Covid19 and Consumer Animus towards Chinese Products – Evidence from Amazon Data

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Abstract

Covid19 has tremendously affected all areas of our lives and our online shopping behaviors have not been immune. China is the first country to report cases of Covid19 and suffer from rising animus in the U.S. In this paper, we study consumer animus towards Chinese products post Covid19 using Amazon data. We tracked all face masks sold on Amazon between Sep. 2019 to Sep. 2020, and collect product information that is available to a real consumer, including reviews. By analyzing both seller-generated (e.g., product name, description, features) and user-generated (e.g., reviews and customer Q&A) contents, we collect information on the country-of-origin as well as consumer animus for the products. Under a fully-dynamic event study design, we find that the average rating drops significantly after a product is identified as made in China for the first time, while no such drop is found for products with other country-of-origin. This negative impact is U-shaped, which quickly expands in the first five weeks, and then gradually fades out within six months. An informative-animus reviews affects the average rating of a Chinese product both directly (through its own rating) and indirectly (through other future ratings), with both mechanisms supported in data. We also provide strong evidence that the drop in average rating is driven by consumer animus instead of product quality.

Section 1 Introduction

"Masks from China, no, no, no !!!!!!"

– A consumer review on Amazon.com

Covid19 has tremendously affected all areas of our lives. Until April 2022, there have been more than 487 million reported cases and more than 6.14 million deaths from Covid19 worldwide[1]. In the United States, the total unemployment rate surged from 3.5% in January 2021 to 14.7% in April 2021[2]. The impacts of Covid19, however, is not equally born by all. Researchers have studied the inequality in Covid19 impacts across genders (Adams-Prassl et al., 2020; Alon et al., 2020), races (Amuedo-Dorantes et al., 2021; Couch et al, 2020), immigration-status (Borjas and Cassidy, 2020), education (Adams-Prassl et al., 2020), and work arrangements (Adams-Prassl et al., 2020). This unequal burden is especially true for the Asian Americans, who is disproportionately affected. Between March 28th to April 25th, 2020, Asian Americans witnessed a 6900% increase in initial unemployment claims in New York, compared to a rise of 1840%, 1260%, and 2100% for the white, black, and Hispanic/Latino workers[3].This phenomenon, however, is just a reflection of and generalization from the rising animus towards China.

Since China was the first countries to report cases of Covid19, it has led many to relate Covid19 with China. To make matters worse, there have been prominent political leaders that have used language to stigmatize China with blame and fear around Covid-19, including the ex-president of the United States. On March 16th, 2020, the then U.S. President Donald Trump first called Covid19 the "Chinese virus" in his posts on Twitter and has used that language ever since in media interviews, at rally speeches, and on social media. Fox news, Newsmax and other fringe networks outlets have continued with this rhetoric. This rising animus towards China is further generalized to Chinese and the Asians. Hahm et al. (2021) records the rise of anti-Asian (including Asian and Asian Americans) discrimination found within the Adult Resilience Experiences Study

[1] Data reported by John Hopkins at https://coronavirus.jhu.edu/map.html.

[2] Data from Bureau of Labor Statistics https://www.bls.gov/charts/employment-situation/civilian-unemployment-rate.htm. The unemployment rate has declined after April 2021, back to 3.8% as of February 2022.

[3] Change is measured compared with similar time in 2019 (March 30th to April 27th). Reported by CNN Business at https://www.cnn.com/2020/05/01/economy/unemployment-benefits-new-york-asian-americans/index.html.

(CARES). Lu and Sheng (2020) finds an immediate rise in anti-Asian animus following the exogenous arrival of first Covid19 case locally, reflected by derogatory racial epithet in Google searches and Twitter posts. On employment, Amuedo-Dorantes et al. (2021) records a declining entrepreneurship among Asian immigrants compared to non-Hispanic whites after January 2020, and find a substantial increase in exits from self-employment for the Asian immigrants. More generally, Bartoš et al. (2021) provides evidence for rising hostility against foreigners from the EU, U.S., and Asia due to the Covid19 Crisis in the Czech Republic. This rising hostility towards foreign people can be partly explained from an evolutionary psychological perspective, where the chronic and contextually aroused feelings of vulnerability to disease motivate negative reactions to foreign (but unfamiliar) immigrants (Faulkner et al., 2004).

The social media has further promoted the propagation of this animus. Croucher et al. (2020) studies social media use and finds that the more social media users believe that their most-used daily social media are fair/accurate/giving facts, the more likely that they believe Chinese pose a threat to U.S. He et al. (2021) analyzes anti-Asian hate speech on Twitter, and finds that in 2020, users who are exposed to hateful content are highly-likely to become hateful.

This phenomenon of rising animus, however, is not unique to Covid19. Historically, researchers have observed rising animus or even hate crime towards certain ethnic groups post profound negative events, such as Arab & Muslim post 9/11 attack (Kaushal et al., 2007); German post WWI (Ferrara and Fishback, 2020), Asian/Arab post 7/7 attack[4] (Hanes and Machin, 2014); and Muslim post Jihadi attacks (Ivandic et al., 2019).

In this paper, we study the animus towards China from a new dimension – online shopping. Unfortunately, online platform has not been a pure land from discrimination. Previous literature has shown the discrimination towards certain racial or ethnic groups via online platforms such as eBay (Ayres et al., 2015), Airbnb (Kakar et al., 2018; Edelman and Luca, 2014), Blocket[5] (Ahmed and Hammarstedt, 2008), local online retailing website (Doleac and Stein, 2013), and online carpooling markets (Tjaden et al., 2018).

After Covid19, consumers might hold animus towards Chinese products, either out of prejudice (e.g., blaming China for the breakout of Covid19) or health concerns (e.g., worrying that

[4] On July 7th, 2005, there was a serious of suicide bombs attacks on London's public transport system.
[5] Blocket.se is one of the largest buy and sell sites for the housing market in Sweden.

Chinese products might carry the virus, which risk is low according to Centers for Disease Control and Prevention[6]). We are interested in how the animus towards China affects the Chinese products. To that end, we compile data covering all face masks sold on Amazon between September 1st, 2019 to September 7th, 2020, including the consumer reviews. We collect information on country-of-origin of a product from both seller-generated (e.g., product name, description, feature) and buyer-generated information (e.g., reviews and customer Q&A).

To avoid the problems raised in Goodman-Bacon (2021) concerning the inclusion of two-way fixed effects under the DID design when treatment time varies, we apply the fully-dynamic event study design as suggested by Borusyak and Xavier (2017). Under this design, we find that, despite of no change in the quality, the average rating of a product drops after being identified as made in China for the first time. This negative impact is U-shaped, which quickly expands in the first five weeks, and gradually fades out within six months. By further splitting Chinese product into high and low reputation using its average rating before the identification, we find that the U-shape decline in product average rating is driven by the high reputation ones. The same pattern is not found among products made in the U.S. or other country-of-origin.

The negative impact of the informative reviews can be explained by the direct (via its own rating) and indirect (via ratings given by other future reviewers) mechanism. The direct impact persists overtime through the high correlation of product average rating from day to day, and decreases in size unambiguously over time. The indirect impact is U-shaped, which first expands in size with more future consumers seeing the review, and then shrinks in size with fewer new consumers see and get affected by the review due to a rising time cost. The explanations via direct and indirect mechanisms are then supported by studying the negative impacts (lagged) informative reviews have on product average rating. Our results are not driven by quality difference between Chinese and non-Chinese products, which is potentially controlled by the product fixed effects. We provide further evidence against the quality story by analyzing the informative reviews and collect information on whether it contains any complaint about product quality. Results on total impacts and indirect impacts are very similar using the informative-animus reviews without quality complaints.

[6] Refer at CDC: https://www.cdc.gov/coronavirus/2019-ncov/more/science-and-research/surface-transmission.html.

The remainder of this paper is organized as follows: Section 2 describes our data and treatment; Section 3 specifies our event study design, shows the results, and explains the mechanisms behind the results; Section 4 provides further evidence and discussions for the mechanisms raised in Section 3; Section 5 concludes our finding and discuss its significance.

Section 2 Data

2.1 Introduction of Data

Amazon has been the biggest online retailer nowadays. In 2021, Amazon is estimated to account for 41% of the total retail ecommerce sales in the U.S., following by Walmart Inc. (6.6%), eBay (4.2%), and Apple (4.0%)[7]. Compared to eBay, Amazon does not have character limit on reviews, which promotes the richness of information expressed in the consumer reviews[8]. We therefore choose Amazon as the online platform to study, and collect data both from Keepa.com and by ourselves.

2.1.1 Product Information

Keepa.com is an online platform tracking products listed on Amazon. For each product, it provides its current and historical information, including product name, product description[9], price[10], sales rank[11], total number of customer ratings, average rating, ASIN, seller information, first day the product is listed, etc. ASIN is Amazon's Standard Identification Number, which uniquely identifies a product that is very narrowly defined (e.g., the same face mask sold by the same seller but of different color or size could be given two separate ASINs)[12]. This level of precision gives us the confidence that the product is identical over time under the same ASIN[13].

One highlight of Keepa.com is that it tracks products (identified by the same ASIN) overtime and provides high-frequency data[14]. For convenience of use, we aggregate data on a daily or weekly basis to construct the panel data that vary by ASIN and date/week. Despite the great richness of data, Keepa.com does not retain information for delisted products. Once a product gets delisted from Amazon, Keepa.com will also remove its data within two weeks, leading to data selection concerns. In our data, however, data selection is not a big problem. We tracked 1630 face

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[7] Data estimated by eMarketer at https://www.emarketer.com/.
[8] There is an 80-character limit on reviews posted on eBay. Compared to Amazon, reviews that express animus towards China on eBay and Yelp.com are very rare.
[9] Including color, size, materials, brand, etc. Note that different products might reveal different information in the product description.
[10] Including listing price, Amazon price, buy-box price, etc.
[11] Note that Amazon does not reveal the actual sales of a product to the consumers. Instead, it provides the sales rank of a product under a specified category.
[12] Therefore, in this paper, an ASIN and a product is used interchangeably.
[13] There are some cases that multiple sellers are selling the same product under the same ASIN (e.g., on September 7th, 2020, only 24.02% of face masks sold on Amazon have multiple sellers). This, however, would not affect our analysis since we study animus towards Chinese products, and the key is to track products instead of sellers.
[14] Most products' information is updated several times daily (see https://keepa.com/#!faq).

masks that are listed on Amazon on September 18th, 2020, and find that only 129 (or 7.91%) of them get delisted until August 15th, 2021.

To better study customer animus towards Chinese products, we focus on the face mask, a product that might be sensitive to many customers post-Covid19.[15] We restricted our sample to products listed on Amazon that meets the following three criteria: (1) have the key word "face mask" in product name; (2) have at least 3 ratings; and (3) fall under the "Health and Household" category. We then manually examine these products to exclude irrelevant ones that pass the three filters and further drop the ones with missing key variables. The number of products retained in the final sample comes down to 1400.[16]

2.1.2 Review Information

Keepa.com does not provide data on customer review details. We therefore manually collected all review data that are publicly available to Amazon customers for the products we are tracking. This data includes, for each review, reviewer name, date of review, review headline, review body, review rating, country of the reviewer, and helpful votes.[17] For each product, we also collect the information on top (positive or critical) reviews.[18] For details on Amazon's regulation of consumer reviews, see Data Appendix.

2.1.3 Matching Products with Reviews

We link the products and reviews by ASIN and date. In our sample, the first face mask sold on Amazon which is now still in operation dates back to July 18th, 2011. We restrict our research period from September 1st, 2019 to September 7th, 2020 for ease of comparison before and after the shock of Covid19 and also for consistency of Amazon policy.[19] In the final sample, we have

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[15] As an essential personal sanitary equipment, we do observe that many consumers express health concerns for face masks that are produced in China, despite the spread of Covid-19 through international shipments is unlikely according to CDC.
[16] Typical examples of such products include face mask straps, face mask filters, and ear savers for face mask.
[17] For an existing review, customers could click on "helpful" button to support the review. Reviews with the highest number of helpful votes would be displayed at the top of the review pages under "top positive review" or "top critical review", depending on the rating given by the reviewer.
[18] For most of the products in our data, Amazon listed the top positive and top critical reviews.
[19] Our choice of study period covers the time pre and post the breakout of Covid19 – January 23rd, 2019. This is the time that city of Wuhan (China) is sealed and the time that people worldwide are aware of this virus. Also see https://www.marketplacepulse.com/articles/amazon-replaces-reviews-with-ratings for the change in policy on Amazon on the rating policy since September 2019. Before the change, customers need to leave a comment if they want to leave a rating for a product. After the change, customers can rate a product without leaving a review text. We therefore choose the time period after the change of this policy.

1400 products and over 70,000 reviews. Note that when we collapse the data into panel of date/week by product, the panel is unbalanced due to arrival of new products during the research period. Figure 1 shows the arrival of new face masks sold on Amazon by day. There is a rising number of new face masks sold on Amazon after the breakout of Covid19 (Jan. 23rd, 2019), which peaks on June 8th, 2020, and decreases after that.

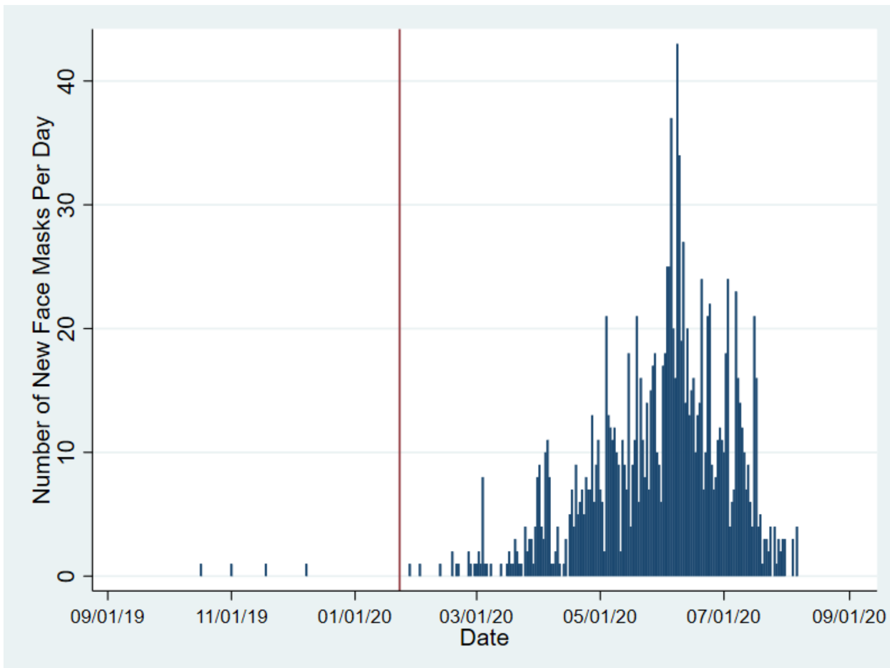

Figure 1: Number of New Face Masks Sold on Amazon by Day

2.2 Treatment of Data

2.2.1 Identify Chinese Products

Amazon does not require sellers to reveal the country-of-origin for products. Therefore, we collect information on a product's revealed origin country from several sources – product name, product description/details/features, consumer reviews, and customer question and answer (Q&A). All this information is also available to real customers.[20]

We first analyze the product name and descriptions/details/feature and collect information on whether a product is made in China. Since this information is provided by the seller herself and

[20] Through our analysis, we try to mimic a real customer and avoid using any information which is beyond the reach of real customers.

does not vary over time, we classify the product as self-identified as Chinese and there is no change in the revealed origin country of the product over time in this case. We then analyze the texts of reviews (including the review headline and review body) and pick out all reviews that mention China one way or the other[21]. Within these reviews, we manually go through them and collect information on whether a review actually identifies the product as made in China.[22] We also use information from customer Q&A, where typically a customer poses a question and sellers or other customers would leave an answer. We manually collect information on country-of-origin information and date that product is first credibly revealed as Chinese.[23] Note that not all products have the customer Q&A section, but "Is it made in China" is a very common question for most face masks with customer Q&A.[24]

Combining all the information sources above, we are able to identify 386 products made in China out of 1400 face masks as of September 7th, 2021. Since customers might hold animus towards Chinese products, only 24 products are self-identified as Chinese, with 93.8% of the Chinese products either identified from reviews or customer Q&A.

There could be cases where Chinese products are not yet identified as of the last day of our research period, but this case shall not be problematic for our study. We carry out the research trying to look exactly from the view of real consumers and we have access to exactly the same information as real consumers do. If we do not observe a product to be made in China, neither do real consumers. And if consumers do not know that a product is Chinese, they would not have hold animus towards the product either. What makes sense eventually is not whether a product is

[21] Specifically, we picked out all reviews that mention China or Chinese, despite of upper or lower case. We also tried some very discriminative ways to mention Chinese (e.g., Ching Chong), but did not spot such cases in our data since Amazon removes comments with offensive language. We find a few reviews which use the expression of "foreign spelling" but we did not count such products as Chinese since it could be from any other non-English-speaking countries. There is also one rare case where customer refers to China as "the communist country". In most of the cases, the use of China/Chinese is adequate to identify Chinese products.

[22] There are a few cases where a review mentions China but does not identify the product reviewed as a Chinese product. E.g., "Overpriced with a bit of price gouging and excessive shipment cost but what can one do these days? At least they are not from China."

[23] If the seller or manufacturer replies and mentions that the product is made in China, we think this information is credible. If it is the consumers that mentioned a product is made in China, we check the answers of other consumers to make sure the information is credible. For credible answers, we then track the first date that it identifies a product as a Chinese product. Typical non-credible answers could include answers like "I guess this is made in China" or competition out of malicious purpose e.g., "Do not buy this product, it is made in China. If you want to buy safe products satisfying FDA standard, you can find them at (links for other sellers)".

[24] In our sample, about 65% of the products has customer Q&A.

actually made in China, but whether a product is "revealed" or "identified" and known to consumers as Chinese.

2.2.2 Types of Reviews

We analyze the review content (including both the headline and body of a review) and divide reviews into three categories based on the information provided and attitudes expressed towards China or Chinese products: non-informative, informative-neutral, and informative-animus.[25] The non-informative reviews do not provide any information on the Chinese identity of a product. The informative reviews, on the other hand, reveal the Chinese identity of a product. The informative reviews are further divided into "neutral" and "animus" depending on whether expressing animus towards China or Chinese products. For the informative reviews, we also collect information on whether a review expresses any complaint about the quality of the product.

In data, among a total of 70,136 reviews, there are 1201 reviews that mention China/Chinese, within which only 132 reviews are non-informative.[26] Among the 1069 informative reviews, 826 reviews (or 77.3%) express animus towards China or Chinese products, and only 243 reviews (or 22.7%) are neutral. As for product quality, 25.8% (or 276) of the informative reviews contain complaints about quality, while 74.2% (or 793) of informative reviews are not about product quality. See Table A1 in Appendix for examples of each type of informative reviews. Despite the small number of informative reviews, their impacts could be larger since they catch more attention from other customers reflected by more helpful votes[27]. Within our sample, a review on average gets 2.58 helpful votes. For an informative review, however, this number is 5.84, with informative-neutral reviews get 4.28 helpful votes and informative-animus reviews get 6.30 helpful votes.

Figure 2 shows the distribution of ratings within all Chinese products identified by the end of our research period, by non-informative and informative reviews. For the non-informative reviews, 50.04% give 5-star rating while only 20.36% give 1-star rating. This pattern is reversed within

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[25] Specifically, we first use keyword of China/Chinese to pick out the reviews which mentions China. Within these reviews, we manually go through them to collect information on three questions: Does this review express animus towards China/Chinese products? Can we identify this product as Chinese? Does this review contain any complaint about quality of the product?

[26] An example of non-informative review that mentions China/Chinese is (review body): "Made in USA and much better than ones we've bought made in China."

[27] By default, customers are more likely to see reviews with more helpful votes since reviews are shown in descending order in terms of number of helpful votes they get. This could be changed by the consumer if she wishes to review the comments in order of date instead of by number of helpful votes.

informative reviews, where 56.22% give 1-star rating and only 12.07% give 5-star rating. Within informative reviews, on average, the neutral ones give higher ratings than the animus ones, and the share of animus reviews decreases by ratings. From 1-star to 5-star ratings, the share of animus reviews among the informative reviews are, respectively: 96%; 81%; 64%; 45%; and 23%. Table A2 in Appendix shows some examples of informative-animus reviews from consumers at each rating.

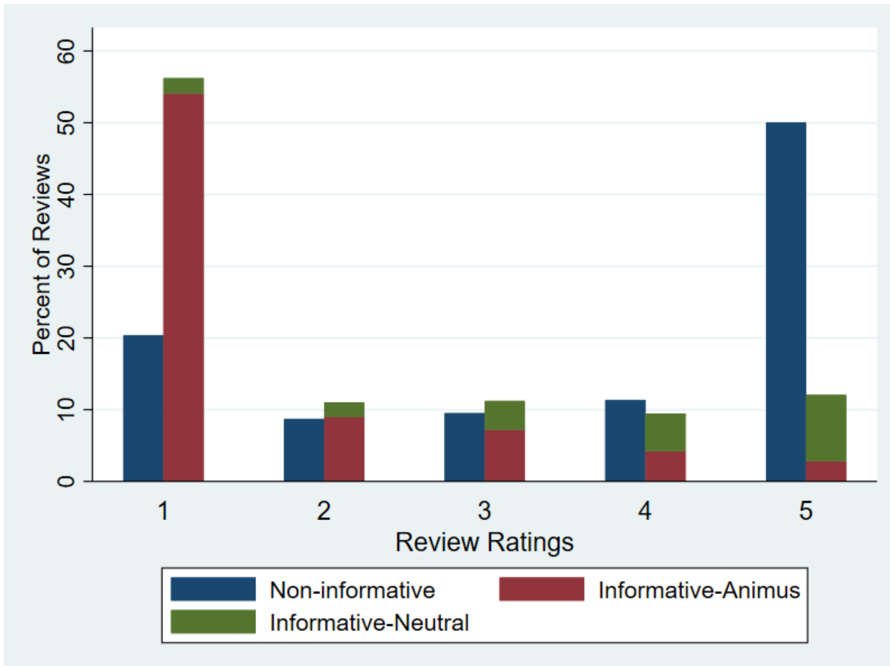

Figure 2: Rating Distribution of Chinese Products by Review Category

Note: Sample is limited to Chinese products identified by the end of research period. Reviews are divided into non-informative, informative-animus, and informative-neutral, with the last two categories stacked.

2.2.3 Other Countries of Origin

We apply similar analysis for other countries to collect information on products' country-of-origin by first searching the country names and then manually go through the reviews and customer Q&A to correct mis-information.[28] See Figure 3 for summary of country-of-origin.

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[28] Specifically, to correct for cases where a country name is mentioned in the review but the review does not identify the country-or-origin of the product; or cases where the customer Q&A mentions the country-or-origin but is not credible. We use the name list of countries from the World Bank to search within the relevant reviews. Considering cases where a country is mentioned in the reviews but under an alternative name, we slightly change the name list to

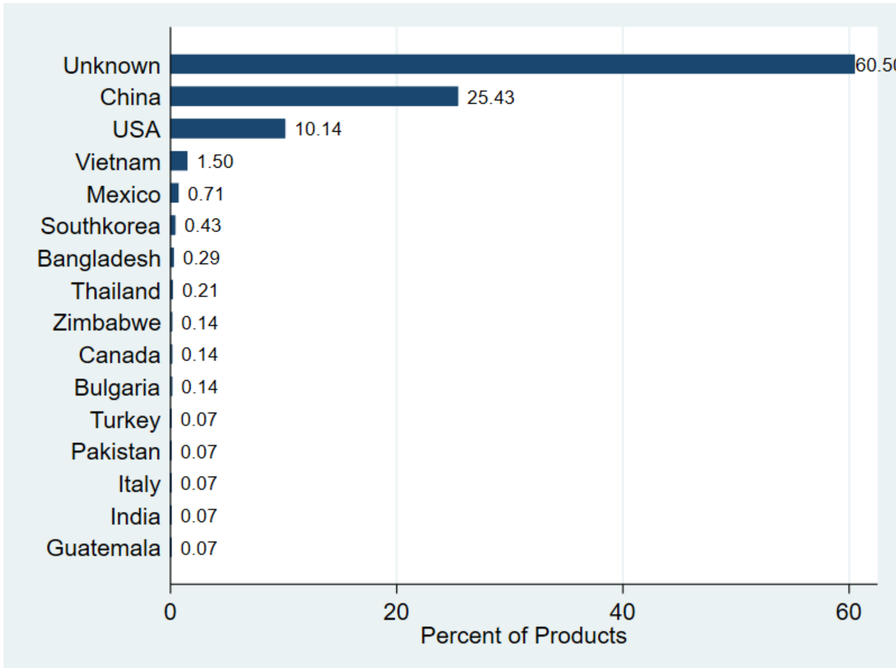


Figure 3: Share of Products by Country-of-Origin

By the end of our research period, 60.50% of the products' country-of-origin remain to be unknown. For the known ones, the face masks sold on Amazon in the U.S. are revealed to come from 21 countries, including U.S. itself. Out of the 1400 face masks in our sample, China is the biggest country-of-origin identified (25.43%), following by USA (10.14%), with the rest of the countries summing up to less than 4% of the face masks.

2.3 Summary Statistics on Chinese products

Table 1 below compares the products from China and other countries (including the unknown) at both the first and last day in the research period. Comparing the price, there is no evidence that Chinese products charge lower price after Covid19. If anything, the average price of face masks sold on Amazon is slightly higher for Chinese ones at the last day of the sample period.[29] For average rating, Chinese face masks have similar average rating with ones from other countries,

improve the chances a country name is identified. If a product is said to come from Korea without further specification, we will take it as South Korea. For United States, we use the key words of, in upper and lower cases, United States, USA, U.S., and America. A product is only identified as U.S. if it is confirmed in reviews or Q&A as made and shipped within the U.S., and not identified with other country-of-origin.

[29] In empirical analysis, we further carry out event study on the price of products after being identified as Chinese.

both at the start and end of research period.[30] On average, the Chinese products have more sales than non-Chinese ones, but this gap becomes smaller at the end of research period. Chinese face masks receive way more ratings than non-Chinese products, and the number of ratings greatly expanded during the research period for both of them.[31] At September 1st, 2019, Chinese sellers are on average in business for shorter time, which is reversed by September 7th, 2020, due to the arrival of new products during the research period.

Table 1: Summary Statistics (Mean Only)

	Sep. 1st, 2019		Sep. 07th, 2020	
	Chinese	Others	Chinese	Others
Price	16.27	16.71	18.17	17.84
Average Rating	4.06	4.11	4.06	4.08
Rescaled Sales Rank	55.47	37.65	53.63	48.56
Number of Rating	21.96	3.57	458.43	161.84
Days in Business	697	728	175	113
ASIN count	27	16	396	1014

Note: Summary statistics are based on the first day (September 1st, 2019) and last day (September 7th, 2020) of our sample. Amazon does not provide actual number of sales, and only provides the sales rank under a specific product category. In this table the sales rank is re-scaled from 0 to 100, where a larger index means more sales.

[30] This does not mean that Chinese products are not discriminated. Instead, this is because the impacts of being identified as Chinese products are short-lived. See the empirical part of for more information.

[31] This could be related to the rising of sales of face masks or that the share of consumers who leaves a rating changes overtime. However, since we do not observe the actual number of sales of a product from Amazon, we cannot distinguish between the two cases.

Section 3 Event Study

3.1 Empirical Model

In this part, we run event study on the impact on average rating for a product to be identified as made in China for the first time. Goodman-Bacon (2021) has pointed out problems associated with the inclusion of two-way fixed effects under the DID design when treatment time varies. We therefore apply a fully-dynamic design of event study in this part, as suggested by Borusyak and Jaravel (2017). Regression below specifies the empirical model:

$$Y_{it} = \alpha + \sum_{k=-\infty}^{\infty} \beta_k Treat_{ik} + \beta_X X_{it} + \theta_i + \theta_t + \varepsilon_{it}$$

The data are aggregated on week-product level as panel. The dependent variable is the average rating, which varies by product (ASIN) i and time (week) t. $Treat_{ik}$ is a dummy variable, which equals one if at time t, product i is k weeks from first time ever being identified as made in China from reviews. Specifically, $k = t - K + 1$ where K denotes the time when a product is first time ever being identified as Chinese. The time difference k can be positive or negative/zero, depending whether time t is after or before/equals identification time K, and k equals one at the first week a product is ever identified as Chinese. Control variables X_{it} include price and sales rank[32]. θ_i is product fixed effect, which absorbs potential quality difference across products[33]. θ_t is time fixed effect, which absorbs any potential common supply-side (e.g., scarcity of product) or demand-side variations (e.g., change of policy on requirement of wearing face masks). This event study design provides good exogenous variation under the assumption that conditional on time and product fixed effect as well as the price and sales of a product, the arrival of a review that first time reveals the Chinese identity of a product is random.

[32] Both controls take logs. The sales ranks are limited under the same category of Health and Household, so they are comparable. The ideal variable would be actual sales but unfortunately Amazon does not provide data on the actual sales of products. We therefore use sales rank to proxy for actual sales on Amazon, with larger rank meaning smaller actual sales amount.

[33] Since ASIN can precisely identify a product even up to color and size, we are confident that the quality of the product under the same ASIN does not vary over time.

3.2 Empirical Results

3.2.1 Main Result of Event Study

Results of event study are shown in Figure 4.

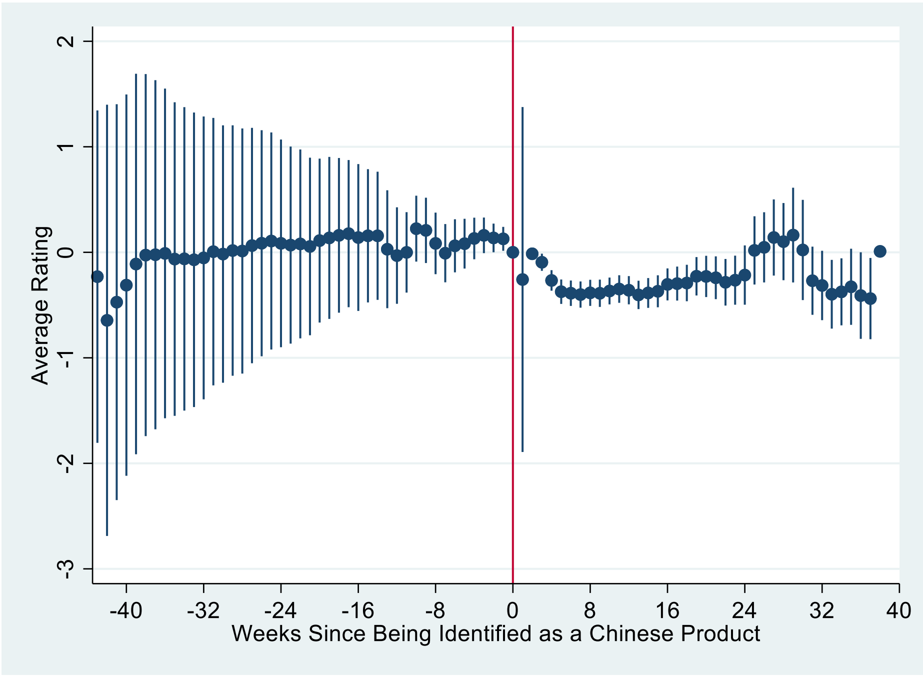


Figure 4: Event Study for Chinese Products

Based on Figure 4, there is no evidence of declining trend of average rating before a product is identified as Chinese. However, once a product is identified as made in China, despite there is no change in the actual quality of the product, the average rating declines, and this drop persists overtime and fades out in six months. At the first several weeks (before week -39), there is a large rise in average rating, and in the last several weeks (after week 30), there is a sudden drop of average rating. Both these patterns are a bit inconsistent with the data in between. Part of the reason is that there is very few samples for the first and last several weeks, so these coefficients are driven by just a few products (e.g., for time difference before -41 and after 27 weeks, there are fewer than five products). Appendix Figure 1 shows the count of products for each time difference k (in weeks).

The result provides evidence for consumer animus towards Chinese products. The average rating first drops and slowly recovers since the informative reviews affects average rating both directly and indirectly. The direct mechanism refers to the impact of a review on the average rating through its own rating. As shown in Figure 2, most of the informative reviews are informative-animus and give low ratings, which directly lower the average rating of a product. The direct impact decreases over time unambiguously.[34] The indirect mechanism refers to the impact of a review on the average rating through ratings given by other (future) customers. Since overtime, a growing number of (future) consumers see an existing informative review, the indirect impact of the review first increases. However, with the arrival of new reviews, over time consumers are also less likely to see an existing an informative review due to higher time cost going back to more outdated reviews. Therefore, the indirect impact first grows overtime and then decreases. Combining the direct and indirect impact therefore gives us a U-shaped total impact. It is unlikely that this pattern is driven by difference between the product quality of Chinese products compared to others. Since ASIN is very narrowly defined, which ensures the precise tracking of the same face mask, the product fixed effect will absorb any quality difference between products. The actual quality of a product does not change upon the time point that it is identified as Chinese, and as shown in the data section, 74.2% of the informative reviews are not about quality.

In the next section, we will provide more evidence and explanation of the direct and indirect impacts of the informative reviews, as well as having more discussion to distinguish our results from explanation via product quality.

3.2.2 Heterogenous Impacts across Subgroups

We then study the heterogenous impacts of consumer animus across high and low reputation Chinese products. Based on the average rating for the week right before a product is identified as Chinese (at $k=0$), products are divided into high-reputation (above-median) and low-reputation (below-median) groups. Results are shown in Figure 5.

The Event Study results among all Chinese products are driven by Chinese products of higher reputation. As shown in Figure 5, before being identified, Chinese products with high reputation having a clear pattern of increasing average pattern. Once being identified, its average rating goes

[34] However, we cannot preciously pin down the impact of one extra rating on the average rating of a product due to ambiguity of Amazon's algorithm in calculation. Before 2015, Amazon uses simple/unweighted average to calculate the average rating. In 2015, Amazon switched to a more complicated machine-learning algorithm. Look at Appendix for more details.

through a drop that takes the U-shape, with the negative impacts fading out within 6 months. For the low-reputation ones, however, being identified as Chinese has little impact, since they already had low average rating even before the identification. Similar as above, results at both ends of the time have fewer products and we not interpret much from them.[35]

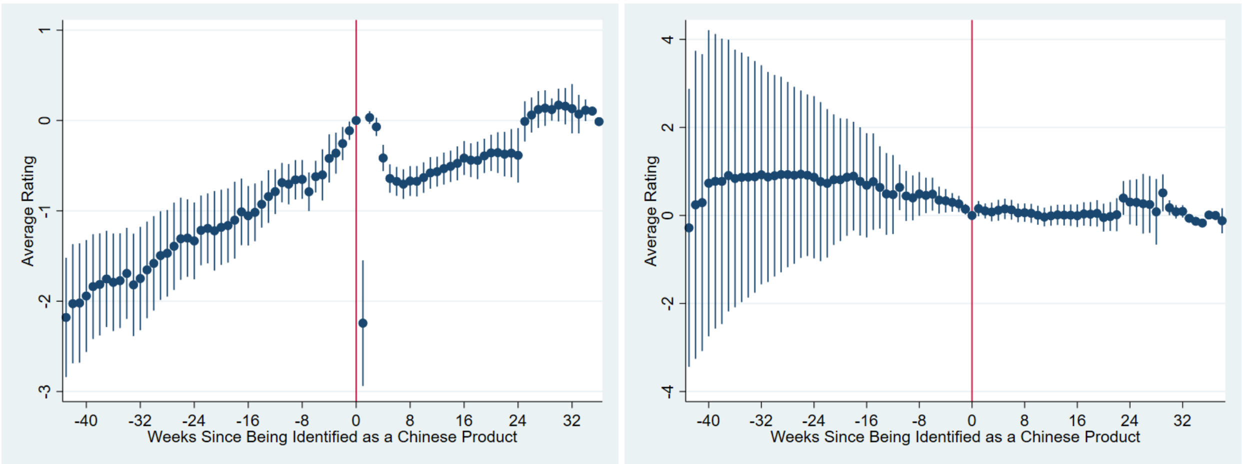


Figure 5: Event Study for Chinese Products – High (left) and Low (right) Reputation

Notes: Chinese products are divided into high-reputation (above-median) and low-reputation (below-median) ones depending on their average rating at the week right before a product is identified as Chinese.

3.2.3 Placebo Using Other Countries

We run the same event study using, respectively, products from U.S. and all other countries (excluding U.S. and China). Placebo results are shown in Figure 6.

There is no similar pattern of a drop in average rating for U.S. and other country-of-origin products as the Chinese ones. If anything, there is a declining trend in the average rating for these products, which stops upon their country-of-origin are identified. The placebo result further supports our interpretation that consumers hold animus towards China and Chinese products. Note that as shown in Figure 6, since only 10.14% products are U.S. and less than 3.93% of the products have other country-of-origin (besides China and U.S.), the sample sizes of the placebo tests are also much smaller than the main result.[36]

[35] Specifically, for the high-reputation group, weeks before -29 and after 24 have fewer than 5 products. For the low-reputation group, weeks before -37 and after 23 have fewer than 5 products.
[36] For U.S. products, weeks before -15 and after 22 have fewer than 5 products. For other countries' products, weeks before -3 and after 10 have fewer than 5 products.

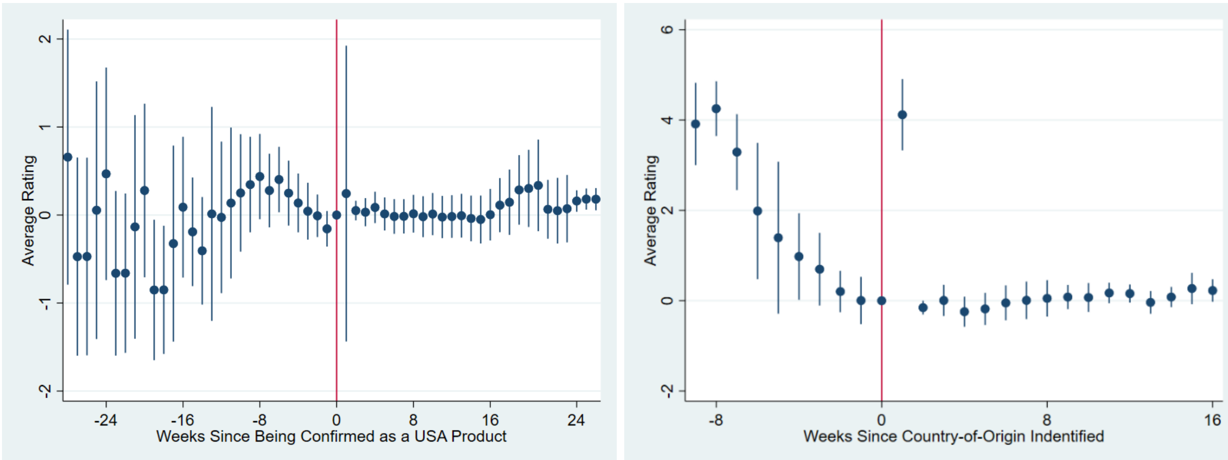


Figure 6: Placebo Event Study of Non-Chinese Products – U.S. (left) and Other Countries (right)

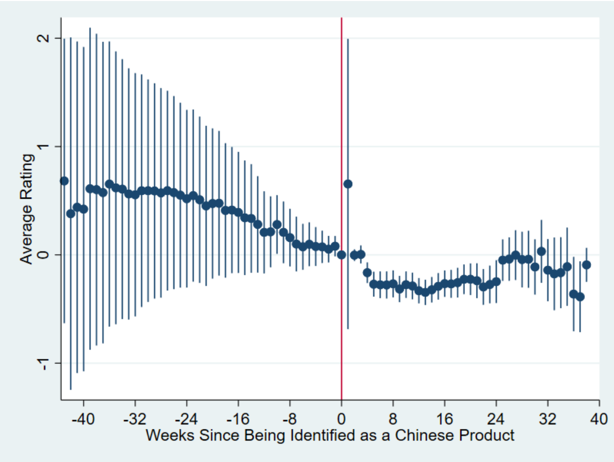
Notes: Non-Chinese products are further divided into U.S. products and products from all other countries besides China and U.S. A product is classified as U.S. only when it is both identified/confirmed as U.S. and there is no information suggesting the product has other country-of-origin in the reviews.

3.2.4 Robustness Checks

We carry out two robustness checks. For the first robustness check, we further combine information from customer Q&A in identifying the time that a product is ever identified as Chinese. Results are in Figure 7. The pattern is similar to our main result, with drop in average rating after a product being identified as Chinese for the first time, and this negative impact fades out within 6 months. Compared to the main result, however, there is decreasing trend of average rating before the identification.

For the second robustness check, we use the cumulative share of 1-star rating reviews as the dependent variable, instead of product average rating. Results are in Figure 8. There is a rise in the cumulative shares of 1-star rating reviews after a product is identified as made in China for the first time, which fades out in 6 months. However, there is also pre-trend of increasing share of 1-star rating reviews before the identification.

Overall, results are similar to the main analysis, but with some pre-trends.



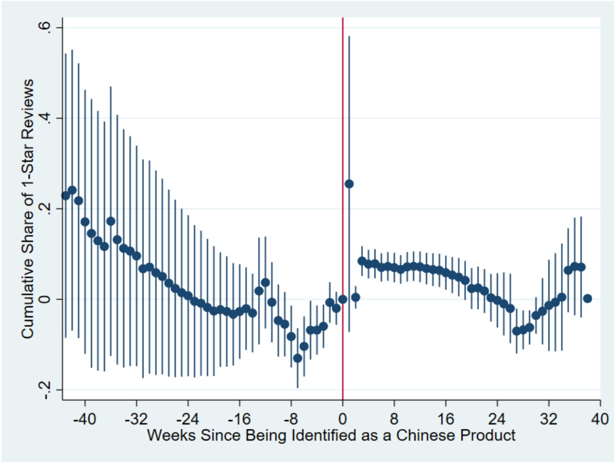


Figure 7: Event Study for Chinese Products – Combining Reviews and Customer Q&A

Figure 8: Event Study for Chinese Products – Dependent Variable Using Share of 1-Star Reviews

3.2.5 Event Study on Price

We carry out the same analysis on price. The dependent variable is now the log of price, and controls are now average rating and sales. Product and time fixed effects are included as in the main analysis.

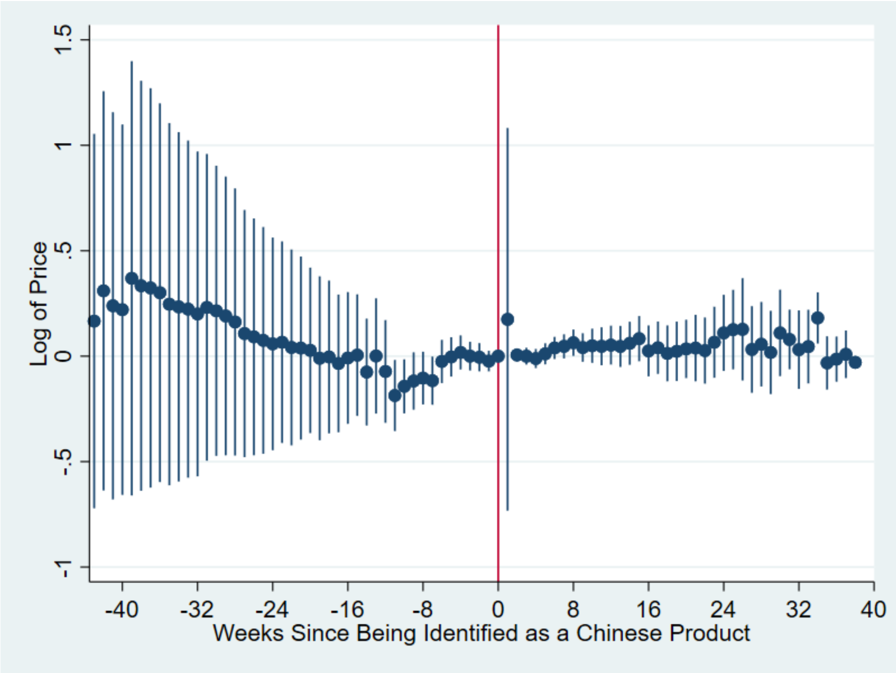


Figure 9: Event Study for Chinese Products – Dependent Variable Using Log of Price

As shown by results in Figure 9, there is no drop in price as we found in average rating. There is no evidence that sellers lower the price in response to products being identified as made in China. This is different from the finding in Lucking-Reiley et al. (2007) about the measurable effect of seller's rating on the prices on eBay. The difference in findings might relate to the product scarcity of face mask, especially at the first several months after the breakout of Covid19. Due to scarcity, consumers have limited ability to switch away from a Chinese face mask even if they hold animus towards it, and sellers therefore do not have the incentive to lower the price. Cabral and Xu (2021) studied the price gouging behavior of 3M masks sellers on Amazon due to product scarcity, and found that between mid-January to mid-March 2020, these masks charge 2.72 times higher price than Amazon sold them in 2019. We will provide more evidence in the empirical part below on product scarcity and consumer's response to it.

Section 4 Direct and Indirect Impacts

As explained in Section 3, an informative review can have direct and indirect impacts on the product average rating. In this section, we will provide more discussion and evidence on these direct and indirect impacts. We will also provide more evidence on the animus consumers hold towards Chinese products, further distinguish our results from the quality story, and discuss logics behind consumers' purchasing behavior with rising animus.

4.1 Impacts of Informative Reviews – Direct and Indirect

There are two mechanisms that an informative review can affect the average rating of a product. The direct mechanism specifies that an informative review affects the average rating of a product by directly going into the calculation of the average rating[37]. The indirect mechanism specifies the impact an informative review has on the average rating via affecting the (future) ratings left by other consumers.

For the direct impact, as shown in the data section, since a much higher share of informative reviews give 1-star ratings, they have an unambiguous negative direct impact on the average rating. In the Appendix, we show that conditional on the price, sales, average rating, as well as the product and time fixed effect, the ratings are 1.35-star lower for the informative reviews and 1.82-star lower for the informative-animus reviews, which is a large difference for a rating system that ranges between one and five. The direct impact decreases over time with arrival of new reviews and the informative review being more outdated.[38] In the Appendix, we also show that the product average rating is highly correlated over time in our sample (correlation coefficient equals 0.97). [39] Through the high correlation of average rating, the negative direct impact persists, but decreases in size over time.

[37] To be specific, the rating of the review is used in the calculation of the average rating.
[38] Essentially, it is the weight assigned to the informative review in calculation of average rating decreases over time. However, since Amazon uses a machine-learning algorithm of calculating product average rating after 2015, and that Amazon might have more information than what is publicly available to a customer, we cannot specify the change of this weight overtime.
[39] This controls for price, sales rank, product fixed effect, and time fixed effect. The correlation is 0.98 without these controls.

For the indirect impact, an informative review can affect the future ratings via other (future) reviewers who read the existing informative review. Previous researchers have found similar "indirect impacts" where one negative opinion invites another. Cabral and Hortacsu (2010) finds that after a seller receives the first negative feedback, subsequent negative feedback arrives 25% more rapidly than the first one, leading to an increase in the negative feedback rate. Moe and Trusov (2011) also find that the previously posted ratings significantly affect future rating behavior. Specific to animus, He et al. (2021) finds users exposed to hateful contents on Twitter and highly likely to become hateful. There could be several cases for the indirect impact to work. First, an informative review provides information which might not be previously known or noted by a consumer.[40] A discriminative consumer could choose to leave a low rating for the product after knowing a product is Chinese from an informative review. The informative review does not need to be the first review ever to identify the Chinese product, since consumers will pay higher time cost to dig into more outdated reviews.[41] Second, since 77.3% of the informative reviews express animus towards China or Chinese products, this might increases the likelihood that a future consumer leaves a low rating out of animus either due to increase in animus towards China or decrease in cost of expressing animus. There is no evidence that consumers are more likely to leave a review (despite of informative or not) after the product is identified as made in China. If anything, the average ratio of number of reviews over number of ratings see a small decreases for a Chinese product after the identification (see Appendix).[42] In both the "extra information" case and "higher likelihood of expressing animus" case, the future consumer could also choose to click on "Helpful" to increase the helpful votes for the informative review. The increase of number of helpful votes would affect the weights assigned to the informative review in calculation of average rating, as well as increase the probability that another future consumer will see this existing informative review.[43]

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[40] There could be cases when a product is already self-identified as Chinese, or that previous reviews or customer Q&A has already mentioned the product is made in China, but a consumer does not notice the information.

[41] A consumer can choose to look at the reviews sorted by date so that more outdated reviews might have a higher cost to be seen by a future consumer. As regulated by Amazon, each review page only contains 10 reviews. We consulted the customer service and up to our knowledge, there is no method that a customer can adjust the number of reviews per page shown to her.

[42] However, there is no significant decrease observed for products of other country-of-origin.

[43] Look at https://www.feedbackwhiz.com/blog/how-does-amazon-calculate-product-ratings/ for what might affect the weight assigned to a review rating to the calculation of average rating of a product. These factors might include, verified purchase, number of helpful votes, age of the review, and the richness and length of the review text.

Comparing the direct and indirect mechanism, the direct mechanism is more like a "one-time shock" which persists over time via correlation of average rating overtime; the indirect mechanism, however, has "several shocks" with more and more future consumers seeing the informative reviews.

4.2 Empirical Model and Results

To provide empirical evidence on the change of direct and indirect impact overtime, we use the empirical models below:

$$Y_{it} = \alpha + \beta S_{i,t-m} + \beta_X X_{it} + \theta_i + \theta_t + \varepsilon_{it}$$

$$Y_{it} = \alpha + \beta_1 S_{i,t-m} + \beta_2 Y_{i,t-m} + \beta_X X_{it} + \theta_i + \theta_t + \varepsilon_{it}$$

To better observe the variation of impacts over time, data here is collapsed into product by day panel (instead of week as in the event study).[44] The dependent variable here is the product average rating, which varies by product i and day t. $S_{i,t-m}$ denotes the share of informative (or informative-animus) reviews of product i on day t-m ($m \in [0, t-1]$), which is the m-day lag of share of informative reviews. $Y_{i,t-m}$ denotes the m-day lag of the product average rating. Similar as in the event study analysis, controls contain log of price and sales rank, and we include the product and time (day) fixed effect.

Comparing these two specifications, β captures the total impact of informative reviews, both directly and indirectly; β_1 captures only the indirect impact, since $Y_{i,t-m}$ has controlled for the direct impact which persists via the high correlation of average rating. Results using informative reviews are shown in Figure 10, with the left showing total impacts and right one showing indirectly impacts.[45]

[44] Note that in the event study, we only care for the first time ever a product is identified as Chinese and collapsing into weeks does not really lose much information. Here, however, we take into account all informative reviews, and daily data will give us more variation.
[45] Since data is now collapsed into product-day (instead of week), I only show the first 12 weeks here for clarity of data.

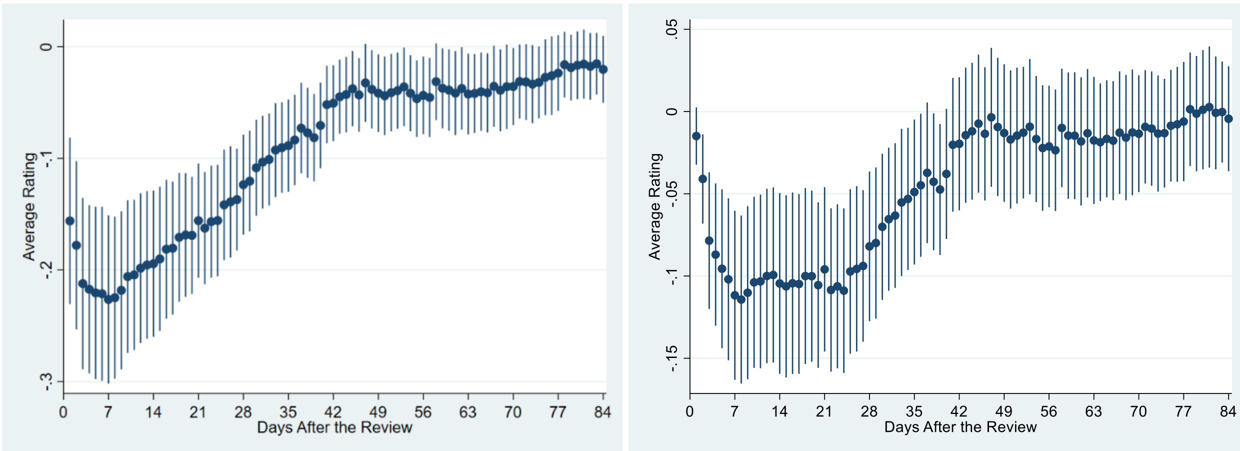

Figure 10: Average Rating and Share of Informative Reviews

Note: Standard errors clustered by ASIN. Controls include price, sales rank, and lag of share of informative-animus reviews, with the x-axis showing the days for this lag. The right figure further controls for corresponding lag of average rating.

As explained above, the total impact (left figure) is U-shaped over time, which size first expands over the first week and then gradually shrinks (at a faster speed during week 2 to 7, and then at a slower speed). The indirect impacts show a similar pattern as the total impact, but of a smaller size. In first week, the indirect impact expands with many more future consumers seeing the informative review; then during the second to fourth week, the indirect impact remains at similar size with more future consumers continuing to see the informative review; after the fourth week, the size of the indirect impact shrinks overtime due to fewer and fewer future consumers see the review due to rising time cost of going through the product review pages. This provides supporting evidence of our story of how an informative review affects future consumers over time. In Appendix Figure B1, we carry out the same analysis using the share of informative-animus reviews. The patterns are similar but that the impacts of informative-animus reviews are more negative. This is because, on one hand, the informative-animus reviews give on average lower ratings, and thus have larger direct impact; on the other hand, the indirect impact is also larger, since (as discussed above), the informative-animus reviews can work through the “higher likelihood of expressing animus” besides the “extra information” indirect mechanism. This explanation is supported by larger (in size) indirect impacts of informative-animus reviews (left of Figure B1) compared to the informative ones (left of Figure B1 in Appendix).

4.3 Animus versus Quality

One might worry that instead of the animus towards China, the negative impact of informative reviews is driven by the lower quality of products made in China. As we have shown in all previous results, this is unlikely to be the case since the quality difference has already been controlled by the inclusion of product fixed effect. In this part, we provide further evidence against the quality explanation.

For the informative reviews, we analysis the texts of reviews and collect information on whether a review contains any complaint about the quality of the product. As stated in the data section, 74.2% of informative reviews are not about product quality. To show that animus instead of product quality drives the story, we now carry out the analysis again using the share of informative-animus reviews that do not contain any complaint about the quality of the product. Results are shown in Figure 11, which is very similar to the pattern using all informative-animus reviews (in Appendix). If anything, using informative-animus reviews that do not contain any quality complains give slightly larger-size coefficients at the peak than using all informative-animus reviews. These results give strong evidence that our findings in this paper are not driven by the quality story, but rather show consumer animus towards China and Chinese products.

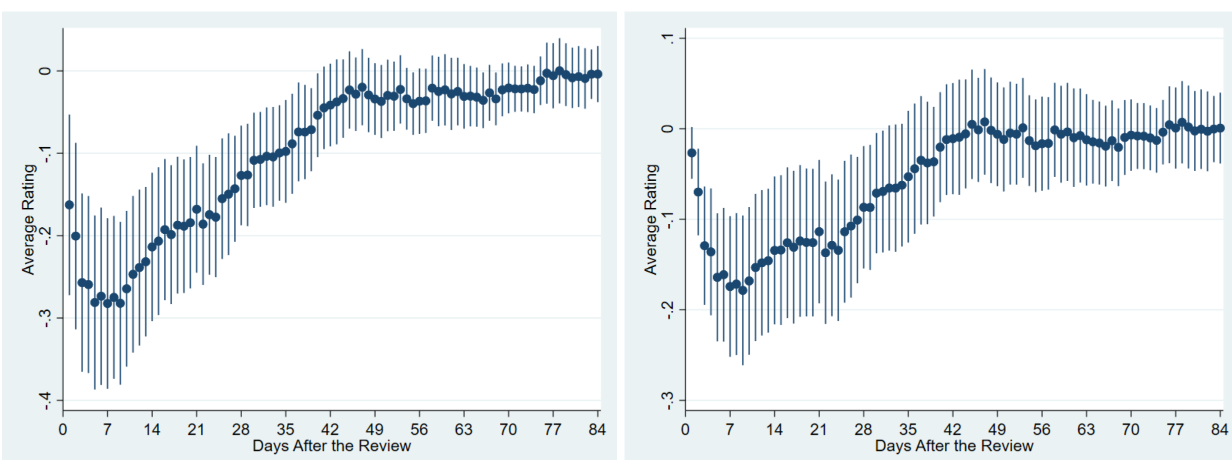

Figure 11: Average Rating and Share of Informative-Animus Reviews with No Quality Complaint

Note: Standard errors clustered by ASIN. Controls include price, sales rank, and lag of share of informative-animus reviews that do not contain any complaint about product quality, with the x-axis showing the days for this lag. The right figure further controls for corresponding lag of average rating.

4.4 Animus and Purchase – Information Friction and Product Scarcity

It is an interesting question that why consumers buy the Chinese products at first place if they hold animus towards them. Why do they choose to buy a Chinese product and then leave a low rating or a review expressing the animus, instead of simply buying a non-Chinese product? There are mainly two reasons behind it: information friction and product scarcity.

The information friction explanation states that the consumers simply do not know that a product is made in China before they come across the informative review. This could either because there is no information revealing the Chinese identity of the product; or that there is such information, but the consumer missed it due to the time cost of collecting country-of-origin information for a product. As a piece of evidence for information friction, among the 386 Chinese products identified as of September 7th, 2021, only 24 products are self-identified. The product scarcity explanation states that due to the scarcity of face masks, especially during the first several months after the breakout of Covid19, there is limited choice on Amazon, and consumers are restricted from switching away from Chinese products. Cabral and Xu (2021) recorded and studied such scarcity in 3M face masks and price gouging behavior of sellers on Amazon mid of January to mid of March, 2020. In our sample, there are only 43 products at the start of the research period, with 62.8% of them made in China. Appendix Figure A1 shows the arrival of new products by day within the research period. There is also supporting evidence for these two explanations from the reviews (see Table A3 in Appendix for some typical examples).

Section 5 Conclusion

Covid19 has tremendously affected all areas of our lives and our online shopping behaviors have not been immune. China is the first country to report cases of Covid19, and suffers from rising consumer animus towards its products, either out of prejudice or health concerns. Amazon, the largest online shopping platform nowadays, has witnessed this rising consumer animus.

In this paper, we provide evidence of this rising consumer animus towards Chinese products post Covid19 and study its impact on the product average rating on Amazon. We collect information on all face masks sold on Amazon between September 1st, 2019 and September 7th, 2020, including the consumer reviews.[46] Using the same information that is available to a real consumer, including seller-generated and user-generated information, we identify the country-of-origin of the products.[47] By analyzing the text of reviews, we further divide reviews into non-informative and informative ones, depending on whether it identifies a product to be made in China. The informative reviews are then divided into animus and neutral ones, depending on whether it expresses animus towards China or Chinese products.

Under a fully-dynamic event study design, we find that, despite of no change in the quality, the average rating of a product drops after being identified as Chinese for the first time.[48] This negative impact is U-shaped, which quickly expands in the first five weeks, and gradually fades out within six months. By further splitting Chinese product into high and low reputation using its average rating before the identification, we find that the U-shape decline in product average rating is driven by the high reputation ones. Similar patterns are not found among products made in the U.S. or other country-of-origin.

The negative impact of the informative reviews can be explained by the direct (via its own rating) and indirect (via ratings given by other future consumers) mechanism. The direct impact persists overtime through the high correlation of product average rating from day to day, and

[46] Specifically, all face masks that meets the three filtering criteria: (1) product name contains "face mask" (2) at least three ratings (3) under "Health and Household" category.

[47] Specifically, the seller-generated information includes product name, product features, and product description or details. The user-generated information here refers to the consumer reviews. We also use information from customer Q&A, which can either be seller-generated or user-generated information since both sellers and users can respond to a raised question.

[48] Product quality is controlled by the product fixed effects.

decreases in size unambiguously over time. The indirect impact is U-shaped, which first expands in size with more future consumers seeing the review, and then shrinks in size with rising time cost for the review to be seen and thus to affect fewer new consumers. The explanations via direct and indirect mechanisms are then supported by studying the negative impacts (lagged) informative reviews have on product average rating. Our results are not driven by quality difference between Chinese and non-Chinese products, which is potentially controlled by the product fixed effects. We provide further against the quality story by analyzing the informative reviews and collect information on whether it contains any complaint about product quality. Results on total impacts and indirect impacts are very similar using the informative-animus reviews without quality complaints.

The findings in this paper about consumer animus towards China and product average rating on Amazon provides another dimension to look at the impact of the rising animus towards China in the U.S., besides what is recorded in the literature (e.g., Hahm et al., 2021; Lu and Sheng, 2020; Amuedo-Dorantes et al., 2021). The impact might go beyond product average rating to affect the profits (e.g., via price and sales) of Chinese sellers on Amazon with product scarcity being less of a concern over time, and that consumers can more easily switch away from Chinese products. This is supported by literature, where researchers study the impact of reviews on product demand, price, and revenue (e.g., Chevalier and Mayzlin, 2006; Luca, 2016; Cabral and Hortacsu, 2010; Lucking-Reiley et al., 2007). The negative impacts of reviews with animus provides support for platforms of online retailers on screening of reviews, e.g., Amazon removes reviews with offensive language. Our study also bears realistic meanings and can be extended to other political or health events which might increase consumer animus towards products associated with a certain country or region, such as the Russo-Ukrainian War and the following boycott of Russian products.

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Appendix

A Data Appendix

Table A1: Examples of Informative Reviews by Category

Category	Count	Example
Informative-animus	826	They ship from China you know where the virus first broke out
Informative-neutral	243	Reasonable price for standard basic face mask made in China.
Informative with quality complaints	276	Don't buy it, this is poison mask made in China, after using it for couple of minutes it gave me headache, confusion
Informative without quality complaints	793	The masks look good, but are made in China, and the box says Non-Medical!

Table A2: Examples of Informative-Animus Reviews at Each Rating

Rating	Review Title	Review Body
5	comfortable mask, finally	Liked the mask. Disliked the fact that it is made in China!
4	Made in China!?	These masks seem to be working ok. The biggest disappointment was that they were made in China. After the Covid Pandemic, we are very suspicious of ANY items made in China.
3	Straight Outta China	Came straight from a factory in China, not exactly what I was looking for during a pandemic that started there. Seem to be VERY cheaply made.
2	china	they ship from china you know where the virus first broke out
1	Crap	Made in china!!! Nuff said

Table A3: Evidence from Reviews on Why Buying a Chinese Product Despite Animus

Review Title	Review Body
Good product but made in China	… Should have researched the manufacturer more fully. Had I known they were made in China, most likely would not have purchased this.
Made in CHINA	Warning: these come directly from China. Package is written in Chinese. I have thrown them away. Make your own mask; it will be safer.
FYI These are made in China	Sold by a US company, but made in China.
Fast shipping--nice mask	I questioned getting a mask from China, but couldn't find one in the US. …
It’s Just “okay”, here’s why	When I purchased this 2 weeks ago, it had enough good reviews and the fact that there was only few to select from on Amazon hat WASNT made in China. I purchased few. …
Works well for me	I find it troubling that it's so difficult to find masks on Amazon that is not from China. I spent nearly an hour digging into every surgical mask trying to find ones not from China. …

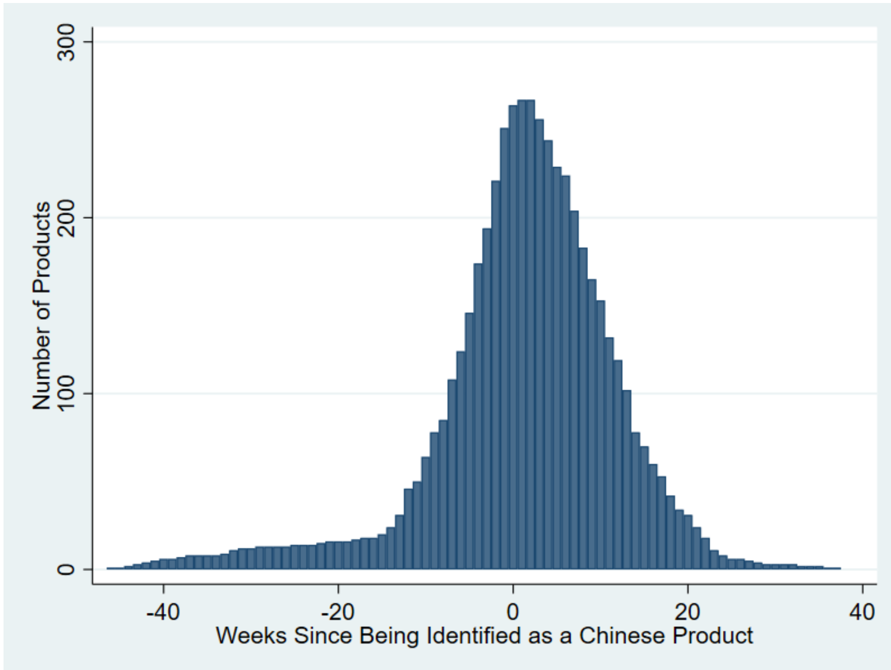

Figure A1: Number of Products by Time Difference k (in Weeks)

B Empirical Appendix

B1 Direct Impact – Ratings of Informative Reviews

The sample is limited within Chinese products that have been identified by the end of research period. Below is the empirical model.

$$Y_{itc} = \alpha + \beta D_{itc} + \beta_X X_{itc} + \theta_i + \theta_t + \varepsilon_{itc}$$

Data is on review level, varying by product i, time t, and review c. The dependent variable is the rating of a review. D is dummy here, denoting either being informative or informative-animus. Other variables bear the same meaning as in the main regression.

Table B1: Ratings of Informative Reviews

	Rating of a Review	
	(1)	(2)
Informative	-1.346***	
	(0.0721)	
Informative-Animus		-1.817***
		(0.0706)
Controls	Yes	Yes
Date	Yes	Yes
ASIN	Yes	Yes
Observations	37,037	37,037
R-squared	0.161	0.169

Note: Standard errors in parentheses, clustered by ASIN, *** p<0.01, ** p<0.05, * p<0.1 The sample is limited to Chinese products that are identified by the end of research period. Controls include price, sales rank, and average rating of a product. In column (1), the dummy denotes whether a review is informative. In column (2), the dummy denotes whether a review is informative-animus.

B2 Direct Impact – Correlation of Product Average Rating Over Time

For this regression, we use the full sample (including products of all country-of-origin, including the unknowns). Below is the empirical model.

$$Y_{it} = \alpha + \beta Y_{it-1} + \beta_X X_{it} + \theta_i + \theta_t + \varepsilon_{it}$$

Data is panel, and varies by product i and time (day) t. The dependent variable is the average rating of product i on day t, and Y_{it-1} is the lag of average rating of product i. Other variables bear the same meaning as in the main regression.

Table B2: Correlation of Product Average Rating by Day

	Average Rating	
	(1)	(2)
Lag Average Rating	0.983***	0.968***
	(0.000645)	(0.00128)
Controls	No	Yes
Date	No	Yes
ASIN	No	Yes
Observations	150,541	150,170
R-squared	0.981	0.981

Note: Standard errors in parentheses, clustered by ASIN, *** p<0.01, ** p<0.05, * p<0.1 The sample includes all products in our data. In column (1), no controls or fixed effects are included. In column (2), price, sales rank, product fixed effect, and date fixed effect is controlled.

B3 Identification of Country-of-Origin and Review-Rating Ratio

For this regression, the sample is limited to products with known country-of-origin. Below is the empirical model.

$$Y_{it} = \alpha + \beta D_{it} + \beta_X X_{it} + \theta_i + \theta_t + \varepsilon_{it}$$

Data is panel, and varies by product i and time (day) t. The dependent variable is the ratio of number of reviews over number of ratings for product in on day t, and D_{it} is the dummy of whether the product's country-of-origin has been ever identified for product i on day t. Other variables bear the same meaning as in the main regression.

Table B3: Review-Rating Ratio and Country-of-Origin Identification

	Review-Rating Ratio	
	(1)	(2)
Whether Identified	-0.0123**	-0.00469
	(0.00484)	(0.0117)
Controls	Yes	Yes
Date	Yes	Yes
ASIN	Yes	Yes
Observations	49,673	20,852
R-squared	0.107	0.132

Note: Standard errors in parentheses, clustered by ASIN, *** p<0.01, ** p<0.05, * p<0.1 Controls include price, sales rank, and average rating. In column (1), only Chinese products are included (identified by the end of the research period). In column (2), products of known country-of-origin besides China are included.

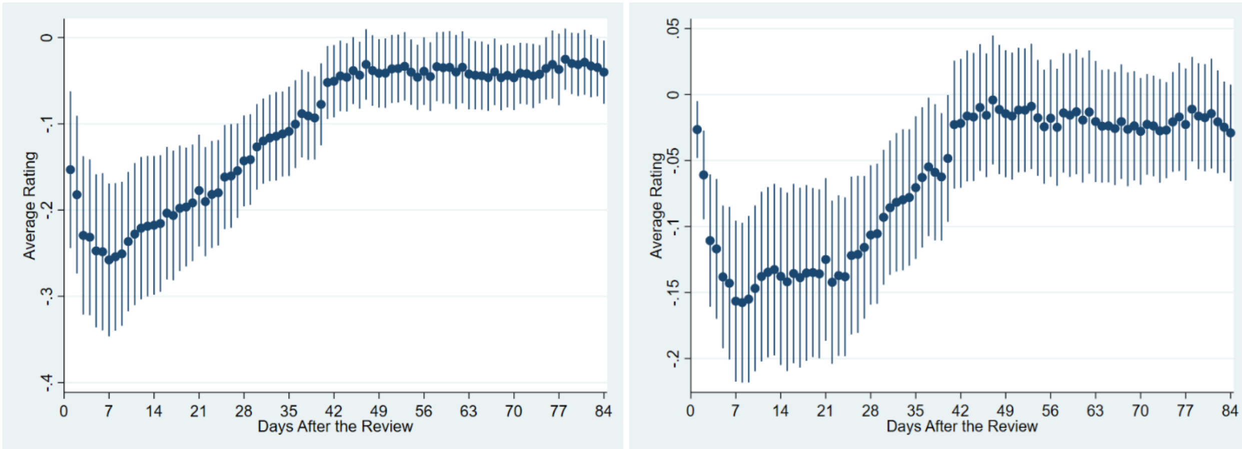

Figure B1: Average Rating and Share of Informative-Animus Reviews

Note: Standard errors clustered by ASIN. Controls include price, sales rank, and lag of share of informative-animus reviews, with the x-axis showing the days for this lag. The right figure further controls for corresponding lag of average rating.

C Amazon Appendix

C1 Reviews Regulation on Amazon

A consumer can leave a comment without buying the product, but such comment will not have the "verified purchase" label, and highly likely will be removed by Amazon (and it needs approval to be displayed in this case). Therefore, most of the reviews/comments are from consumers who actually purchase the product.[49] Note that a product review is different from seller feedback. A consumer can rate a seller or provide seller feedback, but this is available only when a consumer clicks into the seller details. In this paper, we focus on consumer reviews.

Offensive language would be removed by Amazon, and therefore we did not find any reviews with discriminative names for Chinese.[50]

After a consumer orders from a third-party, she can leave a review or ratings within 90 days from the date of order. If a consumer leaves a review before the arrival of the product, it will not have the "verified purchase" label.

For the calculation of average rating of a product, Amazon now uses a machine-learning model instead of simple/unweighted average.[51] This algorithm is not revealed to the public and applies multiple criteria on review authenticity. Amazon does not take into account ratings without "verified purchase" into calculation of product average rating until more details are added (e.g., texts, images, or videos).

[49] Look at an example at Amazon.com: Customer reviews: Black Disposable Face Masks, 100 Pack Black Face Masks 3 Ply Filter Protection. On March 16th, 2022, out of a total of 4844 reviews, 4703 reviews (or 97%) are verified purchases.

[50] For more details on regulations of reviews for Amazon, refer to https://www.amazon.com/gp/help/customer/display.html?nodeId=G5T39MTBJSEVYQWW.

[51] Refer to https://www.amazon.com/gp/help/customer/display.html?nodeId=GQUXAMY73JFRVJHE for Amazon's own explanation.