The Market for Fake Reviews

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Abstract

We study the market for fake product reviews on Amazon.com. These reviews are purchased in large private internet groups on Facebook and other sites. We hand collect data on these markets to understand what products buy fake reviews and then collect a panel of data on these products' ratings and reviews on Amazon, as well as their sales rank, advertising, and pricing policies. We find that a wide array of products purchase fake reviews, including products with many reviews and high average ratings. Buying fake reviews on Facebook is associated with a significant but short-term increase in average rating and number of reviews. We exploit a sharp but temporary policy shift by Amazon to show that rating manipulation has a large causal effect on sales. Finally, we examine whether rating manipulation harms consumers or whether it is mostly used by high-quality or young products in a manner akin to advertising. We find that after firms stop buying fake reviews, their average ratings fall and the share of one-star reviews increases significantly, particularly for young products, indicating rating manipulation is mostly used by low-quality products and is deceiving and harming consumers.

1 Introduction

Online markets have from their first days struggled to deal with malicious actors. These include consumer scams, piracy, counterfeit products, malware, viruses, and spam. And yet online platforms have become some of the world's largest companies in part by effectively limiting these malicious actors and retaining consumer trust. The economics of these platforms suggest a difficult trade-off between opening the platform to outside actors such as third-party developers and sellers and retaining strict control over access to and use of the platform. Preventing deceptive or fraudulent actions is key to this trade-off. Third-party participants may have strong incentives to manipulate platforms, such as increasing their visibility in search rankings via fake downloads (Li et al., 2016), increasing revenue via bot-driven advertising impressions (Wilbur and Zhu, 2009; Gordon et al., 2021), manipulating social network influence with fake followers, manipulating auction outcomes, defrauding consumers with false advertising claims (Rao and Wang, 2017; Chiou and Tucker, 2018; Rao, 2021), or manipulating their seller reputation with fake reviews (Mayzlin et al., 2014; Luca and Zervas, 2016).

We study this last form of deception or fraudulent activity: the widespread purchasing of fake product reviews. Fake reviews may be particularly harmful because they not only deceive consumers into purchasing products that may be of low quality, but they also erode the long-term trust in the review platforms that is crucial for online markets to flourish (Cabral and Hortacsu, 2010; Einav et al., 2016; Tadelis, 2016). Therefore, if user feedback and product reviews are not trustworthy, in addition to consumers being harmed, platform values may suffer as well.

We study the effect of rating manipulation on seller outcomes, consumer welfare, and platform value. Despite this practice being unlawful, we document the existence of a large

and fast-moving online market for fake reviews.[1] This market features sellers posting in private online groups to promote their products and solicit willing customers to purchase them and leave positive reviews in exchange for compensation.[2] These groups exist for many online retailers, including Walmart and Wayfair, but we focus on Amazon because it is the largest and most developed market. We collect data from this market by sending research assistants into these groups to document what products are buying fake reviews and the duration of these promotions. We then carefully track these products' outcomes on Amazon.com, including posted reviews, average ratings, prices, and sales rank. This is the first data of this kind, in that it provides direct evidence on both the fake reviews themselves and on detailed firm outcomes from buying fake reviews.

In general, because consumers value trustworthy information and e-commerce platforms value having good reputations, their incentives should be aligned in that they both want to avoid fake reviews. However, this may not always be the case. In particular, platforms may benefit from allowing fake positive reviews if these reviews increase their revenue by generating sales or allowing for higher prices. It may also be the case that fraudulent reviews are not misleading in the aggregate if higher quality firms are more likely to purchase them than lower quality firms. They could be an efficient method for high-quality sellers to solve the "cold-start" problem and establish reputations. Indeed, Dellarocas (2006) shows that this is a potential equilibrium outcome. In an extension of the signal-jamming literature on how firms can manipulate strategic variables to distort beliefs, he shows that fake reviews are mainly purchased by high-quality sellers and, therefore, increase market information under

[1]The FTC has brought cases against firms alleged to have posted fake reviews, including a case against a weight-loss supplement firm buying fake reviews on Amazon in February 2019. See: `https://www.ftc.gov/news-events/press-releases/2019/02/ftc-brings-first-case-challenging-fake-paid-reviews-independent`.
On May 22, 2020, toward the end of our data collection window, the UK Competition and Markets Authority (CMA) announced it was opening an investigation into these practices. See: `https://www.gov.uk/government/news/cma-investigates-misleading-online-reviews`.

[2]This practice is closely related to the use of incentivized reviews. The requirement that the reviews be positive to receive payment and the lack of disclosure are how we differentiate "fake" reviews from "incentivized" reviews. In the latter case, sellers offer discounted or free products to potential reviewers in exchange for posting an informative review. While incentivized reviews have raised concerns as well since they may be biased upward, in principle, they can allow for authentic feedback and typically involve disclosure.

the condition that demand increases convexly with respect to user rating. Due to the way ratings influence product rankings in search results in competitive markets, it is plausible that this property may hold. Other attempts to model fake reviews have also concluded these may benefit consumers and markets (Glazer et al., 2020; Yasui, 2020). The mechanism is different, but this outcome is similar to signaling models of advertising for experience goods. Nelson (1970) and later Milgrom and Roberts (1986) show that separating equilibria exist where higher quality firms are more likely to advertise because the returns from doing so are higher for them. This is because they expect repeat business or positive word-of-mouth once consumers have discovered their true quality. Both Wu and Geylani (2020) and Rhodes and Wilson (2018) study models of deceptive advertising and conclude that this practice can benefit consumers under the right conditions. To the extent that fake reviews generate sales, which generate future organic ratings, a similar dynamic may play out in our setting. In this case, fake reviews may be seen as harmless substitutes for advertising rather than as malicious. It is therefore an empirical question whether firms and regulators should view rating manipulation as representing a significant threat to consumer welfare.

Our research objective is to answer a set of currently unsettled questions about online rating manipulation. How does this market work, in particular, what are the costs and benefits to sellers from buying fake reviews? What types of products buy fake reviews? How effective are they at increasing sales? Does rating manipulation ultimately harm consumers or are they mainly used by high quality products? That is, should they be seen more like advertising or outright fraud? Do fake reviews lead to a self-sustaining increase in sales and organic ratings? These questions can be directly answered using the unique panel nature of our data.

Using a team of research assistants, we construct a sample of approximately $1,500$ products observed soliciting fake reviews over a nine-month period. We might expect these products to be new products with very few reviews or else low-quality products with very low ratings from organic reviews that must be countered with fake positive reviews. Instead,

we find a wide assortment of product types in many categories, including many products with a very large number of reviews at the time we first observe them buying fake reviews. These products also tend not to have especially low ratings, with an average rating slightly higher than comparable products. Almost none of the sellers purchasing reviews in these markets are well-known brands, consistent with research showing that online reviews are more effective and more important for small independent firms than for brand name firms (Hollenbeck, 2018).

We then track the outcomes of these products before and after the buying of fake reviews using data collected from Amazon. In the weeks after they purchase fake reviews, the number of reviews posted per week roughly doubles. Their average rating and share of five-star reviews also increase substantially. We also observe a substantial increase in search position and sales rank at this time. The increase in average ratings is short-lived, with ratings falling back to the previous level within two to four weeks, but the increase in the weekly number of reviews, sales rank, and position in search listings remains substantially higher more than four weeks later. We also track the long-term outcomes associated with the rating manipulation. We track outcomes after the last observed post soliciting fake reviews and find that the increase in sales is not self-sustaining. Sales fall significantly after the fake review campaign ends. New products with few reviews, which might be using fake reviews efficiently to solve the cold-start problem, see a larger increase in sales initially but a similar drop-off afterward.

We also document how the platform regulates fake reviews. We see that Amazon ultimately deletes a very large share of reviews. For the products in our data observed buying fake reviews, roughly half of their reviews are eventually deleted. The deletions seem well targeted, but they occur with an average lag of over 100 days, thus allowing the short-term boost in ratings, reviews, and sales that we document.

Next, we leverage these deletions to measure the causal effect of fake reviews on sales. Our previous results are descriptive only, and the increase in sales we document could be

attributed in part to factors other than fake reviews, include unobserved demand shocks, advertising, or price cuts. To isolate the effect of rating manipulation on sales, we take advantage of a short period in which Amazon mass deletes a large number of reviews. Products that purchased fake reviews just before this period do not receive the boost in positive reviews as other products that bought fake reviews, but they behave similarly otherwise, allowing us to use these products as a control group. Comparing outcomes across products, we find that rating manipulation causes a significant increase in sales rank.

Lastly, we track reviews and ratings after the fake review purchases end to provide evidence of potential consumer harm. If the products continue to receive high ratings from consumers after they stop buying reviews, it would suggest the fake reviews are more akin to advertising and are mainly bought by high quality products, potentially to solve a cold-start problem. In this case, consumers may not be harmed and the platform might not want to regulate fake reviews too strictly. If, by contrast, their ratings fall and they begin to receive many one-star ratings, it suggests that these consumers have been deceived into buying products whose true quality was lower than they expected at the time of purchase and, therefore, they overpaid or missed out on a higher quality alternative. While there is an inherent limitation in using ratings to infer welfare, we nevertheless find that the evidence primarily supports the consumer harm view. The share of reviews that are one-star increases substantially after fake review purchases, relative to before. This pattern also holds for new products and those with few reviews. Text analysis confirms that these one-star reviews are distinctive and place a greater focus on product quality.

Prior studies of fake reviews include Mayzlin et al. (2014), who argue that in the hotel industry, independent hotels with single-unit owners have a higher net gain from manipulating reviews. They then compare the distribution of reviews for these hotels on Expedia and TripAdvisor and find evidence consistent with review manipulation. Luca and Zervas (2016) use Yelp's review filtering algorithm as a proxy for fake reviews and find that these reviews are more common on pages for firms with low ratings, independent restaurants, and

restaurants with more close competitors. Anderson and Simester (2014) show examples of a different type of fake review: customers rating apparel products on a brand site who never purchased those products. Using lab experiments, Ananthakrishnan et al. (2020) show that a policy of flagging fake reviews but leaving them posted can increase consumer trust in a platform.

We contribute to this literature in two primary ways. First, we document the actual market where fake reviews are purchased and characterize the sellers participating in this market. This data gives us a direct look at rating manipulation, rather than merely inferring their existence. Second, we observe firm outcomes both before and after they purchase fake reviews. This allows us to understand the short- and long-term effectiveness of rating manipulation and assess whether and when consumers are harmed by them.

This research also contributes to the broader academic study of online reviews and reputation. By now, it is well understood that online reviews affect firm outcomes and improve the functioning of online markets (see Tadelis (2016) for a review). There is also a growing body of research showing that firms take actions to respond to online reviews, including by leaving responses directly on review sites (Proserpio and Zervas, 2016) and changing their advertising strategy (Hollenbeck et al., 2019). A difficult tension has always existed in the literature on online reviews, coming from the fact that the reviews and ratings being studied may be manipulated by sellers. By documenting the types of sellers purchasing fake reviews and the size and timing of their effects on ratings and reviews, we provide guidance to future researchers on how to determine whether review manipulation is likely in their setting.

Finally, we contribute to the literature on fraudulent activity in marketing. This research studies practices such as fake news on social media (Chiou and Tucker, 2018), and deceptive online advertising (Rao, 2021; Wu and Geylani, 2020). The theoretical literature on deceptive practices has emphasized that there are generally conditions when these might make markets more efficient and possibly even benefit consumers (Dellarocas, 2006; Rhodes and Wilson, 2018). Therefore, it is up to empirical researchers to document the use of fraudulent practices

to inform the debate on how regulators and firms should respond to these practices.

The rest of the paper proceeds as follows: Section 2 describes our data collection procedure and the settings of our paper; Section 3 presents a discussion of the costs and benefits of buying fake reviews; Section 4 presents descriptive results on the short term changes in outcomes like average ratings, number of reviews, and sales rank in the weeks following the buying of fake reviews, the long-term changes in these variables, and Amazon's response to fake reviews; Section 5 estimates the causal effect of fake reviews on sales; Section 6 documents evidence that consumers feel harmed or deceived after purchasing fake review products; and, finally, Section 7 discusses our findings and provides concluding remarks.

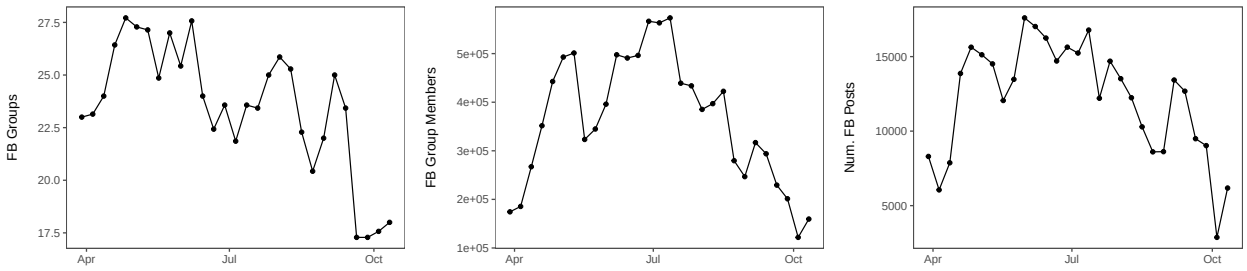
2 Data and Settings

In this section, we document the existence and nature of online markets for fake reviews and discuss in detail the data collection process and the data we obtained to study fake reviews and their effect on seller outcomes, consumer welfare, and platform value. Specifically, we collected data mainly from two different sources, Facebook and Amazon. From Facebook, we obtained data about sellers and products buying fake reviews, while from Amazon we collect product information such as reviews, ratings, and sales rank data.

2.1 Facebook Groups and Data

Facebook is one of the major platforms that Amazon sellers use to recruit fake reviewers. To do so, Amazon sellers create private Facebook groups where they promote their products by soliciting users to purchase their products and leave a five-star review in exchange for a full refund (and in some cases an additional payment). Discovering these groups is straightforward for interested reviewers; it only requires using the Facebook search engine to retrieve a list of them by searching for "Amazon Review." We begin by documenting the nature of these markets and then describe how we collect product information from them.

Figure 1: Weekly number of FB groups, members, and seller posts



Discovering groups We collected detailed data on the extent of Facebook group activity during a four-month period, from March 28, 2020 to Oct 11, 2020. Each day, we collected the Facebook group statistics for the top 30 groups by search rank, only including groups where sellers recruit fake reviewers. During this period, on average, we identify about 23 fake review related groups every day. These groups are large and quite active, with each having about 16,000 members on average and 568 fake review requests posted per day per group. We observe that Facebook periodically deletes these groups but that they quickly reemerge. Figure 1 shows the weekly average number of active groups, number of members, and number of posts between April and October of 2020.[3]

Within these Facebook groups, sellers can obtain a five-star review that looks organic. Figure 2 shows examples of Facebook posts aimed at recruiting reviewers. Usually, these posts contain words such as "need reviews," "refund after pp [PayPal]" with product pictures. The reviewer and seller then communicate via Facebook private messages. To avoid being detected by Amazon's algorithm, sellers do not directly give reviewers the product link; instead, sellers ask reviewers to search for specific keywords associated with the product and then find it using the title of the product, the product photo, or a combination of the two.

The vast majority of sellers buying fake reviews compensate the reviewer by refunding the cost of the product via a PayPal transaction after the five-star review has been posted (most sellers advertise that they also cover the cost of the PayPal fee and sales tax). Moreover, we

[3]The total number of members and posts likely overstates the true amount of activity due to double-counting the same sellers and reviewers across groups.

observe that roughly 15% of products also offer a commission on top of refunding the cost of the product. The average commission value is $6.24, with the highest observed commission for a review being $15. Therefore, the vast majority of the cost of buying fake reviews is the cost of the product itself.

Reviewers are compensated for creating realistic seeming five-star reviews, unlike reviews posted by bots or cheap foreign workers with limited English skills, which are more likely to be filtered by Amazon's fraud detection algorithms. First, the fact that the reviewer buys the product means that the Amazon review is listed as a "Verified Purchase" review; second, reviewers are encouraged to leave lengthy, detailed reviews that include photos and videos to mimic authentic and organic reviews.[4] Third, sellers typically request that the reviewer wait 10 days after the purchase is made before posting the review, although reviewers who are anxious to be paid do not always follow this guidance. Finally, sellers recruit only reviewers located in the United States, with an Amazon.com account, and with a history of past reviews.

This process differs from "incentivized reviews," where sellers offer free or discounted products or discounts on future products in exchange for reviews. Several features distinguish fake reviews from incentivized reviews. The payment for incentivized reviews is not conditional on the review being positive, whereas reimbursement for fake reviews requires a five-star rating. Incentivized reviews, in principle, contain informative content for consumers, whereas in many cases the reviewer posting a fake review has not used or even opened the product. Finally, incentivized reviews typically involve disclosure in the form of a disclaimer contained in the review itself that the product was received for free or at a discount in exchange for the review. Amazon has at times allowed incentivized reviews and even has formally sponsored them through its Vine program and its "Early Reviewer Program," but the company considers fake reviews a violation of its terms of service by both sellers and reviewers, leaving them subject to being banned from the platform if caught.

[4]The fact that these fake reviews are from verified purchases indicates that an identification strategy like the one used in Mayzlin et al. (2014) will not work in settings like ours.

Discovering products To discover products that are promoted, we rely on research assistants. We assign a few active Facebook groups to each one of them and ask them to select Facebook posts randomly. Facebook displays the posts in a group in an order determined by some algorithm that factors in when the post was made as well as engagement with the post via likes and comments. Likes and comments for these posts are relatively rare and so the order is primarily chronological. We directed our research assistants to randomize which products were selected by scrolling through the groups and selecting products in a quasi-random way while explicitly ignoring the product type/category, amount of engagement with the post, or the text accompanying the product photo.

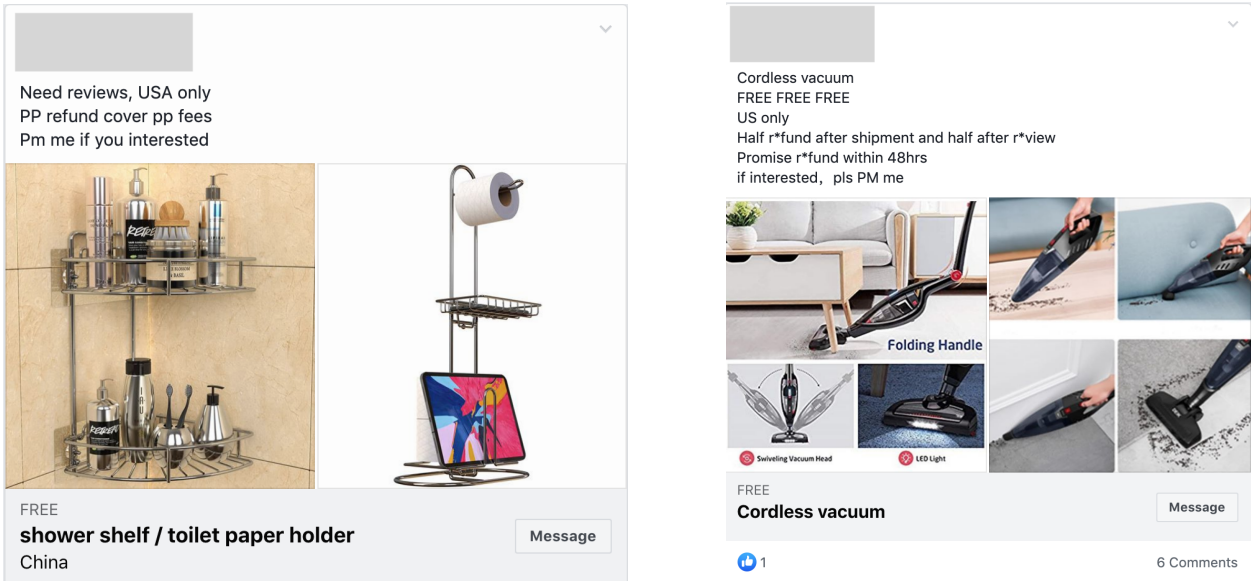
Given a Facebook post, the goal of the research assistants is to retrieve the Amazon URL of the product. To do so, they use the keywords provided by the seller. For example, in Figure 2, the search words would be "shower self," "toilet paper holder," and "cordless vacuum."

After a research assistant successfully identifies the product, we ask them to document the search keywords, product ID, product subcategory (from the Amazon product page), date of the Facebook post, the earliest post date from the same seller for the same product (if older posts promoting the same product exist), and the Facebook group name.

We use the earliest Facebook post date as a proxy for when the seller began to recruit fake reviewers. To identify when a seller stops recruiting fake reviews for a product, we continuously monitor each group and record any new posts regarding the same product by searching for the seller's Facebook name and the product keywords. We then use the date of the last observed post as a proxy for when the seller stopped recruiting fake reviews.

We collect data from these Facebook fake review groups using this procedure on a weekly basis from October 2019 to June 2020, and the result is a sample of roughly 1,500 unique products. This provides us with the rough start and end dates of when fake reviews are solicited, in addition to the product information.

Figure 2: Examples of Fake Review Recruiting Posts



2.2 Amazon Data

We use the Amazon information obtained by the research assistants to collect data about products buying fake reviews from Amazon.com.

Search Results Data For each product buying fake reviews, we repeatedly collect all information from the keyword search page results, i.e., the list of products returned as a result of a keyword search query. This set of products is useful to form a competitor set for each focal product. We collect this information daily and store all information available on these pages including price, coupon, displayed rating, number of reviews, search page number, whether the product buys sponsored listings, and the product position in each page.[5]

Review Data We collect the reviews and ratings for each of the products observed buying fake reviews on a daily basis. For each review, we store the following variables: rating, product ID, review text, presence of photos, and helpful votes.

Additionally, we collect the full set of reviews for each product on a bimonthly basis. The

[5]Using page number and product position, we can compute the keyword search position of every product.

reason for this is that it allows us to measure to what extent Amazon responds to sellers recruiting reviews by deleting reviews that it deems as potentially fake.

In addition to collecting this data for the focal products, we collect daily and bi-monthly review data for a set of 2,714 competitor products to serve as a comparison set. To do so, for each focal product we select the two competitor products who show up most frequently on the same search page as the focal product in the seven days before and seven days after their first FB post. The rationale is that we want to create a comparison set of products that are in the same subcategory as the focal products and have a similar search rank. We collect these products' reviews data from Aug 14th, 2020 to Jan 22rd, 2021.

Sales Rank Data We rely on Keepa.com and its API to collect sales rank data for the products soliciting fake reviews. We collect this data twice a week for focal products and any products that appear in the category data discussed above. Amazon reports a measure called Best Seller Rank, whose exact formula is a trade secret, but which translates actual sales within a specific period of time into a ranking of products by sales levels.

2.3 Descriptive Statistics

Here, we provide descriptive statistics on the set of roughly 1,500 products collected between October 2019 to June 2020.

We use this sample of products to characterize the types of products that sellers promote with fake reviews. On the one hand, we might expect these products to be primarily new products with few or no reviews whose sellers are trying to jump-start sales by establishing a good online reputation. On the other hand, these might be products with many reviews and low average ratings, whose sellers resort to fake reviews to improve the product reputation and therefore increase sales.

Table 1: Focal Product Categories and Subcategories

Category	N	Subcategory	N
Beauty & Personal Care	193	Humidifiers	17
Health & Household	159	Teeth Whitening Products	15
Home & Kitchen	148	Power Dental Flossers	14
Tools & Home Improvement	120	Sleep Sound Machines	12
Kitchen & Dining	112	Men's Rotary Shavers	11
Cell Phones & Accessories	81	Vacuum Sealers	11
Sports & Outdoors	77	Bug Zappers	10
Pet Supplies	62	Electric Back Massagers	10
Toys & Games	61	Cell Phone Replacement Batteries	9
Patio, Lawn & Garden	59	Light Hair Removal Devices	9
Electronics	57	Outdoor String Lights	9
Baby	42	Cell Phone Charging Stations	8
Office Products	30	Electric Foot Massagers	8
Automotive	29	Meat Thermometers & Timers	8
Arts, Crafts, & Sewing	21	Aromatherapy Diffusers	7
Camera & Photo	19	Blemish & Blackhead Removal Tools	7
Clothing, Shoes & Jewelry	14	Cell Phone Basic Cases	7
Computers & Accessories	12	Portable Bluetooth Speakers	7

Table 1 shows a breakdown of the top 20 categories and subcategories for our sample of products. The use of fake reviews is widespread across products and product categories. The top categories are "Beauty & Personal Care," "Health & Household," and "Home & Kitchen," but the full sample of products comes from a wide array of categories as the most represented category still only accounts for just 13% of products, and the most represented product in our sample, Humidifiers, only accounts for roughly 1% of products. Nearly all products are sold by third-party sellers.

We observe substantial variation in the length of the Facebook fake reviews recruiting

period, with some products being promoted for a single day and others for over a month. The average length of the Facebook promotion period is 23 days and the median is six days.

Turning to the product age (measured using the first date the product was listed on Amazon), we find that the mean and median product age when these products first begin soliciting fake reviews is 229 days and 156 days, respectively. This suggests that products collecting fake reviews are rarely new and without any reputation. Indeed, out of the 1,500 products we observe, only 17 of them solicit fake reviews in their first week after the product appears on Amazon, and only 94 solicit fake reviews in their first month.

Next, we compare the characteristics of our focal products to a set of competitor products. We define competitor products as those products that appear on the same page of search results for the same product keywords as our focal products. Even with these restrictions, we obtain a set of about 200,000 competitor products.

Table 2 compares the focal products with their competitors over several characteristics. We observe that while they are not extremely new when soliciting fake reviews, the focal products are significantly younger than competitor products, with a median age of roughly 5 months compared with 15 months for products not observed buying fake reviews. Moreover, our focal products charge slightly lower average prices than their competitors, having a mean price of $33 (compared with $45 for the comparison products). However, this result is mainly driven by the right tail of the price distribution. Fake review products actually charge a higher median price than their competitors, but there are far fewer high-priced products among the fake review products than among competitors. This may reflect the fact that a primary cost of buying fake reviews is compensating the reviewer for the price of the product. In other words, the more expensive a product is, the more costly is to buy fake reviews.[6]

[6]We illustrate this in detail in Section 3.

Table 2: Characteristics of Focal Products and Comparison Products

	Count	Mean	SD	25%	50%	75%
Displayed Rating						
Fake Review Products	1,315	4.4	0.5	4.1	4.5	4.8
All Products	203,480	4.2	0.6	4.0	4.3	4.6
Number of Reviews						
Fake Review Products	1,425	183.1	493.5	10.0	45.0	167.0
All Products	203,485	451.4	2,619.0	13.0	59.0	250.0
Price						
Fake Review Products	1,425	33.4	45.0	16.0	24.0	35.0
All Products	236,542	44.7	154.8	13.0	21.0	40.0
Sponsored						
Fake Review Products	1,425	0.1	0.3	0.0	0.0	0.0
All Products	236,542	0.1	0.3	0.0	0.0	0.0
Keyword Position						
Fake Review Products	1,425	21.4	16.1	8.0	16.0	33.0
All Products	236,542	28.2	17.3	13.0	23.0	43.0
Age (days)						
Fake Review Products	1,305	229.8	251.1	77.0	156.0	291.0
All Products	153,625	757.8	797.1	257.0	466.0	994.0
Sales Rank						
Fake Review Products	1,300	73,292.3	151,236.4	7,893.3	26,200.5	74,801.5
All Products	5,647	89,926.1	323,028.9	5,495.0	21,610.0	72,563.5

Table 3: Seller Characteristics

	Count	Mean	SD	25%	50%	75%
Focal Sellers						
Number of Products	660	23.9	83.9	3.4	7.8	15.2
Number of Reviews	642	176.9	297.0	34.0	81.2	201.1
Price	655	37.2	71.1	16.4	23.5	37.2
Seller Country						
Mainland China	798	0.8				
United States	112	0.1				
Hong Kong	13	0.0				
Japan	7	0.0				
Canada	6	0.0				

Note: This table shows information on seller characteristics, where the number of products, number of reviews and price variables are calculated as averages taken over all seller products. Variable counts differ based on the structure of Amazon seller pages making data collection impossible for some sellers. The number of observations for seller country is calculated at the product level.

Turning to ratings, we observe that products purchasing fake reviews have, at the time of their first Facebook post, relatively high product ratings. The mean rating is 4.4 stars and the median is 4.5 stars, which are both higher than the average ratings of competitor products. Although, we note that ratings may of course be influenced by previous unobserved Facebook campaigns. Only 14% of products have initial ratings below four stars and only 1.2% have ratings below three stars, compared with 19.5% and 3% for competitor products. Thus, it appears that products purchasing fake reviews do not seem to do so because they have a bad reputation.

We also examine the number of reviews. The mean number of reviews for focal products is 183, which is driven by a long right tail of products with more than 1,000 reviews. The median number of reviews is 45, and roughly 8% of products have zero reviews at the time

they are first seen soliciting fake reviews. These numbers are relatively low when compared with the set of competitor products, which has a median of 59 reviews and a mean of 451 reviews. Despite these differences, it seems that most of the focal products are not buying fake reviews because they have very few or no reviews.

The last comparison is in terms of sales. We observe that the focal products have slightly lower sales than competitor products as measured by their sales rank, but the difference is relatively minor.

Turning to brand names, we find that almost none of the sellers in these markets are well-known brands. Brand name sellers may still be buying fake reviews via other (more private) channels, or they may avoid buying fake reviews altogether to avoid damage to their reputation. This result is also consistent with research showing that online reviews have larger effects for small independent firms relative to firms with well-known brands (Hollenbeck, 2018).

Finally, to better understand which type of sellers are buying fake reviews, we collect one additional piece of information. We take the sellers' names from Amazon and check the U.S. Trademark Office for records on each seller. We find a match for roughly 70% of products. Of these products, the vast majority, 84%, are located in China, more precisely in Shenzhen or Guangzhou in the Guangdong province, an area associated with manufacturing and exporting. The distribution of sellers by country-of-origin and other seller characteristics are shown in Table 3. This table shows that most sellers sell fewer than 15 products, with a median 7.8 products. Their products tend to have fewer than 200 reviews, similar to the focal products. The sellers' other products are also priced similarly to the focal products.

To summarize, we observe purchases of fake reviews from a wide array of products across many categories. These products are slightly younger than their competitors, but only a small share of them are truly new products. They also have relatively high ratings, a large number of reviews, and similar prices to their competitors.

3 The Simple Economics of Fake Reviews

We build on the results from the previous section on how the fake review marketplace works, and briefly show the costs and benefits of buying fake reviews. We start by focusing on the costs the sellers incur when buying a fake review.

First, to buy one fake review, a seller must pay to the reviewer:

$$P(1 + \tau + F_{PP}) + Commission \tag{1}$$

Where P is the product's list price, τ is the sales tax rate, F_{PP} is the PayPal fee, and Commission refers to the additional cash offered by the seller, which is often zero but is sometimes in the \$5-10 range. After the reviewer buys the product, the seller receives a payment from Amazon of:

$$P(1 - c)$$

Where c is Amazon's commission on each sale. So the difference in payments or net financial cost of one review is:

$$P(1 + \tau + F_{PP}) + Commission - P(1 - c) = P(\tau + F_{PP} + c) + Commission$$

This is the share of the list price that is lost to PayPal, Amazon, and taxes, along with the potential cash payment. Along with this financial cost the seller bears the production cost of the product (MC), making the full cost of one fake review:

$$Cost = MC + P(\tau + F_{PP} + c) + Commission \tag{2}$$

If we define the gross margins rate as λ such that $\lambda = \frac{P-MC}{P}$, we can show that equation 2 becomes

$$Cost = P(1 - \lambda + \tau + F_{PP} + c) + Commission \tag{3}$$

This defines the marginal cost of a fake review to the seller. The benefit of receiving one fake review is a function of how many organic sales it creates Q_o and the profit on those sales, which is:

$$Benefit = Q_o P(\lambda - c) \tag{4}$$

where again c refers to Amazon's commission from the sale. Setting equations 3 and 4 equal allows us to calculate the break-even number of organic sales Q_o^{BE}. This is the number of extra incremental sales necessary to exactly justify buying one fake review. If the seller does not offer an additional cash commission, and the vast majority of sellers do not, this can be written as:

$$Q_o^{BE} = \frac{1 - \lambda + \tau + F_{PP} + c}{\lambda - c} \tag{5}$$

Where the direct effect of price drops out and this is just a function of the product markup and observable features of the market. We take these market features as known:

- $\tau = .0656$[7]
- $F_{PP} = 2.9\%$
- Amazon commission c varies by category but is either 8% or 15% in almost all cases.[8]

The result for products in the 8% commission categories is:

$$Q_o^{BE} = \frac{1.175 - \lambda}{\lambda - .08} \tag{6}$$

Thus the break-even level of incremental sales needed to justify buying one fake review is a simple expression of a product's price-cost margin. It is clear that products with larger markups require fewer incremental organic sales to justify a fake review purchase. This is for two reasons that this analysis makes clear. First, because the cost of a fake review is

[7]https://taxfoundation.org/2020-sales-taxes/. We aggregate by taking an average of state and local sales taxes.

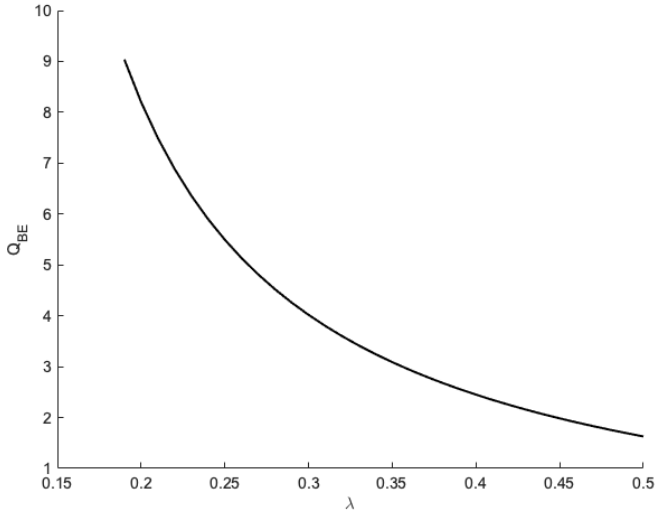
[8]https://sellercentral.amazon.com/gp/help/external/200336920.

lower since conditional on price the marginal cost is lower, and second because the benefit of an organic sale is larger for products with larger markups.

Figure 3 plots equation 6 where the X-axis is λ and the Y-axis is Q_o^{BE}. It shows that for products with relatively low markups the break-even number of organic sales approaches 10 but for products with relatively high markups this number is below 1.

Note that this is not a theoretical model of the full costs and benefits of fake reviews, many of which are not accounted for, including the risk of punishment and the extent to which Q_o varies as a result of product quality. This is merely a simple description of the direct financial costs and benefits sellers face and how they determine the profitability cutoff for Q_o. Nevertheless, several direct implications follow from this analysis. First, the economics of fake reviews can be quite favorable for sellers since a fairly small number of organic sales are needed to justify their cost. In practice, cheap Chinese imported products often have very large markups such that these sellers only need to generate roughly one additional organic sale to profit from a fake review purchase.

Figure 3: Organic Sales Needed to Justify 1 Fake Review



Second, this is especially the case for lower quality products with larger markups. For a concrete example, imagine two products that both list a price of $25. Product A costs $15

to produce and product B costs $20 to produce because A is of lower quality than B. For product A $Q_o^{BE} = 2.4$ and for product B $Q_o^{BE} = 8.1$. The lower cost product needs far fewer organic sales to justify the expense of one fake review.

Third, this analysis makes clear why we are unlikely to observe fake negative reviews applied to competitor products, as in Luca and Zervas (2016) and Mayzlin et al. (2014). The cost of a fake review for a competitor product is significantly higher because it requires the firm buying the review to incur the full price of the competitor's product, and the benefit is likely to be lower because the negative effect on competitor sales is indirect and dispersed across potentially many other products.

4 Descriptive Results on Product Outcomes After Buying Fake Reviews

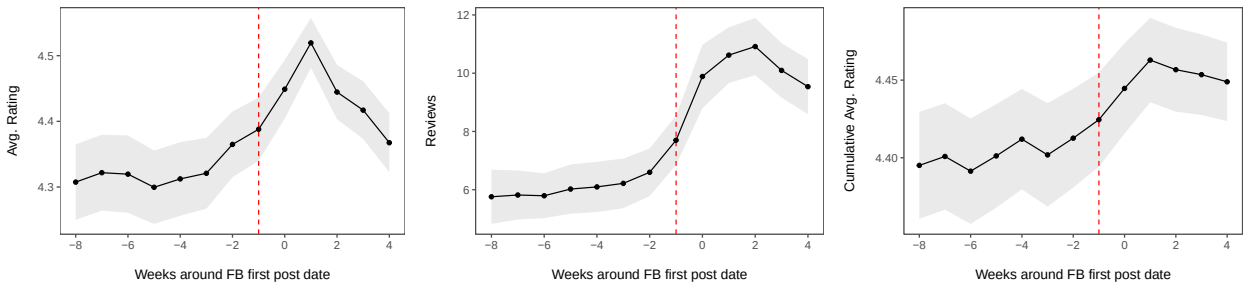
In this section, we quantify the extent to which buying fake reviews is associated with changes in average ratings, number of reviews, and sales rank, as well as other marketing activities such as advertising and promotions. To do so we take advantage of a unique feature of our data in that it contains a detailed panel on firm outcomes observed both before and after sellers buy fake reviews. We stress that, in this section, the results are descriptive in nature. We do not observe the counterfactual outcomes in which these sellers do not buy fake reviews, and so the outcomes we measure are not to be interpreted strictly as causal effects. We present results on the causal effects of fake reviews on sales outcomes in Section 5.

We first present results in the short term, immediately after they begin buying fake reviews, including for subgroups of products. We then show results for the long-term persistence of these effects after the fake review recruitment period has ended. Finally, we show descriptive results on the extent to which Amazon responds by deleting reviews.

4.1 Short-term Outcomes After Buying Fake Reviews

We begin by quantifying the extent to which buying fake reviews is associated with changes in average ratings, reviews, and sales rank in the short term. To evaluate these outcomes, we partition the time around the earliest Facebook recruiting post date (day 0) in 7-day intervals. For example, the interval 0 includes the days in the range [0,7) and the interval -1 includes the days in the range [-7,0). We then plot the quantity of interest for eight 7-day intervals before fake reviews recruiting start and four 7-day intervals after fake reviews recruiting starts. We focus on roughly four weeks after fake reviews recruiting starts because, in this section, we are interested in discussing short-term effects (recall that the mean length in days of a Facebook campaign is 23 days in our dataset). We start by showing results visually by plotting the raw data, and then calculating and displaying the magnitude of these changes using pooled regressions.

Figure 4: 7-day average ratings, 7-day average number of reviews, and cumulative average ratings before and after fake reviews recruiting begins. The red dashed line indicates the last week of data before we observe Facebook fake review recruiting.



Ratings and reviews We start by looking at how ratings and reviews change after the seller begins buying fake reviews. In the left panel of Figure 4 we plot the weekly average rating. Several interesting facts emerge from this figure. First, the average ratings increase by about 5%, from 4.3 stars to 4.5 stars at its peak, after Amazon sellers start recruiting fake reviewers. Second, this increase in rating is short-lived, and it starts dissipating just two weeks after the beginning of the recruiting of fake reviews; despite this, even after four weeks after the beginning of the promotion, average ratings are still slightly higher than

ratings in the pre-promotion period. Third, the average star-rating starts increasing roughly two weeks before the first Facebook post we observe, suggesting that we may not be able to capture with high precision the exact date at which sellers started promoting their products on Facebook. Despite this limitation, our data seems to capture the beginning date of the fake review recruitment fairly well.

Next, we turn to the number of reviews. In the middle panel of Figure 4, we plot the weekly average number of posted reviews. We observe that the number of reviews increases substantially around interval 0, nearly doubling, providing suggestive evidence that recruiting fake reviewers is effective at generating new product reviews at a fast pace. Moreover, and differently from the average rating plot, the increase in the weekly number of reviews persists for more than a month. This increase in the number of reviews likely reflects both the fake reviews themselves and additional organic reviews that follow naturally from the increase in sales we document below. Finally, Figure 4 confirms that we are not able to capture the exact data at which the Facebook promotion started.

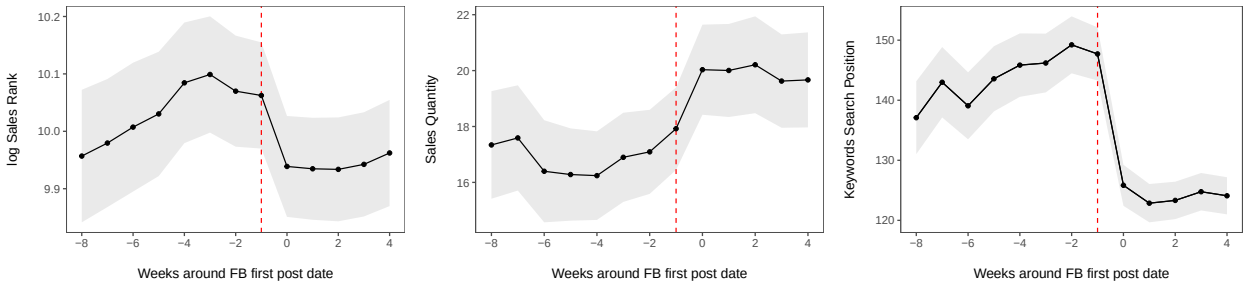
Does this increase in positive reviews lead to higher displayed product ratings? To answer this question, in the right panel of Figure 4, we plot the cumulative average rating before and after the Facebook promotion starts. We observe a positive change centered around the beginning of the promotion and that stabilized for about two weeks after the promotion begins, after which the increase starts to dissipate.

Sales rank In the left panel of Figure 5 we plot the average log of sales rank. This figure reveals several facts. First, the figure shows that the sales rank of products that are eventually promoted is increasing between the intervals -8 and -3. This suggests that Amazon sellers tend to promote products for which sales are falling. Second, recruiting fake reviewers is associated with a large decrease in sales rank (i.e., product sales increase). This decrease is likely reflecting both the initial product purchases by the reviewers paid to leave fake reviews as well as the subsequent increase in organic sales that follow. Finally, the increase in sales

lasts for at least several weeks.

The center panel of Figure 5 plots sales in units sold. Amazon does not display this metric but it is possible to measure sales in units for a subset of products and then estimate the relationship between rank and units. Appendix B describes how we collect this data and model the relationship, and more details are available in He and Hollenbeck (2020). We plot the observed sales and point estimates of estimated sales around the time of the first FB post and see a sharp increase in average units sold, from around 16 units per week to roughly 20.

Figure 5: 7-day average sales rank before and after fake reviews recruiting begins (left), sales in units (center), and keyword search position (right) before and after fake reviews recruiting begins. The red dashed line indicates the last week of data before we observe Facebook fake review recruiting.

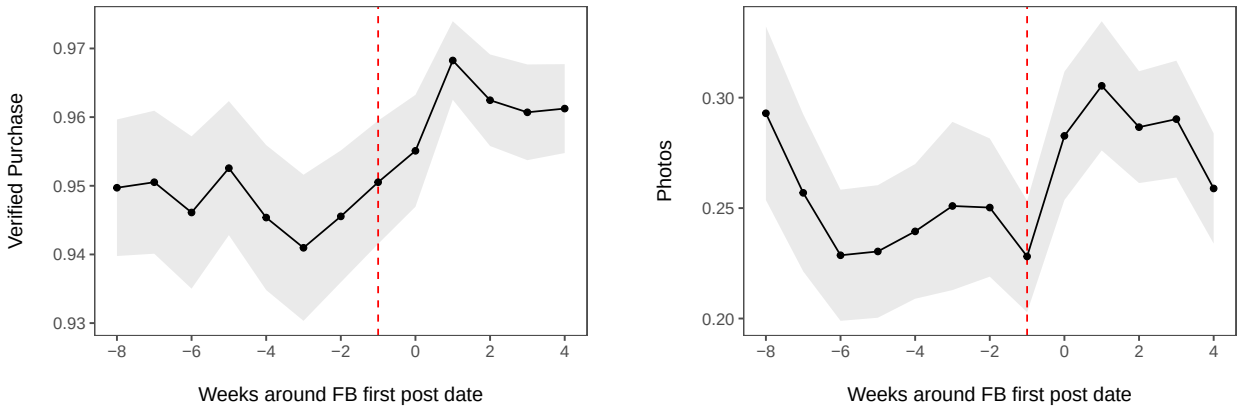


Keyword search position So far we have shown that recruiting fake reviews is associated with improvements in ratings, reviews, and sales. One reason for observing higher sales may be that higher ratings signal higher quality to consumers, who then are more likely to buy the product. A second reason for higher sales is that products recruiting fake reviews will be ranked higher in the Amazon search results due to them having higher ratings and more reviews (both factors that are likely to play a role in determining a product search rank). To investigate whether this is the case, in the right panel of Figure 5 we plot the search position rank of products recruiting fake reviews. We observe a large drop in search position rank corresponding with the beginning of the Facebook promotions, indicating that products recruiting fake reviews improve their search position substantially. Moreover, this change

seems to be long-lasting as the position remains virtually constant for several weeks.

Verified purchases and photos Next, we investigate the relationship between recruiting fake reviewers and whether reviews are written by someone who actually bought the product (Amazon "verified purchase" reviews) and the number of photos associated with the reviews. An important aspect of the market for fake reviews is that reviewers are compensated for creating realistic reviews, meaning they actually buy the product and can therefore be listed as a verified reviewer, and they are encouraged to post long and detailed reviews. We plot these two quantities in Figure 6. In the left panel, we show changes in 7-day interval average verified purchase reviews. Despite being quite noisy in the pre-promotion period, the figure suggests that verified purchases increase with the beginning of the promotion. Turning to the number of photos (right panel) we observe a sharp increase that begins around interval -1 suggesting an increase associated with the beginning of the Facebook promotion.

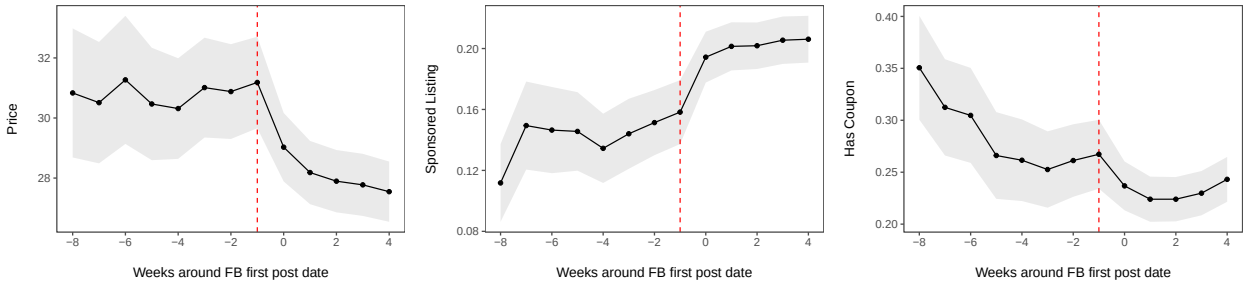
Figure 6: 7-day average verified purchase and number of photos before and after fake reviews recruiting begins. The red dashed line indicates the last week of data before we observe Facebook fake review recruiting.



Marketing activities Finally, we investigate to what extent recruiting fake reviewers is associated with changes in other marketing activities such as promotions (sponsored listings and coupons). We plot these quantities in Figure 7. We observe a substantial negative change in prices (left panel) that persists for several weeks. We also observe a persistent

increased use of sponsored listings suggesting that Amazon sellers complement the Facebook promotion with advertising activities. This result contrasts with Hollenbeck et al. (2019) which finds that online ratings and advertising are substitutes and not complements in the hotel industry, an offline setting with capacity constraints. Finally, we observe a small negative (albeit noisy) change in the use of coupons.

Figure 7: 7-day average sponsored listings and coupon. The red dashed line indicates the last week of data before we observe Facebook fake review recruiting.



4.2 Short-Term Regressions

We have so far shown the outcomes associated with recruiting fake reviews visually. We now show the same results in a regression context to test whether the changes in outcomes we observe are statistically meaningful when a full set of fixed effects is included as well as to quantify the size of these changes for all products and specific subgroups of products.

We use data from the interval [-8,4] weeks around the first FB post and estimate the following equation on each outcome variable:

$$\text{y} = \beta_1 \text{ After}_{it}^{\leq 2} + \beta_2 \text{ After}_{it}^{>2} + \alpha_i + \tau_t + \epsilon_{it}, \tag{7}$$

where $\text{After}_{it}^{\leq 2}$ is a dummy for the time period from zero to two weeks after the beginning of the Facebook promotion and $\text{After}_{it}^{>2}$ is a dummy for the time period after that. This divides up our sample into three periods: a before period, a period in which short-term changes should be present, and a period in which more persistent changes should be present.

In each case we include year-week, τ_t, and product fixed effects, α_i. We include data on the 2,714 competitor products for which we have collected daily review data. These products are never observed buying fake reviews, so their After_{it} dummies are all set at zero.

The results for each variable for all products are shown in Table 4.[9] Consistent with our visual analysis, we see significant short-term increases in average rating, number of reviews, sales, and search position (keyword rank). The increase in weekly average rating is roughly .11 stars. We also see significantly higher use of sponsored listings in this period and a significant increase in the share of reviews that are from verified purchases. There are also positive coefficients for the longer-term dummy for the number of reviews and search position, confirming that the changes in these variables are more persistent.

Table 4: Short-term Outcomes After Recruiting Fake Reviews Including the competitive set of products

	(1) Avg. Rating	(2) log Reviews	(3) log Sales Rank	(4) log Keyword Rank	(5) Sponsored	(6) Coupon	(7) log Photos	(8) Verified	(9) log Price
$\leq$ 2 wks	0.107***	0.445***	−0.260***	−0.412***	0.044***	0.002	0.022***	0.022***	−0.013**
	(0.019)	(0.017)	(0.022)	(0.028)	(0.009)	(0.013)	(0.006)	(0.003)	(0.004)
$>$ 2 wks	0.034	0.320***	−0.246***	−0.434***	0.061***	−0.007	0.003	0.018***	−0.016**
	(0.021)	(0.020)	(0.028)	(0.030)	(0.010)	(0.014)	(0.007)	(0.004)	(0.005)
N	186389	247218	193381	91733	94122	94122	186389	186389	92361
R^2	0.22	0.67	0.81	0.64	0.55	0.52	0.15	0.15	0.98

Note: All specifications include product and year-week FE. Cluster-robust standard errors (at the product level) in parentheses.
Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Overall, we observe that when sellers purchase fake reviews there is an immediate and substantial increase in the number of reviews they receive and average ratings. Additionally, these products increase their use of marketing activities such as sponsored listings at this time, and the net outcome associated with these is a large increase in their sales that persist for several weeks.

[9]The high R^2 are likely due to the inclusion of product and year-week fixed effects fixed effect.

4.2.1 Heterogeneous effects

Next, we expand these regressions for the main variables of interest to also include interactions for products belonging to notable subgroups to understand whether there are heterogeneous outcomes associated with fake review purchase timing. These tables are located in Appendix A.1 and show results for average ratings, weekly number of reviews, sales rank, keyword position, and use of sponsored listings. We also consider these heterogeneous effects in the long-term product outcomes described in the next subsection.

New vs. old products The first interaction we test is for products that we call "cold-start" products, i.e., those who have only been listed for fewer than four months and have accumulated eight or fewer reviews. We might expect these products to have different outcomes than older and more established products in terms of the size of the short-term increase in ratings, reviews, and sales and whether these effects are self-sustaining in the longer term. In fact we do observe different outcomes, specifically that these products' sales increase by a much larger margin than for regular products, as shown in Table 15. They also get a larger increase in number of reviews (Table 14) but do not see an increase in weekly average rating (Table 13). This last result may be due to the fact that cold-start products typically start out with a perfect five-star rating, which inevitably decreases as more reviews are added.

High- vs. low-price products The second interaction is based on whether products are listed above or below the median price for the products in our sample. We estimate that products with below-median prices receive a much larger and more sustained increase in average ratings and keyword position, and increase their use of advertising by a larger margin, but these do not translate into a larger sales increase.

Durable vs. nondurable products The third interaction is based on whether products are durable vs. nondurable. We categorize products as durable or nondurable, using the method described in Appendix A. We find that nondurable products (around 10% of prod-

ucts) perform similarly to low-priced products, with larger effects for ratings, reviews, and position but smaller increases in sales rank.

Search vs. experience products The fourth and final interaction is based on whether products are experience vs. search products. We categorize products as being either search or experience goods using the method described in Appendix A. We might expect rating inflation to have larger effects for experience goods than search goods. We do find that the search goods get a smaller increase in sales despite getting a larger increase in keyword position, but these effects are not statistically significant.

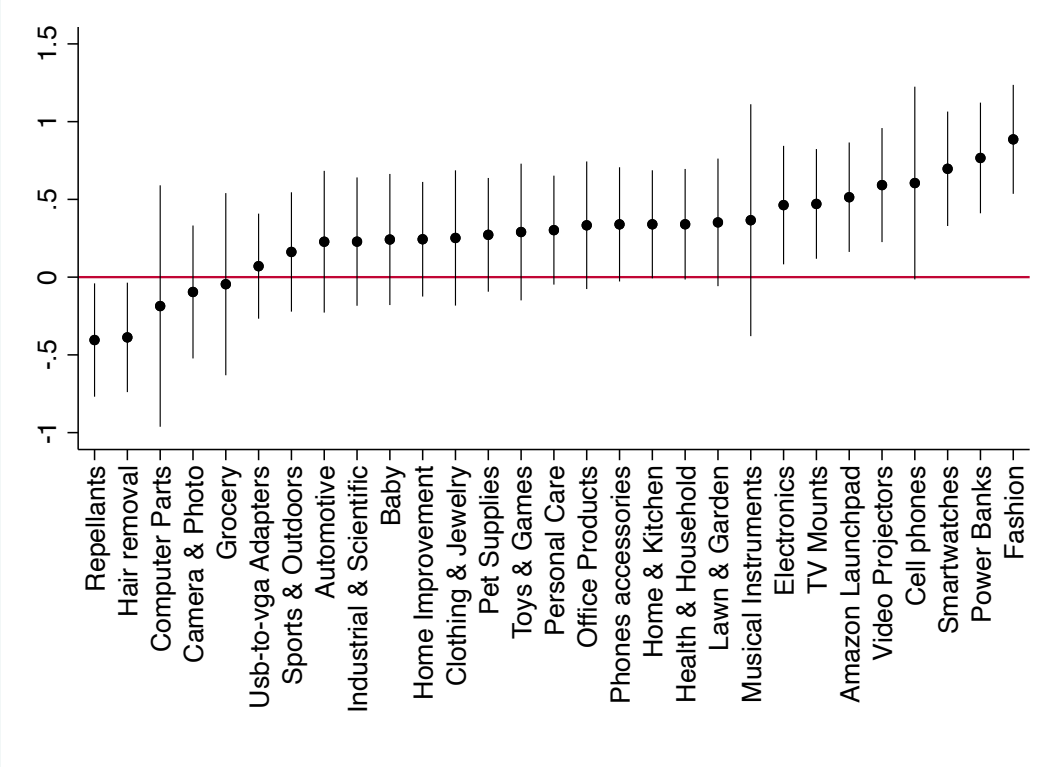
Sales effect by category Lastly, we analyze the key outcome variable, change in sales rank, to see how it varies across product categories. To do so, we estimate Equation 7, but replacing product fixed effects with category fixed effects. We plot the coefficients on these category fixed effects in Figure 8, where the red horizontal line indicates the mean change normalized to zero. The figure shows significant differences across categories in the size of the increase in sales rank, with the largest increases in sales coming from the insect repellent category and hair removal category, and significantly smaller increases in sales in the fashion category, as well as in cellphones, smartwatches and power banks.

4.3 Long-term Outcomes After Buying Fake Reviews

In this subsection, we describe what happens after sellers stop buying fake reviews. We are particularly interested in using the long-term outcomes to assess whether buying fake reviews generates a self-sustaining increase in sales. If we observe that these products continue to receive high organic ratings and have high sales after they stop recruiting fake reviews, we might conclude that fake reviews are a potentially helpful way to solve the cold start problem of selling online with limited reputation.

We therefore track the long-term trends for ratings, reviews, and sales rank. Similar to Section 4.1, we partition the time around the last Facebook recruiting post date (day 0) in

Figure 8: Cross-category Changes in Sales Rank



Note: This figure plots category-level coefficients of a regression of sales rank on a dummy for the two-week period following a products' first FB post.

7-day intervals, and plot the quantity of interest for four 7-day intervals before fake reviews recruiting stop (thus covering most of the period where products recruited fake reviews) and eight 7-day intervals after fake reviews recruiting starts. Doing so, we compare the Facebook promotion period (negative intervals) with the post-promotion period (positive intervals) after sellers had stopped buying fake reviews. We first provide the results visually using plots of the raw data, followed by pooled regression analysis for the key outcome variables.

Ratings and Reviews The long-term changes in ratings and reviews associated with fake reviews are shown in Figure 9. We observe that the increase that occurs when sellers buy fake reviews is fairly short. After one to two weeks from the end of the Facebook promotion, both the weekly average rating and the number of reviews (left and middle panel, respectively) start to decrease substantially. The cumulative average rating (right panel) drops as well.

Figure 9: 7-day average number of average ratings, reviews, and average share of one-star reviews before and after fake reviews recruiting stops. The red dashed line indicates the last week of data in which we observe Facebook fake review recruiting.

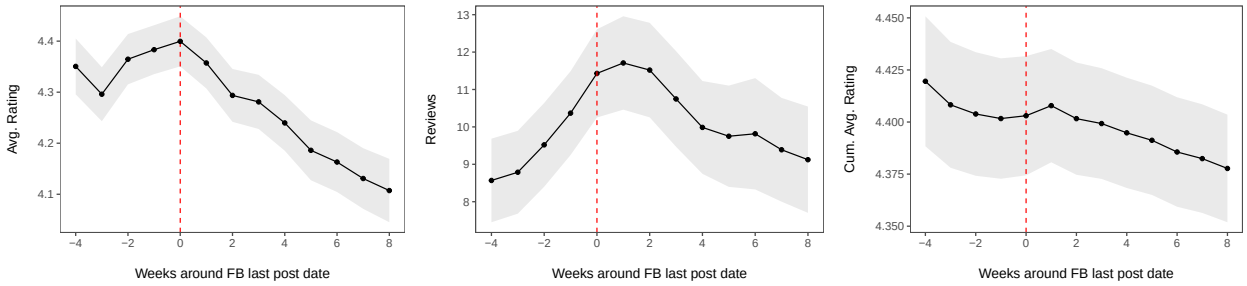
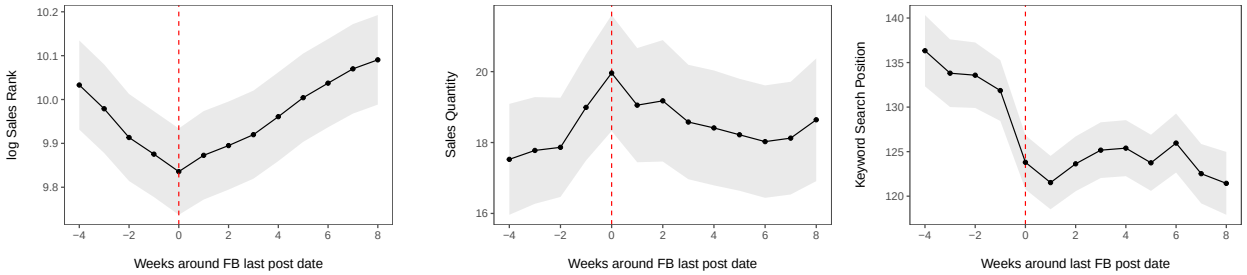


Figure 10: 7-day average sales rank, sales in units, and keyword rank before and after fake review recruiting stops. The red dashed line indicates the last week of data in which we observe Facebook fake review recruiting.



Interestingly, these products end up having average ratings that are significantly worse than when they began recruiting fake reviews (approximately interval -4).

Sales Rank The left panel of Figure 10 shows the long-term trend in the average log sales rank. It shows that sales decline substantially after the last observed Facebook post. This suggests that the increase associated with recruiting fake reviews is not long lasting as it does not lead to a self-sustaining set of sales and positive reviews.

The middle panel of Figure 10 shows sales in units, estimated using the procedure described in Appendix B. The result is consistent with rank, showing that sales peak during the week of the last FB post and subsequently decline.

Keyword search position The right panel of Figure 10 shows the long-term trend in average keyword search position. We observe that after the Facebook campaign stops, the

downward trend in search position stops but does not substantially reverse even after two months. Therefore, all products enjoy a better ranking in keyword searches for a relatively long period after fake review recruiting stops.

The relatively stable and persistent increase in search position suggests that this measure may have a high degree of inertia. After an increase in sales and ratings causes a product's keyword rank to improve, it does not decline quickly, even when sales are decreasing. This also suggests that the decrease in sales shown in Figure 10 does not come from a reduced product visibility but from the lower ratings and increase in one-star reviews. Finally, while we demonstrate in the next section that Amazon deletes a large share of reviews from products that recruit fake reviews, the inertia in keyword rank suggests it does not punish these sellers using the algorithm that determines organic keyword rank. This could therefore serve as an additional policy lever for the platform to regulate fake reviews.

4.4 Long-term Regressions

Similar to how we presented results for the short-term outcomes, we now show the same results in a regression context. To do so, we take the interval [-4,8] weeks around the last FB post and regress each outcome variable on a dummy for the time period from one to three weeks afterward, as well as an additional dummy for the time period after that. In each case, we include year-week and product fixed effects.

We show separate regressions for each of the main variables of interest and include interactions for products belonging to the same set of subgroups used in Section 4.2, with the same goal of understanding whether there are heterogeneous outcomes associated with fake review purchase timing. These tables are all located in Appendix A.2 and show results for average ratings, weekly number of reviews, sales rank, keyword position, and use of sponsored listings.

The overall results, shown in the first column of each table, confirm the visual analysis that shows that average ratings, number of reviews, sales and keyword position all fall after

fake review recruiting ends. However, some of the increases in these variables are still present in the first week or two after the last FB post.

Turning to the heterogeneous effects, we find that "cold-start" products ratings fall even further than for regular products, but that their increase in number of weekly reviews is more persistent. This is consistent with the fact that the decrease in sales rank is larger and more persistent for "cold-start" products. We don't find differences in terms of keyword rank, and find that the use of sponsored listings decreases for "cold-start" products while it increases for the rest of the products.

We find that the average ratings of low-priced products decrease less than high-priced products in the first two weeks after the Facebook promotion ends. Turning to reviews, we find that the number of reviews for low-priced products decreases by much less than for high-priced products. Accordingly, we find that sales rank increases more for high-priced products. Keyword rank keeps dropping with a slightly stronger effect for low-priced products. Finally, we observe a long-term (2+ weeks) increase in sponsored listings for higher-priced products.

In the long term, the nondurable products experience a smaller decrease in ratings, while durable products seem to be more resilient to the loss of reviews in the 2 weeks following the end of the Facebook promotion, after which reviews decrease for all products in a similar way. We do not find any difference in sales rank across durable and nondurable products, but we find a larger decrease in keyword rank for nondurable products.

Finally, turning to search vs. experience, the only difference we find is in term of the use of sponsored listings, which is more persistent for experience products.

4.5 Amazon's Response

In this subsection, we provide evidence on the extent to which Amazon is aware of the fake review problem and what steps it is taking to remove these reviews.

While we cannot observe reviews that are filtered by Amazon's fraud detection practices and never made public, by collecting review data on a daily and bimonthly basis, we can

observe if reviews are posted and then later deleted. We calculate the share of reviews that are deleted by comparing the full set of observed reviews from our daily scraper with the set of reviews that remain posted at the end of our data collection window. We find that for the set of products observed recruiting fake reviews, the average share of ultimately deleted reviews is about 43%. This suggests that, to some extent, Amazon can identify fake reviews.

To further characterize Amazon's current policy, we next analyze the characteristics of deleted reviews and the timing of review deletion.

Characteristics of Deleted Reviews In Table 5, we report the mean and standard deviation for several review characteristics for deleted and non-deleted reviews and deleted reviews, respectively. Following the literature on fake reviews, we focus on characteristics that are often found to be associated with fake reviews. Specifically, we focus on whether the reviewer purchased the product through Amazon (verified purchase), review rating, number of photos associated with the review, whether the reviewer is part of Amazon's "Early Reviewer Program", i.e., is one of the first users to write a review for a product the length of the review title, and the length of the review.[10]

We find that deleted reviews have higher average ratings than non-deleted reviews. This is driven by the fact that the vast majority of deleted reviews are five-star reviews (see Figure 11). Deleted reviews are also associated with more photos, shorter review titles, and longer review text. In general, we might expect longer reviews, those that include photos, and those from verified purchases to be less suspicious. The fact that these reviews are more likely to be deleted suggests that Amazon is fairly sophisticated in targeting potentially fake reviews.[11] Finally, we find no difference for whether the review is associated with a verified purchase or tagged as "Amazon Earlier Reviews."[12]

[10]For more details about the "Early Reviewer Program," we refer the reader to `https://smile.amazon.com/gp/help/customer/display.html?nodeId=202094910`.

[11]This result contrasts with Luca and Zervas (2016), who find that longer reviews are less likely to be filtered as fake by Yelp.

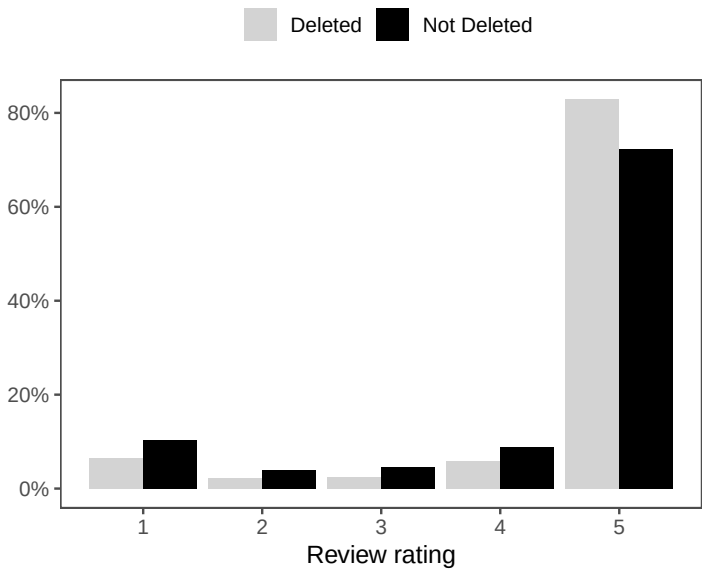
[12]We find that Amazon does not delete any reviews tagged as "Amazon Earlier Reviews" potentially because Amazon's process to identify and select early reviewers drastically reduces the possibility of these reviews being fake.

Table 5: Comparing deleted and non-deleted reviews characteristics

	Deleted Reviews	Non-deleted Reviews
Verified purchase	0.98	0.96
	(0.16)	(0.20)
Review rating	4.65	4.24
	(0.98)	(1.37)
Number of photos	0.35	0.19
	(0.93)	(0.72)
Early reviewer	0.00	0.01
	(0.00)	(0.11)
Title length	9.81	21.08
	(13.94)	(13.80)
Review length	236.73	198.75
	(222.88)	(231.68)

Note: Standard deviations in parentheses.

Figure 11: Rating distribution for deleted and non deleted reviews



When Are Reviews Deleted? Finally, we analyze when Amazon deletes fake reviews for focal products. We do so by plotting the number of products for which reviews are deleted over time relative to the first Facebook post, i.e., the beginning of the buying of fake reviews. To do so, we partition the time in days around the first Facebook post and then plot the number of products for which reviews are deleted. Because products recruit fake reviews for different time periods, we perform this analysis by segmenting products based on the quartiles of campaign duration. Figure 12 shows the results of this analysis.

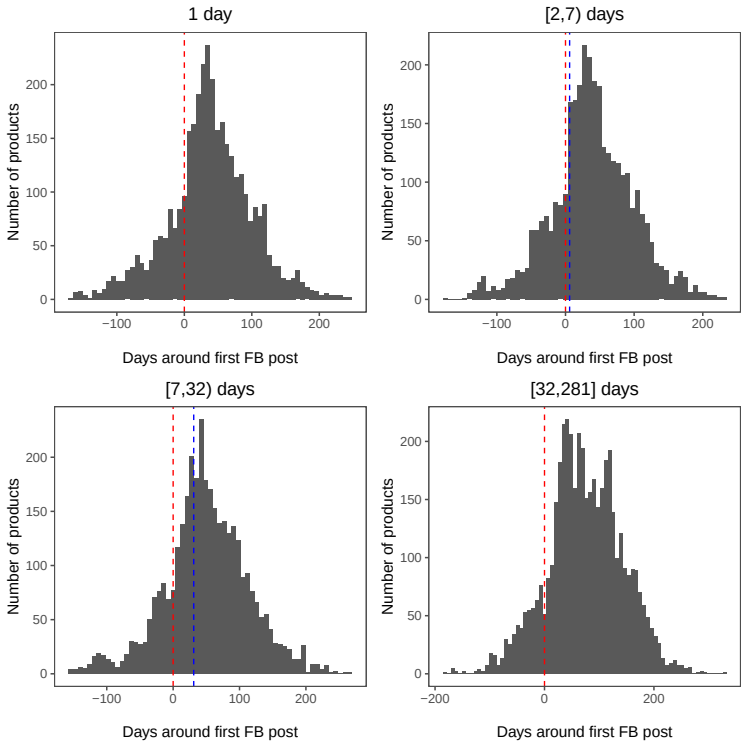
What emerges from this figure is that Amazon starts deleting reviews for more products after the Facebook campaign begins and often it does so only after the campaign terminated. Indeed, it seems that most of the review deletion happens during the period covering the two months after the first Facebook post date, but most campaigns are shorter than a month. A simple calculation suggests that reviews are deleted only after a quite large lag. The mean time between when a review is posted and when it is deleted is over 100 days, with a median time of 53 days.

This analysis suggests the deleted reviews may be well-targeted at fake reviews, but that there is a significant lag between when the reviews are posted and when they are deleted; and this lag allows sellers buying fake reviews to enjoy the short-term benefits of this strategy discussed in Section 4.1. In the next section, we show that there is one time period in our data during which Amazon's deletion policy changes significantly, and we use this period to identify the causal effects of fake reviews on sales.

5 The Causal Effect of Fake Reviews on Sales

The results presented so far are descriptive and should not be interpreted as measuring causal effects. There are two concerns in estimating the effect of rating manipulation on sales. The first is that sellers buying fake reviews may time these purchases around unobserved shocks to demand, either positive or negative. While the product fixed effects included in the results

Figure 12: Number of products for which reviews are being deleted over time relative to the first Facebook post date. The red dashed line indicates the first time we observe Facebook fake review recruiting, and the blue dashed line indicates the last time we observe Facebook fake review recruiting.

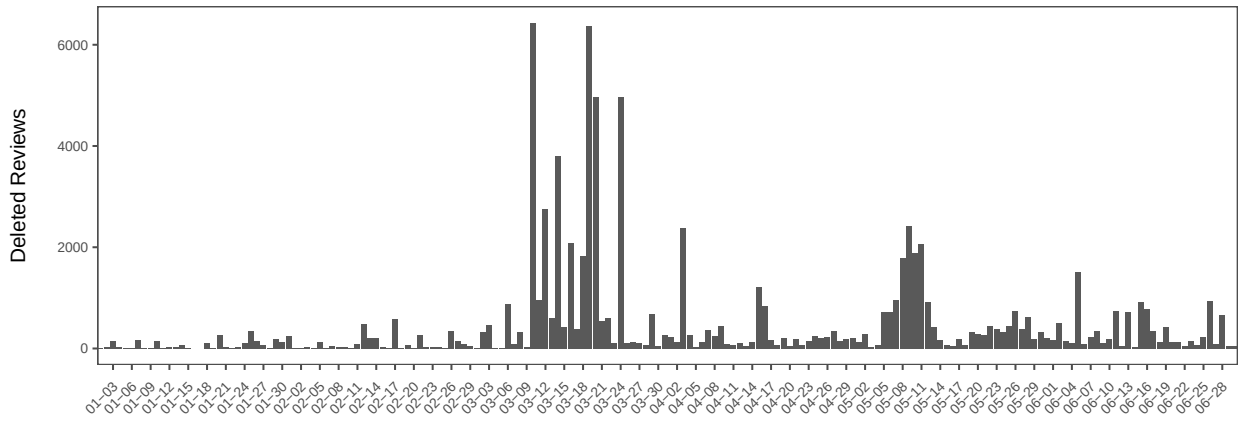


presented in Table 4 capture time-invariant products' unobserved heterogeneity, they would not capture these shocks. The second concern is that we observe that many sellers cut prices and increase advertising at the same time they recruit fake reviews, making it difficult to isolate the effect of fake reviews on sales.

In this section, we exploit a temporary change in Amazon policy to isolate and measure the causal effect of fake review recruiting on sales. This allows us to establish that this is a profitable strategy for sellers and understand the magnitude of the effects that fake reviews can have on sales.

To accomplish this, we take advantage of an event that occurred during our sample period that provides a clean measurement of the effects of fake review recruiting. As we discussed at length in Section 4.5, Amazon deletes a large number of reviews. Figure 13 shows the amount of review deletion over time during our sample period for the products seen buying

Figure 13: Amazon deleted reviews by date



fake reviews. There is one occasion during mid-March 2020 when Amazon undertakes a large-scale purge of reviews with much higher rates of deletion than normal.[13] Assuming sellers had no foresight that this review purge was about to be undertaken, a subset of the sellers who recruited fake reviews had the misfortune of doing so during or just before the review purge occurred. Therefore, the products of these unlucky sellers should have no (or a much smaller) increase in positive reviews after they recruited fake reviews compared to the other products. We thus refer to the products that recruited fake reviews just before or during the review purge as control products and all other products that recruited fake reviews at different times as treated products. We can therefore employ a difference-in-differences (DD) strategy that compares sales of treated products before and after they buy fake reviews with respect to a baseline of changes in sales of control products, and estimate the causal effect of rating manipulation on sales.

In our case, the DD identification strategy requires four assumptions to hold to identify a causal effect. First, Amazon should not have strategically selected the products for which reviews were deleted, i.e., control products should be similar to treated products in both observable and unobservable characteristics. Second, the review purge should be effective at preventing the control products from acquiring fake reviews. Third, treated and control

[13]There is another spike in review deletion in May of 2020, but it affects substantially fewer reviews and is not as long-lasting.

products should not differ in their use of marketing activities that can affect sales. Fourth, the parallel trends assumption should hold, i.e., pre-treatment sales trends for treated and controls products should be similar.

We start by presenting the empirical strategy setup, we then test each of the assumptions discussed above, and finally, we proceed to estimate the effect of fake review recruiting on sales.

5.1 Empirical strategy setup

We start by taking the midpoint date of the review purge, which is March 15, and defining our set of control products as all products whose first observed Facebook post is in the interval [-2,1] weeks around this date. This results in 74 control products. The 1,307 products whose sellers started recruiting fake reviews outside of this window is the set of treated products.

We then estimate a standard DD regression which takes the following form:

$$y_{it} = \beta_1 \text{ Treated}_i + \beta_2 \text{ After}_{it} + \beta_3 \text{ Treated}_i \times \text{After}_{it} + \alpha_i + \tau_t + X_{it}^{'}\gamma + \epsilon_{it}, \tag{8}$$

where y_{it} is the outcome of interest for product i at year-week t, $Treated_i$ is an indicator for whether product i is treated and $After_{it}$ is an indicator for the period after the first observed Facebook post for product i. α are product fixed effects to account for time-invariant product characteristics that could be correlated with the outcome, and τ are year-week fixed effects to account for time-varying shocks to the outcome that affect all products (e.g., holidays). The coefficient β_2 measures the effect of fake review recruiting for control products and the coefficient of interest, β_3, is the classical DD estimate and it measures the difference in sales for treated products. We estimate the regression in Equation 8 using OLS and clustering standard errors at the product level.

5.2 Identification checks

Treated and control products are similar To test this assumption, we show that (1) treated and control products are similar in most of their observable characteristics, and (2) Amazon does not seem to select specific products with the review purge. In Table 6 we compare treated and control products over a large set of variables by taking the average over the period [-8,-2) weeks before the products begin to recruit fake reviews.[14] We find that control products are older, with lower average weekly ratings, and more cumulative reviews. To reduce concerns about this difference, we employ Propensity Score Matching (Rosenbaum and Rubin, 1983) to match treated and controls products on these variables and thus obtain a more balanced set of products. We describe this procedure in detail in Appendix C.

Table 6: Comparison of Treated and Control Products

	Control	Treated	t-stat
Age	9.84	7.15	2.36*
Weekly Avg. Ratings	4.10	4.32	−2.07*
Cum. Avg. Ratings	4.32	4.43	−1.36
Weekly Reviews	5.21	5.78	−0.33
Cumulative Reviews	234.80	109.90	3.11**
Price	27.10	33.60	−1.38
Coupon	0.23	0.26	−0.37
Verified	0.92	0.93	−0.60
Number of Photos	0.25	0.26	−0.15
Category	41.60	40.20	0.42

Note: t-test for equality of means for treated and control units. Means are computed at the interval level for the period [-8,-2) weeks.
Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Turning to Amazon's criteria of selecting which products' reviews are deleted, in Appendix D, we show that review deletion during the purge period is highly concentrated on individual reviewers and is not targeted at specific products, further reassuring us that

[14]We exclude weeks [-2,-1] because the analysis in Section 4.1 suggests that for some products, outcomes start to change up to two weeks before the first Facebook post.

Amazon selection should not be an issue for this analysis.

Manipulation Check Here we present evidence showing that the review purge creates a valid set of control products. To do so, the purge must prevent these products, who were observed attempting to buy fake reviews, from receiving the treatment of an increase in reviews. We do so by estimating Equation 8 with the outcome set to be the log of cumulative reviews. We report these results in column 1 of Table 7. As expected, $After$ is small and close to zero, suggesting that there is no increase in reviews for control products. However, the interaction coefficient $After \times Treated$, is positive and significant and suggests that the number of cumulative reviews for treated products increased by approximately 10% more than control products.

Table 7: Diff-in-Diff Estimates

	(1) log Cum. Reviews	(2) Sponsored	(3) Coupon	(4) log Price	(5) log Sales Rank
After	0.047	0.014	0.011	−0.003	0.198*
	(0.036)	(0.026)	(0.047)	(0.009)	(0.097)
After × Treated	0.099*	0.027	−0.031	0.006	−0.375**
	(0.048)	(0.032)	(0.046)	(0.013)	(0.116)
PSM Sample	Yes	Yes	Yes	Yes	Yes
N	12620	7477	7477	7417	11553
R^2	0.96	0.65	0.65	0.99	0.87

Note: All specifications include product and year-week FE. Cluster-robust standard errors (at the product level) in parentheses.
Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Marketing activities are similar To investigate whether treated and control products' marketing activities are similar, we estimate Equation 8 for three different outcomes: (1) whether product i buys sponsored listings: (2) whether product i offers discounts through coupons; and (3) product i price. We report these estimates in columns 2-4 of Table 7. We do not observe any statistically significant change in sponsored listings, coupons, and price after the first Facebook post for both treated and control products. Therefore, the

assumption about marketing activities being similar across treatment and control products is satisfied.

Parallel trends Finally, we test the parallel assumption. To do so we estimate the following Equation:

$$y_{it} = \beta_1 \text{ Treated}_i + \beta_2 \text{ After}_{it} + \gamma \text{ Treated}_i \times \text{Week}_{it} + \alpha_i + \tau_t + X_{it}^{'}\gamma + \epsilon_{it}, \tag{9}$$

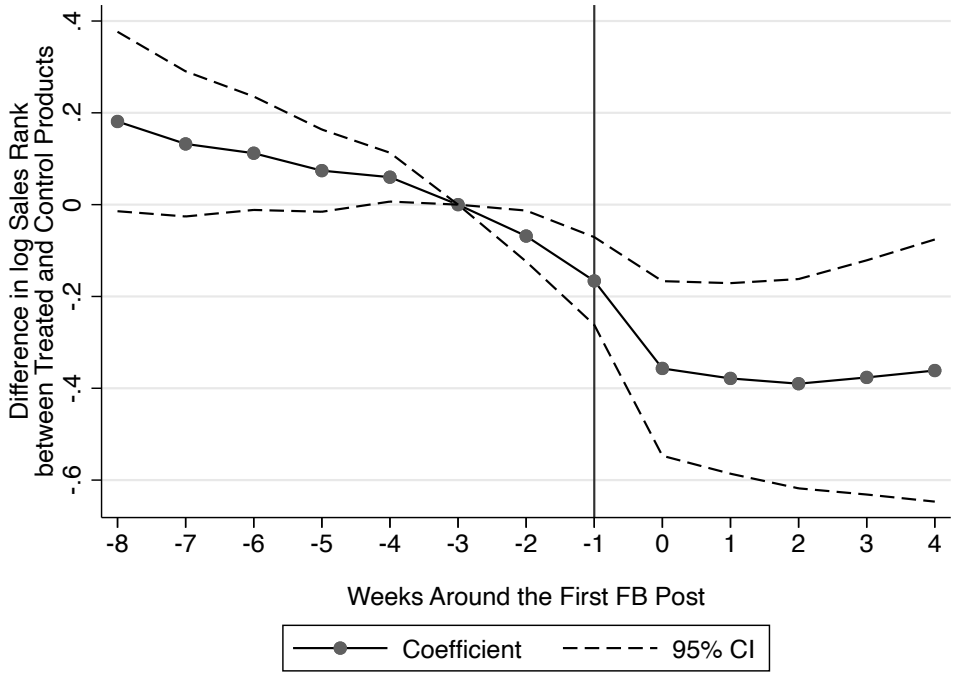
where everything is as in Equation 8, and $Week_{it}$ represents a set of dummies identifying 7-days intervals around the first Facebook post of each product. The γ coefficients can be interpreted as weekly treatment effects estimated before and after the treatment with respect to the baseline week -3.[15] We plot these estimates along with their 95% confidence intervals in Figure 14. Two findings emerge from this figure. First, while there is a decreasing trend in the pre-treatment period, the estimates are indistinguishable from zero, suggesting that the parallel trends assumption is satisfied. Second, in the post-treatment period, we observe a large decrease in sales rank for treated products associated with the start of the fake review recruiting (week 0), which points to a strong effect of fake reviews on sales. We proceed to estimate the magnitude of this effect next.

5.3 The effect of fake reviews on sales

To measure the causal effect of fake reviews on sales, we estimate Equation 8 using as the outcome the log of sales rank. We report these estimates in column 5 of Table 7. First, we find that the sales rank of control products increases about 22%. This is in line with the evidence we provided in Section 4.1 where we showed that products start recruiting fake reviews after sales fall for a prolonged period. In the absence of rake reviews, sales are therefore likely to continue to fall and thus sales rank should increase. Second, and in line

[15] We choose to set the baseline week to be -3 because, as we discussed in Section 4.1 we observe that for some products outcomes start to change at week -2

Figure 14: The evolution of the treatment effect, i.e., the difference in log Sales Rank between treated and control products.



with what we observed in Figure 14, we estimate that compared to control products, treated products see a reduction in sales rank of 45.5%. The overall effect of fake reviews on sales rank for treated products ($\beta_1 + \beta_2$) is about 16%.

5.4 Robustness checks

Sensitivity to the Purge window Here we show that the sales estimates are not too sensitive to the choice of the window around the review purge used to select the set of control products. We do so by reporting in Table 8 the estimates for sales rank using three alternative windows around the mid-purge date: [-2,2] weeks, [-1,2] weeks, and [-1,1] weeks. However, we caution the reader that changes in the review purge window can affect how well we capture the review purge.[16]. Therefore, we argue that the most reliable estimates are those reported in Table 7.

[16]We discuss when this happens in Appendix E where we replicate Table 7 for the three alternative windows [-2,2] weeks, [-1,2] weeks, and [-1,1] weeks

Table 8: Diff-in-Diff using different purge windows

	(1)	(2)	(3)
Purge Window	[-2,2]	[-1,2]	[-1,1]
After	0.166*	0.178*	0.198
	(0.070)	(0.077)	(0.115)
After × Treated	−0.325***	−0.338***	−0.377**
	(0.086)	(0.092)	(0.131)
PSM Sample	Yes	Yes	Yes
N	12512	12512	11553
R^2	0.85	0.85	0.87

Note: All specifications include product and year-week FE. Cluster-robust standard errors (at the product level) in parentheses.

Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Continuous Treatment To further reduce concerns about our results being driven by the way in which we select control products, here we show that our estimates are robust to a continuous definition of the treatment. To do so, for each product, we define a treatment variable, *log Purge Distance*$_i$, which is equal to the log of the absolute value of the difference in days between the mid-purge date (March 15, 2020) and the date of the first Facebook post of each product. We then estimate Equation 8, but replacing the binary treatment variable with this new continuous treatment. We report these results in Table 9. We observe that for small values of the treatment variable, i.e., for products whose first Facebook post is very close to the mid-purge date, there is no or small increase in the number of reviews and a positive effect on sales. However, as the distance increases, the opposite is true for products far from the mid-purge date. For example, at the median *log Purge Distance*$_i$ which is 3.89, the increase in cumulative reviews is about 22% ($p < 0.01$) and the decrease is sales rank is about 17% ($p < 0.01$).

Placebo review purge To further reinforce the validity of our estimates, we perform a placebo test in which we create a placebo review purge by moving the mid-purge date either four weeks back or four weeks forward. We estimate Equation 8 using these thresholds and report these results in Table 10. As expected, we observe that recruiting fake reviews has

Table 9: Estimates using a continuous treatment variable

	(1) log Cum. Reviews	(2) Sponsored	(3) Coupon	(4) log Price	(5) log Sales Rank
After	0.040	−0.042	−0.034	−0.025	0.362*
	(0.070)	(0.047)	(0.067)	(0.019)	(0.146)
After × log Purge Distance	0.041*	0.019	0.009	0.004	−0.135***
	(0.019)	(0.013)	(0.018)	(0.005)	(0.037)
N	15789	9543	9543	9463	15077
R^2	0.93	0.64	0.67	0.99	0.87

Note: All specifications include product and year-week FE. Cluster-robust standard errors (at the product level) in parentheses.
Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

a negative effect on sales rank for control products and that this effect is not different for treated products.[17]

Table 10: Estimates using placebo review purges

	(1) 4 weeks before	(2) 4 weeks after
After	−0.166*	−0.142*
	(0.079)	(0.060)
After × Treated	0.027	0.001
	(0.086)	(0.065)
N	15077	15077
R^2	0.87	0.87

Note: All specifications include product and year-week FE. Cluster-robust standard errors (at the product level) in parentheses.
Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

6 Evidence of Consumer Harm from Fake Reviews

In this section, we evaluate the potential harm to consumers from fake reviews. To do so, we analyze the long-term trends in consumer ratings for products observed being promoted

[17] We do not use PSM in this exercise to further reinforce the fact that potential differences between treated and control products are not driving the sales effects reported in Table 7 (however, we obtain qualitatively similar results when we apply PSM). In addition, using the full data sample and the real purge, we obtain results consistent with those reported in Table 7.

using fake reviews. If these products continue to receive high ratings after the fake review recruiting period ends it would provide evidence that fake reviews are used by high-quality products in a manner akin to advertising. This would be consistent with the predictions of theoretical results in Dellarocas (2006) and others. If, by contrast, we see declining ratings and observe a large number of one-star reviews, it may suggest that the sellers buying fake reviews are using them to mask the low quality of these products and deceive consumers into buying them.

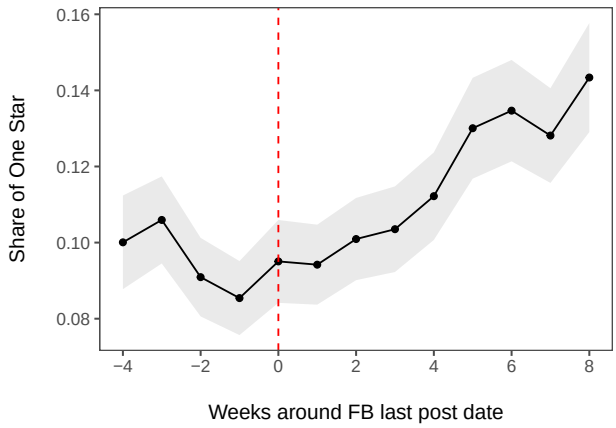
There is an inherent limitation in using ratings to infer welfare because consumers leave ratings for many reasons and generally ratings are not a literal expression of utility. But we argue that when products receive low ratings and a large number of one-star reviews, it indicates that the actual quality of these products is lower than what many customers expected at the time of their purchase. The low ratings are either a direct expression of product quality or an attempt to realign the average rating back toward the true level and away from the manipulated level. In this latter case, we might still infer some degree of consumer harm, either because it indicates consumers paid a higher price than what they would have if the product was not overrated due to rating manipulation, or because the fake reviews caused them to buy a lower quality product than the closest alternative. This analysis is also important from the platform's perspective. An increase in one-star reviews would indicate that fake reviews are a significant problem since they reflect negative consumer experiences that should erode the sense of trust the platform's reputation system is meant to provide.

We therefore track the long-term trends for ratings and the share of reviews that come with a rating of one star, the lowest possible rating, as an indicator of low product quality or consumers who feel they have been deceived into buying these products. Lastly, we perform a detailed text analysis of the post-recruiting one-star reviews to see if they are distinctive compared with other one-star reviews and, if so, what text features they are associated with.

6.1 One-Star Ratings and Reviews

We have already shown in Figure 9 in Section 4.3 that ratings decline after fake review recruiting ends. Figure 15 clearly explains why the average rating is dropping. The share of one-star reviews starts to increase considerably once recruiting fake reviews stops. Interestingly, these products end up having average ratings that are significantly worse than when they began recruiting fake reviews (approximately interval -4).

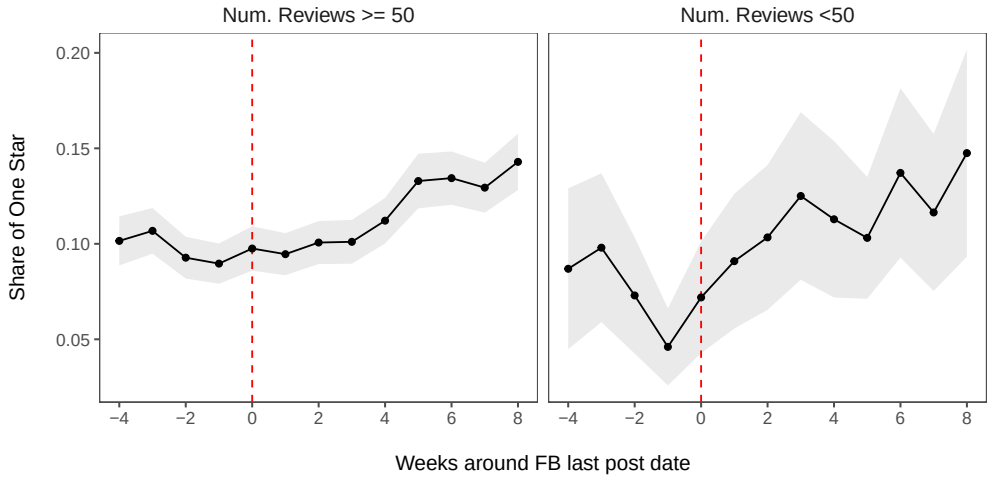
Figure 15: 7-day average share of one-star reviews before and after fake reviews recruiting stops. The red dashed line indicates the last time we observe Facebook fake review recruiting.



Next, we explore the long-term change in the share of one-star reviews for different types of products. It may be the case that while one-star reviews increase after fake review purchases stop, certain products are able to retain high ratings. For example, new products (i.e., products with few reviews or that have been listed on Amazon for a brief period of time) might use fake reviews to bootstrap their reputation, which they can sustain if these products are high-quality products.

To test this hypothesis, we segment products by number of reviews and age. Figure 16 shows how the share of one-star reviews changes for products with fewer than 50 reviews at the time they started recruiting fake reviews compared to all other products. The products with few reviews show a somewhat sharper increase in one-star ratings. Figure 17 shows the same outcome, but for products that have been listed on Amazon for fewer than 60 days

Figure 16: 7-day average share of one-star reviews before and after fake reviews recruiting stops by number of reviews accumulated prior to the fake review recruiting. The red dashed line indicates the last time we observe Facebook fake review recruiting.



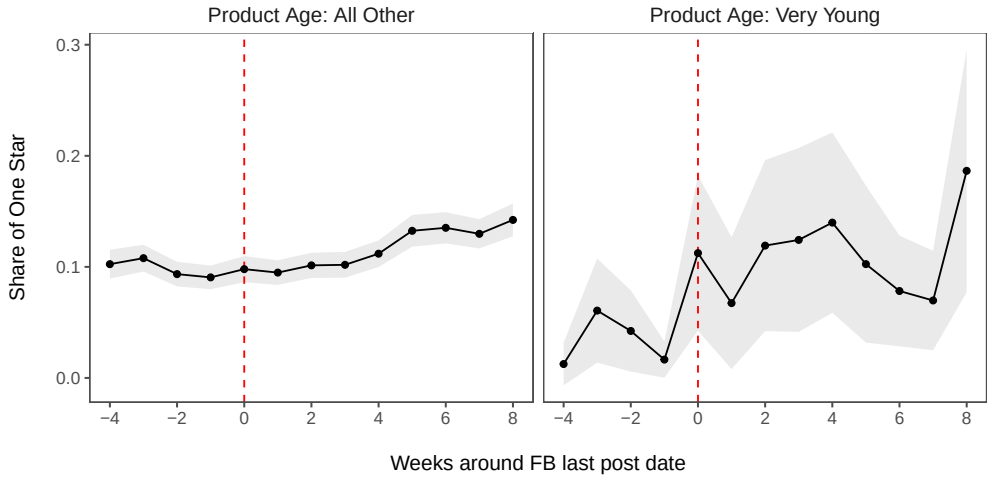
when they started recruiting fake reviews (very young products), compared with the rest of the products. The young products experience a much larger increase in one-star reviews than the other products, with more than 20% of their ratings being one-star two months after they stop recruiting fake reviews. Overall, these results do not support our hypothesis. Instead, they suggest that new products recruiting fake reviews are likely to be low quality products that use fake reviews to inflate their ratings and sales.

6.2 Text Analysis

So far, we have shown increases in the number and share of one-star reviews to provide evidence that consumers are harmed by rating manipulation. Here, we provide additional evidence in support of this hypothesis by using state-of-the-art machine learning algorithms to analyze the text of these negative reviews.

The goal of this analysis is twofold. First, we want to check whether the negative reviews posted after a product buys fake reviews are distinctive; second, if they are indeed different, we want to identify what text features differentiate them. It may be the case, for instance, that one-star reviews increase after any sales spike and this is not a phenomenon specific

Figure 17: 7-day average share of one-star reviews before and after fake reviews recruiting stops by product age (very young products are those listed for fewer than 60 days). The red dashed line indicates the last time we observe Facebook fake review recruiting.



to fake reviews. Our simple model discussed in Section 3 shows that the returns to rating manipulation are more favorable to products with lower production costs, holding all else equal, including price. It therefore predicts that negative reviews from these products are likely to focus on quality issues and value relative to price. By analyzing the text of the reviews, we can test whether the negative reviews received by fake review products are distinctive from regular one-star reviews and use the text features to discern why they are different and whether they indicate harm to consumers.

We perform two types of comparisons. First, we compare the post-campaign one-star reviews for fake review products to the one-star reviews for these same products prior to their first Facebook post. Second, we compare the post-campaign one-star reviews to one-star reviews for a different set of products that were not observed buying fake reviews.

We start by sampling 5,000 one-star reviews of each type: from products recruiting fake reviews prior to the first Facebook post, from those same products after the last Facebook post, and from a set of competitor products.[18] Then, we train a text-based classifiers to predict whether each one-star review is from either before or after fake review recruiting, or

[18]As we discuss in Section 2, competitor products are defined as those products showing up on the same results page for a keyword search as the focal products.

in the second test, from either a product recruiting fake reviews or not. Following standard practice, we split the review dataset into an 80% training sample and a 20% test sample. We present the results using a Naive Bayes Classifier based on tf-idf. Depending on the configuration of the classifier (we can change the number of text features used by the classifier by removing very rare and very popular words), we achieve an accuracy rate that ranges between 61% and 75% and a ROC-AUC score that varies between 66% and 83% for both types of comparisons.[19] These results suggest that, in both cases, the text of the reviews is sufficiently distinctive for the classifier to distinguish between the different kinds of one-star reviews. In other words, despite the products themselves being held constant and their reviews having the same star-rating, the one-star reviews written for products after fake review recruiting contain a significantly different set of words compared with one-star reviews written beforehand. Similarly, these reviews contain a significantly different set of words compared with one-star reviews written for the products that did not recruit fake reviews.

We next look at what are the most predictive text features for distinguishing the different product types. In Table 11, we compare the text features of negative reviews posted before and after rating manipulation by reporting the top 30 features. What emerges from this table is that one-star reviews written after rating manipulation occurs are predicted by text features mostly related to product quality ("work", "broke", "stop work") or value ("money", "waste money") or else explicitly suggest the consumer felt deceived or harmed ("return", "disappoint"). By contrast, the one-star reviews for the same products prior to rating manipulation are associated with idiosyncratic product features, such as "earplug", "milk frother", or "duvet".

In Table 12, we report the top features for the model trained to distinguish between negative reviews from fake review products and competitor products. Again, reviews for fake review products are associated with text features mostly related to product quality ("qualiti",

[19]Other types of classifiers led to similar performance.

"stop work", "work", etc.), value/price ("waste money", "money", "disappoint", etc.); instead, competitors' one-star reviews are predicted by text features mostly related to idiosyncratic product characteristic ("second attach", "fade", "reseal", etc.)

Overall, these results are consistent with one another and add further evidence that consumers who bought products that recruited fake reviews felt deceived in thinking that the products were of higher quality than they really were.

Table 11: Most Predictive Text Features: Before v After Fake Reviews

Period	Top 30 Text Features
Before recruiting fake reviews	muzzl, around neck, duvet, laundri, earplug, needless, milk frother, foam earplug, rectal, topper, espresso, lightn, like go, keep lick, nois reduct, degre differ, like tri, frizzi, espresso machin, wildli, breath, work never, expect much, concert, time open, stori, octob, inflat collar, unsaf, vinegar
After recruiting fake reviews	work, product, money, return, use, month, wast, time, would, wast money, stop, charg, like, even, disappoint, broke, stop work, week, first, tri, light, back, good, bought, batteri, qualiti, item, recommend, purchas, turn

Note: Model accuracy and ROC-AUC are 61% and 66%, respectively

Table 12: Most Predictive Text Features: Focal vs Non-Focal Products

Products	Top 30 Text Features
Recruiting fake reviews	work, product, money, return, use, time, stop, wast, month, would, like, wast money, charg, even, broke, stop work, week, disappoint, good, back, light, first, tri, bought, qualiti, review, turn, batteri, recommend, great
Not recruiting fake reviews	reseal, command, bang, fixtur, apart piec, septemb, product dont, fade, ignit, use never, use standard, terrier, compani make, desktop, love idea, wifi connect, bead, solar panel, inexpens, within year, return sent, compani product, second attach, pure, cycl, thought great, solar charg, blame, bought march, price paid

Note: Model accuracy and ROC-AUC are 63% and 69%, respectively

7 Discussion and Conclusions

It has become commonplace for online sellers to manipulate their reputations on online platforms. In this paper, we study the market for fake reviews on Amazon, one of the world's largest e-commerce platforms. We study how rating manipulation affects seller outcomes both in the short term and in the long term. These two analyses allow us to study both the immediate effectiveness of fake reviews and to understand whether these reviews are harming consumers and online platforms or not.

We find that the Facebook promotion is highly effective at improving several sellers' outcomes, such as number of reviews, ratings, search position rank, and sales rank, in the short term. However, these effects are often short-lived as many of these outcomes return to pre-promotion levels a few weeks after the fake reviews recruiting stops. In the long run, this boost in sales does not lead to a positive self-sustaining relationship between organic ratings

and sales, and both sales and average ratings fall significantly once fake review recruiting ends. Rating manipulation is not used efficiently by sellers to solve a cold-start problem, in other words.

This decrease in ratings once sellers stop buying fake reviews and the large increase in the share of one-star reviews suggest that consumers who bought these products felt deceived. The implication is that they either overpaid for the true quality of the product or bought a different, lower quality product than they would have in the absence of rating manipulation. In addition to harming consumers, rating manipulation likely harms honest sellers and the platform's reputation itself. If large numbers of low-quality sellers are using fake reviews, the signal value of high ratings could decrease, making consumers more skeptical of new and highly rated products. This, in turn, would make it harder for new, high-quality sellers to enter the market and would likely reduce innovation.

Firms are continuously improving and perfecting their manipulation strategies so that findings that were true only a few years ago, or strategies that could have worked in the past to eliminate fake reviews, might be outdated today. This is why studying and understanding how firms manipulate their ratings continue to be an extremely important topic of research for both academics and practitioners. As a testament to this, Amazon claims to have spent over $500 million in 2019 alone and employed over 8,000 people to reduce fraud and abuse on its platform.[20]

Our last finding is to document how Amazon responds to sellers recruiting fake reviews. We find that Amazon responds by deleting reviews at a very high rate. Moreover, we find that Amazon's response is quite sophisticated. The timing of review deletion suggests that it is able to identify which sellers and reviews are likely fake despite these reviews being very similar to real ones. However, while review deletion seems well targeted, there is a large lag between these reviews being posted and then deleted. In practice, this means that currently, Amazon is not able to eliminate the short-term profits from these reviews or the consumer

[20]See: `https://themarkup.org/ask-the-markup/2020/07/21/how-to-spot-fake-amazon-product-reviews`

backlash we see expressed in the large number of one-star reviews.

We can also document that Amazon does not use other potential policy levers at its disposal to regulate fake reviews. We do not observe in our sample that Amazon either deletes many products or bans sellers as a result of them manipulating their ratings. We also do not observe punishment in the products' organic ranking in keyword searches. This keyword ranking stays elevated several months after fake review recruiting has ended, even as Amazon finds and deletes many of the fake reviews posted on the platform. Reducing product visibility in keyword rankings at the time fake reviews are deleted could potentially turn fake reviews from a profitable endeavor into a highly unprofitable one.

It is not obvious whether Amazon is simply under-regulating rating manipulation in a way that allows this market to continue to exist at such a large scale, or if it is assessing the short-term profits that come from the boost in ratings and sales and weighing these against the long-term harm to the platform's reputation. Quantifying these two forces is, therefore, an important area of future research.

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Appendix

A Heterogeneous Effects

The regression tables contained in this appendix divide products into subgroups along four dimensions. The first is the designation of some products as "cold-start" products. These are new products without established reputations, who we may expect to have different incentives to buy fake reviews or different outcomes afterwards. We define these products as cold-start if they have been listed on Amazon for 4 or fewer months and have 8 or fewer reviews. This is roughly 10% of the observed products. Next, we divide products into high and low-priced based on the median price of products measured 1 week prior to when we observe them posting in the FB groups for the first time.

Second, we designate product as high- vs. low-price products by using the median price for the products in our sample.

Third, we designate products as durable vs non-durable. To do so, rather than hand-code products or designate them based on category, we crowdsource this definition. We solicit workers on Amazon MTurk for each product and ask them to select from a menu of commonly accepted definitions of durable and non-durable products. For durability, they view each product and answer whether it is either "Something that should last at 3 or more years before it needs to be replaced" or "Something that is purchased multiple times in a year." They also have the option of selecting neither. We solicit two answers for each product and only designate a product as either durable or non-durable if both workers agree. For the products where the Mturkers disagreed or where one of them chose not to select either phrasing, we treat the product as ambiguous, i.e. not falling into either category. The results are that we code 63% of products as durable, 11% non-durable, and the remainder as ambiguous.

Fourth, we use a similar procedure to define each product as a search good or an experience good, again using Mturk workers and commonly accepted definitions. We define experience goods using the phrase "Need to test this product to tell if it is good or bad" and search goods using the phrase "Can tell if this is a good or bad product just from the de-

scription". They again have the option of selecting neither and we rely on consensus answers. We code 24% of products as search goods and 34% as experience goods.

We present the short-term results in Appendix A.1 and the long-term results in Appendix A.2.

A.1 Short-term Results

Table 13: Short-term Change in Avg. Rating

	(1) Avg. Rating	(2) Avg. Rating	(3) Avg. Rating	(4) Avg. Rating	(5) Avg. Rating
$\leq$ 2 wks	0.107***	0.117***	0.055*	0.080*	0.106***
	(0.019)	(0.019)	(0.024)	(0.033)	(0.026)
$>$ 2 wks	0.034	0.059**	-0.008	-0.002	0.028
	(0.021)	(0.022)	(0.028)	(0.036)	(0.031)
$\leq$ 2 wks $\times$ Coldstart		-0.198**			
		(0.067)			
$>$ 2 wks $\times$ Coldstart		-0.360***			
		(0.080)			
$\leq$ 2 wks $\times$ Low Price			0.121**		
			(0.037)		
$>$ 2 wks $\times$ Low Price			0.097*		
			(0.041)		
$\leq$ 2 wks $\times$ Durable				0.029	
				(0.041)	
$>$ 2 wks $\times$ Durable				0.032	
				(0.045)	
$\leq$ 2 wks $\times$ Nondurable				0.091	
				(0.070)	
$>$ 2 wks $\times$ Nondurable				0.157*	
				(0.073)	
$\leq$ 2 wks $\times$ Search					0.030
					(0.051)
$>$ 2 wks $\times$ Search					0.016
					(0.055)
$\leq$ 2 wks $\times$ Experience					-0.016
					(0.041)
$>$ 2 wks $\times$ Experience					0.008
					(0.047)
N	186389	186389	186389	186389	186389
R^2	0.22	0.22	0.22	0.22	0.22

Note: All specifications include product and year-week FE. Cluster-robust standard errors (at the product level) in parentheses.

Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 14: Short-term Change in Weekly Reviews

	(1) log Reviews	(2) log Reviews	(3) log Reviews	(4) log Reviews	(5) log Reviews
$\leq$ 2 wks	0.445***	0.439***	0.460***	0.417***	0.448***
	(0.017)	(0.018)	(0.023)	(0.030)	(0.025)
$>$ 2 wks	0.320***	0.309***	0.308***	0.268***	0.327***
	(0.020)	(0.021)	(0.028)	(0.038)	(0.030)
$\leq$ 2 wks $\times$ Coldstart		0.091			
		(0.057)			
$>$ 2 wks $\times$ Coldstart		0.142*			
		(0.070)			
$\leq$ 2 wks $\times$ Low Price			-0.034		
			(0.034)		
$>$ 2 wks $\times$ Low Price			0.027		
			(0.039)		
$\leq$ 2 wks $\times$ Durable				0.036	
				(0.038)	
$>$ 2 wks $\times$ Durable				0.067	
				(0.045)	
$\leq$ 2 wks $\times$ Nondurable				0.063	
				(0.058)	
$>$ 2 wks $\times$ Nondurable				0.113	
				(0.075)	
$\leq$ 2 wks $\times$ Search					-0.106*
					(0.043)
$>$ 2 wks $\times$ Search					-0.074
					(0.050)
$\leq$ 2 wks $\times$ Experience					0.057
					(0.039)
$>$ 2 wks $\times$ Experience					0.028
					(0.046)
N	247218	247218	247218	247218	247218
R^2	0.67	0.67	0.67	0.67	0.67

Note: All specifications include product and year-week FE. Cluster-robust standard errors (at the product level) in parentheses.

Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 15: Short-term Change in Log Sales Rank

	(1) log Sales Rank	(2) log Sales Rank	(3) log Sales Rank	(4) log Sales Rank	(5) log Sales Rank
$\leq$ 2 wks	-0.260***	-0.238***	-0.264***	-0.275***	-0.277***
	(0.022)	(0.023)	(0.030)	(0.036)	(0.031)
$>$ 2 wks	-0.246***	-0.217***	-0.263***	-0.252***	-0.249***
	(0.028)	(0.029)	(0.039)	(0.050)	(0.039)
$\leq$ 2 wks $\times$ Coldstart		-0.275**			
		(0.085)			
$>$ 2 wks $\times$ Coldstart		-0.349***			
		(0.100)			
$\leq$ 2 wks $\times$ Low Price			0.007		
			(0.043)		
$>$ 2 wks $\times$ Low Price			0.037		
			(0.053)		
$\leq$ 2 wks $\times$ Durable				0.016	
				(0.046)	
$>$ 2 wks $\times$ Durable				-0.002	
				(0.060)	
$\leq$ 2 wks $\times$ Nondurable				0.051	
				(0.077)	
$>$ 2 wks $\times$ Nondurable				0.060	
				(0.101)	
$\leq$ 2 wks $\times$ Search					0.078
					(0.057)
$>$ 2 wks $\times$ Search					0.057
					(0.073)
$\leq$ 2 wks $\times$ Experience					-0.001
					(0.049)
$>$ 2 wks $\times$ Experience					-0.030
					(0.061)
N	193381	193381	193381	193381	193381
R^2	0.81	0.81	0.81	0.81	0.81

Note: All specifications include product and year-week FE. Cluster-robust standard errors (at the product level) in parentheses.
Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 16: Short-term Change in Log Keyword Rank

	(1) log Keyword Rank	(2) log Keyword Rank	(3) log Keyword Rank	(4) log Keyword Rank	(5) log Keyword Rank
$\leq$ 2 wks	-0.412***	-0.409***	-0.342***	-0.420***	-0.384***
	(0.028)	(0.030)	(0.034)	(0.048)	(0.043)
$>$ 2 wks	-0.434***	-0.440***	-0.361***	-0.419***	-0.396***
	(0.030)	(0.031)	(0.037)	(0.054)	(0.045)
$\leq$ 2 wks $\times$ Coldstart		-0.030			
		(0.074)			
$>$ 2 wks $\times$ Coldstart		0.067			
		(0.086)			
$\leq$ 2 wks $\times$ Low Price			-0.168**		
			(0.057)		
$>$ 2 wks $\times$ Low Price			-0.173**		
			(0.059)		
$\leq$ 2 wks $\times$ Durable				0.035	
				(0.059)	
$>$ 2 wks $\times$ Durable				0.010	
				(0.065)	
$\leq$ 2 wks $\times$ Nondurable				-0.166	
				(0.110)	
$>$ 2 wks $\times$ Nondurable				-0.240*	
				(0.119)	
$\leq$ 2 wks $\times$ Search					-0.084
					(0.082)
$>$ 2 wks $\times$ Search					-0.107
					(0.086)
$\leq$ 2 wks $\times$ Experience					-0.034
					(0.060)
$>$ 2 wks $\times$ Experience					-0.050
					(0.062)
N	91733	91733	91733	91733	91733
R^2	0.64	0.64	0.64	0.64	0.64

Note: All specifications include product and year-week FE. Cluster-robust standard errors (at the product level) in parentheses.
Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 17: Short-term Change in Sponsored Listings

	(1) Sponsored	(2) Sponsored	(3) Sponsored	(4) Sponsored	(5) Sponsored
$\leq$ 2 wks	0.044***	0.049***	0.015	0.067***	0.028*
	(0.009)	(0.010)	(0.012)	(0.016)	(0.013)
$>$ 2 wks	0.061***	0.069***	0.031*	0.086***	0.045**
	(0.010)	(0.011)	(0.013)	(0.018)	(0.014)
$\leq$ 2 wks $\times$ Coldstart		-0.078*			
		(0.031)			
$>$ 2 wks $\times$ Coldstart		-0.114***			
		(0.034)			
$\leq$ 2 wks $\times$ Low Price			0.069***		
			(0.018)		
$>$ 2 wks $\times$ Low Price			0.070***		
			(0.020)		
$\leq$ 2 wks $\times$ Durable				-0.033	
				(0.020)	
$>$ 2 wks $\times$ Durable				-0.032	
				(0.022)	
$\leq$ 2 wks $\times$ Nondurable				-0.027	
				(0.042)	
$>$ 2 wks $\times$ Nondurable				-0.050	
				(0.047)	
$\leq$ 2 wks $\times$ Search					0.008
					(0.028)
$>$ 2 wks $\times$ Search					0.010
					(0.032)
$\leq$ 2 wks $\times$ Experience					0.038*
					(0.019)
$>$ 2 wks $\times$ Experience					0.037
					(0.021)
N	94122	94122	94122	94122	94122
R^2	0.55	0.55	0.55	0.55	0.55

Note: All specifications include product and year-week FE. Cluster-robust standard errors (at the product level) in parentheses.

Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

A.2 Long-Term Results

Table 18: Long-term Change in Avg. Ratings

	(1) Avg. Rating	(2) Avg. Rating	(3) Avg. Rating	(4) Avg. Rating	(5) Avg. Rating
$\leq$ 2 wks	-0.033	-0.026	-0.069**	-0.079*	-0.068*
	(0.018)	(0.019)	(0.022)	(0.031)	(0.026)
$>$ 2 wks	-0.156***	-0.146***	-0.182***	-0.202***	-0.163***
	(0.020)	(0.020)	(0.024)	(0.035)	(0.027)
$\leq$ 2 wks $\times$ Coldstart		-0.121			
		(0.075)			
$>$ 2 wks $\times$ Coldstart		-0.180*			
		(0.079)			
$\leq$ 2 wks $\times$ Low Price			0.106**		
			(0.037)		
$>$ 2 wks $\times$ Low Price			0.077		
			(0.041)		
$\leq$ 2 wks $\times$ Durable				0.059	
				(0.039)	
$>$ 2 wks $\times$ Durable				0.053	
				(0.043)	
$\leq$ 2 wks $\times$ Nondurable				0.104	
				(0.061)	
$>$ 2 wks $\times$ Nondurable				0.131*	
				(0.067)	
$\leq$ 2 wks $\times$ Search					0.081
					(0.048)
$>$ 2 wks $\times$ Search					0.023
					(0.053)
$\leq$ 2 wks $\times$ Experience					0.054
					(0.040)
$>$ 2 wks $\times$ Experience					0.005
					(0.043)
N	187640	187640	187640	187640	187640
R^2	0.22	0.22	0.22	0.22	0.22

Note: All specifications include product and year-week FE. Cluster-robust standard errors (at the product level) in parentheses.

Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 19: Long-term Change in Weekly Reviews

	(1) log Reviews	(2) log Reviews	(3) log Reviews	(4) log Reviews	(5) log Reviews
$\leq$ 2 wks	0.060***	0.042*	0.006	0.001	0.030
	(0.018)	(0.018)	(0.022)	(0.032)	(0.026)
$>$ 2 wks	-0.239***	-0.251***	-0.283***	-0.301***	-0.254***
	(0.020)	(0.021)	(0.026)	(0.038)	(0.030)
$\leq$ 2 wks $\times$ Coldstart		0.259***			
		(0.064)			
$>$ 2 wks $\times$ Coldstart		0.186**			
		(0.071)			
$\leq$ 2 wks $\times$ Low Price			0.156***		
			(0.035)		
$>$ 2 wks $\times$ Low Price			0.128***		
			(0.039)		
$\leq$ 2 wks $\times$ Durable				0.076*	
				(0.039)	
$>$ 2 wks $\times$ Durable				0.083	
				(0.045)	
$\leq$ 2 wks $\times$ Nondurable				0.122	
				(0.065)	
$>$ 2 wks $\times$ Nondurable				0.118	
				(0.073)	
$\leq$ 2 wks $\times$ Search					0.025
					(0.046)
$>$ 2 wks $\times$ Search					0.063
					(0.049)
$\leq$ 2 wks $\times$ Experience					0.074
					(0.040)
$>$ 2 wks $\times$ Experience					0.006
					(0.045)
N	249444	249444	249444	249444	249444
R^2	0.67	0.67	0.67	0.67	0.67

Note: All specifications include product and year-week FE. Cluster-robust standard errors (at the product level) in parentheses.

Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 20: Long-term Change in Log Sales Rank

	(1) log Sales Rank	(2) log Sales Rank	(3) log Sales Rank	(4) log Sales Rank	(5) log Sales Rank
$\leq$ 2 wks	-0.052**	-0.041*	-0.029	-0.056	-0.060*
	(0.019)	(0.020)	(0.024)	(0.035)	(0.029)
$>$ 2 wks	0.082**	0.090**	0.110**	0.063	0.085*
	(0.027)	(0.027)	(0.034)	(0.048)	(0.038)
$\leq$ 2 wks $\times$ Coldstart		-0.151			
		(0.083)			
$>$ 2 wks $\times$ Coldstart		-0.114			
		(0.108)			
$\leq$ 2 wks $\times$ Low Price			-0.065		
			(0.038)		
$>$ 2 wks $\times$ Low Price			-0.079		
			(0.051)		
$\leq$ 2 wks $\times$ Durable				0.008	
				(0.042)	
$>$ 2 wks $\times$ Durable				0.023	
				(0.057)	
$\leq$ 2 wks $\times$ Nondurable				-0.005	
				(0.064)	
$>$ 2 wks $\times$ Nondurable				0.051	
				(0.093)	
$\leq$ 2 wks $\times$ Search					0.055
					(0.050)
$>$ 2 wks $\times$ Search					0.017
					(0.068)
$\leq$ 2 wks $\times$ Experience					-0.010
					(0.042)
$>$ 2 wks $\times$ Experience					-0.019
					(0.057)
N	194840	194840	194840	194840	194840
R^2	0.81	0.81	0.81	0.81	0.81

Note: All specifications include product and year-week FE. Cluster-robust standard errors (at the product level) in parentheses.
Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 21: Long-term Change in Log Keyword Rank

	(1) log Keyword Rank	(2) log Keyword Rank	(3) log Keyword Rank	(4) log Keyword Rank	(5) log Keyword Rank
$\leq$ 2 wks	-0.169***	-0.171***	-0.143***	-0.143***	-0.139***
	(0.017)	(0.018)	(0.021)	(0.031)	(0.025)
$>$ 2 wks	-0.138***	-0.144***	-0.134***	-0.123**	-0.124***
	(0.021)	(0.021)	(0.025)	(0.038)	(0.030)
$\leq$ 2 wks $\times$ Coldstart		0.044			
		(0.073)			
$>$ 2 wks $\times$ Coldstart		0.111			
		(0.088)			
$\leq$ 2 wks $\times$ Low Price			-0.074*		
			(0.035)		
$>$ 2 wks $\times$ Low Price			-0.015		
			(0.042)		
$\leq$ 2 wks $\times$ Durable				-0.018	
				(0.038)	
$>$ 2 wks $\times$ Durable				-0.004	
				(0.045)	
$\leq$ 2 wks $\times$ Nondurable				-0.148*	
				(0.063)	
$>$ 2 wks $\times$ Nondurable				-0.122	
				(0.073)	
$\leq$ 2 wks $\times$ Search					-0.078
					(0.048)
$>$ 2 wks $\times$ Search					-0.034
					(0.056)
$\leq$ 2 wks $\times$ Experience					-0.043
					(0.037)
$>$ 2 wks $\times$ Experience					-0.020
					(0.043)
N	97022	97022	97022	97022	97022
R^2	0.65	0.65	0.65	0.65	0.65

Note: All specifications include product and year-week FE. Cluster-robust standard errors (at the product level) in parentheses.
Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 22: Long-term Change in Sponsored Listings

	(1) Sponsored	(2) Sponsored	(3) Sponsored	(4) Sponsored	(5) Sponsored
$\leq$ 2 wks	0.021***	0.022***	0.012	0.024*	0.012
	(0.005)	(0.006)	(0.007)	(0.010)	(0.008)
$>$ 2 wks	0.036***	0.040***	0.031***	0.040***	0.035***
	(0.007)	(0.007)	(0.008)	(0.012)	(0.009)
$\leq$ 2 wks $\times$ Coldstart		-0.035			
		(0.023)			
$>$ 2 wks $\times$ Coldstart		-0.074*			
		(0.029)			
$\leq$ 2 wks $\times$ Low Price			0.025*		
			(0.012)		
$>$ 2 wks $\times$ Low Price			0.014		
			(0.014)		
$\leq$ 2 wks $\times$ Durable				-0.006	
				(0.012)	
$>$ 2 wks $\times$ Durable				-0.003	
				(0.014)	
$\leq$ 2 wks $\times$ Nondurable				-0.001	
				(0.021)	
$>$ 2 wks $\times$ Nondurable				-0.020	
				(0.025)	
$\leq$ 2 wks $\times$ Search					0.001
					(0.015)
$>$ 2 wks $\times$ Search					-0.012
					(0.018)
$\leq$ 2 wks $\times$ Experience					0.025*
					(0.012)
$>$ 2 wks $\times$ Experience					0.011
					(0.014)
N	99409	99409	99409	99409	99409
R^2	0.56	0.56	0.56	0.56	0.56

Note: All specifications include product and year-week FE. Cluster-robust standard errors (at the product level) in parentheses.

Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

B Sales Data

In this appendix, we first describe how we collect data on sales in units, and then how we convert sales rank to sales in units for instances in which this is unobserved. Amazon does not display metrics on sales quantities, only on an ordinal Best Seller Rank, a number that ranks products based on their rate of sales relative to other products in the same category.

To acquire sales quantity data, we exploit a feature of the Amazon website that allows us to infer the number of units of a product that are currently in stock. To observe a product's inventory, one must simply add to an Amazon cart increasing numbers of units of the product until the seller runs out of stock. At this point, Amazon will display an alert telling the buyer the total number of units available. The highest number of units that can be added to an Amazon cart is 999 and so for products with inventories below 1000 this method allows us to observe the number of units currently in stock. We employ research assistants to collect data using this method for a panel of products every 2 days. By observing inventories repeatedly over time, we can infer the rate of sales.

After collecting inventory data, we first remove observations in which the inventory is 0 or at the upper limit of 999 or if the seller has placed a limit on the number of units that can be purchased. We then calculate the difference in inventories between each two day period. We remove any observations where the inventory increases over this period. We use the remaining data to calculate sales per day. A more detailed description of this procedure and the resulting data can be found in He and Hollenbeck (2020). We observe data on sales in units for 683 of the focal products.

These data do not cover every period and, most importantly, we cannot observe sales data prior to the first FB post of these products. Therefore we estimate the relationship between sales rank and sales in units using the sales data to approximate the level of sales for these missing periods. To do so, we generalize the approach taken by Chevalier and Goolsbee (2003) and estimate a log-log regression with product fixed effects. This provides a good fit, with an adjusted-R^2 of .89. More details on the estimation and alternative models for estimated sales quantities are available in He and Hollenbeck (2020).

Lastly, we then use the regression estimates to infer the missing data on sales units at

different dates for the same set of products based on their observed rank on those dates. We plot these outcomes in the short run and long run in Figures 5 and 10.

C Propensity Score Matching

To reduce concerns about differences between treated and control products that could affect the DD estimates, we employ Propensity Score Matching (PSM) (Rosenbaum and Rubin, 1983) to match treated and control products on the observable variables that are different across treatment conditions, i.e., age, weekly average ratings, and cumulative reviews. To do so, for every product, we average these variables over the period [-8,-2) weeks and then implement PSM using a the Gaussian kernel matching procedure and imposing a common support, i.e., we retain treatment observations whose propensity score is higher than the maximum or less than the minimum propensity score of the controls. We start with 1,412 treated and 78 control products and, after matching, we are left with 987 treated and 48 control products. We verify that PSM eliminates the imbalance between treated and control units by computing a weighted (using the PSM weights) t-test for equality of means of treated and control products. We report the results of this test in Table 23 below.

Table 23: Comparison of Treated and Control Products after matching

	Control	Treated	t-stat
Age	7.78	7.63	0.10
Weekly Avg. Ratings	4.07	4.15	−0.48
Cum. Avg. Ratings	4.34	4.33	0.07
Weekly Reviews	5.11	7.24	−0.72
Cumulative Reviews	109.48	124.69	−0.39
Price	25.74	32.63	−1.20
Coupon	0.24	0.27	−0.30
Verified	0.94	0.95	−0.31
Number of Photos	0.22	0.24	−0.19
Category	43.30	39.32	0.75

Note: Weighted t-test for equalty of means for treated and control units. Means are computed at the interval level for the period [-8,-2) weeks.
Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

D Analysis of the mid-march Amazon purge

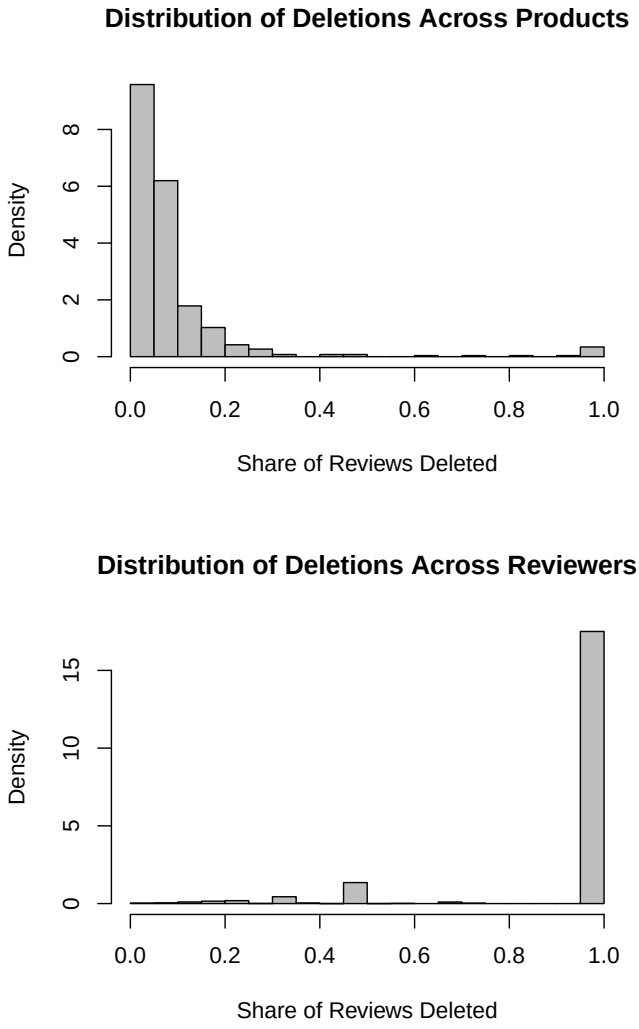
We have done an investigation of the patterns in review deletion across products, time, and reviewers in order to better understand the review "purge" and what selection criterion Amazon is using for these deletions. We focus first on the distribution of deletions across products and across reviewers to determine whether deletions are targeted at specific products buying fake reviews or at reviewers writing them. To give an example of this logic: if 10% of reviews were deleted during the review purge event, it could be that 10% of products were targeted and they all had 100% of their reviews deleted or it could be that specific products were not targeted and all products had about 10% of their reviews deleted. Similar analysis could find if individual reviewers were targeted or if the deletions are uniform across reviewers (of course these are extreme examples - reality must lie somewhere in between.)

We focus our investigation on the focal products (products observed buying fake reviews on Facebook) and find that during the 2-week period we call the review "purge", 3.2% of all 230,000 reviews are deleted. This is a small share of the total stock of reviews but in terms of the flow of deletions is many times higher than during normal periods. These deletions effect 40.6% of products (i.e. they have at least one review deleted) and 3.2% of reviewers.

This suggests deletions are targeted at a small group of specific reviewers and are not targeted at a narrow set of products. We next show the distribution of the share of reviews deleted at both the product and reviewer levels (conditional on having at least one review deleted.) We plot histograms of each in Figure 18.

This figure shows that the vast majority (93%) of products affected by the review deletion event have fewer than 20% of their reviews deleted and nearly half have fewer than 5% of their reviews deleted. Among reviewers, the opposite pattern holds. The vast majority (87.5%) of reviewers have all of their reviews deleted. This evidence is unfortunately biased, however, by the nature of our data collection. We initially only collect reviews at the daily basis for our focal products and so the set of reviewers we analyze here are those who have posted on these products in this time period. We did not scrape these reviewers' other reviews (for non-focal products) at the time, as would be required to track the full share of their reviews deleted at a given point in time. Therefore the vast majority (83%) of these reviewers have

Figure 18: Distribution of Deletions During Purge Event



only 1 review observed to begin with.

Yet, among reviewers with more than 1 review who have reviews deleted, the same pattern does hold. In this group, reviewers with multiple reviews, at least one of which is deleted in the review purge, 77% have 100% of their reviews deleted. When we condition on reviewers having at least 5 reviews the share with all reviews deleted is 78%.

This analysis strongly suggests that individual products are not targeted when Amazon deleted large numbers of reviews in mid-March 2020 but rather that individual reviewers were targeted.

E Diff-in-Diff estimates for all outcomes using alternative purge windows

Here, we report the DD estimates for all outcomes using alternative review purge windows. Similarly to what we did with the main sample, before proceeding to the estimation, we use PSM to balance the treated and control products. In Table 24, we increase the window by one week by using a purge window of [-2,2] weeks around the mid-purge date; in Table 25, we shift the purge window to the left by using a purge window of [-1,2] weeks around the mid-purge date; in Table 26, we reduce the purge window by one week use a purge window of [-1,1] weeks around the mid-purge date. As discussed in Section 5.4, sales estimates are similar to the main estimates using a [-2,1] purge windows (see column 5 of Table 7). However, either increasing or shifting the window to the left reduces our ability to capture the review purge as demonstrated by the estimates in column 1 of Tables 24 and 25 (note, however that despite the estimate not being significant at conventional levels, the increase in cumulative reviews is always larger than that for control products). Instead, the estimates using a smaller window (Table 26) are almost exactly the same as the main estimates reported in Table 7.

Table 24: Diff-in-Diff using purge window [-2,2] weeks around the mid-purge date.

	(1) log Cum. Reviews	(2) Sponsored	(3) Coupon	(4) log Price	(5) log Sales Rank
After	0.087*	0.010	−0.026	−0.021*	0.166*
	(0.039)	(0.021)	(0.043)	(0.010)	(0.070)
After × Treated	0.052	0.038	0.002	0.016	−0.325***
	(0.047)	(0.023)	(0.047)	(0.012)	(0.086)
PSM Sample	Yes	Yes	Yes	Yes	Yes
N	13706	7902	7902	7834	12512
R^2	0.95	0.68	0.68	0.99	0.85

Note: All specifications include product and year-week FE. Cluster-robust standard errors (at the product level) in parentheses.
Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 25: Diff-in-Diff using purge window [-1,2] weeks around the mid-purge date.

	(1) log Cum. Reviews	(2) Sponsored	(3) Coupon	(4) log Price	(5) log Sales Rank
After	0.065	0.006	−0.040	−0.030**	0.178*
	(0.033)	(0.024)	(0.047)	(0.011)	(0.077)
After × Treated	0.077	0.043	0.008	0.024	−0.338***
	(0.046)	(0.026)	(0.050)	(0.014)	(0.092)
PSM Sample	Yes	Yes	Yes	Yes	Yes
N	13706	7902	7902	7834	12512
R^2	0.95	0.68	0.69	0.99	0.85

Note: All specifications include product and year-week FE. Cluster-robust standard errors (at the product level) in parentheses.
Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 26: Diff-in-Diff using purge window [-1,1] weeks around the mid-purge date.

	(1) log Cum. Reviews	(2) Sponsored	(3) Coupon	(4) log Price	(5) log Sales Rank
After	0.054	0.018	−0.020	−0.015	0.198
	(0.041)	(0.031)	(0.052)	(0.010)	(0.115)
After × Treated	0.103*	0.025	−0.016	0.018	−0.377**
	(0.052)	(0.037)	(0.048)	(0.015)	(0.131)
PSM Sample	Yes	Yes	Yes	Yes	Yes
N	12620	7477	7477	7417	11553
R^2	0.96	0.65	0.65	0.99	0.87

Note: All specifications include product and year-week FE. Cluster-robust standard errors (at the product level) in parentheses.
Significance levels: * p<0.05, ** p<0.01, *** p<0.001.