The Value of Reputation in Trade: Evidence from Alibaba[*]

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Abstract

Information frictions are prevalent in the search for exporters especially in developing nations. In this paper, we examine the value of reputation in international trade by exploring China's T-shirt exports on the world's leading trade platform, Alibaba. We first present four new stylized facts about the distribution of Alibaba exports: (1) exports are exceedingly concentrated on superstar exporters; (2) the distribution of price closely mirrors the distribution of exporter reputation while the distribution of export volume is more dispersed; (3) the distribution of exporter revenue becomes more dispersed as exporters age; and (4) the market share of superstar exporters diminishes with the experience of importers. Exploiting qualitative and quantitative attributes of Alibaba's reputation measures, we explain the stylized facts and investigate the heterogeneous trade responses to reputation across countries and over time. We develop a dynamic pricing and reputation model with heterogeneous exporters to show high-quality exporters subsidize learning and earn export premium over time. Our structural estimation finds that observable reputation leads to a 34-percent increase in aggregate export revenue, equivalent to a 29-percent market-wide quality upgrading, and the growth is driven by a dramatic shift in export market allocation towards superstar exporters with the share of top 1-percent exporters rising by 66 percent.

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1 Introduction

Information frictions are prevalent in the matching of exporters and importers. Exporters often undergo costly processes to understand foreign market demand; several recent studies (e.g., Allen, 2014; and Steinwender, 2014) suggest that information frictions on market demand can cause severe distortions in trade, resulting in regional price dispersion and lower aggregate trade. Similarly, importers may lack information and trust on export supply including the quality of an export product and the reliability of exporter service, particularly in developing countries where regulatory infrastructure and contractual environment are weak. In this paper, we investigate how information diffusion through exporter reputation affects trade. When importers face uncertainties on exporter quality and reliability, the reputation of an exporter could provide valuable information for import decisions. However, still little is known empirically how reputation influences export and import behavior and aggregate trade. A central challenge in evaluating the role of reputation in trade is the difficulties of quantifying reputation (or the lack thereof) across firms and markets. In this study, we explore the unique setting of cross-border trade platforms where importers could directly share information on exporter quality and observe exporter reputation to examine the value of reputation in trade.

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 platform has attracted more than 1.1 million active sellers, over 50 million product listings, and a traffic flow of 3.8 million consumers each day, generating 113 billion orders and over $20 billion transactions in 2014 and a global market share that exceeds Amazon and eBay. This rapid rise of 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 visible to foreign markets with ease; importers, who traditionally have to endure high costs to search for suppliers, can now readily access a large number of suppliers and learn about supplier quality from other buyers. These features offer us a rich environment—characterized with large numbers of exporters and importers, low explicit entry cost, quantifiable reputation, and access to all the information observed by the importers—that is ideal for establishing the role of reputation in export growth and separating the effects of other conventional drivers.

Using a transaction-level cross-border trade dataset in the T-shirt industry—a top selling product category on Aliexpress, we first document four novel stylized facts about the distribution of Aliexpress exports. First, compared to China's overall T-shirt exports, exports on Aliexpress are more concentrated on superstar exporters. For example, the top 5-percent exporters account for 71 percent of total export revenue on Aliexpress as opposed to 58 percent in overall T-shirt exports. This evidence stands in sharp contrast with the conventional expectation that lower entry costs, as in the case of online trade platforms, should lead to greater competition. Second, on Aliexpress the distributions of price and reputation closely mirror each other while export volume is more dispersed than both price and reputation. Third, the distribution of exporter revenue on Alibaba becomes more dispersed as exporters age. Fourth, the market share of superstar exporters in a destination diminishes with importers' experience. For example, the market share of top 5-percent exporters is 80 percent for countries with the least experienced importers and falls to less than 10 percent for countries with the most experienced importers.

We explain the above stylized facts by empirically examining the role of reputation in exporters' performance at the intensive and extensive margins and export price. We take advantage of qualitative and quantitative features of reputation on Aliexpress and control for all displayed listing charateristics, including product and service quality, that are observable to buyers. Our main result reveals that a greater reputation based on ratings and substances of comments enables exporters to achieve greater export revenue, higher export volume, and a larger number of buyers and markets. Specifically, exporters with a top-quartile reputation outperform exporters with a bottom-quartile reputation by 35 percent greater export revenue, 17 percent greater export quantity, 16 percent more buyers, and 13 percent more markets. This result is robust to multiple identification strategies including a "peer product" grouping function of the Aliexpress search engine which restricts our comparison to almost identical products (offered by different sellers), 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 highlight that reputation plays an important role in the performance of exporters, even exceeding the effect of observable product quality.

When exploring responses to reputation, we find that the value of reputation is not homogenous across importers and over time. For example, importers from the same country tend to value opinions from each other more than importers from other countries. Importers from countries with a larger market size also exhibit a greater response to reputation. Furthermore, the value of reputation increases with the geographic distance between export and import countries but diminishes with shipping cost. We also exploit the 2014-2015 Russian Ruble crisis, a financial crisis in the largest export destination of T-shirts on Aliexpress, during which the import country experienced a over 50-percent currency devaluation to examine the value of reputation after negative income shocks. The sharp devaluation caused a soaring import price and a drastic decline of real importer income in Russia, the largest T-shirt import country on Alibaba. We find that the negative income shock significantly lowered the reputation elasticity of Russian importers by over 50 percent. The value of reputation also evolves over time. When examining the dynamics in responses, we find the value of reputation depreciates over time; the effect of a positive or negative rating shrinks by half within 3 months.

To offer a theoretical explanation to observed empirical regularities and quantify the economic importance of reputation, we then present a simple dynamic model incorporating information frictions and exporter reputation. We assume that importers cannot observe ex-ante the true quality of a product despite the information disclosed by the exporters, but may leave ex-post information on the product quality after import transactions. Such information will contribute to exporters' overall reputation by allowing future importers to update their beliefs of product quality. In this context, exporters choose prices in each period and the amount of information to disclose to importers, and importers decide in each period on whether to import from a specific exporter. The model delivers a simple solution in which 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. Over time, high-quality exporters will raise prices gradually when positive reputation starts to accumulate and earn rising profits through enhanced reputation observable to future importers. The price dynamics, endogenously set to follow the reputation dynamics, exacerbates over time the dispersion in the distribution of export volume and the market share of top exporters. In the presence of large quality dispersion and observable reputation, high-quality exporters exhibit a particularly greater export premium and a higher likelihood of becoming superstars. These results offer a theoretical understanding that reconciles the documented stylized facts.

Our model also highlights a new source of aggregate export growth through an expedited creation of superstar exporters. Observed reputation shifts importers and reallocates markets from low-quality exporters to high-quality exporters, accelerating the emergence of superstar exporters. These superstar exporters set prices to match their growing reputation and enjoy a rising price premium as well as an expanded market share, leading to an increase in aggregate export revenue. To quantify the economic importance of reputation in aggregate trade flow, we structurally estimate the model and perform various counterfactual experiments including: (1) setting the frictions of reputation diffusion to infinity such that reputation is unobservable; (2) upgrading economy-wide product quality; and (3) raising the variance of product quality. We uncover a quantitatively important trade promoting effect at the aggregate level. Compared to the case in which reputation is unobservable, observable reputation contributes to a 34-percent increase in total annual export revenue, equivalent to the effect of raising economy-wide quality by 29 percent. However, the growth is driven by a dramatic shift in export market reallocation towards superstar exporters. Observable reputation raises the market share of top 1-percent exporters by 66 percent and the market share of top 10-percent exporters by 34 percent. The rise in the concentration of aggregate exports due to reputation is equivalent to increase the dispersion of product quality by 208 percent. In line with our premises, when reputation is observable high-quality exporters earn higher export volume and higher export prices while low-quality exporters become dormant in the shadow of superstar exporters.

The findings of this paper carry important implications for export promotion policy. While lowering explicit export entry costs is important for the ability of small and medium exporters 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 for developing countries where there are poorer regulatory and contractual environment and lower trust from foreign importers. Interventions providing high-quality exporters an opportunity to establish reputation would be helpful for initiating importer learning and upgrading aggregate exports. However, such reputation regimes must be inclusive of new and prospective exporters who could otherwise live under the shadow of established rivals with impaired visibility in export markets.

Our work is motivated by a new emerging literature that addresses the role of information frictions in international trade. Several recent studies provide important insights on how information frictions on market demand can distort trade volume and price. For example, Allen (2014) embeds information frictions in a perfect-competition trade model by allowing exporters to sequentially search for the optimal destination at a certain cost and generates an equilibrium price dispersion across destinations. The empirical finding based on Philippines agricultural trade data highlights the quantitative importance of information frictions which account for roughly half the observed regional price dispersion. Steinwender (2014) exploits a unique historical experiment—the establishment of the transatlantic telegraph connection in 1866—to assess price distortions from demand information frictions. When exporters use market news from destination countries to forecast expected selling prices, information frictions are shown to result in large and volatile deviations from the law of one price and a reduction of information frictions increase trade volume as well as trade volatility. Different from the above two studies on price distortions, Baley et al. (2014) explore how information asymmetry explains the difference between domestic and international trade and influences international risk sharing, an aspect that has been under-stressed. Using an Armington trade model with information asymmetry, the paper argues that ameliorating information asymmetry reduces the fraction of goods traded.

A separate strand of literature offers various solutions to information frictions in the context of cross-boader trade. For example, studies by Head and Ries (1998), Rauch (1999), and Rauch and Trindade (2002) show that ethnic networks and immigration flows can effectively boost trade, especially for differentiated goods where search barriers between buyers and sellers are relatively high. Recent literature focuses more attention on the dynamic feature of information friction reduction via a mechanism of searching and learning. One of the central contributions in this area, Eaton et al. (2014), builds a continuous-time model in which heterogeneous sellers search for buyers in a market and receive product appeal information in the foreign markets from successful transactions. Fit into Colombia-U.S. trade data, the model quantifies several types of trade costs, including the search costs of identifying potential clients and the costs of maintaining business relationships with existing clients. In the end, they evaluate the impact of trade costs and learning on aggregate export dynamics. Dasgupta and Mondria (2014) develop a dynamic, two-country model where home producers differ in product quality which is imperfectly observed by foreign consumers initially. Their research shows that this uncertainty generates an information cost of exporting. An introduction of an intermediation technology enables the sorting of exporters in the model. Several recent empirical studies explore different mechanisms of exporter learning and find that exporters can address information frictions by learning from their own exports (e.g., Albornoz et. al, 2012; Timoshenko, 2015) or the experience of neighboring exporters (e.g., Fernandes and Tang, 2014; Kamal and Sundaram, 2016). Exploring data on the Kenyan rose export sector, Macchiavello and Morjaria (2015) examine a model of relational contracting and show that the volume of trade is constrained by the value of the buyer-seller relationship and the value of the relationship increases with the age of the relationship. They further show that deliveries are an inverted-U shaped function of relationship's age during an exogenous negative supply shock.

Our study complements the above work by highlighting the role of reputation in international trade. The paper investigates how information diffusion through exporter reputation and importer learning influences exporter and importer behavior and the distribution of trade. We directly quantify information diffusion between importers and the reputation of exporters by exploring the unique setting of trade platforms and offer novel evidence on the complex roles of reputation in trade. Using a model of reputation and importer learning, the paper examines not only importers' learning process, but also how exporters may use dynamic pricing strategies to influence the speed of learning and reputation building. By accounting for reputation, the paper is able to explain a variety of newly discovered empirical patterns, including dynamics in the distributions of export price and export revenue, and quantify the previously unexplored roles of reputation in international trade. In the end, we present a new source of aggregate export growth by highlighting the role of reputation in expediting export market reallocation from low-quality to high-quality exporters, a mechanism sharply different from previously stressed mechanisms such as quality upgrading and expansions at extensive margins due to reduced entry costs.

Finally, this paper is also related to a recent literature examining the patterns of online international trade. Hortaçsu et al. (2009) use domestic transactions data from eBay and MercadoLibre to examine geographic patterns of trade between individuals and find that distance continues to be an important deterrent to trade. Similarly, Lendle et al. (2013) use the eBay dataset to examine the empirical regularities of online transactions. They find that, among other observations, a large share of eBay firms exports and the negative effect of distance continues to hold in online trade. Lendle et al. (2016) further show that the effect of geographic distance is 65 percent smaller on eBay than on offline trade and attribute the result to the lower search costs in online trade. Similar to the above studies, this paper explores trade through online intermediaries. However, the paper takes advantage of detailed disaggregated transaction data featuring not only transaction price and quantity but also rich quality and reputation information to investigate both empirically and theoretically the role of information flows in trade.[1]

The rest of the paper is organized as follows. In Section 2, we describe in detail the cross-

[1] More broadly, the paper is also related to an extensive literature on e-commerce even though the literature has primarily focused on domestic commerce. A review of this literature is beyond the scope of this paper; Peitz and Waldfogel (2012) provide a thorough review of recent work on digital economy, in particular, how it has transformed seller and buyer behavior. Within this literature, a number of empirical studies examine the role of seller reputation in domestic e-commerce (see, for example, Cabral and Hortacsu, 2010).

border transaction dataset from Aliexpress. In Section 3, we present emerging stylized facts on the distributions of export revenue, price and reputation. In Section 4, we examine empirically the role of reputation in export performance using reduce form regressions. In Section 5, we present a dynamic model of importer learning and exporter reputation building to explain the empirical patterns and then structurally estimate the model to quantify the importance of reputation and importer learning. The paper concludes in Section 6.

2 Data

2.1 Aliexpress: The Cross-Border Trade Platform

Our data is 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 transactions and has emerged as the go-to 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 220 countries. In 2014, there were more than 1.1 million active sellers on the website attracting more than 3.8 million consumers to visit each day, generating 113 billion orders and over 20 billion dollars of transactions.[2] In the past Single's Day (November 11, 2016), Aliexpress received more than 35 million orders from 230 countries around the world dwarfing both America's Cyber Monday and Black Friday.[3] Up till now, over 50 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 that are 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, which is essential for understanding the role of reputation in trade but difficult to achieve with offline trade data where reputation is not easy 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 a number of additional guarantees sellers may opt to offer such as the "On-time Delivery" within a certain number of days, "Returns Extra" which allows buyers to return the good even if the good is in perfect condition, "Longer Protection" which

[2] http://www.bloomberg.com/news/2013-10-14/how-alibaba-could-underprice-amazon-and-other-things-you-should-know.html

[3] http://www.chinanews.com/cj/2016/11-14/8062663.shtml

allows the buyer to submit a refund request up to 15 days after the order completion date, and "Guaranteed Genuine" which gives the buyer up to three times the payment (shipping cost included) if the product is found to be counterfeit. Sellers' decisions to offer additional, optional guarantees serve in our analysis as another measure of exporter quality. Fourth, Aliexpress does not require a sign-up fee to list a product, thereby essentially removing the entry cost of exporting and allowing sellers of all sizes to enter the international market. Aliexpress does charge sellers 5 percent of total sales value as a service fee for each successful transaction and provides a paid service by allowing sellers to bid to get listed as premier goods. The absence of entry costs allows us to better establish the effect of reputation on export growth, especially at extensive margins which have traditionally been viewed as driven by reductions in entry costs.

When a buyer visits the website to shop for a product, she could first type in key words or browse the menu to search for the good. A list of search results will appear, ranked by default according to relevance to the key words. The buyer is able to change ranking by "Best Match" to ranking by "Orders" (number of past orders), "Top-rated" (buyer rating), "Price," or "Newest." The website also offers various filtering functions—such as a specific price range, free shipping, and sales items—to help buyers find their preferred products more quickly. Buyers can then enter the detailed product listing page for more information. On the listing page, sellers describe product price, product detailed information with supporting images, potential promotions, and return and buyer protection policy. The website also displays, for each listing, buyer feedback scores, the ratio of positive feedbacks, and the most recent six-month transaction history. Each of the transaction history records shows buyer ID, buyer origin country, transaction date, transaction price, transaction quantity, and buyer feedback.

Once a buyer places an order on a particular product, the buyer's payment goes to Aliexpress first. The website then informs the seller of this order so that the seller can start packaging and shipping the product. Most of the products provide free shipping via a certain logistic firm. The payment will be transferred to the seller when the buyer or the logistic firm confirms the arrival of the product. Upon receiving the product, the buyer may leave a feedback for the product including a score of integer from 1 to 5 and descriptive comments. The total number of ratings, the number of ratings for each listing, and the average rating are all displayed. In addition to listing performance, the percentage of positive feedbacks (defined as 4 and 5 stars) a seller received, and a seller's average ratings on whether the item is as described, seller communication, and shipping speed are also provided.

2.2 The T-shirt Industry and Data

Our analysis focuses on cross-border trade transactions in the T-shirt industry (specifically, tank tops) 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—a central variable in our analysis. 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.

More broadly, we obtain three categories of information for each product listing (see Figures 1-2 for a sample listing) and all transaction records from February 2014 to January 2015. We list data details and descriptions as below.

2.2.1 Product (Listing) Characteristics

Price: The current listing price.

Bulk price: The discount price offered by a seller when a buyer purchases a certain quantity of the good.

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

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

Color choice number: The number of color choices.

Size choice: The available sizes of the product.

Available quantity in stock: The current in-stock quantity of the product.

Stylized product characteristics: Type, Targeted Gender, Clothing Length, Item Pattern Type, Fabric Type, Material, Decoration and etc.

Number of customers who added this product to the wish list: Consumers can add a product to their wish lists. Each product listing page displays the number of consumers who have added the product to their wish lists.

Store Promotion: The sellers' promotion or discount on the product.

Return Policy: All sellers on Aliexpress are required to offer a "return and refund" guarantee. When a product is bought and paid but is found not as described or of low quality, the buyer can contact the seller to obtain a full refund or keep the item and agree on a partial refund with the seller. Most listings online offer return and refund services but with some different rules. In our empirical specification, we use dummy variables, *return policy*, to indicate who pays for the return cost and listings without return services are the reference group.

Seller Guarantee: Sellers on Aliexpress may offer a variety of additional guarantees including "On-time Delivery", "Returns Extra", "Longer Protection", and "Guaranteed Genuine". In our empirical specification, we define a variable, *buyer protection*, to capture this information. More than 95 percent of the listings offer return service on Aliexpress, with most listings allowing return services before the completion of a transaction. Some listings offer to accept product returns even 15 days after the completion of a transaction. This variable is a dummy that equals to 1 if a listing offers long protection on return services.

Types of Payment Form: Types of payment form accepted.

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

Estimated delivery time: Estimated number of days for delivery.

Packaging information: The estimated package weight and size.

Number of images posted in product description: To capture the degree of product information disclosed by each seller, we obtain a count of pictures posted in the product description.

Number of words in product description: Similarly, we count the number of words used in the product description.

Related products: A list of related products offered by both the same seller and other sellers is displayed at the bottom of the listing page.

Material Quality: We classify a product's material quality based on information displayed on item specifics of each listing page. All material related words are extracted first and then classified into four types based on the fiber used. We assign a different score to each fiber according to the market values. Generally, synthetic fibers like polymer are viewed as the lowest quality and have the lowest market prices so are assigned a score of 1. Semi-synthetic fibers are assigned a score of 2. Natural plant fibers including cotton are relatively better quality and more expensive than the first two types and are assigned a score of 3. Animal fibers are the most expensive and given a score of 4. As most products are made of a mixture of raw materials, we calculate an average score based on fiber names displayed on each product listing page.

Detailed Description Number: This variable is the number of item specific fields being displayed under the product description section. Buyer can get more information about a listing if more item specifics are listed.

2.2.2 Seller Characteristics

Seller's name, address, start year, and number of sales people online: Aliexpress lists the seller's name, region, start year, and the number of sales people online. However, Aliexpress does not provide sellers' direct contact information such as phone numbers; buyers can only communicate with sellers via an instant communication application.

Seller's top selling product list: Each listing page has a side bar that displays the seller's 5 best selling products including a brief description, a picture, price, and the number of previous orders.

Seller's trending product list: The seller's latest products.

Seller's other product list: A bottom bar on the listing page displays other similar products offered by the same seller.

Seller's product category list: A side bar on the listing page displays the product categories offered by the seller.

Seller's 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 entire transaction history.

2.2.3 Transaction Records

Buyer ID: The 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 the quantity of each transaction.

Transaction date and time: The date and time when the order is placed and the payment transferred to Aliexpress.

Transaction feedback: A rating on the quality of the product and the general service of the seller. Buyers may also leave a comment for the seller.

Our final sample consists of 584,894 transactions from 5,392 sellers, 383,430 buyers, and 16,995 listings over the period of February 2014-January 2015. This dataset 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, buyers and transactions[4]. Second,

[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.

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 does not pose any restrictions on, for example, transaction value and thereby includes all sellers, buyers and activities. This is of particular importance for us to draw a comprehensive picture of exporter distribution. Fourth, the data provides detailed transaction-level information, while alternative datasets from, for example, eBay often disclose only sellers' total sales information by country.[5]

3 Stylized Facts: The Distribution of Exports on Aliexpress

In this subsection, we examine the distributions of exports on Aliexpress and present a number of stylized facts emerging from the data. In some cases, we compare the stylized facts with those arising from Chinese customs trade data in comparable product categories.[6] The majority of Chinese exports are still conducted through offline trade where reputation is not easily and systematically observable; therefore, customs data serve as a benchmark in our study to characterize baseline trade patterns.

First, we present descriptive statistics for the key variables in Table 1. The table shows that there is substantial heterogeneity across Aliexpress exporters in terms of both export unit prices and export volumes. For example, the minimum sales 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 $177,122. We then examine the export revenue of the top 1 percent, 5 percent, 10 percent, and 30 percent of sellers, which are referred to in Freund et al. (2015) as "superstar" exporters. As shown in Table 2, the ratio of median export revenue between the top 1-percent exporters and the rest is around 382 on Aliexpress, greatly exceeding the same ratio 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 and 30 percent and 58 percent, respectively, in customs data. The observed export concentration on Aliexpress is even more compelling when compared with an average market share of 14 percent from top 1-percent firms and 30 percent from top 5-percent firms reported in Freund et al. (2015).

[Insert Figures 3 and 4]

These observations are also depicted in Figure 3 where we plot the export share accounted

[5] Most existing e-Commerce literature relies on transactions with feedbacks and uses feedback frequency to proxy actual transaction volume (Cabral and Hortacsu, 2010). But many buyers do not leave feedbacks online. In our sample, only 36 percent of the transactions have associated feedbacks. Including transactions without feedbacks will give us a much more comprehensive description of trade patterns.

[6] We rely on the latest 2010 customs trade data for comparison. The product category used in the customs data is T-shirts, singlets and other vests, knitted or crocheted which has HS-4 digit of 6109.

for by exporters and listings at different percentiles.[7] It is evident that the top-percentile exporters or listings account for a significantly greater share of total exports on Aliexpress than in overall exports. We further plot the kernel density curves of export revenue using Aliexpress and customs data in Figure 4, respectively. While the distribution of export revenue is overall less dispersed on Aliexpress as shown in the left panel, the right tail of the curve is thicker for Aliexpress as shown in the right panel suggesting that top exporters exhibit a greater export premium on Aliexpress. The first stylized fact summarizes this finding:

Stylized Fact 1: *Exports on Alibaba are more concentrated on superstar exporters than Chinese exports overall.*

Next we compare the distributions of price, reputation and export volume. We find, as shown in Figure 5, that the distributions of price and reputation closely mirror each other and are both relatively concentrated at the center. In contrast, the distribution of export volume is much more spread out and exhibits significantly thicker left and right tails. If export volume is merely determined by price, we would expect to see distribution of export volume and price in similar shape. However, we observe the distribution of export volume is more skewed to the left indicating a greater reduction in bottom listings' export volume than can be explained by price. This observation is summarized in Stylized Fact 2.

[Insert Figure 5]

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

To explore the dynamic pattern of how heterogenous exporters grow, we now track a cohort of listings over time by comparing their distribution as brand-new exporters with their distribution a year later.[8] To control for exit and entry into the market, we focus here on listings who start to export at the beginning of our sample period. Figure 6 shows that export revenue becomes more dispersed at the 4th quarter compared with what we observe in the 1st quarter.[9] This is observed on both tails of the distributions, in particular, the distribution of export revenue where a greater share of exporters appear on both the left and right tails. This finding is summarized as Stylized Fact 3.

[Insert Figure 6]

[7] We refer to an exporter-product pair as a unique listing.

[8] Aliexpress displays the total order number on the index page during our sample period. We identify new exporters by calculating the difference between reported total order number and observed total order number during the sample period and define exporters with a zero difference as new exporters.

[9] This result is robust to different time units. Both monthly revenue and half-year revenue show similar results.

Stylized Fact 3: *The distribution of export revenue becomes more dispersed as exporters age.*

Next, we examine the heterogeneous responses of importers to listings' reputation (measured by listings' past performance) across country. Here the analysis concentrates on top listings whose sales are above 95 percentile and we plot their market share in each country against country characteristics in Figure 7. We find that the export revenue share of superstar exporters in a country increases with the number of importers in that country but diminishes with the experience of importers (measured by the number of products previously imported). For example, the market share of top 5-percent exporters is 80 percent for the least experienced importers and falls to, on average, less than 10 percent for the most experienced importers. An implication of importer learning emerges from this finding. Importers, especially those with less import experience, tend to make their purchase decisions based on exporters' past performance. For experienced importers, information on an exporter's past performance would only marginally influence their purchase decisions. This observation is summarized as Stylized Fact 4.

[Insert Figure 7]

Stylized Fact 4: *The market share of superstar exporters increases with the number of importers in a country and diminishes with the experience of importers.*

4 Evaluating the Role of Reputation

In this section, we present empirical evidence on how reputation affects export patterns to offer first-step insights into the value of reputation in trade. Specifically, we explore the impact of reputation on exporters' intensive margin and buyer and destination extensive margins. After establishing the baseline results, we then present evidence on heterogeneous responses to reputation across import countries and over time.

4.1 Baseline Results

We proceed by first estimating the following equation:

$$y_{sit} = \alpha + \theta_{sit}\beta + \mu_t + \gamma_s + \varepsilon_{sit} \tag{1}$$

where y_{sit} is the natural log of export revenue, export quantity, average export quantity per buyer, the number of buyers, or the number of markets for each listing i sold by exporter s in week t, and θ_{sit} is a vector of variables capturing the information available to buyers on the characteristics of product i including price, material quality, the number of pictures posted by the exporter, whether the exporter offers buyer protection and guaranteed return, and exporter reputation measured by past buyer ratings.[10] In addition, we control for exporter and week fixed effect to exclude the effect of exporter ability. We focus on the coefficient of the rating variable which indicates the average effect of reputation on exports. The weekly rating variable is computed by following the website's algorithm of taking averages of ratings in the past 6 months which is the same as the website rating that can be observed by importers at any time. The ratings are scaled from 1 to 5. To control for potential nonlinearity, 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 expect to see a rising positive effect on exports for listings with higher ratings.

We find in Table 3 that observable product and service quality matters in export performances. 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. 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 41 percent more export revenue, 21 percent more export volume, 20 percent more buyers, and 16 percent more export markets. Listings rated between 3 and 4 also outperform low rating groups, but the magnitude is smaller indicating higher ratings bring higher export premium. We further compare the reputation effect on export extensive margins, including the number of importers and number of markets, with the effect on intensive margin measured by average exports per importer. We find a larger reputation effect on extensive margins than on intensive margin. Among all the estimates, the elasticity of average quantity per buyer with respect to reputation is the lowest. These observations, depicted in Figure 8, are in line with the market reach and expansion pattern generally observed in online markets.[11]

[Insert Figure 8]

4.2 The Substance of Information

To further identify the role of reputation, we next explore the content of buyer comments accompanying each rating, which provides an additional useful source of information. Specifically, we explore the content of comments provided by previous importers to examine how the substance

[10] We adjust dependent variables by adding 1 before taking natural logs to include observations of zero export values.

[11] Cai, Jin, Liu and Zhou (2014) empirically show that an introduction of Centralized Feedback (CF) system decreases repeated business (intensive margin) but strengthens market expansion into new buyer regions and new product categories. Nosko and Tadelis (2015) focus on reputation externality on quality of the platform and document buyer exiting caused by bad reputation.

of information might affect future importers' decisions. We identified a complete list of words that have appeared in the comments and counted the number of positive and negative words in comments over the latest 6 months. As some buyers tend to be specific about their purchasing experience, they comment on delivery process, product trial experience and even return service. Therefore the number of positive and negative words would be a good representation of the extent to which previous buyers feel positive or negative about their purchases. Examples of positive key words include "good", "excellent", and "superior", while examples of negative bad key words include "bad", "poor", and "awful".[12] As shown in Table 4, we find that even after controlling for past ratings and the total number of words in past comments, listings with a larger number of negative words still perform significantly worse in all dimensions, with each additional negative word leading to 11 percent less export revenue, 7 percent less export quantity, 6.5 percent fewer importers, and 4.6 percent fewer markets. Listings with more positive comments, on the other hand, do not perform differently than listings without any comments.

4.3 The Heterogeneous Response to Reputation

To further explore how exporters can benefit from reputation, we turn to importers and investigate how heterogeneous importers might respond to the same exporter's reputation differently. We first distinguish between the sources of reputation and show how importer responses to reputation could vary with the origin of information. Then we explore how heterogeneous importers' responses to reputation can be explained by country characteristics.

The Source of Reputation and the Origin of Importers In the first exercise, we examine whether and how importers might respond to the listings' reputation in the importers' home country differently than exporter reputation in other countries. To do so, we divide ratings of each listing to two groups: ratings from the import country and ratings from all other countries and regress listing-destination-time specific export volume on both of them controlling for other listing features. We plot the estimation results in Figure 9. We find that importers respond more favorably and strongly to a positive reputation among fellow buyers from the same importing

[12] The list of key words appearing in positive comments includes: good, great, excellent, superior, nice, perfect, brilliant, happy, incredible, like, love, comfort, cool, awesome, amazing, congratulations, appreciate, beautiful, benefit, accurate, durable, best, benevolent, correct, creative, cute, decent, deserve, encourage, enjoy, favor, gorgeous, pleasant, recommend, quick, rapid, satisfied, and worthwhile.

The list of key words appearing in negative comments includes: abandoned, argued, awful, broke, awkward, bad, abnormal, abolished, absence, absent, absurd, alert, angry, annoyed, burn, cheat, collapse, complain, confused, crumble, crushed, damage, danger, deceive, defect, dirt, disappoint, disaster, discrepancy, discrete, dishonest, dishonorable, disjointed, dislike, dismal, dispute, doubt, drawback, fail, fake, horrible, inaccurate, inadmissible, inadvertently, inappropriate, inattentive, incommunicable, incomplete, inconsistent, inconvenience, junk, mislead, mismatch, misplaced, missing, mistake, negative, poor, problem, regret, suck, unacceptable, unanswered, unattractive, unavailable, unbalanced, unclean, unclear, uncomfortable, unexpected, unmatched, unpleasant, unreliable, unsatisfied, worst. Another issue is use of "not" in a comment. It's quite hard to determine whether a "not" in a sentence means not good or not bad. So we drop all those comments that we cannot classify as positive or negative.

country. In particular, listings rated higher than 4 by home importers export 32.5 percent more than listings with the lowest ratings. But listings rated higher than 4 by other foreign importers export only 16.3 percent more than listings with the lowest ratings. A similar pattern emerges for listings who received an average rating between 3 and 4 from home country importers. In contrast, for listings with a rating between 2 and 3, the elasticities with respect to low ratings from same-country buyers v.s. low ratings from foreign buyers are not significantly different from each other, indicating that importers respond to a bad reputation similarly regardless of its source.[13] Overall, importers put more weight on a listing's reputation earned locally instead of globally. This result indicates that the source of reputation could affect importers' perceptions of the same information. Even though feedbacks of each listing are observable to all importers, importers still trust local peers more than others.

[Insert Figure 9]

In the second exercise, we examine how the responses to reputation could vary systematically with import country characteristics by interacting reputation with import country characteristics such as GDP, distance to exporter country (China), and remoteness from the rest of the world. We expect to see that reputation can serve as a reduction in information frictions from long geographic distance and taste difference. The regression results are presented in Table 5. We focus on the coefficient of the interaction term and find that the value of a good reputation is stronger in import countries with a larger GDP. One explanation could be the composition of buyers. Countries with a large market size tend to have a large number of new buyers who rely on reputation for information. In the meantime, the value of reputation is also found to increase in the distance and remoteness of the import country, while separately controlling for shipping cost, suggesting that import countries further away from exporters suffer higher information costs and are more likely to rely on exporters' reputation for import decisions.

The Response to Reputation after an Income Shock: Russian Ruble Crisis After examining how responses to reputation could vary across countries, we next examine how responses to reputation could change during income shocks by exploring the Russian ruble Crisis in 2014. As shown in Table A.1, Russia is the largest T-shirt export market on Aliexpress by all accounts including export revenue, export volume, and the number of exporters. According to TNS Russia, Aliexpress was the No. 1 e-commerce website in Russia as of July 2014, attracting 16 million users of 12 to 64 years of age; in comparison, eBay was ranked No. 3 in e-commerce, attracting 8.2 million users. Across all websites (both commerce or non-commerce), Aliexpress was the 10th most popular website in Russia by internet traffic, ranked next to Facebook.

[13] The table of regression results is upon request. We define countries whose share of world imports is less than 0.1 percent as ROW in the sample data and run a country-month regression on listings with ratings from at least two countries.

Beginning in June 2014, Russia entered into a deep financial crisis following the collapse of the Russia ruble whose value against U.S. dollars declined by more than 50 percent by the end of January 2015. The sharp devaluation of the Russia ruble was triggered by various causes including the rapid drop of the crude oil price and a subsequent decline of foreign investors' confidence in the Russian economy and led to a sudden and substantial negative income shock for Russian importers and consumers at large.

We explore this exogenous negative income shock to evaluate how the value of reputation change over time. To proceed, we perform the baseline analysis separately for the period before the ruble devaluation and the period after the ruble devaluation. The results are reported in Figure 10. We find that importers are significantly less responsive to reputation after the Russian ruble devaluation, in terms of both export quantity and the number of importers. In particular, top rated exporters, with an average rating higher than 4, export 36.7 percent more volume and reach 89 percent more buyers than exporters with the lowest ratings before devaluation. However, their advantage from a positive reputation drops to only 14 percent more exports and 46 percent more buyers after devaluation. We observe similar patterns for average ratings from 3 to 4 and from 2 to 3. The results suggest that a negative income shock among importers lowers the value of a good exporter's reputation. When importers experienced an income reduction, they become less sensitive to both good and bad reputations.

[Insert Figure 10]

4.4 The Dynamic Value of Reputation

Now we investigate how the value of reputation might evolve over time. This exercise helps answer two key questions in exporter growth over time led by reputation. First, does the effect of a reputation shock decay over time? We decompose the displayed average rating for each listing on the website into monthly ratings and examine how the effect of a reputation shock changes over time. Second, heterogeneous exporters may benefit differentially from the same reputation shock. Take an example of a high-quality exporter and a low-quality exporter, a good rating on the high-quality exporter could attract more good ratings in the future, while the same rating might appear as a transitory shock to low-quality exporters as future buyers might provide different information offsetting the previous good rating. Therefore evaluating the long-run effects of reputation also allows us to uncover the path of reputation building for heterogeneous exporters. To answer these two questions, we first plot the marginal value of each 1-star and 5-star ratings over a 6-month window for all listings. Figure 11 shows a clear pattern of reputation decay over time. In the first month, each 5-star rating can raise export volume by 0.01 percent while this number reduces to 0.001 percent in the 6th month. Similarly, the negative impact from a 1-star rating also changes from -0.08 percent to -0.015 percent displaying a sharp decline. As time passes by, we observe empirically that the influence of earlier ratings evaporates.

[Insert Figure 11]

Next, to assess how exporter heterogeneity interacts with the marginal value of reputation, we re-estimate the value of 5-star ratings and 1-star ratings over time for high quality exporters and low quality exporters. The left part of Figure 12 suggests a larger and longer effect from 5-star ratings on high-quality exporters than low-quality exporters. After 6 months, a 5-star rating still raises the export volume of high quality exporters by 0.01 percent while it no longer poses a significant effect on low-quality exporters. Correspondingly, the right part of Figure 12 shows that 1-star ratings reduce more export volume for low-quality exporters than for high-quality exporters. The estimated marginal value of 1-star ratings is no different from 0 for high-quality exporters. Bad ratings only have a temporary effect on the export volume of high-quality exporters while good ratings only have a temporary effect on the export volume of low-quality exporters. In the long run, the evolution of reputation displays a mean reversion pattern with the average rating revealing the true quality of a listing.

[Insert Figure 12]

4.5 Robustness

In the analysis so far, we have taken advantage of a feature of Aliexpress that allows buyers (and econometricians) to observe all the information available about each listing and controlled for an extensive set of listing characteristics such as material quality, service quality, price, shipping cost and the amount of information provided by the seller to establish the role of reputation. This feature substantially reduces potential omitted variable bias and endogeneity in the reputation variable. In this section, we take further steps and present two extensions of the baseline analysis, exploring Aliexpress' search and rating algorithms, to further establish the causal effect of reputation.

Peer Product Groups First, we utilize a "peer product" grouping function provided by the Aliexpress search engine to categorize products into narrowly defined peer groups. In this function, Aliexpress identifies and groups essentially identical products (T-shirts) offered by different sellers based on product title, item description, and pictures so buyers could more easily search for and compare similar listings. To check how similar listings within one group are, we compare the variation of listing characteristics in the whole sample and with the variation in peer groups using standard deviations and coefficients of variation. Table A.2 shows that the variation is, on average, much smaller within peer groups than across the entire sample. This confirms that Aliexpress' search algorithm indeed groups listings with similar characteristics.[14] In our analysis here, we limit the comparison to listings within the same peer group and thus listings with similar observable (and potentially unobservable) characteristics (except price and reputation) by controling for a peer group fixed effect. Table 6 shows that the effect of reputation remains qualitatively similar to earlier results: listings with more positive ratings perform significantly better than the other listings in the same peer product groups.

Regression Discontinuity Next we further examine the robustness of our results by employing a regression discontinuity design. It is plausible that reputation is correlated with unobserved listing characteristics that could also affect consumer preferences. To address the concern, we explore a feature of Aliexpress' rating system in which the average rating in the past 6 months is rounded and displayed at one decimal point. For example, listings with an average rating between 3.90 and 3.94 will be displayed as 3.9 while listings with an average rating between 3.95 and 3.99 will be 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 smaller and trivial. To implement the regression discontinuity design, we manually compute and recover the average rating of each listing at two decimal points based on historical individual rating information 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 less than 0.1 even though the observable differences are 0.1. Figure 13 depicts the scatterplot of weekly exports on a log scale against average rating normalized by subtracting cutoff value. There is a clear jump at the cutoff from the untreated group to the treated group.

[Insert Figure 13]

In the regression analysis, we incorporate the computed true average rating and estimate the following specification:

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

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 $RATING_{sit}$ is rounded up and 0 if the true rating is rounded down; the parameter λ_1 captures the discontinuous change

[14] There are 2 to 493 listings in each peer group from our sample data. On Aliexpress grouped page, one can see single-listing groups as well as multi-listing groups. Both types of groups are included in the analysis.

in export performance for listings whose displayed ratings are shifted up by 0.1.[15] In addition, we include the computed true rating $RATING_{sit}$ to control for the effects of other observable and unobservable factors. We find in Table 7 that even when controlling 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 in all dimensions. This offers strong further support to our main result and suggests that buyers respond significantly to displayed reputation.[16]

5 A Simple Dynamic Model of Learning and Reputation

In this section, we present a simple dynamic model of learning and reputation to explain stylized facts observed in the previous sections. We consider and compare three different scenarios including a case with complete information, a case with information frictions but no observable reputation, and a case with information frictions and observable reputation. In the end, we show that the model yields results that explain empirical patterns presented before and structurally estimate the model to quantify the importance of reputation in aggregate trade.

5.1 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. After observing the quality draw, the seller decides how much information, a, to disclose to the buyers. The more information disclosed, the more precise the belief that buyers can draw about the product quality. Specifically, we assume that buyers draw an initial belief θ_i^a from a distribution $N(\theta_i, \sigma_u^2(a))$ based on the information disclosed by the sellers. We assume that $d\sigma_u^2(a)/da < 0$, i.e., the variance of the initial quality belief is negatively related to the amount of information disclosed. This assumption indicates that sellers always have some technical difficulties in presenting the true conditions of their product, which is plausible for most products including T-shirts as consumers might need to closely experience the product before knowing its true quality, but the more information disclosed by a seller the more precise consumers' initial belief about the product will be. After a buyer purchases a 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.

[15] In our sample, there are multi-cutoffs 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 cutoffs. See Cattaneo, Keele, Titiunik, and Vazquez-Bare (2016) for a survey. Our specification is essentially equivalent to this alternative strategy.

[16] In the result displayed here, we use 0.5 as the bandwidth for each cutoff. We also tried other smaller bandwidths and the estimation results remain significant.

5.1.1 Demand

Each buyer purchases one unit of the product. We assume, without loss of generality, that buyers arrive sequentially and decide in each period whether to buy from a seller.[17] Buyers, who are also consumers, are assumed to have a discrete choice preference. The indirect utility function from product i for a consumer in country j is given by:

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

where $E(\theta_i|\theta_i^a, \theta_{im}^b)$ is the buyers' belief on product quality, ρ captures consumer's preference weight on perceived product quality, θ_i^a is the initial quality belief drawn based on the information disclosed by the seller, θ_{im}^b represents the seller reputation revealed in m past buyer feedbacks,[18] p_{ijtm} is the delivery price including an iceberg trade cost τ_j at time period t, and 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:

$$d_{ijtm} = \frac{\exp\left[\frac{1}{\sigma}(\rho E(\theta_{im}|\theta_i^a, \theta_{im}^b) - p_{ijtm})\right]}{\sum_{k=1}^{K} \exp\left[\frac{1}{\sigma}(\rho E(\theta_{km}|\theta_k^a, \theta_{km}^b) - p_{kjtm})\right]}, \tag{3}$$

where K is the total number of products.

5.1.2 Buyer Belief Updating

As described earlier, buyers' belief on the product quality is affected by the information disclosed by the seller and the evolving reputation of the seller. We denote $\omega_\theta \equiv 1/\sigma_\theta^2$, $\omega_u(a) \equiv 1/\sigma_u^2(a)$ and $\omega_\varepsilon \equiv 1/\sigma_\varepsilon^2$ 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 will have belief

$$\overline{\theta}_{i0} \equiv E(\theta_{i0}|\theta_i^a) = \frac{\omega_\theta \theta + \omega_u(a_i)\theta_i^a}{\omega_\theta + \omega_u(a_i)}. \tag{4}$$

After period t, buyers' beliefs will be updated whenever there is a new feedback. In period t' when there are m feedbacks,[19] the new coming buyer will have belief

$$\overline{\theta}_{im} \equiv E(\theta_{im}|\theta_i^a, \theta_{im}^b) = \frac{\omega_\theta \theta + \omega_u(a_i)\theta_i^a + m\omega_\varepsilon \theta_{im}^b}{\omega_\theta + \omega_u(a_i) + m\omega_\varepsilon}, \tag{5}$$

[17] We abstract from repeated transactions between a seller-buyer pair because repeated interaction is less important with a centralized feedback system (Cai et al., 2014). This simplification also reflects the important export contribution from the new buyer margin which prevails in trade platforms.

[18] 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.

[19] In the model, t can be used to denote both the time period and the number of feedbacks because the seller's problem will evolve to a new period/state only when there is a new feedback.

where

$$\theta^b_{im} \equiv \frac{\sum_{k=1}^{m} \widetilde{\theta}^b_{ik}}{m} \tag{6}$$

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 disclosed by the seller, and the reputation. The weight of each component is inversely related to the variation of the corresponding quality distribution. For example, reputation with a smaller variation will receive a greater weight in buyers' updated belief. Further, the weight of reputation increases in the number of feedbacks. Several important patterns emerge from the updating process. First, the effect of early feedbacks declines over time. For a customer who can observe m feedbacks in total, the weight on a nth feedback θ^b_{in} is $\frac{\omega_\varepsilon}{\omega_\theta+\omega_u+m\omega_\varepsilon}$ which decreases with m. As reputation starts to build, the contribution of early feedbacks dissipates over time as we show in Section 4.4. Second, reputation building takes time but it will approach a product's true quality in the long run when there are enough feedbacks which is in line with what we observe in Section 4.4.

5.1.3 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:

$$\pi_{ijtm} = (p_{ijtm} - \tau_j - c\theta_i)d_{ijtm}, \tag{7}$$

where d_{ijtm} is the demand function measuring the probability of any incoming buyer purchasing the product. We assume that 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:

$$\pi_{itm} = \sum_{j\in N} q_j(p_{ijtm} - \tau_j - c\theta_i)d_{ijtm}. \tag{8}$$

After entry in the first period, each seller has an exogenous probability δ of exiting (for instance, a seller may receive a random poor reputation and, as a result, no more buyers are willing to buy from the seller).

Each seller has two choice variables, namely, the amount of information to disclose a_i—which affects the variation of buyers' initial belief on the product quality $\sigma^2_u(a_i)$—and the price p_{ijtm}—which is adjustable in each period. Each seller's maximization problem is given by:

$$\max_{a_i,\{p_{ijtm}\}^\infty_{t,m=1}} E_{\{\theta^a_i,\theta^b_{im}\}^\infty_{m=1}} \sum_{t=1}^{\infty} \{[\beta(1-\delta)]^t \sum_{j\in N} q_j[(p_{ijtm} - \tau_j - c\theta_i)d_{ijtm}]\}, \tag{9}$$

where β is the seller's discount rate.

After the seller optimally chooses the information to disclose a_i^* (which, in turn, determines the variation of the disclosed quality σ_u^2 and subsequently ω_u), it will set its delivery price in each market according to the following Bellman equation[20]:

$$\begin{aligned} V_{itm}(\theta_i, \overline{\theta}_{im}, \omega_u^*) &= \max_{\{p_{ijtm}\}_{j\in N}} \frac{\sum_{j\in N} q_j d_{ijtm}}{1-\beta(1-\delta)\sum_{j\in N} q_j(1-d_{ijtm})}[p_{ijtm} - \tau_j - c\theta_i \quad (10) \\ &+\beta(1-\delta)E(V_{i(t+1)(m+1)}(\theta_i, \overline{\theta}_{im+1}, \omega_u^*))]. \quad (11) \end{aligned}$$

where

$$\overline{\theta}_{im} = \frac{\omega_\theta \theta + \omega_u^*(a_i)\theta_i^a + m\omega_\varepsilon \theta_{im}^b}{\omega_\theta + \omega_u^*(a_i) + m\omega_\varepsilon}. \quad (12)$$

5.2 Equilibrium

5.2.1 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 sellers will solve the following problem:

$$V_{it}(\theta_i, \omega_u^*) = \max_{\{p_{ijt}\}_{j\in N}} \sum_{j\in N} q_j\{(p_{ijt} - \tau_j - c\theta_i)\, d_{ijt} + (1-d_{ijt})\beta(1-\delta)V_{it+1}(\theta_i, \omega_u^*)\}, \quad (13)$$

where

$$d_{ijt} = \frac{\exp\left[\frac{1}{\sigma}(\rho\theta_i - p_{ijt})\right]}{\sum_{k=1}^{i} \exp\left[\frac{1}{\sigma}(\rho\theta_k - p_{kjt})\right]}. \quad (14)$$

We have $V_{it+1}(\theta_i, \omega_u^*) = V_{it}(\theta_i, \omega_u^*)$ which yields:

$$V_{it}(\theta_i, \omega_u^*) = \max_{\{p_{ijt}\}_{j\in N}} \frac{\sum_{j\in N} q_j d_{ijt}}{1-\beta(1-\delta)\sum_{j\in N} q_j(1-d_{ijt})}[p_{ijt} - \tau_j - c\theta_i + \beta(1-\delta)E(V_{i(t+1)}(\theta_i, \omega_u^*))],$$

$$p_{ijt}^C = \tau_j + c\theta_i + \sigma, \quad (15)$$

and

$$d_{ijt}^C = \frac{1}{D_j^C} \cdot \exp\left[\frac{1}{\sigma}(\rho\theta_i - \tau_j - c\theta_i - \sigma)\right] \quad (16)$$

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

[20] A derivation of the Bellman equation is included in the Appendix 1.

5.2.2 With Incomplete Information and No Observable Reputation

Now we consider the case of incomplete information without observable reputation; that is, buyers cannot observe the true quality θ_i of the product or learn about exporter's reputation from each other. In this case, the seller's problem in a given period is given by:

$$V_{it}(\theta_i, \overline{\theta}_{it}, \omega_u^*) = \max_{\{p_{ijt}\}_{j\in N}} \frac{\sum_{j\in N} q_j d_{ijt}}{1-\beta(1-\delta)\sum_{j\in N} q_j(1-d_{ijt})}[p_{ijt}-\tau_j-c\theta_i+\beta(1-\delta)E(V_{i(t+1)}(\theta_i, \overline{\theta}_{it}, \omega_u^*))], \tag{17}$$

where

$$d_{ijt} = \frac{\exp\left[\frac{1}{\sigma}(\rho\overline{\theta}_{it} - p_{ijt})\right]}{\sum_{k=1}^{K} \exp\left[\frac{1}{\sigma}(\rho\overline{\theta}_{kt} - p_{kjt})\right]} \tag{18}$$

and

$$\overline{\theta}_{it} = \frac{\omega_\theta \theta + \omega_u(a_i)\theta_i^a}{\omega_\theta + \omega_u(a_i)} \tag{19}$$

is the buyer's belief on product quality based exclusively on the information disclosed by the sellers a_i and does not vary across periods due to the absence of learning from previous buyers.

Solving the above problem yields:

$$p_{ijt}^I = \tau_j + c\theta_i + \sigma \tag{20}$$

and

$$d_{ijt}^I = \frac{1}{D_j^I} \cdot \exp\left[\frac{1}{\sigma}(\rho\overline{\theta}_{it} - \tau_j - c\theta_i - \sigma)\right], \tag{21}$$

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

The aggregate lifetime profit for the seller is

$$\pi_i^I = E_{\theta_i^a} \sum_{j\in N} \frac{q_j \exp\left[\frac{1}{\sigma}(\rho E(\theta_i|\theta_i^a) - \tau_j - c\theta_i - \sigma)\right]\sigma}{(1-\beta)D_j^I}. \tag{22}$$

The seller maximizes the above profits by choosing the amount of information to disclose a_i.

We find that $\partial\pi_i/\partial a_i > 0$ for $\theta_i > \theta$ and $\partial\pi_i/\partial a_i < 0$ for $\theta_i < \theta$. Consequently, high-quality sellers will choose a to minimize $\sigma_u^2(a)$ and make the information as precise as possible, while low-quality sellers will choose a to maximize $\sigma_u^2(a)$ and make the information as vague as possible.

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 low-quality sellers can choose to disclose vague information to earn a higher market belief. 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., $E(d^I_{ijt}) < d^C_{ijt}$, due to buyers' inability to observe the true quality, despite that high-quality sellers disclose precise information to reduce the variance of the buyer belief (See the Appendix 2 for proof). This suggests that export volume will be less dispersed under incomplete information than under complete information.

5.2.3 With Incomplete Information and Observable Reputation

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

First, we can again show that compared to low-quality sellers, high-quality sellers have incentives to disclose more information to reduce the variance of the disclosed quality, $\sigma^2_u(a)$. Second, solving equation (10) yields:

$$p^*_{ijtm}(\tau_j, \theta_i) = \tau_j + c\theta_i + \sigma - \beta(1-\delta)E\left(V_{i(t+1)(m+1)}(\theta_i, \overline{\theta}_{im+1}, \omega^*_u)\right). \tag{23}$$

Comparing the prices across the three scenarios, we find that $p^*_{ijtm} < p^C_{ict} = p^I_{ijt}$; 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 without 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 the reputation is 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 the prices relatively low to subsidize reputation building and then raise price over time when they receive more orders.*

Proof. See Appendix 3. ■

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

$$d^*_{ijtm}(\tau_j, \theta_i) = \frac{1}{D^*_j} \exp\left[\frac{1}{\sigma}(\rho\overline{\theta}_{im} - \tau_j - c\theta_i - \sigma + \beta(1-\delta)E(V_{i(t+1)(m+1)}(\theta_i, \overline{\theta}_{im+1}, \omega^*_u))\right], \tag{24}$$

where

$$\overline{\theta}_{im} = \frac{\omega_\theta \theta + \omega_u(a_i)\theta_i^a + m\omega_\varepsilon \theta_{it}^b}{\omega_\theta + \omega_u(a_i) + m\omega_\varepsilon} \tag{25}$$

and $D_j^* \equiv \sum_{k=1}^{K} \exp\left[\frac{1}{\sigma}(\overline{\theta}_{im} - \tau_k - c\theta_i - \sigma + \beta(1-\delta)E(V_{i(t+1)(m+1)}(\overline{\theta}_{im+1}, \omega_u^*))\right]$. By comparing d_{ijtm} across all scenarios, we show in Appendix 3 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.*

Proof. See Appendix 4. ■

5.3 Testing the Hypothesis: Price Dynamics

Now we empirically examine Proposition 1 from the model and investigate how reputation affects price dynamics. In Table 8, we examine weekly price growth rates and show that, on average, product listing prices tend to rise over time. But there exists significant heterogeneity in weekly price changes across listings. Comparing between new and existing listings, we find that new listings exhibit greater price increases than existing listings. Sellers of new listings are more likely to raise prices than sellers of existing listings. This is in line with our theoretic prediction that new sellers tend to subsidize learning by lowering price upon entry into the market. Further, we consider the following estimating equation:

$$p_{sit} = \alpha + \theta_{sit}\beta + \gamma d_{sit} \cdot quality_{si} + \mu_s + \eta_t + \varepsilon_{sit} \tag{26}$$

where p_{sit} is the logged price of product i sold by seller s in week t, θ_{sit} is a vector of time-variant listing characteristics including past price, quality, and past sales, $d_{sit} \cdot quality_{si}$ is an interaction between past order number and an indicator of above-median quality, μ_s is a seller fixed effect, and η_t is a week fixed effect.[21] We find that past performance matters in the pricing decisions, especially for high-quality exporters. As shown in Table 9, prices of high-quality product listings tend to rise with the number of past orders, consistent with the prediction of Proposition 1. This suggests that high-quality exporters will initially set the prices low to subsidize reputation building and then raise prices over time.

[21] We also use past rating number to proxy past order number as a robustness check as listings with more past orders naturally receive more past ratings.

5.4 Explaining the Stylized Facts

In this section, we show that the stylized facts presented in the previous section can be explained by the model.

5.4.1 Stylized Fact 1: Superstar Exporters

Stylized Fact 1, which states that exports are more concentrated on superstar exporters on Aliexpress, can be directly explained by Proposition 2 where we show that the export premium of high-quality sellers relative to their low-quality peers is greater in the presence of observable reputation. Our model highlights two mechanisms that generate this result. On the one hand, when buyers can easily share information on exporter quality with each other, high-quality exporters can more likely command a larger market share as importers value good reputation. On the other hand, high-quality exporters also have incentives to set the price relatively low initially to subsidize reputation building which, in turn, raises their export premium over their lifetime.

5.4.2 Stylized Fact 2: The Distributions of Price, Reputation and Export Volume

The second stylized fact, which shows that the distributions of price and reputation closely mirror each other while export volume is significantly more dispersed than the two, can also be seen directly in the model. First, in our model the optimal price is a linear function of current consumer belief θ_i, which itself is a linear function of reputation. This determines that the distribution of price must follow closely the distribution of current reputation. Second, as we show $\ln d^*_{ijtm} = \frac{1}{\sigma}(\rho\bar{\theta}_{itm} - \tau_j - p^*_{ijtm}) - \ln D^*_j$, the variation of export volume $\ln d^*_{ijtm}$ must be the sum of the variations of price and reputation. This implies that actual export volume should be more dispersed than both price and reputation.

5.4.3 Stylized Fact 3: Distribution Dynamics

In Proposition 1, we show that sellers, especially high-quality sellers, have incentives to raise prices over time along with the establishment of their reputation. Upon entry into the market, sellers have to sacrifice some short run profits to subsidize learning. As they grow older, there will be growing divergence in reputation and consequently performance between high-quality and low-quality exporters.

5.4.4 Stylized Fact 4: Importer Experience

While our model does not consider heterogeneous buyer responses to reputation, Stylized Fact 4, which shows that less experienced importers place a greater weight on observable reputation and are hence more likely to import from exporters with good reputation, is implicitly incorporated into the model and consistent with the assumption that importers are Bayesian learners who put more weight on information received earlier than later. Inexperienced importers have been exposed to less information and thus have a greater trust on superstar exporters, while experienced importers have collected more information from past experience and are consequently less influenced by information about superstar exporters.

5.5 Structural Estimation

In this section, we structurally estimate the model to quantify the aggregate importance of reputation in aggregate trade. We follow the methods of simulated moments to identify structural parameters. 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 an artificial dataset based on which several moments are computed to match with the true moments. Lastly, we perform a counterfactual experiment by shutting down the learning process and further evaluate the effect of observable reputation on export flows and distribution.

5.5.1 Parameterization

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

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

$$\ln d_{ijt} = -\ln D_j + \frac{\rho}{\sigma}\overline{\theta}_{it} - \frac{1}{\sigma}(p_{it} + \tau_j) \tag{27}$$

which can be simplified to:

$$\ln d_{ijt} = \gamma_{it} + \lambda_j + \varepsilon_{ijt} \tag{28}$$

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 and market size $D_j = \exp(-\lambda_j - \tau_j)$ where τ_j is directly constructed using the delivery fee data from Aliexpress. Each listing on Aliexpress reports delivery fee by different shipping companies. We restrict the shipping company to be China post air mail and use a simple average delivery fee to each country as the proxy for country-specific transportation cost.[22] There are 160 countries in the final regression with an average λ_j of 0.74 and Russia has the highest λ_j of 8.55.

[22] Among all listings, more than 98 percent of the listings provide China Post Air Mail services to all available destination countries. We believe the cross-country shipping cost variation from one single shipping company better reflects the actual transportation cost variation.

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 is consistent with the largest importing countries observed in the sample data.[23]

We recover consumer's preference weight on reputation by relying on the regression discontinuity result from Table 10 on listings.[24] We obtain an average reputation effect from the treated and non-treated group regressions which yield $\frac{\rho}{\sigma} = 1.99$. 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 $0 \leqslant \sigma_u^2 \leqslant 1$.

5.5.2 Estimation Procedure

The above procedure leaves us only four other parameters to be estimated including industry quality distribution parameters $(\theta, \sigma_\theta^2)$, reputation information parameters (σ_ε^2), and the cost parameter (c). The identification comes from over-time variations in export revenue and price. As each exporter responds to past ratings differently because of their quality heterogeneity, we use simulated method of moments to estimate industry quality distribution and cost parameters. We use indirect inference methods to avoid high dimensionality in constructing the likelihood function and recover the sellers' parameters $\Theta \equiv (\theta, \sigma_\theta^2, c, \sigma_\varepsilon^2)$. The simulated method of moments requires finding solutions to the following equation:

$$\hat{\Theta} = \arg\min_{\hat{\Theta}} [\mu(\Theta) - \frac{1}{S}\sum_{s=1}^{S} \mu(\hat{\Theta})_s]' W^{-1} [\mu(\Theta) - \frac{1}{S}\sum_{s=1}^{S} \mu(\hat{\Theta})_s], \tag{29}$$

where $\mu(\Theta)$ is the vector of moments from real data, $\mu(\hat{\Theta})_s$ is the corresponding simulated moments for a parameter set $\hat{\Theta}$ in the s^{th} simulation, and W is weighting matrix. As we have four moments to identify four parameters, we use identity matrix as weighting matrix to find solutions. We also use the annealing algorithm to search parameters to accommodate potential discountinuity and discretized state space.

[23] Alexa only reports the volume of visitors by country for the top 36 origin countries. To reconcile the country number difference between the Alexa data and the transportation 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.

[24] The regression is a modified version of the RDD regression in the previous section. To turn the model into an empirical specification, we take the logarithm of the demand equation. 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 $10 * \lambda_1$.

To find simulated moments, we simulate a panel of N sellers for S times over a fixed set of random draws based on guessed parameters.[25] For each guess of each simulation, we solve for the optimal price policy function (See Appendix 5 for the algorithm of solving the policy function) and let the seller set the price according to the policy function. Next, we simulate importers' purchasing decision as well as their ratings and obtain a panel of sellers' export flows. We use the simulated panel to compute a certain set of moments and compare them with the moments observed from real data. The solution is found by an iterative procedure: we first guess the parameters $\hat{\Theta}_1$ and use this to solve for W_1 and further get $\hat{\Theta}_2(W_1)$ which will give W_2. We repeat this process until $\hat{\Theta}$ converges. We simulate 12,000 firms for 240 periods. In line with the reduced-form empirical estimations, one period is assumed to be one week. The first 96 periods are dropped to exclude the effect of initial conditions. The entire simulation is conducted 10 times and we average the moments from each simulation to exclude random simulation noise. The moments are computed in the same way as in the actual data.

The moments we match include: (1) the mean of $ln(price)$ averaged across listings and periods; (2) the dispersion of $ln(price)$ averaged across periods; (3) the mean of $ln(export\ sales + 1)$ averaged across listings and periods; and (4) the dispersion of $ln(export\ sales + 1)$ averaged across periods. The price moments are informative about the overall quality dispersion among all listings as optimal price is merely determined by listing quality upon full learning. The revenue moments are associated with distribution of feedbacks as cumulative feedbacks affect importer purchasing decisions. Combining all those information helps pin down parameter set Θ.

5.5.3 Estimation Results

The estimated parameter values are reported in Table 11. The model can account for most of the price and export revenue dispersion observed in the empirical data as shown in the first panel of Table 12. We also use non-targeted price and export revenue dispersion measures as a further check for our model performance in the second half panel of Table 12. The model predicts the ratio of the 75-percentile revenue relative to the 25-percentile revenue to be 1.50, compared to 1.65 in the data. The dispersion of price captured by the ratio of 75-percentile relative to 25-percentile is predicted to be 1.62 in the model, in comparison with 1.41 in the data. To assess our model fitness, we compare simulated dispersion of export revenue, price and rating with data in Figure 14. Overall, the estimated model captures most of the price and export revenue variations observed in the data.

[Insert Figure 14]

[25] The size of the simulated sample is similar to the size of the actual sample data.

We further use this model to quantify how observable reputation affects aggregate trade and its distribution. In our model, the variance of information captures frictions in information diffusion. The true product quality will be revealed eventually, but the amount of time it takes to reach full learning varies with the variance of feedbacks. When feedbacks are precise and contain less noise, it becomes easier for future buyers to evaluate a listing and obtain more accurate beliefs. In contrast, if feedbacks are vague and noisy, it would not reduce information diffusion. Therefore, we study the export effects of frictions in information diffusion by adjusting the variance of information in our policy experiments. Specifically, we consider three potential experiments: (1) setting σ_ε^2, the noise in feedback, to infinity so that importers cannot learn from each other and exporter reputation cannot be observed; (2) setting σ_ε^2 to infinity and increasing average quality level to evaluate the equivalent-level of quality upgrading needed to achieve the same level of total exports under observable reputation; and (3) setting σ_ε^2 to infinity and increasing quality variance to evaluate the equivalent-level of quality dispersion needed to achieve the same level of export revenue dispersion under observable reputation.

Our first policy experiment shows that compared to the case in which reputation is completely unobservable, observable reputation contributes to a 34-percent increase in total export revenue. This gain is of particular interest as it uncovers a new channel of export growth through reductions of information frictions. The trade literature of heterogeneous firms usually attributes a major portion of export growth to the entry of new firms or entry into more markets and products via either reductions in entry costs or productivity and quality upgrading (for example, see Melitz, 2003; Bernard, Redding and Schott, 2011; Kugler and Verhoogen, 2012). In our context, we keep the extensive margin and aggregate quality fixed and focus on the effect of an observable reputation. Our analysis suggests that when information frictions are reduced through observable reputation, aggregate export revenue can rise as a ramification of export market demand reallocation from low-quality exporters to high-quality exporters. Early on, importers cannot distinguish between high-quality and low-quality exporters because there is not enough information. Over time, with the establishment of observable reputation, importers are more likely to form a trade relationship with high-reputation high-quality exporters. High-quality exporters gain more from the established reputation and perform better than the case of unobservable reputation. We find that the market share of top 10-percent exporters becomes 34 percent higher and the market share of top 1-percent exporters increases by 66 percent in the presence of observable reputation. This represents a new source of aggregate export growth through an expedited creation of superstar exporters.

To obtain an intuitive understanding on the magnitude of export growth caused by such an effect, we report to what extent market-wide quality needs to increase in a world without observable reputation for a same degree of export growth. Our simulation result shows to achieve the same export growth requires raising economy-wide quality by 29 percent.

Lastly, we turn to the effect of reputation on the export revenue distribution to characterize the size of market composition shifts. To do so, we increase the exporter quality variance to match the logarithm of the export revenue ratio between 99 percentile and 1 percentile in a world with no observable reputation. We find that the rise in the dispersion of export revenue due to reputation is equivalent to increasing the dispersion of product quality by 208 percent. The aggregate export gain is highly unequally distributed across heterogeneous exporters within whom the best exporters receive the most gains.

6 Conclusion

The goal of this paper is to investigate the role of observable reputation, a factor that has received little attention, in international trade. We explore the unique setting of cross-border trade platforms, Aliexpress, to show how importers share information on exporters' quality and how exporters take advantage of the reputation system to promote trade. Using a transaction level export dataset in the T-shirt industry—a top selling product category on Aliexpress, we first document four novel stylized facts about the distribution of Alibaba exports. First, exports are more concentrated on superstar exporters on Aliexpress than in overall customs trade. Second, the distributions of price and reputation closely mirror each other while export volume is more dispersed than both price and reputation. Third, the distribution of export volume becomes more dispersed as exporters age. Fourth, the market share of superstar exporters significantly diminishes with the experience of importers.

We explain the above stylized facts by first empirically examining the role of reputation on individual exporters. To identify the effect of reputation, we explore qualitative and quantitative features of reputation on Aliexpress. We show that the level and substance of an exporter reputation has a significant effect on exports, products with better reputation outperform their peers in the same product group, and a discontinuous shift in the displayed reputation for products with trivial actual differences also poses a strong impact on exports. Our analyses suggest that reputation plays a leading role in the performance of exporters, exceeding the effect of observable product quality. A greater reputation gives exporters extra advantages in achieving greater export revenue and volume as well as a larger number of buyers and markets. We extend the baseline result by showing that the value of reputation is not uniform across importers and over time. How importers respond to reputation is determined by the source of reputation and importer characteristics. For example, importers from the same country tend to value each other's information more than information provided by importers from other countries. Meanwhile a negative income shock significantly lowers the export elasticity to reputation as well as the value of reputation.

To account for the observed empirical regularities and quantify the importance of reputation in aggregate trade, we have developed a simple dynamic model incorporating information frictions and exporter reputation. The model demonstrates 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 will set prices lower in the former case to subsidize importer learning and reputation building. Over time, high-quality exporters will raise prices after reputation is established. Overall, our model provides new insights into the source of export growth. In the presence of large quality dispersion and observable reputation, high-quality exporters exhibit a particularly greater export premium and a higher likelihood of becoming superstars. Hence the best firms gain a larger market share from established reputation and sell their products at higher prices resulting in a market-wide export growth. The effect amounts to a 34-percent increase in aggregate trade value based on our structural estimation and counterfactual analysis, equivalent to the effect of raising market-wide quality by 29 percent. The aggregate export growth is, however, at the expense of rising export concentration on superstar exporters and equivalent to a 208-percent increase in exporter quality heterogeneity.

The findings of this paper convey important implications for the role of information and importer learning in the aggregate value and distribution of trade. While lowering explicit export entry costs is important for the ability of small and medium exporters 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 for developing countries where there are poorer regulatory and contractual environment and lower trust from foreign importers. Efforts like improving market transparency and allowing public access to a market wide reputation system would facilitate export growth. Interventions providing high-quality exporters an opportunity to establish reputation would be helpful for initiating importer learning and upgrading aggregate exports. However, such programs must be inclusive of new and prospective exporters who could otherwise live in the shadow of established superstars with impaired visibility in export markets.

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Appendix

1. Derivation for the Bellman Equation

For each seller i, she needs to pick a market specific price to maximize current period profits and future profits:

$$\begin{aligned} V_{itm}(\theta_i, \overline{\theta}_{im}, \omega_u^*) &= \max_{\{p_{ijtm}\}_{j\in N}} \sum_{j\in N} q_j \{ d_{ijtm} [p_{ijtm} - \tau_j - c\theta_i + \beta(1-\delta) E(V_{i(t+1)(m+1)}(\theta_i, \overline{\theta}_{im+1}, \omega_u^*))] \\ & \quad + (1-d_{ijtm})\beta(1-\delta) V_{i(t+1)m}(\theta_i, \overline{\theta}_{im}, \omega_u^*)\} \end{aligned}$$

Notice that we assume each seller has infinite life with exiting probability of δ, a seller with m feedbacks will face the same choice at any time period t which yields $V_{i(t+1)m}(\theta_i, \overline{\theta}_{im}, \omega_u^*) = V_{itm}(\theta_i, \overline{\theta}_{im}, \omega_u^*)$

If we rearrange terms, the equation becomes

$$\begin{aligned} V_{itm}(\theta_i, \overline{\theta}_{im}, \omega_u^*) &= \max_{p_{ijtm}} \frac{\sum_{j\in N} q_j d_{ijtm}}{1-\beta(1-\delta)\sum_{j\in N} q_j (1-d_{ijtm})} [p_{ijtm} - \tau_j - c\theta_i \\ & \quad + \beta(1-\delta) E(V_{i(t+1)(m+1)}(\theta_i, \overline{\theta}_{im+1}, \omega_u^*))] \end{aligned}$$

2. Solution to the Model under Incomplete Information without Observable Reputation

Substituting $p_{ijt}^I = \tau_j + c\theta_i + \sigma$ into firm profit maximization problem, we have the following problem

$$\max_a V_1 = \int_{\theta_i^a} \sum_{t=1}^{\infty} \{[\beta(1-\delta)]^t \sum_{j\in N} q_j \sigma d_{ijt}\} d\theta_i^a$$

Notice that $\ln d_{ijt} \sim N(\frac{1}{\sigma}(\rho \frac{\omega_\theta \theta + \omega_u \theta_i}{\omega_\theta + \omega_u} - p_{ijt}^I) - \ln G, \frac{\rho^2 \omega_u}{\sigma^2(\omega_\theta+\omega_u)^2})$, $G = \sum_{k=1}^K \exp\left[\frac{1}{\sigma}(\rho\overline{\theta}_{kt} - p_{kjt})\right]$

is a market index which we assume to be sufficiently large relative to an individual seller's sales and treat it as a constant. Then the expected lifetime profit becomes

$$V_1 = \sum_{t=1}^{\infty} \{[\beta(1-\delta)]^t \sum_{j\in N} q_j \sigma \exp[\frac{1}{\sigma}(\rho \frac{\omega_\theta \theta + \omega_u \theta_i}{\omega_\theta + \omega_u} - p_{ijt}^I) - \ln G + \frac{\rho^2 \omega_u}{\sigma^2(\omega_\theta + \omega_u)^2}]\}$$

Differentiating the above equation with respect to the information from the seller a yields:

$$\frac{\partial V_1}{\partial a} = \frac{\partial \omega_u}{\partial a} \sum_{t=1}^{\infty} \{[\beta(1-\delta)]^t \sum_{j\in N} (q_j \frac{\rho \exp(\frac{1}{\sigma}(\overline{\theta}_1 - p_{ij1}^I))}{G} \frac{\omega_\theta(\theta_i - \theta)}{(\omega_\theta + \omega_u)}\} \tag{30}$$

where we neglect the high order partial derivative effect from $\frac{\rho^2\omega_u}{\sigma^2(\omega_\theta+\omega_u)^2}$.

Equation (30) shows that if $\theta_i > \theta$, $\frac{\partial V_1}{\partial a} > 0$; if $\theta_i < \theta$, $\frac{\partial V_1}{\partial a} < 0$. High-quality sellers will post the maximum amount of information online while low-quality sellers will post minimum information.

Next, we compare the equilibrium quantity sold under complete information and incomplete information.

$$\frac{Ed^I_{ijt}(\theta_i)}{d^C_{ijt}(\theta i)} = \exp\{\frac{\rho\omega_\theta(\theta-\theta i)}{\sigma(\omega_\theta+\omega_u)} + \frac{\rho^2\omega_u}{2\sigma^2(\omega_\theta+\omega_u)^2}\}$$

When the high order effect from $\frac{\rho^2\omega_u}{\sigma^2(\omega_\theta+\omega_u)^2}$ is negligible, $\frac{Ed^I_{ijt}(\theta_i)}{d^C_{ijt}(\theta i)} > 1$ if $\theta i < \theta$, and $\frac{Ed^I_{ijt}(\theta i)}{d^C_{ijt}(\theta i)} < 1$ if $\theta_i > \theta$.

3. Proof of Proposition 1.

To prove Proposition 1, we consider a listing with past reputation denoted as $\overline{\theta}_{im} = \frac{\sum_{k=1}^m \widetilde{\theta}^b_{ik} + \theta^a_i + \theta}{m+2}$ which is already known to the public with variance $\frac{1}{\omega}$. Notice that when m increases, we expect to see ω increase for each $\overline{\theta}_{im}$. Therefore, we only need to prove price rises with ω for high θ_i and drops with ω for low θ_i. To simplify notations, we denote feedback $\widetilde{\theta}^b_{ik} = \theta_i + \varepsilon_k$ where $\varepsilon_k \sim N(0, \sigma^2_\varepsilon)$. For $\omega_2 > \omega_1$, we need to determine the sign of the following equation:

$$\begin{aligned}
& E(V_{i(t+1)(m+1)}(\theta_i, \frac{\omega_2\overline{\theta}_{im} + \omega_\varepsilon(\theta_i+\varepsilon_{m+1})}{\omega_2+\omega_\varepsilon}, \omega^*_u)) - E(V_{i(t+1)(m+1)}(\theta_i, \frac{\omega_1\overline{\theta}_{im} + \omega_\varepsilon(\theta_i+\varepsilon_{m+1})}{\omega_1+\omega_\varepsilon}, \omega^*_u)) \\
= & \int_{\{\varepsilon_s\}^\infty_{s=m+1}} \sum_{j\in N} q_j\sigma(\frac{\exp\{\frac{\rho}{\sigma}[\overline{\theta}_{im+1} - \tau_j - c\theta i]\}\exp\{\beta(1-\delta)E(V_{i(t+2)(m+2)}(\theta_i, \overline{\theta}_{im+2}, \omega^*_u))\}}{G} - \\
& \frac{\exp\{\frac{\rho}{\sigma}[\overline{\theta}_{im+1} - \tau_j - c\theta i]\}\exp\{\beta(1-\delta)E(V_{i(t+2)(m+2)}(\theta_i, \overline{\theta}_{im+2}, \omega^*_u))\}}{G})d\{\varepsilon_s\}^\infty_{s=m+1}
\end{aligned}$$

Define $f^l(\overline{\theta}_{im+1}) = \exp\{\frac{\rho}{\sigma}(\overline{\theta}_{im+1} - \tau_j - c\theta i)\}$, $g^l(\overline{\theta}_{im+1}) = \exp[\beta(1-\delta)(EV_{i(t+1)(m+1)}(\theta_i, \overline{\theta}_{im+1}, \omega^*_u))]$, $l = \{1, 2\}$

$$\begin{aligned}
& E(V_{i(t+1)(m+1)}(\theta_i, \frac{\omega_2\overline{\theta}_{im} + \omega_\varepsilon(\theta_i+\varepsilon_{m+1})}{\omega_2+\omega_\varepsilon}, \omega^*_u)) - E(V_{i(t+1)(m+1)}(\theta_i, \frac{\omega_1\overline{\theta}_{im} + \omega_\varepsilon(\theta_i+\varepsilon_{m+1})}{\omega_1+\omega_\varepsilon}, \omega^*_u)) \\
= & \int_{\{\varepsilon_s\}^\infty_{s=m+1}} \sum_{j\in N} q_j\sigma(\frac{f^2(\overline{\theta}_{im+1})g^2(\overline{\theta}_{im+2})}{G} - \frac{f^1(\overline{\theta}_{im+1})g^1(\overline{\theta}_{im+2})}{G})d\{\varepsilon_s\}^\infty_{s=m+1}
\end{aligned}$$

Notice that $g^l(\overline{\theta}_{im+n}) = \Pi_j \exp\{\beta(1-\delta)q_j\sigma\frac{1}{G}f^l(\overline{\theta}_{im+n})g^l(\overline{\theta}_{im+n+1})\}$.

First, consider m is large enough, we have $\overline{\theta}_{iM+1} \approx \overline{\theta}_{iM}$ and

$$g^l(\overline{\theta}_{iM}) = \Pi_j \exp\{\frac{\beta(1-\delta)q_j\sigma}{G(1-\beta(1-\delta))} \exp\frac{\rho}{\sigma}(\frac{\omega_2\overline{\theta}_{im} + (M-m)\omega_\varepsilon\theta_i + \omega_\varepsilon\sum_{s=m+1}^{M}\varepsilon_s}{\omega_2 + (M-m)\omega_\varepsilon} - \tau_j - c\theta i)\}$$

When $\theta i > \overline{\theta}_{im}$, $f^2(E\overline{\theta}_{is}) < f^1(E\overline{\theta}_{is}), s = \{m+1, ..., M\}$, we determine the signs of the following equation:

$$\begin{aligned} & f^2(\overline{\theta}_{iM-1})g^2(\overline{\theta}_{iM}) - f^1(\overline{\theta}_{iM-1})g^1(\overline{\theta}_{iM}) \\ = \; & f^2(\overline{\theta}_{iM-1})g^2(\overline{\theta}_{iM})[1 - \frac{f^1(\overline{\theta}_{iM-1})g^1(\overline{\theta}_{iM})}{f^2(\overline{\theta}_{iM-1})g^2(\overline{\theta}_{iM})}] \\ = \; & f^2(\overline{\theta}_{iM-1})\Pi_j \exp[\frac{\beta(1-\delta)q_j\sigma}{G(1-\beta(1-\delta))}f^2(\overline{\theta}_{iM})] \\ & *(1 - \frac{f^1(\overline{\theta}_{iM-1})}{f^2(\overline{\theta}_{iM-1})}\Pi_j(\exp\frac{\beta(1-\delta)q_j\sigma}{G(1-\beta(1-\delta))})^{-f^2(\overline{\theta}_{iM})[f^1(\overline{\theta}_{iM})/f^2(\overline{\theta}_{iM})-1]}) \end{aligned}$$

As $f^2(\overline{\theta}_{iM-1}(\{\varepsilon_s\}_{s=m+1}^{M-1}))g^2(\overline{\theta}_{iM}(\{\varepsilon_s\}_{s=m+1}^{M})) - f^1(\overline{\theta}_{iM-1}(\{\varepsilon_s\}_{s=m+1}^{M-1}))g^1(\overline{\theta}_{iM}(\{\varepsilon_s\}_{s=m+1}^{M}))$ is concave on $\{\varepsilon_s\}_{s=m+1}^{M}$, we have the following equation holds.

$$f^2(E\overline{\theta}_{iM-1})g^2(E\overline{\theta}_{iM}) - f^1(E\overline{\theta}_{iM-1})g^1(E\overline{\theta}_{iM}) < 0$$

Second,

$$\begin{aligned} & f^2(\overline{\theta}_{im+1})g^2(\overline{\theta}_{im+2}) - f^1(\overline{\theta}_{im+1})g^1(\overline{\theta}_{im+2}) \\ = \; & f^2(\overline{\theta}_{im+1})g^2(\overline{\theta}_{im+2}) * \{1 - \frac{f^1(\overline{\theta}_{im+1})}{f^2(\overline{\theta}_{im+1})} * \\ & \Pi_j \exp[\frac{\beta(1-\delta)q_j\sigma}{G(1-\beta(1-\delta))}]^{-(f^2(\overline{\theta}_{im+2})g^2(\overline{\theta}_{im+3}) - f^1(\overline{\theta}_{im+2})g^1(\overline{\theta}_{im+3}))}\} \end{aligned}$$

$f^2(\overline{\theta}_{im+1})g^2(\overline{\theta}_{im+2}) - f^1(\overline{\theta}_{im+1})g^1(\overline{\theta}_{im+2})$ is a concave and monotone transformation of $f^2(\overline{\theta}_{im+2})g^2(\overline{\theta}_{im+3}) - f^1(\overline{\theta}_{im+2})g^1(\overline{\theta}_{im+3})$ and $\{\varepsilon_s\}_{s=m+1}^{M}$.

Therefore, $f^2(\overline{\theta}_{im+1})g^2(\overline{\theta}_{im+2}) - f^1(\overline{\theta}_{im+1})g^1(\overline{\theta}_{im+2})$ is a concave function of $\{\varepsilon_s\}_{s=m+1}^{M}$ by backward iteration from $f^2(\overline{\theta}_{iM-1})g^2(\overline{\theta}_{iM}) - f^1(\overline{\theta}_{iM-1})g^1(\overline{\theta}_{iM})$.

Further, if $f^2(E\overline{\theta}_{is+1})g^2(E\overline{\theta}_{is+2}) - f^1(E\overline{\theta}_{is+1})g^1(E\overline{\theta}_{is+2}) < 0$, we get

$$f^2(E\overline{\theta}_{is})g^2(E\overline{\theta}_{is+1}) - f^1(E\overline{\theta}_{is})g^1(E\overline{\theta}_{is+1}) < 0$$

Lastly, by following Jensen's Inequality, we can iterate above result and show

$$E\{f^2(\overline{\theta}_{im+1})g^2(\overline{\theta}_{im+2})-f^1(\overline{\theta}_{im+1})g^1(\overline{\theta}_{im+2})\} < f^2(E\overline{\theta}_{im+1})g^2(E\overline{\theta}_{im+2})-f^1(E\overline{\theta}_{im+1})g^1(E\overline{\theta}_{im+2}) < 0$$

Therefore, for sufficiently high θ_i,

$E(V_{i(t+1)(m+1)}(\theta_i, \frac{\omega_2\overline{\theta}_{im}+\omega_\varepsilon(\theta_i+\varepsilon_{m+1})}{\omega_2+\omega_\varepsilon}, \omega_u^*)) - E(V_{i(t+1)(m+1)}(\theta_i, \frac{\omega_1\overline{\theta}_{im}+\omega_\varepsilon(\theta_i+\varepsilon_{m+1})}{\omega_1+\omega_\varepsilon}, \omega_u^*)) < 0$ which yields $p^*_{ijtm}(\tau_j, \theta_i, \omega_2) > p^*_{ijtm}(\tau_j, \theta_i, \omega_1)$.

4. Proof of Proposition 2.

As $\lim_{m\to\infty} \frac{\omega_\theta\theta+m\omega_u\theta_i}{\omega_\theta+m\omega_u} = \theta_i$, we assume a very large M as the largest number of feedbacks that consumer will use for belief updating. Assuming $\sigma_\theta^2 > \frac{\sigma_\varepsilon^2\sigma_u^{*2}c}{\sigma_u^{*2}(\rho-cM)-\sigma_\varepsilon^2 c}$, we have $\frac{\rho\omega_\varepsilon}{\omega_M+\omega_\varepsilon} > c$. Notice that

$$\frac{dE\left(V_{itM}(\overline{\theta}_{iM})\right)}{d\theta_i} = E\{\sum_{j\in N} q_j \frac{\exp(\frac{\rho}{\sigma}(\overline{\theta}_{iM} - c\theta_i - \tau_j))}{G}(\frac{\rho\omega_\varepsilon}{\omega_M+\omega_\varepsilon} - c)\} > 0$$

To evaluate the volume difference under incomplete information with and without learning, we calculate

$$\begin{aligned}
\frac{d\frac{d^*_{ijtm}(\theta_i,\overline{\theta}_{im})}{d^I_{ijtm}(\theta_i,\overline{\theta}_{im})}}{d\theta_i} &= \frac{d\exp\frac{1}{\sigma}[\beta(1-\delta)E(V_{i(t+1)(m+1)}(\theta_i,\overline{\theta}_{i(m+1)}(\overline{\theta}_{im})))]}{d\theta_i} \\
&= \beta(1-\delta)\int_{\{\varepsilon_i\}_{i=m+1}^{\infty}} \sum_{j\in N}[\frac{q_j\sigma}{G}\exp(\frac{\rho}{\sigma}(\overline{\theta}_{i(m+1)} - p_{ij(t+1)(m+1)}))(\frac{\rho\omega_\varepsilon}{\omega_m+\omega_\varepsilon} - c)] \\
&\quad + \sum_{j\in N}\{\frac{q_j}{G}\exp(\frac{\rho}{\sigma}(\overline{\theta}_{i(m+1)} - p_{ij(t+1)(m+1)}))\beta(1-\delta) * \\
&\quad \sum_{j\in N}[\frac{q_j}{G}\exp(\frac{\rho}{\sigma}(\overline{\theta}_{ijm+2} - p_{ij(t+2)(m+2)}))(\frac{2\rho\omega_\varepsilon}{\omega_m+2\omega_\varepsilon} - c)]\} + ... \\
&> 0
\end{aligned}$$

This is equivalent to

$$\frac{d^*_{ijtm}(\theta_i^h)}{d^*_{ijtm}(\theta_i^l)} > \frac{d^I_{ijt}(\theta_i^h)}{d^I_{ijt}(\theta_i^l)}$$

5. Numerical solution of the firm's dynamic programing problem.

From the model, we know the following firm pricing equation. We assume that learning will stop after 25 periods. Changing this number will not have a significant effect on our estimation result. Backward induction can be used to solve for the optimal price policy at each period:

$$\mathbf{p}^*_{ijtm}(\boldsymbol{\tau}_j, \boldsymbol{\theta}_i) = \boldsymbol{\tau}_j + \mathbf{c}\boldsymbol{\theta}_i + \boldsymbol{\sigma} - \boldsymbol{\beta}(\mathbf{1} - \boldsymbol{\delta})\mathbf{E}\left(V_{i(t+1)(m+1)}(\overline{\theta}_{i(t+1)(m+1)}, \omega^*_u)\right)$$

In each period, a firm will form an expectation about consumers' future belief about its product quality. In period 0 when there is no feedback, the new coming buyer will have belief

$$E(\theta_j|\theta^a_j) = \frac{\omega_\theta\theta + \omega_u(a_j)\theta^a_j}{\omega_\theta + \omega_u(a_j)}, \theta^a_j \sim N(\theta_j, 1/\omega_u(a_j))$$

Before a consumer draws the actual signaled quality, the firm expects the consumer will have a belief that follows a normal distribution

$$\mathbf{N}(\frac{\omega_\theta\theta + \omega_u(a_j)\theta_j}{\omega_\theta + \omega_u(a_j)}, \frac{\omega_u(a_j)}{(\omega_\theta + \omega_u(a_j))^2})$$

In period t,when there are $m-1$ feedbacks, the new coming buyer from country c will have belief

$$E(\theta_j|\theta^a_j, \theta^s_{jm}) = \frac{\omega_\theta\theta + \omega_u(a_j)\theta^a_j + (m-1)\omega_\varepsilon\theta^s_{jm-1} + \theta^s_{jm}}{\omega_\theta + \omega_u(a_j) + m\omega_\varepsilon}, \theta^s_{jm} \sim N(\theta_j, 1/\omega_\varepsilon)$$

where

$$\theta^s_{jm-1} \equiv \frac{\sum_{k=1}^{m-1}\widetilde{\theta}^s_{jk}}{m-1}$$

Before the buyer leaves a feedback, the firm expects that its reputation will follow a normal distribution as below

$$N(\frac{\omega_\theta\theta + \omega_u(a_j)\theta^a_j + (m-1)\omega_\varepsilon\theta^s_{jm-1} + \omega_\varepsilon\theta_j}{\omega_\theta + \omega_u(a_j) + t\omega_\varepsilon}, \frac{\omega_\varepsilon}{(\omega_\theta + \omega_u(a_j) + m\omega_\varepsilon)^2})$$

We proxy the integral of the expected value function by discretizing potential states into M points $\{x_1, x_2, ..., x_M\}$ in the range of $[\theta - 2.5\sigma_\varepsilon - 2.5\sigma_\theta, \theta + 2.5\sigma_\varepsilon + 2.5\sigma_\theta]$. The transition probability is calculated as

$$\Pr(\mathbf{x}^m_j|\mathbf{x}^{m-1}_k) = \mathbf{\Phi}(\frac{0.5*(x^m_{j+1} + x^m_j) - \mu^{m-1}_k}{\sigma_{\mu^{m-1}_k}}) - \mathbf{\Phi}(\frac{0.5*(x^m_{j-1} + x^m_j) - \mu^{m-1}_k}{\sigma_{\mu^{m-1}_k}})$$

where

$$\mu^{m-1}_k = \frac{[\omega_\theta + \omega_u(a_j) + (m-1)\omega_\varepsilon]x^{m-1}_k + \omega_\varepsilon\theta_j}{\omega_\theta + \omega_u(a_j) + m\omega_\varepsilon}, \sigma_{\mu^{m-1}_k} = \frac{\omega^{1/2}_\varepsilon}{\omega_\theta + \omega_u(a_j) + m\omega_\varepsilon}.$$

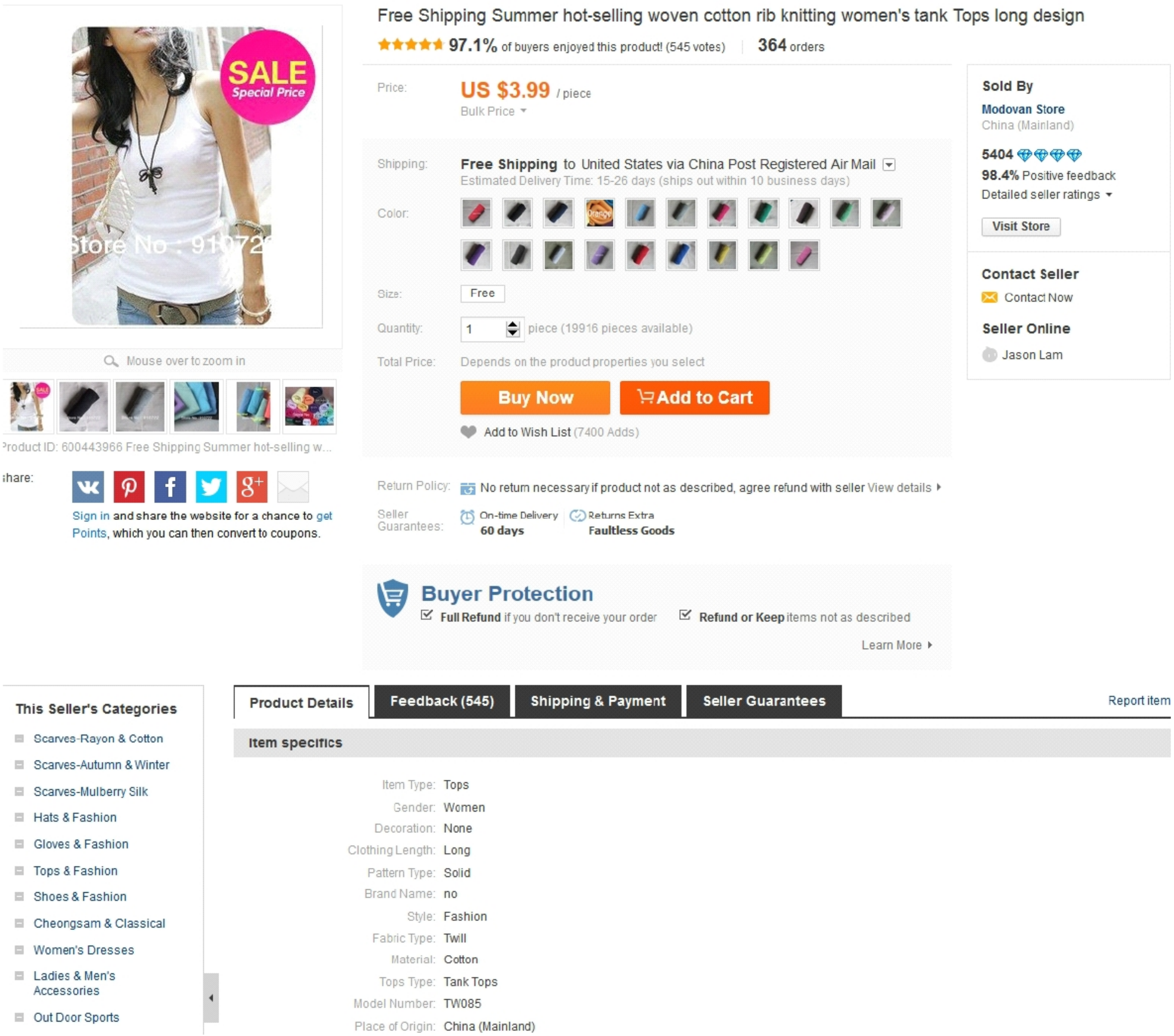

Figure 1: A Sample Listing (part I)

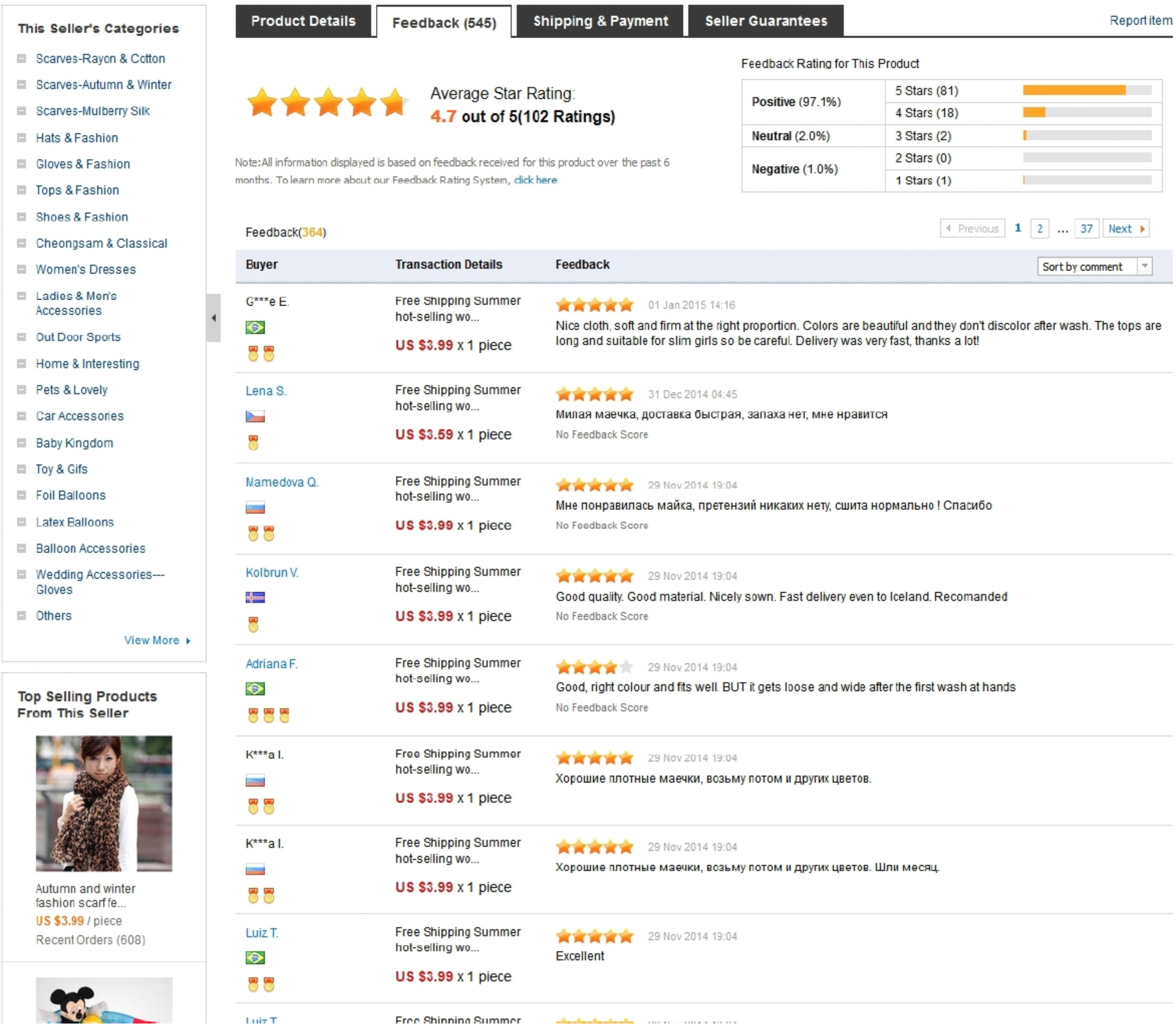

Figure 2: A Sample Listing (part II)

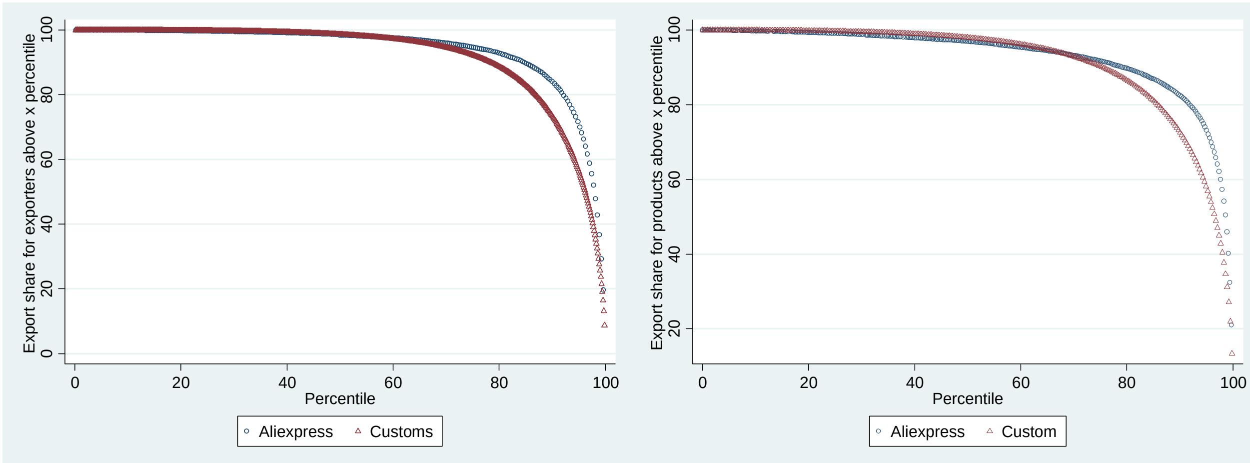

Figure 3: The Market Share of Top Percentile Exporters/Products Online and Offline

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.

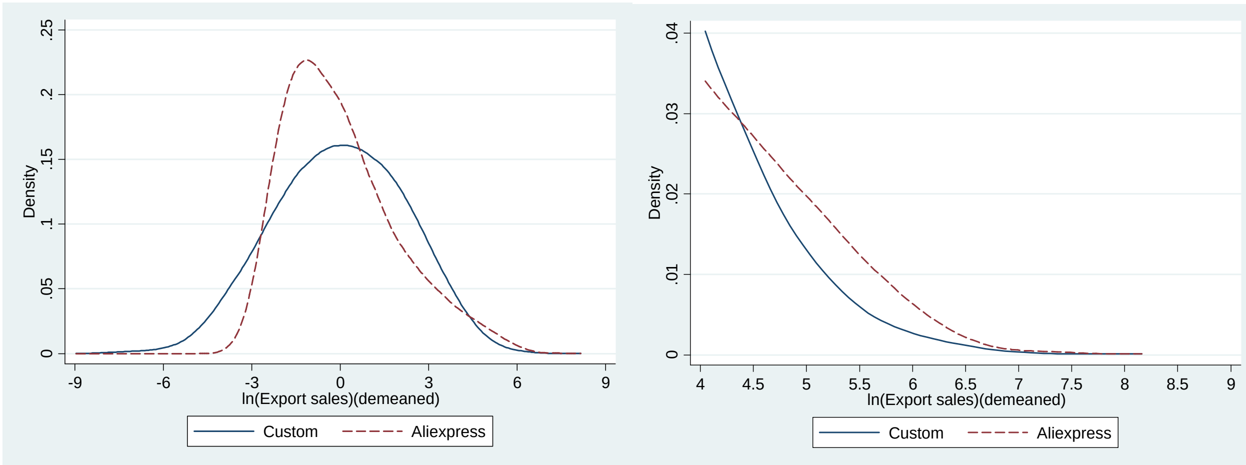

Figure 4: The Distribution of Export Revenue for Custom and Aliexpress

Notes: This figure shows the Kernal density distribution of export revenue at the exporter level for our sample Aliexpress data and Chinese customs data. We zoom in the right tail of the distribution on the right handside graph.

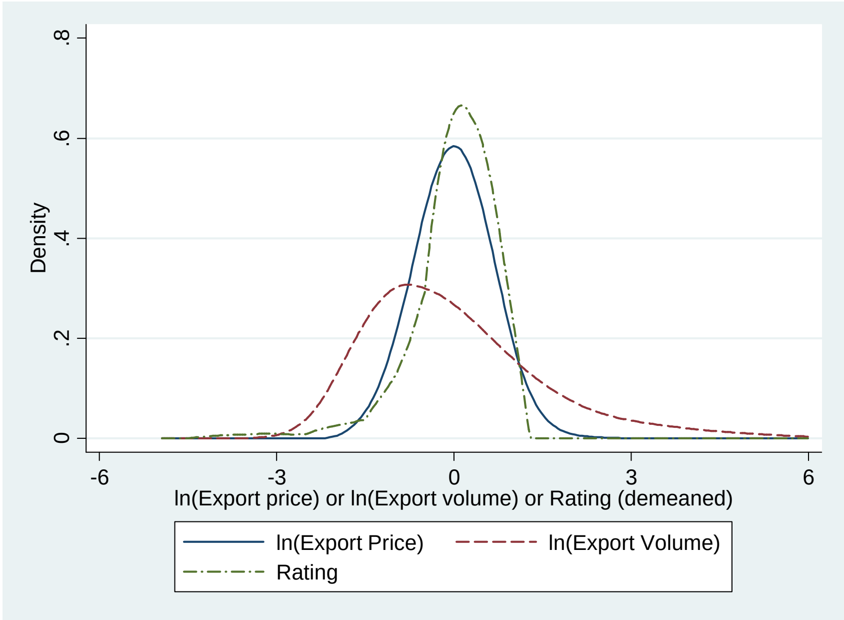

Figure 5: The Distribution of Export Unit Price, Reputation and Volume

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.

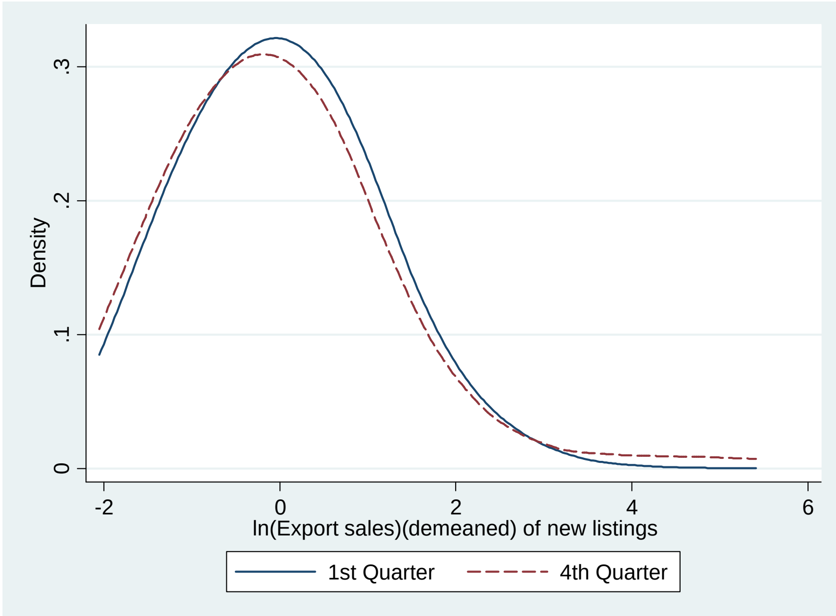

Figure 6: The Distribution of Export Revenue over Time

Notes: This figure presents the distribution of per period export revenue for a cohort of new listings that were born at the beginning of our sample period at the log scale. We track the revenue distribution for listings born in the first quarter of our sample periods.

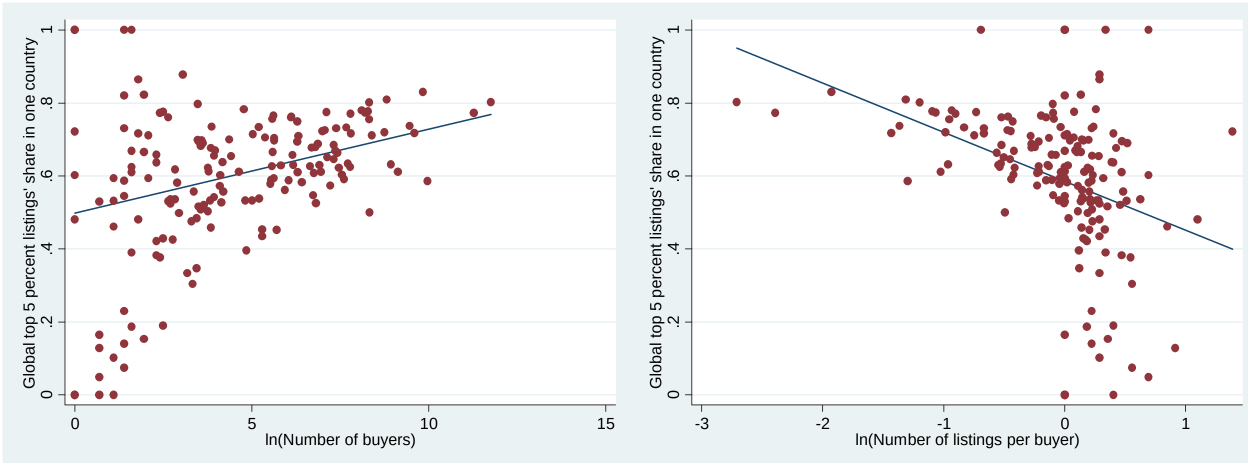

Figure 7: The Market Share of Superstar Exporters and Import-Country Size and Experience

Notes: The left handside figure presents the relationship between the market share of global top 5-percent listings in each import country and the import country size. The right handside figure presents the relationship between the market share of the global top 5-percent listings in each import country and importer experience.

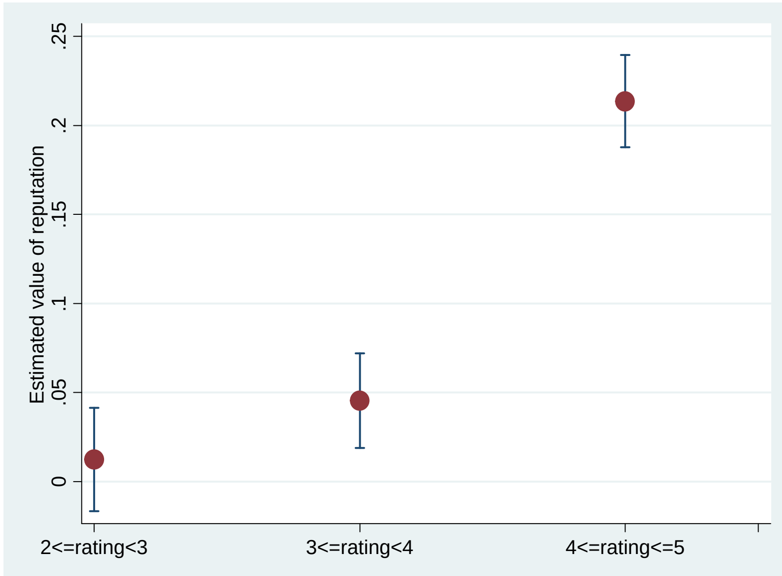

Figure 8: The Estimated Value of Reputation

Notes: This figure shows the elasticities of export revenue with respect to different ratings. The estimates are from the baseline regression in Table 3. We define this as the value of reputation to an exporter and show the 95-percent standard error band for each estimation. The reference rating group is listings with ratings between 1 and 2.

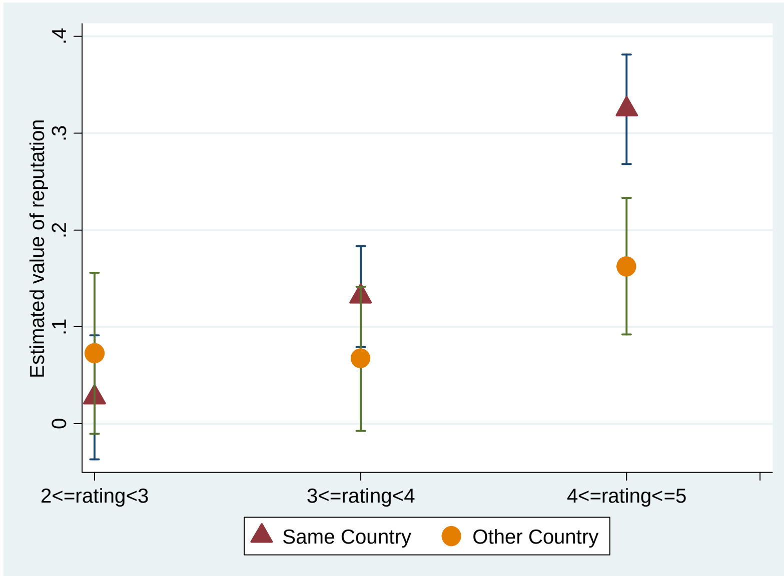

Figure 9: The Value of Reputation by the Origin of Reputation

Notes: This figure presents elasticities of export revenue with respect to different ratings from the importer home country as well as the rest of the world. We show the 95-percent standard error band for each estimation. The reference rating group is listings with ratings between 1 and 2.

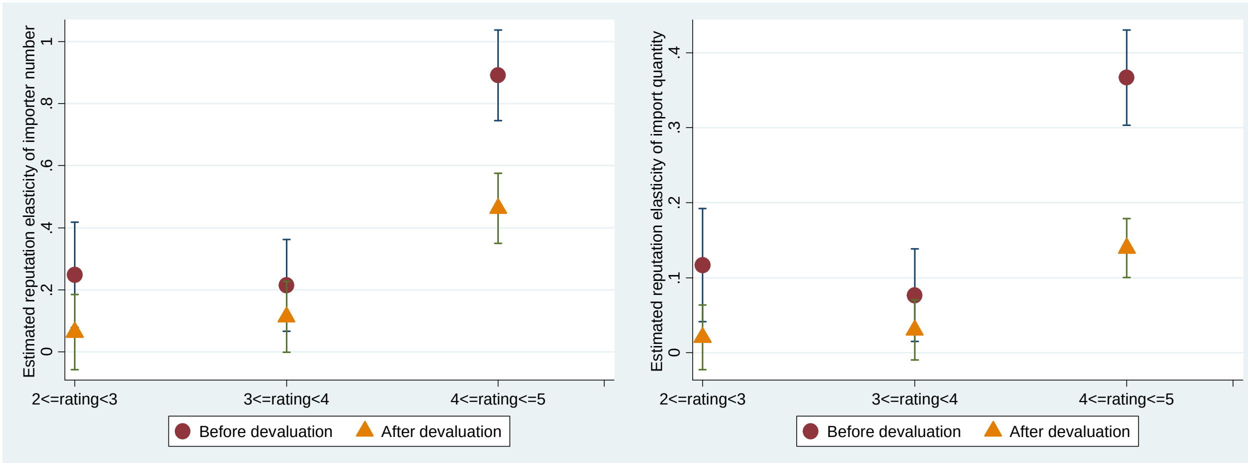

Figure 10: The Value of Reputation Before and After Ruble Crisis

Notes: This figure displays the elasticity of exports to Russia with respect to reputation before and after the Ruble Crisis. We regress export volume/number of importers to Russia on reputation before and after the Ruble crisis controlling for other listing level characteristics at the listing-week level. The 26th week is defined as when the devaluation started. Standard errors are clustered at the listing level and the 95-percent standard error band is shown for each estimation. The reference rating group is listings with ratings between 1 and 2.

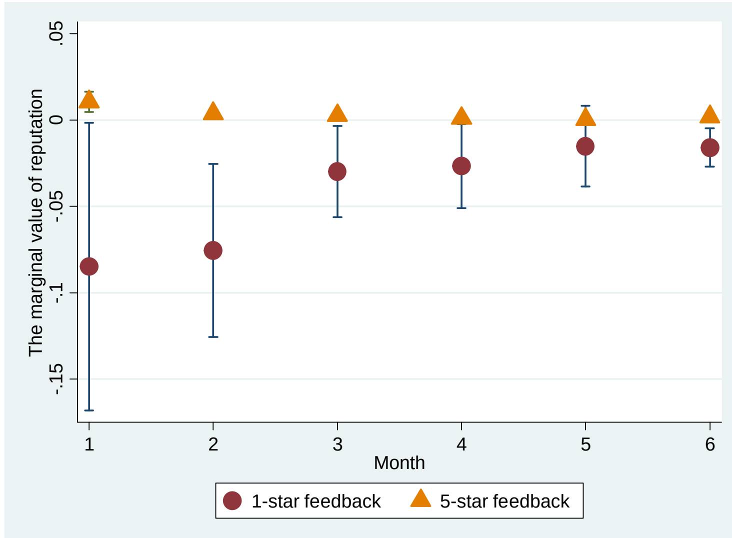

Figure 11: The Marginal Value of Reputation over Time

Note: This figure graphs the marginal value of 1-star and 5-star feedbacks. We regress logged weekly export quantity on the monthly number of 1-star ratings, 2-star ratings, 3-star ratings, 4-star ratings and 5-star ratings controlling for price and other quality measures. The estimated coefficients of monthly 1-star ratings and 5-star ratings are plotted in the graph with the 95-percent standard error band for each estimation.

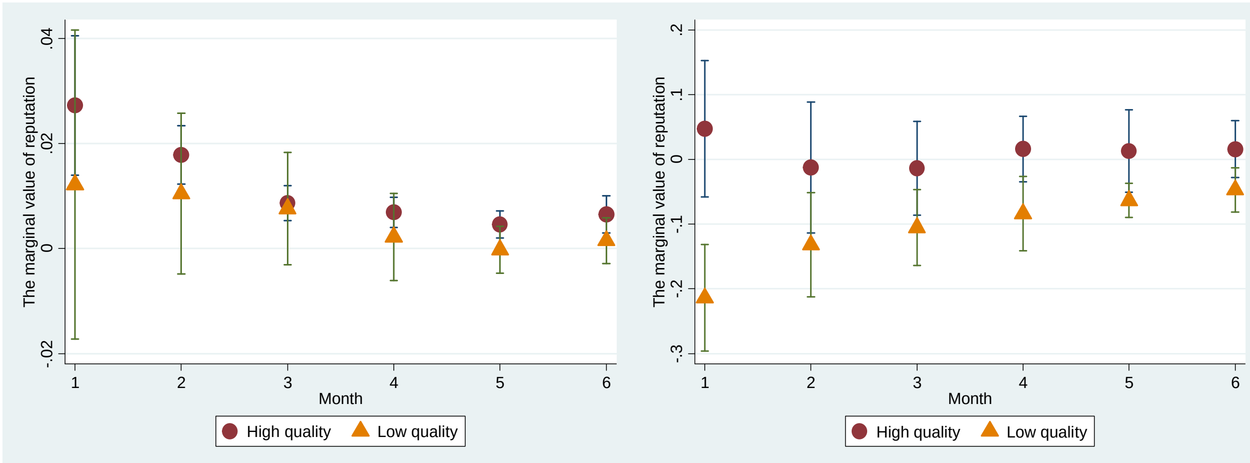

Figure 12: The Marginal Value of Reputation for Heterogeneous Exporters

Note. This figure graphs the marginal value of 1-star and 5-star feedbacks for high and low quality exporters. We regress logged weekly export quantity on the monthly number of 1-star ratings, 2-star ratings, 3-star ratings, 4-star ratings and 5-star ratings controlling for price and other quality measures for high-quality exporters and low-quality exporters. Listings with decoration is defined as high-quality exporters. The estimated coefficients of monthly 1-star ratings and 5-star ratings are plotted in the graph with the 95-percent standard error band for each estimation.

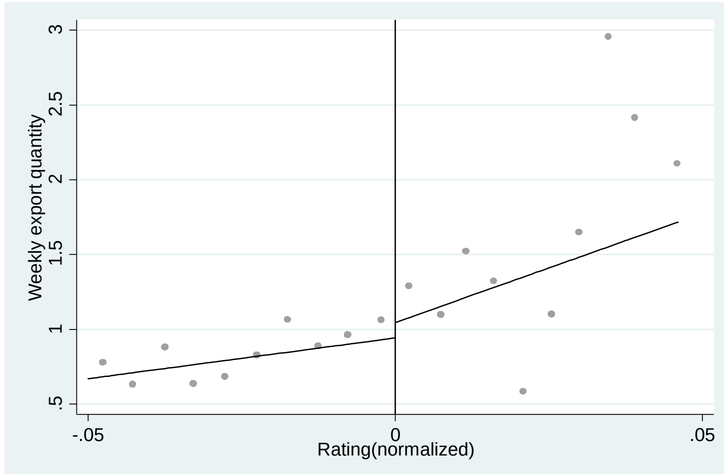

Figure 13: Weekly Exports and Average Rating

Note: This figure plots the relationship between ln(weekly quantity +1) and average rating. Rating is nomarlized relative to its rounding threshold. The right hand side of the threshold represents ratings that are rounded up at one decimal; the left hand side of the threshold represents ratings that are rounded down at one decimal.

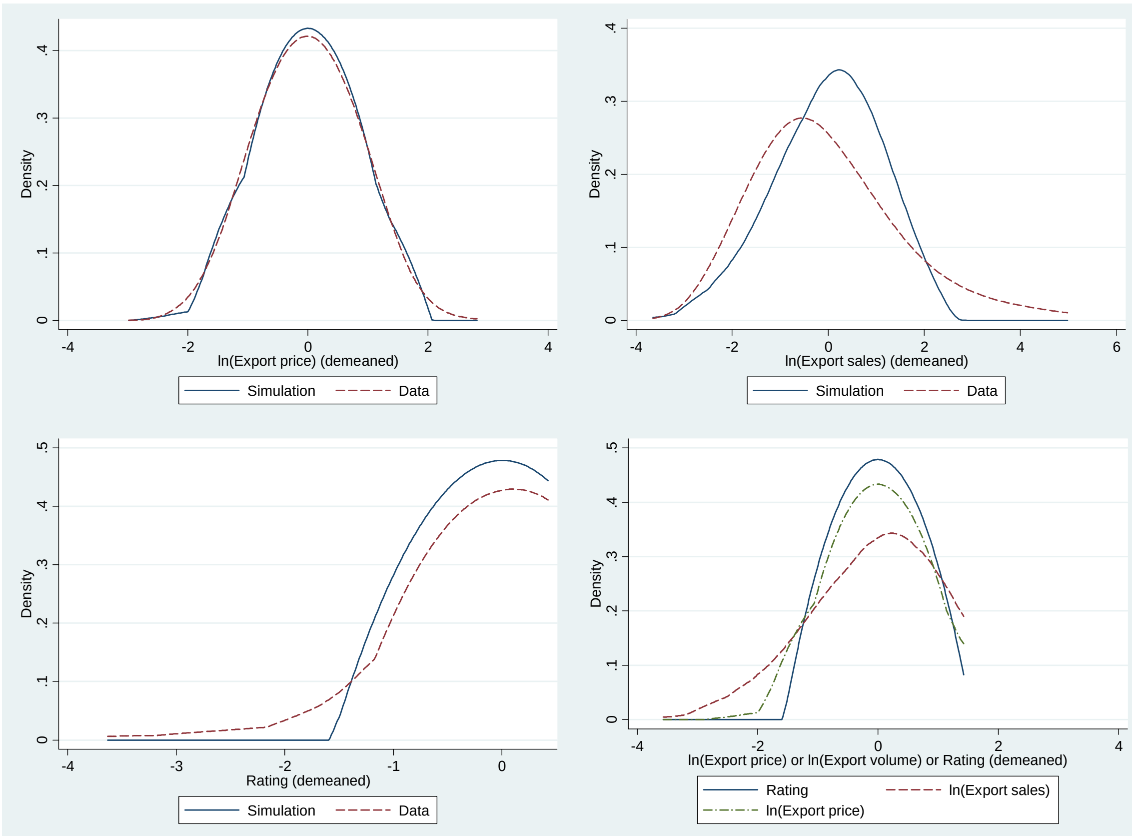

Figure 14: Simulated vs. Actual Dispersion of Price, Sales and Reputation

Notes: This figure compares simulated export price, sales and reputation with actual data. The figure at the bottom right shows a comparison among simulated price, rating and sales.

Table 1: Descriptive Statistics of Exports

	N	Mean	Std. Dev.	Min	Max	5%	50%	95%	99%
Exporter level									
Volume (piece)	5,392	124.04	640.92	1	23,270	1	7	529	2461
Price ($)	5,392	9.41	6.95	0.46	124	2.99	7.84	19.99	35.05
Revenue ($)	5,392	747.42	3751.70	1.73	177,122.80	6.99	54.88	3,273.06	14,382.69
Listing level									
Volume (piece)	16,995	39.36	255.64	1	11,798	1	4	108	802
Price ($)	16,995	9.22	6.15	0.06	124	3.04	7.99	19.29	29.99
Revenue ($)	16,995	237.13	1,289.50	1.68	56,517.28	6.14	29.70	746.14	4,697.96
Rating	11,212	4.60	0.63	1.00	5.00	3.33	4.88	5.00	5.00

Notes: This table reports the descriptive statistics for the main variables.

Table 2: Superstar Exporters

	No. of SS Exporters		SS Median/NSS Median		SS Mean/NSS Mean		SS Share	
	Online	Offline	Online	Offline	Online	Offline	Online	Offline
top 1%	53	108	382.84	155.67	52.66	42.51	0.34	0.30
top 5%	269	540	140.51	67.21	46.15	26.20	0.71	0.58
top 10%	539	1079	74.42	47.35	47.59	24.43	0.84	0.73
top 30%	1617	3237	21.20	26.48	55.79	32.30	0.96	0.93

Notes: This table reports the levels of concentration in Aliexpress and customs exports.

Table 3: The Value of Reputation: Baseline

	(1)	(2)	(3)	(4)	(5)
Dep. Var	revenue	quantity	ave quantity	buyer num	market num
ln(price)	-0.335***	-0.276***	-0.120***	-0.234***	-0.184***
	(0.023)	(0.016)	(0.006)	(0.014)	(0.010)
no rating	0.076***	0.047***	0.018***	0.044***	0.033***
	(0.024)	(0.012)	(0.006)	(0.012)	(0.009)
2<=rating<3	0.029	0.013	0.012	0.009	0.01
	(0.029)	(0.015)	(0.008)	(0.014)	(0.011)
3<=rating<4	0.106***	0.045***	0.032***	0.042***	0.039***
	(0.026)	(0.014)	(0.006)	(0.013)	(0.010)
rating>=4	0.412***	0.214***	0.096***	0.199***	0.160***
	(0.025)	(0.013)	(0.006)	(0.012)	(0.010)
material quality	0.002	0.001	-0.003	0.002	0.001
	(0.013)	(0.008)	(0.003)	(0.008)	(0.006)
buyer protection	0.033	0.04	-0.008	0.043	0.027
	(0.053)	(0.029)	(0.011)	(0.028)	(0.022)
return policy 1	0.142***	0.072***	0.024**	0.072***	0.057***
	(0.044)	(0.024)	(0.010)	(0.023)	(0.018)
return policy 2	0.179*	0.091	0.045**	0.077	0.064
	(0.103)	(0.057)	(0.022)	(0.054)	(0.040)
return policy 3	0.128*	0.071*	0.022	0.070**	0.053*
	(0.069)	(0.038)	(0.015)	(0.035)	(0.027)
ln(size choice num)	0.113***	0.064***	0.025***	0.060***	0.046***
	(0.014)	(0.009)	(0.003)	(0.008)	(0.006)
ln(detailed description num)	0.124**	0.092***	0.023**	0.086***	0.060***
	(0.054)	(0.034)	(0.011)	(0.032)	(0.023)
ln(picture num)	0.069***	0.034***	0.015***	0.031***	0.025***
	(0.011)	(0.007)	(0.002)	(0.007)	(0.005)
constant	2.041***	1.262***	0.577***	1.100***	0.847***
	(0.173)	(0.109)	(0.038)	(0.102)	(0.074)
Seller FE	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y
R2	0.253	0.271	0.213	0.273	0.271
N	526488	526488	526488	526488	526488

Notes: This table shows the results of regressing logged export revenue, volume, volume per buyer, number of buyers and number of markets on rating measures and other controls. Listings without any ratings in the past 6 months are the reference group. The observation is at the exporter-listing-week level. Robust standard errors are reported in parentheses. Standard errors are clustered at the listing level. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Table 4: The Value of Reputation: The Substance of Reputation

	(1)	(2)	(3)	(4)	(5)
Dep. Var	revenue	quantity	ave quantity	buyer num	market num
ln(price)	-0.255***	-0.232***	-0.162***	-0.187***	-0.153***
	(0.020)	(0.012)	(0.015)	(0.011)	(0.009)
number of words	0.002***	0.001***	0.000**	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
number of negative words	-0.109***	-0.071***	-0.003	-0.065***	-0.046***
	(0.034)	(0.023)	(0.002)	(0.022)	(0.016)
number of positive words	0.000	0.000	0.000	0.000	(0.000)
	(0.001)	(0.001)	(0.000)	(0.001)	0.000
no rating	0.256***	0.110***	0.029***	0.098***	0.089***
	(0.024)	(0.012)	(0.010)	(0.011)	(0.009)
2<=rating<3	0.026	0.011	0.033**	0.007	0.009
	(0.029)	(0.014)	(0.013)	(0.013)	(0.011)
3<=rating<4	0.112***	0.050***	0.011	0.046***	0.042***
	(0.026)	(0.013)	(0.010)	(0.012)	(0.010)
rating>=4	0.354***	0.173***	0.016*	0.160***	0.134***
	(0.026)	(0.013)	(0.009)	(0.012)	(0.010)
constant	2.419***	1.278***	1.079***	1.104***	0.946***
	(0.133)	(0.076)	(0.068)	(0.070)	(0.054)
Seller FE	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y
Listing characteristics	Y	Y	Y	Y	Y
R2	0.314	0.37	0.34	0.38	0.356
N	541468	541468	87335	541468	541468

Notes: This table displays results from regressing logged export revenue, export volume, export volume per importer, importer number and market number on the numbers of positive and negative words in comments controlling past rating and listing characteristics. The estimated parameters of other listing characteristics are suppressed to save space. The obsevation is at the exporter-listing-week level. Robust standard errors are reported in parentheses. Standard errors are clustered at listing level. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Table 5: The Value of Reputation and Import Country Characteristics

Dependent var: ln(export quantity+1)				
	(1)	(2)	(3)	(4)
Country characteristics	distance	gdp	shipping time	remoteness
ln(price)	-0.037***	-0.037***	-0.037***	-0.038***
	(0.003)	(0.003)	(0.003)	(0.003)
country characteristics	-0.163***	0.008***	-0.164***	0.273***
	(0.004)	0.000	(0.004)	(0.006)
no rating	-0.012	-0.040***	0.017***	0.008**
	(0.011)	(0.008)	(0.005)	(0.003)
2<=rating<3	-0.041***	-0.035***	0.013*	0.009**
	(0.015)	(0.012)	(0.007)	(0.005)
3<=rating<4	-0.094***	-0.080***	0.019***	0.016***
	(0.017)	(0.011)	(0.006)	(0.004)
rating>=4	-0.153***	-0.197***	0.060***	0.033***
	(0.013)	(0.011)	(0.006)	(0.004)
no rating * country characteristics	0.002	0.002***	-0.003**	0
	(0.001)	(0.000)	(0.001)	(0.000)
2<=Rating<3 * country characteristics	0.005***	0.001***	-0.003*	0.001**
	(0.002)	(0.000)	(0.002)	(0.000)
3<=Rating<4 * country characteristics	0.011***	0.003***	-0.004**	0.001***
	(0.002)	(0.000)	(0.002)	(0.000)
Rating>=4 * country characteristics	0.020***	0.009***	-0.010***	0.001**
	(0.001)	(0.000)	(0.001)	(0.000)
constant	1.665***	-0.117***	0.686***	2.068***
	(0.044)	(0.020)	(0.024)	(0.052)
Seller FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Listing characteristics	Y	Y	Y	Y
R2	0.092	0.092	0.095	0.092
N	6937480	6937480	5423848	6811344

Notes: This table displays results of regressing logged export revenue on average rating, the interaction of average rating and country characteristics and listing characteristics like material quality, buyer protection, return policy, description number, size choice number, picture number. The table suppresses estimated parameters of listing characteristics to save space. Country characteristics include distance, gdp , gdp per capita and remoteness. The observations are at the exporter-listing-month-destination 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 6: The Value of Reputation: Peer Group Comparison

	(1)	(2)	(3)	(4)	(5)
Dep. Var	revenue	quantity	ave quantity	buyer num	market num
ln(price)	-0.551***	-0.397***	-0.188***	-0.348***	-0.280***
	(0.039)	(0.026)	(0.010)	(0.024)	(0.018)
no rating	0.341***	0.151***	0.097***	0.138***	0.119***
	(0.028)	(0.015)	(0.007)	(0.014)	(0.011)
2<=rating<3	0.045	0.028	0.01	0.025	0.019
	(0.033)	(0.018)	(0.009)	(0.016)	(0.013)
3<=rating<4	0.135***	0.073***	0.034***	0.068***	0.053***
	(0.030)	(0.016)	(0.007)	(0.015)	(0.012)
rating>=4	0.409***	0.233***	0.089***	0.218***	0.169***
	(0.030)	(0.017)	(0.007)	(0.016)	(0.012)
material quality	-0.012	-0.005	-0.001	-0.007	-0.005
	(0.020)	(0.012)	(0.004)	(0.012)	(0.008)
buyer protection	0.333***	0.195***	0.058***	0.187***	0.148***
	(0.053)	(0.033)	(0.009)	(0.032)	(0.023)
return policy 1	0.055	0.045	0.003	0.038	0.024
	(0.065)	(0.038)	(0.015)	(0.036)	(0.027)
return policy 2	0.008	0.01	0.001	-0.002	-0.005
	(0.084)	(0.051)	(0.018)	(0.048)	(0.036)
return policy 3	0.162**	0.106**	0.023	0.101**	0.065**
	(0.076)	(0.046)	(0.017)	(0.043)	(0.032)
ln(size choice num)	0.174***	0.110***	0.033***	0.105***	0.079***
	(0.038)	(0.026)	(0.007)	(0.025)	(0.017)
ln(detailed description num)	0.119*	0.085*	0.030**	0.075*	0.054*
	(0.068)	(0.044)	(0.015)	(0.041)	(0.030)
ln(picture num)	0.074***	0.032***	0.018***	0.029***	0.026***
	(0.015)	(0.010)	(0.003)	(0.009)	(0.007)
constant	2.780***	1.429***	0.888***	1.282***	1.097***
	(0.204)	(0.131)	(0.048)	(0.121)	(0.088)
Group FE	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y
R2	0.313	0.324	0.259	0.328	0.328
N	541468	541468	541468	541468	541468

Notes: This table explores exports and reputation variations within peer groups 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 7: The Value of Reputation: RDD Regression

	(1)	(2)	(3)	(4)	(5)
Dep. Var	revenue	quantity	average quantity	buyer num	market num
ln(price)	-0.284***	-0.278***	-0.123***	-0.229***	-0.179***
	(0.026)	(0.018)	(0.006)	(0.016)	(0.012)
rated * treated	0.367***	0.193***	0.081***	0.182***	0.147***
	(0.020)	(0.012)	(0.004)	(0.011)	(0.008)
rated * true rating	0.085***	0.050***	0.014***	0.048***	0.036***
	(0.004)	(0.002)	(0.001)	(0.002)	(0.002)
material quality	-0.006	-0.004	-0.005*	-0.002	-0.003
	(0.015)	(0.009)	(0.003)	(0.009)	(0.006)
buyer protection	-0.042	0.025	-0.040***	0.032	0.011
	(0.061)	(0.035)	(0.012)	(0.033)	(0.026)
return policy 1	0.083*	0.049*	0.007	0.053**	0.039**
	(0.048)	(0.027)	(0.011)	(0.026)	(0.020)
return policy 2	0.195*	0.097	0.051**	0.082	0.071
	(0.114)	(0.066)	(0.025)	(0.062)	(0.046)
return policy 3	0.013	0.012	-0.005	0.016	0.009
	(0.079)	(0.043)	(0.017)	(0.040)	(0.031)
ln(size choice num)	0.107***	0.063***	0.025***	0.058***	0.044***
	(0.016)	(0.010)	(0.003)	(0.010)	(0.007)
ln(detailed description num)	0.200***	0.127***	0.042***	0.119***	0.087***
	(0.062)	(0.040)	(0.012)	(0.038)	(0.027)
ln(picture num)	0.084***	0.040***	0.019***	0.036***	0.029***
	(0.013)	(0.008)	(0.002)	(0.008)	(0.006)
constant	2.529***	1.318***	0.866***	1.134***	0.988***
	(0.185)	(0.120)	(0.039)	(0.112)	(0.081)
Week FE	Y	Y	Y	Y	Y
Seller FE	Y	Y	Y	Y	Y
R2	0.336	0.345	0.286	0.346	0.349
N	395154	395154	395154	395154	395154

Notes: This table shows results of RDD regressions. Rated dummy equals to one when a listing has ratings at time t. Treated equals to one if the rating of a listing is rounded up and zero if the rating is rounded down. We exclude observations with 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 8: Weekly Price Growth Rates (in Percentage Points)

	N	Mean	Std	Min	Max
All Listings	46665	0.05	4.70	-245.45	120.34
New Listings	5536	0.17	5.65	-107.30	120.34
Existing Listings	41129	0.03	4.55	-245.45	105.00

Notes: This table reports the descriptive statistics for the weekly price growth rates. We define weekly price as the first observed price in that week to capture changes of price displayed on the web page.

Table 9: Price Dynamics in Response to Reputation

	(1)	(2)
Dep. Var	ln(price)	ln(price)
l.ln(price)	0.966***	0.965***
	(0.003)	(0.003)
ln(past rating num + 1)	-0.002***	
	0.000	
ln(past order num)		-0.002***
		0.000
decoration * ln(past rating num + 1)	0.001***	
	0.000	
decoration * ln(past order num)		0.001***
		0.000
material quality	-0.001	-0.001
	(0.001)	(0.001)
buyer protection	0	0
	(0.001)	(0.001)
return policy 1	0.004	0.005
	(0.003)	(0.003)
return policy 2	(0.001)	(0.001)
	(0.005)	(0.005)
return policy 3	0.002	0.003
	(0.003)	(0.003)
ln(size choice num)	0.004***	0.004***
	(0.001)	(0.001)
ln(detailed description num)	0.003	0.004*
	(0.002)	(0.002)
ln(picture num)	-0.002**	-0.001**
	(0.001)	(0.001)
constant	0.056***	0.058***
	(0.009)	(0.009)
Seller FE	Y	Y
Week FE	Y	Y
R2	0.99	0.99
N	43998	43998

Notes: This table shows results of regressing prices on lagged prices, number of past ratings, number of past orders and other control variables. 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 10: Structural Estimation: Estimating the Reputation Elasticity

Dep. Var	ln(quantity+1)
price	-0.017***
	(0.002)
rated * treated	0.199***
	(0.013)
material quality	-0.002
	(0.010)
buyer protection	0.022
	(0.036)
return policy 1	0.072**
	(0.029)
return policy 2	0.124*
	(0.067)
return policy 3	0.038
	(0.054)
ln(size choice #)	0.037***
	(0.011)
ln(detailed description #)	0.136***
	(0.047)
ln(picture num)	0.041***
	(0.009)
rated * true rating	0.053***
	(0.004)
constant	0.871***
	(0.132)
Week FE	Y
Seller FE	Y
R2	0.146
N	395154

Notes: This table provides estimates of the reputation elasticity based on the demand equation regression. The regression is similar to RDD regression but uses prices directly as an independent variable to be consistent with the model. We exclude observations with past average ratings 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 11: Structural Estimation: Parameter Estimates

Parameter	Interpretation	Estimates
$log(\bar{\theta})$	log(average quality level)	-2.23
$var(log(\bar{\theta}))$	variance of log(quality)	0.27
$var(\sigma_\epsilon)$	variance of feedback	325.58
$exp(c) * \bar{\theta}$	marginal cost of an average quality product	7.25
σ	markup for an average quality product	1.23
ρ	reputation elsaticity	0.70

Table 12: Structral Estimation: Simulated Moments

Targeted Moment	Data	Model
Panel A		
mean of ln(price)	2.06	2.03
std of ln(price)	0.55	0.55
mean of ln(sales+1)	3.71	3.74
std of ln(sales+1)	1.44	1.43
Objective function value = 0.0023		
Non-targeted moment		
Panel B		
p85/p15 of ln(sales+1)	2.14	2.01
p75/p25 of ln(sales+1)	1.65	1.50
p85/p15 of ln(price)	1.74	1.62
p75/p25 of ln(price)	1.41	1.62
average ln(sale+1) ratio (top 15% firms/ bottom 85% firms)	2.09	1.94
average ln(sale+1) ratio (top 25% firms/ bottom 75% firms)	1.98	2.11

Notes: This table compares simulated moments from the model and observed moments in the data. Panel A reports a comparison for targeted moments and Panel B tests model fitness by looking at non-targeted moments. The last two rows in Panel B use monthly data while all other rows use annual data.

Table A.1 Top Export Market

No.	Export Revenue		Export Volume		Exporters	
	Aliexpress	Customs	Aliexpress	Customs	Aliexpress	Customs
1	Russia	Japan	Russia	Japan	Russia	U.S.
2	Brazil	U.S.	Brazil	U.S.	Brazil	Japan
3	U.S.	Australia	U.S.	Hong Kong	U.S.	Hong Kong
4	Belarus	Hong Kong	Belarus	Australia	Canada	Australia
5	Spain	Panama	Spain	Panama	France	Canada
6	France	Canada	France	Canada	Spain	Korea
7	Canada	Korea	Canada	South Africa	Israel	U.A.E.
8	Chile	Chile	Ukraine	U.A.E.	Belarus	Panama
9	Israel	Russia	Chile	Korea	Australia	Chile
10	U.K.	South Africa	Israel	Chile	U.K.	New Zealand

Notes: This table reports the top export markets in online and offline trade.

Table A.2 Comparisons Within and Across Peer Groups

	Listing Group		All	
	std	cv	std	cv
Price	1.71	0.18	4.73	0.59
Average rating	0.41	0.10	0.62	0.14
Material quality	0.30	0.14	0.72	0.32
Buyer protection	0.10	2.08	0.26	3.59
Guaranteed return	0.36	0.40	0.73	0.67
Size choice number	0.25	0.08	1.96	0.69
Detailed description	2.69	0.34	4.31	0.40
Picture number	8.24	0.61	13.93	0.80

Notes: Standard deviation(std) for listing groups is the average standard deviation for each listing group. Standard deviation for all listings presents cross-section variations among all listings. Coefficient of variation(cv) is constructed following the same procedure. This table only includes results from listing groups that have at least two different listings.