Identifying One-time-Reviewers in All Product Categories on Amazon.com Using Big Data Analytics

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Abstract

Consumers can use information in online product reviews on digital platforms to reduce their uncertainty and search costs. However, reviews on Amazon.com do not contain demographic information for reviewers. Additionally, misinformation, noise, and biases in reviews can reduce consumer welfare. There are limited studies about the types of abnormal reviewers, the impact of their reviews on rating distributions, and the determinants of these abnormal reviewers. For example, one-time reviewers can be regarded as suspicious, but there is no detailed research using cross-category analysis with enough time windows. This paper investigates 571,544,746 Amazon reviews (the secondary dataset) and identifies 142,513,957 one-time reviewers in each category (OT) and 10,309,129 one-time reviewers in all categories (OTA). All categories contain OT and OTA, and their rating distributions are more skewed toward 1-star ratings and less skewed toward 5-star ratings than all reviews. Empirical analysis showed that the number of OTA reviews increases the share of 1-star ratings while decreasing that of 5-star ratings in each category. Further analysis of the subscription boxes category, which shows an extreme share of 1- and 5-star ratings in OTA's reviews (80.69%; 10.94% higher than all reviews in the category), shows that a review is more likely to be written by OTA, if an unverified purchase reviewer writes the review, the review rating is extreme ratings, and the price sentiment in the review is more positive. Additionally, a review for the product is more likely to be written by OTA if the review written for a product contains a longer review headline, a higher average star ratings, a higher share of 5-star ratings, and less share of 1-star ratings in the prior reviews for the product. OTA may be a normal reviewer with polarity self-selection or suspicious reviewers. The results of this paper will be beneficial to identify abnormal reviewers and improve the credibility of user-generated content and digital retail platforms.

Keywords

Digital Platforms, Online Product Reviews, Abnormal Reviewers, Consumer Segmentation, Rating Distributions

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1. Introduction

Due to rapid innovation in big data and artificial intelligence (AI) in digital economics, the importance and impact of digital platforms on consumers, business, and economics have increased during and after the pandemic. The volume, velocity, and variety of user-generated content (UGC) on digital platforms have increased significantly. UGC (e.g., online reviews) in digital retail platforms are generated by consumers, reflect actual consumer experiences with products, and are publicly available for free. Post-purchase information from crowd's online reviews can improve consumer welfare (Reimers and Waldfogel 2021). Accordingly, finding and using valuable information from large, fast-growing, and different types of UGC is essential to understanding consumers, firms, digital platforms, and digital economics. For example, Timoshenko and Hauser (2019) found consumers' needs from online product reviews. Liu et al. (2019) also measured the effect of review content in online product reviews on sales. Additionally, many studies have extensively explored how UGC influences sales on digital platforms (Anderson and Magruder 2012; Chen, 2018; Chevalier and Mayzlin 2006).

However, some digital retail platforms with one-sided review systems (e.g., Amazon.com) allow consumers to write free product reviews while disallowing sellers to write about purchased and reviewed consumers on the review systems (Tadelis, 2016; Cui et al., 2012). Further, consumer product reviews in these digital retail platforms do not contain demographic information of the reviewed consumers. Accordingly, researchers often study UGC without demographic information unless consumers or platforms directly provide it. Online product reviews also contain noise information (e.g., fake reviews; Hollenbeck and Proserpio, 2022; Luca and Zervas, 2016; Mayzlin et al., 2014) and biases (e.g., self-selection biases; Hu et al., 2009; Hu et al., 2017; Langhe et al., 2016; Li and Hitt, 2008; Askalidis et al., 2017). Because many online consumers rely on the post-purchase information in UGC to decrease search costs and product uncertainty, biases, noise, and misinformation in UGC can

reduce consumer surplus, credibility of products and digital retail platforms, and fair market competition. Addressing these challenges can significantly enhance digital shopping experiences, business operations, and platform integrity.

However, there are limited studies about the types of abnormal reviewers and the impact of their reviews on rating distributions, even though many prior studies examined fake reviewers and reviews. Additionally, many studies are based on small and medium-sized cross-sectional or panel data during a short period for a product or product groups in a product category. Accordingly, information from previous reviews by target reviewers and the broader crowd within and across product categories can be omitted. For example, a previous study (Mayzlin et al., 2014) has suggested that one-time reviewers on TripAdvisor could potentially be suspicious. Additionally, Luca and Zervas (2016) stated that reviews written by Yelp users with fewer prior reviews are more likely to be classified as fake reviews by Yelp's fake review filtering algorithm; therefore, reviews written by first-time reviewers showed the highest filtering ratio. However, there has been limited investigation into the prevalence of one-time reviewers across different product categories on digital retail platforms, their behaviors, and their actual impact on the credibility of review systems using real-world online product review big data with enough time windows.

To fill this research gap, this paper investigates 571,544,746 Amazon reviews (Hou et al., 2024) and identifies 142,513,957 one-time reviewers in each category (OT) and 10,309,129 one-time reviewers in all categories (OTA) using cross-categorical digital footprint mining. OT are reviewers who write their first and only review for a given category. OT in a category can be OT in different categories. Therefore, their review in each category is the first and only review; however, they can write more than one review across all categories. Therefore, OTA write their first and only review across all categories, which is the focus group in this study. OTA is a subset of OT. All product categories contain reviews from OT and OTA.

OT and OTA's rating distributions in this paper also show extreme rating distribution toward 1- and 5-star ratings. This finding is consistent with prior studies (Brandes et al., 2022; Hu et al., 2006; Schoenmueller et al., 2020) that showed imbalanced rating distribution of digital platforms. Mayzlin et al. (2014) showed that one-time reviewers' ratings on TripAdvisor are more skewed toward 1- and 5-star ratings compared to all reviews, and Luca and Zervas (2016) also showed that potential fake reviews, filtered by Yelp algorithms, are more skewed toward 1-and 5-star ratings compared to normal reviews on Yelp.com.

However, OTA's rating distribution is more skewed toward negative rating (1-star rating) and less skewed toward positive rating (5-star rating) than all reviews. These results are in contrast to the prior study that stated sellers may have less incentive to purchase negative reviews compared to positive reviews due to higher costs and lower benefits. It also showed that the majority of deleted reviews by Amazon are 5-star ratings. Accordingly, OTA may be normal consumers who write a negative review for the first time because of unusual negative experiences with the products or services (i.e., negative polarity self-selection case). Schoenmueller et al. (2020) showed that polarity self-selection reduces information in online product reviews on Amazon.com. Therefore, investigating OTA reviews, their review behavior, and their effects on rating distribution on digital platforms are important topics. Of course, it is also plausible that some OTA are suspicious reviewers write a negative review for their competition, even though it costs. Instead of detecting fake reviews without ground truth, this study estimates the effect of OTA reviews on rating distributions in all product categories first. Then, this study estimates the determinants of OTA's reviews in the target product category, the subscription boxes category, which shows highly imbalanced ratings toward 1 and 5-star ratings compared to all reviews in the category.

Empirical findings with all product categories show that the increase in the number of OTA reviews increases the share of 1-star ratings (i.e., negative reviews) while decreasing the

share of 5-star ratings (i.e., positive reviews). The impact of the number of OTA reviews is larger for the increase in the share of 1-star ratings than the decline in the share of 5-star ratings. Chevalier and Mayzlin (2006) showed that the effect of 1-star ratings on sales is negative, that of 5-star ratings is positive, and the impact of 1-star ratings is larger than that of 5-star ratings. Accordingly, increasing OTA reviews in each category may have a negative effect on sales of reviewed products, with an increase in 1-star ratings and a decrease in 5-star ratings.

Further analysis for identifying determinants of OTA reviews is applied to reviews in the subscription boxes category. The reviews in the subscription boxes category show a higher share of both 1- and 5-star ratings (18.16% and 62.53%) compared to all reviews (15.89% and 53.86%). Additionally, the extreme ratings share gap between all reviews and OTA reviews in the subscription boxes category is the highest (10.94%) among all categories. Therefore, the abnormality in this category is higher than in other categories. The empirical results revealed that an unverified purchase review with 1- and 5-star ratings for the higher average star ratings and share of 5-star ratings are more likely to be written by OTAs in this category. The outcomes of this project will advance our knowledge of abnormal reviewers, their review behaviors, consumer segmentation, and rating distributions using UGC because this paper is the first descriptive research about one-time reviewers in all categories on Amazon.com using cross-categorial analysis, and the results of this paper will be beneficial to improve the credibility of UGC, review system design, and digital retail platforms, and enhancing consumer welfare.

This research contributes to a multimodal economics analysis using econometric analysis for structured data and large language models (LLMs) for unstructured data (i.e., text data). Scholars in the business and economic fields have focused on structured data like price and average star ratings in UGC studies. For example, Chevalier and Goolsbee (2003) measure the effect of price on demand. However, numerical price information for the subscription boxes

category in this study is missing. This project used a popular LLM model – OpenAI's Generative Pre-training Transformer (GPT) 4o for price sentiment analysis in user-generated review text data. The use of pre-trained language models (LMs) and generative AI (GenAI) presents novel opportunities for analyzing unstructured data, particularly in economic research (Han, 2024; Korinek, 2023; Ludwig et al., 2025). The research framework in this study can be applicable to different products on different platforms and useful for UGC analysis, especially for digital platforms that provide limited user and product information.

Section 2 describes data. Section 3 presents an econometric analysis with aggregated product review data in all categories and an empirical analysis with individual review data in the subscription boxes category. Lastly, section 4 provides conclusions and limitations.

2. Data

To accurately classify types of abnormal reviewers, it is crucial to analyze the entire history of review patterns for each unique reviewer within each product category and across categories. This approach necessitates a comprehensive dataset containing reviewers and product identifiers with timestamps to trace a specific consumer's digital footprint over an extended period. Accordingly, the Google Cloud Platform (GCP) is used to conduct in-depth analyses of consumer behavior and reviewer dynamics in UGC across diverse product categories from Amazon review big dataset (secondary data; Hou et al., 2024).

This study implements the following data-preprocessing steps to identify one-time reviewers in each category (OT) and one-time reviewers in all categories (OTA) using cross-categorical digital footprint mining. First, 571,544,746 reviews datasets for 48,185,048 unique products from 54,514,263 unique reviewers between June 17, 1996, and September 14, 2023, are prepared after removing reviews with 0-star ratings from the secondary raw data as the range of star rating is between 1 and 5-stars. Second, online product reviews and product information datasets are merged based on Amazon standard identification numbers (ASINs).

Third, OT and OTA are identified from all reviews by counting all individual reviewers' cumulative number of reviews over the entire sample period. Fourth, the target category for further analysis, the subscription boxes category, is selected. Fifth, digital footprint mining for prior reviews of each reviewed product in the subscription boxes category is conducted. Jin et al. (2018) mentioned that reviewers are likely to be influenced by prior reviews. Therefore, this study assumes that a consumer may be influenced by prior reviews from other consumers when they post a review of the product as their first time review in the category or the platform. Digital footprint mining is a suitable approach for extracting latent factors from cross-category online product review datasets with reviewer ID, product ID, and timestamps. Sixth, OpenAI's ChatGPT4o, a popular LLM, is used for price sentiment analysis for the subscription boxes category review text data because numerical price information is missing in the dataset and LLMs are suitable for sentiment analysis from user-generated text data.

Rating distribution of a total of 571,544 746 reviews is highly skewed toward 1- and 5-star ratings (10.31% and 65.03%; Table 1). All product categories contain reviews from OT (Table 2). The share of OT's reviews from all reviews is 24.93%. In detail, there is a total of 142,513,957 reviews from 50,939,994 unique OT reviewers for 20,208,041 unique products between November 15, 1996, and September 14, 2023. The rating distribution of OT reviews is highly skewed toward 1- and 5-star ratings (14.91% and 62.54%; Table 2). All product categories also contain reviews from OTA (Table 3). A total of 10,309,129 reviews from 10,309,129 unique OTA reviewers for 1,908,223 unique products between August 8, 1997, and September 12, 2023, are identified from all reviews. The share of OTA reviews in all reviews is 1.8%; however, its rating distribution is more extremely skewed toward 1- and 5-star ratings (20.35% and 58.11%; Table 3). In particular, the share of 1-star ratings in OTA reviews (20.35%) is 10.04% higher than all reviews (10.31%), while the share of 5-star ratings in OTA reviews (58.11%) is 6.92% smaller than that of all reviews (65.03%).

Table 1. Rating distribution of all reviews in each product category

	Product Category	1-star-rating	2-star-rating	3-star-rating	4-star-rating	5-star-rating	Count (% in total)	Share of 1- and 5- ratings
1	All_Beauty	102,080 (14.55%)	43,034 (6.13%)	56,307 (8.03%)	79,381 (11.32%)	420,726 (59.97%)	701,528 (0.12%)	74.52%
2	Amazon_Fashion	303,411 (12.13%)	173,462 (6.94%)	245,471 (9.82%)	352,327 (14.09%)	1,426,268 (57.03%)	2,500,939 (0.44%)	69.16%
3	Appliances	250,453 (11.77%)	79,664 (3.74%)	104,047 (4.89%)	208,216 (9.78%)	1,486,225 (69.82%)	2,128,605 (0.37%)	81.59%
4	Arts_Crafts_and_Sewing	883,616 (9.85%)	417,130 (4.65%)	607,210 (6.77%)	942,344 (10.51%)	6,116,457 (68.21%)	8,966,757 (1.57%)	78.07%
5	Automotive	2,302,427 (11.54%)	851,553 (4.27%)	1,185,429 (5.94%)	2,172,554 (10.89%)	13,443,487 (67.37%)	19,955,450 (3.49%)	78.91%
6	Baby_Products	562,663 (9.33%)	313,177 (5.19%)	437,934 (7.26%)	689,930 (11.44%)	4,025,179 (66.76%)	6,028,883 (1.05%)	76.10%
7	Beauty_and_Personal_Care	2,840,878 (11.88%)	1,275,031 (5.33%)	1,715,821 (7.18%)	2,616,444 (10.94%)	15,463,216 (64.67%)	23,911,390 (4.18%)	76.55%
8	Books	1,316,085 (4.47%)	1,080,897 (3.67%)	2,054,057 (6.97%)	4,632,932 (15.72%)	20,391,478 (69.18%)	29,475,449 (5.16%)	73.65%
9	CDs_and_Vinyl	187,727 (3.89%)	140,557 (2.91%)	283,691 (5.88%)	664,514 (13.77%)	3,550,784 (73.56%)	4,827,273 (0.84%)	77.45%
10	Cell_Phones_and_Accessories	2,802,212 (13.46%)	1,251,658 (6.01%)	1,543,387 (7.42%)	2,446,330 (11.75%)	12,769,358 (61.35%)	20,812,945 (3.64%)	74.82%
11	Clothing_Shoes_and_Jewelry	5,778,281 (8.75%)	3,638,852 (5.51%)	5,529,471 (8.37%)	9,054,462 (13.71%)	42,032,280 (63.65%)	66,033,346(11.55%)	72.40%
12	Digital_Music	6,136 (4.70%)	3,159 (2.42%)	6,392 (4.90%)	14,129 (10.83%)	100,618 (77.14%)	130,434 (0.02%)	81.85%
13	Electronics	5,358,800 (12.21%)	2,257,604 (5.14%)	2,883,065 (6.57%)	5,557,725 (12.66%)	27,829,748 (63.41%)	43,886,942 (7.68%)	75.62%
14	Gift_Cards	12,326 (8.09%)	1,873 (1.23%)	3,271 (2.15%)	6,692 (4.39%)	128,248 (84.15%)	152,410 (0.03%)	92.23%
15	Grocery_and_Gourmet_Food	1,855,049 (12.96%)	695,428 (4.86%)	898,317 (6.27%)	1,256,795 (8.78%)	9,612,930 (67.14%)	14,318,519 (2.51%)	80.09%
16	Handmade_Products	41,592 (6.26%)	20,531 (3.09%)	29,944 (4.51%)	45,247 (6.81%)	526,848 (79.33%)	664,162 (0.12%)	85.59%
17	Health_and_Household	2,772,511 (10.82%)	1,186,802 (4.63%)	1,597,024 (6.23%)	2,750,389 (10.73%)	17,324,619 (67.59%)	25,631,345 (4.48%)	78.41%
18	Health_and_Personal_Care	69,564 (14.08%)	28,895 (5.85%)	36,949 (7.48%)	57,000 (11.54%)	301,713 (61.06%)	494,121 (0.09%)	75.14%
19	Home_and_Kitchen	7,160,456 (10.62%)	3,410,803 (5.06%)	4,600,479 (6.82%)	7,536,382 (11.18%)	44,701,824 (66.31%)	67,409,944 (11.79%)	76.94%
20	Industrial_and_Scientific	584,133 (11.27%)	234,763 (4.53%)	315,792 (6.09%)	560,932 (10.82%)	3,487,385 (67.29%)	5,183,005 (0.91%)	78.56%
21	Kindle_Store	738,729 (2.89%)	812,301 (3.18%)	1,940,802 (7.59%)	5,386,277 (21.06%)	16,699,504 (65.29%)	25,577,613 (4.48%)	68.18%
22	Magazine_Subscriptions	9,685 (13.55%)	3,953 (5.53%)	5,033 (7.04%)	8,206 (11.48%)	44,620 (62.41%)	71,497 (0.01%)	75.95%
23	Movies_and_TV	1,410,250 (8.14%)	766,735 (4.42%)	1,260,217 (7.27%)	2,604,827 (15.03%)	11,286,285 (65.13%)	17,328,314 (3.03%)	73.27%
24	Musical_Instruments	264,352 (8.76%)	131,441 (4.36%)	197,131 (6.53%)	400,387 (13.27%)	2,024,128 (67.08%)	3,017,439 (0.53%)	75.84%
25	Office_Products	1,353,519 (10.54%)	589,120 (4.59%)	799,194 (6.22%)	1,400,675 (10.90%)	8,703,203 (67.75%)	12,845,711 (2.25%)	78.29%
26	Patio_Lawn_and_Garden	2,282,783 (13.84%)	868,187 (5.26%)	1,083,552 (6.57%)	1,782,189 (10.81%)	10,473,336 (63.51%)	16,490,047 (2.89%)	77.36%
27	Pet_Supplies	2,034,198 (12.09%)	957,197 (5.69%)	1,242,552 (7.38%)	1,801,732 (10.71%)	10,792,183 (64.13%)	16,827,862 (2.94%)	76.22%
28	Software	695,854 (14.26%)	239,253 (4.90%)	419,356 (8.59%)	857,082 (17.56%)	2,668,636 (54.68%)	4,880,181 (0.85%)	68.94%
29	Sports_and_Outdoors	1,836,990 (9.37%)	933,101 (4.76%)	1,324,911 (6.76%)	2,518,170 (12.85%)	12,981,998 (66.25%)	19,595,170 (3.43%)	75.63%
30	Subscription_Boxes	2,576 (15.89%)	1,491 (9.19%)	1,752 (10.80%)	1,663 (10.26%)	8,734 (53.86%)	16,216 (0.003%)	69.75%
31	Tools_and_Home_Improvement	3,057,747 (11.33%)	1,291,499 (4.79%)	1,709,616 (6.34%)	3,078,376 (11.41%)	17,845,01 (66.14%)	26,982,256 (4.72%)	77.47%
32	Toys_and_Games	1,631,131 (10.03%)	767,908 (4.72%)	1,103,648 (6.79%)	1,797,010 (11.05%)	10,960,709 (67.41%)	16,260,406 (2.84%)	77.44%
33	Unknown	7,832,796 (12.27%)	3,389,685 (5.31%)	4,767,525 (7.47%)	8,603,831 (13.48%)	39,220,135 (61.46%)	63,813,972 (11.17%)	73.73%
34	Video_Games	589,519 (12.75%)	249,878 (5.40%)	340,086 (7.35%%)	617,251 (13.35%)	2,827,881 (61.15%)	4,624,615 (0.81%)	73.90%
	Sum	58,930,529 (10.31%)	28,106,622 (4.92%)	40,329,433 (7.06%)	72,502,401 (12.69%)	371,675,761 (65.03%)	571,544,746 (100%)	75.34%

* Note: Total 571,544 746 reviews from 54,514,263 unique reviewers for 48,185,048 unique products between June 17, 1996, and September 14, 2023

Table 2. Rating distribution of OT's reviews in each product category

	Product Category	1-star-rating	2-star-rating	3-star-rating	4-star-rating	5-star-rating	Count (% in total OT)	Share of 1- and 5- ratings
1	All_Beauty	88,445 (15.16%)	36,168 (6.20%)	45,674 (7.83%)	63,504 (10.88%)	349,762 (59.94%)	583,553 (0.41%)	75.09%
2	Amazon_Fashion	227,319 (13.09%)	121,864 (7.02%)	164,081 (9.45%)	233,004 (13.42%)	990,438 (57.03%)	1,736,706 (1.22%)	70.12%
3	Appliances	195,823 (13.09%)	59,590 (3.98%)	73,236 (4.89%)	141,926 (9.48%)	1,025,936 (68.56%)	1,496,511 (1.05%)	81.64%
4	Arts_Crafts_and_Sewing	439,988 (14.02%)	177,912 (5.67%)	220,189 (7.02%)	318,530 (10.15%)	1,981,689 (63.15%)	3,138,308 (2.20%)	77.17%
5	Automotive	784,735 (16.72%)	244,887 (5.22%)	282,131 (6.01%)	470,809 (10.03%)	2,909,762 (62.01%)	4,692,324 (3.29%)	78.73%
6	Baby_Products	281,301 (12.01%)	125,053 (5.34%)	151,107 (6.45%)	236,075 (10.08%)	1,549,405 (66.13%)	2,342,941 (1.64%)	78.14%
7	Beauty_and_Personal_Care	1,112,118 (15.92%)	386,625 (5.53%)	431,126 (6.17%)	665,171 (9.52%)	4,392,030 (62.86%)	6,987,070 (4.90%)	78.78%
8	Books	404,654 (6.87%)	215,194 (3.65%)	306,403 (5.20%)	655,282 (11.13%)	4,307,858 (73.15%)	5,889,391 (4.13%)	80.02%
9	CDs_and_Vinyl	65,420 (5.99%)	32,857 (3.01%)	48,758 (4.46%)	102,355 (9.37%)	843,165 (77.17%)	1,092,555 (0.77%)	83.16%
10	Cell_Phones_and_Accessories	1,220,803 (16.40%)	466,463 (6.27%)	503,617 (6.76%)	803,908 (10.80%)	4,450,658 (59.78%)	7,445,449 (5.22%)	76.17%
11	Clothing_Shoes_and_Jewelry	1,439,535 (13.24%)	677,818 (6.24%)	820,213 (7.55%)	1,333,765 (12.27%)	6,598,108 (60.70%)	10,869,439 (7.63%)	73.95%
12	Digital_Music	4,708 (5.34%)	2,254 (2.56%)	4,030 (4.58%)	8,202 (9.31%)	68,890 (78.21%)	88,084 (0.06%)	83.55%
13	Electronics	1,750,289 (16.96%)	580,360 (5.62%)	614,116 (5.95%)	1,147,012 (11.12%)	6,226,940 (60.35%)	10,318,717 (7.24%)	77.31%
14	Gift_Cards	11,386 (9.50%)	1,710 (1.43%)	2,802 (2.34%)	5,370 (4.48%)	98,592 (82.26%)	119,860 (0.08%)	91.76%
15	Grocery_and_Gourmet_Food	862,087 (18.68%%)	244,645 (5.30%)	259,878 (5.63%)	330,937 (7.17%)	2,918,514 (63.23%)	4,616,061 (3.24%)	81.90%
16	Handmade_Products	35,950 (6.78%)	17,407 (3.28%)	24,789 (4.67%)	36,135 (6.81%)	416,344 (78.46%)	530,625 (0.37%)	85.24%
17	Health_and_Household	1,162,341 (14.79%)	395,441 (5.03%)	444,390 (5.65%)	764,886 (9.73%)	5,092,294 (64.79%)	7,859,352 (5.51%)	79.58%
18	Health_and_Personal_Care	64,147 (14.62%)	26,044 (5.94%)	32,451 (7.40%)	48,851 (11.14%)	267,217 (60.91%)	438,710 (0.31%)	75.53%
19	Home_and_Kitchen	1,942,445 (17.00%)	699,775 (6.12%)	736,204 (6.44%)	1,152,671 (10.09%)	6,894,294 (60.34%)	11,425,389 (8.02%)	77.34%
20	Industrial_and_Scientific	377,341 (14.26%)	135,138 (5.11%)	162,575 (6.14%)	264,597 (10.00%)	1,706,633 (64.49%)	2,646,284 (1.86%)	78.75%
21	Kindle_Store	149,705 (5.23%)	102,697 (3.59%)	182,383 (6.37%)	466,603 (16.30%)	1,960,628 (68.51%)	2,862,016 (2.01%)	73.74%
22	Magazine_Subscriptions	8,293 (15.67%)	3,130 (5.91%)	3,615 (6.83%)	5,635 (10.65%)	32,256 (60.94%)	52,929 (0.04%)	76.61%
23	Movies_and_TV	418,983 (11.01%)	145,725 (3.83%)	193,011 (5.07%)	437,202 (11.49%)	2,611,224 (68.61%)	3,806,145 (2.67%)	79.61%
24	Musical_Instruments	152,431 (11.69%)	63,410 (4.86%)	81,715 (6.27%)	159,082 (12.20%)	847,608 (64.99%)	1,304,246 (0.92%)	76.68%
25	Office_Products	755,577 (14.17%)	281,240 (5.28%)	328,307 (6.16%)	539,480 (10.12%)	3,426,497 (64.27%)	5,331,101 (3.74%)	78.45%
26	Patio_Lawn_and_Garden	1,014,330 (18.26%)	330,512 (5.95%)	353,617 (6.37%)	549,537 (9.89%)	3,306,255 (59.53%)	5,554,251 (3.90%)	77.79%
27	Pet_Supplies	785,176 (16.52%)	293,037 (6.17%)	311,297 (6.55%)	449,974 (9.47%)	2,912,078 (61.29%)	4,751,562 (3.33%)	77.81%
28	Software	312,586 (17.93%)	87,122 (5.00%)	130,360 (7.48%)	285,339 (16.37%)	928,045 (53.23%)	1,743,452 (1.22%)	71.16%
29	Sports_and_Outdoors	873,497 (12.93%)	367,669 (5.44%)	441,126 (6.53%)	774,859 (11.47%)	4,298,678 (63.63%)	6,755,829 (4.74%)	76.56%
30	Subscription_Boxes	2,335 (16.14%)	1,355 (9.36%)	1,567 (10.83%)	1,480 (10.23%)	7,734 (53.44%)	14,471 (0.01%)	69.58%
31	Tools_and_Home_Improvement	1,210,972 (16.26%)	417,171 (5.60%)	459,434 (6.17%)	750,193 (10.07%)	4,608,907 (61.89%)	7,446,677 (5.23%)	78.15%
32	Toys_and_Games	785,160 (15.05%)	300,082 (5.75%)	354,831 (6.80%)	526,012 (%)	3,250,466 (62.31%)	5,216,551 (3.66%)	77.36%
33	Unknown	1,963,463 (17.28%)	654,280 (5.76%)	751,344 (6.61%)	1,317,057 (%)	6,673,501 (58.75%)	11,359,645 (7.97%)	76.03%
34	Video_Games	338,793 (16.96%)	117,346 (5.87%)	131,992 (6.61%)	232,684 (%)	1,176,938 (58.91%)	1,997,753 (1.40%)	75.87%
	Sum	21,242,136 (14.91%)	7,811,981 (5.48%)	9,052,369 (6.35%)	15,278,127 (10.72%)	89,129,344 (62.54%)	142,513,957 (100%)	**77.45%**

* Note: Total 142,513,957 reviews from 50,939,994 unique reviewers for 20,208,041unique products between November 15, 1996, and September 14, 2023

Table 3. Rating distribution of OTA's reviews in each product category

	Product Category	1-star-rating	2-star-rating	3-star-rating	4-star-rating	5-star-rating	Count (% in total OTA)	Share of 1- and 5- ratings
1	All_Beauty	1,922 (21.79%)	489 (5.54%)	453 (5.14%)	805 (9.13%)	5,150 (58.40%)	8,819 (0.09%)	80.19%
2	Amazon_Fashion	3,525 (20.56%)	1,137 (6.63%)	1,238 (7.22%)	2,075 (12.10%)	9,170 (53.49%)	17,145 (0.17%)	74.04%
3	Appliances	10,290 (24.87%)	1,865 (4.51%)	1,630 (3.94%)	3,564 (8.61%)	24,024 (58.07%)	41,373 (0.40%)	82.94%
4	Arts_Crafts_and_Sewing	30,244 (22.04%)	8,490 (6.19%)	8,426 (6.14%)	12,586 (9.17%)	77,456 (56.45%)	137,202 (1.33%)	78.50%
5	Automotive	59,969 (24.86%)	12,783 (5.30%)	12,151 (5.04%)	22,187 (9.20%)	134,123 (55.60%)	241,213 (2.34%)	80.47%
6	Baby_Products	23,019 (19.22%)	6,799 (5.68%)	6,347 (5.30%)	10,424 (8.70%)	73,181 (61.10%)	119,770 (1.16%)	80.32%
7	Beauty_and_Personal_Care	125,705 (23.22%)	28,648 (5.29%)	27,254 (5.04%)	47,180 (8.72%)	312,495 (57.73%)	541,282 (5.25%)	80.96%
8	Books	43,532 (8.10%)	20,695 (3.85%)	27,638 (5.15%)	70,944 (13.21%)	374,312 (69.69%)	537,121 (5.21%)	77.79%
9	CDs_and_Vinyl	7,441 (8.68%)	2,873 (3.35%)	3,675 (4.29%)	9,148 (10.67%)	62,590 (73.01%)	85,727 (0.83%)	81.69%
10	Cell_Phones_and_Accessories	111,297 (22.12%)	29,644 (5.89%)	26,880 (5.34%)	49,928 (9.92%)	285,380 (56.72%)	503,129 (4.88%)	78.84%
11	Clothing_Shoes_and_Jewelry	224,498 (17.31%)	82,272 (6.34%)	88,625 (6.83%)	151,147 (11.65%)	750,318 (57.86%)	1,296,860 (12.58%)	75.17%
12	Digital_Music	135 (13.80%)	37 (3.78%)	56 (5.73%)	75 (7.67%)	675 (69.02%)	978 (0.01%)	82.82%
13	Electronics	235,427 (22.07%)	61,596 (5.77%)	56,889 (5.33%)	119,803 (11.23%)	593,110 (55.60%)	1,066,82 (10.35%)	77.66%
14	Gift_Cards	1,013 (27.57%)	87 (2.37%)	119 (3.24%)	202 (5.50%)	2,253 (61.32%)	3,674 (0.04%)	88.89%
15	Grocery_and_Gourmet_Food	88,040 (32.41%)	15,551 (5.73%)	13,268 (4.88%)	16,089 (5.92%)	138,670 (51.05%)	271,618 (2.63%)	83.47%
16	Handmade_Products	864 (11.97%)	265 (3.67%)	256 (3.55%)	340 (4.71%)	5,495 (76.11%)	7,220 (0.07%)	88.07%
17	Health_and_Household	112,829 (20.09%)	25,093 (4.47%)	23,883 (4.25%)	51,774 (9.22%)	348,061 (61.97%)	561,640 (5.45%)	82.06%
18	Health_and_Personal_Care	1,718 (23.35%)	383 (5.20%)	348 (4.73%)	669 (9.09%)	4,241 (57.63%)	7,359 (0.07%)	80.98%
19	Home_and_Kitchen	314,325 (23.78%)	86,583 (6.55%)	76,210 (5.77%)	119,752 (9.06%)	724,903 (54.84%)	1,321,773 (12.82%)	78.62%
20	Industrial_and_Scientific	20,453 (26.68%)	4,521 (5.90%)	4,053 (5.29%)	6,655 (8.68%)	40,988 (53.46%)	76,670 (0.74%)	80.14%
21	Kindle_Store	16,117 (4.76%)	10,673 (6.08%)	20,784 (6.13%)	60,843 (17.96%)	230,400 (68.00%)	338,817 (3.29%)	72.76%
22	Magazine_Subscriptions	488 (30.60%)	97 (3.15%)	119 (7.46%)	160 (10.03%)	731 (45.83%)	1,595 (0.02%)	76.43%
23	Movies_and_TV	50,545 (13.28%)	13,442 (3.53%)	17,081 (4.49%)	42,894 (11.27%)	256,703 (67.44%)	380,665 (3.69%)	80.71%
24	Musical_Instruments	11,104 (18.28%)	3,197 (5.26%)	3,319 (5.46%)	7,342 (12.08%)	35,792 (58.91%)	60,754 (0.59%)	77.19%
25	Office_Products	60,685 (23.15%)	15,265 (5.82%)	13,790 (5.26%)	23,239 (8.87%)	149,111 (56.89%)	262,090 (2.54%)	80.05%
26	Patio_Lawn_and_Garden	77,966 (27.98%)	17,997 (6.46%)	15,095 (5.42%)	25,231 (9.05%)	142,397 (51.10%)	278,686 (2.70%)	79.07%
27	Pet_Supplies	81,549 (23.50%)	22,072 (6.36%)	18,589 (5.36%)	29,520 (8.51%)	195,226 (56.27%)	346,956 (3.37%)	79.77%
28	Software	21,846 (15.25%)	5,298 (5.71%)	9,629 (6.72%)	25,735 (17.97%)	80,720 (56.36%)	143,228 (1.39%)	71.61%
29	Sports_and_Outdoors	73,929 (19.65%)	21,485 (7.13%)	20,050 (5.33%)	40,076 (10.65%)	220,769 (58.67%)	376,309 (3.65%)	78.31%
30	Subscription_Boxes	79 (18.16%)	31 (3.70%)	25 (5.75%)	28 (6.44%)	272 (62.53%)	435 (0.004%)	80.69%
31	Tools_and_Home_Improvement	108,161 (24.92%)	26,163 (6.03%)	23,401 (5.39%)	39,657 (9.14%)	236,691 (54.53%)	434,073 (4.21%)	79.45%
32	Toys_and_Games	71,937 (23.38%)	19,290 (6.27%)	18,331 (5.96%)	28,148 (9.15%)	170,016 (55.25%)	307,722 (2.98%)	78.63%
33	Unknown	69,970 (18.47%)	18,594 (4.91%)	20,866 (5.51%)	44,535 (11.76%)	224,843 (59.36%)	378,808 (3.67%)	77.83%
34	Video_Games	37,033 (24.43%)	9,364 (6.18%)	8,815 (5.81%)	16,306 (10.76%)	80,075 (52.82%)	151,593 (1.47%)	77.25%
	Sum	2,097,655 (20.35%)	572,779 (5.56%)	569,293 (5.52%)	1,079,061 (10.47%)	5,990,341 (58.11%)	10,309,129 (100%)	**78.45%**

* Note: Total 10,309,129 reviews from 10,309,129 unique reviewers for 1,908,223 unique products between August 8, 1997, and September 12, 2023

3. Empirical Analysis

This section first describes empirical results for estimating the effect of OTA reviews on rating distributions in a product category with aggregated data in all product categories over the entire sample period. Second, this section describes findings from empirical analysis for the determinants of OTA reviews in the subscription boxes category, which shows abnormal rating distribution compared to other product categories.

3.1 Econometric analysis with aggregated product review data in all product categories

This section describes empirical findings from a two-way fixed panel model with heteroskedastic robust standard errors to estimate the effect of the number of OTA reviews on rating distribution, especially for rating polarity and imbalance, on Amazon.com.

Table 4. describes the variables in this empirical analysis. The measure of polarity, positive imbalance, and negative imbalance are based on the measure of Schoenmueller et al. (2020). Polarity, positive and negative imbalance (i.e., pos_imbal and neg_imbal), the share of each rating (i.e., s_N_star, where N indicates a star rating), and share for unverified purchase review (i.e., s_unver) for each product category in each year are dependent variables (Table 5). Log transformation is used to account for the scale differences across independent variables. The log transformation of the number of OTA in each category in each year (i.e., log_n_reviews_ota), that of unique asins (i.e., log_n_u_ asins), and that of unique reviewers (i.e., log_n_u_ reviewers) are independent variables (Table 4). Additionally, fixed effect variables for both categories and years are included to consider unobservable time-invariant and time-variant confounders.

Table 4. Variable description (*N*=238)

Variable name	Description	Mean	SD	Min	Max
Polarity	$\frac{\text{\# of 1 and 5 star reviews}}{\text{\# of reviews}}$	0.78	0.05	0.66	0.93
pos_imbal	$\frac{\text{\# of 4 and 5 star reviews}}{\text{\# of 1245 reviews}}$	0.82	0.06	0.61	0.95
neg_imbal	$\frac{\text{\# of 1 and 2 star reviews}}{\text{\# of 1245reviews}}$	0.18	0.06	0.05	0.39

s_1_star	$\frac{\text{\# of 1 star reviews}}{\text{\# of reviews}}$	0.12	0.05	0.02	0.28
s_2_star	$\frac{\text{\# of 2 star reviews}}{\text{\# of reviews}}$	0.05	0.02	0.01	0.11
s_3_star	$\frac{\text{\# of 3 star reviews}}{\text{\# of reviews}}$	0.07	0.02	0.02	0.11
s_4_star	$\frac{\text{\# of 4 star reviews}}{\text{\# of reviews}}$	0.10	0.03	0.04	0.21
s_4_star	$\frac{\text{\# of 5 star reviews}}{\text{\# of reviews}}$	0.66	0.07	0.49	0.87
s_unver	$\frac{\text{\# of unverified purchase reviews}}{\text{\# of reviews}}$	0.09	0.08	0.02	0.45
log_n_reviews_ota	Log(# of OTA's review+1)	9.06	2.22	2.30	12.47
log_n_u_ asins	Log(# of unique asins +1)	11.25	2.19	1.79	14.59
log_n_u_reviewers	Log(# of unique reviewers+1)	12.80	2.04	5.60	15.72
Year	Year			2017	2023
Category	Product category			1	34

The equation (1) is the base model in this section. Y_{it} is a dependent variable (i.e., polarity, positive imbalance, negative imbalance, the share of each rating, and share for unverified purchase review for the product category `i` in the year `t`. There is a total of 34 product categories between 2017 and 2023 years. α_i is the category fixed effect and γ_t is the year-fixed effect. Log transformation of the number of OTA, unique asins (i.e., products), and unique reviewers in the product category `i` in the year `t` are independent variables as follows:

$$(1)\ Y_{it} = \alpha_i + \gamma_t + \beta_1 \text{log_n_reviews_ota}_{it} + \beta_2 \text{log_n_u_ asins}_{it} + \beta_3 \text{log_n_u_reviewers}_{it} + \varepsilon_{it}$$

The empirical results (Table 5) show that increasing the number of reviews from OTA increases the share of 1- and 4-star ratings at a statistically significant 5% level while decreasing the share of 5-star ratings at a statistically significant 10% level. The effect of OTA reviews on the decline of 5-star ratings is larger than that of the increases in 1-star ratings. The effect of OTA reviews on 4-star ratings is the smallest among 1-, 4-, and 5-star ratings. Prior studies (Luca and Zervas, 2016; Mayzlin et al., 2014) pointed out that suspicious reviewers may write positive reviews for their business and negative reviews for competitors' businesses. He et al. (2022) stated that fake reviewers are more likely to write positive fake reviews than negative fake reviews for competitors due to the cost of writing reviews for competitors on Amazon.com. In contrast to this prior study (He et al., 2022), the findings of this paper show

that higher OTA reviews increase the share of negative reviews (i.e., 1-star ratings) and reduce that of positive reviews (i.e., 5-star ratings). One plausible explanation is a negative self-selection case where reviewers with negative online shopping experiences beyond their expectation or tolerance level write their first and only review with a 1-star rating across all product categories. Another possible explanation is that some OTA are suspicious reviewers who want to write a negative review for their competitors instead of writing a good review for themselves, even though they may have less incentive to do so due to the higher cost of writing a review for competitors compared to writing a positive review for their products. However, there is no ground truth data in this paper whether OTA is a normal reviewer with negative self-selection or a suspicious reviewer.

Additionally, increases in the number of unique products (i.e., asin) increase the share of 1-star ratings and unverified purchase reviews at a statistical significance of 10%. More number of unique products in a category increases negative reviews and unverified purchase reviews in the category. Lastly, increases in the number of unique reviewers decrease the share of 1-star ratings at a statistically significance 5%. Increasing the number of unique reviewers by soliciting consumers to post reviews on a digital platform could be a way to reduce negative self-selection in reviews. Additionally, online review solicitations could be a way to reduce extremity bias in online reviews as well. Karaman (2021) showed that online review solicitations on companies' websites reduce 1-star ratings on a third-party review platform (i.e., TripAdvisor.com). Brandes et al. (2022) showed that an unincentivized reminder email for posting a review on a digital travel platform reduces extreme rating reviews. Schoenmueller et al. (2020) demonstrated that sending reviewers to write a review with and without financial incentives reduces extreme ratings on a digital service platform. Nonetheless, the effect of review solicitations on the number of unique reviews and OTA remains as future research.

Additional empirical analyses (Appendix) show consistent results with the empirical

results in Table 5 regardless of the logarithm transformation of dependent variables and exclusion of unknown category reviews.

Table 5. Effect of the number of reviews from OTA on rating distributions

variable	Polarity	pos_imbal	neg_imbal	s_1_star	s_2_star	s_3_star	s_4_star	s_5_star	s_unver
log_n_ reviews_ota	-0.009	-0.035	0.035	0.035**	0.000	-0.001	0.010**	-0.044*	-0.007
	(0.009)	(0.023)	(0.023)	(0.016)	(0.005)	(0.003)	(0.004)	(0.023)	(0.020)
log_n_u_ asins	-0.005	-0.025	0.025	0.024*	-0.001	0.002	0.004	-0.029	0.018*
	(0.008)	(0.020)	(0.020)	(0.014)	(0.005)	(0.004)	(0.003)	(0.021)	(0.009)
log_n_u_ reviewers	0.001	0.061	-0.061	-0.062**	0.001	0.005	-0.007	0.062	-0.014
	(0.017)	(0.040)	(0.040)	(0.027)	(0.009)	(0.005)	(0.007)	(0.041)	(0.023)
year fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
cate fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	238	238	238	238	238	238	238	238	238
adj R^2	0.963	0.927	0.927	0.923	0.940	0.953	0.969	0.937	0.887

* Note: heteroskedasticity robust standard error in parenthesis, * p<.1; ** p<.05; *** p<.01. The sample period is between 2017 and 2023. The number of product categories in the sample dataset is 34, including unknown.

3.2. Econometric analysis with individual review data in the target product category

This section describes empirical results from a binary logistic regression analysis with all reviews in the subscription boxes category, which shows abnormal rating patterns compared to other product categories, to estimate the determinants of OTA's reviews. The target product category is a subscription boxes category, as it showed the highest gap in the share of 1- and 5-star ratings between all reviews and OTA's reviews in the given product category. In detail, the gap in the share of 1-and 5-star ratings between all reviews (69.75%) and OTA reviews (80.69%) in the subscription boxes category is the highest, as of 10.94% among all product categories (Table 6).

The share of 5-star ratings in OTA's reviews in the subscription boxes category (62.53%) is 8.67% higher than all reviews in the subscription boxes category (53.86%). This 5-star rating pattern in the subscription boxes category is different from that of all reviews in all categories. The share of 5-star ratings in all reviews in all categories (65.03%; Table 1) is

7.19% higher than the share of 5-star ratings in all OTA's reviews in all categories (58.11%; Table 3).

The share of 1-star ratings in OTA's reviews in the subscription boxes category (18.16%; Table 6) is 2.27% higher than all reviews in the subscription boxes category (15.89%; Table 6). The share of 1-star ratings in all OTA's reviews in all categories (20.35%; Table 1) is also 19.04% higher than the share of 1-star ratings in all reviews in all categories (10.31%; Table 3).

Overall, the share of 1- and 5-star ratings gap between all reviews and OTA's reviews in each product category is the highest in the subscription boxes category. In addition, the gap of 5-star ratings between all reviews and OTA's reviews in the subscription boxes category is higher than that of 1-star ratings. OTA reviewers in the subscription boxes category are more likely to write positive and negative reviews than all reviewers in the subscription boxes. These OTA reviewers may be normal consumers with positive and negative polarity self-selection or suspicious reviewers. Therefore, this study selects the subscription boxes category as a target category for further analysis to estimate the determinants of OTA in the subscription boxes category.

Table 6. Rating distribution of OT's, and OTA's reviews in the subscription boxes category

Subscription Boxes Category	1-star-rating	2-star-rating	3-star-rating	4-star-rating	5-star-rating	count	Share of 1- and 5- ratings	Unique reviewers	Unique asins
All reviews	2,576 (15.89%)	1,491 (9.19%)	1,752 (10.80%)	1,663 (10.26%)	8,734 (53.86%)	16,216	69.75%	15,237	641
OT's reviews	2,335 (16.14%)	1,355 (9.36%)	1,567 (10.83%)	1,480 (10.23%)	7,734 (53.44%)	14,471	69.58%	14,471	602
OTA's reviews*	79 (18.16%)	31 (7.13%)	25 (5.75%)	28 (6.44%)	272 (62.53%)	435	80.69%	435	61

* Note: The number of OTA reviewers and reviews is the same.

OTA is supposed to write their first and only review across all categories over the entire sample period; therefore, the number of reviewers and reviews are the same. This study constructed the dataset by limiting the first review from all unique reviewers in the subscription boxes category to compare reviews from OTA and other reviewers in the subscription boxes

category. Therefore, the number of reviews in the sample data is the same as the number of unique reviewers in the subscription boxes category as of 15,237.

Table 7 shows the description of the variables. Additionally, a binary dummy variable, whether a review in the subscription boxes category is written by OTA or not, is a dependent variable. Independent variables consist of two groups. One group of independent variables is based on consumer `i`'s review behaviors for a product in the subscription boxes category at time `t` when the reviewer writes a review for the product. Consumer-side independent variables include the reviewer's star ratings, purchase verification status, length of review headline and body text, other consumers' helpfulness vote for the review, and the reviewer's sentiment toward the product's price in the review headline and body text. In particular, the raw dataset for the subscription boxes category does not contain price information for products in the category; therefore, this study uses OpenAI's Application Programming Interface (API) for large language models (LLMs) to classify the sentiment of reviews about the price of the reviewed product with prompt engineering as follows:

Prompt
System Prompt:
You will be provided with Amazon online product review text data. I am running a few minutes late; my previous meeting is running over.
The query will be delimited with \{delimiter} characters.
Your task is to classify its sentiment for price as positive, neutral, or negative.
When you cannot classify the sentiment for price or there is no information about price in the text, please classify the text as neutral.
Additionally, please provide the reason for your sentiment analysis for price in text data in one sentence.
Split the sentiment for price and reason with a comma.
All responses must be a lower character.

* Note: OpenAI's GPT-4o model is used without the randomness of the generated output.

Before sentiment analysis with the above prompt engineering, the review headline and body text are combined and converted as lower characters. The range of price sentiment is positive (*N*=1,942), neutral (*N*= 11,182), and negative (*N*=3,092).

The other independent variables are constructed by digital footprints for the reviewed

products. In detail, the average length of review headline for a product by t-1, the average length of review body text for the product by t-1, the average rating for the product by t-1, the share of each rating for the product by t-1, and the number of reviews, reviewers, and reviews per reviewer for the product by t-1. Fixed dummy variables for the year, month, and date of week are used.

Table 7. Variable description (*N*=15,237)

Variable	Description	Mean	SD	Min	Max
OTA	Whether the review is written by OTA or not	0.03	0.17	0	1
1-star rating	Whether i's star rating is 1 or not.	0.16	0.37	0	1
2-star rating	Whether i's star rating is 2 or not.	0.09	0.29	0	1
4-star rating	Whether i's star rating is 4 or not.	0.10	0.30	0	1
5-star rating	Whether i's star rating is 5 or not.	0.54	0.50	0	1
Verified	Verified purchased reviewer or not	0.88	0.33	0	1
user_summary_len	Length of review headline for the product by i	24.17	16.93	1	176
user_reviewtext_len	Length of review for the product by i	254.48	317.34	0	11,127
Vote	Helpful vote for i's review	5.87	21.27	0	985
price_sentiment*	Price sentiment toward the product by i at t	1.93	0.55	1	3
a_avg_len_summary	average length of review headline for the product by t-1	24.76	5.28	1	97
a_avg_len_reviewtext	average length of review for the product by t-1	263.83	118.89	7	3210.33
a_avg_rating	average rating for the product by t-1	3.80	0.64	1	5
a_5_rating_share	share of 5 ratings on the product by t-1	0.55	0.20	0	1
a_4_rating_share	Share of 4 ratings on the product by t-1	0.10	0.08	0	1
a_2_rating_share	Share of 2 ratings on the product by t-1	0.10	0.09	0	1
a_1_rating_share	Share of 1 ratings on the product by t-1	0.15	0.13	0	1
a_n_reviews	the number of reviews on the product by t-1	228.62	352.72	0	1771
a_n_reviewers	the number of reviewers on the product by t-1	225.23	347.88	0	1752
a_n_reviewers_per	the number of reviews per reviewer by t-1	0.98	0.20	0	2
Year	Year fixed effect			2017	2023
Month	Month fixed effect			1	12
Day of week	Day of week fixed effect			0	6

In contrast to linear regression models, the coefficients of independent variables in logistic regression models cannot directly be interpreted as a marginal effect because binary logistic regression is a nonlinear model (Train, 2009). This study uses the marginal effects of logistic regression models for interpretation rather than coefficients of independent variables (Table 8).

The probability that a review in the subscription boxes is written by OTA is higher when the review rating is 1 or 5-star ratings compared to that of a 3-star rating at a statistical significance of 1% or 5% levels in all models (Table 8). OTA in the subscription boxes category is more likely to post a review for 1- or 5-star ratings. The probability that a review is written

by OTA in a purchase-verified review is lower than that of a purchase-unverified review at a statistically significance 1% level in all models 1-11 (Table 8). OTA in the subscription boxes category is more likely to be a purchase unverified reviewer than a verified reviewer.

More positive sentiment toward a price in a review for the reviewed product in the subscription boxes category increases the probability that the review is written by OTA at a statistically significance 10% level in some models.

An increase in a product's average length of review headline in the prior reviews increases the probability that a review is written by OTA at a statistically significance 5% level. Additionally, the increase in the average star rating and the share of 5-star ratings for a product in the prior reviews improve the probability that the review is written by OTA at a statistically significance 1%. In comparison, an increase in the share of 1-star ratings for a product in prior reviews decreases the probability that the review is written by OTA at a statistical significance of 5%. OTA is more likely to write a review for the product with a higher average starting and a higher share of 5-star ratings in prior reviews before their first and only rating for the product.

The length of the review body text, the number of reviews for a product in the prior reviews, and the number of reviewers for a product in the prior reviews are also statistically significant; however, their marginal effects are neglectable.

Overall, a review in the subscription boxes category is more likely to be written by OTA if an unverified purchase reviewer writes the review, the review rating is extreme ratings, and the price sentiment in the review headline and body text is more positive. In terms of digital footprints variables for the reviewed product, a review is written for the product contains a longer review headline, a higher average star ratings, a higher share of 5-star ratings, and less share of 1-star ratings in the prior reviews for the product, the review for the product is more likely to be written by OTA. A possible explanation is that a consumer had expected high quality based on high average star ratings and the share of 5-star ratings in the prior reviews

for the product; however, dissatisfied with the product after the purchase and gave a 1-star rating for the first time or satisfied with the product after the purchase, and gave a 5-star rating for the first time. Another plausible explanation is that OTA is a suspicious reviewer who provides a 1-star rating for competitive products with a high average star rating and/or a high share of 5-star ratings and gives 5-star ratings for their product to be competitive.

Table 8. Marginal effect of the logit model for OTA reviews (first review only)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
1-star rating	0.0125 ***	0.0145 ***	0.0151 ***	0.0172 ***	0.0175 ***	0.0151 ***	0.0155 ***	0.0161 ***	0.0149 ***	0.0149 ***	0.0150 ***
	(0.0048)	(0.0053)	(0.0055)	(0.0058)	(0.0059)	(0.0055)	(0.0055)	(0.0056)	(0.0054)	(0.0054)	(0.0055)
2-star rating	0.0048	0.0057	0.0051	0.0056	0.0056	0.0049	0.0054	0.0053	0.0052	0.0052	0.0049
	(0.0052)	(0.0055)	(0.0056)	(0.0059)	(0.0059)	(0.0057)	(0.0057)	(0.0057)	(0.0056)	(0.0056)	(0.0056)
4-star rating	0.0023	0.0013	0.0012	0.0007	0.0006	0.0011	0.0012	0.0009	0.0014	0.0014	0.0012
	(0.0050)	(0.0051)	(0.0052)	(0.0053)	(0.0054)	(0.0052)	(0.0052)	(0.0053)	(0.0052)	(0.0052)	(0.0052)
5-star rating	0.0155 ***	0.0134 ***	0.0134 ***	0.0116 ***	0.0111 **	0.0132 ***	0.0131 ***	0.0126 ***	0.0140 ***	0.0140 ***	0.0133 ***
	(0.0039)	(0.0042)	(0.0043)	(0.0044)	(0.0045)	(0.0043)	(0.0043)	(0.0044)	(0.0043)	(0.0043)	(0.0043)
verified	-0.0352 ***	-0.0352 ***	-0.0360 ***	-0.0359 ***	-0.0351 ***	-0.0354 ***	-0.0360 ***	-0.0364 ***	-0.0369 ***	-0.0369 ***	-0.0358 ***
	(0.0034)	(0.0034)	(0.0036)	(0.0035)	(0.0035)	(0.0036)	(0.0035)	(0.0036)	(0.0036)	(0.0036)	(0.0036)
user_ summary _len	-0.0000	-0.0000	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
user_ review_ len	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
vote	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
price_ sentiment		0.0053 *	0.0054 *	0.0049	0.0049	0.0054 *	0.0053 *	0.0051 *	0.0043	0.0043	0.0054 *
		(0.0029)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
a_avg_len_ summary			0.0005 **	0.0006 **	0.0005 **	0.0005 **	0.0005 **	0.0006 **	0.0005 **	0.0005 **	0.0006 **
			(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
a_avg_len_ review text			0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
a_avg_rating				0.0093 ***							
				(0.0024)							
a_5_rating_ share					0.0345 ***						
					(0.0073)						
a_4_rating_ share						-0.0322					
						(0.0199)					
a_2_rating_ share							-0.0237				
							(0.0170)				
a_1_rating_ share								-0.0287 **			
								(0.0122)			
a_n_ reviews									0.0000 ***		
									(0.0000)		
a_n_ reviewers										0.0000 ***	
										(0.0000)	
a_n_ reviewers_ per											-0.0637
											(0.0522)
N	15237	15237	14652	14652	14652	14652	14652	14652	14652	14652	14652

4. Conclusion

The study finds one-time reviewers across all product categories with Amazon review big data, measures the effect of one-time reviewers on rating distributions, and estimates the driving forces of one-time reviewers in all product categories in the abnormal product category.

In detail, the paper shows that all product categories have one-time reviewers in each category (OT) and one-time reviewers in all categories (OTA). Additionally, the share of 1-star ratings in OTA's reviews is higher than all reviews, while the share of 5-star ratings in OTA reviews is smaller than that of all reviews. OTA may be a suspicious reviewer or a normal reviewer with negative polarity self-selection. However, a suspicious reviewer may have more incentive to write a positive review for their products than write a negative review for their competitor's products due to the costs of writing a negative review for the competitor's products. Accordingly, OTA's reviews are more likely to be written by a reviewer with negative polarity self-selection. Of course, ground truth data is necessary to determine whether OTA is a suspicious reviewer or a normal reviewer with negative polarity self-selection.

Empirical results show that an increase in OTA's reviews in a product category increase negative reviews, while decreasing positive reviews in the product category. Further economic analysis for the subscription boxes category, which has a higher share of 1- and 5-star ratings in OTA's reviews than all reviews in the category, shows that a review is more likely to be written by OTA, if an unverified purchase reviewer writes the review, the review rating is extreme ratings, and the price sentiment in the review headline and body text is more positive. Additionally, a review for the product is more likely to be written by OTA if the review written for a product contains a longer review headline, a higher average star ratings, a higher share of 5-star ratings, and less share of 1-star ratings in the prior reviews for the product, These OTA may be a normal reviewer with positive and negative polarity self-selection or a suspicious reviewers.

The results of this paper will be beneficial to identifying abnormal reviewers and consumer segments, improving the credibility of user-generated content, review system design, and digital retail platforms, and enhancing consumer welfare.

One limitation of this study is that the dataset does not contain the true types of reviewers on reviews, whether a reviewer is a normal reviewer with positive or negative self-selection or a suspicious reviewer. Additionally, a large language model (LLM) is used to classify the sentiment of review for the price of the reviewed product in the target product category because there is no price information in the review data for the category. Therefore, there is potential for measurement errors in the predicted value for price sentiment using LLMs. These limitations can open new worthwhile topics for future studies, such as the identification of determinants of the true type of abnormal reviewers with random control trials and their reviews' effect on information in user-generated content and multimodal approaches to minimize measurement errors in text-generated variables.

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Appendix

Table A.1 Effect of the number of reviews from OTA on rating distributions without unknown category

Variable	polarity	pos_imbal	neg_imbal	s_1_star	s_2_star	s_3_star	s_4_star	s_5_star	s_unver
log_n_ reviews_ota	-0.009 (0.009)	-0.035 (0.023)	0.035 (0.023)	0.035** (0.016)	0.000 (0.005)	-0.001 (0.003)	0.010** (0.004)	-0.044* (0.024)	-0.010 (0.020)
log_n_u_ asins	-0.004 (0.008)	-0.025 (0.021)	0.025 (0.021)	0.024* (0.014)	-0.001 (0.005)	0.002 (0.004)	0.003 (0.003)	-0.028 (0.021)	0.017* (0.009)
log_n_u_ reviewers	0.000 (0.017)	0.062 (0.040)	-0.062 (0.040)	-0.062** (0.027)	0.001 (0.009)	0.006 (0.005)	-0.007 (0.007)	0.062 (0.041)	-0.010 (0.023)
year fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
cate fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	231	231	231	231	231	231	231	231	231
adj R^2	0.964	0.926	0.926	0.922	0.940	0.953	0.969	0.937	0.887

* Note: heteroskedasticity robust standard error in parenthesis, * p<.1; ** p<.05; *** p<.01.

The sample period is between 2017 and 2023. The number of product categories in the sample dataset is 33, excluding unknown.

Table A.2 Effect of the number of reviews from OTA on log rating distributions

variable	log polarity	log_pos_imbal	log_neg _imbal	log s_1_star	log s_2_star	log s_3_star	log s_4_star	log s_5_star	log s_unver
log_n_ reviews _ota	-0.005 (0.005)	-0.020 (0.013)	0.029 (0.018)	0.030** (0.014)	0.000 (0.005)	-0.000 (0.003)	0.008** (0.004)	-0.026* (0.015)	-0.005 (0.017)
log_n _u_asins	-0.003 (0.005)	-0.015 (0.012)	0.020 (0.016)	0.020* (0.012)	-0.001 (0.004)	0.002 (0.003)	0.003 (0.002)	-0.018 (0.013)	0.017** (0.008)
log_n_u _reviewers	0.000 (0.010)	0.036 (0.023)	-0.049 (0.031)	-0.051** (0.023)	0.001 (0.009)	0.005 (0.005)	-0.006 (0.006)	0.038 (0.026)	-0.013 (0.021)
year fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
cate fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	238	238	238	238	238	238	238	238	238
adj R^2	0.962	0.921	0.934	0.929	0.941	0.954	0.969	0.933	0.879

* Note: heteroskedasticity robust standard error in parenthesis, * p<.1; ** p<.05; *** p<.01.

The sample period is between 2017 and 2023. The number of product categories in the sample dataset is 34, including unknown.

Table A.3 Effect of the number of reviews from OTA on log rating distributions without unknown category

Variable	log polarity	log_pos _imbal	log_neg _imbal	log s_1_star	log s_2_star	log s_3_star	log s_4_star	log s_5_star	log s_unver
log_n_ reviews_ota	-0.005 (0.005)	-0.020 (0.013)	0.029 (0.018)	0.030** (0.014)	0.000 (0.005)	-0.001 (0.003)	0.008** (0.004)	-0.026* (0.015)	-0.008 (0.017)
log_n_u_ asins	-0.002 (0.005)	-0.014 (0.012)	0.019 (0.016)	0.020* (0.012)	-0.001 (0.004)	0.002 (0.003)	0.003 (0.002)	-0.017 (0.013)	0.016* (0.008)
log_n_u_ reviewers	-0.000 (0.010)	0.036 (0.023)	-0.049 (0.032)	-0.052** (0.023)	0.001 (0.009)	0.006 (0.005)	-0.006 (0.006)	0.038 (0.026)	-0.010 (0.021)
year fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
cate fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	231	231	231	231	231	231	231	231	231
adj R^2	0.962	0.920	0.933	0.928	0.942	0.954	0.969	0.932	0.878

* Note: heteroskedasticity robust standard error in parenthesis, * p<.1; ** p<.05; *** p<.01.

The sample period is between 2017 and 2023. The number of product categories in the sample dataset is 33, excluding unknown.

Table A.4 Logit model of OTA reviews (first review only)

Variable	fm1	fm2	fm3	fm4	fm5	fm6	fm7	fm8	fm9	fm10	fm11
1-star rating	0.5641 **	0.6125 ***	0.6178 ***	0.6676 ***	0.6701 ***	0.6152 ***	0.6303 ***	0.6427 ***	0.6210 ***	0.6210 ***	0.6143 ***
	(0.2360)	(0.2375)	(0.2378)	(0.2380)	(0.2380)	(0.2379)	(0.2380)	(0.2379)	(0.2379)	(0.2379)	(0.2378)
2-star rating	0.2510	0.2851	0.2500	0.2666	0.2623	0.2425	0.2622	0.2542	0.2594	0.2595	0.2406
	(0.2736)	(0.2742)	(0.2762)	(0.2763)	(0.2764)	(0.2763)	(0.2763)	(0.2762)	(0.2765)	(0.2765)	(0.2763)
4-star rating	0.1289	0.0722	0.0652	0.0354	0.0289	0.0615	0.0625	0.0492	0.0745	0.0746	0.0649
	(0.2790)	(0.2807)	(0.2809)	(0.2811)	(0.2811)	(0.2809)	(0.2809)	(0.2811)	(0.2811)	(0.2811)	(0.2809)
5-star rating	0.6665 ***	0.5758 ***	0.5646 ***	0.4915 **	0.4707 **	0.5558 **	0.5517 **	0.5328 **	0.5902 ***	0.5904 ***	0.5596 **
	(0.2128)	(0.2184)	(0.2188)	(0.2197)	(0.2198)	(0.2188)	(0.2190)	(0.2192)	(0.2191)	(0.2191)	(0.2188)
verified	-1.2941 ***	-1.2930 ***	-1.2989 ***	-1.2974 ***	-1.2702 ***	-1.2777 ***	-1.2985 ***	-1.3116 ***	-1.3327 ***	-1.3329 ***	-1.2902 ***
	(0.1147)	(0.1147)	(0.1173)	(0.1172)	(0.1174)	(0.1180)	(0.1172)	(0.1173)	(0.1180)	(0.1180)	(0.1175)
user_summary_len	-0.0014	-0.0016	-0.0021	-0.0023	-0.0023	-0.0021	-0.0020	-0.0022	-0.0019	-0.0019	-0.0021
	(0.0030)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)
user_reviewtext_len	-0.0004 **	-0.0004 **	-0.0004 **	-0.0004 **	-0.0005 **	-0.0004 **	-0.0004 **	-0.0004 **	-0.0004 **	-0.0004 **	-0.0004 **
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
vote	-0.0024	-0.0021	-0.0024	-0.0025	-0.0028	-0.0026	-0.0026	-0.0023	-0.0019	-0.0019	-0.0025
	(0.0033)	(0.0032)	(0.0035)	(0.0036)	(0.0038)	(0.0036)	(0.0036)	(0.0034)	(0.0032)	(0.0032)	(0.0036)
price_sentiment		0.1939 *	0.1934 *	0.1774 *	0.1776 *	0.1940 *	0.1910 *	0.1830 *	0.1552	0.1549	0.1930 *
		(0.1064)	(0.1072)	(0.1077)	(0.1078)	(0.1073)	(0.1074)	(0.1075)	(0.1074)	(0.1074)	(0.1072)
a_avg_len_summary			0.0194 **	0.0199 **	0.0194 **	0.0189 **	0.0196 **	0.0199 **	0.0196 **	0.0196 **	0.0203 **
			(0.0090)	(0.0088)	(0.0087)	(0.0089)	(0.0090)	(0.0089)	(0.0093)	(0.0093)	(0.0091)
a_avg_len_reviewtext			0.0000	0.0002	0.0002	0.0000	0.0001	0.0001	0.0002	0.0002	0.0000
			(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
a_avg_rating				0.3346 ***							
				(0.0849)							
a_5_rating_share					1.2471 ***						
					(0.2605)						
a_4_rating_share						-1.1618					
						(0.7155)					
a_2_rating_share							-0.8549				
							(0.6132)				
a_1_rating_share								-1.0359 **			
								(0.4367)			
a_n_reviews									0.0005 ***		
									(0.0001)		
a_n_reviewers										0.0005 ***	
										(0.0001)	
a_n_reviewers_per											-2.2980
											(1.8798)
_cons	-1.4244 ***	-1.7679 ***	-2.3950 ***	-3.6656 ***	-3.0745 ***	-2.2608 ***	-2.3020 ***	-2.2344 ***	-2.3996 ***	-2.3989 ***	-0.0579
	(0.3448)	(0.3934)	(0.4723)	(0.5731)	(0.4919)	(0.4770)	(0.4757)	(0.4792)	(0.4756)	(0.4756)	(1.9734)
ll	-1.87e+03	-1.87e+03	-1.83e+03	-1.82e+03	-1.81e+03	-1.82e+03	-1.83e+03	-1.82e+03	-1.82e+03	-1.82e+03	-1.83e+03
N	15237	15237	14652	14652	14652	14652	14652	14652	14652	14652	14652
aic	3805.067	3803.786	3722.254	3708.171	3701.332	3721.360	3722.167	3718.152	3709.882	3709.695	3722.303
bic	4049.274	4055.625	3987.986	3981.495	3974.656	3994.684	3995.491	3991.476	3983.206	3983.019	3995.627

Table A.5 Logit model of OTA reviews

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
1-star rating	0.5784 **	0.6273 ***	0.6300 ***	0.6834 ***	0.6865 ***	0.6279 ***	0.6424 ***	0.6567 ***	0.6346 ***	0.6346 ***	0.6263 ***
	(0.2359)	(0.2374)	(0.2378)	(0.2380)	(0.2380)	(0.2379)	(0.2380)	(0.2379)	(0.2378)	(0.2378)	(0.2378)
2-star rating	0.2565	0.2903	0.2524	0.2713	0.2681	0.2462	0.2653	0.2572	0.2638	0.2638	0.2428
	(0.2735)	(0.2740)	(0.2760)	(0.2761)	(0.2762)	(0.2761)	(0.2761)	(0.2760)	(0.2763)	(0.2763)	(0.2761)
4-star rating	0.1294	0.0733	0.0625	0.0343	0.0303	0.0609	0.0589	0.0474	0.0719	0.0720	0.0629
	(0.2788)	(0.2805)	(0.2807)	(0.2809)	(0.2809)	(0.2806)	(0.2807)	(0.2808)	(0.2809)	(0.2809)	(0.2806)
5-star rating	0.6641 ***	0.5733 ***	0.5595 **	0.4890 **	0.4704 **	0.5522 **	0.5460 **	0.5293 **	0.5861 ***	0.5863 ***	0.5550 **
	(0.2127)	(0.2183)	(0.2187)	(0.2195)	(0.2196)	(0.2187)	(0.2188)	(0.2191)	(0.2190)	(0.2190)	(0.2187)
verified	-1.3156 ***	-1.3147 ***	-1.3256 ***	-1.3268 ***	-1.2997 ***	-1.3051 ***	-1.3256 ***	-1.3399 ***	-1.3596 ***	-1.3598 ***	-1.3155 ***
	(0.1145)	(0.1144)	(0.1171)	(0.1170)	(0.1172)	(0.1178)	(0.1171)	(0.1172)	(0.1178)	(0.1178)	(0.1174)
user_summary_len	-0.0014	-0.0016	-0.0020	-0.0022	-0.0022	-0.0020	-0.0019	-0.0022	-0.0018	-0.0018	-0.0020
	(0.0030)	(0.0030)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)
user_reviewtext _len	-0.0004 **	-0.0004 **	-0.0004 **	-0.0004 **	-0.0005 **	-0.0004 **	-0.0004 **	-0.0004 **	-0.0004 **	-0.0004 **	-0.0004 **
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
vote	-0.0023	-0.0020	-0.0025	-0.0025	-0.0028	-0.0027	-0.0027	-0.0024	-0.0019	-0.0019	-0.0025
	(0.0033)	(0.0031)	(0.0036)	(0.0036)	(0.0038)	(0.0037)	(0.0037)	(0.0035)	(0.0032)	(0.0032)	(0.0036)
price_sentiment		0.1943 *	0.1960 *	0.1807 *	0.1802 *	0.1955 *	0.1940 *	0.1862 *	0.1567	0.1565	0.1954 *
		(0.1063)	(0.1071)	(0.1076)	(0.1077)	(0.1072)	(0.1072)	(0.1073)	(0.1073)	(0.1073)	(0.1071)
a_avg_len _summary			0.0203 **	0.0208 **	0.0204 **	0.0198 **	0.0204 **	0.0207 **	0.0205 **	0.0206 **	0.0211 **
			(0.0089)	(0.0087)	(0.0086)	(0.0088)	(0.0088)	(0.0088)	(0.0092)	(0.0092)	(0.0090)
a_avg_len _reviewtext			0.0000	0.0002	0.0002	-0.0000	0.0000	0.0001	0.0002	0.0002	-0.0000
			(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
a_avg_rating				0.3365 ***							
				(0.0845)							
a_5_rating_share					1.2495 ***						
					(0.2586)						
a_4_rating_share						-1.1210					
						(0.7062)					
a_2_rating_share							-0.8772				
							(0.6107)				
a_1_rating_share								-1.0195 **			
								(0.4339)			
a_n_reviews									0.0005 ***		
									(0.0001)		
a_n_reviewers										0.0005	
										(0.0001)	
a_n_reviewers_per											-2.4872
											(1.8974)
_cons	-1.4175 ***	-1.7609 ***	-2.4015 ***	-3.6804 ***	-3.0866 ***	-2.2723 ***	-2.3047 ***	-2.2405 ***	-2.4088 ***	-2.4079 ***	0.1286
	(0.3440)	(0.3923)	(0.4688)	(0.5696)	(0.4883)	(0.4735)	(0.4721)	(0.4755)	(0.4720)	(0.4720)	(1.9905)
N	16216	16216	15560	15560	15560	15560	15560	15560	15560	15560	15560
aic	3853.449	3852.147	3767.665	3753.254	3746.297	3766.897	3767.446	3763.676	3754.262	3754.052	3767.412
bic	4099.649	4106.041	4035.501	4028.742	4021.785	4042.386	4042.934	4039.165	4029.751	4029.541	4042.900

* Note: * p<.1; ** p<.05; *** p<.01. The sample period is between 2017 and 2023. Year, month, and the day of week fixed effect are applied

Table A.6 marginal effect for the logit model of OTA reviews

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
1-star rating	0.0121 ***	0.0140 ***	0.0146 ***	0.0167 ***	0.0170 ***	0.0146 ***	0.0150 ***	0.0156 ***	0.0145 ***	0.0145 ***	0.0145 ***
	(0.0046)	(0.0050)	(0.0052)	(0.0055)	(0.0056)	(0.0052)	(0.0053)	(0.0053)	(0.0051)	(0.0051)	(0.0052)
2-star rating	0.0046	0.0055	0.0049	0.0054	0.0054	0.0047	0.0052	0.0050	0.0050	0.0050	0.0047
	(0.0049)	(0.0052)	(0.0053)	(0.0056)	(0.0056)	(0.0053)	(0.0054)	(0.0054)	(0.0053)	(0.0053)	(0.0053)
4-star rating	0.0022	0.0012	0.0011	0.0006	0.0005	0.0011	0.0010	0.0008	0.0012	0.0012	0.0011
	(0.0047)	(0.0048)	(0.0049)	(0.0050)	(0.0051)	(0.0049)	(0.0049)	(0.0050)	(0.0049)	(0.0049)	(0.0049)
5-star rating	0.0145 ***	0.0125 ***	0.0125 ***	0.0109 ***	0.0105 **	0.0124 ***	0.0122 ***	0.0118 ***	0.0131 ***	0.0131 ***	0.0124 ***
	(0.0037)	(0.0039)	(0.0041	(0.0042	(0.0042	(0.0041	(0.0041	(0.0041	(0.0040	(0.0040	(0.0041
verified	-0.0337	-0.0337	-0.0347	-0.0347	-0.0339	-0.0342	-0.0347	-0.0351	-0.0355	-0.0356	-0.0344
	(0.0032)	(0.0032)	(0.0034)	(0.0034)	(0.0033)	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)
user_summary _len	-0.0000	-0.0000	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0000	-0.0000	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
user_reviewtext _len	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
vote	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
price_sentiment		0.0050 *	0.0051 *	0.0047 *	0.0047 *	0.0051 *	0.0051 *	0.0049 *	0.0041	0.0041	0.0051 *
		(0.0027)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)
a_avg_len _summary			0.0005 **	0.0005 **	0.0005 **	0.0005 **	0.0005 **	0.0005 **	0.0005 **	0.0005 **	0.0006 **
			(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
a_avg_len _reviewtext			0.0000	0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
a_avg_rating				0.0088 ***							
				(0.0022)							
a_5_rating_share					0.0326 ***						
					(0.0069)						
a_4_rating_share						-0.0293					
						(0.0185)					
a_2_rating_share							-0.0230				
							(0.0160)				
a_1_rating_share								-0.0267 **			
								(0.0114)			
a_n_reviews									0.0000 ***		
									(0.0000)		
a_n_reviewers										0.0000 ***	
										(0.0000)	
a_n_reviewers_per											-0.0651
											(0.0497)
N	16216	16216	15560	15560	15560	15560	15560	15560	15560	15560	15560

* Note: * p<.1; ** p<.05; *** p<.01. The sample period is between 2017 and 2023. Year, month, and the day of week fixed effect are applied

Table A.7 Logit model of OTA review among one-time reviews

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
1-star rating	0.5656**	0.6108**	0.6186***	0.6686***	0.6704***	0.6145***	0.6312***	0.6438***	0.6207***	0.6207***	0.6158***
	(0.2362)	(0.2376)	(0.2379)	(0.2381)	(0.2381)	(0.2379)	(0.2380)	(0.2379)	(0.2379)	(0.2379)	(0.2379)
2-star rating	0.2404	0.2732	0.2422	0.2595	0.2550	0.2336	0.2540	0.2470	0.2505	0.2506	0.2328
	(0.2737)	(0.2744)	(0.2763)	(0.2765)	(0.2765)	(0.2764)	(0.2764)	(0.2764)	(0.2766)	(0.2766)	(0.2764)
4-star rating	0.1297	0.0755	0.0723	0.0434	0.0359	0.0679	0.0704	0.0568	0.0818	0.0819	0.0723
	(0.2791)	(0.2809)	(0.2811)	(0.2813)	(0.2813)	(0.2810)	(0.2811)	(0.2812)	(0.2813)	(0.2813)	(0.2811)
5-star rating	0.6718***	0.5858***	0.5789***	0.5056**	0.4847**	0.5698***	0.5666***	0.5462**	0.6032***	0.6034***	0.5744***
	(0.2129)	(0.2185)	(0.2189)	(0.2198)	(0.2199)	(0.2189)	(0.2191)	(0.2194)	(0.2192)	(0.2192)	(0.2189)
verified	-1.2646***	-1.2636***	-1.2691***	-1.2675***	-1.2399***	-1.2468***	-1.2691***	-1.2817***	-1.3021***	-1.3024***	-1.2610***
	(0.1149)	(0.1148)	(0.1175)	(0.1174)	(0.1176)	(0.1182)	(0.1174)	(0.1175)	(0.1181)	(0.1182)	(0.1177)
user_summary_len	-0.0015	-0.0017	-0.0022	-0.0024	-0.0024	-0.0022	-0.0021	-0.0023	-0.0019	-0.0019	-0.0021
	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)
user_reviewtext_len	-0.0004**	-0.0004**	-0.0004**	-0.0004**	-0.0005**	-0.0004**	-0.0004**	-0.0004**	-0.0004**	-0.0004**	-0.0004**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
vote	-0.0024	-0.0021	-0.0024	-0.0025	-0.0028	-0.0025	-0.0025	-0.0022	-0.0019	-0.0019	-0.0024
	(0.0033)	(0.0032)	(0.0035)	(0.0035)	(0.0037)	(0.0036)	(0.0036)	(0.0034)	(0.0032)	(0.0032)	(0.0035)
price_sentiment		0.1843*	0.1844*	0.1684	0.1680	0.1846*	0.1816*	0.1743	0.1477	0.1475	0.1840*
		(0.1064)	(0.1073)	(0.1077)	(0.1079)	(0.1074)	(0.1074)	(0.1075)	(0.1074)	(0.1074)	(0.1073)
a_avg_len_summary			0.0192**	0.0200**	0.0195**	0.0188**	0.0196**	0.0199**	0.0195**	0.0195**	0.0202**
			(0.0092)	(0.0090)	(0.0089)	(0.0091)	(0.0092)	(0.0091)	(0.0095)	(0.0095)	(0.0094)
a_avg_len_reviewtext			0.0000	0.0002	0.0003	0.0000	0.0001	0.0001	0.0002	0.0002	0.0000
			(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
a_avg_rating				0.3365***							
				(0.0854)							
a_5_rating_share					1.2545***						
					(0.2622)						
a_4_rating_share						-1.2083*					
						(0.7217)					
a_2_rating_share							-0.8412				
							(0.6185)				
a_1_rating_share								-1.0617**			
								(0.4396)			
a_n_reviews									0.0005***		
									(0.0001)		
a_n_reviewers										0.0005	
										(0.0001)	
a_n_reviewers_per											-2.1948
											(1.8728)
_cons	-1.3988***	-1.7257***	-2.3515***	-3.6366***	-3.0437***	-2.2115***	-2.2629***	-2.1896***	-2.3546***	-2.3539***	-0.1216
	(0.3455)	(0.3942)	(0.4762)	(0.5787)	(0.4966)	(0.4809)	(0.4797)	(0.4835)	(0.4794)	(0.4794)	(1.9662)
N	14471	14471	13933	13933	13933	13933	13933	13933	13933	13933	13933
aic	3764.501	3763.537	3683.613	3669.524	3662.712	3682.527	3683.633	3679.283	3672.547	3672.375	3683.828
bic	4007.058	4013.674	3947.584	3941.037	3934.224	3954.039	3955.146	3950.795	3944.060	3943.888	3955.341

* Note: * p<.1; ** p<.05; *** p<.01. The sample period is between 2017 and 2023. Year, month, and the day of week fixed effect are applied

Table A.8 marginal effect for the logit model of OTA review among one-time reviews

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
1-star rating	0.0131 ***	0.0151 ***	0.0157 ***	0.0180 ***	0.0182 ***	0.0157 ***	0.0162 ***	0.0168 ***	0.0156 ***	0.0156 ***	0.0157 ***
	(0.0051)	(0.0055)	(0.0057)	(0.0060)	(0.0061)	(0.0057)	(0.0058)	(0.0059)	(0.0056)	(0.0056)	(0.0057)
2-star rating	0.0048	0.0057	0.0051	0.0057	0.0057	0.0049	0.0054	0.0053	0.0052	0.0052	0.0049
	(0.0054)	(0.0058)	(0.0059)	(0.0061)	(0.0062)	(0.0059)	(0.0059)	(0.0060)	(0.0058)	(0.0058)	(0.0059)
4-star rating	0.0024	0.0014	0.0014	0.0009	0.0007	0.0013	0.0014	0.0011	0.0016	0.0016	0.0014
	(0.0052)	(0.0053)	(0.0055)	(0.0056)	(0.0056)	(0.0055)	(0.0055)	(0.0055)	(0.0054)	(0.0054)	(0.0055)
5-star rating	0.0165 ***	0.0143 ***	0.0144 ***	0.0125 ***	0.0120 ***	0.0142 ***	0.0141 ***	0.0136 ***	0.0150 ***	0.0150 ***	0.0143 ***
	(0.0042)	(0.0044)	(0.0045)	(0.0046)	(0.0047)	(0.0046)	(0.0045)	(0.0046)	(0.0045)	(0.0045)	(0.0045)
verified	-0.0362 ***	-0.0361 ***	-0.0370 ***	-0.0368 ***	-0.0360 ***	-0.0363 ***	-0.0369 ***	-0.0373 ***	-0.0379 ***	-0.0379 ***	-0.0367 ***
	(0.0036)	(0.0036)	(0.0037)	(0.0037)	(0.0037)	(0.0037)	(0.0037)	(0.0037)	(0.0037)	(0.0037)	(0.0037)
user_summary _len	-0.0000	-0.0000	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
user_reviewtext _len	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Vote	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
price_sentiment		0.0053 *	0.0054 *	0.0049	0.0049	0.0054 *	0.0053 *	0.0051	0.0043	0.0043	0.0054 *
		(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)
a_avg_len _summary			0.0006 **	0.0006 **	0.0006 **	0.0005 **	0.0006 **	0.0006 **	0.0006 **	0.0006 **	0.0006 **
			(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
a_avg_len _reviewtext			0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
a_avg_rating				0.0098 ***							
				(0.0025)							
a_5_rating_share					0.0364 ***						
					(0.0077)						
a_4_rating_share						-0.0352 *					
						(0.0211)					
a_2_rating_share							-0.0245				
							(0.0180)				
a_1_rating_share								-0.0309 **			
								(0.0129)			
a_n_reviews									0.0000 ***		
									(0.0000)		
a_n_reviewers										0.0000 ***	
										(0.0000)	
a_n_reviewers _per											-0.0639
											(0.0546)
N	14471	14471	13933	13933	13933	13933	13933	13933	13933	13933	13933

* Note: * p<.1; ** p<.05; *** p<.01. The sample period is between 2017 and 2023. Year, month, and the day of week fixed effect are applied