The Value of Platform Endorsement*

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Abstract

Many digital platforms with large product assortments endorse a select group of items to facilitate user choice. However, while it seems intuitive that such endorsement may increase the sales of endorsed items, little is known about its effect on unendorsed items, and on the platform. Using data from a field experiment conducted by an online freelance platform, we examine the effect of exposure to platform endorsement on user search and purchase behavior. We find that exposure to platform endorsement increases user search and purchases not only for endorsed services, but also for unendorsed services. We link the increase in search and purchases to an increase in the perception of the quality of services offered on the platform. We further explore heterogeneity in the effect of platform endorsement and find that the effect of exposure to platform endorsement on purchase is more pronounced for users with a higher propensity to purchase. We discuss implications for platforms, merchants, and regulators.

Keywords: Platform endorsement, field experiment, online freelance platform, spillover effects

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1 Introduction

The rapid growth of digital platforms and their increasingly large assortments mean that users searching for products or services online face an unprecedented number of options. While large assortments allow firms to meet the heterogeneous needs of a diverse group of users, they likewise present a challenge because a large number of options makes it more difficult for users to choose any option at all (Iyengar and Lepper, 2000). In order to facilitate choice and increase the probability that users purchase on the platform, many platforms have started endorsing a selected group of offerings. For example, Amazon endorses some products with a badge titled "Amazon's Choice" and Etsy indicates some products as "Etsy's picks."

Intuitively, platform endorsement may generate additional sales for endorsed items.[1] However, it is not clear how it impacts unendorsed items. Merchants are concerned that endorsing a selection of items may reduce sales of competing unendorsed items (Faherty et al., 2017).[2] This, in turn, has sparked concerns among policymakers about the anti-competitive nature of such practices.[3] Understanding the effect of platform endorsement on unendorsed items is also relevant for digital platforms themselves. Since platforms derive revenues from the sale of both endorsed and unendorsed items, they care about whether endorsement simply directs demand from unendorsed to endorsed items or increases overall sales. Lastly, merchants of both endorsed and unendorsed items wish to understand the benefits of endorsement as well as the risk of their sales cannibalization without it. Given the importance of understanding the effect of platform endorsement to digital platforms, merchants, and regulators, we investigate in this study the impact of platform endorsement on endorsed items, unendorsed items, and the platform as a whole.

[1] https://www.hostaway.com/tips-to-become-an-airbnb-superhost/

[2] https://www.modernretail.co/platforms/why-washington-wants-to-break/-up-amazon-explained/

[3] EU implemented platform-to-business regulations to address fairness concerns relating to situations where platforms' decision to make certain items more prominent can have consequences on merchants. See https://digital-strategy.ec.europa.eu/en/policies/platform-business-trading-practices

We focus on one of the world's largest online freelance platforms where freelancers post services and users search for freelancers to perform specific tasks (e.g., app development, graphic design, and translation). In a large-scale field experiment, the platform tested the effect of showing an endorsement badge on the search results page for a select number of services. The platform used a proprietary algorithm, unknown to both freelancers and users, to select high quality services for endorsement. Variables such as price, average rating, and the number of completed orders entered the algorithm. Users browsing the website were randomly assigned to either a treatment or a control group for the duration of the experiment. When treatment group users viewed an eligible service on the search results page, an endorsement badge would be displayed for this service, broadly similar to how Amazon presents its endorsement badge. Control group users did not see the badge. Except for the endorsement badge, all other aspects of service listings and search results, including the algorithm that ranks search results, were identical across the two groups.

Since the number of services qualifying for endorsement was limited and many search queries did not return a qualifying service, we focus on the average treatment effect on the treated (ATT). This means that we restrict our analysis to users who were exposed to at least one endorsed service in the treatment group and, in the case of the control group, to at least one service eligible for endorsement. However, we find that some user characteristics are no longer fully balanced between the control and treatment groups in the pre-treatment period. To ensure balance on users' pre-treatment characteristics between the two groups, we use inverse probability weighting (IPW) (Atefi et al., 2018; Azoulay et al., 2009, 2011) and further control for user characteristics in our regression.

We investigate the effect of exposure to platform endorsement on users' purchases as well as on search behavior. Our results show that exposure to platform endorsement greatly benefits endorsed services. It results in a 25.0% increase in clicks and a 40.6% increase in sales of endorsed services. Surprisingly, exposure to platform endorsement also increases search for and sales of unendorsed services. This translates into an increase in the average number of impressions by 4.1%, clicks by 2.0%, and orders by 3.1% per user. Given the large number of unendorsed services relative to endorsed services available on the platform, 66.7% of the increase in orders stems from unendorsed services and 33.3% from endorsed services.

We then explore heterogeneity in the effect of platform endorsement on unendorsed services. First, we focus on spatial proximity between unendorsed and endorsed services. We find that endorsement increases clicks and orders of unendorsed services located farther away from the endorsed service and hurts clicks and orders of unendorsed services located close to the endorsed service. Second, we focus on price similarity between unendorsed and endorsed services. We find that dissimilar-priced unendorsed services benefit more from the spillover effects of platform endorsement than services with price points similar to those of endorsed services.

To examine why platform endorsement increases users' search and purchases for unendorsed services, we explore three possible mechanisms. First, endorsement might change users' perception of the quality of services offered on the platform. Second, endorsement could attract attention, resulting in attention spillovers to unendorsed services. Third, the novelty of platform endorsement may increase user interest in the platform. Through a series of tests, we find that the increase in search and purchases of unendorsed services is consistent with platform endorsement improving users' perception of the quality of services available on the platform. Attention spillovers and the novelty of endorsement appear unlikely to be the driving forces behind this increase.

Lastly, we investigate how users with different propensities to purchase differ in their response to platform endorsement. We use two measures to proxy for users' propensity to purchase – the number of past purchases and whether a user self-identified as a business user. Overall, we find that platform endorsement is more effective in increasing purchases for users with a higher propensity to purchase.

Our research contributes to four streams of literature. First, it adds to existing studies that have examined the impact of platform endorsement or certification (Elfenbein et al., 2015; Farronato et al., 2020; Hui et al., 2016; Zhan et al., 2024). Unlike prior research that focuses on the effect of endorsement on purchases of endorsed items, our research is the first to explore the effect of endorsement on both search and purchases of both endorsed and unendorsed items. Second, our study relates to literature that investigates how platforms can use various marketing tools to reduce information asymmetry. Previous studies have explored tools such as ratings and reviews (Chevalier and Mayzlin, 2006), rankings (Ghose et al., 2012; Ursu, 2018), online advertising (Sahni and Nair, 2020; Fong et al., 2019), and personalized recommendations (Horton, 2017; Linden et al., 2003). Our contribution to this literature centers on estimating the impact of endorsement on digital platforms—a novel information disclosure tool—on users' behavior. Third, our findings relate to research on the demand spillover effects of marketing activities (Lewis and Nguyen, 2015; Sahni, 2016; Liang et al., 2019) by illustrating how exposure to platform endorsement can result in positive demand spillovers for unendorsed items, as a result of users perceiving services of the platform to be of higher quality. Lastly, our study extends the body of knowledge on online freelance markets (Yoganarasimhan, 2013; Pallais, 2014; Stanton and Thomas, 2015; Horton, 2019; Kanat et al., 2018; Chan and Wang, 2018; Bairathi et al., 2023) by demonstrating how an online freelance platform's endorsement can facilitate user choice and improve matching outcomes.

Our findings have implications for platforms, merchants, and regulators. First, for digital platforms, our results demonstrate that even small changes in platform design can have a tangible revenue impact and alter users' perceptions of the platform as a whole. More specifically, our findings indicate that platform endorsement is a useful tool to facilitate user search and purchase on the platform. In addition, we find that platforms may benefit from directing endorsement efforts towards the type of items that are of interest to users with a higher propensity to purchase as these users will be more likely to respond to platform endorsement. Second, we document that merchants can benefit significantly from users' increased search for and purchase of endorsed items. At the same time, for merchants whose items do not receive an endorsement, our results provide some reassurance that their sales may not be negatively impacted by the introduction of platform endorsement, but instead may even increase. Third, our results are relevant for regulators who are concerned about whether such practices might be anti-competitive and whether these practices should raise fairness concerns.[4] We show that even though platform endorsement disproportionately benefits endorsed items, it does not generally come at the cost of lower sales of unendorsed items.

2 Empirical Setting and Data

2.1 Empirical Setting

Online freelance platforms have been growing steadily for the past decade and revenues have been projected to grow from $3.4 billion in 2019 to $9.2 billion in 2026.[5] Our data come from a major freelance platform where freelancers from across the world offer users services that can be completed remotely. The platform maintains a directory of freelancers, develops a reputation system, and conducts quality checks of services. On this platform, freelancers post their services with detailed descriptions and prices. Freelancers can provide services across a wide range of categories, including graphic design, language translation, and programming. Users can search either by navigating the menu of predefined service categories or by entering a search query. In both cases, the platform presents a list of services as search results.

[4] See fairness and anti-competitive discussions in Faherty et al. (2017) and `https://www.modernretail.co/platforms/why-washington-wants-to-break/-up-amazon-explained/`

[5] `https://www.globenewswire.com/news-release/2021/05/26/2236099/0/en/Global-freelance-platform-market-size-is-projected-to-boom-at-a-CAGR-of-15-3-during-2021-2026.html`. Retrieved on June 21, 2023.

Figure 1(a) shows a mock-up of the search results. For each service offering, users can see key service attributes such as price, average rating, number of ratings, and a picture or a video describing the service provided by the freelancer. By clicking on a listing, users can find a more detailed service description, information on delivery time, reviews, or work samples. If users find the service to be a good match, they can place an order.

2.2 Experimental Design

The platform conducted a field experiment for a period of 27 days in 2019 with 598,772 users to understand the effect of platform endorsement on sales. The platform selected high-quality service offerings as eligible for receiving an endorsement badge, using a proprietary algorithm. Variables such as price, average rating, and the number of completed orders entered the algorithm. Since individual services had to qualify, this setting is distinct from other empirical examples where a platform certified merchants and consequently endorsed their entire range of items. Note that freelancers cannot pay the platform to obtain an endorsement badge. Overall, 1.2% of services that were displayed to users in our data during the period of the study were eligible for endorsement.

In the experiment, users were randomly assigned to either a control or a treatment group for the duration of the experiment. Control group users were not exposed to an endorsement badge. Treatment group users saw an endorsement badge when they saw an eligible service on the search results page (see Figure 1(b)).[6] The platform displayed no more than one endorsement badge on each search results page. In cases where multiple service listings qualified for endorsement, the badge was shown for the first qualifying listing only. If none of the service listings qualified, treatment group users would not see an endorsement badge. If a user searched over multiple pages, the endorsement badge might be shown on each page

[6]The endorsement badge was not displayed on the individual service page after a user clicked on a particular service offering.

if an eligible service was available on each page.

The algorithm that ranks search results did not differ between control and treatment group users. The ranking algorithm also did not personalize search results in any way such as based on users' past behavior on the platform (search or purchase) or whether they were in the treatment or control groups. The only difference between the treatment and the control groups was whether an endorsement badge was shown for an eligible service in the search results.

[Insert Figure 1 here]

2.3 Data

We use three data sets from the company. The first data set records users' detailed browsing and purchase behavior over the period of the experiment as well as for two weeks prior to the start of the experiment. The second data set documents users' past number of orders and whether they self-identified as either personal or business users during the registration process. The third data set reports key characteristics of the service offerings.

The sample includes the full set of 598,772 registered users who were part of the experiment. The platform tracked these users using their unique IDs so that repeat visits could be mapped to the same account.[7] On average, a user had placed 15.3 orders on the platform prior to the start of the experiment, although there is significant variation across users (standard deviation 97.98). 43.0% of users placed at least one order before the beginning of the experiment. Among the 33.9% of users who provided information on whether they are a business or personal user, 34.4% self-identified as business users.

Our data record users' search and purchase behaviors, summarized in Table 1. Since the experiment was conducted for the website accessed through desktop or laptop browsers

[7]It is possible that a single account is used by multiple users, which would add noise to our data.

only, we exclude any activities on mobile browsers or in apps. The firm uses two metrics to measure the degree to which users interact with service listings on the platform: impressions and clicks. The firm counts as an impression each time a service offering is displayed to a user on a search results page on their device. If a user does not scroll down the search results page to where a specific offering would be displayed, an impression is not counted for that offering. On average, a user saw 233.3 impressions of service listings on search results pages during the period of the experiment. The number of impressions varies across users because users differ in how frequently they browse the website, how far they scroll on an individual webpage, and whether they click to the next search results pages.

The platform counts as a click when a user clicks on a service listing on the search results page. On average, users clicked on 6.2 listings to view more detailed service information and placed 0.2 orders during the experiment.[8] In addition, throughout the experiment period, a user had an average of 2.6 sessions on the platform.

Table 1 further reports information at the session level. On average, a user saw 90.5 impressions of service listings, clicked on 2.4 services, and placed 0.06 orders within a session.

[Insert Table 1 here]

Among all users, 50.1% were assigned to the treatment group and 49.9% to the control group. We conduct a randomization check based on purchase history, self-identified user type, and browsing behavior during the two-week period prior to the start of the experiment. Table 2 demonstrates that there are no significant differences in the number of impressions, clicks, and orders across treatment and control group users. For users who placed an order on the platform during this period, we find no significant difference in the purchase price, average rating of the purchased services (conditional on the service being rated), and the number of ratings for purchased services. Users from both groups placed a similar number of

[8]The high maximum number of impressions, clicks, and orders evident in Table 1 is likely a result of high demand from business users.

orders on the platform during their entire purchase histories. Finally, control and treatment groups comprise a similar share of business users. Together, these checks suggest that the randomization was successful.

[Insert Table 2 here]

Over the period of the experiment, users encountered a total of 2,061,030 unique service listings. Among those, 1.2% were eligible for the platform endorsement. For each individual service listing, we observe the price, the average star rating, the number of ratings, the ranking, and the service category. We also observe whether for each particular listing an endorsement badge was displayed on the search results page. The average position of the endorsed service on the first page of the search results is 6.5 (standard deviation 7.4).

Table 3 compares endorsed and unendorsed services. While all the endorsed services are rated, only 59% of unendorsed services received at least one rating. Conditional on being rated, endorsed services are rated 0.1 points higher and have more than twice the number of ratings compared with unendorsed services. Finally, endorsed services have higher prices.

[Insert Table 3 here]

3 Estimation and Results

3.1 Model-free evidence

Table 4 documents the impact of platform endorsement on impressions, clicks, and purchases. Users in the treatment group viewed a significantly higher number of impressions relative to users in the control group, mainly a result of treatment group users viewing more impressions of unendorsed services. Given that the platform's ranking algorithm remains the same between the control and treatment groups and the platform endorsed at most one service per search results page, it is not surprising that the number of impressions of endorsed services does not differ significantly between the control and the treatment group. Users in the treatment group clicked on significantly more services than users in the control group, a result of an increase in clicks on both endorsed and unendorsed services. Further, we find users in the treatment group placed significantly more orders for endorsed services. They also placed more orders for unendorsed services, though this increase is not statistically significant for the full sample of users.

[Insert Table 4 here]

The initial model-free evidence suggests that platform endorsement benefits endorsed services and does not have a negative impact on unendorsed services. In addition, it increases user search on the platform. We next use empirical models to quantify the impact of platform endorsement on user search and purchase.

3.2 Empirical Specification

We estimate the effect of platform endorsement on impressions, clicks, and orders. Since the number of impressions, clicks, and orders are count measures, we use a Poisson regression framework (King, 1988; Greene, 2003) and model the Poisson parameter as a function of the treatment indicator and a vector of covariates that includes user and browsing characteristics. That is, we assume that the dependent variable of interest for user i browsing in category c, $Y_{i,c}$, is drawn from a Poisson distribution with parameter $\lambda_{i,c}$:

$$Pr(Y_{i,c} = y) = \frac{\exp(-\lambda_{i,c})\lambda_{i,c}^{y}}{y!},\ y = 0, 1, 2, ...,$$

and

$$ln(\lambda_{i,c}) = \beta_0 + \beta_1 Treatment_i + \beta_2 X_{i,c}, \tag{1}$$

where $Treatment_i$ is a dummy indicating whether user i is in the treatment group. $X_{i,c}$ is a vector of covariates that includes the number of purchases made by user i before the beginning of the experiment, week fixed effects indicating the time of a user's first visit to the platform during the experiment, and category fixed effects capturing the possibility that browsing intensity and purchasing probability may differ across categories. We cluster standard errors at the user level to account for potential correlations among multiple observations of a user.

The parameter of interest is β_1, which captures the effect of being eligible to view a platform endorsement badge on impressions, clicks, and orders. Since the experiment has an intent-to-treat design, i.e. users in the treatment group are eligible to view a platform endorsement badge but not guaranteed, β_1 captures the ITT estimates.

Column (1) of Table 5 summarizes the estimated ITTs of platform endorsement using a Poisson specification for the full range of outcome variables. To interpret the results from a Poisson model, we translate the estimates into percentage change.[9] These results are consistent with the model-free evidence. We find that platform endorsement increases total impressions by 4.4%, driven mainly by a 4.4% increase in impressions of unendorsed services. It increases total clicks by 1.8%, driven by a 24.3% increase in clicks on endorsed services and 1.8% increase in clicks on unendorsed services. Finally, platform endorsement results in a 38.3% increase in orders of endorsed services although the increase in total orders and orders of unendorsed services is not significant.

[Insert Table 5 here]

3.3 Average Treatment Effect on the Treated (ATT)

The previous results show the impact of platform endorsement on all users in the treatment group. However, focusing our analysis on the average treatment effect on the treated (ATT),

[9]The percentage change from a Poisson model equals $(\exp(\beta_1) - 1)$.

that is the difference in the behavior of users in the treatment group who were exposed to an endorsed service and users in the control group who would have been exposed to an endorsed service had they been in the treatment group is more informative. First, since this was a pilot study, the platform only endorsed a small number of services. Consequently, 35% of users in the treatment group were not exposed to the endorsement badge, since no service in their search results was eligible for endorsement. This suggests that the ITT estimate may change with an increase in endorsed services which would lead to a higher proportion of users being exposed. This may, for example, be the case when the platform rolls out endorsement at scale. Second, focusing on the ATT will provide more generalizable results for other platforms, where a varying share of users may be exposed to an endorsement badge.

As is typical in experiments with an ITT design, we observe whether a treatment group user had been exposed to the treatment. However, a unique advantage of our setting, relative to many other experiments with an ITT design, is that for control group users we likewise know whether they would have been exposed to the treatment, had they been in the treatment group as we observe their exposure to an endorsement-eligible service. Hence, to estimate the ATT, we focus on the users who were exposed to an endorsed service in the treatment group and users who were exposed to an endorsement-eligible service in the control group. Estimating the ATT directly using this approach is preferable relative to an instrumental variable approach since it allows us to prune away those users who would never have been exposed and thus reduce noise in the estimator, as demonstrated by Johnson et al. (2017).

However, likely due to inherent randomness in users' search patterns, we find that some user characteristics are no longer fully balanced between the control and treatment groups in the pre-treatment period. During the two weeks prior to the experiment, treatment group users have a higher number of impressions (p-value = 0.02) and clicks (p-value = 0.05) than control group users, but the two groups do not differ significantly on the number of orders, purchase price, rating of purchased services, total lifetime orders, and the proportion of business users (see Table A1 in Online Appendix).[10] To ensure the treatment and control groups are comparable and to achieve balance in their characteristics, we use inverse probability of treatment weighting (IPW) (Azoulay et al., 2009; Atefi et al., 2018) and control for user characteristics. IPW uses propensity scores to ensure balance in user characteristics across control and treatment groups by weighting each individual user by the inverse probability of receiving the treatment.

We first estimate the propensity score (the probability of a user to view an endorsement-badged service), $\hat{p_i}$, using a logit model (Rosenbaum and Rubin, 1983), $Pr(D_i = 1) = Pr(\alpha_0 + \alpha_1 Z_i + \epsilon_i)$, where D_i indicates whether user i was in the treatment group and Z_i is a vector of user attributes prior to the experiment. We include three sets of variables in Z_i. The first set of variables captures a user's behavior on the platform during the two-week time period leading up to the experiment, specifically the number of impressions, clicks, and orders. We include the pre-treatment browsing and purchase behavior of users to estimate the propensity score since users who browse more, may also have a higher baseline probability of purchasing. The second set of variables relates to a user's history on the platform and includes the total number of lifetime orders prior to the experiment, an indicator for whether the user registered before the start of the experiment and, for those who registered before the experiment, the time since registration. The third set of variables includes the first day the user is observed during the experiment and the first category browsed during the experiment.[11] The results on the estimation of the propensity score (p-value for χ^2 statistic $= 0.0034$) are available in Online Appendix A.

[10]We discussed this slight imbalance with the firm, and they confirmed that there is no systematic selection at play, suggesting that the differences observed are likely attributable to random.

[11]The platform assigned each service to a category. We rely on this data to account for which category a user browsed. For an individual search, we assign categories based on the services listed in the search results page. If at least 80% of services returned to a search fall into a single category, we assign that category to the search. If less than 80% of services fall into a single category, we assign the category "other." The vast majority of searches can be assigned to a single category. Only 15.7% of search results fall into "other."

Second, we estimate the dependent variable with Equation (1), using weighted maximum likelihood. The weights (w_i) are calculated on the basis of the estimated propensity scores $\hat{p_i}$ by $w_i = \frac{D_i}{\rho} + \frac{\hat{p_i}(1-D_i)}{\rho(1-\hat{p_i})}$, where D_i indicates user i is in the treatment group and ρ is the fraction of treated units in the sample. The parameter of interest, β_1, captures the ATT. The controls in Equation (1) help reduce the variance of the estimator and improve precision in addition to making the estimator more robust (p.930 Wooldridge (2010)).

The IPW approach requires the assumption of unconfoundedness; that is, conditional on Z_i, the vector of user attributes before the start of the experiment, the outcome variable of interest is mean independent of treatment assignment. Given that our sample is from a field experiment and we include pre-treatment browsing and purchase behavior in Z_i to estimate propensity scores and re-weight the exposed sample of users, we argue the unconfoundedness assumption holds. To provide evidence that the re-weighting of observations is successful, we examine the covariate balance between the re-weighted control and treatment groups. Table 6 shows that inverse probability weighting achieved a good balance between control and treatment group users who were exposed to services eligible for an endorsement badge.

[Insert Table 6 here]

3.4 The Effect on User Search and Purchase

Column (2) of Table 5 summarizes the ATT estimates for the effect of platform endorsement. Based on the results in the top panel, we find that exposure to platform endorsement results in a 4.0% increase in the number of impressions. This increase in impressions is mainly driven by a 4.1% increase in impressions for unendorsed services. We find that the impact of endorsement on the impressions for endorsed services is insignificant. This is not surprising given that the platform's ranking algorithm remains the same between the control and treatment groups and that the platform displays no more than one endorsement badge on a search results page. As a result, if users scroll down further on a search results page, they will see more impressions of unendorsed services but not of endorsed services.

The results in the middle panel of Column (2) of Table 5 suggest that exposure to platform endorsement increased total clicks by 2.1%, clicks on endorsed services by 25.0%, and clicks on unendorsed services by 2.0%. Although the percentage increase in clicks for unendorsed services may appear to be much lower than the corresponding increase in clicks for endorsed services, the sheer number of unendorsed services available on the platform means that the absolute increase in clicks is much larger for unendorsed services than for endorsed services: the increase in clicks for endorsed services contributes 34.9% to the total increase in clicks while the increase in clicks for unendorsed services contributes 65.1%.

We next turn to purchases. Results in the bottom panel of Column (2) of Table 5 demonstrate that users placed 3.1% more orders on the platform as a result of exposure to the endorsement badge. This is a result of a 40.6% increase in endorsed service orders and a 2.2% increase in unendorsed service orders. The reduction in noise that we achieve using the ATT estimate means that we can now detect a significant effect of endorsement on orders of unendorsed services and consequently total orders on the platform.

Importantly, 33.3% of the total increase in orders is driven by the increase in endorsed service orders and 66.7% by the increase in unendorsed service orders. In order to evaluate the impact on revenue, we compare average order price between the control and treatment group and find that the average order price does not differ significantly between the two groups. This suggests that a 3.1% increase in orders due to exposure to the platform endorsement badge translates into a roughly 3.1% increase in revenue for the platform.

Recall that the platform endorsed no more than one service on a search results page. As such, one concern may be that the impact on unendorsed services could be a result of an increase in clicks and purchases on services that qualify for endorsement that did not receive an endorsement badge because they were not the first qualifying service listed on a search results page. If this were the case, the results would not generalize to unendorsed services more broadly. To check that the effect on unendorsed services is not driven by services that qualify for endorsement but did not receive a badge due to their position in the search results, we estimate the spillover effect only on those unendorsed services that did not qualify for platform endorsement. Table 7 demonstrates that exposure to platform endorsement increases search and sales for services that did not qualify for endorsement.

[Insert Table 7 here]

Finally, we conduct a series of robustness checks. First, we show that our results are robust to a battery of different specifications including linear regression, t-tests (without using controls), using propensity scores as a control rather than IPW, and negative binomial regression (see Online Appendix D and E). Second, we demonstrate that our estimated ATT from the IPW approach is consistent with the estimated ATT using an instrumental variable approach (see Online Appendix B). The advantage of estimating ATT with our approach relative to using instrumental variables is that our approach allows us to prune away those users who would never have been exposed to the endorsement badge and thus reduces noise in the estimator (Johnson et al., 2017). Finally, our results are robust to estimating ATT without weighting.[12] Overall, our results demonstrate that exposure to platform endorsement is effective in increasing revenue for the platform and generally does not negatively affect unendorsed services.

3.5 Heterogeneity in the Effect on Unendorsed Services

We explore whether the effect varies with an unendorsed service's proximity to an endorsed service in search results and the price similarity of endorsed and unendorsed services.

[12]The results for ATT without IPW and the results without linear controls and are available with the authors on request.

3.5.1 Proximity in Search Results Listing

We examine the heterogeneous effect of platform endorsement across unendorsed services based on their location relative to the endorsed service in the same set of search results. On one hand, platform endorsement might attract user attention not only towards the endorsed service, but also towards unendorsed services located near the endorsed service (Kawaguchi et al., 2021), potentially leading to greater spillover effects on services located nearby. On the other hand, there is evidence suggesting that when one service attracts user attention, less attention may be available to process other services on display nearby (Kahneman, 1973; Hong et al., 2004).

To test for the role of proximity in search results, we first identify sessions where treatment group users were exposed to a platform endorsement badge. Within these sessions, we identify services that were located spatially close to the endorsed service; that is, services located in the row above, in the same row, or in the row below. We consider all other services to be spatially distant. We follow a similar logic for control group users. That is, we focus on sessions where users were exposed to an endorsement-eligible service and within these sessions identify services that were located spatially close to the endorsement-eligible service. We then examine if the effect of platform endorsement differs between services located near the endorsed service and services located farther away.

Column (1) of Table 8 shows that exposure to platform endorsement significantly increases clicks for unendorsed services located farther from the endorsed service (see Online Appendix C for the estimation equation). At the same time, it significantly decreases clicks for unendorsed services located close to the endorsed service. Column (2) indicates that similarly exposure to platform endorsement increases orders for unendorsed services located far from the endorsed service, but decreases orders of unendorsed services located close to the endorsed service in search results.

[Insert Table 8 here]

3.5.2 Price Similarity of Services

We examine whether the effect of platform endorsement on unendorsed services varies with similarity in prices between endorsed and unendorsed services. If the attributes of an endorsed service serve as a reference point to evaluate unendorsed services, unendorsed services with price points similar to the endorsed service may benefit. Alternatively, given the same price point, users might prefer purchasing the endorsed service, in which case unendorsed services similar in price to an endorsed service might not benefit from the endorsement.

We identify sessions among treatment group users in which users were exposed to a platform endorsement badge and focus on unendorsed services in the same category as the endorsed service. Within these sessions, we identify services that are similar in price to the endorsed service. We define a price that is within $5 of the endorsed service's price as being similar and price points farther away as being dissimilar. We follow a similar logic for control group users, focusing on sessions where users were exposed to an endorsement-eligible service and on unendorsed services in the same category as the endorsement-eligible service. Again, we identify services that are similar in price to the endorsement-eligible service and those that are not. We then examine the spillover effects on clicks and orders for services with prices that are more or less similar to the price of the endorsed service in the search results.

The results are presented in Table 8 (see Online Appendix C for estimation equation). Column (3) demonstrates that the combined effect on similarly priced services is not significantly different from zero. Along similar lines, Column (4) shows a significant increase in orders of services with different price levels and a null effect for services with similar price levels as the endorsed service (-0.03, p = 0.174).[13]

[13] Based on the coefficient estimates, the effect of exposure to platform endorsement on orders of similarly priced unendorsed services is $0.0356 - 0.0657 \approx -0.03$.

We further examine similarity in terms of average ratings and the number of ratings but do not detect any further heterogeneity in the treatment effect across unendorsed services.

4 Why Does Platform Endorsement Increase Search and Purchase?

The finding that platform endorsement leads to an increase in clicks and purchases of endorsed services is intuitive and in line with prior research that demonstrates that users' search for and purchase of a focal item can increase due to marketing interventions such as advertising (Sahni and Nair, 2020) and rankings (Ursu, 2018). However, it is less clear why platform endorsement increases search for and sales of unendorsed services. Understanding this mechanism is important as it helps to contextualize our findings and can offer insights into the generalizability of the results. We investigate three possible mechanisms that may contribute to the increase in search and purchase of unendorsed services. First, platform endorsement might change users' perceived quality of offerings on the platform overall. Second, platform endorsement might draw attention to endorsed services and lead to attention spillovers. Third, the novelty of platform endorsement might increase user interest in the platform.

4.1 Perceived Quality Change

Platform endorsement may suggest to users that the platform is actively involved in curating its offerings. As such, it may increase users' beliefs about the overall quality of services on the platform. In previous studies, Kumar and Benbasat (2006) demonstrate that the mere act of providing decision support tools like recommendations or reviews improves the perceived usefulness of a website. Vijayasarathy and Jones (2001) find that decision support tools can increase the number of products considered. In our context, platform endorsement might likewise improve users' confidence in the quality of the services offered.

In addition to signaling a platform's active involvement in curating the offering, exposure to high-quality endorsed services may further cause buyers to update their beliefs regarding the distribution of quality of the available services. Previous studies in the context of eBay and Airbnb have shown that buyers update their beliefs about the quality of all merchants on a platform based on the purchase experience with a few individual sellers (Nosko and Tadelis, 2015; Jaffe et al., 2017). In our context, if an endorsement badge makes users more likely to notice endorsed services that are of higher than average quality, buyers may in turn adjust their beliefs regarding the quality of other services on the platform.

This increase in the perceived quality of offerings could lead users to conduct additional search (De Corniere, 2016; Zhou, 2020) since incremental search is more likely to result in the discovery of a better match. Increased search and improved perceived quality may make it more likely that users will find a service that fits their needs and, thus, increase overall purchases, including of unendorsed services. We test for this mechanism in two ways.

First, we leverage the fact that the platform offers services in different categories and that 57.3% of users search for services across at least two categories. If platform endorsement changes users' perception of the overall service quality, then any such effect should not be limited to the category where a user viewed an endorsement badge, but should also hold for categories where the user did not view an endorsement badge. If, by contrast, platform endorsement does not alter the perception of the overall quality of services on the platform, the increase in search activity should be confined to categories where users viewed an endorsement badge.

To test for this, we identify among treatment group users those who were exposed to a platform endorsement badge in one product category and later browsed on any subsequent day in other categories where they were not exposed to a badge. Among these users, we focus our analysis only on categories where users did not view an endorsement badge after previously being exposed to an endorsement badge. We follow a similar logic for control group users in that we focus on categories where control group users were not exposed to an endorsement-eligible service following a prior exposure to an endorsement-eligible service in a different category. If platform endorsement changes users' perception of the overall quality of services, then we expect treatment group users to browse and click more than control group users even in categories where they were not exposed to endorsement. Alternatively, if platform endorsement operates only via other channels such as attention or novelty, but not by altering users' perceived quality of services, we would not expect users in the treatment group to browse and click more than control group users in categories where they were not exposed to endorsement-eligible services.

Column (1) in Table 9 illustrates that treatment group users who were previously exposed to a badge in a different category view more impressions than control group users who were never exposed to a badge.[14] Column (2) indicates that these users likewise click more in categories in which they were not exposed to platform endorsement. Column (3) indicates that the increase in impressions and clicks feeds through to an increase in orders for users in the treatment group relative to users in the control group.[15] Moreover, we find that this increase in impressions and clicks does not differ significantly from the increase in impressions and clicks in categories where users were exposed to an endorsement badge (see Table G1 in Online Appendix G). This result is in line with the proposed mechanism that platform endorsement improves users' expectations regarding the overall quality of services across the platform, resulting in more search and purchase of both endorsed and unendorsed services.

[Insert Table 9 here]

[14] The pre-treatment covariates between the control and treatment group observations for the sub-sample of users used in this analysis are well balanced, see Table F1 in Online Appendix F

[15] Note that the selection of users who browse multiple categories means that we are focusing on a subset of more active users. This explains the greater effect sizes in Table 9 relative to Table 5.

Second, we analyze the effect of platform endorsement on orders conditional on a user having clicked on a service offering. If platform endorsement improves perceived quality, then we would expect a user to be more likely to purchase a service, conditional on having clicked on the service and viewing it in more detail. This is because conditional on clicking a service, users exposed to endorsement should still evaluate a service to be of higher quality relative to users not exposed to an endorsement badge and hence place more orders even after accounting for the additional clicks induced by endorsement. To test for this, we estimate the impact of exposure to platform endorsement on orders after controlling for the number of clicks.[16]

Column (1) of Table 10 shows that after controlling for the number of clicks, treatment group users purchase more on the platform than control group users. Columns (2) and (3) show the results hold for endorsed and directionally hold for unendorsed services. We further find the effect on endorsed services to be substantially larger than on unendorsed services, consistent with the main findings.

[Insert Table 10 here]

4.2 Attention Spillovers

A second potential mechanism for the increase in impressions and clicks for unendorsed services could be attention spillovers. Previous research has shown that certain marketing interventions like product recommendations increase users' attention not only towards recommended but also towards non-recommended products (Kawaguchi et al., 2021). Such an increase in attention could lead to an increase in consideration and ultimately purchase of non-recommended products. Following a similar logic, platform endorsement could increase

[16]We recognize that by conditioning on the number of clicks, the users in the control and treatment groups in this analysis may not be fully comparable. However, notwithstanding this caveat, the analysis provides useful support to our theory.

attention not only for endorsed services, but also for competing unendorsed services, leading to more search and purchases of both.

Huang et al. (2021) show that attention spillovers are strongest for items that are categorically similar to the focal item and items that are spatially close to the focal item. This is because attention spreads based on Gestalt grouping cues; that is, the mind tends to organize visual data by grouping smaller objects to form larger groups (Wertheimer, 1938; Duncan, 1984; Wannig et al., 2011). Thus, attention spillovers can be stronger among items considered to be a part of the same group.

However, two pieces of results reported in previous sections suggest that attention spillovers are unlikely to be the mechanism at work. First, if attention were the main driver behind the increase in search, then we would expect the increase in users' search to be significantly higher in categories where users are exposed to an endorsement badge relative to categories where they are not exposed to it (Huang et al., 2021). The finding presented in Section 4.1 that users' search increases similarly in the category where an endorsement is shown and in other categories where it is not shown suggests that attention is unlikely to be the main mechanism behind the increase in search.

Second, in Section 3.5.1 we analyzed the spatial location of endorsed and unendorsed services in search results. If attention was driving the increase in search, the effect should be stronger for services displayed spatially closer to the endorsed service in search results than for services that are displayed farther away (Huang et al., 2021). The results in Table 8 demonstrate that services located nearby received fewer clicks and fewer orders than services located farther away, a result in line with users' limited attention (Kahneman, 1973; Hong et al., 2004) but not supportive of attention spillovers to nearby services.

4.3 Novelty

The third possible mechanism behind the effect of platform endorsement could be that the novelty of the endorsement badge results in curiosity among users and leads them to explore further and search more (Berlyne, 1950; Hu et al., 2019).

To investigate the novelty mechanism, we rely on the fact that novelty wears off over time. We identify among treatment group users those who were exposed to a platform endorsement badge on at least two separate calendar days. We follow a similar logic for control group users in that we focus on users who were exposed to an endorsement-eligible service on at least two separate calendar days. If novelty is driving the increase in search for unendorsed services, we would expect the novelty effect to wear off starting with the second exposure to the platform endorsement badge.

Table 11 shows the results.[17] The interaction term between the treatment and the second exposure to platform endorsement captures the effect of platform endorsement on search over subsequent exposures. The statistically insignificant estimate suggests that the effect of platform endorsement on impressions does not attenuate over subsequent exposures. In contrast, for clicks, we find that the effect of platform endorsement becomes more pronounced over subsequent exposures to the endorsement badge. This pattern contradicts the novelty mechanism but is consistent with a gradual increase in quality perceptions as such an effect may wear-in over subsequent exposures.

[Insert Table 11 here]

In order to ensure that this finding is not an outcome of the chosen empirical specification, we conduct an additional analysis. We focus on users who were exposed to a platform endorsement badge on six separate calendar days. We follow a similar logic for the control

[17] The pre-treatment covariates between the control group and treatment group observations for the subsample of users used in this analysis are well balanced, see Table F2 in Online Appendix F.

group. We pool the browsing behavior from the first to the third exposure and browsing behavior from the fourth to the sixth exposure separately. If novelty is driving the increase in search for unendorsed services, we would expect the treatment effect of platform endorsement to wear off over time and the increase in search due to endorsement should attenuate over subsequent exposures to the endorsement badge. Consistent with our earlier findings, we find no evidence that the increased search is a result of the novelty of the endorsement badge (results are available in Table G2 of Online Appendix G). We thus conclude that the novelty of the endorsement badge alone is unlikely to explain the increase in browsing and clicks for unendorsed services.

4.4 Implications of Mechanism

Our analyses indicate that the increase in search and purchases of unendorsed services is consistent with the explanation that the perceived quality of services available on the platform improves as a result of platform endorsement. Attention spillovers and novelty are unlikely to be the mechanisms behind this increase.

Such insights into the mechanism matter for the platform. First, an increase in the perceived quality of items should give the platform confidence that endorsing some items may indeed benefit other unendorsed items. Thus, the platform can reassure merchants whose items are not endorsed that their sales may increase as a result of introducing endorsement.

Second, our mechanism evidence demonstrates that platform endorsement has positive spillover effects on a broad range of unendorsed services. This is in contrast to an explanation based on attention spillovers that would have predicted an effect on only a smaller range of similar services. The insight that spillovers apply widely, and not only to a select group of unendorsed items, is useful for platforms when positioning the endorsement feature towards service providers or merchants. Additionally, our finding that nearby services might suffer suggests that platforms should avoid consistently displaying the same unendorsed service close to an endorsed service as this may negatively affect that service's sales and make the platform less attractive for such merchants.

Third, it is useful to understand that spillover effects on unendorsed items are not a result of the immediate novelty of the feature, but instead have longer-lasting effects.

5 Heterogeneous Effects of Platform Endorsement

Our results so far have demonstrated that, across the entire treated population, exposure to platform endorsement increases search and purchases. A better understanding of which user segments are more responsive to platform endorsement can help platforms better implement this feature. For example, a platform may want to ensure that it prioritizes allocating endorsement efforts to the types of services that are of interest to those users who are most responsive, rather than distributing their attention equally across items or categories. This matters at the stage of testing endorsement when a platform may wish to understand the maximum possible effect size it can achieve when endorsing items. Beyond testing the endorsement feature, a platform may want to ensure that it continuously allocates attention to endorsing especially those items or categories that are of interest to users who are most likely to respond to endorsement. This approach would help the platform reap the greatest possible rewards from platform endorsement.

To explore heterogeneous treatment effects, we focus on a set of variables that are indicative of users' propensity to purchase. Though previous research indicates that users' propensity to purchase may relate to their responsiveness to marketing interventions, there is conflicting evidence as to the direction of the effect. One stream of research suggests that users with a higher propensity to purchase are less likely to respond to marketing interventions because they rely more on their own judgement in decision making (Hernández-Ortega et al., 2008; Holloway et al., 2005). By contrast, another stream of research has demonstrated that users with a higher purchase propensity may be more likely to be influenced by marketing interventions, but such interventions may be insufficient to induce purchases for users with a lower propensity to purchase (Shin and Sudhir, 2010; Gopalakrishnan and Park, 2021; Sahni et al., 2019). We empirically evaluate heterogeneity in users' responsiveness to platform endorsement along two user attributes that proxy for their propensity to purchase.

5.1 Past Purchase Behavior

As a first proxy for users' propensity to purchase, we focus on users' past purchase behavior. Prior research suggests that users with more past purchases typically have a higher propensity to purchase (Fader et al., 2005; Lewis, 2004). As a result, we expect that a user's propensity to purchase during the time period covered by our experiment increases with the number of purchases during the two weeks prior to the experiment. We examine if endorsement badges are more effective for users with a higher number of past purchases.[18]

We first verify for control group that users with more purchases in the previous two weeks purchase more during the experiment (see Online Appendix H). We then include an interaction term between the treatment and the total number of orders placed in the two-week pre-treatment period. The interaction term quantifies the relative change in orders between users with a different number of past orders. The significant positive estimates on the interaction term in Column (1) in Table 12 demonstrate that exposure to platform endorsement increases total orders by 1.84% for a one unit increase in orders placed by users in the past two weeks. Hence, users with more past purchases are more likely to increase their purchases in response to an endorsement badge. This also holds true for the number of endorsed service orders (Column (2)) and unendorsed service orders (Column (3)).

[Insert Table 12 here]

[18]One might alternatively posit that a user who recently purchased may be less likely to repurchase due to satiation. However, in our context, we focus on users who actively browse the website during the experimental period, indicating some need for the services.

5.2 User Type

Next, we proxy users' propensity to purchase based on whether a user self-identified as a business or personal user upon registration. Recall that 33.9% of users provided this information when registering with the platform. We hypothesize that business users, due to their recurring needs, have a higher propensity to purchase. Indeed, this holds true in our data where in the control group business users make 1.64 times more purchases compared to personal users ($p < 0.01$; see Online Appendix H).

We investigate whether the treatment effect is more pronounced for business users. The interaction term *Treatment* × *Business user* captures the relative effect of exposure to platform endorsement for business users compared with personal users. Column (4) in Table 12 shows that exposure to platform endorsement is significantly more effective in increasing total orders for business users relative to personal users. Exposure to platform endorsement increases total orders for business users by 8.54% compared to personal users. Columns (5) and (6) show directionally similar patterns for orders of endorsed and unendorsed services although the interaction effect is not significant for endorsed services, which is likely a result of the significantly smaller number of endorsed services.

Overall, our results indicate that platform endorsement has a greater impact on users who have a higher propensity to purchase. This implies a platform may benefit from prioritizing endorsement efforts towards items or categories that these types of users are most interested in; for example, when piloting such schemes in order to evaluate the maximum benefit that can be achieved with platform endorsement or in order to reap the maximum possible benefit from platform endorsement when allocating scarce resources to identify items to be endorsed.

6 Conclusion

With the rapid growth of digital platforms and the large product variety they offer, firms are increasingly developing new tools to help users navigate their assortments and improve matching outcomes. One such tool is platform endorsement. Popular examples of platform endorsement include “Amazon’s Choice” badge and “Etsy’s Picks.” While exposure to platform endorsement may increase sales for endorsed items, the impact of exposure to platform endorsement on competing unendorsed items and on the platform as a whole is less clear.

Our paper investigates the effect of exposure to platform endorsement on user search and purchase behavior for both endorsed and unendorsed offerings by leveraging data from a field experiment conducted by an online freelance platform. Consistent with intuition, we find that exposure to platform endorsement results in a large increase in search for and purchases of endorsed services. Surprisingly, our results demonstrate that exposure to platform endorsement also leads to more search for and purchases of unendorsed services. At the platform level, exposure to endorsement increases the total number of orders by 3.1%. Of this increase, 33.3% stems from an increase in orders of endorsed services and 66.7% stems from an increase in orders of unendorsed services. In sum, we find that exposure to platform endorsement has a positive impact on endorsed services, a positive spillover effect on unendorsed services, and increases overall purchases on the platform.

We document that the main mechanism for the positive spillover effect of platform endorsement on unendorsed services is that endorsement improves users’ overall quality perception of services available on the platform. As users expect to find services of higher quality, users’ expected benefit from search increases, resulting in more impressions and clicks. This increased search and higher perceived quality make it more likely that users find a service that fits their needs and ultimately become more likely to order both endorsed and unendorsed services. We also explore two alternative mechanisms – that platform endorsement leads to an increase in attention and that the novelty of the endorsement badge entices users to search more – but find little support for either.

We then explore user-level heterogeneity in the effect of platform endorsement. For a platform, understanding which types of users are most likely to respond to endorsement is useful because it helps the platform direct efforts to items or categories of items that are of most interest to users who are more responsive to endorsement. Specifically, we examine if platform endorsement is more effective in increasing orders for users with a higher or a lower propensity to purchase. We identify two measures to proxy for users' propensity to purchase - prior purchases on the platform and whether users self-identified as business or personal users. Throughout, we find that exposure to platform endorsement is more effective in increasing orders of both endorsed and unendorsed services for users with a higher propensity to purchase relative to users with a lower propensity to purchase.

Our findings are important for platforms, merchants, and regulators. For digital platforms, the implications are threefold. First, they demonstrate that endorsing specific items increases revenues without adversely affecting unendorsed items on average. Second, on a broader level, they demonstrate that even small changes in platform design can significantly impact revenues, in this case because they alter users' perception of the platform as a whole. Third, the insight that users with a higher propensity to purchase are more responsive to platform endorsement allows platforms to prioritize endorsement efforts towards items or categories that these users are most interested in. For merchants, our results indicate that platform endorsement increases sales of endorsed items significantly, justifying competition among merchants for endorsed status on platforms. In addition, they offer some reassurance to merchants whose items are not endorsed, as their sales are not typically cannibalized by endorsed items and may even experience an increase. Last, in recent years regulators have become increasingly concerned about fairness in digital markets and the impact of marketing interventions on competition. Our results suggest that in contexts like ours, where high-quality items are selected for endorsement, worries about negative spillover effects from endorsement and reduction in sales of unendorsed items are largely unfounded.

There are, of course, limitations to our results. First, our results come from a particular platform that focuses on endorsing high-quality items and only displays at most a single endorsed item per search results page. It is possible the effect may vary across empirical settings, for example, if items are selected based on characteristics other than their quality or if a larger number of items are endorsed on a search results page. Second, our study is focused on the short- and medium-term effects of endorsement; we are unable to measure long-run changes in prices, in the quality of items, or sellers' entry and exit decisions in response to platform endorsement. Third, we are unable to determine whether the total increase in orders on the platform is a result of users making a transaction they would otherwise not have made (e.g., hiring a translator instead of doing the translation themselves) or choosing this platform over competing freelance platforms and any other service providers. Notwithstanding these limitations, we believe that our paper, by documenting the effect of platform endorsement on search for and purchases of endorsed and unendorsed items, represents a useful contribution to our knowledge about an important tool that can facilitate user choice.

Declarations

Funding and Competing Interests

All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript. The authors have no funding to report.

The firm that provided the data had the right to review and comment. However, it did not have the right to request changes. Further, it did not give any comments that would have resulted in changes in the paper.

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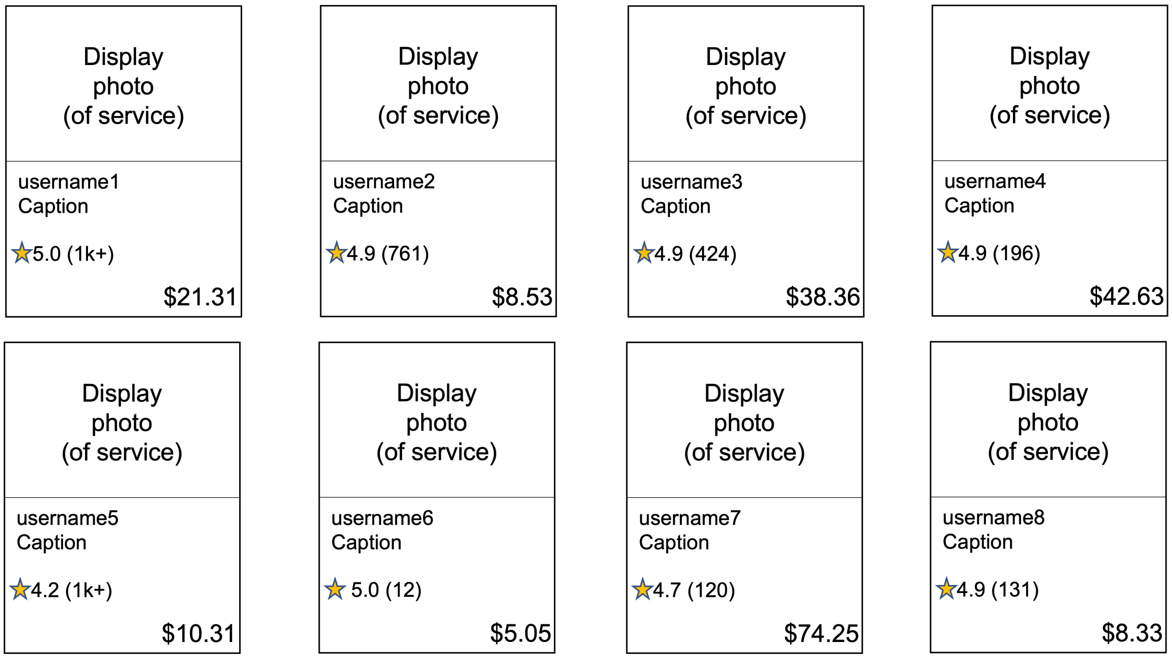
Figures and Tables

Figure 1: Mock-up of user interface comparison for treatment and control group users

(a) Search results for control group users



(b) Search results for treatment group users

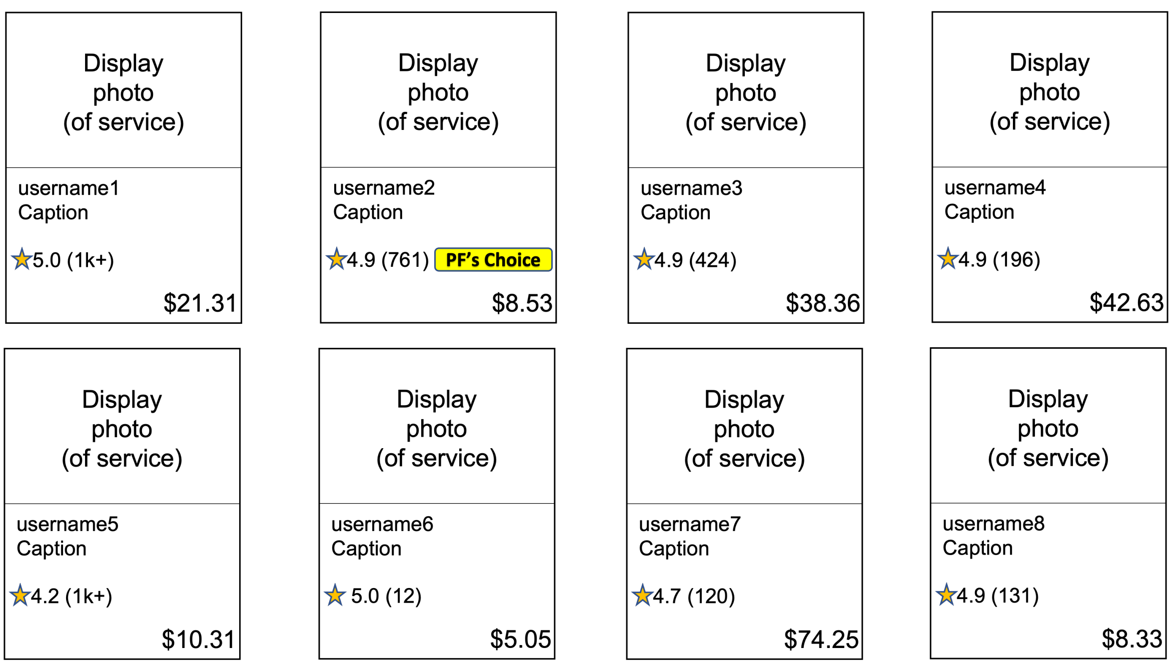


Table 1: Summary statistics

	N	Mean	Median	SD	Min	Max
User level						
# Impressions	598,772	233.26	63	1,191	1	134,944
# Clicks	598,772	6.23	2	17.35	0	3,537
# Orders	598,772	0.25	0	0.91	0	160
Business user[a]	170,440	0.34	0	0.47	0	1
# Sessions	598,772	2.58	1	7.01	1	3,311
Session level						
# Impressions	1,544,441	90.46	40	203.83	1	16,334
# Clicks	1,544,441	2.41	1	4.73	0	444
# Orders	1,544,441	0.06	0	0.29	0	18

[a] This information is only available for a subset of users

Table 2: Covariate balance

	N	Control	Treatment	p-value
# Impressions	598,772	104.96	108.33	0.13
# Clicks	598,772	2.60	2.64	0.17
# Orders	598,772	0.10	0.10	0.11
Purchase price	31,718	35.86	35.48	0.60
Rating of purchased service (If rated)	28,957	4.92	4.92	0.15
# Ratings of purchased service	31,718	515.44	539.54	0.34
# Lifetime Orders	598,772	15.27	15.35	0.74
% Business users	170,440	0.34	0.34	0.20

Table 3: Comparison of platform endorsed and unendorsed services

	Endorsed services Mean (SD)	Unendorsed services Mean (SD)	Diff. in means Δ (SD)	p-value
If rated	1 (0.00)	0.59 (0.00)	0.41 (0.00)	0.00
Star rating (1-5)	4.96 (0.00)	4.86 (0.00)	0.10 (0.00)	0.00
# Ratings	775.32 (6.93)	333.06 (1.65)	442.26 (7.12)	0.00
Price	51.85 (0.71)	38.82 (0.08)	13.03 (0.72)	0.00
N	24,096	2,036,934		

Star rating and number of ratings calculated for services that have been rated.

Table 4: Descriptives at user level for impressions, clicks, and orders

	Control	Treatment	p-value
# Impressions	227.92	238.58	0.00
# Endorsed impressions	2.79	2.82	0.61
# Unendorsed impressions	225.13	235.77	0.00
# Clicks	6.17	6.29	0.01
# Endorsed clicks	0.14	0.18	0.00
# Unendorsed clicks	6.03	6.11	0.06
# Orders	0.246	0.249	0.28
# Endorsed orders	0.005	0.007	0.00
# Unendorsed orders	0.241	0.242	0.78

The data cover 598,772 users during the period of the experiment.

Table 5: Estimates of the effect of platform endorsement on impressions, clicks, and orders

	(1) ITT	(2) ATT
Dependent Variables		
Total Impressions	0.0431***	0.0396***
	(0.0128)	(0.0145)
Endorsed impressions	0.0212	0.0209
	(0.0220)	(0.0222)
Unendorsed impressions	0.0434***	0.0399***
	(0.0128)	(0.0145)
Total Clicks	0.0175***	0.0212***
	(0.0066)	(0.0076)
Endorsed clicks	0.217***	0.223***
	(0.0153)	(0.0155)
Unendorsed clicks	0.0175**	0.0201**
	(0.0081)	(0.00942)
Total Orders	0.0130	0.0308***
	(0.0092)	(0.0105)
Endorsed orders	0.324***	0.341***
	(0.0400)	(0.0399)
Unendorsed orders	0.0053	0.0213**
	(0.0093)	(0.0107)
Category controls	Yes	Yes
Past purchase controls	Yes	Yes
First visit week	Yes	Yes
Observations	1,114,995	834,853

Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Covariate balance after re-weighting observations

	N	Control	Treatment	p-value
# Impressions	392,613	140.68	140.27	0.91
# Clicks	392,613	3.16	3.16	0.97
# Orders	392,613	0.11	0.11	0.99
Purchase price	22,414	35.16	35.66	0.56
Rating of purchased service (If rated)	20,588	4.92	4.92	0.47
# Ratings of purchased service	22,414	534.42	532.10	0.94
# Lifetime Orders	392,613	15.82	15.81	0.97
% Business users	117,413	0.34	0.34	0.18

Table 7: Effect on unendorsed non-qualifying services

	(1) #Unendorsed not qualifying impressions	(2) #Unendorsed not qualifying clicks	(3) #Unendorsed not qualifying orders
Treatment	0.0381***	0.0194**	0.0219**
	(0.0145)	(0.00951)	(0.0108)
Category controls	Yes	Yes	Yes
Past purchase controls	Yes	Yes	Yes
First visit week	Yes	Yes	Yes
Observations	834,853	834,853	834,853
Log likelihood	-387,876,285.2	-10,404,565.9	-735,689.7

Clustered standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Effect on search based on spatial distance and price similarity

	(1) #Unendorsed clicks	(2) #Unendorsed orders	(3) #Unendorsed clicks	(4) #Unendorsed orders
Treatment	0.0153*	0.0411***	0.0132	0.0356**
	(0.00806)	(0.0156)	(0.00818)	(0.0168)
Services located nearby	-1.277***	-1.223***		
	(0.00576)	(0.0164)		
Treatment × Services located nearby	-0.0313***	-0.0847***		
	(0.00795)	(0.0237)		
Similarly priced			-1.136***	-0.904***
			(0.00898)	(0.0192)
Treatment × Similarly priced			-0.00964	-0.0657**
			(0.0122)	(0.0278)
Category controls	Yes	Yes	Yes	Yes
Past purchase controls	Yes	Yes	Yes	Yes
First visit week	Yes	Yes	Yes	Yes
Observations	1,553,692	1,553,692	1,553,692	1553692
Log likelihood	-7,172,083.4	-434,880.5	-6,645,897.5	-379,713.0

Clustered standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Browsing and purchases in categories without exposure to platform endorsement

	(1) #Impressions	(2) #Clicks	(3) #Orders
Treatment	0.0713***	0.0268*	0.0639**
	(0.0232)	(0.0145)	(0.0282)
Category controls	Yes	Yes	Yes
Past purchase controls	Yes	Yes	Yes
First visit week	Yes	Yes	Yes
Observations	110,640	110,640	110,640
Log likelihood	-13,451,640.3	-686,829.2	-68,303.7

Clustered standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sample restricted to browsing behavior of users after the first exposure to platform endorsement-eligible service in categories where they were not exposed to platform endorsement-eligible service during the period of the experiment.

Table 10: Number of orders conditional on clicks

	(1)	(2)	(3)
	#Orders	#Endorsed orders	#Unendorsed orders
Treatment	0.0222**	0.337***	0.0163
	(0.0105)	(0.0400)	(0.0107)
# Clicks	0.00293***		
	(0.000347)		
# Endorsed clicks		0.0106***	
		(0.00162)	
# Unendorsed clicks			0.00138***
			(0.000190)
Category controls	Yes	Yes	Yes
Past purchase controls	Yes	Yes	Yes
Week of first arrival controls	Yes	Yes	Yes
Observations	834,853	834,853	834,853
Log likelihood	-752,584.4	-45,426.7	-740,027.1

Clustered standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Effect over time

	(1)	(2)	(3)	(4)	(5)	(6)
	#Impressions	#Endorsed impressions	#Unendorsed impressions	#Clicks	#Endorsed clicks	#Unendorsed clicks
Treatment	0.00829	-0.00743	0.00851	-0.000542	0.200***	-0.00709
	(0.0117)	(0.0132)	(0.0118)	(0.00931)	(0.0157)	(0.00949)
Second exposure	0.934***	0.841***	0.935***	0.587***	0.574***	0.587***
	(0.0153)	(0.0167)	(0.0154)	(0.00994)	(0.0166)	(0.0100)
Treatment × Second exposure	0.0282	0.0516	0.0279	0.0274*	0.0587**	0.0265*
	(0.0226)	(0.0354)	(0.0226)	(0.0148)	(0.0254)	(0.0150)
Category controls	Yes	Yes	Yes	Yes	Yes	Yes
Past purchase controls	Yes	Yes	Yes	Yes	Yes	Yes
First visit week	Yes	Yes	Yes	Yes	Yes	Yes
Observations	477,981	477,981	477,981	477,981	477,981	477,981
Log likelihood	-278,557,153.0	-3,874,065.9	-276,651,532.7	-5,552,269.3	-404,724.9	-5,461,583.5

Clustered standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Effect on orders by past purchase experience and business vs. personal users

	(1)	(2)	(3)	(4)	(5)	(6)
	#Orders	#Endorsed orders	#Unendorsed orders	#Orders	#Endorsed orders	#Unendorsed orders
Treatment	0.0163*	0.332***	0.00655	-0.0153	0.252*	-0.0221
	(0.0107)	(0.0400)	(0.0108)	(0.0310)	(0.133)	(0.0313)
Orders in past 2 weeks	0.0263***	0.0228***	0.0264***			
	(0.00390)	(0.00433)	(0.00390)			
Treatment × Orders in past 2 weeks	0.0182***	0.0167**	0.0183***			
	(0.00663)	(0.00688)	(0.00663)			
Business user				0.965***	1.126***	0.961***
				(0.0283)	(0.126)	(0.0285)
Treatment × Business user				0.0820**	0.186	0.0777*
				(0.0406)	(0.160)	(0.0412)
Category controls	Yes	Yes	Yes	Yes	Yes	Yes
Past purchase controls	Yes	Yes	Yes	Yes	Yes	Yes
First visit week	Yes	Yes	Yes	Yes	Yes	Yes
Observations	834,853	834,853	834,853	834,853	834,853	834,853
Log likelihood	-753,154.4	-45,433.5	-737,505.9	-241357.0	-13654.7	-236781.5

Clustered standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Online Appendix

A Propensity Score

Table A1 shows the balance checks for users exposed to endorsement-eligible items during the pre-treatment period. We find that treatment group users have a significantly higher number of impressions (p-value=0.02) and clicks (p-value=0.05) than control group users in the pre-treatment period. However, the two groups do not differ significantly on other dimensions like number of orders, purchase price, rating of purchased services, total lifetime orders, and the proportion of business users. Our interpretation of the data is that the inherent randomness in search patterns leads to the imbalances we observe. To correct for these imbalances, we use IPW.

Table A1: Covariate balance before re-weighting observations

	N	Control	Treatment	p-value
# Impressions	392,613	132.77	140.27	0.02
# Clicks	392,613	3.08	3.16	0.05
# Orders	392,613	0.11	0.11	0.16
Purchase price	22,414	36.24	35.86	0.60
Rating of purchased service (If rated)	20,588	4.92	4.92	0.14
# Ratings of purchased service	22,414	491.34	515.44	0.34
# Lifetime Orders	392,613	15.70	15.81	0.75
% Business users	117,413	0.34	0.34	0.20

Table A2 shows the result of the propensity score estimation. We include pre-treatment browsing and purchase behavior of users in estimation of the propensity score because we believe these could be correlated with the probability that a user encounters an endorsement badge. For instance, users who are inherently more likely to browse and purchase might be more likely to come across an eligible service.

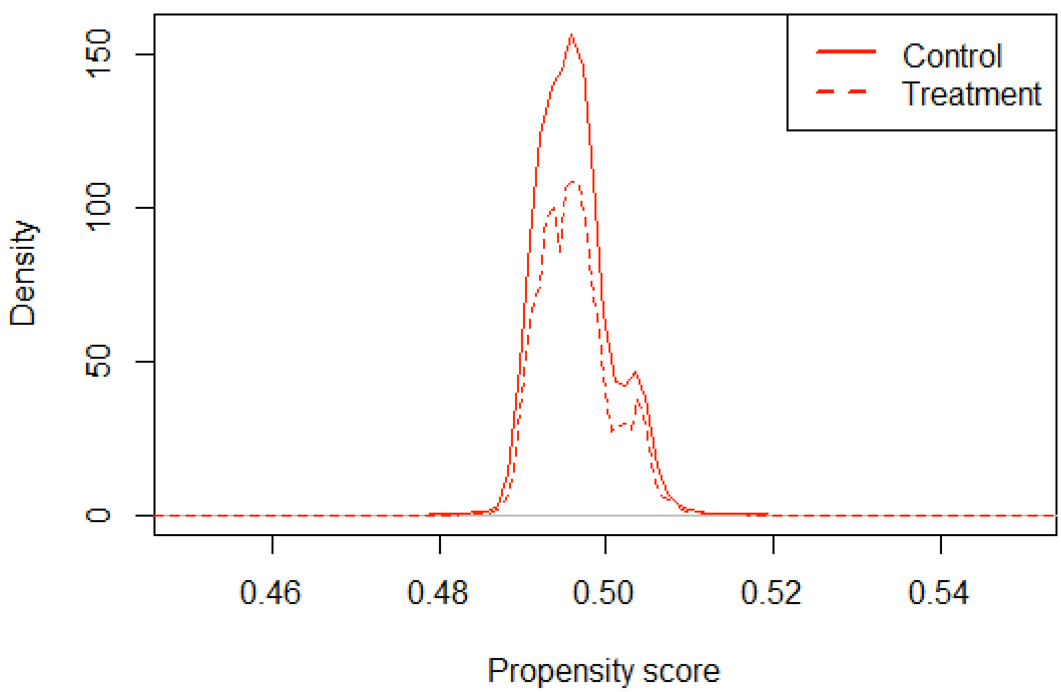
Table A2: Propensity score estimation

	Dependent variable:
	Treatment
	Logistic regression
If browse	0.010
	(0.009)
#Impressions	0.00000
	(0.00000)
#Clicks	0.0004
	(0.0003)
#Orders	-0.013^{**}
	(0.005)
If registered	-0.011
	(0.009)
Total lifetime orders	0.00001
	(0.00003)
Age on platform	0.00000
	(0.00001)
Days to first visit	-6.552
	(16.181)
If category#1	0.028^{**}
	(0.012)
If category#2	-0.016
	(0.010)
If category#3	-0.005
	(0.012)
If category#4	0.026
	(0.031)
If category#5	0.009
	(0.015)
If category#6	0.002
	(0.012)
If category#7	0.010
	(0.019)
If category#8	-0.023
	(0.016)
Constant	-0.008
	(0.011)
Observations	392,613
Log Likelihood	$-272{,}109.400$

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A1 shows the distribution of estimated propensity scores in the control and treatment groups. There are two key takeaways. First, the distributions of propensity scores are similar in the control and treatment groups. Second, a large proportion of observations have a propensity score close to 0.5. Both patterns make sense because our data come from a randomized experiment.

Figure A1: Distribution of propensity scores



B ATT Using Instrumental Variable Estimation

To estimate ATT in a randomized experiment with an intent-to-treat design, researchers often use an instrumental variable (IV) approach where randomization is used as an instrumental variable. In settings where researchers lack information about the users in the control group who would have received the treatment had they been in the treatment group, this approach is useful since it helps identify users in the control group who would have been exposed to the treatment had they been in the treatment group.

In contrast, in our setting we have full information on users in the control group who would have been exposed to the endorsement badge had they been in the treatment group. This is because regardless of being in the control or treatment group, a user might still be exposed to an eligible service. The only difference is that for users in the treatment group, an endorsement badge is displayed on an eligible service, while for control group users, the endorsement badge is not displayed on an eligible service. Thus, using this information we can estimate the ATT directly rather than estimating the ATT indirectly using the IV approach. Compared to an IV approach, estimating the ATT directly by removing those users who would never have been exposed to the endorsement badge from the analysis reduces noise in the estimator (Johnson et al., 2017). Consequently, in our analysis we focus on users who were exposed to an endorsement-eligible service at least once during the experiment.

To demonstrate the robustness of our results, we report the ATT using an instrumental variable regression. We use the random assignment as the intrumental variable. Table B1 shows the results from the first stage of the two stage least square estimation. We conduct this analysis at a user level and control for users' pre-treatment browsing and purchase behavior and user characteristics. We find that the randomiz assignment explains users' exposure to the platform endorsement badge.

Table B2 summarizes the IV results for impressions, clicks, and orders from the second stage using a linear regression. The results for impressions and clicks mirror the findings from our estimation approach except for clicks for unendorsed services which is no longer significant ($p = 0.108$). For orders, the estimates obtained from the IV approach directionally mirror those of our specification. However, the effect on total orders becomes insignificant when using IV. This outcome is not surprising since, as previously explained, the IV estimators are less efficient and more noisy than the direct estimation of the ATT.

Table B1: First stage of IV regression

	(1) First Stage
Treatment	0.745***
	(0.000581)
Total lifetime orders	0.0000176***
	(0.00000225)
If browsed (pre-experiment)	0.0247***
	(0.000781)
# Impressions (pre-experiment)	0.00000411***
	(0.000000303)
# Clicks (pre-treatment)	0.000494***
	(0.0000269)
# Orders (pre-treatment)	0.00138***
	(0.000365)
If registered	-0.00306***
	(0.000813)
Age on platform	-0.00000622***
	(0.000000469)
First arrival day	-0.00173***
	(0.000150)
Constant	0.0492***
	(0.00133)
Category controls	Yes
First visit week	Yes
Observations	1,114,995
R sq.	0.597

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B2: Effect of platform endorsement on impressions, clicks, and orders: IV

	(1) Linear
Impressions	5.263***
	(1.877)
Endorsed impressions	0.0247
	(0.0469)
Unendorsed impressions	5.238***
	(1.855)
Clicks	0.0582**
	(0.0279)
Endorsed clicks	0.0268***
	(0.00206)
Unendorsed clicks	0.0590
	(0.0367)
Orders	0.00254
	(0.00158)
Endorsed orders	0.00140***
	(0.000170)
Unendorsed orders	0.00114
	(0.00156)
Category controls	Yes
Past purchase controls	Yes
First visit week	Yes
Controls used in the first stage	Yes
Observations	1,114,995

Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Estimation Equations for Section 3.5

We estimate how the effect of platform endorsement varies with the spatial distance of a service to the endorsed service for results shown in Columns (1)-(2) of Table 8 using the following specification:

$$\begin{aligned} ln(\lambda_{i,c,s}) = \beta_0 + \beta_1 Treatment_i + \beta_2 \mathrm{I}(\text{services located nearby})_{i,c,s} + \\ \beta_3 \times Treatment_i \times \mathrm{I}(\text{services located nearby})_{i,c,s} + \beta_4 X_{i,c,s}, \end{aligned} \tag{2}$$

where we assume that the dependent variable of interest for user i browsing in category c in session s, $Y_{i,c,s}$, is drawn from a Poisson distribution with parameter $\lambda_{i,c,s}$. All other variables are as defined in detail in Section 3.2 in the paper.

Similarly, to estimate how the effect of platform endorsement varies across services that are priced similarly to the endorsed service for results shown in Columns (3)-(4) of Table 8, we use the following specification:

$$\begin{aligned} ln(\lambda_{i,c,s}) = \beta_0 + \beta_1 Treatment_i + \beta_2 \mathrm{I}(\text{similarly priced})_{i,c,s} + \\ \beta_3 \times Treatment_i \times \mathrm{I}(\text{similarly priced})_{i,c,s} + \beta_4 X_{i,c,s}, \end{aligned} \tag{3}$$

where we assume that the dependent variable of interest for user i browsing in category c in session s, $Y_{i,c,s}$, is drawn from a Poisson distribution with parameter $\lambda_{i,c,s}$. All other variables are as defined in detail in Section 3.2 in the paper.

D Linear Regression Results

Table D1 shows the results using a linear regression for impressions, clicks, and orders. The majority of results are directionally consistent and have the same significance levels (an exception is the effect for unendorsed orders in the linear specification that now has a p-value = 0.101).

Table D1: Effect of platform endorsement on impressions, clicks, and orders

	(1) Linear
Impressions	6.037***
	(2.215)
Endorsed impressions	0.0465
	(0.0496)
Unendorsed impressions	5.990***
	(2.189)
Clicks	0.0812***
	(0.0295)
Endorsed clicks	0.0281***
	(0.00206)
Unendorsed clicks	0.0816**
	(0.0391)
Orders	0.00387***
	(0.00150)
Endorsed orders	0.00145***
	(0.000170)
Unendorsed orders	0.00242
	(0.00148)
Category controls	Yes
Past purchase controls	Yes
First visit week	Yes
Observations	834,853

Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Tables D2-D6 demonstrate robustness when using a linear specification for the robustness tests and mechanism checks. In the heterogeneity analysis regarding business versus personal users, the results are consistent in both direction and significance level (Columns(1)-(3) of Table D7) except for results for endorsed orders. In the analysis regarding orders in the past two weeks, the effect of endorsement on total orders and on unendorsed orders while directionally consistent is no longer significant (Columns(4)-(6) of Table D7). This is not surprising given that the linear estimator is less efficient for count data.

Table D2: Effect on unendorsed non-qualifying services

	(1) Unendorsed not qualifying impressions	(2) Unendorsed not qualifying clicks	(3) Unendorsed not qualifying orders
Treatment	5.627***	0.0777**	0.00245*
	(2.152)	(0.0388)	(0.00147)
Category controls	Yes	Yes	Yes
Past purchase controls	Yes	Yes	Yes
First visit week	Yes	Yes	Yes
Observations	834853	834853	834853
R sq.	0.00845	0.0125	0.0201

Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D3: Effect on search based on spatial proximity and price similarity

	Unendorsed clicks (1)	Unendorsed orders (2)	Unendorsed clicks (3)	Unendorsed orders (4)
Treatment	0.0341*	0.00191**	0.0242	0.00126*
	(0.0188)	(0.000785)	(0.0149)	(0.000647)
Services located nearby	-1.667***	-0.0350***		
	(0.0115)	(0.000531)		
Treatment × Services located nearby	-0.0437**	-0.00258***		
	(0.0172)	(0.000783)		
Similarly priced			-1.236***	-0.0226***
			(0.00952)	(0.000468)
Treatment × Similar priced			-0.0225	-0.00179**
			(0.0141)	(0.000695)
Category controls	Yes	Yes	Yes	Yes
Past purchase controls	Yes	Yes	Yes	Yes
First visit week	Yes	Yes	Yes	Yes
Observations	1553692	1553692	1553692	1553692
R sq.	0.0575	0.0128	0.0397	0.00929

Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D4: Browsing and clicks in categories without exposure to platform endorsement

	Impressions (1)	Clicks (2)	Orders (3)
Treatment	3.906***	0.0561*	0.00474**
	(1.327)	(0.0308)	(0.00240)
Category controls	Yes	Yes	Yes
Past purchase controls	Yes	Yes	Yes
First visit week	Yes	Yes	Yes
Observations	110640	110640	110640
R sq.	0.00580	0.00745	0.00906

Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sample restricted to browsing behavior of users after the first exposure to platform endorsement-eligible service in categories where they were not exposed to platform endorsement-eligible service during the period of the experiment.

Table D5: Number of orders conditional on clicks

	Orders	Endorsed orders	Unendorsed orders
	(1)	(2)	(3)
Treatment	0.00289**	0.00126***	0.00176
	(0.00145)	(0.000192)	(0.00144)
# Clicks	0.0121***		
	(0.00111)		
# Endorsed clicks		0.00666*	
		(0.00366)	
# Unendorsed clicks			0.00807***
			(0.00137)
Category controls	Yes	Yes	Yes
Past purchase controls	Yes	Yes	Yes
Week of first arrival controls	Yes	Yes	Yes
Observations	834853	834853	834853
R sq.	0.0718	0.00820	0.0597

Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D6: Effect over time: Impressions, Clicks

	Impressions	Endorsed impressions	Unendorsed impressions	Clicks	Endorsed clicks	Unendorsed clicks
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.694	-0.0114	0.705	-0.00131	0.0184***	-0.0197
	(1.204)	(0.0183)	(1.196)	(0.0273)	(0.00144)	(0.0269)
Second exposure	150.6***	1.783***	148.8***	2.324***	0.0641***	2.260***
	(3.857)	(0.0523)	(3.821)	(0.0471)	(0.00207)	(0.0461)
Treatment × Second exposure	8.380	0.150	8.229	0.142**	0.0247***	0.118*
	(5.776)	(0.114)	(5.709)	(0.0726)	(0.00388)	(0.0712)
Category controls	Yes	Yes	Yes	Yes	Yes	Yes
Past purchase controls	Yes	Yes	Yes	Yes	Yes	Yes
First visit week	Yes	Yes	Yes	Yes	Yes	Yes
Observations	477981	477981	477981	477981	477981	477981
R sq.	0.0120	0.00516	0.0120	0.0175	0.0102	0.0170

Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D7: Effect on orders by business vs. personal users and past orders

	Orders	Endorsed orders	Unendorsed orders	Orders	Endorsed orders	Unendorsed orders
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.00148	0.000546*	-0.00203	-0.000421	0.00129***	-0.00171
	(0.00264)	(0.000281)	(0.00259)	(0.00303)	(0.000173)	(0.00300)
Business user	0.137***	0.00378***	0.133***			
	(0.00492)	(0.000456)	(0.00484)			
Treatment × Business user	0.0160**	0.00261***	0.0133*			
	(0.00705)	(0.000706)	(0.00696)			
Orders in past 2 weeks				0.0461***	0.000512***	0.0456***
				(0.00575)	(0.000156)	(0.00566)
Treatment × Orders in past 2 weeks				0.0135	0.000493**	0.0130
				(0.00968)	(0.000226)	(0.00960)
Category controls	Yes	Yes	Yes	Yes	Yes	Yes
Past purchase controls	Yes	Yes	Yes	Yes	Yes	Yes
First visit week	Yes	Yes	Yes	Yes	Yes	Yes
Observations	267689	267689	267689	834853	834853	834853
R sq.	0.0319	0.00316	0.0309	0.0371	0.00215	0.0365

Clustered standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

E Robustness

We conduct a battery of robustness checks to ensure that the results are not driven by the specific functional form of the Poisson regression. These checks include model-free t-tests, Poisson regression using propensity score as a control rather than inverse probability weighting, and a negative binomial regression.

First, Table E1 presents results from t-tests and shows that the results on impressions, clicks, and orders, including endorsed and unendorsed services, are consistent with the results reported in Poisson specification.

Table E1: User level impressions, clicks, and orders after re-weighting

	Control	Treatment	p-value
# Impressions	317.60	332.96	0.00
# Endorsed impressions	4.65	4.78	0.21
# Unendorsed impressions	312.95	328.18	0.00
# Clicks	8.14	8.36	0.00
# Endorsed clicks	0.24	0.30	0.00
# Unendorsed clicks	8.72	8.95	0.00
# Orders	0.301	0.311	0.00
# Endorsed orders	0.008	0.011	0.00
# Unendorsed orders	0.293	0.300	0.04

The data covers 392,613 users during the period of the experiment.

Second, Column (1) of Table E2 shows the coefficient estimates for the number of impressions, clicks, and orders using a Poisson regression with propensity scores as a control. Again, the results are robust. Note that controlling for the propensity score makes the assumption that the treatment effect is homogeneous across units with different propensity scores (Wooldridge, 2010), which may not hold in our setting, as shown in Section 5.

Third, Column (2) of Table E2 shows the coefficient estimates for the number of impressions, clicks, and orders using an IPW estimation as in the paper but with a negative binomial model specification. Again, the results are robust except for the the effect on orders of unendorsed services. While directionally consistent, we lose significance (p-value = 0.116).

Together, this set of results suggest that our findings are not driven by functional form assumptions.

Table E2: Estimates of the effect of platform endorsement on impressions, clicks, and orders

	(1) Poisson regression Control for propensity score	(2) NBD regression
Dependent Variables		
Total Impressions	0.0414**	0.0246**
	(0.0172)	(0.0108)
Endorsed impressions	0.0257	0.0026
	(0.0232)	(0.0140)
Unendorsed impressions	0.0416**	0.0251**
	(0.0173)	(0.0109)
Total Clicks	0.0233***	0.0191***
	(0.00748)	(0.00683)
Endorsed clicks	0.226***	0.221***
	(0.0152)	(0.01455)
Unendorsed clicks	0.0224**	0.0173**
	(0.00925)	(0.00809)
Total Orders	0.0311***	0.0259**
	(0.0106)	(0.0102)
Endorsed orders	0.341***	0.348***
	(0.0400)	(0.0402)
Unendorsed orders	0.0216**	0.0163
	(0.0108)	(0.0104)
Category controls	Yes	Yes
Past purchase controls	Yes	Yes
First visit week	Yes	Yes
Propensity score controls	Yes	No
Observations	834,853	834,853

Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

F Pre-Treatment Covariate Balances for Sub-Samples

To check whether the sub-sample of users used in the analysis for Table 9 (which examines whether platform endorsement improves users' perception of quality of services available on the platform) are balanced, we test the pre-treatment covariate balance between the control group and treatment group users for this analysis. Results are shown in Table F1 and indicate that the two groups are balanced, with none of the p-value below 0.10.

Table F1: Covariate balance for mechanism analysis

	N	Control	Treatment	p-value
# Impressions	76,557	310.14	304.27	0.63
# Clicks	76,557	7.26	7.42	0.33
# Orders	76,557	0.24	0.24	0.94
Purchase price	8,832	35.52	34.86	0.63
Rating of purchased service (If rated)	8,159	4.92	4.92	0.31
# Ratings of purchased service	8,832	461.96	476.44	0.75
# Lifetime Orders	76,557	40.63	38.34	0.20
% Business users	28,213	0.40	0.41	0.57

For the analysis of the novelty mechanism in Table 11 that uses a sub-sample of users, we check the pre-treatment covariate balance between the control group and treatment group observations. The results in Table F2 below show that the two groups are balanced, with none of the p-values below 0.10.

Table F2: Covariate balance for novelty analysis

	N	Control	Treatment	p-value
# Impressions	115,755	357.06	343.37	0.22
# Clicks	115,755	6.84	6.77	0.59
# Orders	115,755	0.21	0.21	0.92
Purchase price	11,361	34.68	35.75	0.35
Rating of purchased service (if rated)	10,555	4.92	4.92	0.19
# Ratings of purchased service	11,361	486.35	526.86	0.32
# Lifetime orders	115,755	32.86	32.17	0.55
% Business users	43,007	0.35	0.36	0.20

G Additional Analyses Regarding the Mechanism

We also compare the increase in search and purchase for categories in which users were exposed to an endorsement-eligible service relative to categories where they were not exposed to an endorsement-eligible service, conditional on being previously exposed to an endorsement-eligible service in another category. Table G1 shows that the increases in impressions, clicks, and orders in categories where users were not exposed to an endorsement-eligible service do not differ significantly from the increases in impressions, clicks, and orders in categories where users were exposed to an endorsement-eligible service. This result is in line with the proposed mechanism that platform endorsement improves users' beliefs in the overall quality of services across the platform, resulting in more search and purchase of both endorsed services and unendorsed services.

Table G1: Mechanism: Change in perceived quality in categories with exposure and categories without exposure

	#Impressions	#Clicks	#Orders
	(1)	(2)	(3)
Treatment	0.0643***	0.0247*	0.0576**
	(0.0233)	(0.0145)	(0.0282)
In exposed category	1.609***	1.059***	0.758***
	(0.0223)	(0.0136)	(0.0239)
Treatment × In exposed category	-0.00474	0.00413	-0.0134
	(0.0324)	(0.0197)	(0.0324)
Category controls	Yes	Yes	Yes
Past purchase controls	Yes	Yes	Yes
First visit week	Yes	Yes	Yes
Observations	331,579	331,579	331,579
Log likelihood	-246,228,564.8	-4,320,605.5	-328,468.8

Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table G2 shows a further check for the novelty mechanism. We identify among treatment group users those who were exposed to a platform endorsement badge on six separate calendar days.[19] We follow a similar logic for control group users. We combine the browsing behavior of users starting from the first exposure to the endorsement badge through the third exposure and consider it as one period. We combine the browsing behavior of users starting from the fourth exposure to the endorsement badge through the sixth exposure occasion into a second period. We then compare the change in impressions and clicks from the first period to the second period between the treatment and control groups. The interaction term between the treatment and the next three visits captures the effect of platform endorsement on search over subsequent exposure. The statistically insignificant estimate suggests that the effect of platform endorsement on search does not attenuate over subsequent exposure. The results are consistent with the main analysis and we find no evidence that the effect of platform endorsement wears off over time.

We thus conclude that the novel feature of an endorsement badge alone is unlikely to explain the increase in browsing and clicks for unendorsed services.

[19]We limit the sample to users with exposure to endorsement on exactly six separate days to ensure a large enough sample size while also allowing enough opportunity for the novelty effect to wear-off. The result from this analysis is robust to a change in the number of exposures. The results are similar if we limit the sample to users who are exposed on exactly two, three, four, and five different calendar days.

Table G2: Novelty mechanism: Users with exposure to eligible services on six unique days

	(1)	(2)	(3)	(4)	(5)	(6)
	#Impressions	#Endorsed impressions	#Unendorsed impressions	#Clicks	#Endorsed clicks	#Unendorsed clicks
Treatment	-0.0702	-0.00379	-0.0710	-0.0346	0.133**	-0.0396
	(0.0540)	(0.0299)	(0.0544)	(0.0422)	(0.0556)	(0.0430)
Next three visits	-0.0817	-0.0384	-0.0822	-0.118***	-0.104*	-0.119***
	(0.0368)	(0.0229)	(0.0371)	(0.0327)	(0.0547)	(0.0332)
Treatment × Next three visits	0.0456	-0.0239	0.0464	0.0449	-0.00132	0.0463
	(0.0491)	(0.0329)	(0.0495)	(0.0444)	(0.0742)	(0.0451)
Category controls	Yes	Yes	Yes	Yes	Yes	Yes
Past purchase controls	Yes	Yes	Yes	Yes	Yes	Yes
Week of first arrival controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,703	20,703	20,703	20,703	20,703	20,703
Log likelihood	-9,647,495.0	-114,744.1	-9,628,550.6	-286,148.5	-20,538.3	-282,887.4

Clustered standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

H Purchase Propensity for Control Group Users

We examine whether users who have purchased more in the two-week pre-treatment period have a higher propensity to purchase. We focus on control group users only and examine the number of orders placed by users during the period of the experiment as a function of the number of orders they placed in the pre-treatemnt period. Column (1) of Table H1 shows that users with more purchases in the pre-treatment period place a higher number of orders during the experiment.

Next, we examine whether business users have a higher propensity to purchase than personal users. We focus on control group users only and examine the number of orders placed by users during the period of experiment as a function of whether they are business users. Column (2) of Table H1 shows that business users place a higher number of orders during the experiment compared to personal users.

Table H1: Purchase propensity for control group users

	(1) #Orders	(2) #Orders
Orders in past 2 weeks	0.0272***	
	(0.00412)	
Business user		0.972***
		(0.0283)
Category controls	Yes	Yes
Past purchase controls	Yes	Yes
First visit week	Yes	Yes
Observations	418,874	134,120
Log likelihood	-187,699.7	-59,598.3

Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data sample includes control group users exposed to an endorsement-eligible service.