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Abstract

We study consumer response towards sponsored search advertising and how to improve advertising performance on a large e-commerce platform. Our research design is based on a field experiment which randomizes the salience of ad disclosure to consumers, and a natural experiment which eradicates a listing-level quality certificate for all listings because of a system glitch. Results suggest that consumers dislike search advertising in our setting, but quality certificates mitigate this aversion and increase advertising sales.

Keywords: sponsored search advertising, quality certificates, e-commerce.

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1 Introduction

Advertising fuels the digital economy.[1] Among different formats of digital advertising, sponsored search accounts for 41.4% of the total revenue.[2] Two questions are of first-order importance for advertising publishers and policy makers: how do consumers respond to sponsored search advertising, and, given this, how can ad publishers improve ad performance?

The answer to the first question is ambiguous both theoretically and empirically. On the one hand, the existence of advertising can induce a signalling equilibrium where only high-quality firms advertise (Nelson (1974); Milgrom and Roberts (1986)), and can therefore help consumers find their desired products. On the other hand, if consumer search is costly and products have already been ranked based on some desirability metrics (e.g., predicted conversion rate), distortions of the "organic" ranking from sponsored search can obfuscate search and reduce the purchase likelihood. Meanwhile, empirical evidence on the effect of sponsored search on total sales, which is often based on field experiments in e-commerce settings, is also mixed, ranging from a positive effect on a food delivery app in Asia (Sahni and Nair (2020a)), to an overall null effect on an e-commerce marketplace in India (Abhishek et al. (2022)), to a negative effect (Moshary (2021)) on eBay. The theoretical ambiguity and wide-ranging empirical evidence suggest that consumer response to ads may critically depend on institutional details in a particular market (discussed in Section 6) and therefore should be measured on a case-by-case basis instead of being assumed.

Despite the mixed evidence, a consistent finding among the empirical studies is that consumers change their behavior because of their *knowledge* about a listing's advertising sponsorship. Given the informational nature of ad disclosure (i.e., disclosing that a listing is sponsored), to explore the second question on improving ad performance, it is natural to ask how signals about match quality interact with ad disclosure in shaping consumer behavior. In e-commerce, such signals are typically based on reputation mechanisms, such as ratings and quality certificates. Theoretically, the interaction between ad disclosure and reputation mechanisms is unclear and depends on consumer perception of sponsored search ads (i.e., the first question): If consumers view ad disclosure as a signal of high quality, they may rely less on reputation signals in discerning product quality in the presence of advertising. Alternatively, if consumers dislike ads, they may rely more on reputa-

[1]In 2021, Google received 80% of revenue through advertising, and Facebook, about 99%. Amazon's share of revenue from advertising business is fast-growing, at a pace of 32% in Q4 2021. These three companies combined represent roughly 10% of the value in the U.S. stock market. https://www.csis.org/blogs/strategic-technologies-blog/fragility-digital-advertising-and-future-attention-economy-part-i (accessed 2022/05/15).

[2]https://searchengineland.com/us-search-ad-revenue-78-billion-2021-383518 (accessed 2022/05/15).

tion signals to overcome the negative impact of ad disclosure. Therefore, the interaction between reputation signals and ad disclosure is an empirical question, which has barely been studied before.

We fill this gap by leveraging two experiments and rich data from eBay, a globally popular e-commerce marketplace,[3] to shed light on the interaction of ad disclosure and reputation mechanisms. To do this, we first study consumers' response to sponsored listings (henceforth, ad listings) in the case of eBay. Specifically, we use a field experiment which randomizes case types of the word "sponsored" displayed on ad listings on the search results page: in either regular capitalization ("Sponsored") or in all caps ("SPONSORED"). We interpret the all-cap condition as more salient ad disclosure compared to the regular capitalization condition. Under this interpretation, we find that more salient ad disclosure causes consumers to substitute away from ad listings and click and buy from organic listings (henceforth, non-ad listings) instead; total spending decreases but is not quite statistically significant. These findings suggest that consumers dislike ads, which is consistent with the results established in Moshary (2021), who studies an experiment that turns off sponsored search for 3% of users on the same platform. Our field experiment complements the one in Moshary (2021) because we are able to manipulate only (the salience of) ad disclosure while holding constant other aspects of what consumers see and, in particular, the ordered list of products on the search results page (more details in Section 2). The consistency in results from both papers strengthens the conclusion of consumers' ad aversion in our empirical setting.

Next, given consumers' aversion to ads, we study our second research question on how to improve ad performance and, specifically, the role of reputation mechanisms in this. We perform two analyses: (1) how consumers' ad aversion differs by the existence of a listing-level quality certificate and (2) how the effect of the quality certificate differs between ad and non-ad listings. For the first analysis, we reuse the field experiment. We find that beyond the overall negative effect from salient ad disclosure, ad listings with a quality certificate experience a smaller drop in clicks and sales than those without the quality certificate. For example, ad listings with the quality certificate experience a sales drop of 6.8%, compared to a 18.7% drop for those without the quality certificate. The heterogeneous treatment effects suggest that quality certificates can alleviate consumer aversion to ads.

To quantify the causal impact of the quality certificate on ad and non-ad listings, we move on to the second analysis based on a natural experiment (i.e., a system glitch), which eradicates the

[3]eBay was the second most visited e-commerce marketplace globally in 2021. https://www.webretailer.com/b/online-marketplaces/ (accessed 2022/05/15).

quality certificate for all listings on the website within a three-week window. We use a difference-in-differences specification to quantify the differential impacts of losing the quality certificate between ad and non-ad listings. We find that ad listings lose significantly more sales than non-ad listings do. Specifically, the purchase-through rate of ad listings drops by 14.2% more compared to that of non-ad listings. We also run two robustness analyses: an alternative identification strategy based on comparing listings that lost the quality certificate earlier during the glitch vs. later, and a matching approach where we compare sessions that differ only in the number of listings with the quality certificate but are otherwise identical in terms of search keywords, the ordered list of products on the search results page, listings' ad status, and prices. The results from the robustness analyses are broadly consistent with those from the simple DiD analysis.

Considering all results, our key takeaway is that in settings where consumers are averse to sponsored search advertising, quality certificates can mitigate consumers' aversion to ads and increase ad sales. Since search advertising has been comprising a larger share of business revenue, ad publishers and platform managers should consider highlighting quality signals to improve ad performance. Additionally, we note that consumer response to ads may vary drastically across contexts and market institutions. Therefore, policy makers need to carefully measure this parameter on a case-by-case basis as a first step towards effective regulations.

2 Related Literature

Our paper is closely related to a growing literature that uses experiments to study consumer response to sponsored search advertising. The evidence is mixed. On the one hand, some papers show that consumers benefit from search ads because the action of advertising entails useful information on the underlying product quality. For example, Sahni and Nair (2020a) show that ad disclosure increases the probability that a consumer calls the advertised restaurant on a food delivery app in Asia. Sahni and Zhang (2019) show that users of a search engine in the United States prefer a marginally higher level of advertising. On the other hand, other papers show that consumers dislike search ads because of their lower match quality relative to organic listings that would have taken the same positions without sponsored search. For example, Moshary (2021) studies an experiment on eBay that shuts down sponsored search ads for a random set of users, and finds that ad suspension increases these users' total spending on the platform. Joo et al. (2021) find that consumers dislike sponsored ads in prime positions of the search results in an e-commerce marketplace in India. Related, Simonov and Hill (2021) find on Bing.com that the stolen traffic of a competitor brand that bids on its rival brand is of low quality, highlighting the importance of search results' relevance for consumer conversion. Lastly, Abhishek et al. (2022) find mixed evidence on consumer perception of ads, which depends on product categories with different degrees of information asymmetry on product relevance between the platform and sellers in that category.

The wide-ranging empirical evidence suggests that consumer response to ads may critically depend on market institutions, which we discuss in Section 6.[4] This observation justifies the need for our field experiment, which varies the salience of ad disclosure, to study consumers' ad preference in our setting. Note that the experiment in Moshary (2021), which compares consumer behavior if consumers see organic vs. sponsored search results, does two things: the distortion of the ordered list of products under organic search and (the pure signalling value of) disclosing the "sponsored" signal. In comparison, our experiment holds constant the ordered list (and other aspects on the search results page) and manipulates only (the salience of) ad disclosure. This design allows us to estimate the marginal effect of indicating to consumers that an ad listing is an ad (in a more salient way). In this sense, our experiment design is similar to the one in Sahni and Nair (2020a), which also holds the ordered list of search results fixed to estimate the signaling value of ad disclosure. Despite the different designs, the similar qualitative results from both our experiment and the one in Moshary (2021) strengthen the conclusion of consumers' ad aversion in our empirical setting. This result contributes to the literature by proving that consumers dislike ads in some contexts. Therefore, researchers should not directly extrapolate these estimates across contexts.

Next, we contribute to the literature on the value of quality certificates by providing evidence on how a quality certificate interacts with advertising. Prior literature has shown that quality certificates provide useful information to consumers and steer demand in predictable ways in many contexts (see summaries by Dellarocas (2003); Dranove and Jin (2010); Einav et al. (2016); Tadelis (2016)), and, in particular, the Top Rated Seller certification badge and other reputation mechanisms on eBay (e.g., Resnick et al. (2006); Cabral and Hortacsu (2010); Saeedi (2019); Elfenbein et al. (2015); Hui et al. (2022)).[5] Our paper contributes to this literature by studying the interaction

[4] Similar mixed evidence is also found for other types of ads. While some research shows that consumers value informative advertising, such as for ads in Yellow Pages (Rysman (2004)), in magazines (Kaiser and Song (2009)), and on TV (Tuchman et al. (2018)), others show that consumers are annoyed by ads on TV (Wilbur (2016)) and in music streaming apps (Huang et al. (2018)), and by display ads (Goldstein et al. (2014)), especially when consumers have privacy concerns (Goldfarb and Tucker (2011)).

[5] Similar findings in other contexts include restaurants (Jin and Leslie (2003) and Dai and Luca (2020)), e-commerce marketplaces (e.g., Chevalier and Mayzlin (2006); Park et al. (2021)), review websites (e.g., Luca (2016)), online labor market (e.g., Barach et al. (2020)), and food choices (e.g., Bollinger et al. (2011) and Bai (2018)).

between quality certificates and advertising from the platform's (or the consumers') perspective.[6] There are a few papers that study related questions from firms' perspective: Hollenbeck et al. (2019) study hotels on Tripadvisor and find that those with higher ratings spend less on advertising (off Tripadvisor) than the lower-rated ones. Dai et al. (2022) show that restaurants that received a free advertising package on Yelp experienced higher customer purchase intention than those that did not, and this increase is larger for higher-rated restaurants. While these two papers study firms' strategy or revenue related to advertising, our paper focuses on how consumers react to advertising by varying the salience of ad disclosure. Another difference is that the two papers essentially estimate ads' treatment effect heterogeneity by seller reputation (a covariate), which does not directly speak to the causal effect of reputation on consumer response to advertising, because a seller's reputation is not randomly assigned. In our paper, besides studying ads' heterogeneous treatment effect, we also manipulate consumers' knowledge about a seller's reputation information using the system glitch and estimate how the causal effect of quality certificates differs by ad vs. non-ad listings. Our results indicate that the value of the quality certificate is greater for ads than for non-ads, which suggests that platforms should highlight quality signals to improve ad performance.

Lastly, our paper is also related to the large literature on the effectiveness of sponsored search ads for individual advertisers (e.g., Blake et al. (2015); Dai et al. (2022); Johnson et al. (2017)). Instead of taking the perspective of individual sellers, we focus on the site-wide effect of ad disclosure by manipulating the disclosure of all active ads, as discussed before. Also, our paper is related to the literature on the design of sponsored search ads, such as rules to efficiently allocate ad slots (Athey and Ellison (2011), Yao and Mela (2011), Choi and Mela (2019)) and the role of positions and ranking (Ghose et al. (2014), Narayanan and Kalyanam (2015), Jeziorski and Moorthy (2018), Ursu (2018)). In particular, our paper speaks to issues regarding native ads (Aribarg and Schwartz (2020), Sahni and Nair (2020b), Revel et al. (2021)). Our findings imply that platforms could gain revenue from less salient ad disclosure (i.e., more native), although we cannot extrapolate the results to extreme cases of non-disclosure, or speak to the long-term effect.

3 Background

In this section, we describe eBay's sponsored search advertising and the eBay Plus program. On eBay, after consumers type in search queries, they see a search results page with both sponsored

[6]Prior work has studied the interaction between quality certificates and other mechanisms on digital platforms, e.g., peer ratings (Farronato et al. (2020)), logistic signals (Hui et al. (2020)), and buyer warranty (Hui et al. (2016)).

listings (i.e., ads) and organic listings (i.e., non-ads). Their ranking is based on a score that depends on the quality of the listing, which is proprietary to eBay and is correlated with click-through rates, and the ad rate submitted by sellers. The ad rate is a bid between 0 and 100% submitted by the seller, representing a fraction of sales price (0% corresponds to non-ad listings). eBay uses a "cost per action" pricing mechanism for advertising during our sample period: a seller pays for an ad only if that listing sells. Another feature on eBay's sponsored advertising is that a listing appears at most once on a search results page either as an ad or non-ad. The two types look the same except that ad listings carry a "Sponsored" badge on search results pages, as shown in Figure 2. Non-ad listings have a blank spot instead.

The eBay Plus program was introduced in June 2018 on the eBay Australia website. The program is a combination of a quality certification program for sellers and a loyalty program for buyers. To issue quality certificates, eBay conducts a monthly seller evaluation and privately labels sellers Top Rated Seller if they meet some predetermined requirements based on historical sales and measured quality.[7] Top Rated Sellers can then get a public, listing-level eBay Plus badge if they offer one-day handling and free shipping, accept returns, and meet some other requirements for the product on that listing.[8] The eBay Plus badge appears on search results pages as shown in Figure 1 (Top Rated Seller status does not), and sellers can potentially benefit from this trust signal.[9] To summarize, eBay Plus is a listing-level quality certificate awarded to sellers who have passed some minimum thresholds of historical sales and measured quality, and offer good logistic service on a listing.

The eBay Plus program is also a loyalty program for buyers. Specifically, buyers can join it by paying an annual membership fee of AUD $49. The members enjoy three benefits: they can (1) upgrade the shipping of eBay Plus items to express delivery for free if sent to a metropolitan address; (2) get a $5 voucher every month to spend on eBay Plus items; (3) get free returns on eBay Plus items. All buyers, regardless of their membership status, see the eBay Plus badge on the website. However, because the eBay Plus badge is not just a quality signal, we also use the same

[7] More specifically, in terms of historical sales, a seller needs to have at least 100 transactions and AUD $1000 in sales on the eBay Australia site in the past year. In terms of measured quality, a seller needs to have no more than 0.3% transactions with unresolved buyer claims, no more than 0.5% of transactions with unresolved buyer claims or seller-initiated cancellations, and no more than 5% of transactions with late shipment in the previous year.

[8] The other requirements are that the listing should be shipped from and be returnable to addresses within Australia, be in fixed price format, and be not too heavy or bulky. To be eligible for the badge, sellers also need to upload tracking information for at least 95% of their eBay Plus orders.

[9] Besides the signaling value of eBay Plus, its other benefits are (1) buyers can exclusively shop for eBay Plus items if they use a filter toggle; (2) sellers enjoy additional seller protection: eBay removes buyer feedback if the buyer is found to be abusive, and removes feedback on late shipment due to factors outside sellers' control; (3) sellers can get an express shipping cost refund up to AUD $4.

Figure 1: eBay Plus Badge on a Search Results Page

field experiment done on the eBay United States site, and use the eBay Top Rated Plus badge, which is a quality certificate but not a loyalty program, as a robustness check for the main results.

4 Field Experiment on Ad Disclosure

4.1 Consumer Response to Sponsored Search Ads

To estimate consumer response to search ads, the ideal experiment would be to manipulate ad disclosure on product listings on search results pages across consumers while holding the ordered list of products fixed. Because sponsored search advertising had existed on eBay long before the study period, results from this ideal experiment would inform us of consumer preference for ads (at the margin) in the equilibrium where sellers have chosen their optimal level of advertising and consumers correctly anticipate this. However, this experiment is not feasible in many countries because ad disclosure is mandatory by law. To our knowledge, Sahni and Nair (2020a) and Sahni and Nair (2020b) are rare exceptions that randomize ad disclosure on a restaurant platform in Asia, where such laws are absent. Instead, we exploit a field experiment that can arguably approximate the ideal experiment. Between August 29, 2020, and September 11, 2020, eBay randomized (at the user level) the case type of the word "sponsored" displayed on ad listings on the search results page. Specifically, during the experimental period, users in the control group experienced less salient ad disclosure and saw "Sponsored" in regular capitalization (Figure 2, left). There was no such change for consumers in the treatment group, who saw "SPONSORED" in all caps just like before the experiment (Figure 2, right). We refer to the no-change group as the treatment group because we want to study the effect of more salient ad disclosure. This experiment was designed under the assumption that consumers are more likely to notice ad disclosure in all caps. All other aspects are the same across the two groups. Lastly, the same experiment was implemented on four eBay

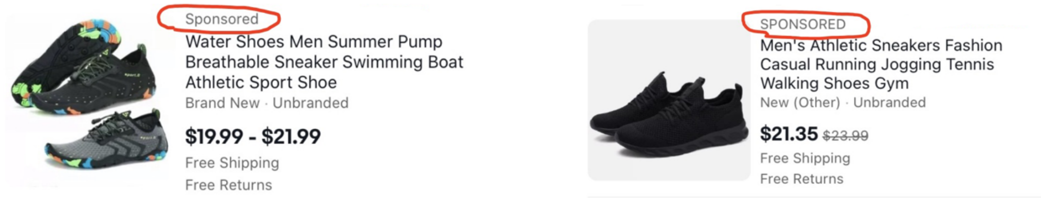


Figure 2: Field Experiment on the Salience of Ad Disclosure

sites: Australia (AU), Germany, UK, and US sites. Our main analyses focus on the experiment on the AU site because our second, natural experiment took place on this site. That said, we use the experiment on the US site for the robustness analysis.

As mentioned, the randomization is done at the user level, where a user is defined as a cookie.[10] Specifically, the first 3.5 million users who interact with the eBay AU website on the first day of the experiment enter the experiment and have a 50% chance of being assigned to the treatment or the control group. The users then retain their initial assignment throughout the experiment.

In Table 1, we check if baseline balance holds in our experiment. We compare the treatment and control users on a set of covariates measured based on the three months before the start of the experiment, by regressing each of the covariates on the treatment dummy. We find that control group users on average have 5.7 search sessions, spend 164.8 seconds on the website, complete 0.8 transactions, buy 1 unit of product, and spend AUD $30.6.[11] Across these measures, we do not find statistically significant differences between treatment and control users, consistent with a valid randomization.

To estimate the treatment effect of more salient ad disclosure, we leverage the following cross-sectional regression:

$$Y_i = \alpha + \beta Treat_i + \epsilon_i, \tag{1}$$

where Y_i is the outcome of user i for the entire experimental period; $Treat_i$ is the treatment dummy that equals 1 for the treatment group and 0 for the control group; and ϵ_i is the user specific idiosyncratic error term. Our coefficient of interest β measures the average treatment effect of

[10] Technically, a user can have multiple cookies if they access eBay from multiple devices or if they clear their cache on the browsers. Lin and Misra (2022) show that cookie-level randomization can over- or under-estimate the treatment effect at the user level. The good news is that more than 85% of users have only one cookie during the experiment, so the fragmentation bias is likely small in our setting.

[11] The numbers correspond to users in the experiment, which represent a fraction of users on the eBay AU site.

Table 1: Baseline Balance

	(1) Number of Sessions	(2) Session Duration in Seconds	(3) Number of Transactions	(4) Quantity Bought	(5) Spending in AUD
Treat	-0.002	-0.582	-0.002	-0.001	-0.242
	(0.018)	(0.897)	(0.004)	(0.005)	(0.217)
Constant	5.706***	164.772***	0.844***	1.034***	30.583***
	(0.012)	(0.635)	(0.003)	(0.004)	(0.154)
Observations	3,561,581	3,561,581	3,561,581	3,561,581	3,561,581
R-squared	0.000	0.000	0.000	0.000	0.000

Notes: Outcome variables are users' covariates measured based on the three months before the experiment. One observation is a user. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2: The Effect of More Salient Ad Disclosure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Number of Clicks			Number of Purchases			Sales in AUD	
	All	Ads	Non-Ads	All	Ads	Non-Ads	All	Ads	Non-Ads
Treat	-0.030	-0.177***	0.148***	0.000	-0.014***	0.014***	-0.136	-0.247***	0.111
	(0.019)	(0.004)	(0.017)	(0.004)	(0.002)	(0.003)	(0.087)	(0.019)	(0.083)
Constant	6.039***	1.055***	4.985***	0.323***	0.087***	0.237***	7.569***	1.509***	6.061***
	(0.014)	(0.003)	(0.012)	(0.003)	(0.002)	(0.002)	(0.061)	(0.014)	(0.059)
Observations	3,561,581	3,561,581	3,561,581	3,561,581	3,561,581	3,561,581	3,561,581	3,561,581	3,561,581
R-squared	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Results based on Equation 1. One observation is a user. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

more salient ad disclosure (i.e., from "Sponsored" to "SPONSORED"). We study the effect of ad disclosure on the number of clicks, the number of purchases, and sales in AUD, at the user level and by listing type (ads vs. non-ads).

Regression results of Equation 1 are reported in Table 2. Column (1) shows that more salient ad disclosure has no significant impact on total clicks (p-value is 0.126), and columns (2) and (3) provide evidence that an average consumer substitutes away from clicking on ad listings (a 16.8% drop) and clicks on non-ad listings (a 3.0% increase) instead. Similarly, in columns (4), (5), and (6), we observe no significant effects on the overall number of purchases when ads are made more salient, and find that consumers buy less from ad listings and substitute towards non-ad listings. Lastly, columns (7), (8), and (9) suggest a negative effect on the overall GMV (t-stat is 1.56), a strong negative effect on ad GMV (a 16.4% drop), and a weak positive increase in non-ad GMV. We provide robustness to these results by controlling for the dependent variables in Table 1 as covariates, specifically, the pre-experiment search sessions, session duration, number of transactions, quantities purchased, and spending. Table A1 reports qualitatively similar results after covariate adjustment.

Overall, results in Table 2 suggest that more salient ad disclosure causes consumers to substitute away from ad listings and click and buy from organic listings. The results suggest that consumers dislike ads, a finding that is consistent with the one in Moshary (2021). As discussed in Section 2, a notable feature of our experiment is that we preserve ordered lists of products on search results pages and vary only the salience of ad disclosure. The consistent results from the two papers strongly suggest consumers' ads aversion in our empirical setting.

4.2 Heterogeneous Treatment Effects by Certification Status

Given consumers' aversion towards ads, we now study ways to improve ad performance, and, specifically, the role of quality certificates. To do so, we first analyze how consumers' ad aversion differs by the existence of the eBay Plus badge (henceforth, the badge). Specifically, we use the experiment to identify the heterogeneous treatment effects of increasing the salience of ad disclosure across the four types of listings (defined as their ad status by badge status) in users' first search sessions after the beginning of the experiment. We focus on the first session of each user because what users see in subsequent sessions may be affected by users' reactions to their initial ad exposure, which makes the results for subsequent sessions difficult to interpret.

Table 3 reports the results based on Equation 1 on ads and non-ads in Part I and Part II, respectively. In each panel, we report treatment effect estimates on number of clicks, purchases, and sales for badged and non-badged listings. The last two rows of each panel report the treatment effects as a percentage change over the baseline (i.e., β/α) and the p-value of the test of equality of two percentage changes between the badged and non-badged listings. Comparing columns (1) and (2), we find that ads–non-badged listings experience a significant drop in clicks (-19.6%), while ads-badge listings' experience an increase in clicks (10.2%, not statistically significant), although the difference in the two percentage changes is statistically insignificant. Columns (3) and (4) show a drop in purchases for both ads-badged and ads–non-badged listings, with ads–non-badged listings experiencing a greater drop in percent terms (-4.5% vs. -23.5%), and the difference has a p-value of 0.107. Lastly, we find similar results on sales in columns (5) and (6), where the sales drop in ads–non-badged listings is 18.7%, while the drop in ads-badged listings is statistically insignificant, at 6.8%. In addition, the percentage drop in ads–non-badged listings is significantly greater than

Table 3: Heterogeneous Treatment Effects of More Salient Ad Disclosure by Certification Status

Part I.	Ads					
	(1)	(2)	(3)	(4)	(5)	(6)
	Number of Clicks		Number of Purchases		Sales in AUD	
	Badged	Non-Badged	Badged	Non-Badged	Badged	Non-Badged
Treat	0.009	-0.031**	-0.001	-0.003**	-0.011	-0.044***
	(0.019)	(0.014)	(0.001)	(0.001)	(0.008)	(0.007)
Constant	0.092***	0.158***	0.013***	0.013***	0.167***	0.238***
	(0.014)	(0.010)	(0.001)	(0.001)	(0.006)	(0.005)
Observations	1,526,673	3,352,982	1,526,673	3,352,982	1,526,673	3,352,982
R-squared	0.000	0.000	0.000	0.000	0.000	0.000
Percentage change	10.2%	-19.6%	-4.5%	-23.5%	-6.8%	-18.7%
Equality of percentage changes	p=0.178		p=0.107		p=0.033	
Part II.	**Non-Ads**					
	(7)	(8)	(9)	(10)	(11)	(12)
	Number of Clicks		Number of Purchases		Sales in AUD	
	Badged	Non-Badged	Badged	Non-Badged	Badged	Non-Badged
Treat	0.004	0.055	0.001***	0.002*	0.012	0.015
	(0.005)	(0.047)	(0.000)	(0.001)	(0.009)	(0.018)
Constant	0.108***	0.448***	0.012***	0.026***	0.247***	0.726***
	(0.004)	(0.033)	(0.000)	(0.001)	(0.006)	(0.013)
Observations	2,293,925	3,514,870	2,293,925	3,514,870	2,293,925	3,514,870
R-squared	0.000	0.000	0.000	0.000	0.000	0.000
Percentage change	3.7%	12.3%	12.7%	8.5%	5.0%	2.0%
Equality of percentage changes	p=0.461		p=0.529		p=0.516	

Notes: Results based on Equation 1. One observation is a user. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

that of ads-badged listings, as shown by the p-value of 0.033 from the between-model equality test.

In Part II, we find that more salient ad disclosure generally leads to more clicks, purchases, and sales in the non-ads–badged and non-ads–non-badged listings. Columns (1) and (2) show that the increase in clicks for non-ads–non-badged listings is 12.3%, whereas the increase in clicks for non-ads–badged listings is only 3.7%. The percent effect for non-ads–badged listings is greater than that for non-ads–non-badged listings in purchases and sales (12.7% vs. 8.5%, and 5% vs. 2%, respectively). However, these differences in the percent effects between badged– and non-badged–non-ads are statistically insignificant.

Taken together, evidence in Table 3 suggests that when ad disclosure is made more salient, beyond the overall negative effect from salient ad disclosure, shown in Table 2, ad listings with a quality certificate experience a smaller drop in clicks and sales than those without the quality certificate. However, eBay Plus on eBay Australia is a combination of a quality certification program and a consumer membership program, as described in Section 3. To check if the heterogeneous results are driven by the quality certification role, we repeat the analyses using the same experiment done on the eBay US site. On the US site, the corresponding listing-level badge is Top Rated Plus. This badge and eBay Plus have very similar requirements, but Top Rated Plus is a pure quality certification program.[12]

Table A2 in the appendix reports the results. Again, we find that the negative effect on clicks, purchases, and sales from more salient ad disclosure is less negative for ad listings with the Top Rated Plus badge than for ad listings without it (-18.2% vs. -19.6%, -13.6% vs. -18.8%, -8.4% vs. -14.5%, respectively; p-value of the difference in the percent effect is 0.081 for sales). For non-ads, there is generally a positive effect on the outcomes because consumers substitute away from ad listings and click on and buy more non-ad listings instead. In particular, the positive spillover effect in terms of percentage changes on clicks and purchases is significantly higher for eTRS listings than for non-eTRS listings. The qualitatively similar results on the two sites strongly suggest that quality certificates alleviate the extent to which consumers dislike ads in our setting.

5 Natural Experiment on a Quality Certificate

In the previous section, we leveraged a field experiment that manipulates the salience of ad disclosure. Our evidence so far suggests consumer aversion to sponsored search ads, as well as a reduced aversion if ads are badged and perceived as high quality by consumers. However, a concern with the heterogeneous treatment effects by a listing's quality certification status is that a listing's badge status is not randomly assigned and therefore cannot be interpreted causally. In this section, we strengthen our results by providing evidence from a natural experiment that exogenously removes quality certificates from the entire market.

Specifically, we leverage a system glitch on the eBay AU site in March 2020 that eradicated the eBay Plus badge from all listings in a three-week window: The share of badged listings decreases quickly after March 27, 2020, shrinking by half in two weeks and disappearing in the third week. The system glitch happened because eBay AU wanted to change the requirements for the eBay Plus program (from eBay Plus 1.0 to eBay Plus 2.0), but instead it accidentally eliminated the eBay

[12]Specifically, eBay evaluates sellers monthly and privately labels sellers as Top Rated Seller if they have a minimum of $1,000 in sales and 100 transactions in the past 12 months, no more than 0.3% of transactions with unresolved buyer claims, no more than 0.5% of transactions with unresolved buyer claims or seller-initiated cancellations, and no more than 3% of transactions with late shipment in the previous year. Top Rated Sellers receive a public Top Rated Plus badge on a listing if it offers one day or less handling time and 30-day or longer returns with the money-back option. There are two benefits of this badge: it has a signalling value to consumers and sellers get a 5% discount on the commission rate charged by eBay.

Plus badge for all listings in the three weeks after March 27, 2020, and the switch to eBay Plus 2.0 was successful, with the badge starting to reappear from the fourth week after March 27, 2020. The technical glitch affected only the certification badge, not anything else. For example, the search ranking algorithm is not a direct function of the certification badge, and therefore eliminating the eTRS Plus badge does not change the ranking of a product listing—a feature that we exploit later for a matching analysis.

We first check the claimed exogeneity of the technical glitch by plotting the time series of the share of badged listings separately for ads and non-ads. Figure 3 shows similar decreases in the share of badged listings for both ad and non-ad listings. In addition, we plot the share of badged listings for some of the most searched keywords on the eBay AU website. Figure 4 shows that while these keywords differ in their ex ante share of badged listings, the share goes down immediately after March 27, 2020, and becomes 0 for all keywords in three weeks. Results from both figures are consistent with the system glitch being an exogenous shock that is uncorrelated with listing or product types. This increases our confidence on the claim on the exogeneity of the technical glitch, and therefore the credibility of using this natural experiment to identify the effect of the quality certificate on ad effectiveness.

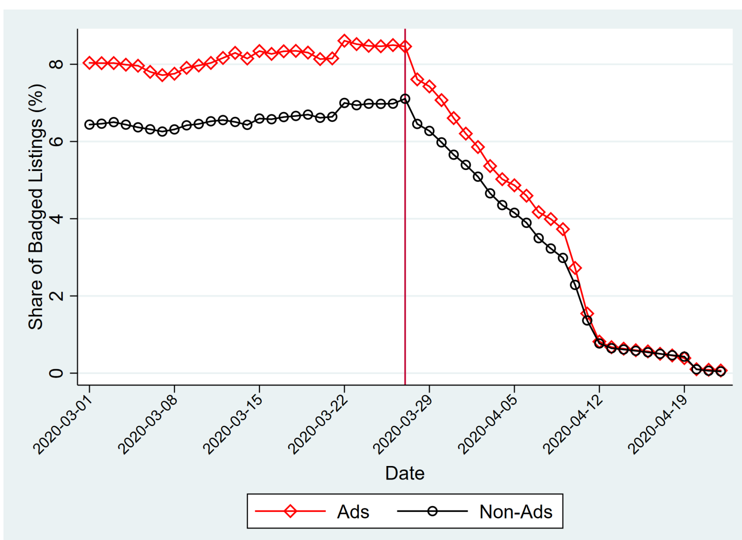


Figure 3: Share of Listings with eBay Plus, Ads vs. Non-ads

How does the removal of badges affect ads and non-ads differently? In Figure 5, we plot the time series of purchase-through rate (PTR hereafter) of listings that were badged before the technical glitch, separately for ads and non-ads.[13] The PTR of a listing is defined as the number of purchases

[13] As Figure 3 shows, the share of listings that are badged before the glitch is approximately 8.5% for ads and 7%

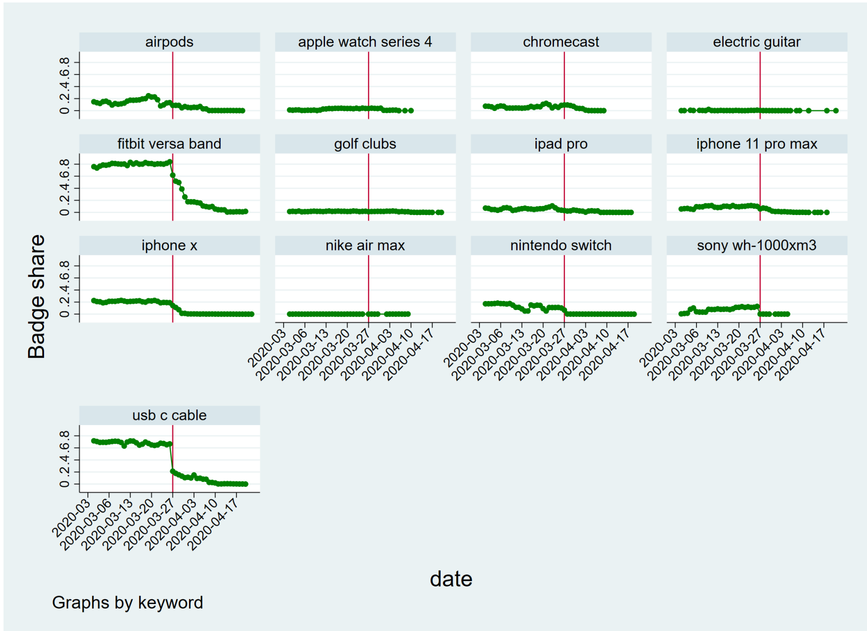


Figure 4: Share of Listings with Quality Certificate, Most Popular Keywords

per 1000 user impressions. To plot the graph, we normalize the PTR of ads and non-ads by their respective values on the day before the technical glitch (i.e., March 26, 2020). This normalization facilitates the interpretation of changes in percentage terms, and masks the raw values to preserve the data confidentiality. We find that ad and non-ad listings follow similar time trends before the system glitch, but that a gap appears immediately after the glitch. In particular, ad PTR decreases compared to non-ad PTR. We take this as model-free evidence that the quality certificate benefits ads relative to its effect on non-ads.

We adopt a DiD analysis to quantify the differential effect of badge removal between ads and non-ads. Essentially, the DiD specification compares the before-after change in ad PTR and non-ad PTR. The estimation sample is the same one used in Figure 5 (i.e., at the listing type-by-day level, where the listing type is either ads or non-ads). On the right hand side of the regression, we include an indicator for ad listings, its interaction with the post dummy (i.e., on or after March 27, 2020), and date fixed effects. Regression results are reported in column 1 of Table 4: after the glitch, the drop in ad PTR is 14.2 percentage points larger than the percentage drop in non-ad PTR.

One potential concern is that the above estimate may be driven by selection bias. For example, the advertising decision is a seller choice. It is possible that as badges are being erased, high-quality sellers advertise less, which could potentially explain the widening gap in PTR over time. This

for non-ads. In this analysis, we focus on listings that are badged before the glitch because we are interested in the effect of badge removal for ads and non-ads.

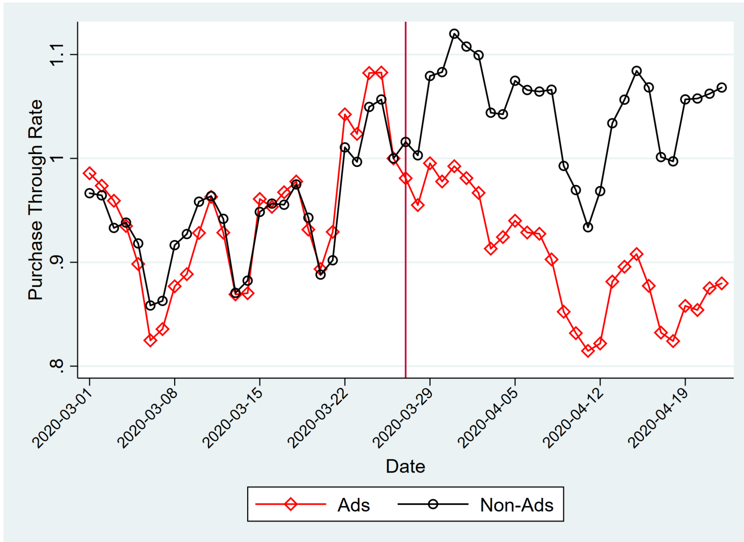


Figure 5: Differential Effect of Removing Quality Certificate: Ads vs. Non-Ads

Table 4: Differential Effect of Certificate Badge Removal: Ads vs. Non-Ads

	(1) Purchase-through Rate	(2) Purchase-through Rate
Ads	-0.000	-0.002
	(0.007)	(0.009)
Lost badge		-0.007
		(0.009)
Ads×Post	-0.142***	-0.006
	(0.009)	(0.013)
Ads×Lost badge		-0.002
		(0.013)
Lost badge×Post		-0.069***
		(0.013)
Ads×Lost badge×Post		-0.066***
		(0.018)
Constant	0.996***	0.955***
	(0.003)	(0.005)
Observations	106	212
R-squared	0.954	0.864
Date Fixed Effects	Yes	Yes

Notes: Outcome variable is the number of purchases per 1000 user impressions. One observation is a listing type-by-day in column 1 and is a listing type-by-ads-by-day in column 2. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

motivates us to focus on listings that existed on Day -1 (i.e., March 26th, 2020), and track the PTR of these listings only, in order to avoid the dynamic selection of new listings after the glitch, whose ad status can be an outcome of the glitch. Results based on the refined sample remain similar.

Besides the regression specification used in column 1 of Table 4, we also leverage an alternative specification that compares contemporaneous changes in outcomes from listings that immediately lost their badge after the system glitch with listings that lost their badge later on. The idea is as follows: if the drop in PTR after the system glitch is indeed driven by fewer badges on the search results page, then it follows that we should see a larger impact from listings that have already lost their badge compared to those that have not yet lost their badge. To test this necessary condition empirically, we distinguish existing listings that lost their badge in the first week after the glitch from existing listings that did not lose their badge in the first week after the glitch (but will lose it after the first week).[14] In Figure 6, we report the time series of the average PTR of the four listing types: listings that were badged (in the first week after the glitch) and listings that lost the badge in the first week, by the listing's ad status. We make two observations from this graph. First, regardless of ad status, listings that lost their badge are hurt more compared to those that had not lost their badge yet (hallow dots vs. solid dots). Second, the above-mentioned difference is larger for ads than for non-ads, given that the drop from "ads, badge" to "ads, lost badge" is bigger than the drop from "non-ads, badge" to "non-ads, lost badge".

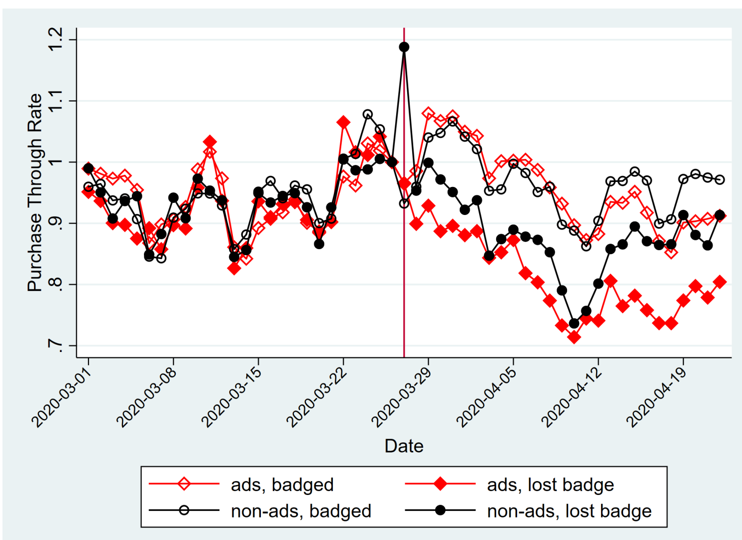


Figure 6: Differential Effects of Removing Quality Certificate: Badged vs. Lost Badge, by Ads

[14] As robustness checks, we also change the time window to two weeks or three weeks to define lost badges or not. We find very similar patterns across alternative time windows.

To quantify the differential effects between ads and non-ads, we estimate a DiD regression with a three-way interaction. The estimation results are reported in column 2 of Table 4. Among non-ad listings, the glitch causes an additional 6.9 percentage point drop in PTR for listings that lost their badge (relative to those that had not lost their badge yet). For ad listings, this additional drop is almost twice as large (13.5 percentage points) and statistically significant.

Figure 7: Differential Effects of Removing Quality Certificate: Ads vs. Non-Ads, by Search Rank

Next, since ad listings typically occupy better positions on search results pages than non-ad listings do, one potential concern is that our results may be explained by the effect of rank alone, instead of consumer aversion to ads. That is, it is possible that better-ranked listings are hurt more when quality certificates are removed. To verify if this alternative explanation holds in our context, we contrast the average PTR of ads and non-ads, by rank, and report the time trends in Figure 7. For example, the first sub-figure shows the average PTR if the top ranked listing is an ad vs. non-ad. For each rank, both time series are normalized by their respective values at Day -1. We report only rank 1–5 and rank 15–18 because these ranks have both ad and non-ad listings.

Figure 7 shows that across ranks, ad and non-ad listings generally follow similar pre-trends, but ad listings seem to have a decreased PTR after the onset of the technical glitch to eBay Plus. That is, when we hold the rank constant, we still observe a more negative shock of removing the quality certificate to ad listings than to non-ad listings, suggesting that ad aversion is due to consumer perception of ads as a quality signal, instead of ad listings being better ranked.

5.1 A Matching Approach

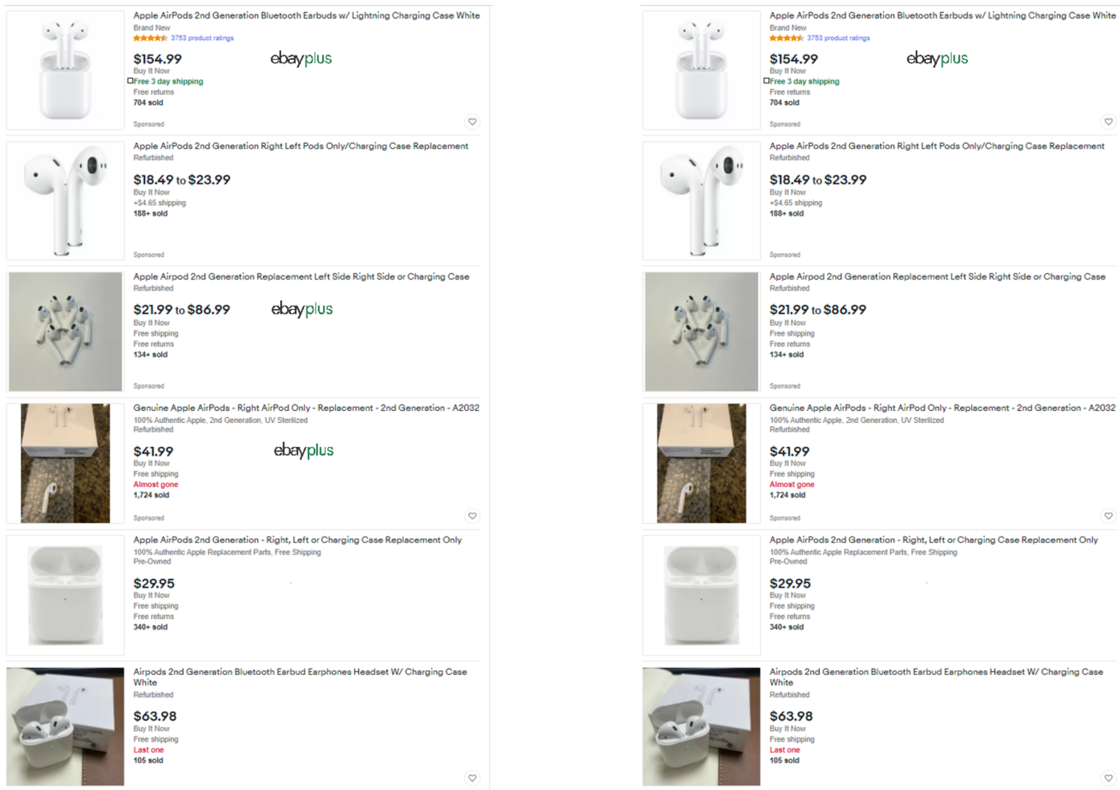
The results so far are based on data aggregated across many search sessions within the coarse categorization of ads by badge. Next, we conduct an analysis at a more granular level, which allows us to adjust for session-level characteristics when estimating the impact of quality certificates on ads and non-ads.

Specifically, we match sessions (i.e., search result pages) during the sample period, where they are identical in the following aspects: (1) the search keywords, (2) the returned ordered list of search results, (3) the ad status in each search position, and (4) the price of each listing. We restrict the matches to meet the above-mentioned conditions for the first 15 listings [15], and we use these first 15 listings of a session in the sample. We allow the matches to differ only in the number of listings with badges. Figure 8 provides an example of two matched sessions, where one session has three badges (Figure 8a) and the other has only one (Figure 8b). Essentially, this strict matching of search results sessions allow us to hold many things constant, such as the exact listings, the rank order, ad status, and prices, while varying only the badge count by the sudden removal of the badge due to the glitch. This way we are able to more cleanly identify the badge effect on ad effectiveness.

That said, we note a few caveats for this matching-based method. First, since it took three weeks for all the badges to be eliminated during the system glitch, our matched sessions are typically from different days, which makes this method essentially an event study analysis. This means that even though the matched sessions are usually just one or two days apart, we still need to take into consideration the possible time trend across days. Given this, we keep only matches whose sessions are one day apart from each other. The second caveat is that estimation from the matched sample gives more weight to standardized products, such as consumer electronics, because they are more likely to be matched given our strict matching criteria, compared to heterogeneous products such as collectibles. Lastly, the matching is done only on the first 15 listings of each search result, because of a tradeoff between matching precision and statistical power.

Using the matched search sessions approach, we study the badge effect on the number of clicks, purchases, and sales at the session level by ads. This is done by regressing the outcome variables on the number of badges in ad listings and the number of badges in non-ad listings, controlling for match fixed effects. Essentially, we exploit the variation in ads-badges and non-ads-badges within

[15] But listings down the list could meet these conditions as well. We choose the cutoff at 15 listings so that we have good sample size. Out of all search sessions with a sale, the first 15 positions on the first search result page account for 75% of all sales (in AUD) based on the data from the month before the start of our experiment.



(a) (b)

Figure 8: An Example of Matched Search Results Sessions

the matched sessions. Regression results are reported in Table 5. First, we find that the presence of badges in ad listings boosts the sales of ad listings, according to columns (1)–(3), but at the same time it reduces the sales of non-ad listings, as seen in columns (4)–(6). We interpret this as direct evidence that when ads have quality certificates, consumers are willing to buy more ad listings and buy fewer non-ad listings. However, when we increase the badges in non-ads, we see that ad clicks and purchases are increased, but non-ad listings' sales are not increased. This spillover effect is interesting because normally one would think that ad listings and non-ad listings are competitors, so giving one side quality signals will naturally lead to fewer sales of the other. However, the results suggest that quality signals in non-ad listings can help ad listings better. This can happen if consumers are uncertain about the quality of ad listings, so when their competitors (i.e., non-ad listings) are of high quality, consumers may update their belief on the quality of ad listings and buy more of them instead. This is similar to the findings that ads may cause a positive spillover effect to competitors in Sahni (2016). Taken together, evidence suggests that ad listings, as well as non-ad listings, can benefit greatly from certification badges.

Table 5: Matched Search Sessions: Effect of Badges in Ad Listings and Non-Ad Listings

	(1)	(2)	(3)	(4)	(5)	(6)
		Ads			Non-Ads	
	Number of Clicks	Number of Purchases	Sales in AUD	Number of Clicks	Number of Purchase	Sales AUD
No. Badges in Ads	0.004	0.004***	0.085**	-0.007	-0.003**	-0.122**
	(0.004)	(0.002)	(0.036)	(0.005)	(0.001)	(0.051)
No. Badges in Non-Ads	0.010***	0.003**	0.028	-0.004	-0.000	-0.040
	(0.003)	(0.001)	(0.029)	(0.004)	(0.001)	(0.041)
Matched Session Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	148,536	148,536	148,536	148,536	148,536	148,536
R-squared	0.304	0.267	0.272	0.281	0.256	0.334

Notes: Results based on matched search sessions, which are identical in search keywords, the returned ordered list of search results, the ad status in each position, and the price of each listing. One observation is a session. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

6 Concluding remarks

This paper studied two related research questions: Are consumers averse to sponsored search ads, and what roles do quality certificates play in increasing ad effectiveness? We took advantage of a field experiment and a natural experiment on an e-commerce platform. We found that consumers dislike sponsored search advertising and that quality certificates alleviate consumer aversion to ads.

Our results have a couple of implications for managers and policy makers. To start, our results, together with the mixed empirical evidence in other studies, suggest that consumer response towards ads may critically depend on market institutions. We discuss four of them. Starting with the first two factors, note that if the search performance of the platform is high, any perturbation of the already optimal organic search ranking will likely lead to fewer sales. The search performance would depend on two things, the quality of data and the search algorithm. First, higher data quality means that the platform has less asymmetric information about product quality. The data quality typically depends on the product nature and the amount of data accumulation.[16] Second,

[16]For example, the products in Moshary (2021) and Joo et al. (2021) are retail products, and e-commerce platforms have typically acquired much back-end data on the sellers of the products (e.g., through ratings, quality certificates, and consumer claims). The product nature and the abundance of data allow the platform to have good information on the underlying product and seller quality, which in turns allows the platform to rank products effectively on its search results page. In comparison, platforms have worse information on restaurant quality in Sahni and Nair (2020a) and on different websites in Sahni and Zhang (2019), both of which are more of experience goods. Therefore, the ranking in the latter cases is not as effective, and a perturbation of it due to sponsored search may improve its effectiveness if the amount of asymmetric information (from the platform's perspective) is high. In fact, Abhishek et al. (2022) find consistent evidence that ad listings perform worse in electronics categories and better in clothing

the search ranking algorithm essentially maximizes two things: click-through rate and some quality metrics. The weights set on these two metrics can potentially explain the differences in the empirical findings.[17] The third factor is the fee structure of ads, e.g., whether it is based on cost-per-click (CPC) or cost-per-action (CPA), which can affect the composition of advertisers in equilibrium, thereby affecting sales.[18] Lastly, another thing that could affect consumer response towards ads is the platform's rule on duplicate listings, which defines whether an organic listing promoted to ads still appears in its original position in the list of organic search results. This design choice could affect consumers' inference about ad quality by being able (or not) to observe its organic ranking, and hence affect their search and purchase decision.[19]

Because various market institutions can dramatically change consumers' response towards advertising, managers and policy makers need careful measurement of this parameter on a case-by-case basis as a first step towards effective management or policy regulation, instead of assuming that this parameter will be qualitatively the same across all settings. We leave empirical evaluations of the different mechanism designs for future work.

The second implication from our work is that in settings where consumers dislike sponsored search advertising, quality certificates can mitigate consumers' aversion towards ads and increase ad sales. Since search advertising has been comprising a larger share of business revenue, ad publishers and platform managers should consider highlighting quality signals, such as reputation signals, to improve ad performance. Other types of signals, such as on good deals, fast shipping, and seller warranties, may also interact with advertising. We leave these topics for future work.

and shoes categories, a finding that is likely explained by the amount of asymmetric information between the seller of the products and the platform. Also, the finding in Yang et al. (2021) that advertising can disproportionately help new products is also consistent with its informative role.

[17]The optimal weight would depend on the search engine's revenue model and its discount factor, i.e., its relative value on the incremental revenue from each click today versus higher revenue from repeated user interactions with the platform in the future due to high-quality clicks.

[18]As argued in Choi and Mela (2019), CPC incentivizes high-quality sellers to advertise, because their high conversion rate will justify the high per-click fees. On the other hand, CPA may incentivize more bidding from low-quality sellers, because they do not need to pay any fee unless the product is sold. Long et al. (2022) study a related question on setting optimal ad fees taking into account the information learned from sellers' advertising bids. In the previous literature, the platform in Sahni and Nair (2020a) uses CPC, and the platform in Moshary (2021) uses CPA. Therefore, the difference in the signalling effect of ad disclosure could potentially be explained in part by the different advertiser pools on the two platforms.

[19]For example, in Sahni and Nair (2020a), duplicate listings are allowed, whereas in Moshary (2021), they are not allowed. This means that buyers can infer the quality of the advertiser in the first setting by observing the position of the organic listing (corresponding to the ads) in the list of organic search results. This then could give rise to a positive signaling value of ad disclosure, which captures quality information that is not observed by the platform.

References

Abhishek, V., K. Jerath, and S. Sharma (2022). The impact of sponsored listings on online marketplaces: Insights from a field experiment. *Available at SSRN 3013468*.

Aribarg, A. and E. M. Schwartz (2020). Native advertising in online news: Trade-offs among clicks, brand recognition, and website trustworthiness. *Journal of Marketing Research 57*(1), 20–34.

Athey, S. and G. Ellison (2011). Position auctions with consumer search. *The Quarterly Journal of Economics 126*(3), 1213–1270.

Bai, J. (2018). Melons as lemons: Asymmetric information, consumer learning and quality provision. Technical report, Working paper.

Barach, M. A., J. M. Golden, and J. J. Horton (2020). Steering in online markets: the role of platform incentives and credibility. *Management Science*.

Blake, T., C. Nosko, and S. Tadelis (2015). Consumer heterogeneity and paid search effectiveness: A large-scale field experiment. *Econometrica 83*(1), 155–174.

Bollinger, B., P. Leslie, and A. Sorensen (2011). Calorie posting in chain restaurants. *American Economic Journal: Economic Policy 3*(1), 91–128.

Cabral, L. and A. Hortacsu (2010). The dynamics of seller reputation: Evidence from ebay. *The Journal of Industrial Economics 58*(1), 54–78.

Chevalier, J. A. and D. Mayzlin (2006). The effect of word of mouth on sales: Online book reviews. *Journal of marketing research 43*(3), 345–354.

Choi, H. and C. F. Mela (2019). Monetizing online marketplaces. *Marketing Science 38*(6), 948–972.

Dai, D., H. Kim, and M. Luca (2022). Which firms gain from online advertising? evidence from a field experiment. *Working Paper*.

Dai, W. and M. Luca (2020). Digitizing disclosure: The case of restaurant hygiene scores. *American Economic Journal: Microeconomics 12*(2), 41–59.

Dellarocas, C. (2003). The digitization of word of mouth: Promise and challenges of online feedback mechanisms. *Management science 49*(10), 1407–1424.

Dranove, D. and G. Z. Jin (2010). Quality disclosure and certification: Theory and practice. *Journal of Economic Literature 48*(4), 935–63.

Einav, L., C. Farronato, and J. Levin (2016). Peer-to-peer markets. *Annual Review of Economics 8*, 615–635.

Elfenbein, D. W., R. Fisman, and B. McManus (2015). Market structure, reputation, and the value of quality certification. *American Economic Journal: Microeconomics 7*(4), 83–108.

Farronato, C., A. Fradkin, B. Larsen, and E. Brynjolfsson (2020). Consumer protection in an online world: An analysis of occupational licensing. Technical report, National Bureau of Economic Research.

Ghose, A., P. G. Ipeirotis, and B. Li (2014). Examining the impact of ranking on consumer behavior and search engine revenue. *Management Science 60*(7), 1632–1654.

Goldfarb, A. and C. Tucker (2011). Online display advertising: Targeting and obtrusiveness. *Marketing Science 30*(3), 389–404.

Goldstein, D. G., S. Suri, R. P. McAfee, M. Ekstrand-Abueg, and F. Diaz (2014). The economic and cognitive costs of annoying display advertisements. *Journal of Marketing Research 51*(6), 742–752.

Hollenbeck, B., S. Moorthy, and D. Proserpio (2019). Advertising strategy in the presence of reviews: An empirical analysis. *Marketing Science 38*(5), 793–811.

Huang, J., D. Reiley, and N. Riabov (2018). Measuring consumer sensitivity to audio advertising: A field experiment on pandora internet radio. *Available at SSRN 3166676*.

Hui, X., G. Z. Jin, and M. Liu (2022). Designing quality certificates: Insights from ebay. Technical report, National Bureau of Economic Research.

Hui, X., M. Liu, and T. Chan (2020). Targeted incentives, broad impacts: Evidence from an e-commerce platform. *Broad Impacts: Evidence from an E-commerce Platform (October 11, 2020)*.

Hui, X., M. Saeedi, Z. Shen, and N. Sundaresan (2016). Reputation and regulations: Evidence from ebay. *Management Science 62*(12), 3604–3616.

Jeziorski, P. and S. Moorthy (2018). Advertiser prominence effects in search advertising. *Management science 64*(3), 1365–1383.

Jin, G. Z. and P. Leslie (2003). The effect of information on product quality: Evidence from restaurant hygiene grade cards. *The Quarterly Journal of Economics 118*(2), 409–451.

Johnson, G. A., R. A. Lewis, and E. I. Nubbemeyer (2017). Ghost ads: Improving the economics of measuring online ad effectiveness. *Journal of Marketing Research 54*(6), 867–884.

Joo, M., J. Shi, and V. Abhishek (2021). Seller incentives in sponsored product listings on online marketplaces. *Available at SSRN 3896716*.

Kaiser, U. and M. Song (2009). Do media consumers really dislike advertising? an empirical assessment of the role of advertising in print media markets. *International Journal of Industrial Organization 27*(2), 292–301.

Lin, T. and S. Misra (2022). Frontiers: the identity fragmentation bias. *Marketing Science 41*(3), 433–440.

Long, F., K. Jerath, and M. Sarvary (2022). Designing an online retail marketplace: Leveraging information from sponsored advertising. *Marketing Science 41*(1), 115–138.

Luca, M. (2016). Reviews, reputation, and revenue: The case of yelp. com. *Com (March 15, 2016). Harvard Business School NOM Unit Working Paper* (12-016).

Milgrom, P. and J. Roberts (1986). Price and advertising signals of product quality. *Journal of political economy 94*(4), 796–821.

Moshary, S. (2021). Sponsored search in equilibrium: Evidence from two experiments. *Available at SSRN 3903602*.

Narayanan, S. and K. Kalyanam (2015). Position effects in search advertising and their moderators: A regression discontinuity approach. *Marketing Science 34*(3), 388–407.

Nelson, P. (1974). Advertising as information. *Journal of political economy 82*(4), 729–754.

Park, S., W. Shin, and J. Xie (2021). The fateful first consumer review. *Marketing Science*.

Resnick, P., R. Zeckhauser, J. Swanson, and K. Lockwood (2006). The value of reputation on ebay: A controlled experiment. *Experimental economics 9*(2), 79–101.

Revel, M., A. Tohidi, D. Eckles, A. Jadbabaie, et al. (2021). Native advertising and the credibility of online publishers.

Rysman, M. (2004). Competition between networks: A study of the market for yellow pages. *The Review of Economic Studies 71*(2), 483–512.

Saeedi, M. (2019). Reputation and adverse selection, theory and evidence from ebay. *RAND Journal of Economics*.

Sahni, N. S. (2016). Advertising spillovers: Evidence from online field experiments and implications for returns on advertising. *Journal of Marketing Research 53*(4), 459–478.

Sahni, N. S. and H. S. Nair (2020a). Does advertising serve as a signal? evidence from a field experiment in mobile search. *The Review of Economic Studies 87*(3), 1529–1564.

Sahni, N. S. and H. S. Nair (2020b). Sponsorship disclosure and consumer deception: Experimental evidence from native advertising in mobile search. *Marketing Science 39*(1), 5–32.

Sahni, N. S. and C. Zhang (2019). Are consumers averse to sponsored messages? the role of search advertising in information discovery.

Simonov, A. and S. Hill (2021). Competitive advertising on brand search: Traffic stealing and click quality. *Marketing Science 40*(5), 923–945.

Tadelis, S. (2016). Reputation and feedback systems in online platform markets. *Annual Review of Economics 8*, 321–340.

Tuchman, A. E., H. S. Nair, and P. M. Gardete (2018). Television ad-skipping, consumption complementarities and the consumer demand for advertising. *Quantitative Marketing and Economics 16*(2), 111–174.

Ursu, R. M. (2018). The power of rankings: Quantifying the effect of rankings on online consumer search and purchase decisions. *Marketing Science 37*(4), 530–552.

Wilbur, K. C. (2016). Advertising content and television advertising avoidance. *Journal of Media Economics 29*(2), 51–72.

Yang, J., N. S. Sahni, and H. Nair (2021). Advertising as information for ranking e-commerce search listings. *Available at SSRN 3895782*.

Yao, S. and C. F. Mela (2011). A dynamic model of sponsored search advertising. *Marketing Science 30*(3), 447–468.

Online Appendix

A Tables

Table A1: The Effect of More Salient Ad Disclosure with Covariate Adjustment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Number of Clicks			Number of Purchases			Sales in AUD		
	All	Ads	Non-Ads	All	Ads	Non-Ads	All	Ads	Non-Ads
Treat	-0.027	-0.177***	0.150***	0.001	-0.014***	0.014***	-0.121	-0.245***	0.124
	(0.017)	(0.004)	(0.015)	(0.004)	(0.002)	(0.003)	(0.086)	(0.019)	(0.082)
pre-experiment	0.363***	0.029***	0.334***	-0.001***	-0.000***	-0.000**	0.012***	-0.009***	0.020***
search_sessions	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.004)	(0.001)	(0.004)
pre-experiment	0.003***	0.000***	0.002***	-0.000***	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***
session_duration	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
pre-experiment	0.545***	0.060***	0.485***	0.042***	-0.003***	0.045***	-0.120***	-0.179***	0.059**
transactions	(0.006)	(0.001)	(0.005)	(0.001)	(0.001)	(0.001)	(0.028)	(0.006)	(0.027)
pre-experiment	-0.084***	0.023***	-0.107***	0.080***	0.026***	0.054***	0.908***	0.322***	0.586***
quantity purchased	(0.004)	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)	(0.021)	(0.005)	(0.020)
pre-experiment	-0.000***	-0.000***	-0.000	0.000***	0.000	0.000***	0.057***	0.008***	0.049***
spending	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	3.172***	0.746***	2.426***	0.209***	0.066***	0.143***	5.006***	1.148***	3.858***
	(0.012)	(0.003)	(0.011)	(0.003)	(0.002)	(0.002)	(0.062)	(0.014)	(0.060)
Observations	3,561,581	3,561,581	3,561,581	3,561,581	3,561,581	3,561,581	3,561,581	3,561,581	3,561,581
R-squared	0.223	0.061	0.228	0.027	0.003	0.030	0.031	0.017	0.024

Notes: Results based on Equation 1 with additional controls. One observation is a user. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A2: Heterogeneous Treatment Effects Using Experiment on the US Site

Part I.	Ads					
	(1)	(2)	(3)	(4)	(5)	(6)
	Number of Clicks		Number of Purchases		GMV in USD	
	Badged	Non-Badged	Badged	Non-Badged	Badged	Non-Badged
Treat	-0.008***	-0.019***	-0.000***	-0.001***	-0.007***	-0.021***
	(0.001)	(0.005)	(0.000)	(0.000)	(0.002)	(0.003)
Constant	0.046***	0.097***	0.003***	0.005***	0.082***	0.147***
	(0.001)	(0.004)	(0.000)	(0.000)	(0.002)	(0.002)
Observations	20,401,651	31,955,592	20,401,651	31,955,592	20,401,651	31,955,592
R-squared	0.000	0.000	0.000	0.000	0.000	0.000
Percentage change	-.182	-.196	-.136	-.188	-.084	-.145
Equality of percentage changes	p=0.794		p=0.321		p=0.081	
Part II.	**Non-Ads**					
	(7)	(8)	(9)	(10)	(11)	(12)
	Number of Clicks		Number of Purchases		GMV in USD	
	Badged	Non-Badged	Badged	Non-Badged	Badged	Non-Badged
Treat	0.012**	0.012**	0.001**	0.000*	0.008	0.017**
	(0.005)	(0.005)	(0.000)	(0.000)	(0.006)	(0.009)
Constant	0.103***	0.367***	0.006***	0.014***	0.217***	0.619***
	(0.004)	(0.004)	(0.000)	(0.000)	(0.004)	(0.006)
Observations	27,096,595	34,120,425	27,096,595	34,120,425	27,096,595	34,120,425
R-squared	0.000	0.000	0.000	0.000	0.000	0.000
Percentage change	.12	.033	.11	.03	.036	.028
Equality of percentage changes	p=0.098		p=0.098		p=0.786	

Notes: Results based on Equation 1. One observation is a user. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.