Covid19 and Consumer Animus Towards Chinese Products: Evidence from Amazon Data*

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Abstract

We tracked all facemasks sold on Amazon from Sep. 2019 to Sep. 2020 and analyzed seller-generated product information as well as user-generated reviews. Using a fully dynamic event study we found the average user rating of a facemask dropped significantly following the first consumer review or question and answer stating it was made in China, but not of other countries. This drop expanded in the first three weeks after the identification of Chinese products but then gradually faded out within twelve weeks. The U-shape post identification is explained by a review's direct (its own rating) and indirect (other consumers' ratings) impact on average rating and is driven by Chinese products with high reputation. By analyzing consumer reviews, we provided strong evidence that the drop in average rating was driven by consumer animus to China and Chinese products rather than product quality or shipping.

Keywords: Consumer Animus, Chinese Products, Amazon

JEL Codes: Z13, L81, D22, J71

* We would like to thank Timothy Bond, Chong Xiang, Victoria Prowse, Miguel Sarzosa, and Farid Farrokhi. We are also thankful for comments from participants at the APPAM Fall Research Conferences, Southern Economic Association Annual Meetings, Midwest Economics Association Annual Meeting, and Northeast Ohio Economics Workshop. This research received the Krannert Doctoral Research Fund (from Purdue University) in 2021. Opinions expressed here are those of the authors and not of any institution.

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I. Introduction

Covid19 has tremendously affected all areas of our lives. As of 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 impact 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 Asian Americans. 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]

In this paper, we studied the animus towards China and Chinese products in online shopping. Unfortunately, online sales are not immune from discrimination. Previous literature has shown 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 (Ahmed and Hammarstedt, 2008), local online retailing websites (Doleac and Stein, 2013), and online carpooling markets (Tjaden et al., 2018).

Since China was the first country 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 Covid19, including the ex-president of

[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.

the United States. On March 16th, 2020, 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 Asians. Hahm et al. (2021) recorded the rise of anti-Asian (including Asian and Asian Americans) discrimination found within the Adult Resilience Experiences Study (CARES). Lu and Sheng (2020) found an immediate rise in anti-Asian animus following the exogenous arrival of first Covid19 case locally, reflected by derogatory racial epithets in Google searches and Twitter posts. Using location data for mobile devices, Huang et al. (2023) found Asian restaurants experienced an 18.4% decrease in consumer traffic compared to non-Asian restaurants; and this decrease was higher in areas with higher levels of support for Donald Trump. On employment, Amuedo-Dorantes et al. (2021) recorded declining entrepreneurship among Asian immigrants compared to non-Hispanic whites after January 2020, and found a substantial increase in exits from self-employment for 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 (and unfamiliar) immigrants (Faulkner et al., 2004).

Social media has further promoted the propagation of this animus. Croucher et al. (2020) studied social media use and found that the more social media users believed that their most-used daily social media are fair/accurate/giving facts, the more likely that they believed Chinese pose a threat to U.S. He et al. (2021) analyzed anti-Asian hate speech on Twitter, and found 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 Arabs/Muslims post-9/11 (Kaushal et al., 2007); Germans post-WWI (Ferrara and Fishback, 2020), Asians/Arabs post-7/7 attack (Hanes and Machin, 2014); and Muslims post-Jihadi attacks (Ivandic et al., 2019).[4]

After Covid19, consumers might hold animus towards China and Chinese products, either out of prejudice (e.g., blaming China for the outbreak of Covid19) or health concerns (e.g., worrying that Chinese products might carry the virus, which risk is low according to Centers for Disease Control and Prevention).[5] In this paper, we investigate how animus towards China affects Chinese products, specifically facemasks. To that end, we compiled data covering all facemasks sold on Amazon between September 1, 2019, to September 7, 2020, including all consumer reviews. We collected information on the country-of-origin of a product from both seller-generated (e.g., product name, description, feature) and buyer-generated (e.g., reviews and customer Q&A) information. Our paper does not distinguish between animus towards Chinese products/China and animus towards Chinese citizens/Asian Americans. Amazon has the regulatory policy against hate speech on racism, and we did not find any comments directly expressing racism against Chinese in our data (e.g., use of racial slurs against Chinese).[6] However, it is possible that a consumer leaves a negative comment for a Chinese product out of racism, and there is evidence that the attitude towards Asian Americans post Covid19 extended towards Chinese restaurants (Huang et al., 2023).

[4] On July 7, 2005, there was a serious of suicide bombs attacks on London's public transport system.
[5] Refer at CDC: https://www.cdc.gov/coronavirus/2019-ncov/more/science-and-research/surface-transmission.html.
[6] Amazon has the regulatory policy against hate speech. On their website, it is clearly stated that "You are not allowed to express hatred for people based on characteristics like race, ethnicity, nationality, …" We also search in our data using racial slurs against Chinese and find no such cases. For regulations on Amazon's policy against racism and consequences of violations, see Appendix E.

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 applied the fully dynamic event study design as suggested by Borusyak and Xavier (2017). Under this design, we found that, despite no change in quality, the average rating of a product drops once being identified as made in China. This negative impact is U-shaped, which quickly expands in the first three weeks, and gradually fades out within twelve weeks. By further splitting Chinese product into high and low reputation, we found that the U-shape in product average rating is driven by the high reputation ones. We did not find similar pattern among products made in the U.S. or any other countries.

The negative impact of the informative reviews can be explained by the direct (via their own ratings) and indirect (via ratings given by other future consumers) mechanism. The direct impact persists over time 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 seeing and getting affected by the review (due to a rising time cost) as well as the shifting away of more hostile consumers from revealed Chinese products. The explanations via direct and indirect mechanisms are then supported by studying the negative impacts (lagged) informative reviews have on product average ratings. 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 collecting information on whether it contains any complaint about product quality. Results are very similar using informative reviews without quality complaints.

II. Data

II.A. Data Introduction

Amazon is the largest online retailer. In 2021, it is estimated to account for 41% of the total retail ecommerce sales in the U.S., followed by Walmart Inc. (6.6%), eBay (4.2%), and Apple (4.0%).[7] Unlike eBay, Amazon does not have a character limit on its reviews, which promotes the richness of information expressed in the consumer reviews.[8] We therefore choose Amazon as the online platform to study, and collected data from both from Keepa.com and directly from Amazon.

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, price, sales rank, total number of customer ratings, average rating, ASIN, seller information, first day the product is listed, etc.[9] 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). This level of precision gives us the confidence that the product is identical over time under the same ASIN.[10] In this paper, ASIN and product are used interchangeably. One highlight of Keepa.com is that it tracks products (identified by the same ASIN) over time and provides high-frequency data.[11]

[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] 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.

[10] 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.

[11] Most products' information is updated several times daily (see https://keepa.com/#!faq).

We aggregate data on a daily/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 about delisted products. Once a product gets delisted from Amazon, Keepa.com will remove its data within two weeks. In our sample, data selection due to removal is not a big problem – we tracked 1630 face masks that were listed on Amazon on September 18, 2020, and found that only 129 (or 7.91%) of them got delisted by August 15, 2021.[12]

To better study customer animus towards Chinese products, we focus on the facemask, a product that might be sensitive to many customers post-Covid19. We restricted our sample to products listed on Amazon that meet 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.[13] The number of products retained in the final sample comes down to 1400.

Review Information. Keepa.com does not provide data on customer review details. We therefore manually collected all review data that is 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.[14] For each

[12] We do not expect that many Chinese products gave up their old ASINs after being identified and then re-register under a different ASIN. With the shortage (especially right after the breakout of Covid19) in 2020, we expect even a smaller share of face masks (than 7.91%) dropped out in our sample period. With the shortage in facemasks and price-gouging (Cabral and Xu, 2021), Chinese sellers might be reluctant to de-list and re-list for the following reasons: (1) With a new ASIN, they cannot link their old consumer reviews. Despite that they could now hide their Chinese identity, consumers might hesitate to buy a newly listed product with no reviews. Using data from Taobao.com, Zhao et al. (2019) find review volume to be an important determinant of products sales. (2) It takes time and effort to go through the de-listing and re-listing process, which incurs cost and potential sales loss during the time the product is de-listed. (3) With severe shortage, consumers are limited in choices to switch away from an identified product (e.g., sample reviews listed in Appendix Table A.7), and this further lowers the incentive for sellers to de-list and re-list.

[13] Typical examples of such products include face mask straps, face mask filters, and ear savers for face mask.

[14] 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.

product, we also collect information on top (positive or critical) reviews.[15] For details on Amazon's regulation of consumer reviews, see Appendix E.

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 still in operation dates back to July 18, 2011. We restrict our research period from September 1, 2019, to September 7, 2020, for ease of comparison pre and post the shock of Covid19 and for consistency of Amazon policy.[16] In the final sample, we have 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. Appendix Figure A.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, with the number peaking on June 8, 2020, and decreasing after that.

II.B. Data Treatment

Identify Chinese Products. Amazon does not require sellers to reveal the countries-of-origin for products. We therefore collect information on a product's revealed origin country from several sources, including product name, product description, consumer reviews, and customer question and answer (Q&A).[17] All the information we use is also available to real customers.[18]

[15] For most of the products in our data, Amazon listed the top positive and top critical reviews.

[16] Our choice of study period covers the time pre and post the breakout of Covid19. According to the World Health Organization (WHO), its Country Office located in China first notified the International Health Regulations about the reported cases of "viral pneumonia" in Wuhan on December 31, 2019 (https://www.who.int/news/item/29-06-2020-covidtimeline). 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.

[17] Some products might have product details or product features instead of product description.

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

We first analyze the seller-generated contents (product name and description) and collect information on whether a product is made in China. If a product is identified in this way, we classify the product as self-identified Chinese product and there is no change in the revealed origin country of the product over time. We then analyze the user-generated contents (the texts of reviews, including review headline and body) and pick out all reviews that mention China.[19] Within these reviews, we manually go through them and collect information on whether a review actually identifies the product as made in China.[20] 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 and date that a product is first credibly revealed as Chinese.[21] 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.[22]

Combining all the information sources above, we can identify 386 products to be made in China out of 1400 face masks as of September 7, 2021. Among the Chinese face masks, only 24 products are self-identified, with the rest of 93.8% 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

[19] Specifically, we picked out all reviews that mention China or Chinese, in upper or lower case. We also tried racial slurs against 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 almost all of the cases, the use of China/Chinese is adequate to identify Chinese products.

[20] 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."

[21] 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 consumer 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)".

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

trying to look 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.

Fake Reviews. Amazon has regulatory rules to ensure genuine consumer-post reviews (see Appendix E). The reviews will be checked both automatically and by humans before being posted and viewed by other consumers. Amazon also attach "Verified Purchase" labels if the reviewer "bought or used the item on Amazon and paid a price available to most Amazon shoppers". Amazon does not include a consumer's rating into the calculation of the product's overall rating without "Verified Purchase" until "a customer adds more details in the form of text, image, or video". To get around the potential problems of fake reviews (e.g., from competitors), we manually checked the comments in our database. To mimic the response of real consumers, for fake reviews found in data, we do not count them into the identification of Chinese products. It is possible that some competitors might leave a well-disguised review stating that a product is made in China but was not detected as fake reviews by us. However, this will not discount our results since a real consumer would not know the review is fake either. If a consumer leaves a low rating because he/she believes in a fake review to identify a product as made in China, that also counts as consumer animus towards China/Chinese products for us. Essentially, it is not about whether a product is actually made in China, but whether a product is identified and considered by consumers to be made in China.[23]

Types of Reviews. We analyze the review content and divide reviews into three categories based on the information provided and attitudes expressed towards China or Chinese products: non-

[23] There could be products that are not made in China but identified in comments as Chinese, as well as products that are actually made in China but never identified. If anything, the existence of such cases just made our argument on consumer animus stronger.

informative, informative-neutral, and informative-animus.[24] 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.[25] 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 A.1 in Appendix for examples of each type of informative reviews. Despite the small number of informative reviews, their impact could be much larger since they catch more attention from other customers reflected by a higher number of helpful votes.[27] In our sample, a review gets 2.58 helpful votes on average, compared to 5.84 votes for an informative review (separately, 4.28 for informative-neutral reviews and 6.30 for informative-animus).

Figure 1 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,

[24] 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?

[25] We further use machine learning to check our decision on expression of animus. On average, the computer's decisions match with our manual decisions in 83.9% of the trials, which shows the robustness of our manual tags. We provide more explanations on the steps of machine learning in the Appendix D.

[26] An example of non-informative review that mentions China/Chinese is: "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.

50.04% of consumers give a 5-star rating while only 20.36% give a 1-star rating. This pattern is reversed for informative reviews, where 56.22% give a 1-star rating and only 12.07% give a 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 A.2 in the Appendix shows some examples of informative-animus reviews from consumers at each rating. The rising animus towards China/Chinese products is related to the breakout of Covid19. In Appendix Figure A.2, A.3, and A.4, we provide more evidence on the clear rise in informative/informative-animus reviews (both in number and share), and in the share of products identified as made in China. In our sample, there is no review that specifically identifies a product to be made in China before the breakout of Covid19.

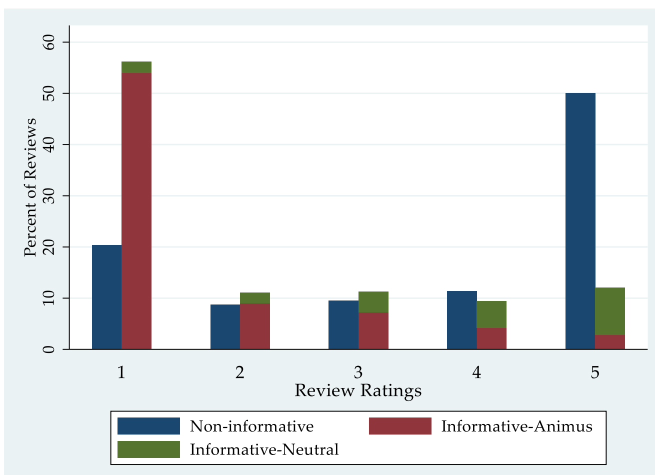

FIGURE 1. RATING DISTRIBUTION OF CHINESE PRODUCTS BY REVIEW CATEGORY

Notes: 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.

Other Countries of Origin. We apply similar analysis for other countries to collect information on products' countries-of-origin – first search the country names and then manually analyze the reviews and customer Q&A to correct misinformation.[28] At the end of our research period, 60.50% of the products' countries-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 USA). 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. In 2020, U.S. imported a total value of $19.6 billion on face and eye protection, with $16.6 billion (or 84.4%) imported from China.[29] It is possible that not all Chinese products in our sample are identified by the consumers by the end of the research period. This does not affect our results since what matters is not whether a product is actually made in China, but rather whether a product is perceived by consumers to be made in China.[30] See Appendix Figure A.5 for country-of-origin distribution in our sample.

II.C. Summary Statistics on Chinese Products

Table 1 below compares the products from China (pre- and post-revelation, separately) and other countries (including the unknown ones). Column 1 uses all Chinese products before they are revealed; Column 2 uses all Chinese products after they are revealed; and Column 3 uses the whole sample periods for the products that are never revealed to be made in China in the research period. On average, the Chinese products have more sales, receive a larger number of ratings, and are in

[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 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 countries-of-origin.

[29] Data from the World bank, see United States Face and eye protection (630790) imports by country | 2020 | Data.

[30] We use the same information available to real consumers, and if we cannot identify a product to be made in China, neither will a real (potential) consumer. If anything, the existence of never identified Chinese products would only make our results more robust, since the empirical studies below would use these never identified Chinese products in the comparison group.

business for a longer time than the non-Chinese ones. Before revelation, the Chinese products receive similar average rating as the non-Chinese ones, but post-revelation, the Chinese products receive lower ratings on average. There is no evidence that Chinese products charge lower prices than the non-Chinese ones, and on average, prices of Chinese product are even higher post- than pre-revelation. This can be explained by price stickiness and product scarcity (which varies over time). Raw prices are contaminated by the common time trend, and the empirical results in the next section provide better comparison with the inclusion of time fixed effects.

TABLE 1. SUMMARY STATISTICS (MEAN ONLY)

	Chinese		Non-Chinese
	Not-yet-revealed	Revealed	
Price	19.13	20.57	18.21
Average Rating	4.06	3.81	4.03
Rescaled Sales Rank	54.77	52.77	48.14
Number of Rating	38.43	202.63	37.61
Days in Business	293.11	192.14	104.28
Observations (by ASIN-Day)	18,190	31,483	101,891
Unique ASIN count	386		1014

Notes: The first column is calculated using the Chinese products while they are not-yet-revealed. The second column is calculated using the Chinese products after they are already revealed. The third column is calculated using the whole sample period (September 1, 2019 to September 7, 2020) among all products not revealed to be made in China by the end of the research period. 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.

III. Event Study

III.A. Empirical Model

In this section, we perform an 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.

$$(1) \qquad Y_{it} = \alpha + \sum_{k=-\infty}^{\infty} \beta_k Treat_{ik} + \beta_X X_{it} + \theta_i + \theta_t + \varepsilon_{it}$$

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 on 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.[31] θ_i is product fixed effect, which absorbs potential quality difference across products.[32] 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 fully dynamic event study design provides good exogenous variation under the assumption that conditional on time and

[31] Both controls take natural 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.

[32] 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.

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.[33]

III.B. Empirical Results

***Main Result of Event Study*.** Results of the event study are shown in Figure 2, where we combine product identification information from both consumer reviews and customer Q&A.[34] For pre-trend, there is no statistically significant pre-trend. However, once a product is identified as made in China, the average rating declines. This drop quickly expands in the first three weeks and then gradually fades out in twelve weeks. Note that despite that we only show results within 30 weeks before and 20 weeks after identification, in all realizations of regression (1) we use all periods as stressed by Borusyak and Jaravel (2017) to make the design fully dynamic.[35] See Figure A.6 in Appendix for the full graph. We suppressed results in the first and last several relative weeks due to the small number of treated products in these periods (e.g., for relative time before week -36 and after week 29, there are fewer than ten treated products). Appendix Figure A.7 shows the count of treated products for each relative week k. The estimate for week one is less precious since the first week contains a mixture of "will-be" and "just" treated Chinese products when we collapse data into weeks.[36]

[33] The inclusion of the time fixed effect and the use of the non-China products as comparison group can take care of potential changes in the general pool of consumers over time.

[34] We apply the eventdd code in STATA, as instructed by Clarke and Tapia-Schythe (2021).

[35] In total, there are 46 leads and 37 lags.

[36] To be specific, weeks are collapsed relative to the September 1st, 2019, the start time of the sample. The time in week is therefore "absolute time" that can reflect actual time, and therefore the inclusion of time fixed effect can account for time-varying information such as product scarcity. To be consistent, the "weeks since being identified as a Chinese product" is also measured using the difference between "absolute time" and the week being first identified then plus one. Therefore, the "first week" will be collapsed within a mixture of will-be-treated and just-treated days. E.g., if a product is identified as Chinese in the sixth day of week N, then week N is the first week for identification. However, the average rating (as well as prices and sales rank) in first week contains information of both the will-be-treated (day one to five of the week) and just-treated (day six and seven of the week) days.

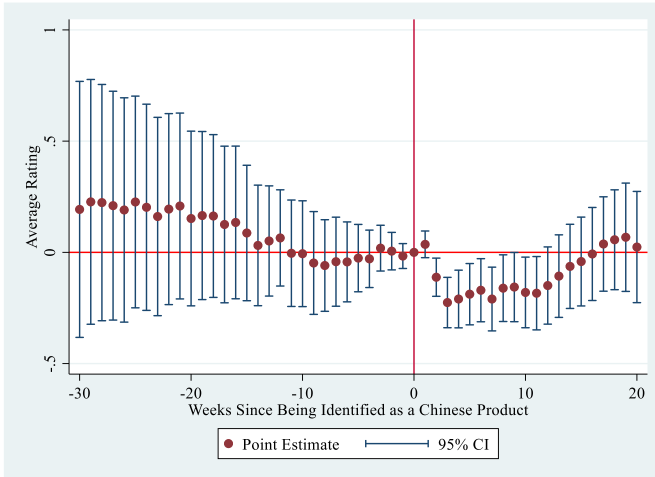

FIGURE 2. EVENT STUDY FOR CHINESE PRODUCTS

Notes: Fully dynamic event study for Chinese products, where time is measured relative to the first time a product is ever identified to be made in China (by week). The sample contains 20,054 observations (by week-ASIN).

The result provides evidence for consumer animus towards Chinese products. The average rating first drops and slowly recovers since the informative reviews affect 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 1, most of the informative reviews are informative-animus and give low ratings, which directly lowers the average rating of a product. The direct impact decreases over time unambiguously.[37] The indirect mechanism refers to the impact of a review on the average rating through ratings given by other (future) customers. Since in the first several weeks, a growing number of future consumers see an existing informative review over time, the indirect impact of the review will increase at first. However, with the arrival of new reviews, after several weeks consumers will be less likely to see an existing informative review due to higher time cost going back to more outdated reviews. Moreover, potential change in the consumer pool for Chinese products could also contribute to the rebound. The inclusion of the

[37] However, we cannot precisely 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. See Appendix E for more details.

(absolute) time fixed effects could take care of the general change in the supply side (e.g., product scarcity) or demand side (e.g., consumer pool). However, if more animus consumers switch away from already-revealed Chinese products when they have more choices (e.g., in later periods with less severe product scarcity), the remaining consumers might be less sensitive on the country-of-origin, and this could also contribute to the rebound in average rating. The indirect impact therefore first expands over time and then decreases. In Appendix Figure A.8, we show the share of reviews that discuss the country-of-origin (all countries, including US, China, and other foreign countries) and that only mentioning China by week. We can see constant attention on country-of-origin since the breakout of Covid19, and this lasts till the end of our research period. The attention on country-of-origin concentrates on China/Chinese products. Combining the direct and indirect impact, we therefore see a U-shaped total impact. In the next section, we will provide more explanations of the direct and indirect impacts of the informative reviews, and more discussion to distinguish our results from a product quality story.

Throughout our analysis, we always control prices besides the study where we use price as the dependent variable. This is important since prices might affect ratings through shaping consumers' expectations. Li and Hitt (2010) find that consumer reviews may reflect the difference between quality and price (perceived value). Gan et al. (2017) study the star ratings using online restaurant reviews, and find the difference in star ratings significantly explained by consumers' sentiments in five attributes including price. Carnehl et al. (2024) also discuss the strategic pricing and its direct and indirect impact price on reviews – higher prices could worsen reviews by reducing the value of money but could also improve reviews by only attracting consumers with a strong taste for the product. In our sample, we find a negative but not significant correlation between prices and ratings (Appendix Table A.3). To get around potential over-controlling problems since price itself might respond upon identification, we run a robustness check when prices are not controlled. Results are in Appendix Figure A.9. Our results are robust to the exclusion of prices from controls.

We did not find any evidence that the ratings themselves dropped before a product was identified to be made in China. In Figure 2, there is no decreasing pre-trend in average rating before the identification. We also look at negative reviews about a product in the following empirical studies, and there is no evidence of rising/higher share of one-star reviews before a product is identified to be made in China. In Appendix Figure A.10, we show the difference in the average rating using the not-yet-revealed Chinese products subtracting the non-China products. There is no pattern of decreasing average rating if a Chinese face mask's identity is not revealed (compared to non-China products). There is also evidence from consumers reviews that they are not aware of the product is made in China before they buy it. We list three consumer reviews as examples in Appendix Table A.4. The switching away of consumers would only attenuate our results. These consumers hold the strongest animus towards China since they are the ones who would rather pay the extra cost in searching than to buy an already-revealed Chinese face mask. The drop in average rating would be even larger without the switching away of these consumers with the strongest animus.

If there are time-specific factors that only affects the Chinese products (e.g., on the supply side), this cannot be captured by the time fixed effects. The use of the comparison group could alleviate the concern since the "non-China" products in the comparison group might contain products that are made in China but never revealed by consumers in our sample period. In 2020, data from World Bank shows that 84.4% of the face and eye protection import in U.S. was from China. In our sample, 60.5% of face masks remain to have unknown country-of-origin by the end of the research period, and we would expect that some products with "unknown" sources are actually made in China. We find evidence of rising animus towards China and Chinese products after the breakout of Covid19, and consumers also pay more attention to the origin country of products on whether it is made in China. Appendix Figure A.3 shows no consumer comments targeting products with Chinese origin before the breakout of Covid-19. After the breakout of Covid19, on average, the share of informative and informative-animus reviews is higher, with no clear pattern of clustering. Appendix Figure A.8 also shows constant attention on all country-of-origin post Covid-19, which lasts till the end of our research period, and the attention on country-of-origin concentrates on China/Chinese products. For more evidence on treatment timing, we show the distribution (by week) of number of products first-time identified as made in China as well as the cumulative number of Chinese products identified, combining information from both consumer comments and customer Q&A (Appendix Figure A.11). The incidence of identification is spread over time (since the breakout of Covid19), with a rising total number of already identified Chinese products over time. In Appendix Figure A.12, we show the share of newly identified Chinese products over the total number of all products in our sample (by week). There is constant identification of Chinese products over time even by the end of our research period. Both figures show evidence on constant attention and animus towards China post Covid19. We do not observe Chinese products being identified altogether (e.g., clustering at a single week) but rather that more and more Chinese products are identified over time, with variation in timing of identification. This might relate to the frequent (new) events related to Covid-19 in our sample period that constantly remind consumers of the virus and of China.[38]

Quality. It is unlikely that this pattern is driven by difference between the product quality of Chinese products compared to others. First, ASIN is very narrowly defined, which ensures the precise tracking of the same face mask, and the product fixed effect will absorb any quality

[38] The Centers for Disease Control and Prevention provides a list of the timeline and events for Covid-19, see https://www.cdc.gov/museum/timeline/covid19.html.

difference between products. Second, the actual quality of a product does not change upon the time point that it is first identified as Chinese. Third, as shown in Appendix Table A.1, 74.2% of the informative reviews are not about (perceived) quality.[39] We also replicate our analysis using fully-dynamic event study but now the first-time identification are limited to reviews which identified products to be made in China but contained no complaints about product quality. Results are shown in Figure 3. Once a product is found by consumers to be made in China (without any complaints on quality), its average rating drops but the negative impact gradually fades out within 8 weeks post identification. The pattern is similar to the main result in Figure 2, showing that our main findings are not driven by lower (perceived) quality.

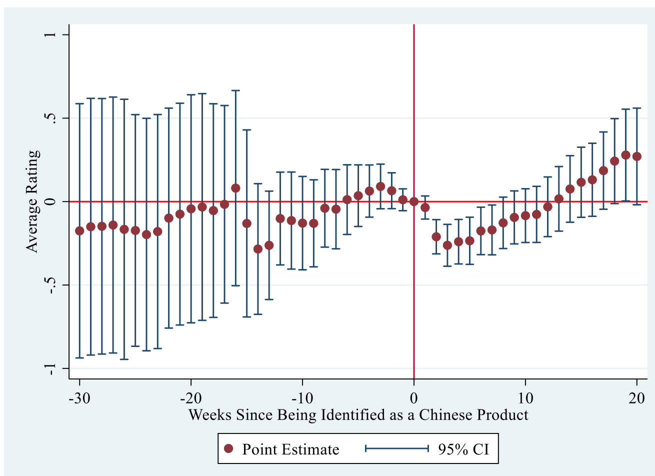

FIGURE 3: EVENT STUDY FOR CHINESE PRODUCTS (NO QUALITY COMPLAINT)

Notes: Fully dynamic event study for Chinese products, where time is measured relative to the first time a product is ever identified to be made in China (by week). The identification of being made in China contains no complaint on the quality of the product. The sample contains 20,054 observations (by week-ASIN).

Since shipping time is not included in "quality", one might worry the impact of (potentially longer) shipping time for Chinese products on ratings. On Amazon, consumers can see the

[39] In our data, these complaints on quality typically include: flimsy/thin, unpleasant smell, break easily, cheap materials, uncomfortable, strings too short, cannot breathe normally, badly stitched, poorly made, loose ear bands, no filter, poorly glued, shrink after wash, do not fit, no adjustable strap, filters do not work, fabric is heavy, skin irritating, single layer, package broke, and color faded.

estimated shipping time before the payment is completed (e.g., on the product page, in the cart, and at checkout), so they have the idea of the estimated shipping time before the product arrives. However, it is possible that consumers still give low ratings for shipping because (1) they ignore the estimated shipping time given on Amazon; (2) the actual shipping time might be longer than estimated; and (3) they still complain about the shipping time despite knowing that it will be long beforehand. To show that our results are not driven by shipping time, we also collect information on whether an informative review contains any complaint about shipping. In our sample, only 12.07% of the informative reviews (129 reviews out of 1069) discussed shipping, and only 7.11% of them (76 reviews) complained about the shipping time of the product. There are 53 reviews (4.96%) informative reviews discussing shipping with no complaint about the shipping time of that product (sample reviews listed in Appendix Table A.5). We then replicate our main results further excluding complaints about quality or shipping, and results in Appendix Figure A.13. Our results are robust, but the negative impact fades out (insignificant at 5%) starting from week 8 after the first identification.

Heterogenous Impacts across Subgroups**.** We then study the heterogenous impacts of consumer animus across high and low reputation Chinese products. Based on the average residual ratings before identification, we divide Chinese products into high- and low-reputation groups.[40] Results are shown in Figure 4 and 5. The drop in average rating among all Chinese products are driven by those of higher reputation. Before identification, if anything, Chinese products with high

[40] To absorb the time-varying factors (e.g., general supply and demand shocks), we use the residual rating with time fixed effects. Each week-ASIN observation is assigned either high (above median) or low (below median) in reputation based on the residual rating, which generates a dummy which equals to one for high and 0 for low. Since we apply a fully-dynamic event study, the same product should be consistently assigned to the high/low group throughout the sample period. We therefore collapse the dummy by ASIN, and rank the products based on this value. Products in the top quartile are the high-reputation group, and products in the bottom quartile are the low-reputation group. Products in the second and third quartile show mixed evidence on reputation (e.g., a product with a value of 0.5 means that compared with all other products sold in the same week, half of the times it receives a higher average rating than median, and half of the times it receives a lower average rating than median, and this would be hard for us to consistently put it into a high/low reputation group).

reputation have an increasing trend in average rating, but this trend is no longer significant starting from week -7 prior to identification. The significant result for week -30 does not carry much information since it only has 2 Chinese products (compared to 118 Chinese products in week 0). Once identified, there is a significant drop in average rating, peaking at week 5 post identification. The negative impact persists over time and is still significant at 5% in week 19. The low-reputation Chinese products, however, do not suffer from identification. There were not any significant leads nor lags. Similar as above, results at both ends of the relative time have fewer products and are suppressed.[41]

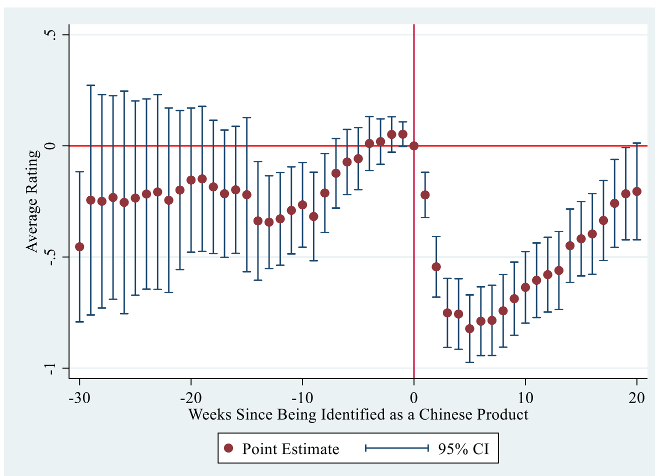

FIGURE 4. EVENT STUDY FOR CHINESE PRODUCTS – HIGH REPUTATION

Notes: Fully dynamic event study for Chinese products, where time is measured relative to the first time a product is ever identified to be made in China (by week). Chinese products are divided into high-reputation and low-reputation ones depending on their average residual ratings (with time fixed effects) in the pre-treatment (prior revelation) periods. The sample contains 4,985 observations (by week-ASIN).

[41] Specifically, for the high-reputation group, weeks before -13 and after 22 have fewer than 10 treated products. For the low-reputation group, weeks before -12 and after 18 have fewer than 10 treated products.

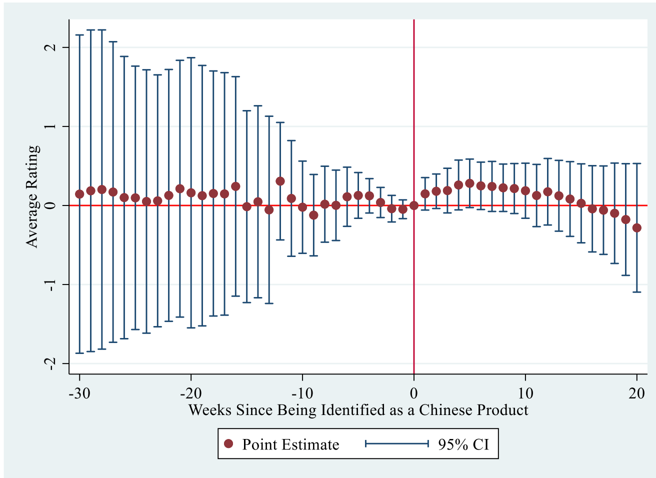

FIGURE 5. EVENT STUDY FOR CHINESE PRODUCTS – LOW REPUTATION

Notes: Fully dynamic event study for Chinese products, where time is measured relative to the first time a product is ever identified to be made in China (by week). Chinese products are divided into high-reputation and low-reputation ones depending on their average residual ratings (with time fixed effects) in the pre-treatment (prior revelation) periods. The sample contains 4,985 observations (by week-ASIN).

Placebo Using Other Countries. To show that the animus is specific to China and not more generally for foreign products, we further collect the information on whether a product is identified to be not made in the U.S. As placebo, we then perform the same event study among, respectively, all products which are identified to be foreign (Figure 6), all products which are identified as foreign and their countries-of-origin are specified (Figure 7), and all products that are confirmed in the reviews as made in the U.S. (Figure 8). There is no similar pattern of a drop in average rating for other foreign products as we observe for the Chinese ones. There is no consistent evidence of a rise in rating once a product is confirmed to be made in the U.S either. The placebo result further supports our interpretation that consumers hold animus towards China and Chinese products. Note that the sample size is smaller for products with known country-of-origin but not made in China - only 10.14% products are U.S. and less than 3.93% of the products have other specified countries-of-origin (besides China and U.S.), compared to 25.43% products made in China. The leads and lags are therefore shorter with the smaller sample size.[42]

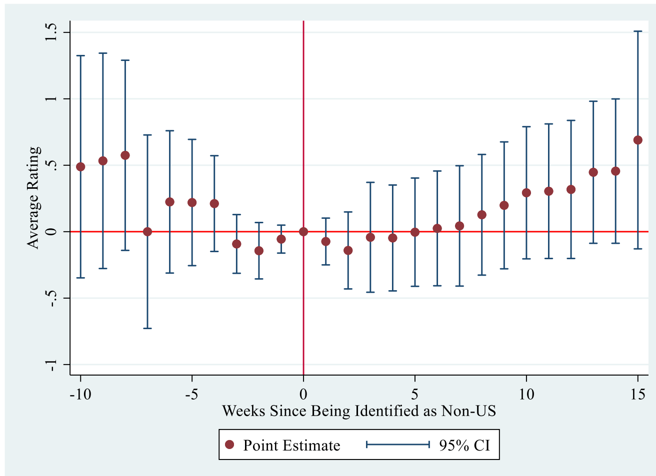

FIGURE 6. PLACEBO EVENT STUDY OF ALL NON-US PRODUCTS BESIDES CHINA

Notes: Products that are identified as not made in the U.S., including those with country-of-origin not specified. The sample contains 13,822 observations (by week-ASIN).

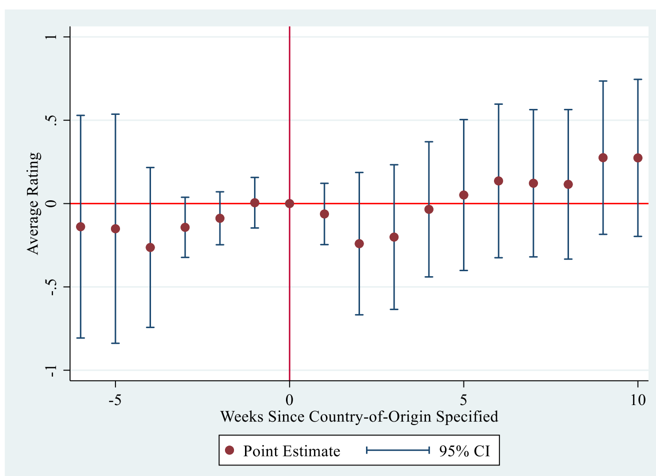

FIGURE 7. PLACEBO EVENT STUDY OF ALL NON-US PRODUCTS BESIDES CHINA (COUNTRY SPECIFIED)

Notes: Products that are identified with a specific country-of-origin that is foreign but not China. The sample contains 13,397 observations (by week-ASIN).

[42] For all other foreign products, weeks before -7 and after 14 have less than 5 products. For other foreign countries with their country-of-origin specified, weeks before -3 and after 10 have less than 5 products. For confirmed U.S. products, weeks before -15 and after 22 have fewer than 5 products.

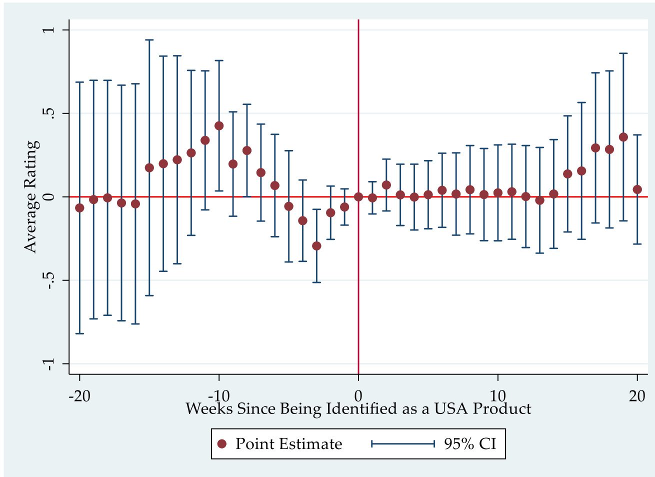

FIGURE 8. PLACEBO EVENT STUDY USING CONFIRMED U.S. PRODUCTS

Notes: 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 countries-of-origin in the reviews. The sample contains 15,625 observations (by week-ASIN).

Robustness Checks. We carry out three robustness exercises. First, we only use consumer reviews in identifying the time that a product is first identified as made in China. Results are in Figure 9. The pattern is similar to our main result, with a drop in average rating right after a product being identified as Chinese for the first time, and this negative impact fades out within nine weeks. There is no significant pre-trend before identification. Note that the decreasing pattern starting from week 4 is clearer here than in Figure 2, since the indirect impact through the higher cost of seeing dated information works better for consumer reviews than customer Q&A.[43] On Amazon, the customer Q&A could be answered both by consumers and by sellers, while reviews feature consumer-only information. Not all products provide a customer Q&A part on Amazon.[44]

For the second robustness check, we use the cumulative share of 1-star rating reviews as the dependent variable. Results are in Figure 10. There is no clear pattern before identification, but upon treatment, there is a significant rise in the cumulative shares of 1-star rating reviews, which

[43] The Q&A session is typically way shorter than all consumer reviews, and therefore information in Q&A is less likely to have a constantly increasing searching cost over time as the consumer reviews (where an old review is harder to find with the arrival of new reviews).

[44] We checked in Jan 2021 on the Q&A, and 34.8% of the products did not have the Q&A part.

decreases very slowly over time. Starting from week 14, the impact is no longer significant. This further supports our explanation that upon being found to be made in China, there is an increase in low-rating reviews due to animus from consumers towards China/Chinese products.

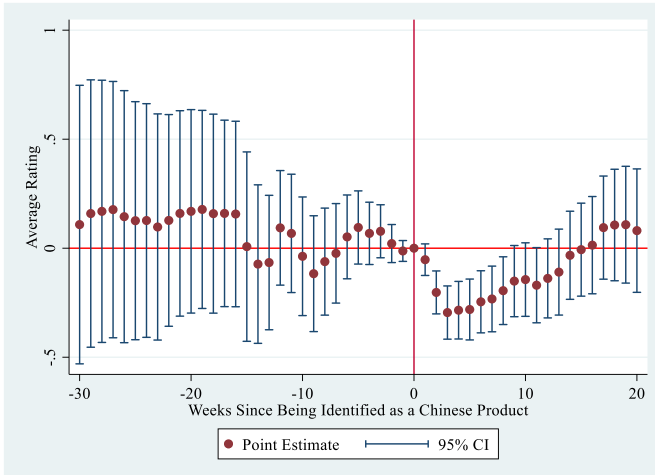

FIGURE 9. EVENT STUDY FOR CHINESE PRODUCTS – CONSUMER REVIEWS ONLY

Notes: Fully dynamic event study for Chinese products, where time is measured relative to the first time a product is ever identified to be made in China (by week) in the consumer reviews. The sample contains 18,197 observations (by week-ASIN).

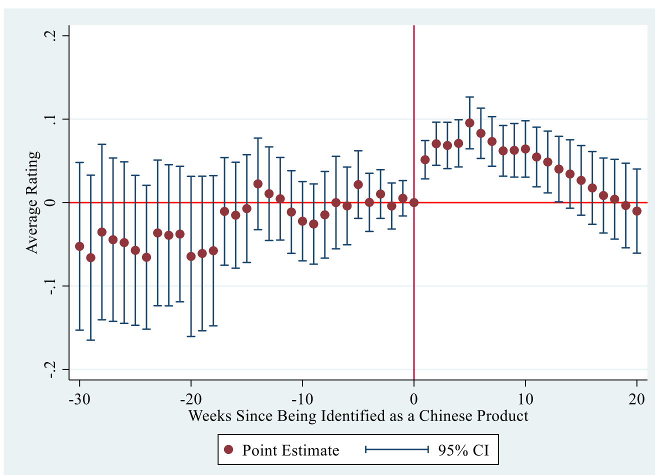

FIGURE 10. DEPENDENT VARIABLE USING CUMULATIVE SHARE OF 1-STAR REVIEWS

Notes: Fully dynamic event study for Chinese products, where time is measured relative to the first time a product is ever identified to be made in China (by week). The dependent variable is the cumulative share of one-star ratings. The sample contains 20,068 observations (by week-ASIN).

For the third robustness check, to show that our results are not driven by a general animus towards all foreign countries, we replicate our main analysis in Figure 2 but now replace the comparison group as the non-US products that are not made in China, including those foreign products with unspecified country-of-origin.[45] In Figure 11, we find a similar drop as in Figure 2, but the impact fades out faster (not significant since week 6) than using all other products as the comparison group (not significant since week 12). This might relate to the smaller sample size used in Figure 11 than in Figure 2.[46] This provides strong evidence that consumers hold animus specifically for China/Chinese products, and our results are not driven by the general animus towards all non-US products. In Appendix Table A.6, we also list some consumer reviews where their preference of products made in other foreign countries over China is clearly stated.

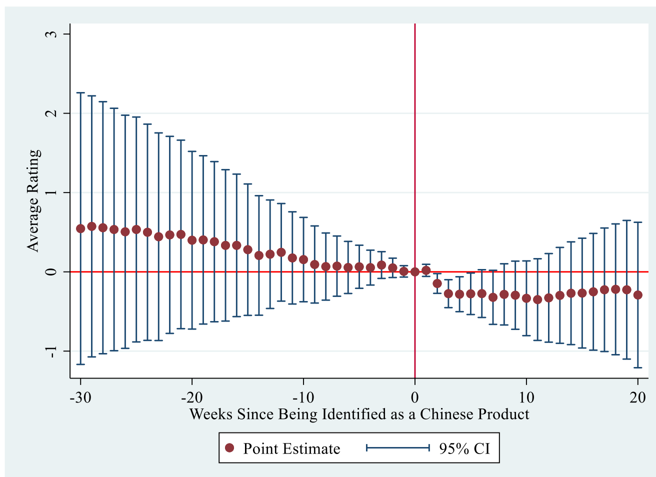

FIGURE 11. EVENT STUDY FOR CHINESE PRODUCTS (COMPARISON GROUP NON-US)

Notes: Fully dynamic event study for Chinese products, where time is measured relative to the first time a product is ever identified to be made in China (by week). Here we limit the comparison group to products which are identified to be non-US, but are not identified to be made in China, including those foreign products with unspecified country-of-origin. The sample contains 7,635 observations (by week-ASIN).

Event Study on Price. We carry out the same analysis on price. The dependent variable is now the natural log of price, and controls are now average rating and sales.[47] Product and time fixed effects are included as in the main analysis. As shown in Figure 12, there is no consistent pre-trend in price for Chinese products relative to other countries-of-origin before identification. If anything,

[45] We find only 571 comments mentioned the products to be non-US, and 82.3% of them (470 comments) also specify the foreign country, with 389 comments also identify the products to be made in China.

[46] The sample for Figure 11 contains 7,635 observations while Figure 2 uses 20,054 observations, with 7073 observations for Chinese products in both regressions.

[47] If we exclude average rating in the control variables, the pattern will be similar. Results are suppressed here to save space.

week -6 shows a significant positive result. After identification, however, there is a drop in price, which fades out starting from week 9. The drop in price, however, is not large – at week 8, the relative price Chinese sellers charge (over comparable products made in other countries) is only 6.15% lower compared to the week right before the Chinese identify of the products are revealed.[48]

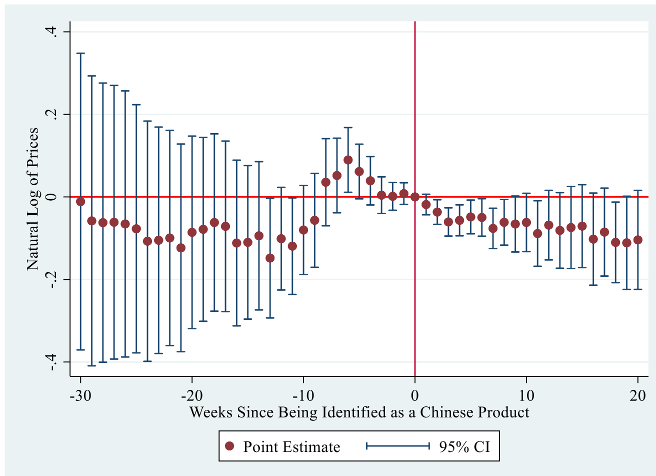

FIGURE 12. EVENT STUDY FOR CHINESE PRODUCTS – DEPENDENT VARIABLE USING LOG OF PRICE

Notes: Fully dynamic event study for Chinese products, where time is measured relative to the first time a product is ever identified to be made in China (by week). Here the dependent variable is the natural log of price. The sample contains 20,054 observations (by week-ASIN).

Lucking-Reiley et al. (2007) documented the measurable effect of seller's rating on the prices on eBay.[49] The small response in prices could be explained by price stickiness and product scarcity. Using daily listing prices from online platform, Gorodnichenko et al. (2018a) finds no evidence of prompt response in prices to unanticipated macroeconomic shocks and Gorodnichenko et al. (2018b) documents relatively long spells of fixed prices. There was scarcity in face masks and price-gouging during the first several months after the breakout of Covid19, as documented by Cabral and Xu (2021), and sellers might not have the incentive to lower their price.[50] For one,

[48] Unfortunately, Amazon does not provide data on actual sales (only sales rank instead), so we cannot estimate the impact on revenue for the Chinese sellers.
[49] Lucking-Reiley et al. (2007) finds that a 1% increase in negative feedback rating leads to a 0.11% decrease in auction price on average.
[50] 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.

Chinese sellers themselves might only have limited face masks in storage; for another, not all consumers can quickly switch away from Chinese sellers. We will provide more evidence in the next empirical part on product scarcity and consumer response to it.

Event Study on Sales. We carry out the same analysis for sales. The dependent variable is now the sales index, and controls are now average rating and natural log of price.[51] Amazon does not show consumers the actual sales data, but only the sales rank under certain product categories. We limit our study to face masks under "Health and Household" for the comparability of sales rank data. We further rescale the sales rank variable to construct a sales index (ranging between 0 and 100) where a larger index means more sales. Product and time fixed effects are included as in the main analysis.

Results are shown in Figure 13. Before identification, Chinese products have a significant trend of rising rank of sales among all sellers, which is reversed post identification, with a significant and clear decreasing pattern starting in week 4. Some consumers with animus switch away from Chinese products to other sellers, despite that there is no change of quality for the product.

The rising pre-trend could be driven by the faster expansion of sales for Chinese sellers compared to the non-China facemasks before their Chinese identity is revealed. This can be explained by the shortage that limit the expansion of non-China products. After the breakout of Covid19, there was a worldwide shortage in personal protective equipment, as documented by WHO and discussed in Cohen et al.(2020).[52] During this time, before they are identified, the Chinese sellers might expand faster since they are less restricted in supply.[53] In the literature,

[51] If we exclude average rating in the control variables, the pattern will be similar. Results are suppressed here to save space.

[52] The news on shortage reported by WHO can be accessed at https://www.who.int/news/item/03-03-2020-shortage-of-personal-protective-equipment-endangering-health-workers-worldwide.

[53] This can be supported by trade data from the World Bank – in 2020, U.S. imported a total value of $19.6 billion on face and eye protection, with $16.6 billion (or 84.4%) imported from China. Data from United States Face and eye protection (630790) imports by country | 2020 | Data.

Chevalier and Mayzlin (2006) find that the new, favorable reviews lead to an increase in sales using data on books sold on Amazon.com and Barnesandnoble.com. With the arrival of new favorable reviews before their identity revelation, the Chinese sellers will have expanded sales, which explains the pre-trend. To show this, in Appendix Figure A.14 we further include in controls the share of five- and four-star reviews in the regression, and this removes the strong pre-trend.[54] However, this also removes the clear drop in sales since we are now "over-controlling". Since 77.3% of informative reviews are informative-animus, which features low ratings, the inclusion of the lagged share of five- and four-star reviews also controls one of the mechanisms - the impact of reviews on future consumers. It then comes as no surprise that the "switching away" in sales is now smaller and less significant.

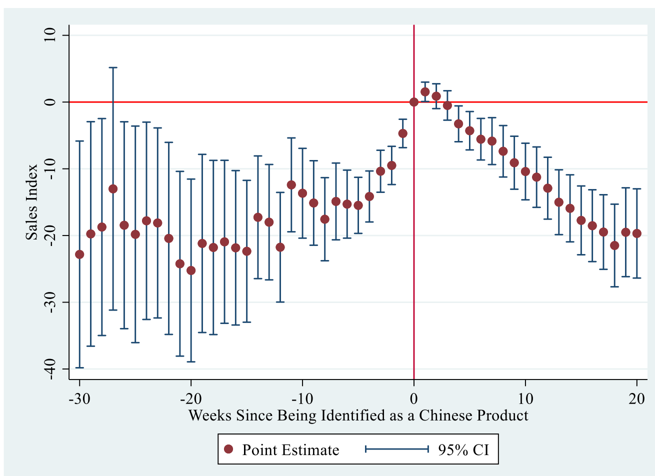

FIGURE 13. EVENT STUDY FOR CHINESE PRODUCTS – DEPENDENT VARIABLE USING SALES

Notes: Fully dynamic event study for Chinese products, where time is measured relative to the first time a product is ever identified to be made in China (by week). Here the dependent variable is the sales index. The sample contains 20,054 observations (by week-ASIN).

[54] However, this also removes the clear drop in sales since we are now "over-controlling". Since 77.3% of informative reviews are informative-animus, which features low ratings, the inclusion of the lagged share of five- and four-star reviews also controls one of the mechanisms - the impact of reviews on future sales. It then comes as no surprise that the "switching away" in sales is now smaller and less significant.

IV. Direct and Indirect Impacts

As explained in the last section, an informative review can have direct and indirect impacts on the 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 distinguishing our results from the quality story, and discuss the logic behind consumers' purchasing behavior with rising animus.

IV.A. Impacts of Informative Reviews – Direct and Indirect

There are two mechanisms by which 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.[55] The indirect mechanism specifies the impact an informative review has on the average rating by 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 Appendix C, 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 the arrival of new reviews and the informative review being more outdated.[56] In Appendix C, we also show that the product

[55] To be specific, the rating of the review is used in the calculation of the average rating.

[56] 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 over time.

average rating is highly correlated over time in our sample.[57] Through the high correlation of average rating, the negative direct impact persists but decreases in size over time.

For the indirect impact, an informative review can affect the future ratings via other (future) reviewers who read the existing informative review. First, an informative review provides information which might not be previously known or noted by a consumer.[58] Appendix Table A.4 lists some consumer reviews which clearly stated that they did not know the products were made in China at time of purchase. A discriminative consumer could choose to leave a low rating for the product after knowing a product is made in China 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 find more outdated reviews.[59] 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. For empirical evidence, in Appendix Figure A.15 and A.16, we run a fully dynamic event study studying the number of reviews over number of ratings (Appendix Figure A.15) and the number of newly arrived reviews (Appendix Figure A.16) post first-time identification of Chinese products. We find that after a Chinese product gets identified, it receives more reviews compared to the non-China products. However, there is no persistent pattern of consumers who leave a rating more likely to leave a comment for Chinese products post identification. Previous researchers have found similar "indirect impacts" where one

[57] The correlation coefficient equals 0.97, with controls for price, sales rank, product fixed effect, and time fixed effect. The correlation is 0.98 without these controls.

[58] 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.

[59] 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.

negative opinion invites another. For the increase in the level of animus, He et al. (2021) find users exposed to hateful content on Twitter and highly likely to become hateful. Hsueh et al. (2015) also document that online comments could directly influence the readers' expression of prejudice, both consciously and unconsciously. For consumers more inclined to leave a negative comment, Cabral and Hortacsu (2010) find 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. Chevalier and Mayzlin (2006) find that consumer purchasing behavior respond more intensively to negative reviews than to positive reviews. In both the "extra information" case and "higher 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.[60]

Comparing the direct and indirect mechanism, the direct mechanism is 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.

IV.B. Empirical Model and Results

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

[60] See 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.

$$(2) \qquad Y_{it} = \alpha + \beta S_{i,t-m} + \beta_X X_{it} + \theta_i + \theta_t + \varepsilon_{it}$$

$$(3) \qquad Y_{it} = \alpha + \beta_1 S_{i,t-m} + \beta_2 Y_{i,t-m} + \beta_X X_{it} + \theta_i + \theta_t + \varepsilon_{it}$$

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).[61] 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. Controls include 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 over time.

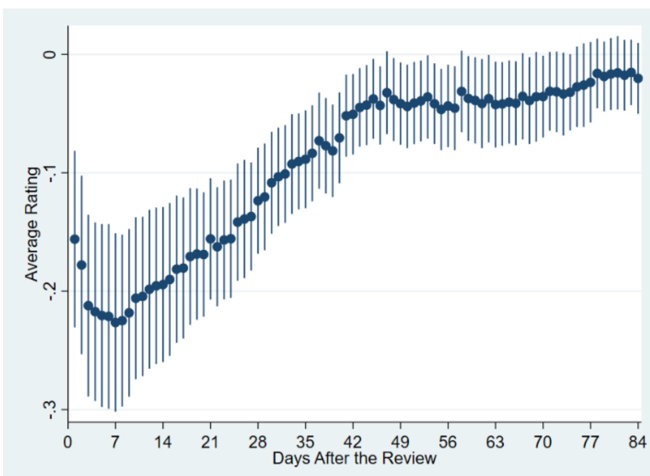

FIGURE 14. AVERAGE RATING AND SHARE OF INFORMATIVE REVIEWS (TOTAL IMPACT)

Notes: 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.

[61] 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.

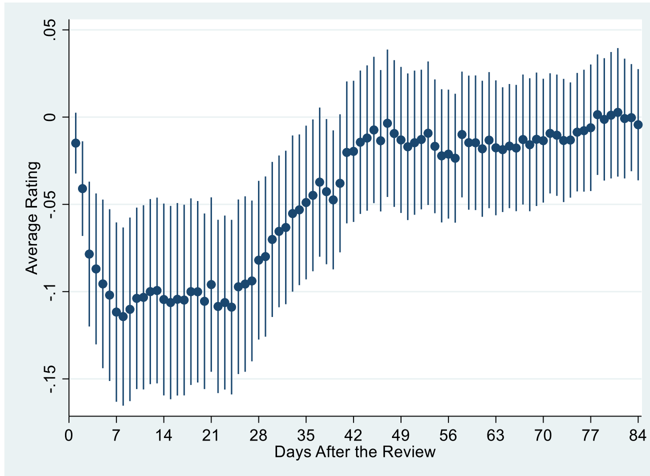

FIGURE 15. AVERAGE RATING AND SHARE OF INFORMATIVE REVIEWS (INDIRECT IMPACT)

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

Results using informative reviews are shown in Figure 14 and 15, with Figure 14 showing total impacts and Figure 15 showing indirect impacts. As explained above, the total impact 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 the 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 with a 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 C.1 and Figure C.2, we carry out the same analysis using the share of informative-animus reviews. The patterns are similar, but the impacts of informative-animus reviews are more negative. This is because, on one hand, the informative-animus reviews give lower ratings on average, and thus have larger direct impact; on the other hand, the indirect impact is also larger, since the informative-animus reviews can also 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 (Figure C.2) relative to informative ones (Figure C.1).

IV.C. 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 analyze 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 16 and Figure 17, which is very similar to the pattern using all informative-animus reviews (in Appendix C). If anything, using informative-animus reviews that do not contain any quality complaints 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 Chinese products.

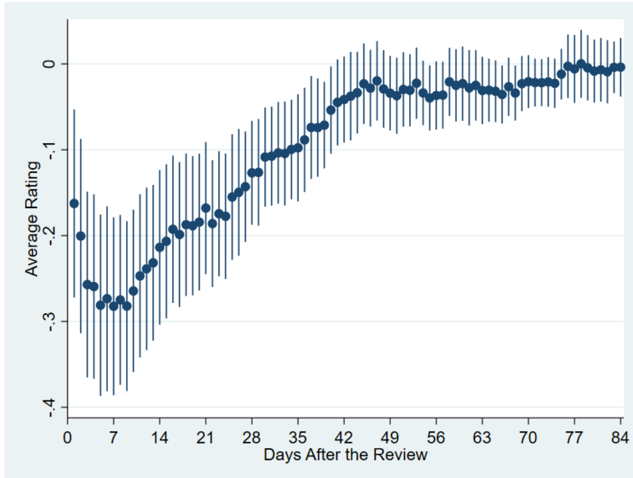

FIGURE 16. AVERAGE RATING AND SHARE OF INFORMATIVE-ANIMUS REVIEWS WITH NO QUALITY COMPLAINT (TOTAL IMPACT)

Notes: 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.

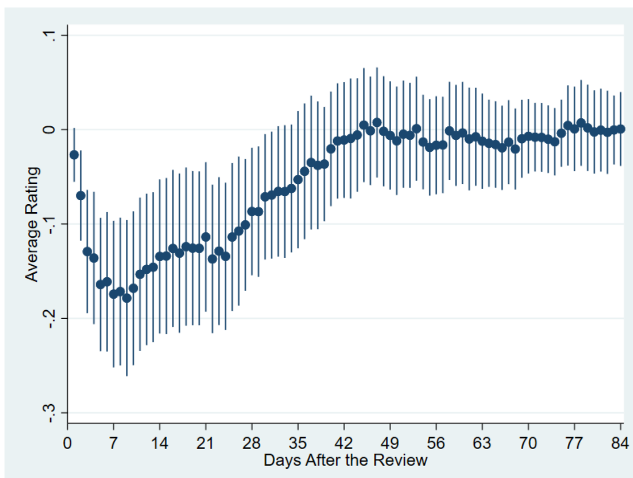

FIGURE 17. AVERAGE RATING AND SHARE OF INFORMATIVE-ANIMUS REVIEWS WITH NO QUALITY COMPLAINT (INDIRECT IMPACT)

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

IV.D. Animus and Purchase – Information Friction and Product Scarcity

It is an interesting question why consumers with animus buy Chinese products at the first place. There are mainly two reasons: information friction and product scarcity.

For information friction, consumers might simply not know that a product is made in China before they see the informative review, either because there is no information revealing the Chinese identity of the product or that there is such information, but consumers miss it due to the time cost of collecting information on country-of-origin for a product. Among the 386 Chinese products identified as of September 7, 2021, only 24 products are self-identified. For product scarcity, some consumers are restricted from switching away from Chinese products due to the scarcity of face masks, especially during the first several months after the breakout of Covid19. In March 2020, WHO warned about the shortage in personal protective equipment. Cabral and Xu (2021) recorded 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 (later found to be) made in China. This is also supported by data reported by the World Bank – in 2020, U.S. imported a total value of $19.6 billion on face and eye protection, with $16.6 billion (or 84.4%) imported from China. Appendix Figure A.1 shows the arrival of new products by day within our research period. In Table A.4 and A.7 in Appendix, we also list some typical reviews that support these two explanations. In Figure 13, we do find evidence that post identification, some consumers switch away from the Chinese face masks, but it is also true that not all consumers pay the searching cost to switch away, especially at times with product scarcity.

V. 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, 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 average rating of products on Amazon. We collect information on all face masks sold on Amazon between September 1, 2019 and September 7, 2020, including the consumer reviews.[62] Using the same information that is available to real consumers, including seller-generated and user-generated information, we identify the countries-of-origin of the products.[63] 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 no change in quality, the average rating of a product drops after being identified as Chinese for the first time. This negative impact is U-shaped, which quickly expands in the first three weeks, and then gradually fades out within twelve weeks. By further splitting Chinese product into high and low reputation based on average rating, we find that the drop in products' average rating is driven by the high reputation ones. Similar patterns are not found among products made in the U.S. or other countries-of-origin.

[62] 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.

[63] 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.

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 over time 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 rising time cost for the review to be seen and thus to affect fewer new consumers. The indirect impact can also work through the shifting away of consumers with more animus from revealed Chinese products. 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 collecting information on whether it contains any complaint about product quality and shipping. Results are similar using informative reviews without quality nor shipping 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; Huang et al., 2023). 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. It is interesting to note that, with consumer animus, even neutral comments could generate negative results for some sellers. 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. Companies located in event-related countries or regions might consider diversifying their production locations and they might benefit from building local collaborations to avoid consumer animus.

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A TABLE APPENDIX

TABLE A.1. 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	I have no complaints about the quality of the this mask. It is well made and the adjustable nose and ear piece was the selling point for me. All that said, I was disappointed when I saw the packaging said "Made in China"...I would not have bought it had I know ahead of time.

TABLE A.2. 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 A.3. AVERAGE RATING AND PRICES

	Dependent Variable: Average Rating					
	ASIN-Day			ASIN-Week		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(price)	-0.0141	-0.0728	-0.00319	-0.0143	-0.0647	-0.0257
	(0.0441)	(0.0742)	(0.00258)	(0.0437)	(0.0698)	(0.0157)
Lag Average Rating			0.968***			0.808***
			(0.00128)			(0.00724)
Controls	No	Yes	Yes	No	Yes	Yes
Date or Week	No	Yes	Yes	No	Yes	Yes
ASIN	No	Yes	Yes	No	Yes	Yes
Observations	151,564	151,564	150,170	23,240	23,240	21,846
R-squared	0.000	0.637	0.981	0.000	0.634	0.888

Notes: We study the correlation between average rating and prices in this table. In columns 1, 2, and 3, we use the panel data collapsed by ASIN and day. In columns 4, 5, and 6, we use the panel data collapsed by ASIN and week. In Column 1 and 4, no controls nor any fixed effects are included. In Column 2 and 5, sales is controlled, and time and ASIN fixed effects are included. In Column 3 and 6, we further include the lagged average rating by one period (day for Column 3 and week for Column 6).

TABLE A.4. EXAMPLES FROM CONSUMER REVIEWS (INFORMATION FRICTION)

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	They're made in China! I looked for country of origin while trying to decide to purchase and nothing about where these are made.
A good quality mask BUT made in China	I have no complaints about the quality of the this mask. It is well made and the adjustable nose and ear piece was the selling point for me. All that said, I was disappointed when I saw the packaging said "Made in China"...I would not have bought it had I know ahead of time.

TABLE A.5. SAMPLE CONSUMER REVIEWS (DISCUSSED SHIPPING TIME WITHOUT COMPLAINT)

Review Title	Review Body
2 week delivery from China and a perfectly functional mouth and nose covering	The package of 50 procedure masks arrived from China to Washington State in 2 weeks. That is excellent time.
Fast shipping--nice mask	The mask fits well, seems pretty well made, and shipping was only around 10-11 days from China.
Good quality mask	Arrived fast. Seems of good quality. I feel safe using it. Just did not expect it to be package stating from China.

TABLE A.6. EXAMPLES FROM CONSUMER REVIEWS (CHINA V.S. OTHER FOREIGN COUNTRIES)

Review Title	Review Body
Good Fit.	…Made in Vietnam so not China a plus.
Awesome Black Reusable Masks worth the coin!	…I was super excited when I seen they were Made in Mexico! Surprisingly not in China as most are.
Overpriced and not breathable!	…The only plus for it is that is was made in Korea - Not Chiina!...

TABLE A.7. EXAMPLES FROM CONSUMER REVIEWS (SEARCHING COST)

Review Title	Review Body
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. …

B FIGURE APPENDIX

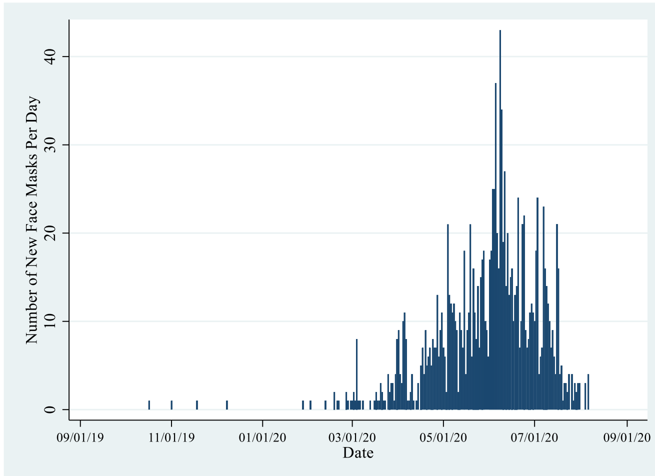

FIGURE A.1. NUMBER OF NEW FACE MASKS SOLD ON AMAZON BY DAY

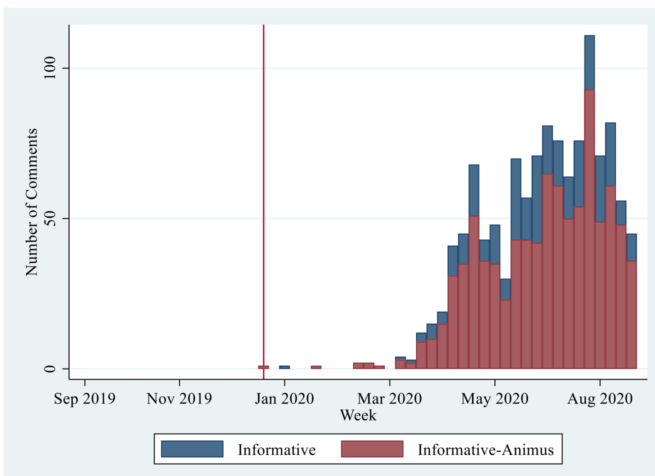

FIGURE A.2. NUMBER OF INFORMATIVE REVIEWS (BY WEEK)

Notes: The total number of informative and informative-animus reviews by week (since Sep 1st, 2019). The reference line marks the breakout of Covid19. The horizontal axis marks the corresponding month and year for week 1, 10, 20, 30, 40, and 50 since Sep 1st, 2019.

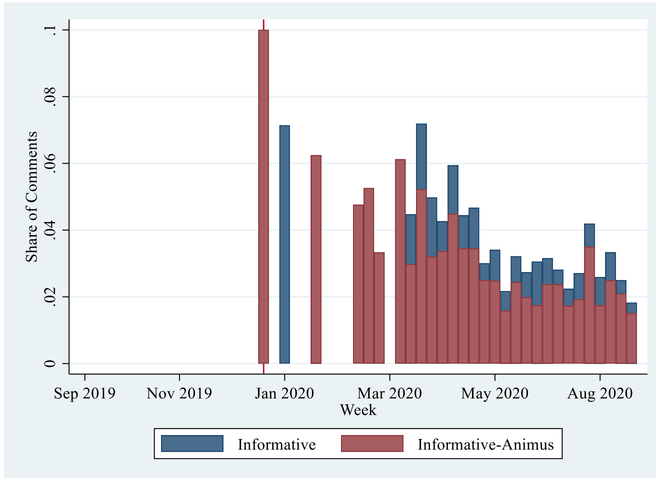

FIGURE A.3. SHARE OF INFORMATIVE REVIEWS (BY WEEK)

Notes: The share of informative and informative-animus reviews by week (since Sep 1st, 2019) among the Chinese products identified by the end of the research period. The reference line marks the breakout of Covid19. The horizontal axis marks the corresponding month and year for week 1, 10, 20, 30, 40, and 50 since Sep 1st, 2019.

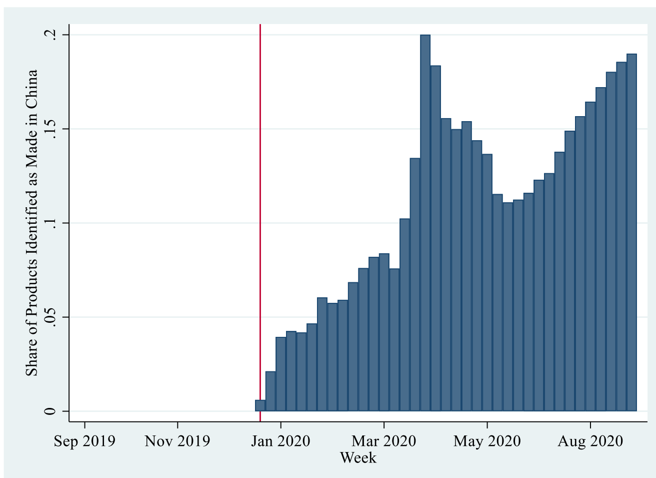

FIGURE A.4. SHARE OF PRODUCTS IDENTIFIED AS MADE IN CHINA

Notes: The cumulative share of products identified as made in China by week (since Sep 1st, 2019). The reference line marks the breakout of Covid19. The horizontal axis marks the corresponding month and year for week 1, 10, 20, 30, 40, and 50 since Sep 1st, 2019.

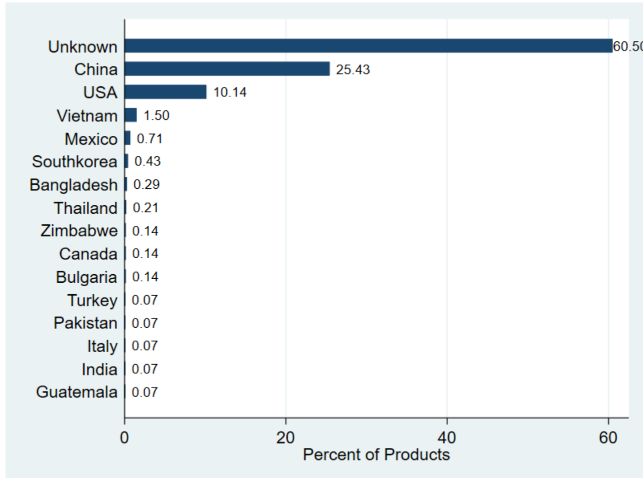

FIGURE A.5. SHARE OF PRODUCTS BY COUNTRY-OF-ORIGIN

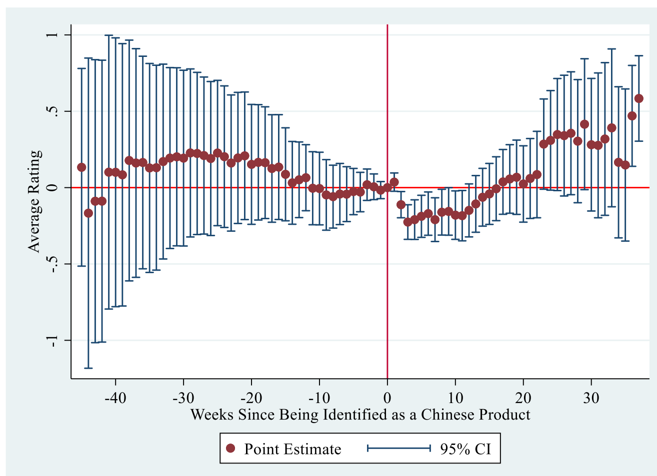

FIGURE A.6. EVENT STUDY FOR CHINESE PRODUCTS – FULL FIGURE

Notes: Fully dynamic event study for Chinese products, where time is measured relative to the first time a product is ever identified to be made in China (by week). The sample contains 20,054 observations (by week-ASIN). Note that for the relative time before week -36 and after week 29, there are fewer than ten treated products.

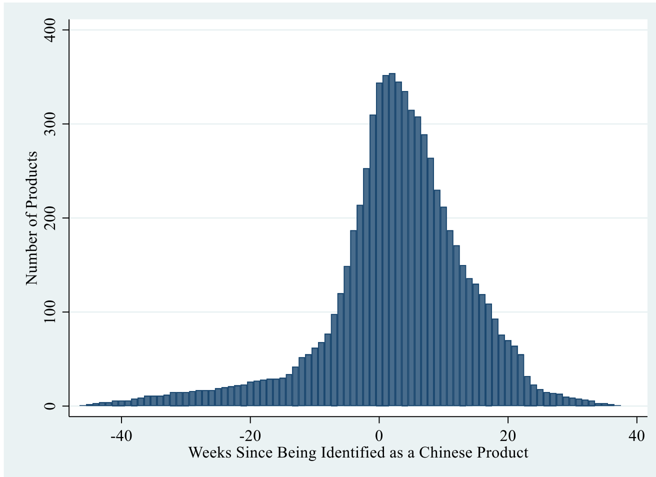

FIGURE A.7. NUMBER OF TREATED PRODUCTS BY TIME DIFFERENCE K (IN WEEKS)

Notes: Here k denotes the relative time (relative to the first week that a product is identified to be made in China), where k = t – K + 1 (t is the absolute time and K is the first week of identification). For example, k = 1 means the first week that a product is ever identified as made in China. The distribution of k is clustered around the middle because the timing of first identification varies across products, and not all products have the relative k at both ends (e.g., -30 and 30). For example, if a product was only sold on Amazon for 6 weeks by the end of our research period, and it was identified to be made in China at the fourth week, then after collapsed into the product-week panel, this product only has 6 observations for k (specifically, k = -2, k = -1, k = 0, k = 1, k = 2, and k = 3) with no observations for k smaller than -2 nor larger than 3.

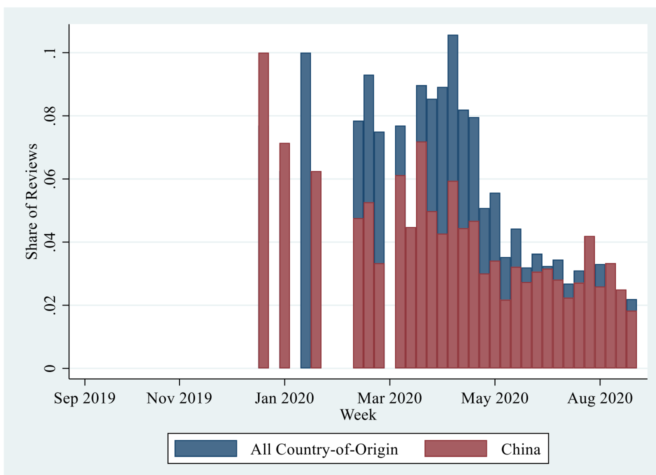

FIGURE A.8. SHARE OF REVIEWS ABOUT COUNTRY-OF-ORIGIN BY WEEK

Notes: The blue bar shows the share of reviews that discuss the country-of-origin by week, and this covers all countries including US, China, and other foreign countries. The red bar shows the share of reviews that discusses China/Chinese products.

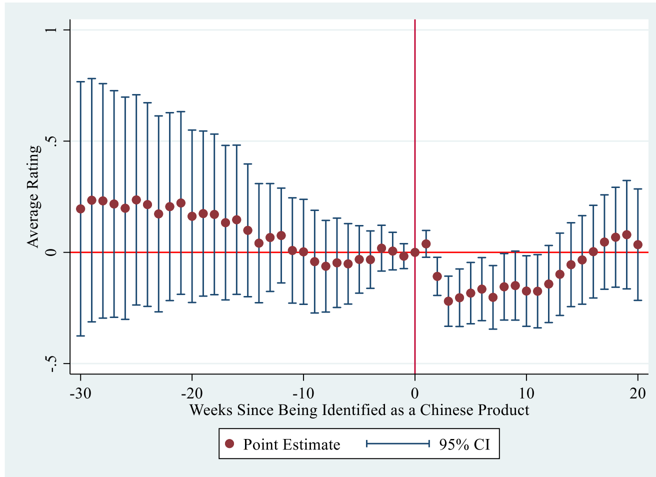

FIGURE A.9. EVENT STUDY FOR CHINESE PRODUCTS – NOT CONTROLLING FOR PRICES

Notes: Fully dynamic event study for Chinese products, where time is measured relative to the first time a product is ever identified to be made in China (by week). Here we exclude prices from the control variables. The sample contains 20,254 observations (by week-ASIN).

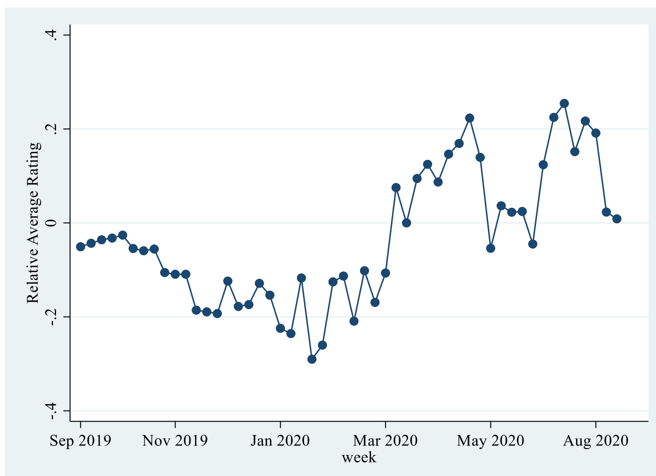

FIGURE A.10. AVERAGE RATING GAP OF NOT-YET-REVEALED CHINESE PRODUCTS TO NON-CHINA PRODUCTS

Notes: The vertical axis uses the difference in average rating between not-yet-revealed Chinese products and the non-China products. The horizontal axis marks the corresponding month and year for week 1, 10, 20, 30, 40, and 50 since Sep 1, 2019.

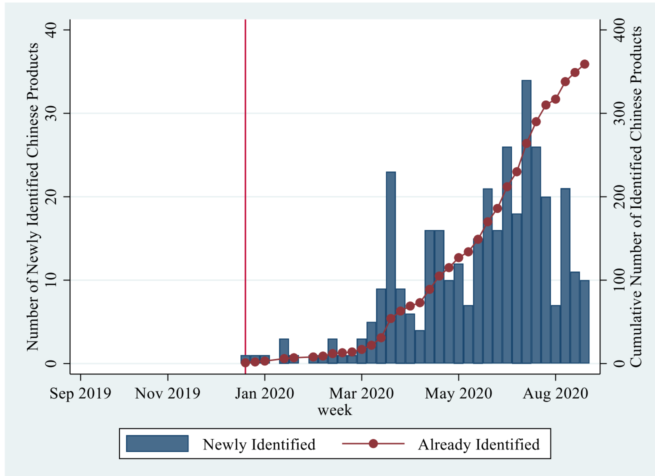

FIGURE A.11. NUMBER OF NEWLY IDENTIFIED AND ALREADY IDENTIFIED CHINESE PRODUCTS (BY WEEK)

Notes: The number of newly identified and cumulative number of identified Chinese products by week (since Sep 1st, 2019). The reference line marks the breakout of Covid19. The horizontal axis marks the corresponding month and year for week 1, 10, 20, 30, 40, and 50 since Sep 1st, 2019.

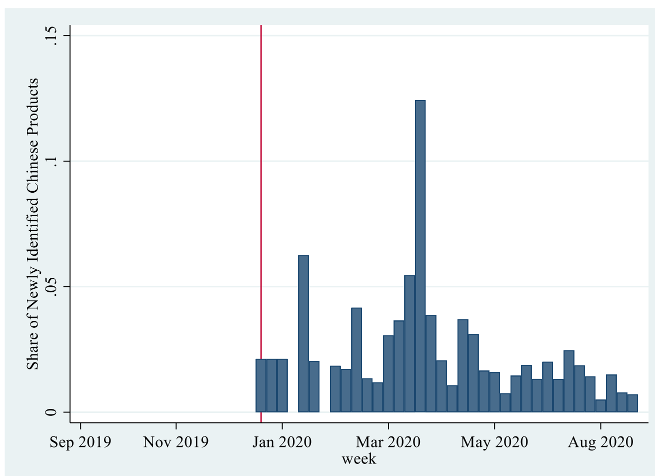

FIGURE A.12. SHARE OF NEWLY IDENTIFIED CHINESE PRODUCTS (BY WEEK)

Notes: The share of newly identified Chinese products over the total number of products by week (since Sep 1st, 2019). The reference line marks the breakout of Covid19. The horizontal axis marks the corresponding month and year for week 1, 10, 20, 30, 40, and 50 since Sep 1st, 2019.

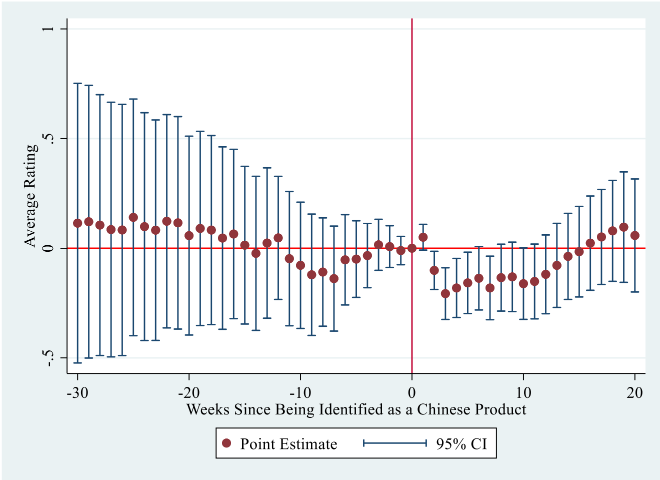

FIGURE A.13. EVENT STUDY WITH NO COMPLAINTS ON QUALITY NOR SHIPPING

Notes: Fully dynamic event study for Chinese products, where time is measured relative to the first time a product is ever identified to be made in China (by week). The identification of being made in China contains no complaint on the quality nor shipping of the product. The sample contains 19,259 observations (by week-ASIN).

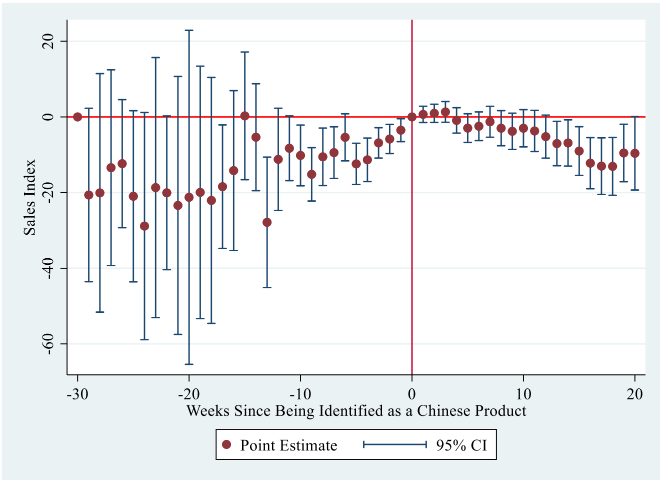

FIGURE A.14. EVENT STUDY FOR CHINESE PRODUCTS – DEPENDENT VARIABLE USING SALES

Notes: Fully dynamic event study for Chinese products, where time is measured relative to the first time a product is ever identified to be made in China (by week). Here the dependent variable is the sales index. Here we further include the share of five-star reviews and the share of four-star reviews that arrived in the last week as control variables. The sample contains 8,464 observations (by week-ASIN).

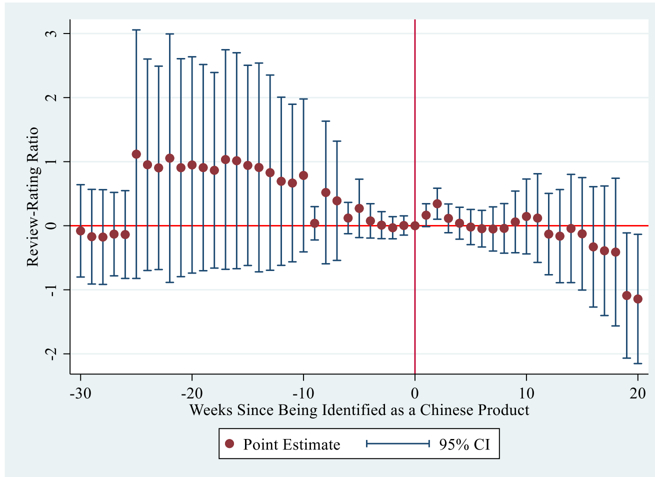

FIGURE A.15. EVENT STUDY ON RATIO OF NUMBER OF REVIEWS OVER NUMBER OF RATINGS

Notes: Fully dynamic event study for Chinese products, where time is measured relative to the first time a product is ever identified to be made in China (by week). Dependent variable is the ratio of number of reviews over number of ratings (since consumers can choose to leave a rating without leaving a comment). The sample contains 20,068 observations (by week-ASIN).

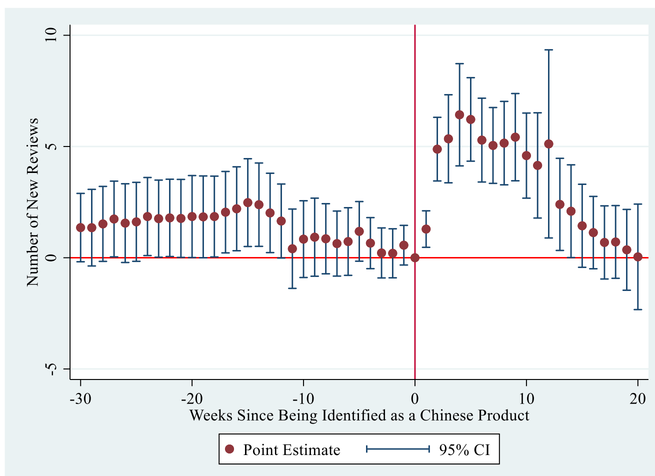

FIGURE A.16. EVENT STUDY ON NUMBER OF NEW REVIEWS

Notes: Fully dynamic event study for Chinese products, where time is measured relative to the first time a product is ever identified to be made in China (by week). Dependent variable is the number of new reviews. The sample contains 18,903 observations (by week-ASIN).

C EMPIRICAL APPENDIX

***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.

$$(\text{C.1}) \qquad Y_{itc} = \alpha + \beta D_{itc} + \beta_X X_{itc} + \theta_i + \theta_t + \varepsilon_{itc}$$

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 C.1. 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

Notes: 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.

TABLE C.2. 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

Notes: 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.

***Direct Impact – Correlation of Product Average Rating Over Time*.** For this regression, we use the full sample (including products of all countries-of-origin, including the unknowns). Below is the empirical model.

$$(\text{C.2}) \qquad Y_{it} = \alpha + \beta Y_{it-1} + \beta_X X_{it} + \theta_i + \theta_t + \varepsilon_{it}$$

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.

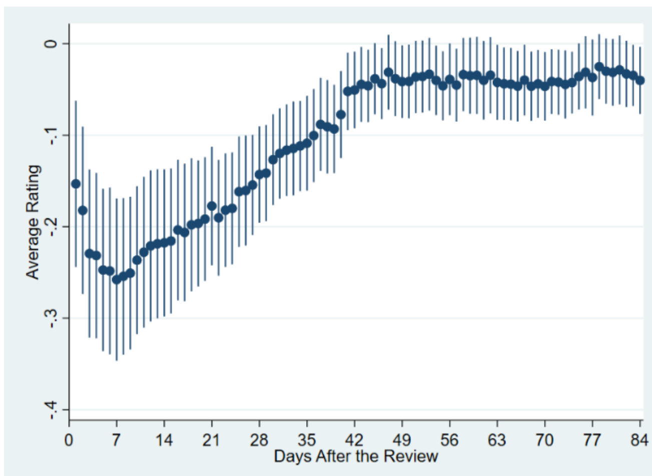

FIGURE C.1. AVERAGE RATING AND SHARE OF INFORMATIVE-ANIMUS REVIEWS (TOTAL IMPACT)

Notes: 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.

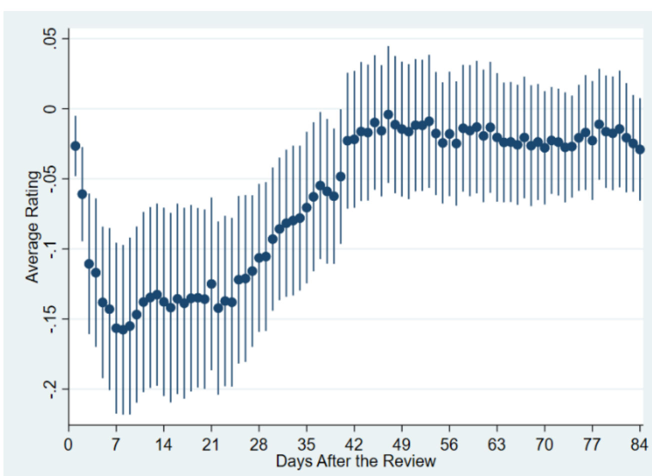

FIGURE C.2. AVERAGE RATING AND SHARE OF INFORMATIVE-ANIMUS REVIEWS (INDIRECT IMPACT)

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

D MACHINE LEARNING APPENDIX

In our analysis, we manually go through the reviews to decide whether they contain any animus towards China or Chinese product. To verify our decisions on whether reviews express animus, we use machine learning to train the computer with our manual decisions and then let the computer to make its decisions on the expression of animus. The computer makes the same decisions as us in 83.9% of the reviews, showing the robustness of our manual results. Specifically, we follow three steps as listed below.

First, we clean up and organize the raw review data using techniques such as stopword removal (which filters out words that do not carry much meaningful information e.g., “and”, “is”, “the”, “in”), lemmatization (which reduces words to their base form in lower cases e.g., “Running”, “RAN” and “runs” would all be reduced to “run”), and tokenization (which breaks down sentences into words e.g., “Extremely hot and gets wet from perspiration” will be broken into “extremely”, “hot”, “and”, “gets”, “wet”, “from”, “perspiration”). After this treatment, the reviews are now structured in a way that the computer can easily understand and correctly analyse.

Second, we carry out the keyword analysis by feeding all the informative consumer reviews to computer and applying the term-frequency-inverse document frequency (TF-IDF) method. In this step, after processing the treated consumer reviews from Step 1, the computer then figures out a certain number of significant words and assigns weights to these significant words based on the frequency of occurrences. With the significant words and weights, the computer then saves the information contained in all consumer reviews into a matrix, where each column denotes one significant word and each row denotes one consumer review, and the value of each element is assigned by the computer based on frequency. A word will be assigned a higher weight if it has low frequency among all reviews (e.g., “I”, “we”, “it” will carry lower weights since the computer assumes such words to carry less meaning when they almost occur in all reviews) but high frequency within certain reviews (e.g., repeated "smell", "flimsy" will carry higher weights since the computer assumes such repeated words within one review to convey important message).

Third, we train the model with the treated consumer reviews from Step 2 as well as the manually assigned decision of whether a consumer review contains animus towards China or Chinese products. We randomly and evenly split the sample into 5 groups – A, B, C, D, E. We use group A, B, C, D to train the model, and then use group E to test our results. For the training, this is similar to adding our manual decision as a dependent variable, and let the computer find the best way to estimate the value of the dependent variable using the matrix in Step 2. For the testing, in group E, the computer "predicts" whether a review contains animus based on its experience from the training and compares it with the manual decisions. We replicate the training and testing process five times where groups rotate as the testing group. On average, the computer's decisions match with our manual decisions in 83.9% of the trials.

E AMAZON APPENDIX

Review 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.[64] 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.[65] Amazon's regulation on hate speech and consequences of violations are displayed in Table E.1 and E.2 below.

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. On Amazon, to purchase a product, one needs to create an account. To write reviews, leave ratings, answer customer questions, and vote for helpful reviews, Amazon requires that a consumer "must have spent $50 on Amazon.com, using a credit or debit card, in the past 12 months". In Table E.3, we replicate Amazon's statement on genuine reviews.

For the calculation of the average rating of a product, Amazon now uses a machine-learning model instead of simple/unweighted average.[66] This algorithm is not revealed to the public and applies multiple criteria on review authenticity. Amazon does not take into account ratings without

[64] 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.

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

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

"verified purchase" into calculation of product average rating until more details are added (e.g., texts, images, or videos).

Table E.1. Amazon's Policy on Hate Speech

Hate speech You are not allowed to express hatred for people based on characteristics like: • Race • Ethnicity • Nationality • Gender • Gender identity • Sexual orientation • Religion • Age • Disability It's also not allowed to promote organizations that use such hate speech.

Table E.2. Amazon Policy on Consequences of Violations

Consequences for violations Violations of our guidelines make the community less trustworthy, safe, and useful. If someone violates the guidelines, we may: • Remove their content • Limit their ability to use community features • Remove related products • Suspend or terminate their account • Withhold payments If we find unusual reviewing behavior, we might limit the ability to submit reviews. If we reject or remove your review for guidelines violation, you won't be allowed to review that product again. If someone violates state and federal laws, including the Federal Trade Commission Act, we might take legal action. This action may result in civil and criminal penalties.

Table E.3. Amazon Policy on Genuine Reviews

How We Keep Reviews Trustworthy and Useful To ensure only genuine customers post reviews, we have submission requirements. Only customers who have spent at least $50 on Amazon in the last 12 months can submit ratings and reviews. Before posting a review, we check if it meets our Community Guidelines. That includes our rules against creating, editing, and removing reviews in exchange for compensation. We check if the reviewer bought or used (e.g., streamed) the item on Amazon and paid a price available to most Amazon shoppers. If we confirm both, we label the review with **Verified Purchase**. Reviews without this label can also be helpful. For example, a customer buys an item from a different company, but wants to share their opinion on Amazon.

Our automated and human checks stop millions of suspicious reviews before customers ever see them. We also take legal action against groups that pay customers to post fake reviews. See our anti-manipulation policy.

We listen to customers. If you think a review violates our guidelines, or someone offers you compensation to create, edit, or remove a review, please tell us. See the **How to report violations** section in our Community Guidelines.