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Trust and Disintermediation: Evidence from an Online Freelance Marketplace

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Abstract

As an intermediary improves trust between two sides of its market to facilitate matching and transactions, it faces an increased risk of disintermediation: with sufficient trust, the two sides may circumvent the intermediary to avoid the intermediary's fees. We investigate the relationship between increased trust and disintermediation by leveraging a randomized control trial on a major online freelance marketplace. Our results show that enhanced trust increases the chance for high-quality freelancers to be hired. When the trust level is sufficiently high, however, it also increases disintermediation, which offsets the revenue gains from the increase in the hiring of high-quality freelancers. We also identify heterogeneity across clients and freelancers in their tendencies to disintermediate.

Keywords: Disintermediation, Intermediary, Trust, Online Marketplace

JEL Codes: L14, L86, O33

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"*We worry about this problem [disintermediation] every single day. Once a consumer builds a relationship with a local shop, we figure that consumer will not use Openbay anymore, and will go directly to the shop.*" [1]

— Rob Infantino, founder and CEO of Openbay, an online marketplace for auto repair

"*Maybe our retention was a lot better, but it was retention off the platform.*"[2]

— Former employee of Homejoy, an online marketplace of home service providers

1 Introduction

Intermediaries are everywhere in our economy, including brokers in the finance and insurance industry, headhunters in the labor market, distributors in retail, housing agents in real estate, and online platforms in the information technology industry. It has been estimated that intermediaries contribute 34% of the US gross domestic product as of 2010 (Spulber 2011). Economists have long recognized the importance of intermediaries in providing matching and facilitating transactions (e.g., Parker and Van Alstyne 2005; Armstrong 2006; Rochet and Tirole 2006; Edelman and Wright 2015; Hagiu and Wright 2015). In the meantime, all intermediaries face the risk of disintermediation—the action of the two sides circumventing an intermediary to transact directly to avoid the intermediary's fees.[3]

Disintermediation is prevalent. Traditional book publishers' role as an intermediary was weakened as Amazon enabled authors to sell directly to readers through its self-publishing services.[4] Li & Fung, a supply chain management company that connected global retail brands with Chinese manufacturers, suffered from

[1] Source: 2017 Digital Transformation Summit, Harvard Business School, Boston, MA, April 2017.

[2] "What really killed Homejoy? It couldn't hold on to its customers." *Forbes.* https://www.forbes.com/sites/ellenhuet/2015/07/23/what-really-killed-homejoy-it-couldnt-hold-onto-its-customers/#6c2905991874, accessed December 2017.

[3] The intermediary may charge a subscription fee and/or a transaction fee. In both cases, disintermediation can occur when users transact directly and stop paying the intermediary after they are matched.

[4] "Amazon signs up authors, writing publishers out of deal." *New York Times*. http://www.nytimes.com/2011/10/17/technology/amazon-rewrites-the-rules-of-book-publishing.html, accessed December 2017.

continuous revenue decline as retailers disintermediated to work with manufacturers directly.[5] Online platforms such as Homejoy went out of business because their consumers transacted with service providers outside the platforms. Despite the importance of disintermediation for firms' strategies and survival, there is scant literature on the issue, perhaps because of the difficulty of observing and measuring disintermediated transactions.

We study the relationship between trust and disintermediation, leveraging a randomized control trial on an online platform. We also take advantage of the conversations recorded online to provide direct evidence of users' intention to disintermediate. A number of studies have shown that building trust is crucial for platforms to facilitate matching among users (e.g., Resnick and Zeckhauser 2002; Cabral and Hortaçsu 2010). Significant trust, however, can also reduce the platform's importance in facilitating transactions through services such as monitoring transactions, escrow payment, dispute settlement, and refunds for failed transactions (e.g., Edelman and Hu 2016). Feeling less need for such services, users who trust each other are incentivized to take their transactions off the platform to avoid the fees. Under this disintermediation risk, it is therefore unclear whether it is always optimal for platforms to build more trust.[6]

We leverage a randomized control trial on a large online freelance marketplace examine how enhanced trust affects disintermediation and the platform's value capture. The platform enables clients to find freelancers who satisfy the clients' job requirements and provides features for the two sides to contract, collaborate, invoice, and pay. The platform charges a service fee of approximately 10% on each transaction's value. In the randomized control trial, the platform provider shows a random sample of clients the freelancers' Satisfaction Scores (SSs), a new measure of the reputation of a freelancer's business developed based on its complete work history on the platform. Our results show that enhanced trust

[5] "Hong Kong's Li & Fung faces dilemma of 'innovate or die'." *Financial Times*. https://www.ft.com/content/a8ffc290-1b69-11e7-bcac-6d03d067f81f, accessed December 2017.

[6] Many platform providers have policies to prevent disintermediation, but these are often difficult to enforce. See, for example, Airbnb's policy on user disintermediation (https://www.airbnb.com/help/article/199/what-should-i-do-if-someone-asks-me-to-pay-outside-of-the-airbnb-website, accessed December 2017) and TaskRabbit's policy on outside payment (https://support.taskrabbit.co.uk/hc/en-gb/articles/217904223-The-Spirit-of-Payments-on-the-TaskRabbit-Platform, accessed December 2017).

increases the chance for high-quality freelancers to be hired. But it also increases disintermediation between clients and freelancers with high SSs, as evidenced by significantly lower charges and hours reported for these jobs, and by the stronger intention to disintermediate expressed in chat messages between clients and freelancers. In the end, the increased disintermediation offsets the revenue gains from the increase in the hiring of high-quality freelancers. We also find that the tendency to disintermediate increases when users are geographically near each other, jobs are easily divisible, and clients themselves have high ratings. In the appendix, we also provide a stylized model of disintermediation and show that under certain conditions, increased trust could reduce a matching platform's profit through increased disintermediation.

Our study contributes to the literature on online reputation and user trust. Previous literature emphasizes the importance of user reputation for successful business transactions (e.g., Forman, Ghose, and Wiesenfeld 2008; Cabral and Hortaçsu 2010), the need to improve user reputation measures to improve transaction quality (Jin and Kato 2006; Kapoor and Tucker 2017), the design of online reputation systems to enhance trust among users (e.g., Resnick and Zeckhauser 2002), and how user reputation aggregated from past feedback affects platforms' demand and revenues (e.g., Reinstein and Snyder 2005; Dai et al. 2017). There is also literature on digital disintermediation and its economic impact on two-sided markets (e.g., Waldfogel 2012; Peukert and Reimers 2017). A few papers in the supply chain management literature also examine supplier encroachment as a form of circumventing the intermediary and selling directly to the market (e.g., Arya, Mittendorf, and Sappington 2007). However, the goal of disintermediation in this literature is to improve the overall efficiency of the value chain and has different causes than the disintermediation discussed in our paper. None of these studies discusses the potential drawback of increased trust.

2 Background and Study Design

Our empirical context is a major online freelance marketplace. A number of studies have examined the value of such platforms in online hiring (e.g., Agrawal, Horton, Lacetera, and Lyons

2013; Agrawal, Lacetera, Lyons 2016; Stanton and Thomas 2016) and for conducting experiments (e.g., Horton, Rand, and Zeckhauser 2011). Jobs posted on the platform cover a wide range of categories, such as Web, Mobile & Software Development, Design & Creative, Translation, Administrative Support, Accounting & Consulting, Writing, and Customer Service. At the time of the study, the platform charged freelancers a service fee of approximately 10% of the amount they billed a client. Disintermediation could take place in two ways. First, clients and freelancers can "chat" with each other any time on the platform. They may agree to take jobs off the platform to avoid the fee before they initiate any projects. Second, durative transactions allow them to try each other out on the platform and then disintermediate for the rest of the job to avoid the fee, especially when the transaction lasts for an extended period. The latter approach to disintermediation has two advantages: (a) clients can test freelancers' capabilities during the trial period and (b) clients and freelancers, having started out on the platform, can leave each other positive reviews after they mark the job as complete. Our study focuses on the latter scenario.

As soon as a client posts a job, a *job opening* is created, which typically includes a name, work description, requirements, and deadline. Any freelancer can submit a proposal to the client for the job. Once the client chooses a freelancer, the job is *filled* and a service contract (referred to herein as a *job assignment*) is created between them. A job assignment remains active until both sides agree to close it. Figure I illustrates the process flow of a typical job on the platform.

A job can be fixed-price or hourly. The price for a fixed-price job is negotiated and set between a client and a freelancer at the time of contracting; they can agree that the client will pay the total amount when the project is completed or will pay in stages according to agreed-upon milestones. For an hourly job, an hourly rate is decided at contracting; then the freelancer can start working on the job and record working hours manually or using time tracking software available through the platform. The client can verify the freelancer's invoices based on work-in-progress screenshots. When a payment occurs, the platform first charges the client and holds the payment in escrow. The client has four days to review and dispute the amount. After the dispute period ends, the escrow fund is released to the freelancer.

Since its founding, the platform has used a basic five-star rating system to reflect user satisfaction. When a project is finished, the client and the freelancer are asked to review each other. Both clients and freelancers have a five-star rating, shown on their user profiles, that equals the average of all ratings received from closed jobs. That system has many shortcomings: First, the average ratings from clients' past reviews does not take into account jobs with no ratings, nor does it allow for older ratings and more recent ratings to be weighted differently (e.g., Dai et al. 2017). Second, ratings can be easily manipulated or face the issue of reciprocity and thus do not distinguish freelancers from each other enough to help identify high- versus low-quality freelancers (Nosko and Tadelis 2015). Finally, the five-star rating system tends to reward freelancers who complete many small and short-term projects but does not favor those who work on big and longer-term projects.

For these reasons, the platform designed a new measure of past client satisfaction called "Satisfaction Score" (SS), which offers a more complete picture of a freelancer's business. It incorporates multiple factors, including clients' feedback, jobs with disputes, jobs with no feedback, job sizes, and repeated jobs with the same clients. To avoid strategic manipulation by freelancers, the company does not disclose its implementation or the exact composition of the score. The goal of SS is to provide a more accurate reference to enable high-quality freelancers to stand out. Given SS's advantages over the five-star system, we expect a high SS to enhance the trust between clients and freelancers, thus increasing perceived value creation from transactions but also reducing the platform's value in facilitating transactions.

We leverage a randomized control trial that ran from February 13 to March 10, 2015 and included a random sample of registered clients on the platform. The sample size is around 3% of total registered clients and is sufficient to have enough job assignments in the treatment and control groups during the study period. Fifty percent of the sample is selected as the treatment group. When choosing a freelancer, those clients can observe both the SSs and the five-star ratings, whereas clients in the control group can only see the five-star ratings. Figure II shows user profiles shown to both groups of clients. In Table I, we compare the treatment and control clients' past transaction data in the six months before the study to ensure random assignment of clients into these two groups. The study design allows us to examine the causal effect that trust-building through SSs has on job outcomes.

3 Data and Variables

We collect all of the job openings and assignments created by all of the clients in the sample during the study period. 24,732 clients from the treatment group and 24,458 clients from the control group posted at least one job during that period. Dropping jobs that were not filled and observations in which the freelancer's SS was not available leaves a final sample of 33,561 job assignments. [7]

The outcome of interest is the amount of disintermediation. We take two new approaches to measuring it. As an indirect approach, we identify disintermediation using job outcomes that might imply jobs ending

[7] By design, an SS is only available after a freelancer has sufficient historical job data on the platform, usually after five projects or having worked with at least three clients. Freelancers with missing SSs appear the same to clients in the treatment and control groups and thus are not considered part of the study.

prematurely or with partial payment. We extract the working-hour data recorded by the freelancers' time-tracking software and denote the number of working hours for each assignment as *Hours*. For this variable, we have observations only for hourly jobs. Similarly, jobs having small payments could signal disintermediation if clients pay only a small amount during a trial period on the platform and conduct the rest of the transaction off the platform. We use *Total Charge* to represent the total amount paid once a job is closed.

As a direct approach, we quantify clients' and freelancers' intentions to disintermediate by leveraging the platform's keyword search of chat messages sent between them during the study period. The platform uses a text-analysis tool to detect sensitive words that imply disintermediation. The list of sensitive words together with their weights was developed by the company, using a large amount of data from past transactions. Over the years, the platform has refined its algorithm and the dictionary based on its data on actual disintermediation and its other trials in deterring disintermediation. Table II shows examples of the sensitive words and phrases. For each message associated with a given job assignment, we sum up the numeric values of sensitive words and use the maximum value among all messages as the disintermediation score for that assignment (*Disintermediation_Score*). Compared to approaches that add up sensitive words in all messages or that take an average of all messages, our approach has two advantages. First, users who communicate more are likely to use more sensitive words; our measure is independent of the frequency of communication. Second, because users typically express their desire to disintermediate in only a few sentences and hence not all messages are useful for detecting disintermediation, our approach allows us to focus on the messages that are most likely related to disintermediation. Out of the total of 33,561 assignments, 29,690 have historical messages, for which the platform tries to detect sensitive words that imply the users' intent to disintermediate. For job assignments whose messages have no sensitive words, *Disintermediation_Score* is 0; otherwise, it is a positive integer.

For each assignment, the dummy variable *Treated* equals 1 if the client is in the treatment group and 0 otherwise. In the study, the key factor that leads to different levels of trust between the treatment and control group clients is whether or not the freelancer's satisfaction score is revealed to the client. Figure III illustrates the distribution of satisfaction scores in the assignment sample. The treatment effect differs when the revealed satisfaction score is high compared to when it is low. While revealing a high SS shows that the freelancer is trustworthy and helps build trust, revealing a low SS may reduce a client's trust in the freelancer. To account for this difference, we create a dummy variable *SS_High*, which is 1 if SS ≥ 90%, since the platform explicitly informs its treated clients that an SS above 90% is considered "excellent."[8]

We also construct variables to capture heterogeneity across job assignments. Firstly, clients and freelancers in the same geographical location may have a lower cost of collaborating and making payments off the platform, and similar cultural backgrounds may allow them to build up trust more easily. Therefore, we create the dummy variable *Same_Country*, which equals 1 when the client's and the freelancer's user profiles show them to be in the same country, and equals 0 otherwise.

If a job is modular—that is, more likely to be divided into parts without affecting the overall quality of the outcome (e.g., Baldwin and Clark 2000)—the client may find it easier to offer a freelancer a part on the platform so that they can leave each other positive reviews, and then take the rest off the platform. We therefore expect the impact of a high SS to be greater for such jobs. Two types of job are considered more divisible than others: (a) hourly jobs and (b) fixed-price jobs with more than one hired freelancer. We compute the percentage of such jobs in each of the platform's 13 job categories and rank the categories by that percentage from high to low; the percentages range from 54% to 95%. We create dummy variables to put all job categories into three groups based on the extent to which the jobs are *divisible*: the *Divisible_High* = 1 group, the *Divisible_Med* = 1 group, and the baseline group. *Divisible_High* equals 1 for the three categories with a percentage of divisible jobs in the top 10% of the divisibility distribution: Customer Service, Sales & Marketing, and Accounting & Consulting. The baseline group includes the least-divisible job categories, whose percentage of divisible jobs is in the bottom 10% of the distribution: Translation, and

[8] As a robustness check, we replace the threshold for *SS_High* with 75%. All our findings still hold. The use of this dummy variable allows us to take the non-linear effect of SSs into account.

Design & Creative. For the rest of the categories whose divisibility is between the top and the bottom 10% of the distribution, *Divisible_Med* equals 1.

Because jobs that last for a long time cost a large amount of money and generate the most value to the platform, they face the highest risk of disintermediation because clients and freelancers have the most incentive to cut the job and transact off the platform. Therefore, we use the expected job duration, which ranges from “less than 1 week” to “more than 6 months” and is chosen by the client when posting the job, to create a dummy variable called *Long_Term*. The expected job duration is self-reported and is optional regardless of the job type. For any job that has an expected duration, *Long_Term* equals 1 when the expected duration is more than six months and equals 0 when it is no more than six months.

Lastly, we test how client reputation might affect the tendency to disintermediate. Freelancers may be more willing to disintermediate with a trustworthy client. Using a client’s past transactions and corresponding five-star rating feedback, we compute the fraction of five-star jobs in each client’s job history, and create the dummy variable *Client_Rating_High*, which equals 1 when that fraction is higher than the median for all clients and 0 otherwise.

3.1 Summary Statistics

Table III provides summary statistics for all variables. The unit of analysis is a job assignment. The average SS in our sample is 0.739 and the mean for *SS_High* is 0.364, meaning that 36.4% of the freelancers hired by the clients have an SS of 90% or higher. The two indirect measures for disintermediation, *Hours* and *Total_Charge*, have substantial variation across job assignments and are highly skewed, so we use their logarithms in our regression analysis.

Table IV compares the three key dependent variables for the treatment and control groups after the treatment. We partition our sample by *SS_High*. After the treatment, the values of the three dependent variables for high-SS assignments differ significantly between the treatment and control groups. The treated job assignments have fewer total hours, lower total charges, and higher disintermediation scores, all suggesting a greater likelihood of disintermediation. For low-SS assignments, we observe no significant differences in the three dependent variables between the two groups.

4 Empirical Results

4.1 Job Fill Rates and Platform Revenue

We first analyze the impact of disclosing satisfaction scores on the job fill rate and on the platform's revenue. We begin by comparing the job fill rate for all job openings posted by clients in the treatment versus the control group. We denote the ratio of the total number of filled jobs for a group during the study period to the total number of job openings for that group as the *Fill Rate*. We also calculate the number of days before a job opening is filled. We find that, despite the slight difference in the fill rates between hourly and fixed-price jobs, there is no significant difference between the treatment and control groups in either their job fill rates or the number of days to fill job posts. In addition, a similar number of jobs were posted for each group, with the treatment group clients posting only 1.3% more jobs than the control group clients, which is not statistically significant. The number of days to fill is 0.48% shorter for the treatment group than the control group, and the fill rate difference is 0.51%; neither of the differences in these two measures is statistically significant between the two groups.[9] These results show that revealing SSs does not appear to have a significant effect on job postings or job fill rates, which is consistent with the result from our model in the appendix that when there is a sufficient number of freelancers, job fill rates will not change with better reputation measures.

Next, we investigate whether revealing SSs affects high- versus low-quality freelancers' probabilities of being hired. We obtain data on all freelancers who submitted proposals for the jobs posted by clients in the study. Simple summary statistics of the portion of high-SS freelancers hired in the treatment and control groups show that the percentage of high-SS freelancers hired in the treatment group is 4.1% higher than

[9] The actual values of the measures are not reported, as requested by the company, to protect the company's data confidentiality.

that in the control group. Then, we use a linear probability model regressing a *Hired* dummy on *SS_High*, *Treated*, and the interaction between them. The regression results in Table V show that (a) from Model (1), freelancers with higher SSs are significantly more likely to be hired than freelancers with low SSs, whereas whether the client is in the treatment or control group has no significant impact on the freelancer's chance of being hired, and (b) from Model (2), revealing SSs significantly increases a high-quality freelancer's chance by 0.48% on a base of 2.8%. Thus, revealing SSs benefits high-quality freelancers in this market.

Finally, we examine the impact of the treatment on the platform's revenue from job assignments created during the experiment. The results of the two-sample t-test show that the average revenue from each job does not significantly change for the treatment group compared to the control group (the ratio between treatment group and control group is 0.996). This result holds regardless of job type. We also checked the percentage of "Successful" jobs— jobs that were completed with no abnormal endings such as "Inactivity," "No response," or "Cancelled"— for the two groups, and found that there is only a 0.41% difference in the percentages of successful jobs, which is not statistically significant. Overall, there is no evidence that introducing SSs generates additional revenue for the platform.

These findings raise an interesting question: while SSs lead to more hires of higher-quality freelancers, who often command higher prices (in the control group the average total charge from a job involving a high-SS freelancer is 2.23 times that of a job involving a low-SS freelancer), and with the same job fill rate, why doesn't the platform earn more revenue? We next provide evidence that disintermediation is a key factor offsetting the potential gain.

4.2 Evidence of Disintermediation

We investigate whether treated clients are more likely to disintermediate when freelancers' SSs are high, with the following difference-in-differences regression specification:

$$Y = \beta_0 + \beta_1 Treated + \beta_2 SS\_high + \beta_3 Treated \times SS\_high + \varepsilon. \quad (1)$$

The unit of analysis is the job assignment. Table VI reports the regression results. *Log(Hours)* is the dependent variable in Models (1) and (2). We find from Model (1) that, on average, treated jobs take fewer working hours and jobs with high-SS freelancers take more hours. Model (2) includes the interaction variable and shows that the treatment of revealing a freelancer's SS reduces the hours needed for high-quality freelancers to finish the job by 14.3% for the treatment group relative to the control group.

In Models (3) and (4), we use *Log(Total_Charge)* as the dependent variable and find similar results. Revealing a high-quality freelancer's SS to the client decreases the amount the client spends on the assignment by 8.6% relative to the control group.

We also use a direct text-analysis measure as a third indicator for disintermediation. In Models (5) and (6), we use *Log(Disintermediation_Score)* as the dependent variable. We find that when clients can observe freelancers' SSs, they are significantly more likely to disintermediate if the freelancer has a high SS.

Overall, the evidence suggests that increased trust could lead to more disintermediation. As a result, although SS makes clients more likely to work with high-quality freelancers, the expected revenue increase could be canceled out by disintermediation. We perform a back-of-the-envelope analysis to estimate the revenue loss due to disintermediation. If the treatment were rolled out to our control group as well as to the treatment group, the control group's percentages of high- and low-SS freelancers hired—31.4% and 68.6%, respectively—would switch to the treatment group's 35.5% and 64.5%. In other words, the proportion of high-quality freelancers hired by the control group would go up by 4.1% (35.5% - 31.4%). Also, the average total charge from a high-SS-freelancer job in the control group is 2.23 times that of a low-SS-freelancer job in the control group, so replacing one low-SS-freelancer job with one high-SS-freelancer job in the control group would increase the job's total charge by 223% - 1 = 123%. Putting all of this together, the hypothetical rollout of SSs to all clients would create 4.1% more high-SS-freelancer jobs, each generating 123% more revenue, so total revenue should have increased by roughly 123% × 4.1% = 5.0% from revealing SS—if it were not offset by disintermediation. Notice that, even in the control group, there is already some level of disintermediation. Our estimated revenue loss is just the additional revenue loss because of more disintermediation on top of the baseline disintermediation.

4.3 Heterogeneous Tendencies to Disintermediate

We now examine a variety of factors that might affect the tendency to disintermediate:

Geographical proximity. When the client and freelancer are in the same country, they tend to have similar cultural backgrounds that allow them to build up trust more easily than those in different countries. Proximity also reduces their cost of collaborating outside the platform, since they may have many other convenient channels for payment. Hence, the impact of SSs on disintermediation should be higher for jobs involving clients and freelancers from the same country.

Model (1) of Table VII reports the regression results, using our direct measure, the logarithm of *Disintermediation_Score*, as the dependent variable and including *Same_Country* as the moderator.[10] The coefficient for the three-way interaction suggests that clients and high-quality freelancers in the same country are indeed more affected by the treatment.

Job divisibility. The tendency of disintermediation may also vary for different job categories. Some job categories are by nature modular and can be divided into independent parts. It is easier to perform part of such a job on the platform and then complete it off the platform without jeopardizing the overall integrity of the task. We thus expect the impact of treatment to be greater for more divisible jobs.

Model (2) of Table VII reports the results. As expected, the increase in disintermediation scores for treated clients who hired high-quality freelancers is greater for divisible jobs.

Expected duration. Since large jobs that last for a long time tend to cost the most while also generating the most platform revenue, clients and freelancers have more incentive to disintermediate on such jobs. Therefore, we expect to see that, if a job is *Long-Term*, there should be a greater impact of the treatment than for short-term jobs.

From Model (3) of Table VII, we can see that long-term jobs indeed have a significantly higher disintermediation score for treated clients and high-quality freelancers compared to short-term jobs.

[10] The results when using the two indirect measures, *Log(Hours)* and *Log(Total_Charge)*, as the dependent variables are qualitatively similar.

Client rating. Having seen that the disintermediation tendency varies with the freelancers' business reputation, we investigate whether it also varies with the clients' reputation. We expect that, given the same SSs, freelancers tend to trust highly-rated clients more and are therefore more willing to take the job off the platform.

We repeat the analysis using *Client_Rating_High* as the moderator and report the results in Model (4) of Table VII. We find that when both freelancer and client are trustworthy, revealing more information about the freelancer's business reputation encourages users to build up trust on the platform and boosts their willingness to work off the platform.

We also examined the client's size as a factor that leads to a heterogeneous tendency of disintermediation on the platform, based on self-reported client size data. As clients who hire for large companies are usually less concerned about cost and more concerned about quality, they tend to place more value on the platform's role in facilitating transactions and thus have less incentive to disintermediate, even with trustworthy freelancers. We expect individual clients or clients who post jobs for smaller companies to be more sensitive to job cost than clients who post jobs for companies with more than the median number of employees in our sample. We do not find significant results, although the sign of the three-way interaction is in the expected direction. The lack of significance could be due to insufficient data, since the information on firm size is self-reported and is missing for 97.4% of the jobs in our sample. But it could also be that since the service fee is a fixed percentage of the transaction value and can become substantial for large jobs, large clients may find the savings from disintermediation attractive.

5 Robustness Checks

5.1 Contamination between the Treatment and Control Groups

As in other field experiments, contamination between the treatment and control groups could be a concern. In our setting, treated clients may be better able to target high-quality freelancers, so that the control clients may face a worse pool of prospective job applicants. We may thus overstate the treatment effect when we compare the quality of freelancers hired by clients in the two groups. This concern is mitigated by two factors. First, the total number of clients in the trial constitutes only 3% of all clients on the platform. Second, the platform has substantially more freelancers than clients. Indeed, the job fill rates of the two groups are not different. We also conduct a t-test to compare the mean SSs of freelancers who *apply* to job posts in each group. We find that there is no significant difference between the SSs of applicants in the treatment group and in the control group (p=0.49).

5.2 Selection of Freelancers

Prior to the availability of SS, clients may use price as a quality signal and choose freelancers who charge more. But with SS available, clients may also choose freelancers who have a high SS but charge less because these freelancers are more efficient and can finish their jobs faster. While this story does not explain our results based on *Disintermediation_Score*, it is consistent with our results that jobs with high-SS freelancers in the treatment group take less time and cost less.

To test this alternative explanation, we calculate, for each freelancer, the average number of job hours and average total charge for all assignments during the six months prior to the study; we denote these as *Past_Hours* and *Past_Total_Charge*. We then repeat our analysis in Models (1) through (4) of Table VI, with the logarithms of *Past_Hours* and *Past_Total_Charge* as dependent variables. If high-SS freelancers are hired because they can work more efficiently and therefore charge less, we should still observe this difference between the treated and the controlled high-SS freelancers prior to the study.

Table VIII reports the results. We find that high-SS freelancers hired by treated clients during the study do not appear to work faster or charge less than high-SS freelancers in the control group prior to the study. This result boosts our confidence that the changes in these outcomes during the study are caused by greater disintermediation.

5.3 Client Satisfaction with High-SS Freelancers

Another potential explanation is that high SSs may raise the treated clients' expectations of the freelancers, and the clients may therefore end jobs prematurely and pay less as a result of dissatisfaction rather than of disintermediation.

To test this alternative explanation, we collect data on the clients' ratings of the freelancers after each job assignment in our sample. The number of jobs for which the client did not leave any feedback is similar for both the treatment group (30.1%) and the control group (29.8%). We replicate the analysis in Table IV, replacing the dependent variable with the client rating of each assignment. Table IX shows that neither the coefficient for being in the treatment group in Model (1) nor the coefficient of the interaction term in Model (2) is statistically significant. Thus, our findings are not driven by inferior job quality or by reduced client satisfaction with high-SS freelancers' work.

5.4 Clients' Strategic Choice of Job Type

After observing SSs, clients interested in disintermediation might strategically select hourly jobs, as they are more conducive to disintermediation. We test this using data on clients' job openings and running several t-tests to compare the number of hourly versus fixed-price jobs clients posted over time.

Overall, the distribution of job types is different (p=0.029) between the treatment and control groups, with clients in the treatment group posting a slightly larger portion (1.2% higher) of hourly jobs than clients in the control group. We split the job opening sample into a subsample of clients' first job posts and a subsample of the rest of the job posts, and then repeat the comparison for each subsample. We find no difference (p=0.986) in the distributions of job types between the treatment and the control groups in the subsample of clients' first jobs. But there is a significant difference (p=0.0004) for the subsample of the rest of the job posts: the percentage of hourly jobs posted was 3.5% higher for the treatment group. This suggests that while treated clients do not appear to take SSs into account when they post their first job (as most become aware of SSs when they review proposals for their first job posts), they are more likely to post hourly jobs afterwards. The results are consistent with the explanation that treated clients on average are more inclined to disintermediate.

6 Discussion and Conclusion

Our study provides empirical evidence that when a platform owner seeks to capture value from facilitating matching and transactions, enhancing trust among its users is not always beneficial because it may encourage disintermediation. We also identify a number of factors that make users more likely to disintermediate, including geographic proximity and job divisibility.

This study has two important limitations. First, we examine only one type of disintermediation. In reality, there are other ways that users can disintermediate an online platform. For example, a user can use a platform to find an ideal match, then directly contact the other party without ever starting a transaction on the platform. In the study, the fill rate does not significantly decrease for the treated clients, but this type of disintermediation could happen more frequently in other settings. A user may also complete one transaction on a platform, then take all future transactions with that party off the platform. These possibilities suggest that we may have underestimated the effects of disintermediation. Future research can examine these kinds of disintermediation.

Second, our study looks only at the short-term effect of building trust. As more users realize the benefits of disintermediation, the negative effects of enhanced trust on platform revenue could increase. On the other hand, rolling out an improved reputation measure may encourage more new users to join the platform, thus leading to revenue gain in the long run.

Future research can also evaluate various ways for platform owners to combat disintermediation, such as by warning users of potential violation of terms of service when they detect disintermediation, and providing additional services to facilitate transactions so that users are less willing to disintermediate.

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Table I: Comparison of Clients in the Treatment and Control Groups before the Study

Outcome variable	Treatment		Control		Paired t-test
	Mean	Standard error	Mean	Standard error	t-stats
# of days on the platform	611.17	4.62	605.03	4.63	-0.94
# of jobs in the past 6 months	2.60	0.09	2.73	0.15	0.76
Avg. past job feedback	4.81	0.01	4.81	0.01	0.55
Avg. past job hours	12.62	0.41	13.05	0.44	0.71
Avg. past job total charge	197.00	7.77	185.55	5.31	-1.21

Notes. The unit of analysis is a client in the treatment/control group. Variables are calculated using a past assignment sample including participating clients' job outcomes in the 6 months before the study. None of the above paired t-test results is significant. We also checked the percentage of hourly jobs across the two groups and found no significant difference; the numbers are unreported due to protection of confidentiality.

Table II: Examples of Sensitive Words/Phrases Indicating Disintermediation in Messages

off (the platform's name)	Paypal	Venmo
wire me/you/us	avoid fees	apply at/here
outside (the platform's name) / outside of (the platform's name)		
save 10% (or 5%) / save 10 (or 5) percent / save ten (or five) percent		
(my/your/our) (phone / number / phone number / cell phone)		

Table III: Summary Statistics

Variable	Observations	Mean	Std. dev.	Min	Max
Treated	33,561	0.504	0.500	0	1
SS	33,561	0.739	0.258	0	1
SS_High	33,561	0.364	0.481	0	1
Hours	14,593	109.00	349.0	0.183	11365.38
Total_Charge	33,561	679.507	4198.7	0	195731.5
Disintermediation_Score	29,690	7.547	5.653	0	34.1
Same_Country	29,690	0.080	0.272	0	1
Divisible_High	29,690	0.110	0.312	0	1
Divisible_Med	29,690	0.617	0.486	0	1
Long_Term	12,118	0.405	0.491	0	1
Client_Rating_High	29,690	0.534	0.499	0	1

Notes. Number of observations for the main analysis sample is 33,561, except for regressions with *Disintermediation_Score*, which has a non-missing value for 29,690 observations. *Hours* has values only for hourly jobs. *Long_Term* includes only jobs with information on the expected duration.

Table IV: Comparing Treatment and Control Group Observations after Treatment

Outcome variable	Treatment		Control		Paired t-test
	Mean	Standard error	Mean	Standard error	t-stats
Assignments with high freelancer SSs:					
Log(Hours)	2.95	0.04	3.09	0.04	2.80***
Log(Total_Charge)	4.67	0.02	4.76	0.03	2.61***
Log(Disintermediation_Score)	1.77	0.01	1.71	0.01	-3.56***
Assignments with low freelancer SSs:					
Log(Hours)	2.67	0.03	2.67	0.03	0.09
Log(Total_Charge)	4.26	0.02	4.26	0.02	0.10
Log(Disintermediation_Score)	1.84	0.01	1.83	0.01	-1.47

Notes. The unit of analysis is a job assignment from a treatment/control group client during the study. Variables are calculated using the assignment sample for our main analysis. All the paired t-test results in the high-SS group are significant. *** significant at 1%.

Table V: Logistic Regressions of the Treatment Effect on Freelancers' Probability of Being Hired

Model	(1)	(2)
Dependent variable	Hired	Hired
Treated	0.0004	-0.0012***
	[0.0004]	[0.0004]
SS_High	0.0079***	0.0049***
	[0.0004]	[0.0006]
Treated x SS_High		0.0060***
		[0.008]
Observations	895,882	895,882
R-squared	0.0004	0.0005

Notes. The unit of analysis is an application to a job posted by the treatment/control group client during the study. The mean for the dummy variable *Hired* is 0.029; the standard deviation is 0.169. Robust standard errors in brackets. *** significant at 1%.

Table VI: Difference-in-differences Regressions on the Treatment Effect of High SSs on Disintermediation

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Log(Hours)	Log(Hours)	Log(Total_Charge)	Log(Total_Charge)	Log(Disintermediation _Score)	Log(Disintermediation _Score)
Treated	-0.058*	-0.003	-0.034*	-0.002	0.033***	0.018
	[0.030]	[0.037]	[0.019]	[0.024]	[0.010]	[0.012]
SS_High	0.348***	0.422***	0.455***	0.499***	-0.090***	-0.112***
	[0.032]	[0.046]	[0.021]	[0.030]	[0.010]	[0.015]
Treated x SS_High		-0.143**		-0.086**		0.041**
		[0.064]		[0.041]		[0.021]
Observations	14,593	14,593	33,561	33,561	29,690	29,690
R-squared	0.009	0.009	0.015	0.015	0.003	0.003

Notes. Observations are all the job assignments created during the study period. The sample in Column (1) contains only hourly jobs. The sample in Column (3) contains only observations with non-missing disintermediation scores. *SS_High* is defined as the freelancer having a Satisfaction Score greater than or equal to 0.9 at the time of the study. *Treated*, a dummy variable for treatment at the client level, equals 1 if the client is in the treatment group. *Log(Hours)* is the logarithm of the number of hours the freelancer worked on the assignment. *Log(Total_Charge)* is the logarithm of the total amount of money charged at the end of the assignment plus 1. *Log(Disintermediation_Score)* is the logarithm of the disintermediation score computed from all messages associated with the assignment plus 1. Robust standard errors in brackets. *significant at 10%; ** significant at 5%; *** significant at 1%.

Table VII: Heterogeneity in Disintermediation Tendencies

Model	(1)	(2)	(3)	(4)
Treated	0.019	0.006	0.025	0.063***
	[0.013]	[0.023]	[0.023]	[0.017]
SS_High	-0.089***	-0.126***	-0.088***	-0.103***
	[0.015]	[0.028]	[0.028]	[0.021]
Treated x SS_High	0.027	-0.026	-0.016	0.001
	[0.022]	[0.039]	[0.039]	[0.029]
Same_Country	-0.037			
	[0.032]			
Treated x Same_Country	-0.013			
	[0.046]			
SS_High x Same_Country	-0.220***			
	[0.051]			
Treated x SS_High x Same_Country	0.131*			
	[0.075]			
Divisible_Med		0.079***		
		[0.019]		
Divisible_High		0.243***		
		[0.030]		
Treated x Divisible_Med		0.011		
		[0.028]		
Treated x Divisible_High		0.022		
		[0.042]		
SS_High x Divisible_Med		0.011		
		[0.034]		
SS_High x Divisible_High		0.071		
		[0.052]		
Treated x SS_High x Divisible_Med		0.095**		
		[0.047]		
Treated x SS_High x Divisible_High		0.121*		
		[0.072]		
Long_Term			-0.114***	
			[0.026]	
Treated x Long_Term			-0.038	
			[0.037]	
SS_High x Long_Term			-0.042	
			[0.046]	
Treated x SS_High x Long_Term			0.134**	
			[0.063]	
Client_Rating_High				-0.132***
				[0.017]
Treated x Client_Rating_High				-0.089***
				[0.024]
SS_High x Client_Rating_High				-0.020
				[0.029]
Treated x SS_High x Client_Rating_High				0.079*
				[0.041]
Observations	29,690	29,690	12,118	29,690
R-squared	0.005	0.014	0.009	0.013

Notes. The dependent variable in this table is *Log(Disintermediation_Score)*. Observations are the job assignments created during the study with non-missing disintermediation scores. Model (3) includes only jobs with information on the expected duration. Robust standard errors in brackets. *significant at 10%; ** significant at 5%; *** significant at 1%.

Table VIII: Difference-in-differences Regressions on the Treatment Effect of High SSs on Disintermediation, Using Pre-treatment Data

Model	(1)	(2)	(3)	(4)
Dependent variable	Log(Past_Hours)	Log(Past_Hours)	Log(Past_Total_Charge)	Log(Past_Total_Charge)
Treated	0.012	0.013	-0.007	0.006
	[0.020]	[0.022]	[0.017]	[0.020]
SS_High	0.404***	0.406***	0.607***	0.624***
	[0.022]	[0.032]	[0.019]	[0.026]
Treated x SS_High		-0.005		-0.035
		[0.044]		[0.037]
Observations	24,848	24,848	31,825	31,825
R-squared	0.015	0.015	0.035	0.035

Notes. Observations are the job assignments in the main analysis with job outcomes replaced by each freelancer's average past job outcome in the 6 months before the study. There are 33,561 assignments from the study; 31,825 involve a freelancer with at least one previous job in the past 6 months and 24,848 involve a freelancer who worked on an hourly job in the past 6 months.

SS_High and *Treated* are defined as in Table IV. *Log(Past_Hours)* is the logarithm of the average number of hours the freelancer worked on each assignment in the past 6 months. *Log(Past_Total_Charge)* is the logarithm of the freelancer's average total charge per assignment in the past 6 months plus 1. Robust standard errors in brackets. *** significant at 1%.

Table IX: Difference-in-differences Regressions on the Treatment Effect of High SSs on Client Ratings of Freelancers

Model	(1)	(2)
Dependent variable	Client_Rating	Client_Rating
Treated	-0.001	-0.006
	[0.008]	[0.011]
SS_High	0.102***	0.094***
	[0.007]	[0.011]
Treated x SS_High		0.016
		[0.015]
Observations	23,501	23,501
R-squared	0.007	0.007

Notes. Observations are the job assignments in the main analysis with non-missing client feedback. *SS_High* and *Treated* are defined as in Table IV. *Client_Feedback* is the five-star feedback rating that the client left when the job assignment was closed. Robust standard errors in brackets. *** significant at 1%.

Figure I:

Job Process Flow

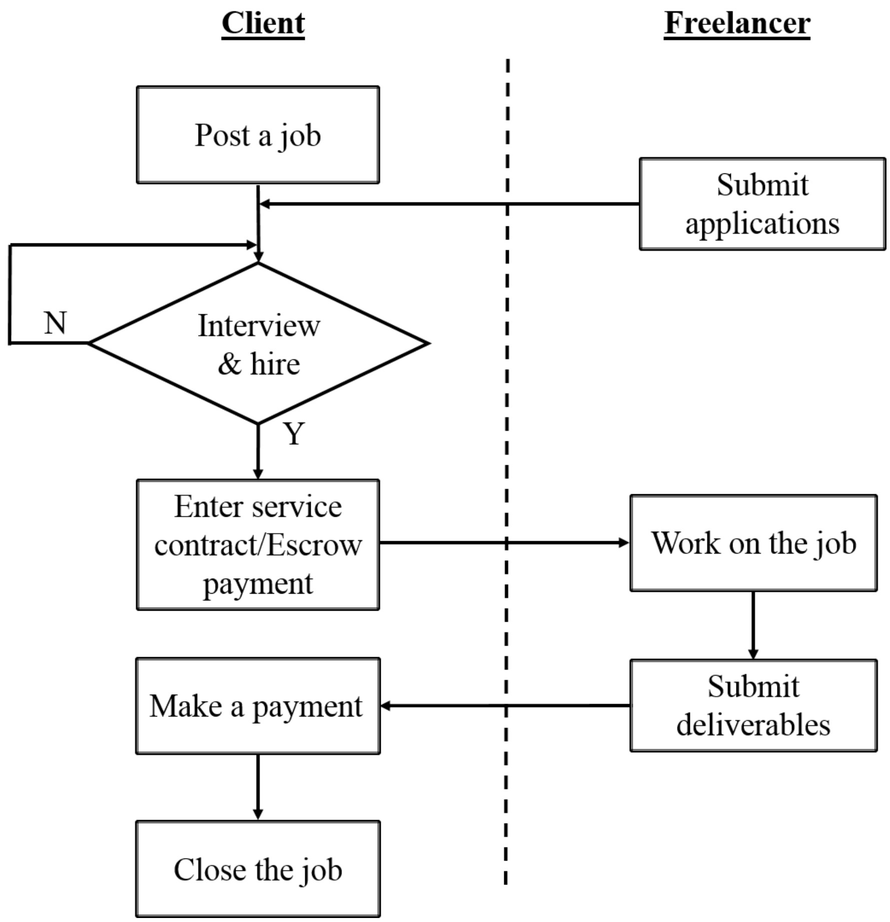


Figure II:

User Information Shown to Treatment and Control Groups

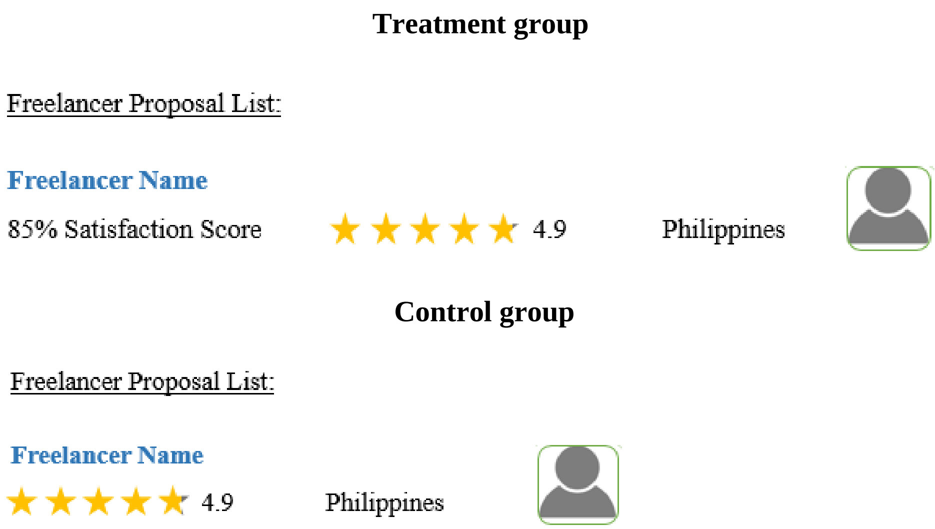
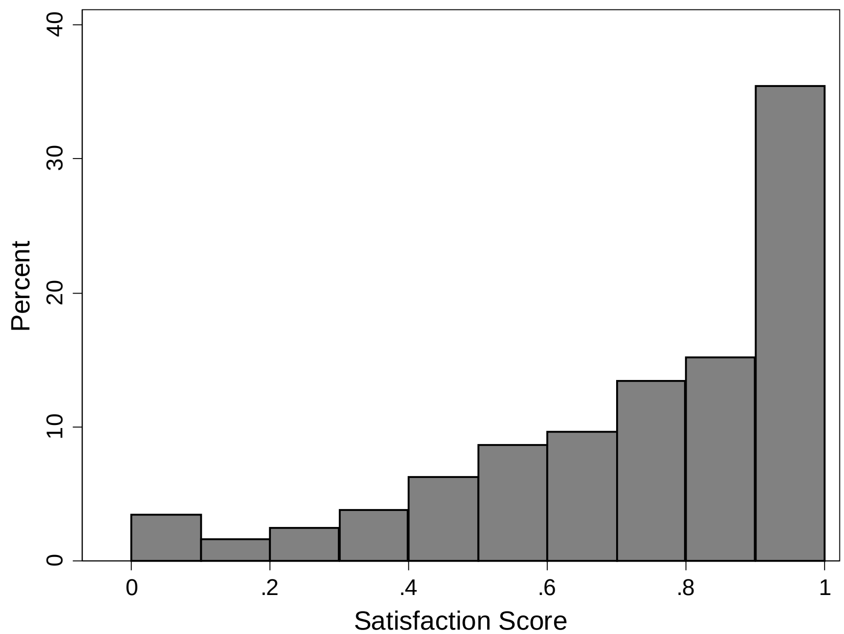


Figure III:

Distribution of Freelancer Satisfaction Scores



Appendix: A Simple Model of Disintermediation

We examine the simplest case of a market with N clients and M freelancers, with no reputation profiles on either side of the market, so that clients (or freelancers) cannot differentiate themselves from others. We next examine the case in which the clients are provided with the freelancers' rating information, so that each freelancer's service quality, q, is observable to the clients, with a fraction θ of the freelancers of type H providing high service quality q_H, and the remaining $1-\theta$ of type L providing low service quality q_L. We also assume that both N and M are large and that $N < M$. For each transaction, a freelancer's deliverables sometimes work successfully while at other times they fail to meet the requirements, and it is assumed that such "reliability," $r()$, where $r'(\cdot) > 0$ and $r''(\cdot) \leq 0$, is a function of the freelancer's quality q. Accordingly, the risk of breakdown for the freelancer's work is $1 - r(q)$. The platform charges clients a service fee of β as a percentage of the total charge for each transaction on the platform, which is deducted from the freelancer's earnings.

The platform enables clients and freelancers to find and transact with each other. Each freelancer chooses a "profile rate," p, as the price for delivering one job. All clients observe the freelancers' prices, choose which freelancer to transact with, and whether to transact on or off the platform. For simplicity, we assume that each client transacts with only one freelancer. A client that purchases a freelancer's service on the platform pays p immediately, β percentage of which is charged by the platform as the service fee while $1-\beta$ percent will go to the freelancer. The client then waits for the job outcome; and the job may fail with a probability of $1 - r(q)$. In case of breakdown, the platform provides a full refund of price p to the client.

In the case of disintermediation, however, while the client still pays $1-\beta$ percent of p to the freelancer, the two sides split the β percentage of service fee, with a portion α going to the freelancer and $1-\alpha$ going to the client, where $\alpha \in (0,1)$ is a constant known to everyone in the market. The client gets no refund if the job fails outside the platform. Meanwhile, regardless of whether the transaction is completed on or off the platform, the freelancer is always paid p before starting the work and hence is indifferent between disintermediating or not; it is the client who decides whether he or she would disintermediate with the freelancer.

In this simplest market, with no reputation profiles on either side, all freelancers price the same and all clients make the same purchasing decisions. The client's utility function is:

$$U_B(transact\ on\ platform) = r(\bar{q})(\bar{q} - p) \tag{A1}$$

$$U_B(transact\ off\ platform) = r(\bar{q})(\bar{q} - (1-\alpha\beta)p) - \big(1 - r(\bar{q})\big)(1-\alpha\beta)p\ , \tag{A2}$$

where $\bar{q}$ = E(q) is the freelancers' expected service quality, and all clients have the same expectation.

A freelancer's pricing is a profit-maximization problem with the constraint that the client's utility is non-negative. When the client and the freelancer transact online:

$$\begin{aligned} &\pi_s(transact\ on\ platform) = (1-\beta)p \\ s.t.\quad &r(\bar{q})(\bar{q} - (1-\alpha\beta)p) - \big(1 - r(\bar{q})\big)(1-\alpha\beta)p < r(\bar{q})(\bar{q} - p) \\ and\quad &r(\bar{q})(\bar{q} - p) \geq 0\ . \end{aligned}$$

The first constraint means that the client's utility from transacting online is greater than her utility from disintermediation. The second constraint is the client's participation constraint. Solving the above equations, we get:

$$\begin{aligned} &\beta < \frac{1 - r(\bar{q})}{\alpha} \\ and\quad &p \leq \bar{q}\ . \end{aligned}$$

Similarly, when the client and the freelancer transact off the platform:

$$\begin{aligned} &\pi_s(transact\ off\ platform) = (1 - \beta + \alpha\beta)p \\ s.t.\quad &r(\bar{q})(\bar{q} - (1-\alpha\beta)p) - \big(1 - r(\bar{q})\big)(1-\alpha\beta)p > r(\bar{q})(\bar{q} - p) \\ and\quad &r(\bar{q})(\bar{q} - (1-\alpha\beta)p) - \big(1 - r(\bar{q})\big)(1-\alpha\beta)p \geq 0\ . \end{aligned}$$

The first constraint means that the client's utility from transacting online is less than her utility from disintermediation. Solving the above equations, we get:

$$\beta > \frac{1-r(\bar{q})}{\alpha}$$
$$and \quad p \le \frac{r(\bar{q})}{1-\alpha\beta}\bar{q}\ .$$

The above results show that, when $\beta < \frac{1-r(\bar{q})}{\alpha}$, client and freelancer choose to transact online, given that the freelancer's price $p \le \bar{q}$. When $\beta > \frac{1-r(\bar{q})}{\alpha}$, the client and the freelancer choose to transact off the platform, conditional on the freelancer's price $p \le \frac{r(\bar{q})}{1-\alpha\beta}\bar{q}$. In the special case of $\beta = \frac{1-r(\bar{q})}{\alpha}$ and $p = \frac{r(\bar{q})}{1-\alpha\beta}\bar{q} = \bar{q}$, the client is indifferent between whether or not to purchase the freelancer's service, and is also indifferent between transacting on or off the platform.

The platform designs a service fee of β at an equilibrium such that: (a) clients are willing to transact online and (b) the service fee is high enough to maximize profit. The equilibrium service fee β is:

$$\beta = \beta^*(\bar{q}) = \frac{1-r(\bar{q})}{\alpha}\ . \tag{A3}$$

Therefore, in equilibrium, all clients are indifferent between transacting or not with any freelancer in the market, and have a 50% chance of disintermediation for each transaction. The overall job fill rate in the market is 1, and the chance for type H freelancers to be hired is $\min\{\frac{\kappa}{2\theta}, 1\}$, where $\kappa \equiv \frac{N}{M}$.

We next examine the case in which the clients are provided with the freelancers' rating information. The freelancers' and the platform's conditions are the same as in the previous case. The clients, however, need to pick one type of freelancer with whom to transact and must compete among a queue of clients to be accepted by the freelancer under the earlier assumption that each client or freelancer can make only one transaction.

We first investigate the client's acceptance rate with each type of freelancer. Assume that the probability for a client to hire a type j freelancer is $A_j,\ j \in H, L$. When a freelancer is matched with multiple clients, the choice will be random. Then the queue length for a type j freelancer is $X_j = NA_j$. Because we assume that each client sends out only one offer and can transact with only one freelancer, we have:

$$\theta X_H + (1-\theta) X_L = \kappa, \qquad \kappa \equiv \frac{N}{M}\ . \tag{A4}$$

The acceptance rate for a client when the freelancer faces a queue of clients is (Ke, Jiang, and Sun 2017):

$$B_j = \lim_{N\to\infty} \sum_{i=1}^{N-1}\left[\binom{N-1}{i} A_j^i \left(1-A_j^i\right)^{N-1-i} \frac{1}{i+1}\right] = \lim_{N\to\infty} \frac{1-\left(1-A_j\right)^N}{NA_j} \tag{A5}$$
$$= \frac{1-e^{-X_j}}{X_j}.$$

The intuition for Equation (A5) is that, conditional on the client offering to a type j freelancer, the probability that a type j freelancer faces a queue of i clients from all of the other $(N-1)$ clients is $\binom{N-1}{i} A_j^i (1-A_j^i)^{N-1-i}$. When competing with a queue of i other clients, the chance for this client to be accepted is $\frac{1}{i+1}$, as the freelancer will randomly select among all of the clients who have offered a job. The overall acceptance rate for the client when offering to a type j freelancer is therefore the sum of all probabilities for queue lengths from 1 to $N-1$, which yields the result. Notice that, when $X_j \to 0$, $\frac{1-e^{-X_j}}{X_j} \to 1$. This means that when there are no other clients offering to the type j freelancer, the acceptance rate B_j for this client becomes 1.

Transacting on versus off the platform. Now, we consider a client's decision to transact on or off the platform, given that a client decides to hire a freelancer. There are four options:

- If the client hires a type H freelancer and transacts on the platform:

$$U_B = B_H[r(q_H)(q_H - p)]\ . \tag{A6}$$

- If the client hires a type H freelancer and transacts off the platform:

$$U_B = B_H[r(q_H)q_H - (1-\alpha\beta)p]\,. \tag{A7}$$

- If the client hires a type L freelancer and transacts on the platform:

$$U_B = B_L[r(q_L)(q_L - p)]\,. \tag{A8}$$

- If the client hires a type L freelancer and transacts off the platform:

$$U_B = B_L[r(q_L)q_L - (1-\alpha\beta)p]\,. \tag{A9}$$

For a client to decide whether to transact on or off the platform, this means comparing either Equations (A6) and (A7) or Equations (A8) and (A9). Equivalently, this is to examine how β changes with q. Thus, the client's on-versus-off the platform decision is determined by the platform's service fee β.

Taking the first-order derivative of Equation (A3) gives us:

$$\beta^{*\prime}(\bar{q}) = -\frac{1}{\alpha} < 0\,. \tag{A10}$$

Because the first-order derivative of β^* with respect to q is always smaller than 0, $\beta^*(q_H) < \beta^*(\bar{q}) < \beta^*(q_L)$. Thus, under $\beta^*(\bar{q})$, which is the same service fee as in the previous scenario, clients who hire type H freelancers all transact off the platform, while clients who hire type L freelancers all transact on the platform.

Queuing decision. The last step is to analyze the client's queuing decision as to which type of freelancer to offer the job to. In equilibrium, we solve for the following set of equations:

$$\begin{cases} B_H[r(q_H)q_H - (1-\alpha\beta)p = B_L[r(q_L)(q_L - p)] \\ \theta X_H + (1-\theta)X_L = \kappa \\ B_j = \dfrac{1-e^{-X_j}}{X_j}, j = H, L. \end{cases} \tag{A11}$$

To solve for the client's queuing decisions X_H and X_L, we substitute in $\beta^*(\bar{q}) = \frac{1}{r(\bar{q})} - 1$, and simplify the right-hand side of the first equation in Equation Set (11) to:

$$B_H\left[r(q_H)q_H - r(\bar{q})\bar{q}\right] = B_L\left[r(q_L)q_L - r(q_L)\bar{q}\right], \tag{A12}$$

where $p = \frac{\bar{q}}{1+\beta} = r(\bar{q})\bar{q}$ and $\bar{q} = \theta q_H + (1-\theta)q_L$. However, as $r(q_H) > r(\bar{q}) > r(q_L)$, $B_H[r(q_H)q_H - r(\bar{q})\bar{q}] > 0 > B_L[r(q_L)q_L - r(q_L)\bar{q}]$ is always true, which means that the client's utility of hiring a type H freelancer is always greater than that of hiring a type L freelancer.

Therefore, in equilibrium, we have several observations. All clients choose to hire type H freelancers, and to transact off the platform. The probability of disintermediation in this model increases to 1 for clients who transact with high-quality freelancers. In reality, the rating information of freelancers cannot perfectly signal each freelancer's quality or risk of job breakdown. Therefore, in practice, we expect to see an increase in the probability of disintermediation in this scenario compared to that in which clients have no freelancer rating information. In addition, the overall job fill rate is $\min\{\frac{\theta}{\kappa}, 1\}$. When there are more high-quality freelancers than clients in the market—that is, when $\kappa < \theta, \kappa \equiv \frac{N}{M}$—the job fill rate equals 1, as in the simplest scenario we discussed earlier. Lastly, the chance for type H freelancers to be hired is $\min\{\frac{\kappa}{\theta}, 1\}$. Note that $\frac{\kappa}{\theta} > \frac{\kappa}{2\theta}$, which means that a high-quality freelancer's chance of being hired increases after the clients observe the freelancer ratings.

Combining these two scenarios brings out some interesting features that are consistent with our empirical results. First, with increased reputation information on the freelancer side, we should observe an increase in the probability of disintermediation. Second, we should also expect an increase in the probability of high-quality freelancers being hired when clients can observe their quality. Third, with many high-quality freelancers in the market, we expect the overall job fill rate not to change with increased reputation information on the freelancer side.