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The Value of Reputation in Trade: Evidence from Alibaba*

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(Work in Progress; Preliminary and Incomplete)

Abstract

Information frictions are prevalent in the matching of exporters and importers. In this paper, we examine the value of reputation in international trade by exploring 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 in superstar exporters; (2) the distribution of price closely mirrors the distribution of exporter reputation while the distribution of export volume is far more dispersed; (3) the distribution of export 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 features of Alibaba's reputation measures and Russian 2014-2015 ruble crisis, we explain the stylized facts and investigate the heterogeneous trade responses to reputation across countries and during a negative income shock. A dynamic price and reputation model further suggests that exporters use dynamic prices to influence the rates of reputation diffusion and export growth. Structural estimation of the model shows that the rise in aggregate exports and export concentration due to reputation is equivalent to raising the mean and variance of exporter quality by 35 and 200 percent, respectively.

JEL Codes: F1
Key Words: reputation, information, superstar, and Alibaba

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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; importers, on the other hand, often struggle to learn about exporters and assess export product and service quality. 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. In this paper, we investigate 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.

The recent rise of trade platforms is rapidly 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; buyers, 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 instantly. In particular, we exploit 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 3.8 million consumer flow each day, generating 113 billion orders and over $20 billion transactions in 2013.

Using a daily trade transaction 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, compared to China's overall exports, exports on Alibaba are more concentrated in superstar exporters, with the top 5-percent exporters accounting for 71 percent of total exports on Alibaba as opposed to 58 percent in overall exports. Second, on Alibaba 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 revenue on Alibaba becomes more dispersed as exporters age. Fourth, the market share of superstar exporters on Alibaba diminishes with the experience of importers. 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.

We explain the above stylized facts by first empirically examining the role of reputation in trade. Our identification strategies explore qualitative and quantitative features of reputation measures on Alibaba, including the substance of buyer comments which enable us to assess the effect of substantive information, a "peer product" grouping function of the Aliexpress search engine which enable us to restrict the comparison to identical products (offered by different sellers), and Aliexpress' rating algorithm which enables us to employ a regression discontinuity design to compare listings whose observed rating differences are greater than their trivial actual rating differences. The analyses suggest that reputation plays an important role in the performance of exporters, exceeding the effect of observable product quality. A greater reputation enables exporters to achieve greater export revenue and volume as well as a larger number of buyers and markets. Exporters with a top-tier reputation outperform exporters with a bottom-tier reputation by 41 percent greater export revenue, 21 percent greater export quantity, 21 percent more buyers, and 16 percent more markets.

When exploring the 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 each other's information more than importers from different countries. Importers from countries with a larger market size and a higher income also exhibit a greater response to reputation. Further, the value of reputation increases in the geographic distance between export and import countries but diminishes in the shipping cost. We also exploit the 2014-2015 Russian ruble crisis during which Russian ruble experienced a devaluation of over 50 percent to examine the value of reputation after negative income shocks. The sharp devaluation caused a drastic decline of 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.

We then present a simple dynamic model incorporating information frictions and exporter reputation to offer a theoretical explanation to observed empirical regularities and quantify the economic importance of reputation. We assume that importers cannot observe ex-ante the true quality of a product despite the information disclosed by the exporters, but may offer ex-post information on the product quality after import transactions and such information will contribute to exporters' reputation and enable future importers to update their beliefs on product quality. In this context, exporters endogenously set the prices in each period and the amount of information to disclose to importers, and importers decide in each period whom to import from. The model shows 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 to profit on the information that has been revealed to future importers. Further, 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 to the greater and continually growing export revenue dispersion documented in the stylized facts.

To quantify the economic importance of reputation in trade, we structurally estimate the model and perform various counterfactual experiments including: (1) setting the friction of reputation diffusion to infinity such that reputation is unobservable; (2) upgrading economy-wide product quality; (3) raising the variance of product quality. We find that compared to the case in which reputation is unobservable, observable reputation contributes to a 42-percent increase in total export revenue, equivalent to the effect of raising economy-wide quality by 35 percent. Observable reputation also exerts a strong effect on the distributions of export price and export revenue. Compared to the case of unobservable reputation, observable reputation raises the market share of top 5-percent exporters by 71 percent and the market share of top 1-percent exporters by 30 percent. The rise in the dispersion of export revenue due to reputation is equivalent to increasing the dispersion of product quality by 208 percent.

As discussed earlier, this paper is closely related to a new emerging literature that explores the role of information frictions in international trade. Information frictions in trade can arise from both the exporter and the importer side. Exporters can be constrained by their knowledge of foreign markets and have to undergo a costly search process to acquire market demand information. Several recent studies shed important new light on how information frictions on market demand can distort trade, resulting in regional price dispersion (Allen, 2014), a deviation from the law of one price (Steinwender, 2014), and risk-sharing trade flows (Baley et al., 2014). Allen (2014) provides important evidence on the effect of such information frictions on the regional dispersion of prices. Using data on agricultural trade in the Philippines and a perfect-competition trade model embedding information frictions and a costly sequential search process by producers, Allen (2014) shows that information frictions are quantitatively important and 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 examine the trade distortions caused by demand information frictions. Exploring historical newspaper records that track information flows across the Atlantic and using a model in which exporters use news to forecast expected selling prices, the paper shows that information frictions result in large and volatile deviations from the Law of One Price and reducing information frictions increase trade volume as well as trade volatility. Different from the above two studies, 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 shows that ameliorating information asymmetry reduces trade and international risk sharing.

Information frictions can similarly exist on the importer side: importers may have limited information about the quality of exporters. 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 success in selling to a buyer reveals information to the seller about the appeal of her product in the market and reduces search costs by improving the seller's visibility. 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, and evaluates 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 and quality is imperfectly observed by foreign consumers initially and show that this uncertainty generates an information cost of exporting. They further show that an intermediation technology and the sorting of exporters arise endogenously in the model.

In addition to the above studies, earlier empirical evidence by, for example, Head and Ries (1998), Rauch (1999), Rauch and Trindade (2002) suggests that reducing information frictions through ethnic networks and immigration flows can effectively boost trade, especially for differentiated goods where search barriers between buyers and sellers are relatively high. Exploring the role of exporter learning, a number of recent studies show that exporters can address information frictions by learning from their own exports (e.g., Eaton et al., 2014; Albornoz et. al, 2012; Timoshenko, 2015) or the experience of neighboring exporters (e.g., Fernandes and Tang, 2014; Kamal and Sundaram, 2015). Another related work by Macchiavello and Morjaria (2015) evaluates the role of buyer-seller relationships in international trade in the presence of imperfect contract enforcement. 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 during an exogenous negative supply shock deliveries are an inverted-U shaped function of relationship's age.

Our paper extends the above literature by investigating how, in the presence of information frictions, information diffusion through reputation could influence the growth and distribution of trade and trade price. We explore the unique setting of trade platforms to directly quantify information diffusion between importers and the reputation of exporters and offer unique evidence on the role 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 new empirical trade patterns and quantify the previously unexplored roles of information and reputation in international trade.

This paper is also related to a recent literature examining the patterns of online international trade. Douglas 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 online transaction data featuring not only transaction price and quantity but also observed quality and information to investigate both empirically and theoretically the role of reputation in trade.[1]

The rest of the paper is organized as follows. In Section 2, we describe the online cross-border transaction dataset from Aliexpress. In Section 3, we present the emerging stylized facts. In Section 4, we examine empirically the role of reputation in export performance. In Section 5, we present a dynamic model of importer learning and exporter reputation 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. The website has attracted more than 1.1 million active sellers and more than 3.8 million consumer flow each day, generating 113 billion orders and over 20 billion dollars of transactions in 2013.[2] 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. 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 description 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

[1] More broadly, the paper is also related to the 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.

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

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 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 could serve in our analysis as another measure of 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 cost allows us to better establish the effect of reputation on export expansion, especially expansion at extensive margins which are often viewed to be driven by 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 at each score, 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, 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 including primarily electronics, 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" and categorizing different fabrics into four types based on the fiber used. We assign a different score to each fiber according to the market values. Synthetic fibers like polymer are generally 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. We calculate an average score based on fibers used for each product listing. We also considered alternative indicators that denote, for example, the use of natural plant fibers and animal fibers and whether the products have any decorative designs.

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.

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 total number of ratings, the number of ratings at each score, the total 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.

Seller Guarantee: Sellers on Aliexpress may offer a variety of additional guarantees including "On-time Delivery", "Returns Extra", "Longer Protection", and "Guaranteed Genuine".

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.

2.2.2 Seller Characteristics

Seller's name, address, start year, and number of sales people online: Aliexpress lists the seller's name, address, 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 online 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. Second, unlike eBay which includes both auction and buy-it-now transactions and hosts both occasional individual and formal business sellers, Aliexpress consists of only buy-it-now type listings and primarily business sellers. This is essential for examining sellers' dynamic pricing strategies. Third, the data does not pose any restrictions on, for example, transaction value and thereby includes all sellers, buyers, and activities. Fourth, the data provides detailed transaction-level information, while alternative datasets from, for example, eBay often disclose only sellers' total sales information by country.

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.

First, we present descriptive statistics for the key variables in Table 1. The tables shows that there is substantial heterogeneity across online sellers in terms of both export unit price and export volume. 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 Alibaba, greatly exceeding the ratio in Chinese overall 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 Alibaba and 30 percent and 58 percent, respectively, in customs data.

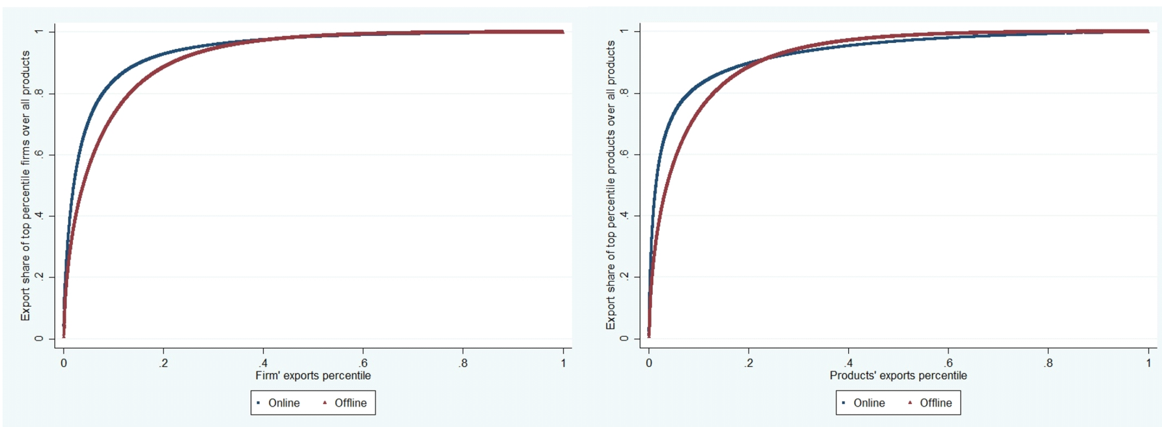

Figure 1: The Market Share of Top Percentile Exporters Online and Offline

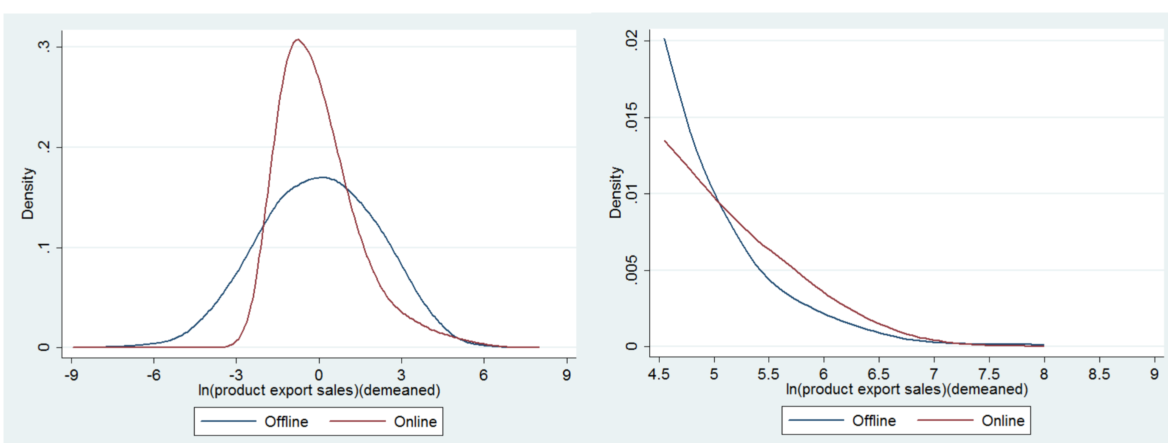

Figure 2: The Distribution of Export Revenue Online and Offline

These observations are also depicted in Figure 1 where we plot the export share accounted

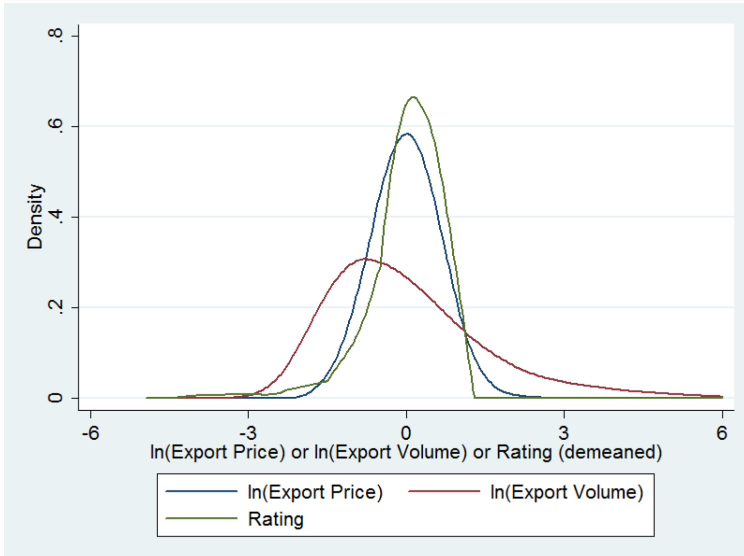

Figure 3: The Distributions of Price, Export Volume, and Reputation

for by exporters and exporter-product pairs at different percentiles. It is evident that the top-percentile exporters or exporter-product pairs account for a significantly greater share of total exports on Alibaba than in overall exports. In Figure 2, we plot the kernel density curves of export revenue using Alibaba and customs data, respectively. While the distribution of export revenue is overall less dispersed on Alibaba as shown in the left panel, the right tail of the curve is thicker for Alibaba as shown in the right panel suggesting that top exporters exhibit a greater export premium on Alibaba. The first stylized fact summarizes this finding:

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

Next we compare the distributions of price, reputation and export volume. We find, as shown in Figure 3, that the distributions of price and reputation closely mirror each other and are both 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. This observation is summarized in Stylized Fact 2.

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

Now we track exporters over time by comparing their distribution as brand-new exporters with their distribution a year later. Figure 4 shows that export revenue and, to a smaller extent, price become more spread out as exporters age. This is observed on both tails of the

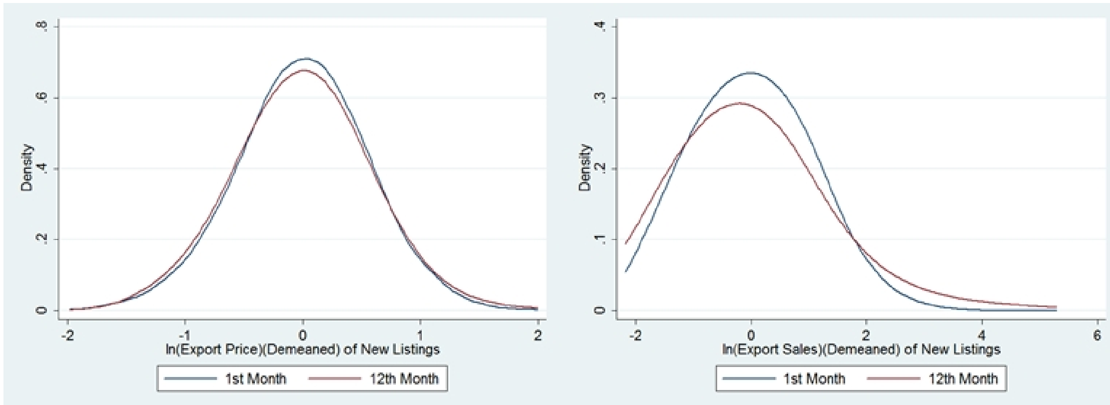

Figure 4: The Distributions of Export Price and Revenue over Time

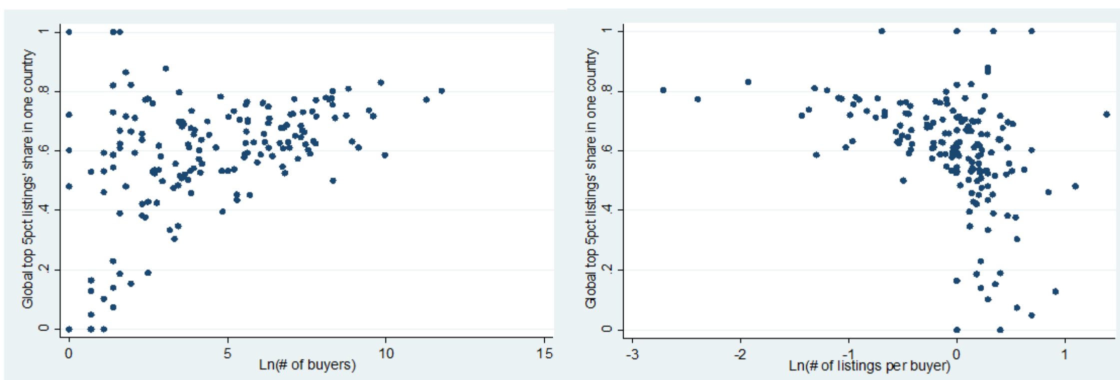

Figure 5: The Market Share of Superstar Exporters and Import-Country Size and Experience

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.

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

Next, we examine the heterogeneous responses of importers to exporters' reputation (measured by exporters' past performance). In Figure 5, we find that the market share of superstar exporters increases with the number of importers in a country but diminishes with the experience of importers (measured by the number of listed products previously purchased). 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. This observation is summarized as Stylized Fact 4.

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 examine empirically how reputation affects export decisions and patterns to offer first-step insights into the value of reputation in trade.

4.1 Baseline Results

We proceed by first estimating the following equation:

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

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 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. In addition, we control for μ_s (the exporter fixed effect) and η_t (the week fixed effect).

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 without ratings by 34 percent more export revenue, 17 percent more export volume, 16 percent more buyers, and 13 percent more export markets. In contrast, listings rated between 1 and 2, the lowest rated group, perform not only worse than listings with higher ratings but also listings without ratings. These findings are depicted in Figure 6.

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 buyers to examine how the substance of information might affect future buyers' decisions. We identified a complete list of words that have appeared in the comments and divided them to positive comments and negative comments. The key words appearing in positive comments include "good", "excellent", "superior", and etc., while the key words appearing in negative comments include "bad", "poor", "awful", and so on.[3] As shown in Table 4, we find that

[3] 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.

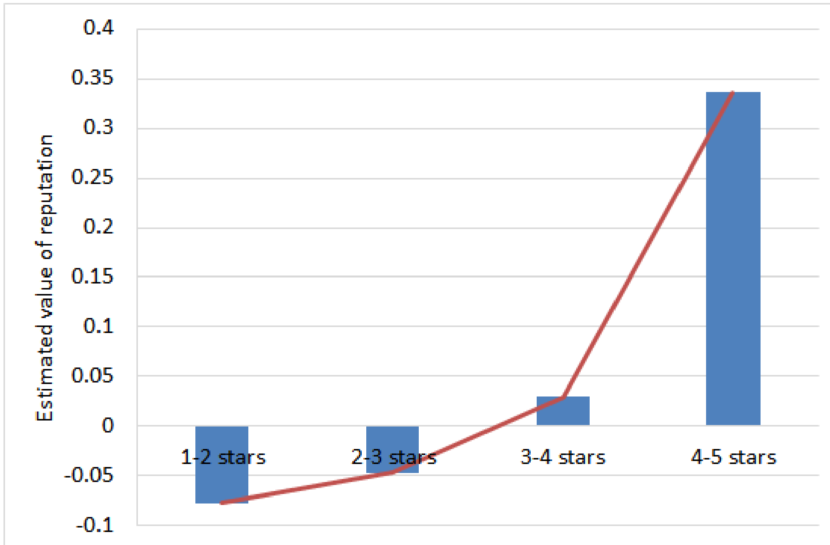

Figure 6: The Estimated Value of Reputation

listings with a larger number of positive comments perform better in all dimensions, with each additional positive comment leading to 3 percent more export revenue, 3 percent more export quantity, 3 percent more importers, and 1.5 percent markets. Listings with more negative comments, on the other hand, do not perform differently than listings without any comments.

4.2 The Heterogeneous Response to Reputation

Next we explore how the response to reputation and the value of reputation might vary across the source of reputation, import countries and time.

The Source of Reputation and the Origin of Importers In the first exercise, we examine whether and how importers might respond to exporter 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 for each import country: ratings from the import country and ratings from all other countries. As shown in Figure 7, we find that importers respond more favorably and strongly to the reputation of an exporter among fellow buyers from the same import country,

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, dishonourable, 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.

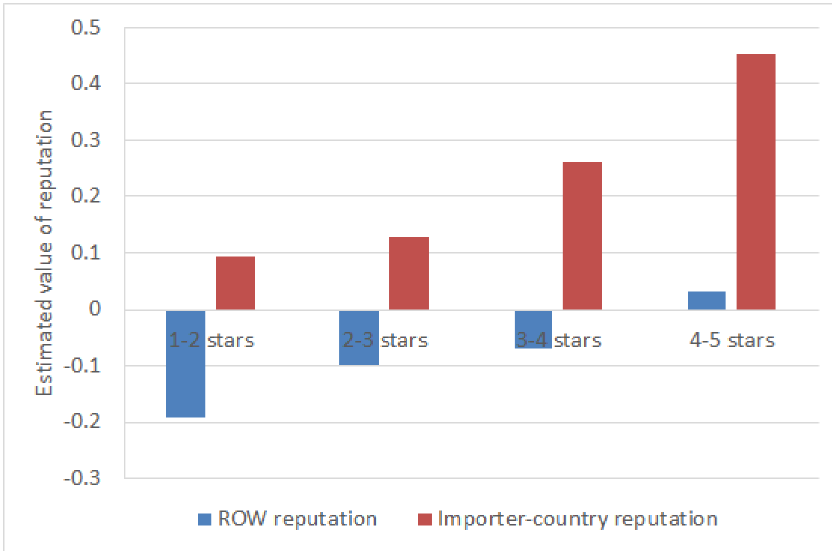

Figure 7: The Value of Reputation by the Origin of Reputation

even when the reputation is not positive. In contrast, importers respond much more critically to the reputation of an exporter in other countries, especially when the reputation is negative.

In the second exercise, we examine how the response to reputation might depend on the similarities between the import country and the source of the reputation. We construct measures of similarities between an import country in period t and import countries in $t-1$ including GDP per capita difference, distance, border, common language, and colonial relationship sharing. We find that countries tend to place a greater weight on exporters' reputation in countries with similar GDP per capita, greater geographic proximity, shared border, and colonial relationship.

In the third exercise, we examine how the response to reputation could vary systematically with import-country characteristics by interacting the reputation measures with import-country characteristics such as GDP, GDP per capita, delivery time, distance to exporter country (China), and remoteness from the rest of the world. The results suggest that the value of a good reputation is stronger in import countries with larger GDP and higher GDP per capita. Countries with a greater market size and a higher income appear to place a greater value on reputation. Further, the value of reputation is also found to increase in the distance and remoteness of the import country, suggesting that import countries suffering greater trade costs including costs of information frictions are likely to place a greater value on reputation.

The Response to Reputation after an Income Shock: Russian Ruble Crisis After examining how the response to reputation could vary across countries, we next examine how the response 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.

Beginning in June 2014, Russia entered into a deep financial crisis as a result of 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 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 the value of reputation during a negative income shock. 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 8. 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. The result suggests that a negative income shock among importers lowers the value of a good exporter reputation as well as the cost of a poor reputation.

4.3 Robustness

Next we examine the robustness of the main findings using various identification strategies that explore unique features of Aliexpress.

Peer Product Groups In the analysis so far, we have controlled for an extensive set of listing characteristics such as material quality, service quality, price, and the amount of information provided by the seller, to establish the role of reputation. Next 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 mostly identical products based on product title, item description, and pictures so buyers could more easily search for and compare similar listings. In our analysis below, we restrict the comparison to listings within the same peer group and thus listings with similar observable (and potentially unobservable) characteristics (except price and reputation). Table 5 shows that the effect of reputation remains qualitatively similar to the earlier results even though the magnitude of the parameters falls as expected: 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

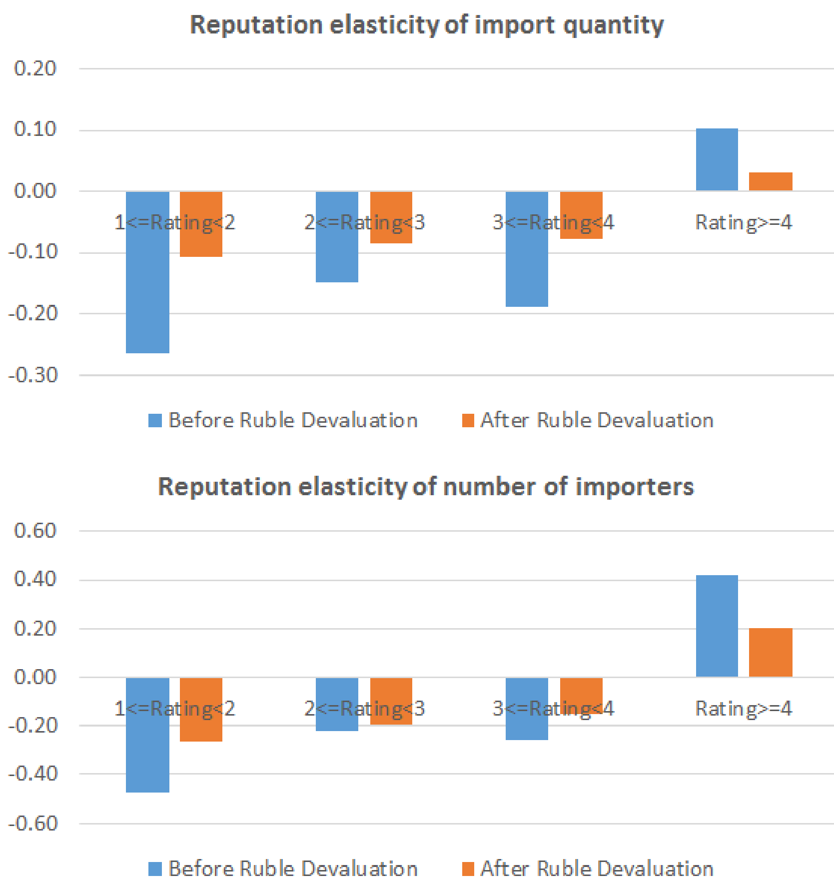

Figure 8: The Value of Reputation after a Negative Income Shock

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. We find in Table 6 that the treated group performs significantly better than the control group in all dimensions, suggesting that buyers respond significantly to the information displayed online.

5 A Simple Dynamic Model of Learning and Reputation

In this section, we present a simple dynamic model of learning and reputation. 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. We then show that the model yields results that explain empirical patterns presented in the previous section and structurally estimate the model to quantify the importance of reputation.

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. Each buyer that purchases product i leaves 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.

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. 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:

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

where $E(\theta_i|\theta_i^a, \theta_{it}^b)$ is the buyers' belief on product quality, ρ captures consumer's preference weight on product quality, θ_i^a is the initial quality belief drawn based on the information disclosed by the seller, θ_{it}^b represents the seller reputation revealed in past buyer feedbacks as of period t, p_{ijt} is the delivery price including an iceberg trade cost τ_j, 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_{ijt}, is given by:

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

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 period 0 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 0, buyers' beliefs will be updated when there is a new feedback. In the period when there are t feedbacks,[4] the new coming buyer will have belief

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

where

$$\theta_{it}^b \equiv \frac{\sum_{k=1}^{t} \widetilde{\theta}_{ik}^b}{t} \tag{6}$$

is the seller's reputation conveyed by past buyers. Note that the buyer's updated belief is a

[4] 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.

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.

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:

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

where d_{ijt} 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:

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

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 $\sigma_u^2(a_i)$—and the price p_{ijt}—which is adjustable in each period. Each seller's maximization problem is given by:

$$\max_{a_i,\{p_{ijt}\}_{t=1}^{\infty}} E_{\{\theta_i^a,\theta_{it}^b\}_{t=1}^{\infty}} \sum_{t=1}^{\infty}\{[\beta(1-\delta)]^t \sum_{j\in N} q_j[(p_{ijt} - \tau_j - c\theta_i)d_{ijt}]\}, \tag{9}$$

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:

$$V_{it}(\theta_i, \overline{\theta}_{it}, \omega_u^*) = \max_{p_{ijt}} \frac{\sum_{j\in N} q_j d_{ijt}}{1-\beta(1-\delta)\sum_{j\in N} q_j(1-d_{ijt})}[p_{ijt} - \tau_j - c\theta_i + \beta(1-\delta)E(V_{it+1}(\theta_i, \overline{\theta}_{it+1}, \omega_u^*))]. \tag{10}$$

where

$$\overline{\theta}_{it} = \frac{\omega_\theta \theta + \omega_u^*(a_i)\theta_i^a + t\omega_\varepsilon \theta_{it}^b}{\omega_\theta + \omega_u^*(a_i) + t\omega_\varepsilon} \tag{11}$$

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, sellers will solve the following problem:

$$\max_{p_{ijt}} \left(p_{ijt} - \tau_j - c\theta_i\right) d_{ijt}, \tag{12}$$

where

$$d_{ijt} = \frac{\exp\left[\frac{1}{\sigma}(\rho\theta_i - p_{ijt})\right]}{\sum_{k=1}^{i} \exp\left[\frac{1}{\sigma}(\rho\theta_k - p_{kjt})\right]}. \tag{13}$$

This yields:

$$p_{ijt}^C = \tau_j + c\theta_i + \sigma \tag{14}$$

and

$$d_{ijt}^C = \frac{1}{D_j^C} \cdot \exp\left[\frac{1}{\sigma}(\rho\theta_i - \tau_j - c\theta_i - \sigma)\right] \tag{15}$$

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.

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 and cannot learn about exporter reputation from each other. In this case, the seller's problem in a given period is given by:

$$\max_{p_{ijt}} \left(p_{ijt} - \tau_j - c\theta_i\right) d_{ijt}, \tag{16}$$

where

$$d_{ijt} = \frac{\exp\left[\frac{1}{\sigma}(\rho\overline{\theta}_{it} - p_{ijt})\right]}{\sum_{k=1}^{K} \exp\left[\frac{1}{\sigma}(\rho\overline{\theta}_{kt} - p_{kjt})\right]} \tag{17}$$

and

$$\overline{\theta}_{it} = \frac{\omega_\theta \theta + \omega_u(a_i)\theta_i^a}{\omega_\theta + \omega_u(a_i)} \tag{18}$$

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:

$$p_{ijt}^{I} = \tau_j + c\theta_i + \sigma \tag{19}$$

and

$$d_{ijt}^{I} = \frac{1}{D_j^I} \cdot \exp\left[\frac{1}{\sigma}(\rho\overline{\theta}_{it} - \tau_j - c\theta_i - \sigma)\right], \tag{20}$$

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

$$\pi_i^I = E_{\theta_i^a} \sum_{j \in N} \frac{q_j \exp\left[\frac{1}{\sigma}(\rho E(\theta_i|\theta_i^a) - \tau_j - c\theta_i - \sigma)\right]\sigma}{(1-\beta)D_j^I}. \tag{21}$$

The seller maximizes the above profit 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., $E(d_{ijt}^I) < d_{ijt}^C$, 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 Appendix 1 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, $\sigma_u^2(a)$.

Second, solving equation (10) yields:

$$p_{ijt}^{*}(\tau_j, \theta_i) = \tau_j + c\theta_i + \sigma - \beta(1-\delta)E\left(V_{it+1}(\overline{\theta}_{it+1}, \omega_u^*)\right). \tag{22}$$

Comparing the prices across the three scenarios, we find that $p^*_{ijt} < p^C_{ict} = p^I_{ijt}$; 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.*

Proof. See Appendix 2. ■

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

$$d^*_{ijt}(\tau_j, \theta_i) = \frac{1}{D^*_j} \exp\left[\frac{1}{\sigma}(\rho\overline{\theta}_{it} - \tau_j - c\theta_i - \sigma + \beta(1-\delta)E(V_{it+1}(\overline{\theta}_{it+1}, \omega^*_u))\right], \tag{23}$$

where

$$\overline{\theta}_{it} = \frac{\omega_\theta \theta + \omega_u(a_i)\theta^a_i + t\omega_\varepsilon \theta^b_{it}}{\omega_\theta + \omega_u(a_i) + t\omega_\varepsilon} \tag{24}$$

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

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

Proof. See Appendix 3. ■

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 7, 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. Further, we consider the following estimating equation:

$$p_{sit} = \alpha + \theta_{sit}\beta + \gamma d_{sit} \cdot quality_{si} + \mu_s + \eta_t + \varepsilon_{sit} \tag{25}$$

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 sales and an indicator of above-median quality, μ_s is a seller fixed effect, and η_t is a week fixed effect. We find that past performance matters in the pricing decisions, especially for high-quality exporters. As shown in Table 8, 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.

5.4 Explaining the Stylized Facts

Now 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 in superstar exporters on Alibaba, 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. That is because when buyers can easily share information on exporter quality with each other, high-quality exporters can more likely command a larger market share and also have incentives to set the price relatively low initially to subsidize reputation building which, in turns, raises their export premium.

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 $\ln d^*_{ijt} = \frac{1}{\sigma}(\rho\overline{\theta}_{it} - \tau_j - p^*_{ijt}) - \ln D^*_j$, the variation of export volume $\ln d^*_{ijt}$ 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 as their reputation is established. This directly explains Stylized Fact 3, where we find the dispersions of price and export revenue grow as exporters age. The dispersion of reputation, in contrast, should behave in the opposite way as buyers learn from each other over time and high-quality sellers establish reputation. There will be less idiosyncrasy in transactions as well as reputation.

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 trust more on current superstar exporters, while experienced importers have more prior information and are consequently less influenced by information about superstar exporters.

5.5 Structural Estimation

We now structurally estimate the model to quantify the importance of reputation in 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.

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:

$$\ln d_{ijt} = -\ln D_j + \frac{\rho}{\sigma}\overline{\theta}_{it} - \frac{1}{\sigma}(p_{it} + \tau_j) \tag{26}$$

which can be simplified to:

$$\ln d_{ijt} = \gamma_{it} + \lambda_j + \varepsilon_{ijt} \tag{27}$$

where d_{ijt} represents the export volume of seller 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 $D_j = \exp(-\lambda_j - \tau_j)$ where τ_j is directly constructed using the delivery fee data from Aliexpress. Each product 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. There are 160 countries in the final regression with an average market size of 2.448.

To measure consumers' probability to arrive 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 Brazil, India, and South Korea.

We recover consumer's weight on reputation by relying on the regression discontinuity result from Table 9 on listings with at least one rating. We obtain an average reputation effect from treated and non-treated group regressions where reputation is standardized relative to the mean following the model's definition, which yield $\frac{\rho}{\sigma} = 0.33$. Because of the endogeneity of price in that regression, we use 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 monthly 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

We estimate the remaining parameters 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 methods 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 $\Theta \equiv (\theta, \sigma_\theta^2, c, \sigma_\varepsilon^2)$. We use simulated methods of moments by finding solutions to the following equation:

$$\hat{\Theta} = \arg\min_{\hat{\Theta}} [\mu(\Theta) - \frac{1}{S}\sum_{s=1}^{S}\mu(\hat{\Theta})_s]' W^{-1} [\mu(\Theta) - \frac{1}{S}\sum_{s=1}^{S}\mu(\hat{\Theta})_s], \tag{28}$$

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. For each iteration, we use $\hat{\Theta}$ to construct the optimal weighting matrix $\hat{W}$ and then find $\hat{\Theta}'$ by using $\hat{W}$. We iterate this process until $\hat{\Theta}$ converges.

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.[5] For each guess of each simulation, we solve for the optimal price policy function (See the Appendix for the algorithm of solving the policy function) and let the seller set the price according to the policy function. 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 15,000 firms for 240 periods. The first 144 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 online 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.

5.5.3 Estimation Results

The estimated parameter values are reported in Table 10. The model can account for most of the price and export revenue dispersion observed in the empirical data as shown in Table 11. In Table 11, we also use non-targeted price and export revenue dispersion measures as a further check for model performance. The model predicts the ratio of 75-percentile revenue relative to 25-percentile revenue to be 1.45, 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 1.48 in the model, in comparison with 1.41 in the data. Overall, the estimated model captures most of the price and export revenue variations observed in the data.

We further use this model to quantify how observable reputation affects aggregate trade and its distribution. We use the model to assess how aggregate exports and the dispersion of price and export revenue will react to the existence of reputation.

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

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; (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.

We find that compared to the case in which reputation is completely unobservable, observable reputation contributes to a 42-percent increase in total export revenue. This gain in export revenue, driven by higher export prices, is equivalent to the effect of raising economy-wide quality by 35 percent. Observable reputation also exerts a strong effect on the distribution of export price and export revenue. Compared to the case of unobservable reputation, observable reputation raises the market share of top 5-percent exporters by 71 percent and the market share of top 1-percent exporters by 30 percent. This is in part due to a more dispersed price distribution when reputation is observable: the ratio of the 99-percentile price over the 1-percentile price increases by 73 percent. The rise in the dispersion of export revenue due to reputation is equivalent to increasing the dispersion of product quality by 208 percent. An economy-wide quality upgrading, on the other hand, will have a limited effect on the distributions of export price and revenue.

6 Conclusion

In this paper, we explore the unique setting of cross-border trade platforms, in particular, Aliexpress founded by Alibaba, where importers could directly share information on exporter quality and observe exporter reputation to examine the value of reputation in trade. Using a daily trade transaction 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 in superstar exporters on Alibaba 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 distributions of price and export volume become 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. To identify the effect of reputation, we explore qualitative and quantitative features of reputation on Alibaba, including the substance of buyer comments which enable us to assess the effect of specific information, a "similar product" grouping function of the Aliexpress search engine which enable us to restrict the comparison to similar products in narrowly defined peer groups, and Aliexpress' rating algorithm which enables us to employ a regression discontinuity design to compare listings whose observed rating differences are greater than their trivial actual rating differences. The analyses suggest that reputation plays a leading role in the performance of exporters, exceeding the effect of observable product quality. A greater reputation enables exporters to achieve greater export revenue and volume as well as a larger number of buyers and markets. We further show that the value of reputation is not equal across importers and over time. For example, importers from the same country tend to value each other's information more than importers from different countries. Exploiting the 2014-2015 Russian ruble crisis, we also find that a negative income shock significantly lowers the reputation elasticity of importers and the value of reputation.

We then present a simple dynamic model incorporating information frictions and exporter reputation to offer a theoretical explanation to observed empirical regularities and quantify the importance of reputation. The model shows 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 to profit on the information that has been revealed to future importers. Further, 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 to the greater and continually growing export revenue and price dispersion documented in the stylized facts.

To quantify the importance of reputation, we structurally estimate the model and show that compared to the case in which reputation is completely unobservable, observable reputation contributes to a 42-percent increase in total export revenue, equivalent to the effect of raising average quality by 35 percent. Observable reputation also raises the dispersion of export revenue to an extent equivalent to increasing the product quality dispersion by 208 percent.

The findings of this paper convey useful implications for the role of information and importer learning in the aggregate value and distribution of trade. While information diffusion through reputation raises the aggregate value of trade, it also exacerbates the concentration of trade among superstar exporters. The reputation of established exporters could constitute a significant entry barrier for new and potential exporters and inhibit their ability to reach importers and import markets. Interventions that provide new and prospective exporters an opportunity to establish reputation would be crucial for initiating importer learning and enhancing the role of reputation in addressing information frictions between exporters and importers.

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Appendix

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

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

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

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

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

$$\frac{\partial V_1}{\partial a} = \frac{\partial\omega_u}{\partial a}\sum_{t=1}^{\infty}\{[\beta(1-\delta)]^t \sum_{j\in N}(q_j\frac{\rho\exp(\frac{1}{\sigma}(\overline{\theta}_1 - p^I_{ij1}))}{G}\frac{\omega_\theta(\theta_i-\theta)}{(\omega_\theta+\omega_u)}\} \tag{29}$$

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

Equation (29) 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 $\theta_i > \theta$.

2. Proof of Proposition 1.

To prove Proposition 1, we consider a listing with past reputation denoted as $\overline{\theta}_{it} = \frac{\sum_{k=1}^t \widetilde{\theta}^b_{ik} + \theta^a_i + \theta}{t+2}$ which is already known to the public with variance $\frac{1}{\omega}$. Notice that when t increases, we expect to see ω increase for each $\overline{\theta}_{ijt}$. 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:

$$\begin{aligned}
& E(V_{it+1}(\theta_i, \overline{\theta}_{it}, \omega^*_u, \omega_2)) - E(V_{it+1}(\theta_i, \overline{\theta}_{it}, \omega^*_u, \omega_1)) \\
= & \int_{\{\varepsilon_i\}^\infty_{i=t+1}} \sum_{j\in N} q_j \sigma(\frac{\exp\{\frac{\rho}{\sigma}[\overline{\theta}_{ijt+1} - \tau_j - c\theta i + E(V_{it+2}(\theta_i, \overline{\theta}_{it}, \omega^*_u, \omega_2))]\}}{G} - \\
& \frac{\exp\{\frac{\rho}{\sigma}[\overline{\theta}_{ijt+1} - \tau_j - c\theta i + E(V_{it+2}(\theta_i, \overline{\theta}_{it}, \omega^*_u, \omega_1))]\}}{G}) d\{\varepsilon_i\}^\infty_{i=t+1}
\end{aligned}$$

First notice that when t is very large and reputation $\overline{\theta}_{iT} \approx \theta_i$, $E(V_{iT}(\theta_i, \overline{\theta}_{it}, \omega^*_u, \omega_2)) = E(V_{iT}(\theta_i, \overline{\theta}_{it}, \omega^*_u, \omega_1))$. Consider period $T-1$:

$$\begin{aligned}
& E(V_{iT-1}(\theta_i, \overline{\theta}_{it}, \omega^*_u, \omega_2)) - E(V_{iT-1}(\theta_i, \overline{\theta}_{it}, \omega^*_u, \omega_1)) \\
= & \int_{\{\varepsilon_i\}^\infty_{i=t+1}} \sum_{j\in N} q_j \sigma(\frac{\exp\{\frac{\rho}{\sigma}[\overline{\theta}_{ijT-1}(\omega_2) - \tau_j - c\theta i + E(V_{iT}(\theta_i, \overline{\theta}_{it}, \omega^*_u, \omega_2))]\}}{G} - \\
& \frac{\exp\{\frac{\rho}{\sigma}[\overline{\theta}_{ijT-1}(\omega_1) - \tau_j - c\theta i + E(V_{iT}(\theta_i, \overline{\theta}_{it}, \omega^*_u, \omega_1))]\}}{G}) d\{\varepsilon_i\}^\infty_{i=t+1}
\end{aligned}$$

where $\overline{\theta}_{ijT-1}(\omega) = \frac{\omega\overline{\theta}_{it} + \omega_\varepsilon[(T-1-t)\theta i + \sum_{k=t+1}^{T-1-t} \varepsilon_k]}{\omega + \omega_\varepsilon(T-1-t)}$ and $G = [1-\beta(1-\delta)\sum_{j\in N} q_j(1-d_{T-1})]$ $\sum_{k=1}^K \exp\left[\frac{1}{\sigma}(\rho E(\theta_{kt}|\theta^a_k, \theta^b_{kt}) - p_{kjt})\right]$ is the constant market index under monopolistic competition.

Consider

$$\begin{aligned}
& \int_{\{\varepsilon_i\}^\infty_{i=t+1}} \exp\{\overline{\theta}_{ijT-1}(\omega_2) - \overline{\theta}_{ijT-1}(\omega_1)\} d\{\varepsilon_i\}^\infty_{i=t+1} \\
= & \int_{\{\varepsilon_i\}^\infty_{i=t+1}} \exp \frac{\omega_\varepsilon(T-1-t)(\omega_1-\omega_2)[\theta_i - \theta + \sum_{k=t+1}^{T-1-t} \varepsilon_k/(T-1-t)]}{[\omega_1 + (T-1-t)\omega_\varepsilon][\omega_2 + (T-1-t)\omega_\varepsilon]} d\{\varepsilon_i\}^\infty_{i=t+1} \\
= & \exp\{ \frac{\omega_\varepsilon(T-1-t)(\omega_1-\omega_2)(\theta_i-\theta)}{[\omega_1 + (T-1-t)\omega_\varepsilon][\omega_2 + (T-1-t)\omega_\varepsilon]} + \frac{\omega_\varepsilon(T-1-t)(\omega_1-\omega_2)^2}{2[\omega_1 + (T-1-t)\omega_\varepsilon]^2[\omega_2 + (T-1-t)\omega_\varepsilon]^2} \}
\end{aligned}$$

Define $f(\theta_i) \equiv \frac{\omega_\varepsilon(T-1-t)(\omega_1-\omega_2)(\theta_i-\theta)}{[\omega_1+(T-1-t)\omega_\varepsilon][\omega_2+(T-1-t)\omega_\varepsilon]} + \frac{\omega_\varepsilon(T-1-t)(\omega_1-\omega_2)^2}{2[\omega_1+(T-1-t)\omega_\varepsilon]^2[\omega_2+(T-1-t)\omega_\varepsilon]^2}$, $f(\theta_i)$ is an increasing function of θ_i. If $f(\widetilde{\theta}^1_i) = 0$, we have $\int_{\{\varepsilon_i\}^\infty_{i=t+1}} \exp\{\overline{\theta}_{ijT-1}(\omega_2) - \overline{\theta}_{ijT-1}(\omega_1)\} d\{\varepsilon_i\}^\infty_{i=t+1} <$ 1 for $\theta_i > \widetilde{\theta}^1_i$ and $\int_{\{\varepsilon_i\}^\infty_{i=t+1}} \exp\{\overline{\theta}_{ijT-1}(\omega_2) - \overline{\theta}_{ijT-1}(\omega_1)\} d\{\varepsilon_i\}^\infty_{i=t+1} > 1$ for $\theta_i < \widetilde{\theta}^1_i$. Therefore, we prove $E(V_{iT-1}(\theta_i, \overline{\theta}_{it}, \omega^*_u, \omega_2)) > E(V_{iT-1}(\theta_i, \overline{\theta}_{it}, \omega^*_u, \omega_1))$ for $\theta_i < \widetilde{\theta}^1_i$ and $E(V_{iT-1}(\theta_i, \overline{\theta}_{it}, \omega^*_u, \omega_2)) <$ $E(V_{iT-1}(\theta_i, \overline{\theta}_{it}, \omega^*_u, \omega_1))$ for $\theta_i > \widetilde{\theta}^1_i$.

Second, we show that if the above conclusion holds for period $T-s$, it will also hold for $T-s-1$. By backward induction, this should hold for all time periods. Consider $\theta_i < \widetilde{\theta}^1_i$, $E(V_{iT-s}(\theta_i, \overline{\theta}_{it}, \omega^*_u, \omega_2)) > E(V_{iT-s}(\theta_i, \overline{\theta}_{it}, \omega^*_u, \omega_1))$,

$$
\begin{aligned}
& E(V_{iT-s-1}(\theta_i,\overline{\theta}_{it},\omega_u^*,\omega_2)) - E(V_{iT-s-1}(\theta_i,\overline{\theta}_{it},\omega_u^*,\omega_1)) \\
> \; & \int_{\{\varepsilon_i\}_{i=t+1}^{\infty}} \sum_{j\in N} q_j\sigma(\frac{\exp\{\frac{\rho}{\sigma}[\overline{\theta}_{ijT-s}(\omega_2) - \tau_j - c\theta i + \beta(1-\delta)E(V_{iT-s}(\theta_i,\overline{\theta}_{it},\omega_u^*,\omega_1))]\}}{G} - \\
& \frac{\exp\{\frac{\rho}{\sigma}[\overline{\theta}_{ijT-s}(\omega_1) - \tau_j - c\theta i + \beta(1-\delta)E(V_{iT-s}(\theta_i,\overline{\theta}_{it},\omega_u^*,\omega_1))]\}}{G})d\{\varepsilon_i\}_{i=t+1}^{\infty}
\end{aligned}
$$

Let $f(\widetilde{\theta_i^2}) \equiv \frac{\omega_\varepsilon(T-2-t)(\omega_1-\omega_2)(\theta_i-\theta)}{[\omega_1+(T-2-t)\omega_\varepsilon][\omega_2+(T-2-t)\omega_\varepsilon]} + \frac{\omega_\varepsilon(T-2-t)(\omega_1-\omega_2)^2}{2[\omega_1+(T-2-t)\omega_\varepsilon]^2[\omega_2+(T-2-t)\omega_\varepsilon]^2}$, when $\theta_i < \min(\widetilde{\theta_i^1},\widetilde{\theta_i^2})$, $E(V_{iT-s-1}(\theta_i,\overline{\theta}_{it},\omega_u^*,\omega_2)) > E(V_{iT-s-1}(\theta_i,\overline{\theta}_{it},\omega_u^*,\omega_1))$.

Consider $\theta_i > \widetilde{\theta_i^1}$, $E(V_{iT-s}(\theta_i,\overline{\theta}_{it},\omega_u^*,\omega_2)) < E(V_{iT-s}(\theta_i,\overline{\theta}_{it},\omega_u^*,\omega_1))$,

$$
\begin{aligned}
& E(V_{iT-s-1}(\theta_i,\overline{\theta}_{it},\omega_u^*,\omega_2)) - E(V_{iT-s-1}(\theta_i,\overline{\theta}_{it},\omega_u^*,\omega_1)) \\
< \; & \int_{\{\varepsilon_i\}_{i=t+1}^{\infty}} \sum_{j\in N} q_j\sigma(\frac{\exp\{\frac{\rho}{\sigma}[\overline{\theta}_{ijT-s-1}(\omega_2) - \tau_j - c\theta i + \beta(1-\delta)E(V_{iT-s}(\theta_i,\overline{\theta}_{it},\omega_u^*,\omega_1))]\}}{G} - \\
& \frac{\exp\{\frac{\rho}{\sigma}[\overline{\theta}_{ijT-s-1}(\omega_1) - \tau_j - c\theta i + \beta(1-\delta)E(V_{iT-s}(\theta_i,\overline{\theta}_{it},\omega_u^*,\omega_1))]\}}{G})d\{\varepsilon_i\}_{i=t+1}^{\infty}
\end{aligned}
$$

Let $f(\widetilde{\theta_i^2}) \equiv \frac{\omega_\varepsilon(T-2-t)(\omega_1-\omega_2)(\theta_i-\theta)}{[\omega_1+(T-2-t)\omega_\varepsilon][\omega_2+(T-2-t)\omega_\varepsilon]} + \frac{\omega_\varepsilon(T-2-t)(\omega_1-\omega_2)^2}{2[\omega_1+(T-2-t)\omega_\varepsilon]^2[\omega_2+(T-2-t)\omega_\varepsilon]^2}$, when $\theta_i > \max(\widetilde{\theta_i^1},\widetilde{\theta_i^2})$, $E(V_{iT-s-1}(\theta_i,\overline{\theta}_{it},\omega_u^*,\omega_2)) < E(V_{iT-s-1}(\theta_i,\overline{\theta}_{it},\omega_u^*,\omega_1))$.

Therefore, for sufficiently high θ_i, $p_{ijt}^*(\tau_j,\theta_i,\omega_2) > p_{ijt}^*(\tau_j,\theta_i,\omega_1)$ and for sufficiently low θ_i, $p_{ijt}^*(\tau_j,\theta_i,\omega_2) < p_{ijt}^*(\tau_j,\theta_i,\omega_1)$.

3. Proof of Proposition 2.

As $\lim_{t\to\infty} \frac{\omega_\theta\theta + t\omega_u\theta_i}{\omega_\theta + t\omega_u} = \theta_i$, we assign a very large T as the last period of consumer belief updating. Assuming $\sigma_\theta^2 > \frac{\sigma_\varepsilon^2\sigma_u^{*2}c}{\sigma_u^{*2}(\rho-cT)-\sigma_\varepsilon^2 c}$, we have $\frac{\rho\omega_\varepsilon}{\omega_T+\omega_\varepsilon} > c$. Notice that

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

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

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

This is equivalent to

$$
\frac{d^*_{ijt}(\theta^h_i)}{d^*_{ijt}(\theta^l_i)} > \frac{d^I_{ijt}(\theta^h_i)}{d^I_{ijt}(\theta^l_i)}
$$

4. 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:

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

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 $t-1$ feedbacks, the new coming buyer from country c will have belief

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

where

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

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

$$N(\frac{\omega_\theta\theta + \omega_u(a_j)\theta_j^a + (t-1)\omega_\varepsilon\theta_{jt-1}^s + \omega_\varepsilon\theta_j}{\omega_\theta + \omega_u(a_j) + t\omega_\varepsilon}, \frac{\omega_\varepsilon}{(\omega_\theta + \omega_u(a_j) + t\omega_\varepsilon)^2})$$

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

$$\Pr(\mathbf{x}_j^t|\mathbf{x}_k^{t-1}) = \mathbf{\Phi}(\frac{0.5 * (x_{j+1}^t + x_j^t) - \mu_k^{t-1}}{\sigma_{\mu_k^{t-1}}}) - \mathbf{\Phi}(\frac{0.5 * (x_{j-1}^t + x_j^t) - \mu_k^{t-1}}{\sigma_{\mu_k^{t-1}}})$$

where

$$\mu_k^{t-1} = \frac{[\omega_\theta + \omega_u(a_j) + (t-1)\omega_\varepsilon]x_k^{t-1} + \omega_\varepsilon\theta_j}{\omega_\theta + \omega_u(a_j) + t\omega_\varepsilon}, \sigma_{\mu_k^{t-1}} = \frac{\omega_\varepsilon^{1/2}}{\omega_\theta + \omega_u(a_j) + t\omega_\varepsilon}.$$

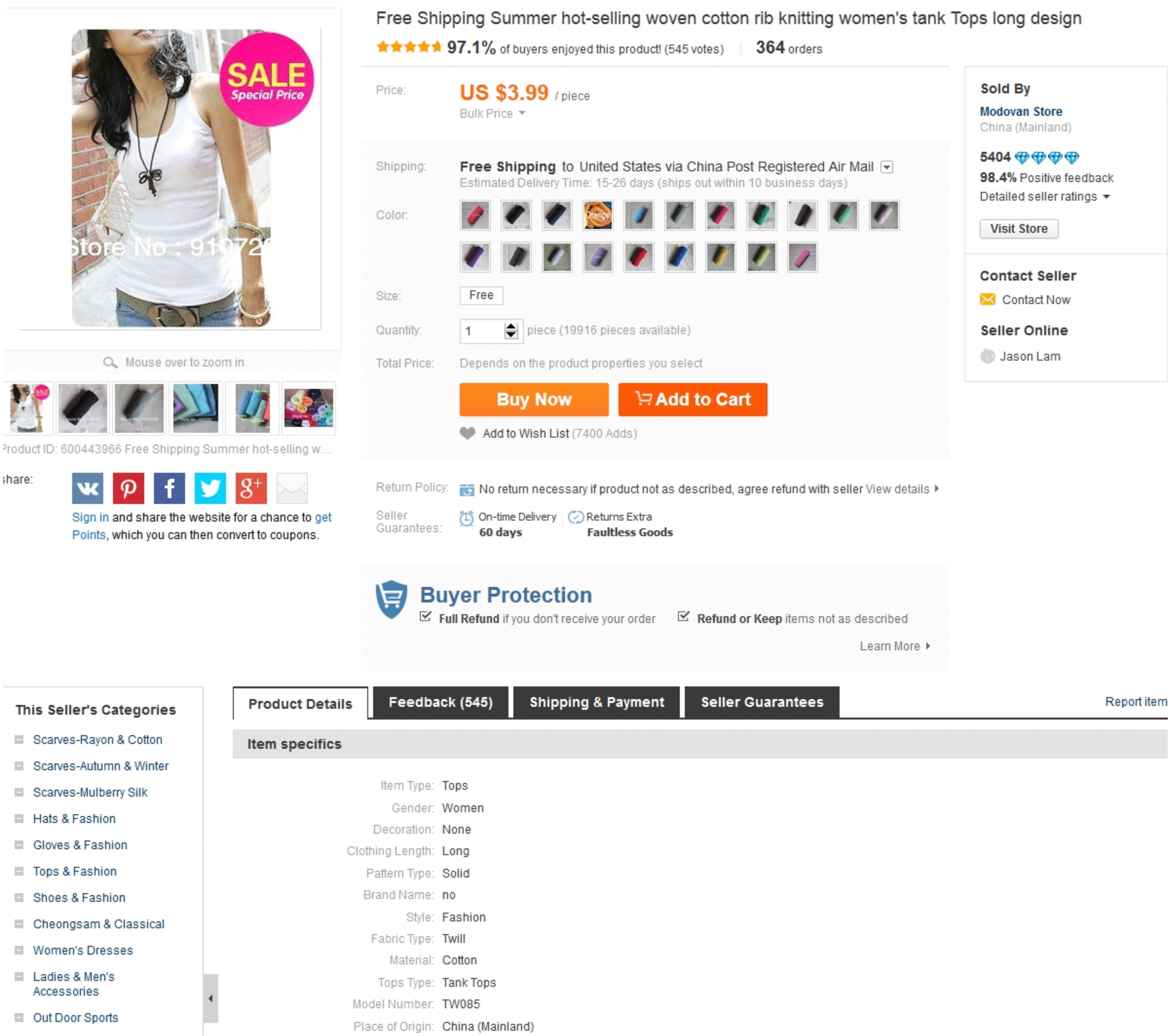

Figure 9: A Sample Listing (part I)

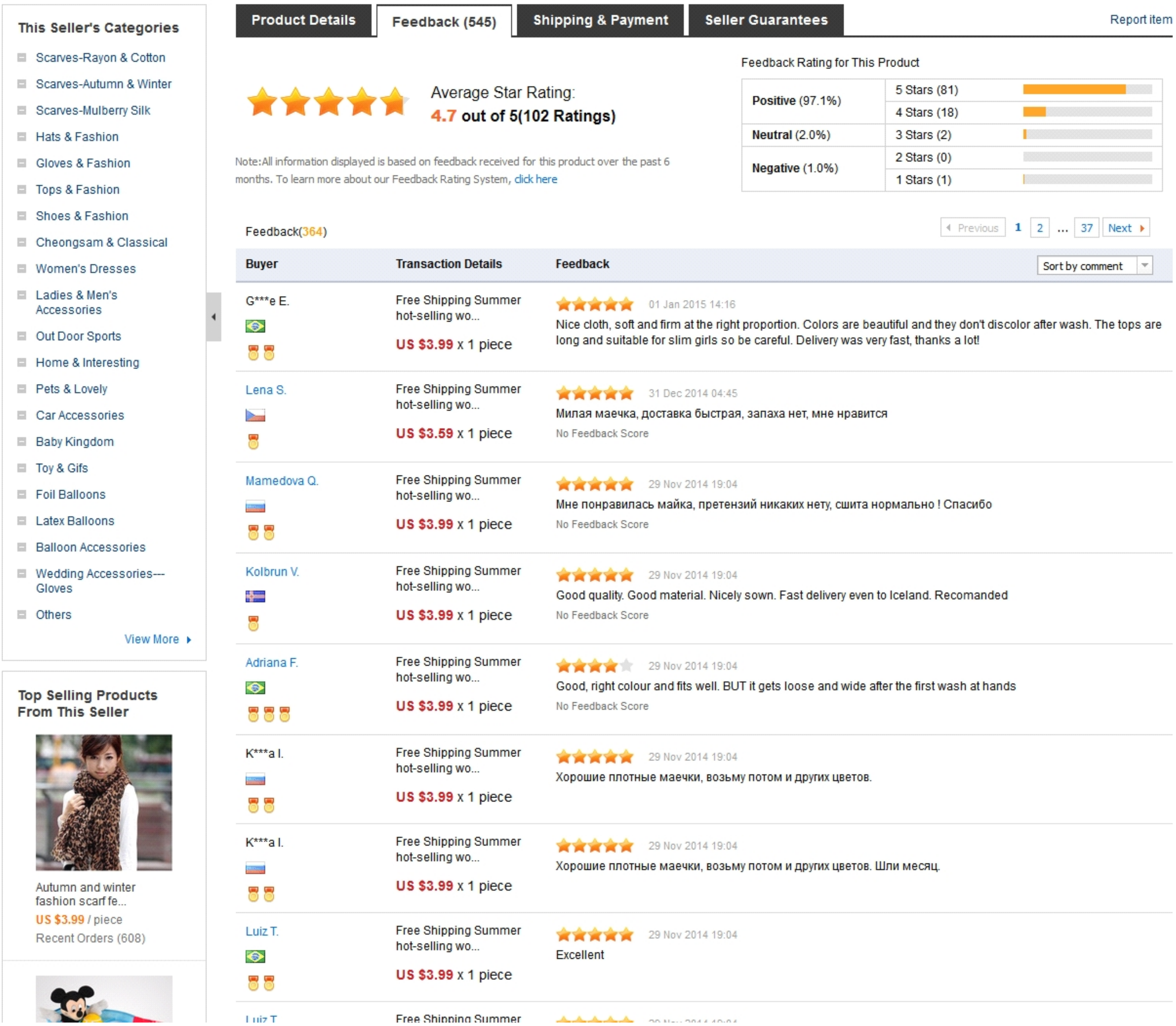

Figure 10: A Sample Listing (part II)

Table 1: Descriptive Statistics

	N	Mean	Std. Dev.	Min	Max	5%	50%	95%	99%
Exporter level									
Export volume (piece)	5,392	124.04	640.92	1	23270	1	7	529	2461
Export unit Price ($)	5,392	9.41	6.95	0.46	124	2.99	7.84	19.99	35.05
Export revenue ($)	5,392	747.42	3751.70	1.73	177122.80	6.99	54.88	3273.06	14382.69
Listing level									
Export volume (piece)	16,995	39.36	255.64	1	11798	1	4	108	802
Export unit price ($)	16,995	9.22	6.15	0.06	124	3.04	7.99	19.29	29.99
Export revenue ($)	16,995	237.13	1289.50	1.68	56517.28	6.14	29.70	746.14	4697.96
Rating score	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

	# 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 online and offline exports.

Table 3: The Value of Reputation: Baseline Results

	(1) ln(revenue)	(2) ln(quantity)	(3) ln(ave quantity)	(4) ln(buyer num)	(5) ln(market num)
ln(price)	-0.337***	-0.277***	-0.121***	-0.235***	-0.185***
	(0.030)	(0.021)	(0.008)	(0.018)	(0.014)
1<=rating<2	-0.077***	-0.048***	-0.018***	-0.044***	-0.034***
	(0.023)	(0.012)	(0.006)	(0.011)	(0.009)
2<=rating<3	-0.047**	-0.034***	-0.005	-0.035***	-0.023***
	(0.019)	(0.010)	(0.005)	(0.009)	(0.007)
3<=rating<4	0.030**	-0.002	0.014***	-0.002	0.005
	(0.015)	(0.009)	(0.003)	(0.008)	(0.006)
rating>=4	0.336***	0.166***	0.078***	0.156***	0.127***
	(0.018)	(0.009)	(0.004)	(0.009)	(0.007)
material quality	0.003	0.001	-0.003	0.003	0.001
	(0.014)	(0.008)	(0.003)	(0.008)	(0.006)
protection	0.035	0.041	-0.007	0.043	0.028
	(0.041)	(0.026)	(0.009)	(0.026)	(0.019)
guaranteed return	0.035	0.02	0.007	0.018	0.014
	(0.038)	(0.018)	(0.009)	(0.017)	(0.014)
ln(size choice num)	0.117***	0.066***	0.026***	0.062***	0.048***
	(0.016)	(0.010)	(0.003)	(0.009)	(0.007)
ln(word num)	0.113*	0.087**	0.021*	0.081**	0.056**
	(0.066)	(0.041)	(0.013)	(0.039)	(0.028)
ln(picture num)	0.069***	0.034***	0.015***	0.031***	0.025***
	(0.013)	(0.008)	(0.003)	(0.007)	(0.005)
constant	2.241***	1.370***	0.615***	1.207***	0.930***
	(0.203)	(0.127)	(0.044)	(0.117)	(0.087)
Seller FE	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y
R2	0.095	0.091	0.084	0.089	0.094
N	526,488	526,488	526,488	526,488	526,488

Notes: This table reports how reputation affects export performances. Standard errors are reported in the parentheses. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

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

	(1) ln(revenue)	(2) ln(quantity)	(3) ln(ave quantity)	(4) ln(buyer num)	(5) ln(market num)
ln(price)	-0.369***	-0.287***	-0.150***	-0.244***	-0.195***
	(0.031)	(0.021)	(0.025)	(0.018)	(0.014)
L. negative comment num	0.263	0.198	0	0.185	0.139
	(0.249)	(0.185)	(0.004)	(0.180)	(0.117)
L. positive comment num	0.056***	0.043***	-0.000*	0.042***	0.026***
	(0.011)	(0.008)	0.000	(0.007)	(0.005)
material quality	0.007	0.003	-0.003	0.004	0.002
	(0.014)	(0.008)	(0.005)	(0.008)	(0.006)
buyer protection	0.001	0.024	-0.004	0.027	0.015
	(0.042)	(0.025)	(0.011)	(0.024)	(0.018)
guaranteed return	0.036	0.02	-0.003	0.019	0.014
	(0.042)	(0.019)	(0.012)	(0.018)	(0.015)
ln(size choice num)	0.122***	0.067***	0	0.063***	0.049***
	(0.017)	(0.010)	(0.005)	(0.009)	(0.007)
ln(word num)	0.077	0.063*	-0.011	0.058*	0.04
	(0.064)	(0.037)	(0.028)	(0.035)	(0.026)
ln(picture num)	0.080***	0.039***	-0.001	0.037***	0.029***
	(0.012)	(0.007)	(0.004)	(0.006)	(0.005)
constant	2.413***	1.428***	1.124***	1.257***	0.986***
	(0.203)	(0.120)	(0.096)	(0.110)	(0.084)
Seller FE	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y
R2	0.112	0.149	0.034	0.155	0.129
N	526,488	526,488	72,355	526,488	526,488

Notes: This table reports how the content of comments affects export performances. Standard errors are reported in the parentheses. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Table 5: The Role of Information in Export Performances: Peer Product Groups

	(1) ln(revenue)	(2) ln(quantity)	(3) ln(ave quantity)	(4) ln(buyer num)	(5) ln(market num)
ln(price)	-0.480***	-0.348***	-0.166***	-0.306***	-0.249***
	-0.055	-0.039	-0.016	-0.034	-0.026
1<=rating<2	-0.272***	-0.130***	-0.077***	-0.120***	-0.100***
	(0.046)	(0.025)	(0.011)	(0.024)	(0.018)
2<=rating<3	-0.218***	-0.097***	-0.068***	-0.088***	-0.077***
	(0.029)	(0.015)	(0.007)	(0.014)	(0.011)
3<=rating<4	-0.155***	-0.065***	-0.049***	-0.057***	-0.052***
	(0.022)	(0.012)	(0.006)	(0.011)	(0.009)
rating>=4	0.166***	0.123***	0.015***	0.120***	0.083***
	(0.020)	(0.011)	(0.005)	(0.011)	(0.008)
material quality	-0.016	-0.008	-0.002	-0.008	-0.006
	(0.019)	(0.011)	(0.004)	(0.011)	(0.008)
protection	0.369***	0.216***	0.066***	0.206***	0.164***
	(0.072)	(0.044)	(0.013)	(0.042)	(0.032)
guaranteed return	0.039	0.022	0.007	0.022	0.015
	(0.028)	(0.017)	(0.005)	(0.017)	(0.012)
ln(size choice num)	0.208***	0.134***	0.045***	0.126***	0.095***
	(0.036)	(0.025)	(0.007)	(0.024)	(0.016)
ln(word num)	0.150**	0.096**	0.035***	0.087**	0.062**
	(0.071)	(0.043)	(0.013)	(0.043)	(0.032)
ln(picture num)	0.071***	0.034***	0.016***	0.032***	0.025***
	(0.015)	(0.009)	(0.003)	(0.009)	(0.007)
constant	2.887***	1.458***	0.886***	1.329***	1.141***
	(0.225)	(0.145)	(0.057)	(0.132)	(0.101)
Group FE	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y
R2	0.118	0.106	0.102	0.106	0.113
N	275,225	275,225	275,225	275,225	275,225

Notes: This table reports how ratings affect export performances within similar product groups. Standard errors are reported in the parentheses. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Table 6: The Role of Reputation in Export Performances: Regression Discontinuity

	(1) ln(revenue)	(2) ln(quantity)	(3) ln(ave quantity)	(4) ln(buyer num)	(5) ln(market num)
ln(price)	-0.295***	-0.265***	-0.124***	-0.218***	-0.174***
	(0.028)	(0.019)	(0.008)	(0.017)	(0.013)
1<=rating<2	-0.235***	-0.096***	-0.073***	-0.086***	-0.079***
	(0.023)	(0.011)	(0.006)	(0.011)	(0.009)
2<=rating<3	-0.202***	-0.079***	-0.060***	-0.074***	-0.065***
	(0.020)	(0.010)	(0.006)	(0.009)	(0.008)
3<=rating<4	-0.153***	-0.062***	-0.047***	-0.056***	-0.050***
	(0.013)	(0.007)	(0.003)	(0.007)	(0.005)
rating>=4	0.067***	0.057***	0	0.056***	0.037***
	(0.014)	(0.007)	(0.003)	(0.007)	(0.005)
1<=rating<2 * treated	0.154	0.047	0.07	0.032	0.051
	(0.227)	(0.093)	(0.068)	(0.075)	(0.071)
2<=rating<3 * treated	-0.023	-0.034	0.001	-0.031	-0.024
	(0.037)	(0.021)	(0.012)	(0.020)	(0.016)
3<=rating<4 * treated	0.101***	0.051***	0.023***	0.049***	0.041***
	(0.013)	(0.008)	(0.003)	(0.008)	(0.006)
rating>=4 * treated	0.147***	0.080***	0.031***	0.075***	0.059***
	(0.006)	(0.004)	(0.001)	(0.003)	(0.003)
material quality	-0.005	-0.002	-0.005*	-0.001	-0.002
	(0.013)	(0.008)	(0.003)	(0.007)	(0.005)
buyer protection	-0.054	0.009	-0.035***	0.014	0
	(0.040)	(0.025)	(0.009)	(0.024)	(0.018)
guaranteed return	0.024	0.014	0.004	0.014	0.01
	(0.037)	(0.016)	(0.009)	(0.015)	(0.013)
ln(size choice num)	0.118***	0.065***	0.028***	0.060***	0.047***
	(0.016)	(0.009)	(0.003)	(0.009)	(0.007)
ln(word num)	0.165***	0.107***	0.037***	0.098***	0.072***
	(0.062)	(0.038)	(0.012)	(0.036)	(0.026)
ln(picture num)	0.077***	0.036***	0.017***	0.033***	0.027***
	(0.012)	(0.007)	(0.003)	(0.007)	(0.005)
constant	2.682***	1.376***	0.884***	1.196***	1.036***
	(0.184)	(0.112)	(0.042)	(0.104)	(0.077)
Week FE	Y	Y	Y	Y	Y
Seller FE	Y	Y	Y	Y	Y
R2	0.141	0.129	0.126	0.128	0.137
N	541,468	541,468	541,468	541,468	541,468

Notes: This table reports how ratings affect export performances using a regression discontinuity design. Standard errors are reported in the parentheses. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Table 7: Weekly Price Growth Rates (in Percentage Points)

	N	Mean	Std	Min	Max
All Listings	22502	1.90	0.48	-2.12	4.13
New Listings	3237	2.04	0.51	-2.12	3.91
Existing Listings	4198	1.73	0.42	0.10	2.96

Notes: This table reports the descriptive statistics for the weekly price growth rates. Standard errors are reported in the parentheses. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Table 8: Reputation and Price Dynamics

	(1) ln(price)	(2) 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+1)		-0.002***
		0.000
high quality * ln(past rating num+1)	0.001***	
	0.000	
high quality * ln(past order+1)		0.001***
		0.000
material quality	-0.001	-0.001
	(0.001)	(0.001)
buyer protection	-0.001	-0.001
	(0.001)	(0.001)
guaranteed return	0.000	0.000
	(0.001)	(0.001)
ln(size choice num)	0.004***	0.004***
	(0.001)	(0.001)
ln(word num)	0.003	0.004
	(0.003)	(0.003)
ln(picture num)	-0.002**	-0.002**
	(0.001)	(0.001)
constant	0.060***	0.063***
	(0.010)	(0.010)
Seller FE	Y	Y
Week FE	Y	Y
R2	0.948	0.948
N	44,044	44,044

Notes: This table examines price dynamics in both pooled- and sub-samples. Product listings are divided to high-quality and low-quality categories based on the material quality and the existence of decorative design, respectively.

Table 9: Structural Estimation: Estimating the Reputation Elasticity

	ln(quantity)
ln(price)	-0.049***
	(0.009)
six-month average rating * treated	0.189**
	(0.075)
six-month average rating	0.238***
	(0.018)
material quality	0.03
	(0.030)
buyer protection	0.173**
	(0.087)
guaranteed return	0.061
	(0.057)
ln(size choice num)	0.106***
	(0.035)
ln(word num)	0.323*
	(0.177)
ln(picture num)	0.084**
	(0.042)
constant	1.089**
	(0.497)
Week FE	Y
Seller FE	Y
R2	0.072
N	62,312

Notes: This table reports how reputation affects export performances. Standard errors are reported in the parentheses. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Table 10: Structural Estimation: Parameter Estimates

Parameter	Interpretation	Estimates
log(theta bar)	log(average quality level)	-6.18
var(log(theta bar))	variance of log(quality)	0.28
var(epsilon)	variance of feedback	196.53
exp(c)*theta bar	marginal cost of an average-quality product	6.63
sigma	markup for an average-quality product	1.13
rho	reputation coefficient	0.64

Notes: This table reports the estimated parameters from structural estimations.

Table 11: Structural Estimation: Estimated Moments

Moment	Data	Model
Panel A: Targeted moments		
mean of ln(annual price)	2.06	1.94
std of ln(annual price)	0.55	0.54
mean of ln(annual sales+1)	3.71	3.82
std of ln(annual sales+1)	1.44	1.51
Panel B: Non-targeted moments		
p85/p15 of ln(annual sales+1)	2.14	2.12
p75/p25 of ln(annual sales+1)	1.65	1.45
p85/p15 of ln(annual price)	1.74	1.49
p75/p25 of ln(annual price)	1.41	1.48

Notes: This table reports the estimated moments from structural estimations.

Table A.1: Top Export Markets

Rank	Export Revenue		Export Volume		Exporters	
	Alibaba	Customs	Alibaba	Customs	Alibaba	Customs
1	Russia	Japan	Russia	Japan	Russia	United States
2	Brazil	United States	Brazil	United States	Brazil	Japan
3	United States	Australia	United States	Hong Kong	United States	Hong Kong
4	Belarus	Hong Kong	Belarus	Australia	Canada	Australia
5	Spain	Panama	Spain	Panama	France	Canada
6	France	Canada	France	Canada	Spain	South Korea
7	Canada	South Korea	Canada	South Africa	Israel	UAE
8	Chile	Chile	Ukraine	UAE	Belarus	Panama
9	Israel	Russia	Chile	South Korea	Australia	Chile
10	United Kingdom	South Africa	Israel	Chile	United Kingdom	New Zealand

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