosing predicted matching probabilities to subjects as they browse peer profiles.

It is also important to recognize that our gender heterogeneity analyses are motivated by the fact that two-sided markets for dating are typically imbalanced, with a majority of users on one side competing on the attention of the minority on the other side. Bearing this unique market structure in mind, the gender heterogeneity we demonstrate is not strictly causal, as other factors may correlate with gender or subjects' own recent interest from peers. Furthermore, although we report reliable causal estimates of our interventions, identifying the underlying mechanisms presents some difficulties. Several pieces of suggestive evidence corroborate our overall story, yet additional research is still needed to tease out these underlying mechanisms (e.g., fear of social rejection, selectivity, niche preferences). It should also be noted that, although our context and analyses suggest that network interference is unlikely to play a major role in our estimates, the potential remains. Accordingly, future work might explore a design-based solution to ensure the robustness of our findings, for example, graph-cluster randomization (Ugander et al. 2013).

Future work might also look to identify targeting opportunities, considering behavioral trace data as well. For example, users' selectivity and confidence may be revealed through other aspects of their on-platform behavior, in the language they employ when messaging peers, or in their profile descriptions. Many dating app users will experience variable interest from peers in the market on a day-to-day basis. Although the data made available to us from our partner platform operationalize only request volumes over the past 30 days, preventing deeper analysis of heterogeneity in subjects' own demand, it would be interesting to delve more deeply into whether and when the dynamics of own demand attenuate and/or amplify capacity concerns. To the extent such dynamics exist, a temporally targeted intervention might also be useful, if relevant information might be delivered toward users at the optimal time and with an ideal framing.

Of course, open questions also remain as to the relative efficacy of our intervention, in terms of the degree to which they drive significant increases in attention to low-demand peers. The statistical significance of our estimates associated with the estimated increase in requests toward low-demand peers is slightly weaker than the other significant results we report ($p = 0.06$). Fortunately, the value of our informational intervention does not hinge solely on its ability to reallocate user attention toward lower-demand peers. Even absent the reallocation of attention toward low-demand peers, a decline in attention toward high-demand peers remains a desirable outcome on its own. Indeed, this is evident from the estimated rise in matching efficiency that we report. The increased matching efficiency implies that the eliminated requests are primarily those that would have been ignored by the recipient anyway. By eliminating those requests, the recipient no longer needs to screen them, and the sender no longer needs to experience the discomfort of being ignored.

Another open question that remains relates to the long-term efficacy of our interventions, relative to other interventions, but also in terms of their joint efficacy. For example, Arnosti et al. (2021) explore the potential value of reducing congestion by imposing an explicit cost on market participants for matching. Intuitively, imposing a charge to apply for jobs should reduce frivolous attempts. In our partner platform, an analogous option exists, in that dating app users must answer a series of peer-defined questions before they can request a match. Accordingly, users can impose a cost on other users by increasing the volume, difficulty, or invasiveness of the questions they post, and thereby reduce congestion. At present, however, users do not appear to take much advantage of this option, as our analyses indicate that although there is a positive significant relationship between peer demand and the number of questions they present to suitors, the relationship is quite small.

Specifically, we estimate that users present one additional question for every additional 200–250 matching requests in the prior 30 days, yet only the top 1% of users on the partner dating application receive that level of interest. Regardless, this finding does not preclude the possibility that our findings here are somehow dependent on the presence of that fixed cost associated with matching requests on the platform. That is, it may be the case that our interventions would be more, or less, effective on other dating platforms in the absence of a matching cost. Future work can explore this possibility. Last, we focused on the key performance indicators of online dating markets such as matching requests and matching outcomes, but do not directly consider platform profit or social welfare implications in our analyses, which we leave as potentially fruitful avenues for future research.

Acknowledgments

The authors thank the special section editors, the associate editor, and the four anonymous reviewers for the constructive feedback, which greatly improved the quality of this work. This work also benefited from feedback received at seminars and workshops at New York University, the University of Miami, the University of Wisconsin–Madison, the University of Illinois, the University of Pittsburgh, Georgia State University, the University of Texas at Dallas, Boston College, Fordham University, and the National University of Singapore. The authors also acknowledge research assistance support from Xingchen Xu.

Endnotes

[1] As one example, in the context of online labor markets, freelancers may be constrained in their available working hours, leading employers to waste their effort soliciting infeasible matches (Horton 2019). As another example, in the context of ride hailing, platforms often experience local demand spikes from riders following the end of a large concert or sporting event (Chen and Sheldon 2015).

[2] A notable difference in dating, which is something also true in other settings, such as digital search, is that an ideal match will, in theory, result in user exit, which superficially suggests that the market might be made "too efficient." Jung et al. (2019, p. 49) note this point, stating that "[t]he interesting aspect of social engagement in the online dating context is that while each particular user may exit a dating site after achieving a successful match, this successful user's departure is a highly desirable outcome for the website. As our conversations with senior executives in the online dating industry indicate, successful matching outcomes are key drivers of positive word-of-mouth recommendations: the success stories of existing users draw in fresh new users to the site." Thus, matching efficiency is a desirable goal for dating platform operators, despite the potential for user exit. Ultimately, most dating platforms face greater churn risk from users who have difficulty finding a match than they do from users who have successfully matched.

[3] We also explored what portion of this text plus demand intervention may be attributable to the textual message framing in particular. Although the partner platform did not implement an experimental condition evaluating message-framing cues in isolation (due to practical concerns), a discontinuity analysis in the neighborhood of the designed peer demand threshold at which the framing cue text was shifted from stating that a user was free to stating a user was busy reveals a significant yet relatively small shift. The magnitude of this local estimate suggests that the cue text's contribution is, on its own, only a small component of the overall treatment effect. That said, future work can more directly explore the relative efficacy value of independently applied textual labels conveying user capacity.

[4] Online dating is found to displace the intermediary role of friends and families (Rosenfeld et al. 2019) and is associated with the fast pace of transition from matching to marriage (Rosenfeld 2017). Furthermore, mobile applications induce online dating users to become socially engaged (Jung et al. 2019).

[5] For example, previous studies have proposed the idea of assortative mating in online dating, wherein individuals pursue partners with similar characteristics (e.g., Schwartz 2013, Xie et al. 2015, Luo 2017). Also, there appear to be significant gender differences among preferences in online dating, in terms of education level (Whyte et al. 2018), height (Hitsch et al. 2010a), and socioeconomic status (Abramova et al. 2016).

[6] The field experiment was internally approved by the corporate partner after considering the potential benefits and minimal harm to the users and follows the terms of service of the mobile application. The company executed the field experiment and provided the research team with the deidentified secondary data from transactional databases and event logs for analyses.

[7] For example, the questions can be related to dating preferences (e.g., what are you looking for in a relationship?), personal interests (e.g., what is your favorite movie and why?), personal experience (e.g., what was your most memorable experience last year?), and future outlook (e.g., what is your dream life?).

[8] The randomization was performed at the user level, using an industry-leading randomization system provided by ByteDance.

[9] Note that the field experiment was the only A/B test running on this version of the application, which ensures that there is no treatment contamination due to other experiments.

[10] Note that a subject observes the treatment text only in others' profile pages and does not observe any change in his or her own profile, as a user's own profile interface does not directly display the Q&A section as seen by peers.

[11] The demand information shown in the experiment, that is, the number of requests in the past 30 days, is dynamic in nature. If a subject joined the platform less than a month before the start of the experiment, the demand information contains the number of requests in their entire user tenure until they are more than 30 days since registration.

[12] Note that our measure of matches does not include the possibility that a small number of requests may have been accepted after our period of study.

[13] It is important to note that we only observe matches that are realized during our two-week period of observation. It is possible that some matches ultimately did occur after our period of observation for requests that were issued here.

[14] The vertical threshold line we placed on the graph is at 9.5 on the x-axis.

[15] It is perhaps worth restating here that our tap-stream analysis incorporating a peer profile fixed effect (referenced immediately above) yields significant treatment effects among male users, even for the basic treatment involving only quantitative demand information.

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