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Maggie X. Chen
George Washington University

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Institute for International Economic Policy
1957 E St. NW, Suite 502
Voice: (202) 994-5320
Fax: (202) 994-5477
Email: **iiep@gwu.edu**
Web: **iiep.gwu.edu**

The Value of Reputation in Trade: Evidence from Alibaba*

Maggie X. Chen†
George Washington University

Min Wu‡
George Washington University

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Abstract

We examine the role of an online reputation mechanism in international trade by exploring T-shirt exports on Alibaba. Exploiting rich transaction data and features of search and rating algorithms, we show that exporters displaying a superior reputation perform significantly better than peers with nearly identical true ratings and observables and the value of reputation rises with the level of information friction and the specificity of information. We develop a dynamic reputation model with heterogeneous cross-country information friction to quantify the effect of the reputation mechanism and find a 20-percent increase in aggregate exports fueled by a market reallocation towards superstars.

JEL Codes: F1, D8

Key Words: reputation, information, superstar, and Alibaba

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†Corresponding Author. Email: xchen@gwu.edu.

‡Email: sylviawu@gwmail.gwu.edu.

1 Introduction

Despite rapid technological progresses in moving goods across space, the world is still far from flat in global trade flows. Searching for sources of trade resistance has become essential for explaining the scale of missing trade. A key potential source is the role of imperfect information where information declines rapidly with distance and country border. Businesses have to undergo costly processes to assess foreign market demand; limited demand information can cause distortions in trade, resulting in regional price dispersion and lower aggregate trade (Allen, 2014; Steinwender, 2018). Information frictions are also prevalent in the matching of exporters and importers. Importers lack information about the quality of exporters; as a result, distrusts often arise especially in developing countries where regulatory infrastructure and contractual environment are weak. So far there is still little evidence on how information frictions faced by importers could affect trade and how opportunities for exporters to build, and importers to learn, exporter reputation could help overcome the hurdle. A central challenge in answering these questions is the difficulties of quantifying reputation (or the lack thereof) across businesses and markets.

In this study, we explore the unique setting of online cross-border trade platforms, where reputation building and learning are enabled in an environment of extensive and heterogeneous information friction, to examine how information diffusion through an observable reputation mechanism affects export patterns, exporter behavior, and importer decisions. Online trade platforms are playing an increasingly prominent role in international trade and the world's retail sector. Cross-border online retails, now accounting for over 15 percent of global retail sales, have increased at an annual rate of 25 percent in recent years, twice the pace of domestic e-commerce growth and five times the pace of total global retail. Our study exploits the world's leading cross-border trade platform, Aliexpress.com, founded by Alibaba in 2010 to serve suppliers in China and consumers around the world. The rapid rise of Aliexpress and other international trade platforms is drastically reforming the ways exporters and importers search, learn and trade. Producers and retailers of all sizes can now make their products available to foreign markets; importers can readily access a large number of suppliers abroad and learn supplier quality from other buyers. These features offer us a rich context—characterized with cross-country variations in the degree of information friction, a regime of quantifiable reputation, and access to uncensored transactions and information—that is ideal for establishing the role of a reputation regime in export growth in separation from the effects of other conventional export drivers.

Using a rich trade transaction dataset in the T-shirt industry—a top selling product category on Aliexpress, we first document novel stylized facts about the distribution of Aliexpress exports. We find that exports on Aliexpress are more concentrated on superstar exporters and listings than what has been documented for offline trade and other major online trade platforms such as eBay for developed-country based businesses. The market share of superstars also increases in markets with less import experience as inexperienced buyers more frequently turn to top performers. Further, the distributions of price and reputation are found to closely mirror each other on Aliexpress while export volume exhibits a more dispersed shape. Over time, as listings from the same cohort age online their distribution of revenue becomes more dispersed.

We then empirically examine the role of the reputation mechanism in exporter performance by controlling for all observable listing and exporter characteristics including observable product and service quality and taking advantage of qualitative and quantitative features of Aliexpress' search and reputation algorithms. Specifically, we use two identification strategies by exploiting a "similar product" grouping function of the Aliexpress search engine, which restricts comparison to products with nearly identical observable attributes such as style and images, and Aliexpress' rating algorithm, which allows us to employ a regression discontinuity design to compare listings whose observed rating differences are greater than their trivial actual rating differences.

The results show that compared to Aliexpress-predefined peers and peers with nearly identical true ratings, listings with a better *displayed* reputation achieve greater export volume, revenue, and numbers of buyers and markets. The effects of the displayed reputation also exceed the effects of observed product and service quality. The substance of reputation also matters. Importers respond more to detailed, codifiable and objective content than general, vague and subjective statements, information concerning less observable attributes (e.g., material quality) than information on observable attributes (e.g., shipping), and negative sentiments than positive sentiments. The value of reputation is also not homogenous across space and subject to gravity between exporters and importers. The value of reputation rises with the geographic and cultural distances between China and an import country where information frictions are likely greater.

To account for the above empirical regularities and quantify the economic importance of the reputation regime, we then present a simple dynamic model incorporating country-pair specific information frictions, quality heterogeneity, and evolving reputation. We assume that importers cannot observe ex-ante the true quality of a product, but may leave ex-post information on the quality after transactions. Such information will contribute to exporters' overall reputation by allowing future importers to update their beliefs on product quality. In this context, exporters choose prices in each period and importers decide in each period whether to import from a specific exporter. The model predicts that exporters will use dynamic pricing strategies to influence the speed of reputation building and importer learning. Comparing the case where reputation is observable with the case where reputation is unobservable, exporters set prices lower in the former case to subsidize importer learning and reputation building and raise prices gradually when positive reputation starts to accumulate. The price dynamics exacerbates over time the dispersion in the distribution of export volume and the market share of top exporters. The effect of reputation as well as the market dominance of superstars is particularly pronounced in countries with large information frictions. These results offer a theoretical rationale that helps reconcile the documented stylized facts.

Our model highlights a new source of aggregate export growth through an expedited creation of superstar exporters. A reputation mechanism shifts importers and reallocates markets from low- or no-reputation exporters to high-reputation exporters, accelerating the emergence of superstar exporters. These superstar exporters set prices to match their growing reputation and enjoy a price premium and expanded market share. To quantify the economic importance of a reputation mechanism in aggregate trade flow, we structurally estimate the model and perform two counterfactual exercises including (i) setting the frictions of reputation diffusion to infinity such that reputation is unobservable and (ii) upgrading economy-wide product quality. We find that compared to the case in which reputation is unobservable, having an observable reputation system can contribute to an over 20-percent increase in total export revenue, equivalent to the effect of raising economy-wide quality by more than 25 percent. The growth is driven by a dramatic export market reallocation towards superstar exporters, significantly raising the market share of top exporters.

This paper is related to a growing literature examining the patterns and effects of online trade exploring e-commerce platforms such as eBay and Alibaba's domestic e-commerce site, Taobao. Hortaçsu et al. (2009) and Lendle et al. (2013) examine geographic patterns of online trade and find distance continues to exert a significant effect. Several recent studies, including Chu and Manchanda (2016), Fan, Ju and Xiao (2016), and Li, Tadelis and Zhou (2018), investigate seller behavior on Taobao and suggest that sellers might offer incentives to boost transaction volume and ratings.[1] This paper investigates the role of a reputation regime in a multi-country trade setting featuring heterogeneous information friction to quantify the role of online reputation regimes in cross-border trade where information frictions increase rapidly with distance and border. The analysis documents new stylized facts on the distributions of online trade and shows both empirically and quantitatively that the value of a reputation regime is not only economically important but also varies substantially across product parameter space, sources, and markets depending on the level of underlying information friction.

Our work is further motivated by a recent literature addressing the roles of information

[1] See Peitz and Waldfogel (2012) and Tadelis (2016) for a thorough review of related work in this literature.

frictions and information mechanisms in international trade. Allen (2014), embedding information frictions in a trade model and exploring Philippines' agricultural trade data, shows that information frictions account for roughly half the observed regional price dispersion. Steinwender (2014) exploits the establishment of the transatlantic telegraph connection in 1866 and finds information frictions result in large deviations from the law of one price and a reduction of information frictions increases trade volume as well as trade volatility. Evidence suggests that exporters could address information frictions by learning from their own exports (Albornoz et. al, 2012) or the experience of neighboring exporters (Fernandes and Tang, 2014; Kamal and Sundaram, 2016). An innovative study by Atkin, Khandelwal, and Osman (2017) conducts a randomized experiment that generates exogenous variation in foreign market access for rug producers in Egypt and offers new evidence of learning by exporting. Macchiavello and Morjaria (2015) and Monarch and Schmidt-Eisenlohr (2019) show that buyer-seller relationships can also serve as an important mechanism for learning.

Finally, our paper builds on several quantitative studies examining the matching of sellers and buyers in the presence of information friction. Using Colombia-U.S. trade data and a continuous-time model in which sellers receive product appeal information from successful transactions, Eaton et al. (2014) quantifies the impact of trade costs and learning on aggregate export dynamics. Dasgupta and Mondria (2018) show that an intermediation technology could enable exporter sorting when product quality is imperfectly observed. Piveteau (2019) builds a dynamic model in which firms slowly accumulate consumers in foreign markets to explain the existence of many small new exporters with low survival rates.

The rest of the paper is organized as follows. In Section 2, we describe the empirical context and the dataset. In Section 3, we present stylized facts and examine empirically the role of reputation in exports. In Section 4, we present a dynamic reputation model in a setting of heterogeneous information friction to rationalize empirical patterns and quantify the economic importance of the reputation regime. The paper concludes in Section 5.

2 Data and Empirical Context

2.1 Aliexpress: The Cross-Border Trade Platform

Our data are obtained from Aliexpress.com, a branch of Alibaba—the largest e-commerce corporation in the world. As the leading international e-commerce market, Aliexpress specializes exclusively in international trade and has emerged as the leading platform for B2C cross-border trade. The website, founded in April 2010 and based in mainland China, serves suppliers in China and consumers in over 230 countries.[2] Over 100 million products are sold on the platform, ranging from clothes and shoes to electronics, home supplies, and automobile accessories.

As a cross-border trade platform, Aliexpress offers a variety of features essential to our analysis. First, Aliexpress posts, for each product listing, the most recent 6-month transaction history—including transaction buyer ID, buyer origin, date, price, and quantity—and buyer feedback—including rating and descriptive comments. Moreover, Aliexpress does not allow exporters to provide direct contact information, making the website the exclusive source of information for importers. These unique features make it possible to quantify information flow and reputation, a challenge when working with offline trade data where reputation is usually difficult to measure quantitatively. Second, sellers on Aliexpress offer detailed product descriptions following a standardized format, making it possible to observe, measure, and compare product quality disclosed by the sellers. Third, Aliexpress provides various buyer protection services, including a "return and refund" guarantee that applies to every product sold and several additional guarantees sellers may opt to offer such as the "On-time Delivery", "Returns Extra", "Longer Protection", and "Guaranteed Genuine". The offering of additional guarantees serves in our analysis as another measure of exporter quality. Fourth, Aliexpress does not require a sign-up fee to list a product, thereby lowering the entry cost of

[2] By 2018, there were more than 1.1 million active sellers on the website attracting more than 150 million consumers and over 600 million visits each month (https://www.chinainternetwatch.com/tag/aliexpress/).

exporting and allowing sellers of all sizes to enter export market.[3] The low entry cost allows us to examine the role of reputation in export growth especially at extensive margins which have traditionally been viewed as driven by reductions in entry cost.

2.2 The T-shirt Industry and Data

Our analysis focuses on transactions in the T-shirt industry (specifically, women's tank top) for two main reasons. First, as Aliexpress hosts only mainland Chinese suppliers and China is the largest textile exporter around the world, T-shirt is one of the top-selling goods on Aliexpress. A large volume of transactions are conducted every day, offering us considerable variations in a precisely defined product category.

Second, compared to other popular products on Aliexpress, the product characteristics of T-shirts are easier to measure and compare. All T-shirt sellers post information following a standardized format, describing, for example, material (e.g., cotton, spandex, and silk), whether the product features decoration, clothing length, and pattern type, thereby making it possible to quantify and compare (observable) product quality. We construct a measure of observable quality using information on "Item Material", "Item Fabric", and "Item Fabric Type". We also consider an alternative indicator that whether the products have any decorative designs like beading and embroidery.

To construct the dataset, we collected information on all the listings (with at least one order) and daily transactions in women's tank-tops category from February 2014 to January 2015. The final sample consists of 584,894 transactions from 5,392 sellers, 383,430 buyers, and 16,995 listings. The dataset, including uncensored information accessible by all visitors of the platform, exhibits several distinct advantages compared to other e-commerce data. First, compared to eBay and Amazon whose majority of transactions are domestic, Aliexpress specializes exclusively in cross-border trade and hosts considerably greater numbers of sellers,

[3] Aliexpress charges sellers 5 percent of the total sales as a service fee for each successful transaction and provides a paid service by allowing sellers to bid to get listed as premier goods.

buyers and transactions.[4] Second, unlike eBay which includes both auction and buy-it-now transactions and hosts both occasional individual and formal business sellers, Aliexpress consists of only buy-it-now type listings and primarily business sellers. This is essential for examining sellers' dynamic pricing strategies. Third, the data do not pose any restrictions on transaction value and include all sellers, buyers and transactions. This is of particular importance for drawing a comprehensive picture of exporter distribution. Fourth, the data provide detailed transaction-level information, while alternative datasets such as eBay often disclose only sellers' total sales by country.[5]

Specifically, we collected three categories of information for each product listing and transaction record. The main variables are described in detail below.[6]

2.2.1 Product (Listing) Characteristics

Price: The current listing price.

The numbers of ratings and transactions and average rating score: the total number of ratings, the number of ratings at each score (1-5), the number of previous transactions, and the average rating score, all based on transactions over the past 6 months.

Total number of transactions: the total number of transactions since the product was listed.

Color choices: the number of color choices.

Size choices: the number of available sizes.

Product characteristics: type, clothing length, item pattern, fabric, material, and decoration.

Return policy: a vector of dummies to indicate who pays for the return cost and listings without return services are the reference group.

Buyer protection: a dummy for listings that offer longer protection (15 days after the com-

[4] Aliexpress does not allow domestic buyers to access the website and only sellers located in China can register as suppliers. This design ensures that all transactions on this platform are exports from China.

[5] Most existing e-Commerce datasets observe only transactions providing feedback and use feedback frequency to proxy actual transaction volume even though many buyers do not leave feedbacks online. In our sample, only 36 percent of the transactions have associated feedbacks. Including transactions without feedbacks provides us a much more comprehensive representation of the trade patterns.

[6] See Section 1 of the Online Appendix for a complete list of the variables.

pletion of a transaction) on return services.

Shipping cost: the available carriers and costs for shipping to each country.

Estimated delivery time: estimated number of days for delivery.

Number of images: the number of pictures posted in product descriptions.

Number of words: the number of words used in product descriptions.

Material Quality: A score of material quality ranging from 1 to 4 classified based on the types of fiber and their market values. Synthetic fibers like polymer, semi-synthetic fibers, natural plant fibers such as cotton, and animal fibers are scored as 1-4, respectively.

2.2.2 Seller Characteristics

Seller name, location, and start year: the seller's business name, location, and start year.

Top selling products: a list of the seller's best selling products including a brief description, a picture, price, and the number of previous orders.

Product categories: a list of product categories offered by the seller.

Feedback score, percentage of positive feedbacks, and detailed ratings: a cumulative feedback score, percentage of positive feedbacks, and detailed ratings on whether the product is as described, communication, and shipping speed based on the seller's transaction history.

2.2.3 Transaction Records

Buyer ID: an ID that uniquely identifies each buyer.

Buyer origin country: the origin country of the buyer.

Transaction price and quantity: the net price (exclusive of the transportation cost) and quantity of each transaction.

Transaction date and time: the date and time of the transaction.

Transaction feedback: a rating and comments on product quality and seller services.

3 Empirical Patterns

In this section, we present empirical evidence emerging from the data describing the distribution patterns of exports and the role of reputation in shaping these patterns.

3.1 The Distribution of Exports on Aliexpress

First, the data record substantial heterogeneity across Aliexpress exporters in terms of both export unit price and export volume. For example, the minimum sales volume is 1 unit in one year while the largest seller sold 23,270 units over the same time period. Export revenue varies from \$1.73 to \$177.12.[7] We then examine the export revenue of the top 1 percent, 5 percent, and 10 percent of sellers, which are referred to in Freund et al. (2015) as "superstar" exporters. The data suggest that the ratio of median export revenue between the top 1-percent exporters and the rest is around 382 on Aliexpress, far exceeding the ratio found in Chinese customs T-shirt exports (155). The shares of export revenue earned by the top 1-percent and 5-percent exporters are 34 percent and 71 percent, respectively, on Aliexpress, in comparison to the 30 percent and 58 percent from the Chinese customs data in the similar product category. The concentration level on Aliexpress also exceeds the level reported for eBay in Lendle et al. (2013) who show that the largest 10-percent sellers account for a 70-percent export market share.[8]

These observations are also depicted in Figure 1 where we plot the export share accounted for by exporters and listings at different percentiles. It is noteworthy, however, that the top listings' market share is not homogenous across countries and varies with the country's average importer experience.[9] Figure 2 shows that the export revenue share of top 5-percent listings in a country decreases with the average number of orders per importer in that country. The negative correlation remains significant when we measure importer experience with the

[7]Table 1 in the Online Appendix reports the summary statistics.

[8]Table 2 of the Online Appendix reports in detail the market share and relative size of superstar exporters on Aliexpress. In Freund et al. (2015), the average market shares of the top 1-percent and the top 5-percent export firms are 14 percent and 30 percent, respectively, based on a cross-country panel of customs data.

[9]The results remain robust when only top exporters are considered.

average number of repeated listings per importer, the average number of repeated orders per buyer, and the share of repeated orders. The observation is consistent with the hypothesis that less experienced importers are more likely to rely on information about exporters' past performance and import from superstar exporters. The first stylized fact summarizes the above findings.

Pattern 1 (superstars): *Exports on Alibaba are concentrated on superstar exporters, especially in markets with less experienced importers.*

Next we compare the distributions of price, reputation, and export volume. We find, as shown in Figure 3, that the distributions of price and reputation closely mirror each other and are both concentrated at the center. In contrast, the distribution of export volume is more spread out and exhibits significantly thicker left and right tails. If export volume is merely determined by price, we would expect to see the distributions of export volume and price in similar shapes. However, we observe that the distribution of export volume is more skewed to the left indicating a greater dispersion than can be explained by price. This observation is summarized in Stylized Fact 2.

Pattern 2 (distributions): *The distributions of price and reputation closely mirror each other while export volume is more dispersed.*

To explore the dynamic pattern of how heterogeneous exporters grow, we now track a cohort of listings over time by comparing their distribution as relatively new exporters to their distribution a year later. To control for exit and entry into the market, we focus here on listings who started exporting at the beginning of our sample period. Figure 4 shows that export revenue became more dispersed at the 4th quarter compared to what we observed in the 1st quarter.[10] This finding is summarized as Stylized Fact 3.

Pattern 3 (evolution): *The distribution of export revenue becomes more dispersed as exporters age.*

[10] In a study of U.S. businesses on eBay, Bar-Gill, Brynjolfsson, and Hak (2016) show that eBay sellers follow a log-normal distribution and over time smaller and younger firms are the fastest growing firms.

3.2 The Trade Effects of Reputation

In this subsection, we present empirical evidence on how reputation affects export patterns to offer first-step insights into the value of reputation in trade. We take advantage of our highly disaggregated data and Aliexpress' search and rating algorithms to explore the impact of reputation on both the intensive margin and the buyer and destination extensive margins. After establishing the baseline results, we then present evidence on heterogeneous responses to reputation across product parameter and geographic space.

A key feature of our analysis is that we are able to observe and control for all the information accessible to importers at the time of import decisions, including information on price, product material, shipping cost, shipping and return services, and sellers. This feature significantly mitigates potential omitted variable bias. Nonetheless we take two additional steps to further establish the causal effect of reputation by exploring in detail Aliexpress' search and rating algorithms.

First, we utilize a "similar product" grouping function provided by the Aliexpress search engine that categorizes products into narrowly defined peer groups based on images and product description keywords. In this function, Aliexpress identifies and groups visually nearly identical products (products with identical main images, similar keywords, and similar titles) offered by different sellers so buyers could easily search for and compare identical products. In addition to similarity in product images and descriptions, listings within peer groups also exhibit lower variations in seller services such as buyer protection and guaranteed return compared to listings in the whole sample.[11]

In our analysis here, we limit the comparison to listings within the same peer group and thus listings with essentially identical styles and similar other observable (and potentially unobservable) characteristics. In addition, we control for exporter fixed effect to exclude the effect of exporter ability, week dummies to control for time trends, and peer group fixed effect to control for all characteristics pertaining to the peer products (i.e., t-shirts with

[11] The mean and median numbers of listings in the peer groups are 45 and 12, respectively.

identical style) and explore only within-group variations.[12] We focus on the coefficient of the rating variable which captures the average effect of reputation on exports. The weekly rating variable is the mean of ratings scaled between 1 and 5 in the past 6 months, observable to importers at any time. To allow for potential nonlinearity in the effect, we use dummy variables to represent ratings from different intervals. Specifically, we use dummy variables to denote no ratings, ratings from 1 to 2, 2 to 3, 3 to 4 and 4 to 5, respectively, and set the reference group to be ratings between 1 and 2.

We find in Table 1 that information matters significantly in export performance. First, listings with more detailed description and more pictures tend to export more and to a larger number of buyers as well as markets. Reputation also plays an important role. Compared to peers with similar observable characteristics, listings with better ratings perform significantly better in terms of export revenue, export volume, export quantity per buyer, and the numbers of export markets and importers. For example, listings rated between 4 and 5, the most highly rated group, outperform those with ratings between 1 and 2 by 26-percent more export revenue, 14-percent more export volume, 13-percent more buyers, and 10-percent more export markets. Listings rated between 3 and 4 also outperform lower-rating groups, but the magnitude is smaller indicating that higher ratings bring greater export premia. Listings without ratings outperform poorly rated groups as well but not as much as listings with good ratings. Further, we notice that observable material and service quality do not appear to have a significant effect. We also compare the effect of reputation on export extensive margins, including the number of importers and the number of markets, with the effect on the intensive margin measured by the average export quantity per importer. We find reputation to exert a greater effect on the extensive margins than on the intensive margin, with the number of buyers in each market exhibiting the greatest elasticity.

Next we consider a further identification strategy by employing a regression discontinuity

[12] Instead of explicitly controlling for listing characteristics such as material quality and the provision and buyer protection and guaranteed return (all of which are time invariant), we also considered using a listing fixed effect and found the main results to be largely similar.

design. To address the concern that reputation could be correlated with unobserved listing characteristics that might affect consumer preferences, we explore a feature of Aliexpress' rating system in which the average rating in the past 6 months is rounded and displayed at the first-decimal place. For example, listings with an average rating between 3.90 and 3.94 are displayed as 3.9 while listings with an average rating between 3.95 and 3.99 are displayed as 4.0. This rounding feature creates a discontinuity in the ratings observed by the buyers even though the actual rating differences, which might be correlated with product observable and unobservable attributes, are trivial. To implement the regression discontinuity design, we manually compute and recover the average rating of each listing at the second-decimal place based on historical individual ratings and divide our sample to a treated group, whose ratings have been rounded up, and a control group, whose ratings have been rounded down. The actual rating differences between the two groups are hence no greater than 0.05 even though the observable differences are 0.1.

We incorporate the computed true average rating and estimate the following equation:

$$y_{sit} = \alpha + \theta_{sit}\beta + \lambda_1 T_{sit} + \lambda_2 rating_{sit} + \mu_s + \eta_t + \varepsilon_{sit} \tag{1}$$

where y_{sit} is the natural log of export outcomes for each listing i sold by exporter s in week t, and θ_{sit} is a vector of listing characteristics. The key variable in our RDD regression is a dummy T_{sit} that equals to 1 if the 2-decimal true rating of a listing denoted by $rating$ is rounded up and 0 if the true rating is rounded down; the parameter λ_1 captures the discontinuous change in export performance for listings whose displayed ratings are shifted up by 0.1.[13] In addition, we include the computed true rating $rating_{sit}$ to control for the effects of other observable and unobservable factors.[14] We find in Table 2 that even when controlling

[13] In our sample, there are multiple cutoffs (e.g., 3.95 and 4.95) below which the displayed rating is rounded down and above which the displayed rating is rounded up. A way to deal with this is to normalize the running variable by subtracting the cutoffs. Our specification by controlling for the displayed rating is essentially equivalent to this strategy.

[14] As a robustness check, we have also used rating dummies for each 0.1 category instead of the true rating in the regression. The RDD treatment effects are quantitatively similar.

for the positive effect of the true rating, the parameter λ_1 remains significantly positive implying that the treated group significantly outperforms the control group. This result suggests that buyers respond significantly to displayed reputation even when the difference in listings' true rating is trivial. These results are summarized below:

Pattern 4 (displayed v.s. true ratings): *Listings with a better displayed rating perform better than peers in Aliexpress-predefined groups and those with nearly identical true ratings.*

3.3 The Substance and Consistency of Information

To further explore the mechanisms through which reputation influences import decisions, we next investigate the content of buyer comments accompanying the ratings as an additional source of information. Specifically, we analyze the textual content of comments provided by previous importers to examine how the substance of information might affect future importers' decisions. Many buyers offer specific feedback about their purchasing experience including the quality of the product, the delivery process, and the return service. We perform a detailed textual analysis on the feedback data to quantify consumer sentiments across product parameter space.[15]

The process, described in detail in Section 2 of the Online Appendix, proceeds in several stages. We first compiled a complete list of words that have appeared in the comments and identified them as positive versus negative. Examples of positive sentiment words include "good", "excellent", and "superior", while examples of negative keywords include "bad", "poor", and "awful". As shown in column (1) of Table 3 and the top panel of Figure 5, we find that even after controlling for rating treatment, true ratings, and the total number of sales (without comments), the numbers of positive and negative keywords still matter. Listings with a larger number of positive keywords in the comments perform significantly better, with each additional positive word leading to 2-percent greater export quantity. The

[15]This exercise also helps mitigate the concerns that ratings might serve as a proxy for seller's knowledge of foreign demand or foreign market regulations. While such knowledge could affect export performance, it is unlikely to shape how importers respond to specific substance of the information.

magnitude of the effect is, however, weaker than the RDD effect (where the rating is bumped up by 0.1) or the effect of a past order. In contrast, a negative key word leads to 6.3-percent less export quantity, suggesting that importers react to negative reputation more strongly than to positive reputation.

We then decompose the texts into specific product parameters to examine how the effect of information might vary across product parameter space. Specifically, seven parameters, namely, material, style, size, color, shipping, other services, and general, were considered and a dictionary comprising synonyms and related terms for each parameter was constructed. To quantify consumer sentiment toward each product parameter, a dictionary of positive and negative sentiment words was constructed for each parameter based on manual and supervised machine learning processes of the raw data. For example, examples of synonyms and related words for material include "fabric", "texture", "cotton", "stretch", and "seam"; positive sentiment words pertaining to material include words such as "comfortable", "soft", "silky", and "feels nice" and negative sentiment words for material include "uncomfortable", "itchy", "rough", "rip", "weak", "tear", "wrinkle", and "shrink". After the keywords were coded, the number of times a positive or negative comment is made about each of the parameters was measured for each review.[16]

Next, we group product parameters to categories with codifiable, specific information v.s. categories with only general statements. The former includes the first 6 parameters listed above, namely, material, style, size, color, shipping and other services. If a review did not contain any keywords pertaining to the 6 specific categories but mentioned a general positive or negative word such as "good" or "awful", then the review is classified as "general". We find in column (2) of Table 3 and the middle panel of Figure 5 that importers exhibit little response to general positive statements; positive information on specific attributes, in

[16] An important issue with classifying the reviews was the effect of the "no words" which could reverse the meaning of a sentence. Using the exist function, we coded comments that used a "no word" preceding a positive word as negative and comments with a "no word" preceding a negative word as either neutral or positive (as robustness checks). For example, if a review stated "the quality of this shirt is not good", the program would recognize that the word good is prefaced by a "no word" and classify the comment as negative rather than positive.

contrast, exerts a positive and significant effect. Each such comment is associated with 5-percent greater export quantity. When the information contains negative information about the listing, both general and specific comments matter with the general negative comments leading to a stronger adverse effect on export quantity.

The effect of information may also vary with the potential degree of information friction underlying product parameters. To explore this, we group product parameters to categories pertaining to observable v.s. less observable attributes. Specifically, style, color, and shipping can be mostly observed ex ante from the platform whereas material quality (e.g., softness and breathability) and size fit are mainly observed ex post after the transaction. It is hence plausible that the latter aspects of the products embody more information frictions and could benefit more from information flows between buyers. This hypothesis is supported in column (3) of Table 3 and the bottom panel of Figure 5 where we find positive comments on observable attributes have no effects on buyers while positive comments on less observable characteristics could boost sales. Interestingly, we also notice that negative information on attributes with ex-ante accessible information can significantly discourage future buyers, suggesting that inconsistency between actual quality and buyers' prior belief could have a strong negative effect.[17]

These results are summarized below:

Pattern 5 (content): *Importers respond more to (i) negative than positive reputation; (ii) codifiable, specific content than general positive statements; and (iii) information pertaining to unobservable attributes (e.g., material) than positive feedback pertaining to observable attributes (e.g., color).*

[17] We also considered explicitly how the consistency of information affects importer decisions. Listings with the same average rating may have very different numbers of feedbacks. The credibility of the average rating is expected to increase with the total number of feedbacks and decrease with the dispersion of ratings. We find evidence consistent with the hypothesis. Receiving more ratings strengthens the positive effects of a higher average rating and listings with more variations in ratings perform significantly worse.

3.4 Gravity in the Value of Reputation

In this subsection, we turn to importers and investigate how different importers might respond to the same exporter's reputation differently depending on the potential level of information friction across geographic space.

If reputation serves as a conduit of information, its effect is expected to increase with the geographic and cultural distances between China and the import country. The results in Table 4 suggest that the value of a positive reputation is stronger in import countries with a greater geographic distance from China even when separately controlling for shipping cost. This finding is consistent with the hypothesis that information friction increases with geographic distance and suggests that because of higher information costs import countries further away from exporters are more dependent on exporters' reputation for import decisions. Similarly, the effect of reputation is found stronger in import countries that do not share a common language with China and have a smaller share of Chinese immigrants, both of which are used as proxies of cultural distance.[18] This finding is summarized below:

Pattern 6 (gravity): *Reputation is more valuable in markets geographically and culturally farther from the export country.*

4 A Dynamic Model of Learning and Reputation

In this section, we present a simple dynamic model of learning and reputation motivated by stylized facts presented in the previous sections and structurally estimate the model to quantify the importance of an observable reputation regime in trade.

[18]In Section 3 of the Online Appendix, we also distinguished between the sources of reputation and find importer responses to reputation could vary with the origin of information. Specifically, we find importers respond more favorably to a positive reputation earned from fellow buyers in the same importing country but react similarly to a mediocre reputation from different sources. Further, similar to Morales, Sheu, and Zahler (2019), we document evidence of extended gravity between third countries and import destinations. Import countries place significantly greater weights on ratings provided by sources geographically and culturally closer, suggesting that even though feedbacks of each listing are observable to all importers, importers value information from local, regional, and similar peers more than other sources.

4.1 Setup

There is a home country and N foreign countries in the world. Sellers in the home country may export their products to the foreign countries. Each seller sells a product i with quality θ_i drawn from a distribution $N(\theta, \sigma_\theta^2)$. The true quality is observable to the seller, but not to the buyers. When a buyer from country j arrives, she will form an initial belief θ_{ij}^a drawn from a distribution $N(\theta_i, \sigma_{uj}^2)$ where σ_{uj}^2 varies across countries reflecting the level of information friction between Chinese exporters and country-j importers. When a country's importers are more informed about Chinese exporters, they form a more accurate belief that is closer to the true quality θ_i. After a buyer purchases product i, she may leave a feedback that contains noise, denoted by $\widetilde{\theta}_i^b \sim N(\theta_i, \sigma_\varepsilon^2)$. The feedback contributes to seller reputation and enables buyers in future periods to update their beliefs.

4.1.1 Demand

Each buyer purchases one unit of the product. We assume buyers arrive sequentially and decide in each period whether to buy from a seller.[19] Buyers, who are also consumers, have a discrete choice preference and the indirect utility function from product i for a consumer in country j is given by:

$$U_{ijtm} = \rho E(\theta_{im} | \theta_{ij}^a, \theta_{im}^b) - p_{ijtm} + \epsilon_i, \tag{2}$$

where $E(\theta_{im} | \theta_{ij}^a, \theta_{im}^b)$ is the buyer's belief on product quality given m past buyer feedbacks,[20] ρ captures consumer's preference weight on perceived product quality, θ_{ij}^a is the initial quality belief drawn by the buyer, θ_{im}^b represents the seller reputation revealed in m past buyer feedbacks, p_{ijtm} is the delivery price including an iceberg trade cost τ_j at time period t, and

[19] We abstract from repeated transactions between a seller-buyer pair because they account for a small share (17 percent) of the data and have been found less important in a centralized feedback system (Cai et al., 2014). The extensive margins, in particular, the buyer margin, are the main source of variations across exporters in our empirical context.

[20] New buyers, regardless of their arrival time t, can only infer product quality based on feedbacks left by previous buyers. Therefore θ_{im}^b is only related to m, not time period t.

ϵ_i is a random term following Type I Extreme distribution with variance σ^2. The probability of a buyer from country j purchasing product i, denoted by d_{ijtm}, is given by:

$$d_{ijtm} = \frac{\exp\left[\frac{1}{\sigma}(\rho E(\theta_{im}|\theta^a_{ij}, \theta^b_{im}) - p_{ijtm})\right]}{\sum_{k=1}^{K} \exp\left[\frac{1}{\sigma}(\rho E(\theta_{km}|\theta^a_{kj}, \theta^b_{km}) - p_{kjtm})\right]}, \tag{3}$$

where K is the total number of products.

4.1.2 Buyer Belief Updating

As described earlier, buyers' belief on product quality is affected by the information provided by the evolving reputation of the seller. We denote $\omega_\theta \equiv 1/\sigma^2_\theta$, $\omega_{uj} \equiv 1/\sigma^2_{uj}$ and $\omega_\varepsilon \equiv 1/\sigma^2_\varepsilon$ and assume that buyers use the Bayesian Rule to update their beliefs.

Specifically, in any period t when there is no feedback, the new coming buyer from country j will have belief

$$\overline{\theta}_{ij0} \equiv E(\theta_{i0}|\theta^a_{ij}) = \frac{\omega_\theta \theta + \omega_{uj}\theta^a_{ij}}{\omega_\theta + \omega_{uj}}. \tag{4}$$

The buyer's beliefs will be updated whenever there is a new feedback. In period t when there are m feedbacks, the new coming buyer will have belief

$$\overline{\theta}_{ijm} \equiv E(\theta_{im}|\theta^a_{ij}, \theta^b_{im}) = \frac{\omega_\theta \theta + \omega_u \theta^a_{ij} + m\omega_\varepsilon \theta^b_{im}}{\omega_\theta + \omega_u + m\omega_\varepsilon}, \tag{5}$$

where $\theta^b_{im} \equiv \frac{\sum_{k=1}^{m} \widetilde{\theta}^b_{ik}}{m}$ is the seller's reputation conveyed by past buyers. Note that the buyer's updated belief is a weighted sum of the mean of the true quality, the quality perceived by the buyer, and the reputation with the weight of each component inversely related to the variation of the corresponding distribution. The weight of reputation also increases in the number of feedbacks, a feature consistent with empirical evidence in Section 3.3.[21]

Three important patterns emerge from the updating process. First, the marginal effect

[21] While buyers' feedbacks affect the quality belief of other buyers, we assume they are unable to affect the true quality of a product. The assumption that sellers cannot respond to feedbacks by adjusting product quality is consistent with the setting of Aliexpress where sellers have little room in changing the quality of a listing once the listing is posted. The main margin of adjustment available to the sellers is pricing.

of feedbacks declines over time. For a customer who can observe m feedbacks in total, the weight she places on an nth feedback $(n < m)$ θ_{in}^b is $\frac{\omega_\varepsilon}{\omega_\theta+\omega_u+m\omega_\varepsilon}$ and decreases with m. As reputation starts to build and the seller accumulates more feedbacks on the product, the contribution of early feedbacks dissipates as we show in Section 3. Second, reputation building takes time and reputation will approach a product's true quality in the long run when there are sufficient feedbacks in line. Third, in line with the empirical evidence in Section 3.4, the marginal effect of reputation increases with the information friction between China and import country, $\frac{\partial\bar{\theta}_{im}}{\partial\omega_u} < 0$. When buyers are less familiar with Chinese sellers, they are more dependent on the reputation information from other buyers.

4.1.3 The Sellers

We follow the monopolistic competition assumption and assume that each seller is small relative to the market, thereby not considering the effect of an individual seller's pricing on the market-wide condition. We also assume that the marginal cost of production is given by $c(\theta_i) = \tau_j + c\theta_i$, where τ_j is the unit trade cost to export to country j. The profit in each period is given by:

$$\pi_{ijtm} = (p_{ijtm} - \tau_j - c\theta_i)d_{ijtm}, \tag{6}$$

where d_{ijtm} is the demand function measuring the probability of an incoming buyer purchasing the product. We assume in each period a buyer from each country j arrives with a probability q_j where $\sum_{j\in N} q_j = 1$. A seller's expected profit in each period t is thus given by:

$$\pi_{itm} = \sum_{j\in N} q_j(p_{ijtm} - \tau_j - c\theta_i)d_{ijtm}. \tag{7}$$

After entry in the first period, each seller has an exogenous probability δ of exiting.

Each seller chooses price p_{ijtm} in market j each period to maximize profits. Each seller's maximization problem is given by:

$$\max_{\{p_{ijtm}\}_{t,m=1}^{\infty}} E_{\{\theta_{ij}^{a},\theta_{im}^{b}\}_{m=1}^{\infty}} \sum_{t=1}^{\infty}\{[\beta(1-\delta)]^{t}\sum_{j\in N} q_{j}[(p_{ijtm}-\tau_{j}-c\theta_{i})d_{ijtm}]\}, \tag{8}$$

where β is the seller's discount rate. In each market j, the seller sets its delivery price according to the following Bellman equation[22]:

$$\begin{aligned} V_{ijtm}(\theta_i,\overline{\theta}_{ijm}) &= \max_{\{p_{ijtm}\}_{j\in N}} \frac{d_{ijtm}}{1-\beta(1-\delta)(1-d_{ijtm})}[p_{ijtm}-\tau_j-c\theta_i \\ &\quad +\beta(1-\delta)E(V_{ij(t+1)(m+1)}(\theta_i,\overline{\theta}_{im+1}))]. \end{aligned} \tag{9}$$

In the following section, we solve the optimal price for each period under different scenarios.

4.2 Equilibrium

With Complete Information We first solve the model under complete information in which the buyer observes the true quality θ_i of each product. In this case, there is no updating on $\overline{\theta}_{im}$ and solving equation (9) yields:

$$\begin{aligned} p_{ijt}^{C} &= \tau_j + c\theta_i + \sigma \\ d_{ijt}^{C} &= \frac{1}{D_j^C}\cdot \exp\left[\frac{1}{\sigma}(\rho\theta_i-\tau_j-c\theta_i-\sigma)\right] \end{aligned} \tag{10}$$

where $D_j^C \equiv \sum_{k=1}^{K}\exp\left[\frac{1}{\sigma}(\rho\theta_k - p_{kjt})\right]$. The optimal price and quantity are constant across periods.

With Incomplete Information and No Observable Reputation Now we consider the case of incomplete information but no observable reputation; that is, buyers cannot observe the true quality θ_i of a product or learn about exporter reputation from each other. The buyer's belief on product quality is hence based exclusively on the distribution of true

[22]A derivation of the Bellman equation is reported in Section 5.1 of the Online Appendix.

quality and initial belief and does not vary across periods due to the absence of learning.

Solving the maximization problem in equation (9) yields:

$$\begin{aligned} p_{ijt}^I &= \tau_j + c\theta_i + \sigma \\ d_{ijt}^I &= \frac{1}{D_j^I} \cdot \exp\left[\frac{1}{\sigma}(\rho\overline{\theta}_{ijt} - \tau_j - c\theta_i - \sigma)\right] \end{aligned} \tag{11}$$

where $D_j^I \equiv \sum_{k=1}^{K} \exp\left[\frac{1}{\sigma}(\overline{\theta}_{kjt} - p_{kjt})\right]$. The optimal price and quantity will again remain the same in each period.

Comparing the present case with the case of complete information, we find that the price as well as the dispersion of price is the same in the two scenarios. However, if the product true quality is relatively low ($\theta_i < \theta$), the expected export quantity under incomplete information will be higher than that under complete information, i.e., $E(d_{ijt}^I) > d_{ijt}^C$, because of buyers' inability to observe true quality. Conversely, if the true product quality is relatively high ($\theta_i > \theta$), the expected export quantity under incomplete information will be lower than that under complete information, i.e., $E(d_{ijt}^I) < d_{ijt}^C$. This suggests that export volume will be less dispersed under incomplete information than under complete information.

With Incomplete Information and Observable Reputation Next we consider the model with incomplete information and observable reputation; that is, buyers may update their product quality belief based on the reputation information provided by other buyers.

Solving equation (9) yields:

$$p_{ijtm}^*(\tau_j, \theta_i) = \tau_j + c\theta_i + \sigma - \beta(1-\delta)E\left(V_{i(t+1)(m+1)}(\theta_i, \overline{\theta}_{ijm+1}, \omega_u^*)\right). \tag{12}$$

Comparing the prices across the three scenarios, we find that $p_{ijtm}^* < p_{ict}^C = p_{ijt}^I$; that is, the optimal price with observable reputation is lower than the optimal price under complete information as well as the optimal price under incomplete information and no observable reputation. This is because in the presence of observable reputation, the future option value lowers the optimal current price and sellers will set prices relatively low initially to subsidize learning. Such incentives to subsidize learning with a lower price are especially strong for high-quality sellers as their future expected values are higher than those of low-quality sellers. But as reputation becomes established, high-quality sellers will gradually raise their prices and eventually—after reputation is fully learned—price at the same level as the optimal price under complete information and the optimal price with incomplete information but no observable reputation. This result is summarized in the next proposition:

Proposition 1 *When there are information frictions and observable reputation, sellers, especially high-quality sellers, will initially set price relatively low to subsidize reputation building and then raise price over time as they receive more orders.*[23]

Next, we obtain the quantity of sales for each product i in each market j:

$$d^*_{ijtm}(\tau_j, \theta_i) = \frac{1}{D^*_j} \exp\left[\frac{1}{\sigma}(\rho\overline{\theta}_{ijm} - \tau_j - c\theta_i - \sigma + \beta(1-\delta)E(V_{i(t+1)(m+1)}(\theta_i, \overline{\theta}_{ijm+1}, \omega^*_u))\right] \tag{13}$$

where $D^*_j \equiv \sum_{k=1}^{K} \exp\left[\frac{1}{\sigma}(\overline{\theta}_{ijm} - \tau_k - c\theta_i - \sigma + \beta(1-\delta)E(V_{i(t+1)(m+1)}(\overline{\theta}_{ijm+1}, \omega^*_u))\right]$. By comparing d_{ijtm} across all scenarios, we show in Section 5.4 of the Online Appendix that when the dispersion of true quality is sufficiently large, the export premium of high-quality sellers is greater in the presence of observable reputation. This finding is summarized in the following proposition:

Proposition 2 *When there are information frictions and the dispersion of true quality is sufficiently large, the export premium of high-quality sellers is greater in the presence of observable reputation.*

The result predicted in Proposition 2 arises from two mechanisms in the model. On the one hand, when buyers can easily share information on exporter quality with each other,

[23] Sections 5.3 of the Online Appendix provides a formal proof of the propositions. Section 4 of the Online Appendix, investigating how reputation affects price dynamics in the data, offers empirical evidence in support of the hypothesis of Proposition 1.

high-quality exporters can more likely command a larger market share. On the other hand, high-quality exporters also have incentives to set prices relatively low initially to subsidize reputation building which, in turn, raises their export premium over their lifetime.

4.3 Structural Estimation

In this subsection, we structurally estimate the model to quantify the importance of the reputation regime in trade. We first parameterize certain parameters from reduced-form regressions and solve the dynamic pricing problem for each firm to get the optimal policy function. The policy rule and the parameter vector are then used to simulate a dataset and match simulated moments with true moments. Lastly, we perform a counterfactual exercise by shutting down the learning process to evaluate the effect of the reputation regime.

4.3.1 Parameterization

Because of the high dimensions of the model, we obtain country-specific parameters from reduced-form regressions and other sources. There are four types of country-specific parameters in this model, i.e., market size($\{D_j\}$), market-specific information friction($\{\sigma_{uj}\}$), transportation cost($\{\tau_j\}$), and consumer search probability($\{q_j\}$).

We derive the market size parameters($\{D_j\}$) from estimating the demand equation:

$$\ln d_{ijt} = -\ln D_j + \frac{\rho}{\sigma}\bar{\theta}_{it} - \frac{1}{\sigma}(p_{it} + \tau_j) \tag{14}$$

which can be simplified to: $\ln d_{ijt} = \gamma_{it} + \lambda_j + \varepsilon_{ijt}$ where d_{ijt} represents the export volume of listing i to country j at time t and γ_{it} is a listing-time fixed effect that controls for all time-variant listing attributes such as price and feedback ratings. We use a vector of country dummies λ_j to estimate market size parameters $D_j = \exp(-\lambda_j - \frac{\tau_j}{\sigma})$ where τ_j is assumed to be 0 as more than 70 percent of the sellers provide free shipping and listing price does not vary across markets on Aliexpress. The estimates suggest an average λ_j of 0.01 and

Russia has the highest λ_j of 0.25, consistent with Russia's rank in the data as the top export destination.

To estimate market-specific information friction($\{\sigma_{uj}\}$), we make the assumption that the true quality of a listing is fully learned after a sufficiently large number of periods (t_n) and the demand for the listing at that time is thus no longer affected by information friction between export and import countries. In contrast, when a listing is new (at t_1), the demand is dependent on not only the listing's true quality but also the information friction. Taking the difference of the demand function between the two periods yields:

$$\ln d_{ijt_n} - \ln d_{ijt_1} = -\frac{\rho}{\sigma}\frac{\omega_\theta \theta}{\omega_\theta + \omega_{uj}} - \frac{1}{\sigma}(p_{it_n} - p_{it_1}) + \varepsilon_{ijt} = \beta\chi_j + FE_{it} + \varepsilon_{ijt}$$

where $\chi_j = -\frac{\rho}{\sigma}\frac{\omega_\theta \theta}{\omega_\theta + \omega_{uj}}$ is a decreasing function of σ_{uj}, the level of information friction between country j and Chinese sellers, FE_{it} is a vector of listing-week dummies to control for all time-variant listing variables such as prices and quality, and ε_{ijt} is the residual term including all the other factors. The market-specific information friction can thus be inferred from estimating the change in $\ln d_{ij}$. Assuming χ_j is a function of the geographic and cultural distances between country j and China proxied, respectively, by country distance, contiguity, sharing language, and the share of Chinese immigrants, we estimate the above equation by comparing new listings' sales in period 1 with their sales after the 25th week and report the results in Table 5.[24] This step allows us to obtain $\frac{\omega_{uj}}{\omega_\theta} = -\frac{\rho\theta}{\sigma\Phi(\chi_j)} - 1$.

To measure consumers' probability of arrival at the export market from each country, we use the volume of visits to the Aliexpress website (www.aliexpress.com) obtained from Alexa, a leading data source of web traffic metrics. The top visitor countries include Russia, Brazil, United States and South Korea which are also some of the largest importing countries observed in the sample data.[25]

[24] The results remained similar when longer time periods were considered.

[25] Alexa only reports the volume of visitors by country for the top 36 origin countries. To reconcile the country coverage difference between Alexa and our data, we assume that unreported countries visit Aliexpress at the same frequency; the total share of visitors from those countries only amounts to 17.4 percent.

We recover consumer's preference weight on reputation by applying RDD to equation (14) and estimating a modified version of column (2) of Table 2.[26] The coefficient of the treated dummy, λ_1, measures the effect of a discontinuous shift in reputation that corresponds to an increase of 0.1 on the displayed average rating. Therefore, the semi-elasticity of demand with respect to reputation in our model is $\frac{\rho}{\sigma} = 10 * \lambda_1 = 2.41$. We obtain an average reputation effect from the treated and non-treated group regressions which yield $\frac{\rho}{\sigma} = 2.41$. Because of the endogeneity of price in that regression, we adopt the markup parameter of the Apparel of Textile Fabrics estimated in Broda and Weinstein (2006) and assume σ to be 17 percent of the average-quality listing's marginal cost.

For the other parameters, we set the weekly discount factor β to be 0.999 and the seller exit rate δ to be 0.02 based on the observation from the Aliexpress data where exit is defined as the withdrawal of a listing. We also normalize $0 \leqslant \sigma_u^2 \leqslant 1$.

4.3.2 Estimation Procedure

There are now four remaining parameters to be estimated, including parameters of the quality distribution $(\theta, \sigma_\theta^2)$, the reputation information friction (σ_ε^2), and the cost parameter (c). The identification of these parameters comes from over-time variations in export revenue and price. As each exporter responds to past ratings differently because of their quality heterogeneity, simulated method of moments is used to estimate industry quality distribution and cost parameters. We also use indirect inference methods to avoid high dimensionality in constructing the likelihood function and recover the sellers' parameters $\Theta \equiv (\theta, \sigma_\theta^2, c, \sigma_\varepsilon^2)$ and the annealing algorithm to search for parameters and accommodate potential discontinuity and discretized state space.

To find simulated moments, we simulate a panel of $12,000$ sellers for 5 years over a fixed set of random draws based on guessed parameters.[27] For each guess of each simulation,

[26] The main difference is that in equation (14) which takes the logarithm of the demand equation, price enters the equation without log.

[27] The size of the simulated sample is similar to the size of the actual sample data. The first two years are dropped to exclude the effect of initial conditions. The entire simulation is conducted 10 times and the

we solve for the optimal price policy function and let the seller set the price according to the policy function.[28] Next we simulate importers' purchasing decisions as well as their ratings and obtain a panel of sellers' export flows. The simulated panel is used to match the following moments with the actual data: (1) the mean of $ln(price)$ averaged across listings and periods; (2) the dispersion of $ln(price)$ measured by the standard deviation of $ln(price)$; (3) the mean of $ln(export\ sales + 1)$ averaged across listings and periods; and (4) the dispersion of $ln(export\ sales + 1)$ across periods. The combination of these information helps us pin down the parameter set Θ.

4.3.3 Estimation Results

The estimated parameter values are reported in Panel A of Table 6. The model can account for most of the price and export revenue dispersion observed in the data as shown in Panel B. When using non-targeted price and export revenue dispersion measures as a further check for the model's performance, we find that the dispersion of price captured by, for example, the ratio of the 75th percentile relative to the 25th percentile is predicted to be 1.42 in the model, in comparison to 1.45 in the data (Panel C).

Next we use the model to quantify how the regime of observable reputation explored in this paper can affect aggregate exports and its distribution. In our model, the variance of information reflects frictions in information diffusion. The true product quality will be revealed eventually, but the amount of time it takes to reach full learning depends on the level of information friction. When information contains less noise and can be diffused more effectively, it becomes easier for future buyers to evaluate a listing and obtain more accurate beliefs. We therefore study the effects of information frictions by adjusting the variance of information in our policy experiments. Specifically, we consider two experiments: (1) setting σ_ε^2, the variation of feedback information, to infinity so that importers cannot learn from each other and exporter reputation cannot be observed; and (2) setting σ_ε^2 to infinity and

moments are averaged to exclude random simulation noise.

[28] See Section 5.5 of the Online Appendix for the algorithm of solving the policy function.

increasing the level of average quality to evaluate the equivalent-level of quality upgrading needed to achieve the same level of total exports under observable reputation.

Our first policy experiment shows that compared to the case in which reputation is completely unobservable, observable reputation can contribute to an over 20-percent increase in total export revenue. We also find the value of the reputation regime varies across countries and rises significantly with the level of the estimated information friction between China and the import country. Across around 100 export markets, the estimated effect of the reputation regime is found to be the greatest for Latin American countries such as Ecuador, Peru, Dominican Republic, Colombia, Bolivia, Argentina, and Brazil, followed by African countries such as Botswana, South Africa, Zambia, Uganda, and Ghana. Eastern European markets are estimated to gain more than Western Europe and North America. Exports to Asia, especially to South Korea, Japan, and Singapore, are estimated to see the smallest effect due to the lowest levels of information frictions.[29]

The above trade gain arises from a new source of aggregate export growth through an expedited market reallocation from low-reputation to high-reputation sellers. Having a system where exporters can build reputation that is observable by importers incentivizes high-quality exporters to subsidize reputation building and helps them command a greater market share under a reputation regime than in the case of unobservable reputation. We find that the market share of top 1-percent exporters increases by over 40 percent in the presence of observable reputation leading to an accelerated creation of superstar exporters.

In our second policy experiment, we aim to obtain an intuitive understanding about the magnitude of export growth caused by the reputation regime. The trade literature of heterogeneous firms and export growth has highlighted the importance of quality upgrading (for example, see Bernard, Redding and Schott, 2011; Kugler and Verhoogen, 2012). Here we assess the extent by which the market-wide quality would need to increase in a world without

[29] It is worth noting that since these estimated gains are derived from a specific reputation regime offered by online trade platforms, the gains from other reputation regimes, especially those present in offline trade, are likely to be quantitatively different. Nevertheless, the theoretical framework presented can plausibly be adapted to fit other empirical contexts and quantify the values of alternative reputation mechanisms.

observable reputation to achieve the same degree of export growth. Our simulation result shows that to achieve the same export growth brought by the reputation system requires raising economy-wide quality by over 25 percent.

5 Conclusion

This paper investigates the role of reputation regimes in trade exploring the unique context of a leading online trade platform, Alibaba. We examine how importers and exporters respond to the opportunities to build and learn exporter reputation. Using a detailed export transaction dataset in the T-shirt industry and exploring qualitative and quantitative features of the reputation system on Aliexpress, we document novel stylized facts about the distribution of online exports and show that both the level and the substance of an exporter's reputation have a significant effect on margins of exports. Products with a better displayed reputation outperform peers with nearly identical observable characteristics and true ratings. Further, how importers respond to reputation is determined by the level of information friction underlying product attributes and trading partners and the specificity of information.

We develop a dynamic model with heterogeneous information frictions and endogenous exporter reputation to account for observed empirical regularities and quantify the importance of the reputation regime. The model demonstrates that exporters use dynamic pricing strategies to influence the speed of reputation building and highlights a new source of export growth through an expedited market reallocation towards reputation exporters. These effects can amount to an over 20-percent increase in aggregate exports, equivalent to the effect of raising market-wide quality by over 25 percent. The value of the reputation regime rises with the level of information friction between export and import countries.

The findings of this paper convey important implications for the role of information flow and importer learning via online trade platforms in the aggregate value and distribution of trade. While lowering explicit export entry costs and quality upgrading are important for the ability of small businesses to penetrate export markets, there are other vital implicit entry barriers as a result of information frictions. Information frictions can be a particularly critical export impediment especially for developing countries and efforts to provide a market-wide reputation system via online trade platforms could facilitate export growth. Such programs must be inclusive of new exporters who could otherwise live in the shadow of established superstars with impaired visibility in export markets.

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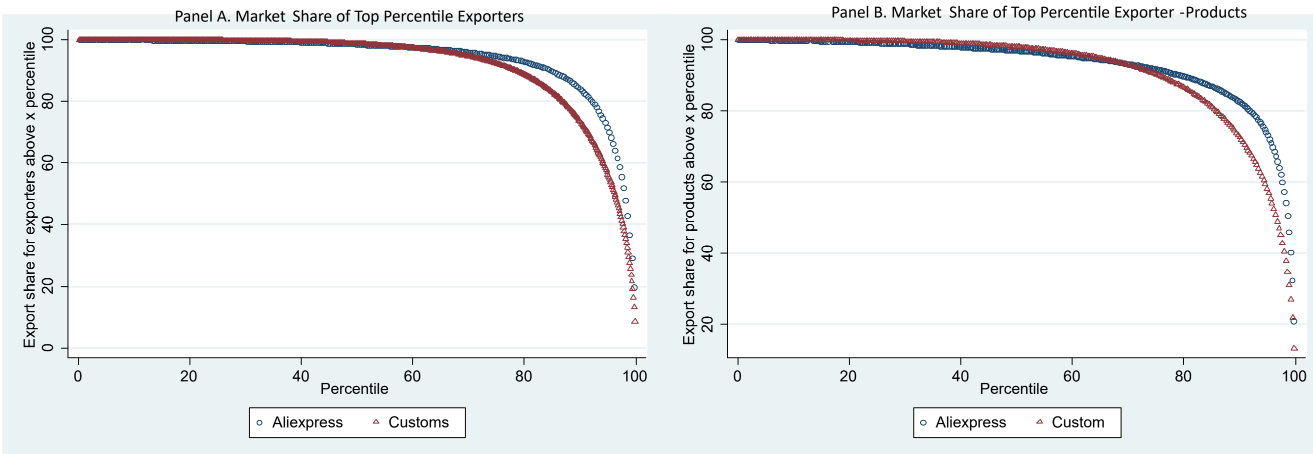

Figure 1: The Market Share of Top-Percentile Exporters/Products Online and Offline

Notes: This figure shows the export market share accounted for by exporters or exporter-product pairs whose sales are above each percentile on the horizontal axis.

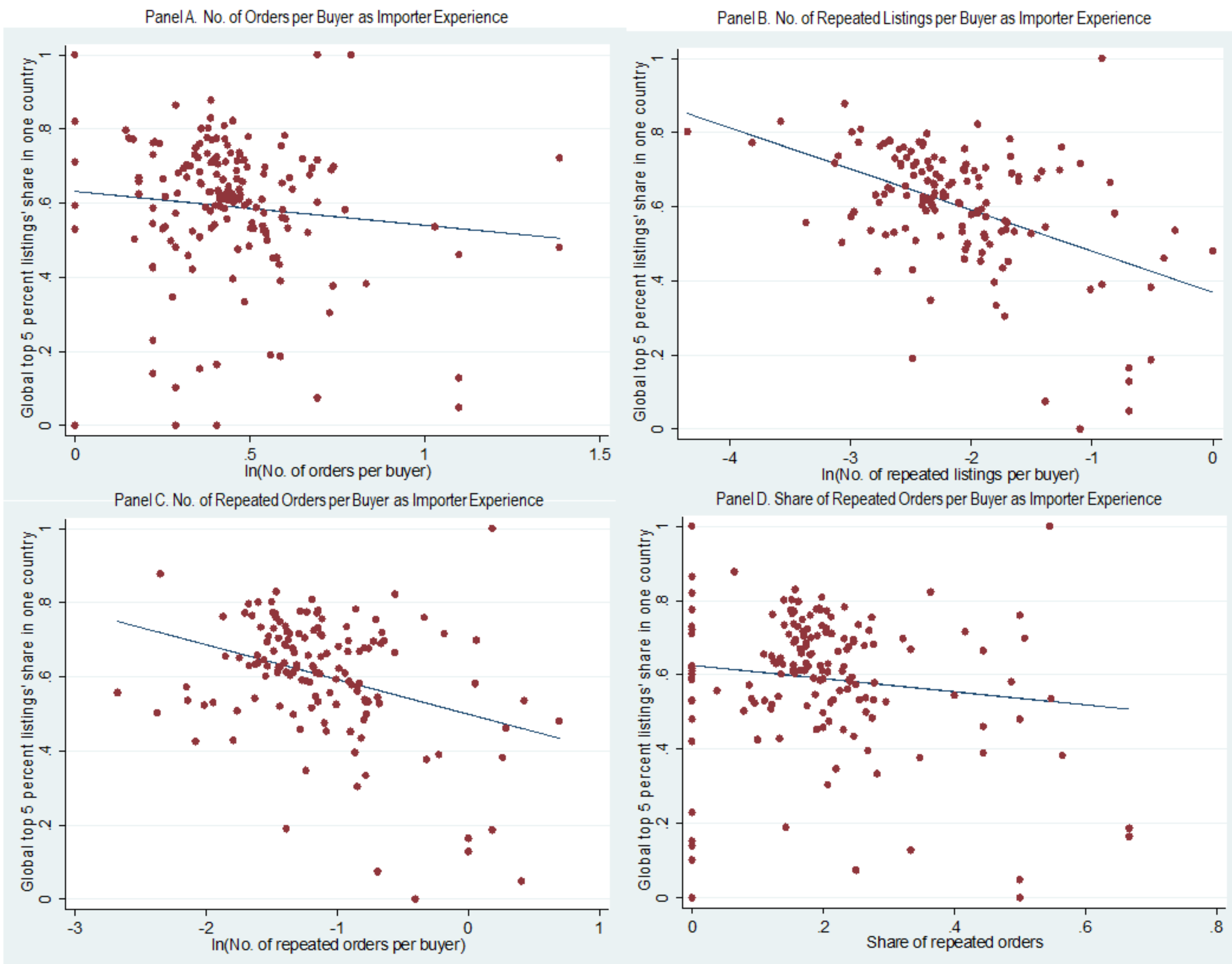

Figure 2: The Market Share of Superstar Listings and Importer Experience

Notes: The figure plots the relationship between the market share of global top 5-percent listings in an import country and the country's importer experience. Importer experience is measured by buyers' average number of orders (top left), average number of repeated listings (top right), average number of repeated orders (bottom left), and share of repeated orders (bottom right). The number of repeated listings refers to the number of listings from which the buyer purchases at least twice. The number of repeated orders refers to the number of repeated transactions between a listing and a buyer.

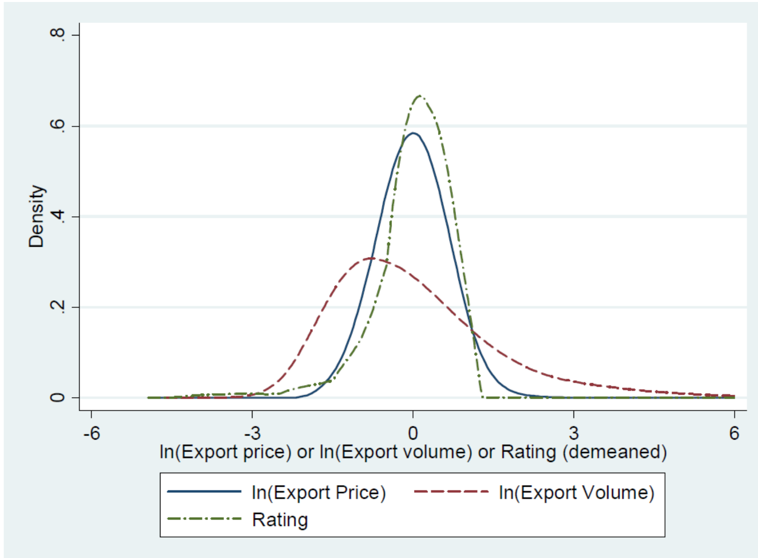

Figure 3: The Distributions of Export Price, Volume and Reputation

Notes: This figure compares the distributions of export unit price, export volume, and listing rating. Unit price is the average price over the sample period and listing rating is the average ratings left by importers over the sample period weighted by the order number. Export volume and unit price are on a log scale.

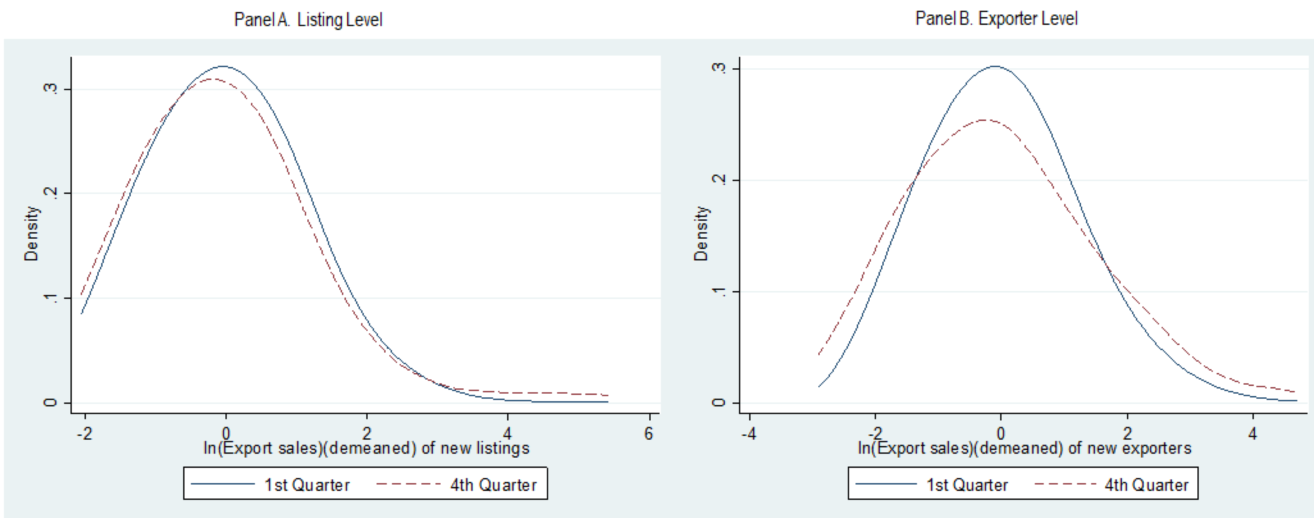

Figure 4: The Distribution of Export Revenue over Time

Notes: This figure plots the distributions of export revenue in the first and fourth quarter for a cohort of new listings/exporters born in the first quarter of the sample period.

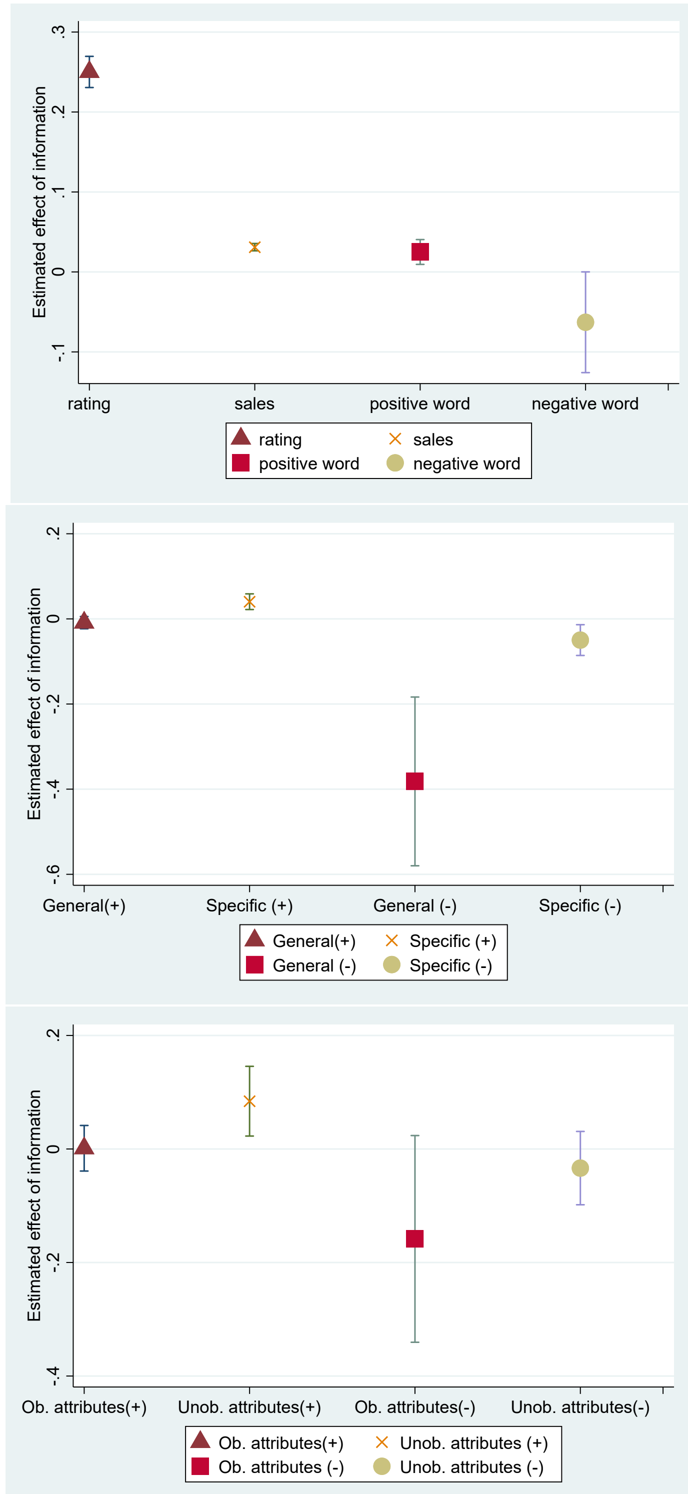

Figure 5: The Substance of Information: Positive v.s. negative; general v.s. specific; observable v.s. unobservable attributes

Notes: The above figures present the estimated elasticities of export quantity with respect to positive v.s. negative comments, general v.s. specific comments, and information on observable v.s. unobservable attributes. The coefficients are plotted with the 95-percent confidence bands.

Table 1: The Value of Reputation: Within-Peer-Group Comparison

	(1)	(2)	(3)	(4)	(5)
	revenue	quantity	ave quantity	buyer num	market num
ln(price)	-0.673***	-0.498***	-0.228***	-0.432***	-0.350***
	(0.076)	(0.048)	(0.018)	(0.046)	(0.034)
no rating	0.411***	0.166***	0.120***	0.152***	0.138***
	(0.026)	(0.014)	(0.007)	(0.013)	(0.010)
2<=rating<3	0.007	-0.003	0.004	-0.004	0.001
	(0.034)	(0.018)	(0.009)	(0.017)	(0.013)
3<=rating<4	0.084***	0.037**	0.024***	0.035**	0.030***
	(0.028)	(0.015)	(0.007)	(0.014)	(0.011)
rating>=4	0.260***	0.140***	0.059***	0.132***	0.106***
	(0.027)	(0.015)	(0.007)	(0.014)	(0.011)
material quality	0.032	0.02	0.007	0.018	0.012
	(0.031)	(0.020)	(0.006)	(0.019)	(0.013)
buyer protection	0.04	0.071	-0.017	0.073	0.047
	(0.088)	(0.050)	(0.018)	(0.047)	(0.037)
return policy 1	-0.062	-0.028	-0.032	-0.02	-0.018
	(0.098)	(0.061)	(0.022)	(0.057)	(0.042)
return policy 2	0.048	0.05	0.016	0.036	0.022
	(0.201)	(0.121)	(0.044)	(0.115)	(0.083)
return policy 3	-0.119	-0.046	-0.042	-0.039	-0.036
	(0.141)	(0.084)	(0.031)	(0.079)	(0.059)
ln(size choice num)	0.162***	0.107***	0.033***	0.100***	0.074***
	(0.048)	(0.032)	(0.009)	(0.030)	(0.021)
ln(detailed description num)	-0.018	-0.016	0.002	-0.024	-0.017
	(0.108)	(0.069)	(0.020)	(0.066)	(0.047)
ln(picture num)	0.034	0.014	0.008*	0.012	0.011
	(0.022)	(0.014)	(0.004)	(0.014)	(0.010)
Group FE	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y
Seller FE	Y	Y	Y	Y	Y
R2	0.410	0.449	0.322	0.459	0.446
N	541,467	541,467	541,467	541,467	541,467

Notes: This table explores export and reputation variations within peer groups where listings have nearly identical observable characteristics (i.e., identical t-shirts) and control for a peer group fixed effect. The observations are at the exporter-listing-week level. Standard errors are clustered at the listing level. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Table 2: The Value of Reputation: RDD Regression

	(1) revenue	(2) quantity	(3) ave quantity	(4) buyer num	(5) market num
ln(price)	-0.544***	-0.552***	-0.201***	-0.464***	-0.349***
	(0.064)	(0.044)	(0.015)	(0.041)	(0.029)
true rating	0.344***	0.180***	0.071***	0.170***	0.133***
	(0.018)	(0.011)	(0.004)	(0.011)	(0.008)
treated	0.327***	0.179***	0.066***	0.170***	0.134***
	(0.020)	(0.012)	(0.004)	(0.012)	(0.009)
material quality	-0.005	-0.006	-0.007	-0.001	-0.003
	(0.038)	(0.025)	(0.007)	(0.023)	(0.017)
buyer protection	0.121	0.096	-0.003	0.096	0.071
	(0.120)	(0.072)	(0.022)	(0.068)	(0.052)
return policy 1	0.269*	0.168**	0.026	0.179**	0.131**
	(0.144)	(0.079)	(0.033)	(0.073)	(0.058)
return policy 2	0.524*	0.314*	0.110*	0.290*	0.224*
	(0.295)	(0.176)	(0.057)	(0.169)	(0.122)
return policy 3	0.08	0.082	-0.011	0.092	0.058
	(0.205)	(0.111)	(0.044)	(0.105)	(0.081)
ln(size choice num)	0.233***	0.151***	0.046***	0.140***	0.102***
	(0.041)	(0.027)	(0.008)	(0.025)	(0.018)
ln(detailed description num)	0.454***	0.297***	0.071**	0.289***	0.203***
	(0.168)	(0.111)	(0.030)	(0.106)	(0.074)
ln(picture num)	0.157***	0.085***	0.032***	0.078***	0.060***
	(0.034)	(0.024)	(0.006)	(0.023)	(0.016)
constant	1.133**	1.242***	0.398***	1.038***	0.675***
	(0.521)	(0.342)	(0.099)	(0.324)	(0.230)
Week FE	Y	Y	Y	Y	Y
Seller FE	Y	Y	Y	Y	Y
R2	0.364	0.387	0.29	0.388	0.379
N	139,246	139,246	139,246	139,246	139,246

Notes: This table shows results of the RDD regressions. The sample is restricted to observations with at least one rating. The "treated" dummy equals 1 if the displayed rating of a listing is rounded up and 0 if the displayed rating is rounded down. We exclude observations with a past average rating of 5 stars because these observations do not have treated group observations. All observations are at the exporter-listing-week level. Standard errors are clustered at the listing level. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Table 3: The Substance of Information

	(1) quantity	(2) quantity	(3) quantity
ln(price)	-0.302***	-0.302***	-0.303***
	(0.020)	(0.020)	(0.020)
treated	0.250***	0.250***	0.249***
	(0.010)	(0.010)	(0.010)
true rating	0.016***	0.016***	0.016***
	(0.004)	(0.004)	(0.004)
orders (w/o reviews)	0.031***	0.031***	0.031***
	(0.002)	(0.002)	(0.002)
positive words	0.025***		
	(0.008)		
negative words	-0.063*		
	(0.032)		
specific - positive		0.035***	
		(0.010)	
specific - negative		-0.048*	
		(0.025)	
general - positive		-0.004	
		(0.007)	
general - negative		-0.336*	
		(0.172)	
unobservable - positive			0.084***
			(0.031)
unobservable - negative			-0.034
			(0.033)
observable - positive			0.001
			(0.020)
observable - negative			-0.158*
			(0.093)
nouns	0.073*	0.075*	0.065*
	(0.039)	(0.041)	(0.035)
Other controls	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
Seller FE	Yes	Yes	Yes
R2	0.469	0.470	0.470
N	285,560	285,560	285,560

Notes: This table shows the effects of the information content. A vector of sentiment measures are included to control for positive and negative consumer sentiments pertaining to either general v.s. specific feedback or observable v.s. unobservable product attributes. All observations are at the exporter-listing-country-week level. Standard errors are clustered at the listing level. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Table 4: The Role of Gravity in the Value of Reputation

	(1)	(2)	(3)	(4)
	quantity	quantity	quantity	quantity
ln(price)	-0.288***	-0.290***	-0.290***	-0.290***
	(0.035)	(0.035)	(0.035)	(0.035)
treated	-0.124	-0.168	-0.136	-0.160
	(0.099)	(0.103)	(0.104)	(0.104)
x distance	0.017	0.023**	0.019*	0.018
	(0.011)	(0.011)	(0.012)	(0.012)
x shipping fee		-0.035**	-0.035**	-0.034**
		(0.014)	(0.014)	(0.014)
x common lang.			-0.098***	-0.083***
			(0.024)	(0.024)
x Chinese immig. share				-0.006***
				(0.001)
true rating	0.025***	0.025***	0.025***	0.025***
	(0.008)	(0.008)	(0.008)	(0.008)
material quality	0.004	0.003	0.003	0.003
	(0.015)	(0.015)	(0.015)	(0.015)
buyer protection	0.053*	0.054*	0.054*	0.054*
	(0.032)	(0.032)	(0.032)	(0.032)
return policy 1	0.027	0.027	0.028	0.028
	(0.033)	(0.033)	(0.033)	(0.033)
return policy 2	-0.036	-0.036	-0.035	-0.035
	(0.088)	(0.089)	(0.089)	(0.089)
return policy 3	0.045	0.046	0.046	0.045
	(0.054)	(0.054)	(0.054)	(0.054)
ln(size choice num)	0.068***	0.070***	0.070***	0.070***
	(0.013)	(0.013)	(0.013)	(0.013)
ln(detailed description num)	0.052	0.053	0.053	0.053
	(0.063)	(0.063)	(0.063)	(0.063)
ln(picture num)	-0.008	-0.008	-0.008	-0.008
	(0.015)	(0.015)	(0.015)	(0.015)
constant	1.107***	1.113***	1.113***	1.128***
	(0.229)	(0.229)	(0.229)	(0.229)
Week FE	Yes	Yes	Yes	Yes
Seller FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
R2	0.248	0.249	0.249	0.249
N	187,410	187,410	187,410	187,410

Notes: This table shows the heterogeneous RDD effect across import countries. The "treated" dummy equals 1 if the displayed rating of a listing is rounded up and 0 if the displayed rating is rounded down and is interacted, respectively, with the distance and shipping cost from China to the import country, whether the import country speaks the same language, and the share of Chinese immigrants. All observations are at the exporter-listing-country-week level. Standard errors are clustered at the listing level. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Table 5: Structural Estimation: First-step Estimation of the Information Friction

	(1) $\ln d_{ijt_n} - \ln d_{ijt_1}$
ln(distance)	-0.124*
	(0.07)
contiguity	0.054
	(0.11)
language	0.029***
	(0.01)
Chinese immigrants share	1.013***
	(0.31)
constant	0.84
	(0.64)
listing-week FE	Y
R2	0.04
N	36,741

Notes: This table estimates cross-country information frictions. The standard errors are clustered at the country level and reported in parentheses. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Table 6: Structural Estimation: Parameter Estimates and Moments

Panel A: Parameters		Estimates
log(average quality level)	$log(\bar{\theta})$	-8.77
variance of log(quality)	$var(log(\bar{\theta}))$	0.45
variance of feedback	$var(\sigma_\epsilon)$	2.62
marginal cost of an average quality product	$exp(c) * \bar{\theta}$	1.1
markup for an average quality product	σ	0.2
reputation elasticity	ρ	0.4

Panel B: Targeted Moments	Data	Model
mean of ln(price)	2.06	2.06
std of ln(price)	0.55	0.54
mean of ln(sales+1)	3.55	3.57
std of ln(sales+1)	1.42	1.47
Objective function value = 0.0001		

Panel C: Non-targeted Moments	Data	Model
p85/p15 of ln(price)	1.74	1.76
p75/p25 of ln(price)	1.42	1.45
p85/p15 of ln(sales+1)	2.16	1.88
p75/p25 of ln(sales+1)	1.65	1.30

Notes: Panel A reports the parameter estimates; panel B reports a comparison of the model and data for targeted moments; Panel C tests the fitness of the model by looking at non-targeted moments.