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Signaling and Quality Upgrading: Evidence from E-commerce Certification in China

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Abstract

E-commerce certification can signal a firm's quality, reducing information frictions and incentivizing quality upgrading. This paper examines the effect of certification on quality upgrading both econometrically and using a novel dynamic structural model. To this end, we collected data from Alibaba.com, one of the world's largest global Business-to-Business platforms, which launched its certification policy, "Gold Supplier," in 2000. We posit that signaling as a Gold Supplier is more costly for lower-quality firms. Combining Alibaba.com data with 2000–2015 Chinese Customs Data, we show that firm export quality increases after becoming a Gold Supplier and the effect is greater for smaller firms. Using the Simulated Method of Moments, we estimate a dynamic structural model that embeds information asymmetry, signaling, and quality upgrading. Counterfactual analysis shows that a 1% reduction in the differential cost of signaling increases total trade by 1.50% and that substantial changes in signaling costs can shift the market equilibrium.

Keywords: Signaling, Quality Upgrading, Certification, E-commerce
JEL codes: F19, F69, L19

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1 Introduction

Information friction makes it difficult for buyers to learn about product quality and the trustworthiness of foreign suppliers (Startz, 2021). Fortunately, the development of e-commerce has enabled certification policies that help firms signal their quality and reduce information asymmetry. While the impact of certification has been discussed by an emerging strand of literature (Jin and Leslie, 2003; Hui et al., 2018; Jin et al., 2021), little is known about how certification, as a signaling technology, can change the market equilibria and affect firm export quality upgrading decisions and total trade flows. This paper posits that choosing to be certified, in other words, signaling, is more costly for lower-quality firms, finding that the possibility of being certified incentivizes firms to upgrade their quality.

Asymmetric information leads to adverse selection, causing market inefficiency (Akerlof, 1970; Spence, 1978). This is a serious problem in large developing countries such as China. After China joined the World Trade Organization (WTO) in 2001, foreign firms sourcing from China have been concerned about fraudulent suppliers and product adulteration (Tang and Babich, 2014; OECD/EUIPO, 2016). Without signaling technology, distinguishing the trustworthiness of firms is difficult. This is especially true for small and medium-sized enterprises (SMEs), which often lack resources to build trade ties. Fortunately, signaling opportunities began to emerge during the same period. In October 2000, Alibaba.com launched a certification policy, "Gold Suppliers (GS)," aiming to help SMEs sell online.[1] It has since become one of the largest global Business-to-Business (B2B) platforms in the world.[2]

To become an entry-level GS firm, Chinese Mainland firms must adhere to the following conditions: (1) pay an annual membership fee of 29,800 RMB (around 4,649 USD[3]), have their legal status verified by a third-party verification company and have their premises examined by Alibaba staff; and (2) learn to use the Alibaba.com platform and present themselves online such as by learning to showcase products, design websites, receive and send quotes, and analyze data.[4] The membership fee, cost of being verified and owning a premise can be regarded as fixed costs. By contrast, the

[1] `https://docs-src.alibabagroup.com/en/news/press_pdf/p090505.pdf`, accessed February 2023.

[2] Alibaba.com is often ranked as the top global B2B marketplace in the world. See links: `https://www.linkedin.com/pulse/worlds-12-b2b-websites-currently-holds-top-ranks-saqib-ilyas/`, `https://tweakyourbiz.com/business/e-commerce/top-b2b-platforms`, `https://www.practicalecommerce.com/20-leading-global-b2b-exchanges-source-products`, accessed June 2023.

[3] Converted using an exchange rate of 6.41. This is the 2012–2018 average official exchange rate between the USD and RMB from the World Development Indicators. Membership fees have remained relatively stable since 2012.

[4] See details for the definition of a Gold Supplier from: `https://www.alibaba.com/help/gold_supplier.html`, accessed July 2023.

costs of learning and presenting firm images and online products vary with firms' quality. Here, quality refers to firms' trustworthiness and reliability, and this is presumably also reflected in firms' product quality. It is easier for higher-quality firms to find proof of their abilities and acquire new skills. In other words, the cost of signaling is higher for lower-quality firms.

The disclosure of certification information can encourage firms to upgrade their quality because it increases the demand for high-quality and certified firms (Jin and Leslie, 2003; Dranove and Jin, 2010). Similarly, Alibaba.com's certification policy separates high-quality from low-quality firms and incentivizes them to upgrade their quality. However, in reality, does the GS certification have such an effect? Further, how do reductions in the cost of signaling affect firms' investments in quality upgrading, total trade flows, and market equilibrium? By answering these questions, this study sheds light on how e-commerce certification affects market equilibrium and firms' export outcomes.

Our contributions to the literature are three-fold. First, to the best of our knowledge, we are the first to study how e-commerce certification affects firm export quality.[5] We studied this both econometrically and using a novel dynamic structural model. Our structural model integrates information frictions, firms' signaling decisions and investment in quality upgrading. Previous literature has not considered the dynamic feature of signaling and investment in quality upgrading[6], and accounting for this helps us understand firms' signaling and investment behavior during their lifecycles. Second, we contribute to the literature by estimating the cost of signaling quality using our structural model and quantify the significance of the signaling mechanism. Third, the reduced-form analysis of our study contributes to the literature by uncovering how various signals available online affect firm online sales.[7]

To study the impact of GS certification on firm quality upgrading, we collected detailed firm-level data from Alibaba.com in September 2018 (hereafter, the Alibaba Data). We began by documenting four stylized facts. First, based on the Alibaba Data alone, we showed that the length of certification is positively associated with

[5] Previous literature has documented increasing product varieties in a large digital platform (Brynjolfsson, Chen and Gao, 2022), the effect of joining an e-commerce platform on firm exports (Carballo et al., 2022) and the number of transactions (Jean et al., 2021); the effect of e-commerce certification on online prices (Saeedi, 2019); the effect of certificantion selectivity on firm quality as measured by Effective Percentage Positive from consumer feedback. No study has been conducted on the effect of e-commerce certification on firm export quality.

[6] Macedoni (2021) developed a static model incorporating certification and exogenous quality withouth considering endogenous quality and dynamic signaling choices, while Feng (2021) developed a quantifiable export model in which firms signal their quality through prices without emphasizing investment in quality upgrading.

[7] Previous literature focuses on online reviews (Chen and Wu, 2021), e-commerce store status (Saeedi, 2019; Hui et al., 2021), and the trade-off of including input measures and output measures on quality certification (Hui, Jin and Liu, 2022). Research has not shown the universe of online signals of quality, such as the number of certifications, trademarks, and patents, as documented in our study.

the firm's online sales after controlling for consumer ratings, various signals that firms send online, and other firm characteristics. Second, based on the Alibaba–Chinese Customs merged data, we showed that firms after becoming GS experience significant increases in their export quality, export revenue, and the number of export varieties and destinations using an event-study. Moreover, these effects are greater for smaller firms. Third, we examined when firms become GS in their lifecycles and found there is a great heterogeneity that could indicate initial firm quality. Fourth, we illustrated that average online sales increase with firms' years of being GS.

Inspired by our four stylized facts, we began by modeling how firms make signaling decisions. We posited that the differential cost of signaling is higher for lower-quality firms. Suggestive evidence from the data verifies our prediction: Higher-quality firms have a higher probability of signaling as GS firms. To further incorporate the dynamic features of firms' signaling decisions and rationalize our stylized facts, we developed a structural dynamic model that embeds information asymmetry, signaling, and upgrading decisions. In this model, heterogeneous suppliers differ in their initial quality and make pricing, signaling, and investment decisions during each period. Using the Simulated Method of Moments (SMM), we estimated the signaling cost, investment cost, and transition parameter. With the estimated parameters in hand, we considered two counterfactuals that quantify the significance of this signaling technology, namely, changing the differential signaling cost or the fixed signaling cost. First, we found that, slight reductions in the differential and fixed signaling costs can boost investment in quality upgrading and total trade flows. Second, large changes in signaling costs can also shift the equilibrium from partially separating to pooling.

The remainder of this paper is organized as follows. Section 2 introduces the related literature; Section 3 introduces Alibaba.com and the data; Section 4 presents the stylized facts; Section 5 describes our model; Section 6 shows the calibration results and counterfactual analysis; and Section 7 concludes the paper.

2 Literature Review

Our study contributes to four strands of research. First, it extends the literature on information frictions in trade. Previous studies have mainly focused on search (Jensen, 2007; Carballo et al., 2022; Bai et al., 2022) and contracting costs (Startz, 2021), matching frictions (Eaton, Kortum and Kramarz, 2022) and documents the friction of quality information (Bai, 2018; Saeedi, 2019). Past reputation (Shapiro, 1983; Cai et al., 2014; Fan, Ju and Xiao, 2016; Chen and Wu, 2021; Bai, Gazze and Wang, 2022), certification by a trusted third-party (Leland, 1979; Elfenbein, Fisman and McManus, 2015; Hui, Jin and Liu, 2022), and warranties (Grossman, 1981; Hui et al., 2016) are ways to mitigate information frictions (Hui et al., 2021). Our study estimates the cost of signaling quality through e-commerce certification and quantifies the significance of the signaling mechanism, offering a new perspective for understanding information frictions.

Second, this study builds on the extant literature on export quality (Khandelwal, 2010; Khandelwal, Schott and Wei, 2013; Feenstra and Romalis, 2014; Zhang, 2018) and the factors that promote quality upgrading, such as market access (Lileeva and Trefler, 2010), trade liberalization (Bas and Strauss-Kahn, 2015), and import competition (Amiti and Khandelwal, 2013). An emerging strand of the literature has begun to uncover the relationship between information asymmetry and firm quality. For instance, Zhao (2018) argues that higher tenure in export markets can signal efficiency and that in equilibrium, higher-tenured firms produce higher-quality goods. This study contributes to this research by showing how e-commerce certification stimulates the upgrading of export quality.

Third, this study contributes to the literature on quality certification and signaling. Quality certification serves as a signal of quality (Saeedi, 2019), and it can stimulate quality upgrading (Jin and Leslie, 2003; Zapechelnyuk, 2020). Macedoni (2021) developed a theoretical model that incorporates information asymmetry, quality and certification. Feng (2021) developed a quantifiable export model in which firms with heterogeneous productivity signal quality through price. However, none of these studies considered the quality upgrading decisions of exporters and accumulative signals. The work by Hui et al. (2021) is the closest comparison to our study. They show that when eBay's certification policy became more stringent, some incumbents were incentivized to upgrade their quality. Our study differs from theirs in two ways. First, we integrated the classical signaling model into an international trade framework, estimated the signaling costs and quantified the significance of signaling using a dynamic structural model. Second, our focus is export quality while theirs is quality measures derived from online feedback. Additionally, owing to data limitations, they could not observe firm quality before firms went online.

Finally, our study complements the literature on e-commerce and its welfare implications. E-commerce creates welfare gains by increasing the number of product variaties (Brynjolfsson, Chen and Gao, 2022), reducing the cost of living (Couture et al., 2018), and alleviating regional inequality (Fan et al., 2018). Moreover, the machine translation technology adopted by eBay boosts export flows (Brynjolfsson, Hui and Liu, 2019). Our study adds to this literature by showing that a certification system can incentivize quality upgrading and increase total trade flows.

3 Background and Data

3.1 Background and the Alibaba Data

China led the world's e-commerce revenue with $1.3 trillion in 2022.[8] Global B2B e-commerce accounted for 82% of all e-commerce sales in 2019.[9] Alibaba.com, established in 1999, was the first business operated by the Alibaba Group and has since evolved into one of the world's largest global B2B platforms.[10] As of March 31, 2022, over 40 million buyers from more than 190 countries sought business opportunities or completed transactions on Alibaba.com.[11]

Alibaba.com posts information on its registered members and Chinese exporters constitute the majority, 90.2% of our data. Once a mainland firm chooses not to renew its membership, within 1 to 2 years, Alibaba no longer maintains its website online.[12]

At the time of data collection, Alibaba.com had three levels of industry classifications. The first-tier classification included nine industries, such as "Machinery, Industrial Parts & Tools" and "Electronics". The second-tier includes 38 industries and the third-tier included 998 industries. The third-tier industry classification was the most detailed one. Examples include "Computer Hardware & Software", "Solar Energy Products", and "Sportswear". Firms can operate in different industries.

We collected information on GS firms on Alibaba.com in September 2018. First, we searched for each of the 998 third-tier product categories on Alibaba.com and then collected data for every supplier after each search.

The status of GS is a paid membership on Alibaba. To become an entry-level GS firm, Chinese Mainland firms must, first, pay an annual membership fee of 29,800 RMB (approximately 4,649 USD), have their legal status verified by a third-party verification company, and have their premises checked by Alibaba staff; second, they need to learn to use the Alibaba.com platform and present themselves online. For instance, they

[8] https://www.statista.com/forecasts/1283912/global-revenue-of-the-e-commerce-market-country, accessed July 2023.

[9] https://unctad.org/press-material/global-e-commerce-jumps-267-trillion-covid-19-boosts-online-retail-sales, accessed June 2023.

[10] Alibaba is seen as playing a dominant role in the B2B market by Statista. Please see: https://www.statista.com/study/44442/statista-report-b2b-e-commerce/, accessed June 2023.

[11] https://www.alibabagroup.com/zh-HK/about-alibaba-businesses-1492016985502908416, accessed August 2023.

[12] The information came from conversations with two Alibaba.com sales staff members.

need to learn to showcase products, design websites, receive and send quotations, and analyze data.[13] Once approved, Alibaba will show the company's verified information online on the firm's TrustPass page (Figure 2), including the company's registration number, company name, date of issue and date of expiry of their license, and display the GS icon next to the company's name to demonstrate that their business has been verified by a third-party agency as a legally registered business. The number of years a member has been a GS on Alibaba is displayed along with the logo and is updated every year. Entry-level GS can escalate to Assessed Suppliers (AS hereafter).[14] AS are verified by top global inspection companies, such as Bureau Veritas, TüV SüD, SGS, and TüV Rheinland. AS can display assessment reports, verified videos of the company's premises, and other verified information, such as main products, certifications, trademarks, and patents.[15] Unfortunately, the year the company became an AS can not be directly observed from the website.[16] Therefore, the focus of this study is all GS which include both entry-level GS and AS. Primary information from the Alibaba Data used in this study includes the following: name of the company; whether the company is a GS or AS; how long it has been a GS; the year that the company was established; how many certificates, trademarks and patents the company has shown online; consumer ratings for AS; employment size; location; online transaction value in the past six months. A detailed explanation of each variable is provided in the empirical analysis in Section 4.

3.2 Gold Supplier Characteristics

In this section, we describe the characteristics of the GS.

Regarding industries where firms operate, the top 3 first-tier industries where mainland GS operate is Construction, Machinery and Electronics. See Figure 1 for a complete list of first-tier industries. Here the top three industries are ranked by the past half-year online revenue. When ranked according to the number of GS firms in each industry, the top three industries did not change significantly. They are Machinery, Construction, and Electronics.[17] The top 3 markets mainland GS self-reported are

[13] Mainland GS are the focus of this study. Alibaba provides different GS packages for suppliers outside China (Global GS).

[14] The membership fee for AS is 80,000 RMB per year.

[15] Entry-level GS can display main products, certifications, trademarks, and patents, but the information will not appear as verified by a third-party.

[16] For example, if an AS shows that it has ten years of membership history, buyers can not see directly when the firm started to become an AS, but only know that it has been a GS for ten years and became an AS at some point in the past.

[17] Based on our search results, only 18.5 % of GS firms operate in only one first-tier industry. Thus, we identified the main industry by matching the main products that GS firms report online with the first-tier industry classification by minimizing their Jaro-Winkler distance. The Jaro-Winkler distance is suitable for matching repeatedly appearing words.

North America, domestic market and Western Europe.[18]

Regarding firm location, the top three provinces with the largest number of new GS in 2017 were Guangdong (36%), Zhejiang (22%) and Jiangsu (9%).[19] The city with the highest number of new GS in 2017 was Shenzhen. Both facts are in line with those reported by other research institutes.[20] Figure 3 shows the geographic distribution of the new GS in 2017.

Regarding ownership, 70% of GS are private enterprises and 2% are foreign.[21] Regarding size, 66% of GS have fewer than 100 employees, 30% between 100 and 500, with 4% over 500 employees. Thus, most Alibaba.com firms are SMEs.[22]

Regarding export revenue and firm qualifications, the average online export revenue in the past six months was 36,365 USD. Furthermore, 47% show certifications (e.g. ISO, RoHS) online, and 19% have ISO 9000, which certifies quality management systems and can be regarded as a signal of quality (Verhoogen, 2008). Lastly, 14% have trademarks and 10% own patents.

3.3 Merging with the 2000-2015 Chinese Customs Data

The 2000–2015 Chinese Customs Data record the transaction value and quantity, mode of trade, mode of transportation and the firm's Chinese name for each import and export transaction in China. It has a unique ID for each Customs firm, which is also the export license number some firms reported on Alibaba.com.

Chinese Customs Data primarily recorded the Mandarin names of firms. However, the Alibaba Data contain firms' English and Mandarin names as well as the export license number (if reported by firms). Therefore, matching the Alibaba Data and the Chinese Customs Data requires several steps. First, for firms that do not report their Mandarin names, we used `qcc.com`, the leading corporate credit verification platform

The use of Jaccard distance does not significantly change our description. However, as the main product information has repeated words, the Jaro-Winkler distance is more appropriate. Additionally, the matching accuracy is approximately 80%. Construction refers to Home, Lights & Construction and Machinery refers to Machinery, Industrial Parts and Tools.

[18] Firms report their market shares in different markets; here the top three markets are the three most popular markets that firms reported as their top market.

[19] The Qianzhan Research Institute in China also reported that in 2018, Guangdong, Zhejiang and Jiangsu had the most cross-border e-commerce sellers and that these three provinces represent over half of cross-border e-commerce sellers in China. See the link for Qianzhan Research Institute's report summary in Mandarin: `https://www.qianzhan.com/analyst/detail/220/190620-b7b7e86d.html`, accessed June 2023.

[20] According to Qichacha Research Institute in China, Shenzhen has the most e-commerce entities among China's cities in 2020. See the link for a Mandarin report: `http://www.sznews.com/news/content/2020-11/10/content_23706280.htm`, accessed June 2023.

[21] The rest include different types of limited liability companies whose ownership can not be directly identified.

[22] According to the Standards of SMEs in China, industrial enterprises with less than 1000 employees or less than 400 million RMB in annual revenue are classified as SMEs. The criteria for SMEs differ across industries. See the following link (in Mandarin) for details: `http://www.gov.cn/zwgk/2011-07/04/content_1898747.htm`, accessed June 2023.

officially filed in China, to search for the English names and obtain the corresponding Mandarin names, if available. Second, for companies that report their eighteen-digit registration codes, we used `credit.customs.gov.cn`, the credit publicity platform of import and export business in China, to search for their registration codes and obtain their Chinese names and export license numbers. Third, we used Chinese firm names and firms' export license numbers to match the Alibaba Data with the 2000-2015 Chinese Customs Data. When matching the Chinese names, we recoded the common Mandarin strings in both datasets to improve the matching accuracy.[23] In the data, 112,990 out of 125,303 (90%) GS firms came from mainland China. A total of 89,332 China's GS firms were established no later than 2015.

In the end, 37,221 GS firms were matched to the Customs data, accounting for 33% of all GS, or 42% of China's GS firms established before 2015. Moreover, 99% (36,881) of firms were matched using their Chinese names, and 1% (340) matched using their export licenses.

3.4 Quality

Export quality is the main focus of this paper. We estimate export quality following Khandelwal, Schott and Wei (2013). They derive a specification for estimating quality from a CES (Constant Elasticity of Substitution) demand (KSW hereafter). Firm f exports HS6 product h to destination d in year t. Let σ indicate the elasticity, q and p indicate quantity and price respectively. The specification is:

$$\ln q_{fhdt} + \sigma \ln p_{fhct} = \alpha_{hdt} + \epsilon_{fhdt} \tag{1}$$

α_{hdt} is a product-country-year fixed effect.[24] Quality is estimated within each HS2 industry. Quality in a (h, d, t) market is $\lambda^*_{fhdt} = \frac{\epsilon^*_{fhdt}}{\sigma-1}$. The intuition is that, conditional on prices, higher sales will be attributed to higher quality. The estimates for elasticity σ come from Broda, Greenfield and Weinstein (2006).

Quality may not be comparable across industries. There are two ways to aggregate quality to the firm-year level. First, Lim, Trefler and Yu (2022) propose demeaning quality within each (h, d, t) market and aggregate it using export weights to the firm

[23]For example, in Mandarin, there are multiple ways to indicate a "corporation", such as Jituan and Jituangongsi. We recode them into the same expression to improve the matching accuracy.

[24]KSW use product and country-year fixed effects. Here we think quality may have common components in each product-country-year market. Thus we include the fixed effect at this level.

level (the demean aggregation hereafter). Specifically,

$$quality\_ksw_{ft} \equiv \sum_{(h,d)} \omega_{fhdt} \left(\lambda^*_{fhdt} - \bar{\lambda}^*_{hdt}\right) \tag{2}$$

where ω_{fhdt} is Chinese firm f's exports in year t to market (h, d, t) as a share of its total exports in year t:

$$\omega_{fhdt} \equiv \frac{p_{fhdt}q_{fhdt}}{\sum_{(h',d')} p_{fh'd't}q_{fh'd't}} \tag{3}$$

Here, $\lambda^*_{fhdt} - \bar{\lambda}^*_{hdt}$ carries the interpretation of the percentage change of quality relative to the market mean as λ^*_{fhdt} is quality estimates in logs. However, logarithms approximate the percentage changes closely only when the changes are small.[25] To address this issue, we calculate the percentile of quality within each (h, d, t) market as pc_{fhdt} and further aggregate the quality to firm-year level using export weights (the percentile approach hereafter). Hence, the second firm-year level quality measure is defined as:

$$quality\_kswp_{ft} = \sum_{hdt} \omega_{fhdt} \cdot pc_{fhdt} \tag{4}$$

where ω_{fhdt} is defined in equation (3).

In our robustness test, we also estimate quality following Lim, Trefler and Yu (2022) (LTY hereafter). They develop the estimation based on Berry (1994) and Khandelwal (2010):

$$\ln q_{fhdt} = \beta^H \ln p_{fhdt} + \lambda^H_f + \lambda^H_{hdt} + \lambda^H_{pt} + \lambda^H_{fhdt} \tag{5}$$

where λ^H_f, λ^H_{hdt} and λ^H_{pt} are firm, market and province-year fixed effects. We estimate this seperately by each sector H. A firm's quality is $\lambda\_LTY_{fhdt} = \lambda^H_f + \lambda^H_{hdt} + \lambda^H_{pt}$ and we aggregate this up to the ft level by first subtracting the hdt market mean and then take the weighted average of the demeaned term. To overcome the endogeneity issue when estimating demand, we employ a cost-side instrument for prices following Wang (2011) and we denote this measure of quality as $quality\_iv$.[26]

[25] See details from: `https://www.uio.no/studier/emner/sv/oekonomi/ECON4150/v13/undervisningsmateriale/loglinearnote-.pdf`, accessed July, 2023

[26] As in Wang (2011), to capture common cost shocks, we construct the instrument using prices charged by firms producing goods under the same HS 4-digit code at the same city in China; to avoid common demand shocks, we use prices from carefully selected markets that are far away enough both geographically and in levels of development. The idea is, according to Wang (2011), firms in Dongguan exporting to both Japan and Kenya. The two markets are geographically distant and differ in their levels of development. We can reasonably assume that they face different demand shocks, however, simultaneously, experience the same input shocks due to the firms' same location. Specifically, for a firm located in city m exporting goods h to country d, the prices charged by any exporter will be used to construct an instrument for $\ln P_{fhdt}$ if the following two criteria are met: First, the geographic distance between country d and d' is above the 30th percentile in the distribution of geographic distance among all country pairs available in the Customs Data. Second, the per capita GDP of country d' is at least 1.5 times the standard deviation of the world distribution away from country d. The instrument for $\ln P_{fhdt}$ is then the average of prices of observations with subscript $\ln P_{f'h'd't}$:

We use *quality_ksw* in our baseline and use *quality_kswp* and *quality_iv* in the robustness tests. Moreover, inspired by Verhoogen (2008), we use the number of ISO 9000 certifications that firms reported online as an alternative measure of quality.

4 Stylized Facts

We first documented four stylized facts about GS from our data. These facts suggest that online frictions in quality information exist and firms make efforts to signal their quality online. They also pointed out the role of the signaling mechanism in addressing these frictions.

Fact 1. Years of Certification Is Positively Associated With Online Sales Controlling for Other Signals Online.

Existing literature shows that consumer ratings can affect firm sales (Chen and Wu, 2021). Based on the Alibaba Data, we first demonstrate that, controlling for consumer ratings and other firm characteristics, years of certification are still positively associated with firm online sales. Let f and i denote the firm and industry, respectively. We estimate the following model:

$$Sale_f = \sum_i \delta_i + \lambda_r + A_f + year\_gs_f + X_f + \epsilon_f \tag{6}$$

Firms can operate in multiple industries, thus we include one dummy for each of the second-tier 38 industries.[27] $Sale_f$ represents the online transaction revenue in the past six months on Alibaba.com and it shows an interval of transaction value if the value exceeds 10 USD.[28] Thus, we used an interval regression to estimate this model.[29] Errors are clustered at the firm level to control for possible correlations within the firm.

The key explanatory variable is *year_gs*, which represents the logged total number of years the firm has obtained a GS certification. X_f includes the following control variables. *age* indicates logged firm age. *certificate*, *patent* and *trademark* indicate

$IV_{fhdt} = \overline{\ln P_{f'h'd't}}$ where h' includes all HS 6-digit products under the same HS 4-digit product.

Lim, Trefler and Yu (2022) develop a novel instrument for prices, which is the average wage paid by firms in the same city as firm f but not in the same industry. However, industry-city level wage data from the Annual Survey of Manufacturing Firms in China are only available for 2000-2007 and 2011-2013. This prevents us from estimating the quality for firms from 2008 to 2010 and from 2014-2015 and for smaller firms in the Customs Data, which account for a large share of GS firms. Moreover, the instrument from Wang (2011) uses more data variation and can be constructed for most exporters, thus constituting a good instrument for our setting.

[27]See section 2.1 for the introduction for industries on Alibaba.com. We did not use the 998 third-tier industries because we want to control for common characteristics in large sectors rather than small industries.

[28]For instance, "10+" indicates value between 10 and 100 USD, "100+" indicates value between 100 and 1000 USD.

[29]The interval regression is a generalization of Tobit model. See *intreg* command in Stata.

the logged number of certificates, patents, and trademarks shown online by the GS firm respectively, representing firm qualifications.[30] *customer* is a dummy variable indicating whether the firm lists a previous customer online.[31] *private* indicates private enterprises while *foreign* indicates foreign enterprises. *small* is a dummy variable indicating whether the number of employees is below 100 people.[32] Finally, *assess* is a dummy variable indicating whether the firm is an AS.[33] Data on consumer ratings are available for AS.[34] *rating* captures the overall consumer rating, ranging from 1 to 5.

In column 1 of Table 4, we include all GS in the sample and only include $year\_gs$. The coefficient is 0.099. In column 2, after controlling for firm age, size, and other firm characteristics such as ownership and qualifications, the coefficient for $year\_gs$ becomes 0.177. Columns 3 to 4 consider only AS with rating data available. In column 3, when we only include $year\_gs$, the coefficient is 0.224, significant at the 1% level. In column 4, when we include more firm characteristics including ratings, the coefficient for $year\_gs$ becomes 0.350, significant at the 1% level, and the coefficient for rating is positively significant. Meanwhile, the number of certificates and the number of trademarks are significantly and positively associated with firms' online sales in columns 2 and 4. And the coefficients for certificates, patents and trademarks are smaller than the coefficient for years of GS. From columns 5-8, we change the dependent variable to $ln(sales + 1)$ as a robustness test and repeat the regressions in columns 1-4. From column 5-8, the coefficients for $year\_gs$ are significant and positive at 1% level and become much larger compared to columns 1-4 due to the inclusion of zero sales.

Overall, the results suggest that the years of certification are significantly and positively associated with firms' online sales, even after controlling for online ratings (Chen and Wu, 2021). Other online signals, such as the number of certifications, patents and trademarks are also positively associated with online sales. However, because firms first need to become GS to show their certifications, patents and trademarks, the years of GS is the primary signal online. Moreover, it is the most apparent certification that consumers would notice online and, according to our estimates, it serves as one of the strongest signals of quality online. This motivates us to further investigate the effect of GS certification on firms' export outcomes in the next section.

[30] We take ln(x+1) for certifications, patents and trademarks to include the observations of zeros. Examples of certificates are ISO 9000 or RoHS.

[31] For instance, the most popular customer of Gold Suppliers is Walmart.

[32] In the data, the number of employees is reported in a range. Thus, we use dummy variables to proxy firm size.

[33] See Section 2.1 for the introduction for Assessed Suppliers.

[34] 10% of GS (11,250) are Assessed Suppliers. Among them, 53% of them (6,352 firms) have positive consumer ratings. And among the 6,352 firms that have positive number of reviews, the median number of reviews is 3. One possible reason is that buyers are not incentivized to share information about suppliers (Zhao, 2018).

Fact 2. GS Certification Increases Firm Export Revenue, Export Varieties, Export Destinations and Export Quality.

In this section, we estimate the effect of GS on firms' export performances. Based on the Alibaba–Chinese Customs merged data, We use an event-study approach that relies on the variation before and after firms become GS. Even though we observe firms not matched as GS in the customs data, they can either never register as GS, or register once but decide to quit. Including these firms in the event-study design may cause an upward bias in our estimate.

Moreover, even if we observe firms that never register as GS, they can be systematically different from GS.[35] To address this issue, following Jacobson, LaLonde and Sullivan (1993), McCrary (2007) and Lafortune and Schönholzer (2022), we first employed an event-study approach and relied only on within-firm changes in outcomes over time for GS firms. Having said this, the endogeneity issue may arise at the firm-year level. To address this concern, we employed the Time Series Cross Section (TSCS) matching techniques developed by Imai, Kim and Wang (2021) to examine the robustness of our results. The reduced-form estimates provide suggestive evidence on how the GS certification affects firm export outcomes.

1. Event-Study Specification

Firm f in industry i is located in city r.[36] The outcome variables y_{ft} include export revenue, the number of export varieties, the number of export destinations, and export quality. To reduce biases due to time-invariant firm differences and city-industry-year characteristics, we include firm and city-industry-year fixed effects, indexed by α_f and α_{rit} respectively. Standard errors are clustered at the firm level to account for possible serial correlations across time. t_f^* denotes the first year that the firm becomes a GS. D_{ft}^k is a dummy variable indicating k year(s) before or after t_f^*. Hence, the event-study specification is as follows:

$$y_{ft} = \alpha_f + \alpha_{rit} + \sum_{\underline{c}}^{\bar{c}} \beta_k \cdot D_{ft}^k + \epsilon_{ft} \tag{7}$$

[35]For example, e-commerce like Alibaba.com usually serve small and medium enterprises.

[36]Industry i is defined by the largest HS2 sector that the firm imports and exports from 2000-2015.

$$where \quad D_{ft}^{k} = \begin{cases} \mathbb{1}[t \leq t_f^* + \underline{c}], & k = \underline{c} \\ \mathbb{1}[t = t_f^* + k], & \underline{c} < k < \overline{c} \\ \mathbb{1}[t \geq t_f^* + \overline{c}], & k = \overline{c} \end{cases}$$

$k = -1$ is excluded, thus the estimates are measured relative to $t_f^* - 1$. Thus, β_k captures the effect of GS certification on export outcomes k year(s) before or after the firm first becomes a GS relative to one period before becoming a GS. Here, endpoints are binned at $\underline{c} = -2$ and $\overline{c} = 2$.[37] In our event-study, we use only GS sample.[38] Moreover, we drop trading firms identified following Ahn, Khandelwal and Wei (2011) because they do not produce their own products.[39]

Baseline Results

Figure 4 shows the coefficients, β_k, estimated from equation (7) and their 95% confidence intervals (CI). The outcome variables are the log of export revenue, log of the number of export varieties, log of the number of export destinations, and export quality $quality\_ksw$.

Figure 4 shows that all β_{-2} are insignificant. It suggests that firms before becoming GS show little rising or falling pre-trends. Specifically, firms after becoming GS witness 0.15 unit increase in export quality, 65.6% increase in export revenue, 27.5% increase in the number of varieties, and 52.3% increase in the number of destinations. Consistent with Carballo et al. (2022), we found a significant effect of e-commerce on firm exports. Our reduced-form analysis contributes to the literature by further uncovering the effect of e-commerce certification on firm quality, the number of export varieties[40], and the number of export destinations.

Figure 5 illustrates the coefficients for alternative measures of quality: $quality\_kswp$ indicates the quality measure using percentile approach, $quality\_iv$ indicates the quality estimate using IV, and $ISO9000$ indicates the logarithm of the total number of ISO 9000 certifications that firms reported online plus one. Through all three alternative measures of quality, we see a significant increase in firm quality after firms obtained the GS certification. The coefficients of Figures 4 and Figure 5 are also reported in Table 5.

[37] We chose these endpoints because the median GS survive for four years in the Customs Data, one year longer than the median Customs firm. Choosing endpoints as three does not alter our estimates significantly.

[38] We use GS firms that registered no later than 2015 because the latest Customs data is available in 2015.

[39] The number of trading firms account for 18.7% in our sample. Including them do not alter our results significantly.

[40] Brynjolfsson, Chen and Gao (2022) documents a rising number of book varieties in a large digital platform without focusing on export varieties

Figure 6 illustrates the event-study coefficients following Callaway and Sant'Anna (2021) and Sun and Abraham (2021). The results demonstrate that the positive association between GS and firm export quality is still robust. The pre-trends are justifiable because in the dynamic model in the following sections, some firms are motivated to upgrade their quality before becoming GS. Moreover, the slope of the positive increase in quality after becoming GS is steeper than the slope of the pre-trends, indicating the effect of GS on quality is still present.

The Differential Effect of Gold Supplier

Alibaba aims to serve SMEs. Thus, the effects of GS may differ by firm size. We use the initial export revenue as a proxy for firm size.[41] We examine the differential effect of GS by separately estimating equation (7) for smaller and larger firms. The estimates in Figure 6 show that, one year after firms become GS, smaller firms see 0.26 unit, 103%, 35.9%, and 68.9% increases in export quality, revenue, varieties and destinations, respectively, while the estimates are 0.067, 34.9%, 20.1%, and 38.6% for larger firms. Our estimates also indicate that smaller firms benefited more. This finding is consistent with the fact that Alibaba.com aims to SMEs.

To summarize, the empirical evidence suggests that GS certification is positively associated with firms' online sales, and after firms become certified, they witness a significant increase in export revenue, varieties, destinations and export quality. Additionally, the effects are greater for smaller firms. Although we control for firm fixed effects in the event-study estimates, the effects can suffer from biases caused by unobserved time-variant firm capabilities. Moreover, the identifying assumption of the event-study design is that the timing of the event is conditionally random, which may not be true in our context. Once firms submit the information required for GS memebrship, the timing of the GS is likely close to their submission date. Thus, the next section employs the TSCS matching techniques developed by Imai, Kim and Wang (2021) to further address the endogeneity concern caused by firm-time level unobserved factors and to estimate the causal impact of GS on export quality.

2. Difference-in-difference Estimator

The key to the Difference-in-difference(DiD) approach is finding a suitable control group for the treated group and ensuring that the control and treated groups exhibit similar trends in the dependent variables. However, firms become GS in different years,

[41] Here the initial export revenue means the export revenue at the earliest year that firm ever exported from 2000-2015.

posing challenges for rigorous matching techniques. Fortunately, Imai, Kim and Wang (2021) proposed a matching method in this context.[42] The details of the matching process, the examination of both the balance of covariates, and the parallel trend assumption can be found in Appendix C.

The average treatment effect (ATT) of GS on export quality is plotted in Figure 9. The x-axis shows the 0-2 periods after becoming GS. The y-axis represents the estimated ATT. When using the Mahalanobis distance approach to match control groups, ATT is 0.055 at t=0, 0.058 at t=1, and 0.10 at t=2. When using the propensity score weighting approach, ATT is 0.053 at t=0, 0.076 at t=1, and 0.13 at t=2. These coefficients are significant at the 1% level except for the coefficient, 0.058, estimated using the Mahalanobis distance method, significant at the 5% level. The magnitudes of the estimates, 0.058 and 0.076, are smaller than the event-study's β_1, 0.15, possibly because the TSCS matching approach correct for the biases from unobserved firm capability. Taken together, conservatively, the estimated ATT of GS stands at 0.053-0.055 right after becoming GS, reaching 0.058-0.076 at one period after becoming GS and 0.10-0.13 in two periods after becoming GS. Our DiD estimator shows the robustness of our results.

Fact 3. Conditional on Survival, Most Firms Become GS Within the First Two Years After Formation While Some Choose to Wait and Signal.

We now turn our attention to the timing of firms becoming GS during their lifecycles. The earlier a firm is established, the longer it may become a GS firm. Therefore, we compare the timing of becoming GS within each age cohort. We observe firms that survived until 2018 and were GS firms in 2018. The Alibaba Data show how long they have been established and how long they have been a GS firm.[43]

$$Share(G = k|Age = h) = \frac{Frequency(G = k, Age = h)}{\sum_{k>0} Frequency(G = k, Age = h)} \tag{8}$$

where $Frequency(G = j, Age = k)$ is the number of firms with GS year j and age k.

The conditional distribution of G given age is shown in Figure 11. For $k = 1$, one-year-old firms should all be GS so that they can be observed in the data. Among two-year-old firms in the data, 71% choose to signal only in the second year after their birth, 29% choose to signal immediately after they were born and continued signaling

[42] They overcome many shortcomings of previous methods, such as dependence on parameter assumptions, and few tools to detect matching quality (Imai, King and Stuart, 2008; Imai, Kim and Wang, 2021).

[43] Age=2019-Firm Established Year, the year the firm became GS=2019-G

for two periods. Note that firms that quit GS certification before 2018 were not included in the data. For $k = 4$ to 9 cohorts, the data show a clear U-shape; for each age cohort, firms that just became GS and firms that waited for one period after birth and then continuously signaled both accounted for a large share.

In Nov 2008, in the wake of the financial crisis, Alibaba.com introduced a 2,900 USD GS plan to supplement the previous 7,300 USD plan. This explains the large share of firms registered as GS in GS Year 10 (2009). Henceforth, we focus on GS entering since 2012 because, starting in 2012, the criteria for becoming a GS remained relatively stable.[44]

[Insert Figure 11]

Fact 4. Online Sales Increase with Years of Being Certified

Finally, we examine the relative sales of GS conditional on the years of signaling, that is, the years of GS. Relative sales are defined as the mean of mid-point online sales for each age cohort relative to the mean of mid-point online sales for $G = 7$ group:

$$Relative\_sales_k = \frac{\overline{sales_f(G = k)}}{\overline{sales_f(G = 7)}}, k = 1, 2, \ldots, 7 \tag{9}$$

[Insert Figure 10]

Figure 10 shows that online sales increases with years of certification as a GS, and the positive slope declines as GS year increases. We will rationalize this fact using our model.

In the next section, we use theoretical models to study the relationship between quality and firms' signaling decisions, and further consider firms' investment in quality upgrading.

5 Model

We first build a static model incorporating information asymmetry and signaling, extending the framework in Feenstra and Romalis (2014). The prediction from the model

[44] Beginning in the fourth quarter of 2011, the Gold Supplier membership fee for entry-level GS is 29,800 RMB. Please see page 15, Alibaba.com Announcement of Annual Results for the Year Ended December 2011: `https://www1.hkexnews.hk/listedco/listconews/sehk/2012/0221/ltn20120221171.pdf`, accessed June 2023. Moreover, in October 2011, Alibaba introduced the Onsite Check which required the premises of firms to be checked by Alibaba.com's staff to ensure onsite operations. Please see: `https://www.alibabafaq.com/faq2_what-is-onsite-check-202.html`, accessed February 2023.

is verified. Next, motivated by the need to model the selection process, we build a dynamic model further considering firms' decisions to upgrade their quality. The key assumption in the model is that the cost of signaling is higher for lower quality firms (single-crossing property).

5.1 A Static Model

5.1.1 Demand

A producer of good ω has quality θ_ω. Each producer only produces one good. The representative consumer can not observe firm quality θ_ω[45], but forms an expectation of quality, $E(\theta_\omega|g_\omega)$, based on the binary signal g_ω that a firm sends, i.e. whether it obtains a GS certification. $E(\theta_\omega|g_\omega)$ is also the belief function in this signaling game. $\mathbf{g}$ denotes the vector of signals that all firms send.

The consumer has income I and consumes q_ω units of each good. $\sigma > 1$ denotes the constant elasticity of substitution. Hence, the consumer's utility is:

$$U = E(\int q_\omega^{\frac{\sigma-1}{\sigma}} \theta_\omega d\omega|\mathbf{g}) = \int_\omega [q_\omega^{\frac{\sigma-1}{\sigma}} E(\theta_\omega|g_\omega)]d\omega \tag{10}$$

Maximizing the consumer's utility subject to a budget constraint $\int_\omega p_\omega q_\omega d\omega = I$, we have the demand function:

$$q_\omega = I[\frac{p_\omega}{E(\theta_\omega|g_\omega)}]^{-\sigma} P^{\sigma-1} \tag{11}$$

where $P = (\int_\omega p_\omega^{1-\sigma}[E(\theta_\omega|g_\omega)]^\sigma d\omega)^{\frac{1}{1-\sigma}}$ is the aggregate price index. It shows that the quantity sold increases in the consumer's expectation of firm quality, holding other variables fixed. For simplicity, we now suppress the notation for ω.

5.1.2 Supply

Nature draws the firm's initial quality type θ from a probabilistic distribution function $f(\theta)$, $\theta \in [\underline{\theta}, \overline{\theta}]$. Firms operate under monopolistic competition. The firm chooses price p and whether to signal g. If the firm chooses to signal, $g = 1$; otherwise $g = 0$. It is more costly for low quality firms to signal as a GS. Hence, the cost of signaling is $s(\theta)$, where $s'(\theta) < 0$ and $s(0) > 0$. For simplicity, assume that the marginal cost is

[45] Quality is not observed before consumption for experience goods (Nelson, 1970) and is expensive to judge for credence goods (Darby and Karni, 1973). Moreover, the difficulty of determining the suppliers' trustworthiness is also an important source of information asymmetry.

constant for all firms, denoted by κ. $\kappa = \tau \cdot c$ where c denotes the marginal cost of production and τ denotes the iceberg trade cost.

Hence the firm's profit is revenue minus production cost and signaling cost:

$$\pi = (p - \kappa) \cdot I[\frac{p}{E(\theta|g)}]^{-\sigma} P^{\sigma-1} - s(\theta) \cdot g \tag{12}$$

Maximizing the firm's profit, we have $p = \frac{\sigma\kappa}{\sigma-1}$. Substitute it into equation (12), we have:

$$\pi = B[E(\theta|g)]^{\sigma} - s(\theta) \cdot g \tag{13}$$

where $B \equiv I\sigma^{-\sigma}(\sigma-1)^{\sigma-1}\kappa^{1-\sigma}P^{\sigma-1}$.

In the next section, we define the equilibrium concept for the signaling game, then solve for firms' optimal signaling choices.

5.1.3 Equilibrium

We now define the Perfect Bayesian Nash Equilibrium (PBNE) for this signaling game between firms and the representative consumer:

Definition 1. The set of firm signaling decisions given their type $g(\theta)$, the consumer's demand function $q(g)$ and her beliefs $E(\theta|g)$ constitutes a PBNE if:

(i) The firms' signaling decisions are optimal given the consumer's demand function.

(ii) The consumer's demand function is optimal given the firms' signaling decisions.

(iii) The belief function is derived from the firms' signaling decisions using Bayes' rule where possible.

Two types of equilibria exist: partially separating equilibria and pooling equilibria.[46] Denote $g(\theta)$ as the optimal signaling decision for firm with quality θ. Now we examine the conditions for each equilibrium. All proofs for the following propositions can be found in Appendix D.

Proposition 1 (A partially separating equilibrium): Consider the class of partially separating equilibria where higher-quality firms signal and lower-quality firms do not. An equilibrium in this class is defined by a cutoff θ^* such that $g(\theta) = 1$ for $\theta > \theta^*$ and $g(\theta) = 0$ for $\theta < \theta^*$. The type θ^* is indifferent between signaling and not signaling.

Proposition 2 (Pooling equilibria): Two pooling equilibria exist. First, a pooling equilibrium where firms do not signal exists if $\pi_1 < \pi_0$ and $\pi_1 > 0$, $\forall\, \theta$. Second, a

[46] A fully separating equilibrium does not exist because we have binary signals but continuous types. In a partially separating equilibrium, we can still tell that signaling firms are relatively high-quality ones.

pooling equilibrium where firms all signal exists if $\pi_1 > \pi_0$ and $\pi_0 > 0, \forall\, \theta$.

It is important to bear in mind that, holding other parameters fixed, when the signaling cost is too high or too low, we will live in a pooling equilibrium where quality is indistinguishable. We examine the case where a partially separating equilibrium exists because in reality, after Alibaba.com launched its GS certification policy, we observe some firms signal while others do not. In other words, due to the reduction in signaling costs brought by Alibaba.com, the economy has moved from a pooling equilibrium to a partially separating one. In the next section, we examine the prediction from Proposition 1 in the data.

5.1.4 Connecting Model with Data

Proposition 1 shows that in a separating equilibrium, high-quality firms signal while low-quality firms do not. However, if we try to examine this prediction in all Chinese Customs data, we would face a selection issue because all the GS firms matched in the Customs data are firms that survived till 2018, and it is not certain that the unmatched firms in the Chinese Customs data are not GS and whether they survived till 2018. Thus, we also focus on all GS firms to alleviate this bias. The all GS sample includes GS firms that registered as GS before 2015 and registered as GS from 2015-2018. Thus the comparison is among those firms that would ultimately become GS and we can make sure that they all survive till 2018.

A firm f in industry i is located in city r.[47] The outcome variables gs_{ft} is a dummy variable indicating whether firm f is a GS in year t. $quality_{ft}$ includes $quality\_ksw$ and $quality\_kswp$ defined in Section 3.4. We include firm and city-industry-year fixed effects, indexed by α_f and α_{rit} respectively. Standard errors are clustered at the firm level to account for possible serial correlations across time. To alleviate the selection issue, we look at the entire Customs data from 2000-2015 and the GS firms sample separately. We run the following regression in the two samples:

$$gs_{ft} = \alpha_f + \alpha_{rit} + quality_{ft} + \epsilon_{ft} \tag{14}$$

The results reported in Table 7 show that higher quality firms tend to become GS no matter in all Customs data or in GS firms data.

[Insert Table 7]

So far, the prediction from a static model has been examined. Motivated by the

[47]Industry i is defined by the largest HS2 sector that the firm imports and exports from 2000-2015.

need to model the selection process in our data and consider accumulative signals, in the next section, we build a dynamic model further incorporating firm investment and signaling decisions during their lifecycles.

5.2 A Dynamic Model

In a dynamic setting, firms not only choose prices and signaling decisions but also choose a non-negative amount of investment x used in quality upgrading. Thus a dynamic model helps to capture the joint decision of a firm to signal quality and to invest in quality. In the data, the total years of signaling can be observed, which is the result of the signaling choices that firms make in each period. In each period, events occur in the following order:

1. The representative consumer forms an expectation of quality at the beginning of period t.

2. Conditional on the consumer's expectation of quality, incumbent firms make signaling and investment decisions and then face the exit shock. Signaling and investment decisions made in period t are realized at the begining of period $t+1$.

3. Entrants enter and the process of entry takes a full period. Entrants in period t become incumbents at the begining of period $t+1$.

If the firm chooses to signal at this period, $g = 1$; otherwise $g = 0$. Denote the total signaling years, or the years of being a GS, at the beginning of this period as G; the total signaling years at the beginning of next period as G'. In the model, if a Mainland firm chooses not to renew its GS membership, Alibaba deletes its profile next period[48], hence:

$$G' = \begin{cases} G + g, & g = 1 \\ 0, & g = 0 \end{cases} \tag{15}$$

For simplicity, we parameterize the cost of signaling $s(\theta)$ as $a_1 - a_2 \cdot \theta$, where $a_1 = a_3 + max(a_2 \cdot \theta)$ so that the total cost of signaling is positive for all quality levels. Think of it as two components: first, a fixed membership fee represented by the minimum of $a_1 - a_2 \cdot \theta$, defined as a_3; second, a differential signaling cost represented by the negative slope $-a_2$. Note that the signaling cost is larger for lower quality firms. The single crossing property makes high-quality firms more likely to signal.

Then we consider the investment decision. Following the parameterization in Ericson and Pakes (1995), the unit investment cost is c, transition probability $p(\theta'|\theta)$ is $\frac{bx}{1+bx}$

[48] In reality, Alibaba will delete its profile within 1 or 2 years. Without loss of generality, here we assume Alibaba deletes its profile next period in our model.

for moving to the next higher quality, $\frac{1}{1+bx}$ for staying at the same quality, where b governs the likelihood of upgrading. For simplicity, we abstract away the interactions between firms in Ericson and Pakes (1995).

Therefore, in the partial equilibrium, firm profit is sales revenue minus production cost, signaling cost and investment cost:

$$\begin{aligned}\pi(\theta, G, x, g) = A(p-\kappa)\cdot p^{-\sigma}[E(\theta|G)]^{\sigma}P^{\sigma-1} - s(\theta) - cx \\ = B[E(\theta|G)]^{\sigma} - s(\theta) - cx\end{aligned} \tag{16}$$

where $B \equiv A\sigma^{-\sigma}(\sigma-1)^{\sigma-1}\kappa^{1-\sigma}P^{\sigma-1}$ and $p = \frac{\sigma\kappa}{\sigma-1}$.

The Bellman equation is:

$$V(\theta, G) = max_{x,g}\{\pi(\theta, G, x, g) + \beta' E(V(\theta', G'|\theta, G))\} \tag{17}$$

where $\beta' \equiv \beta(1-\delta)$ and δ denotes the exit rate. In the model, only firms with $G = 0$ enter in each period.

5.3 Equilibrium

In equilibrium, we assume that firms have rational expectations. In this equilibrium, first, the representative consumer maximizes its utility as per equation (10); second, firms make signaling, investment and price decisions as per equation (17); third, the consumer's conditional expectation of firm quality given total years of signaling, $E(\theta|G)$, coincides with the result of firms' decisions, hence:

$$E(\theta|G=k) = \int \mu(\theta|G=k)\cdot\theta d\theta,\ k = 0, 1, ..., K \tag{18}$$

where $\mu(\theta|G=k)$ is the conditional probability of firm quality given G and K is the total number of quality levels.[49] Firms at period t consist of entrants from t_e, t_e=0, 1, 2,...., N. In the data, GS in 2018 consist of entrants in 2018 which became GS in 2018, entrants in 2017 which became GS in 2017 or 2018, so on so forth.[50] Moreover, at each period, incumbents face a constant exit rate δ.

To simplify the analysis, firms entering at different periods are expected to face the same conditional expectation and thus have the same decision rules. This condition

[49] In computation, we discretize quality into K different levels.

[50] Firms that became GS in the past but opt out of GS before 2018 can not be observed in our data. Thus, entrants in 2017 which became GS in 2017 or 2018 refer to entrants in 2017 which became GS in 2017 and renewed its membership in 2018 as well as entrants in 2017 which only chose to become GS in 2018. The same logic applies to entrants in other years.

holds under the following assumption: the economy starts at period 1 with m total mass of entrants and the total mass of entrants grows at a constant rate λ. Therefore, the mass of entrants that entered T periods ago vanishes to a sufficiently small number when T is sufficiently large and thus the conditional expectation of quality remains constant. The following proposition formalizes this argument.

Proposition 3 (Constant Expectation): A sufficient condition for a constant conditional expectation $E(\theta|G)$ across different periods is that the total mass of entrants grow at a constant rate of λ and exit at a rate of δ, where λ^{n-T} is limited and $\delta^T \to 0$. The proof can be found in Appendix D.

In the steady-state, $E(\theta|G)$ is time-invariant. At least two types of equilibria exist: first, pooling equilibria where all firms signal or all firms do not signal; second, a partially separating equilibrium where some firms signal and others do not. In the data, we observe a partially separating equilibrium and this is the focus of the paper.

6 Structural Estimation

In this section, we estimate the model using the Simulated Method of Moments (SMM) (McFadden, 1989) to match the moments in the data. We introduce exogenous parameters, the moments we match and the parameters estimated. Computation procedures can be found in Appendix E.

6.1 Exogenous Parameters

In this section, we set up the exogenous parameters in the model.

States We use 10 quality levels uniformly drawn between 0.1 and 1.[51] We chose $G = 0, 1.., 8$ for two reasons: first, since 2012, firms have faced relatively stable membership fee and the largest GS year that firms can reach in 2018 is 7 in the data; second, in the model, once firms reach the maximum GS year, they can not exceed it even if they still choose to signal. In other words, firms accumulate at the highest GS year. This is the data moment that we don't match because it differs from reality. Thus the maximum of G is set to 8 for ease of computation.

Quality Distribution of Entrants The quality distribution of entrants is taken from the Customs data. After calculating firm quality using the KSW approach, we normalize the quality measure betweeon 0 and 1 by by dividing the quality measure by the difference between its maximum and minimum. Entrants are defined as firms

[51] Similarly, Ericson and Pakes (1995) use intergers to represent different levels of firm quality. In our robustness test, using different number of quality levels does not significantly alter our result.

that did not export last period but export during this period. Then we divide firms into 10 quality bins by the quality measure and calculate the shares of entrants within each bin and average them from 2012 to 2015 as the quality distribution of entrants that was fed into our model.

Elasticity Following the median elasticity estimated by Broda, Greenfield and Weinstein (2006), we set the elasticity of substitution σ to 3.4. Our results remain robust when considering alternative values of elasticity, such as 4 as in Melitz and Redding (2015) and 5 as in Fan et al. (2018).

Market Size In the model we assume that marginal cost is constant across firms as in Klette and Kortum (2004).[52] From equation (16), the revenue is $B[E(\theta|G)]^{\sigma}$, where $B \equiv A\sigma^{-\sigma}(\sigma-1)^{\sigma-1}\kappa^{1-\sigma}P^{\sigma-1}$ and $p = \frac{\sigma\kappa}{\sigma-1}$. To simplify the analysis, we assume firms face the same market demand and normalize B to 1 for all firms. B remains constant for all firms when $AP^{\sigma-1}$ also remains constant. Thus, the difference in revenue among firms come from expectation $E(\theta|G)$ only.

Entry and Exit We take calculate λ, the growth rate of the new entrants from 2012-2015 Chinese Customs Data, which is 0.14. We calculate the exit rate as the number of firms no longer exist next period relative to the total number of firms from the same period, which is 0.18.

Fixed Signaling Cost Under the above assumptions of quality bins and market size, the maximum sales profit that a company can achieve is normalized to 1. The actual signaling cost is 4649 USD.[53] From the Alibaba.com data, the average mid-point export sales in the past six months for firms establishing since 2012 is 31,399.11 USD, thus a_3 is set to 0.0740.[54]

In the next section, we introduce the parameters estimated using the SMM in our model.

6.2 Moments and Parameter Estimation

The parameters that remained to be estimated include signaling cost a_2, investment cost c and transition parameter b. The differential signaling cost affects firms' signaling decisions while the investment cost and transition parameter affect firms' invesmtent and signaling decisions: when investment cost is lower and transition probability is higher, it is easier for firms to upgrade and signal as GS; these two parameters affect

[52] Under CES demand, firms set prices as a constant markup over marginal cost. Thus, firms' prices do not differ. We can not observe online prices from our data, thus we abstract away the price variations.

[53] 29800 RMB/6.41 where 6.41 is the average official exchange rate for RMB from 2012-2018. Exchange rate data come from World Development Indicators of the World Bank.

[54] 29800/6.41/(31399.11*2)=0.0740, here we simply assume the full-year online sales is twice of half-year sales.

the quality distribution of GS for each GS year and thus the relative sales.

Therefore, three sets of moments are used to estimate the three parameters:

1. Firms' timing of becoming GS as defined in Equation (8);

2. The relative sales of GS firms conditional on how long they have been a GS as defined in Equation (9).

3. The distribution of firm quality in different quality bins.

The first and second moments are calculated from the Alibaba Data while the third moment is calculatd from 2012–2015 Chinese Customs Data. After calculating firm quality using the KSW approach, we normalize the quality measure by dividing it by the difference between its maximum and minimum. Then we divide firms into 10 quality bins by their quality measure and calculate the shares of firms within each bin every year and average them from 2012 to 2015 as our third moment, the distribution of firm quality.

Denote ψ as the vector of parameters to be estimated. The Simulated Method of Moments (SMM) chooses parameters ψ to minimize the distance between the model moments and the data moments. The SMM estimator is given by

$$\hat{\psi} = \underset{\psi}{argmin}\, g(\psi)' W g(\psi) \tag{19}$$

where $g(\psi) = m(\psi)_{data} - m(\psi)_{sim}$, $m(\psi)_{data}$ is a vector of moments from the data and $m(\psi)_{sim}$ is a vector of simulated moments from the model. Following Benhabib, Bisin and Luo (2019), the weighting matrix is a diagonal matrix with identical weight.[55]

We calculate standard errors of our parameter estimate using numerical derivatives, which is standard procedure in the literature. The variance-covariance matrix for our parameter estimate is:

$$Q(W) = \left[\frac{\partial m(\psi_0)_{sim}{}'}{\partial(\psi)} W \frac{\partial m(\psi_0)_{sim}}{\partial(\psi)} \right]^{-1} \tag{20}$$

where $\frac{\partial m(\psi_0)_{sim}{}'}{\partial(\psi)}$ is the derivative of the vector of simulated moments with respect to the parameter vector. Standard errors are the square roots of $Q(W)$.

In the next section, we show the estimation results and the match of the moments.

6.3 Estimation Results

The estimated parameters and their standard errors are reported in Table 8.

[55] See Altonji and Segal (1996) for a justification for adopting an identical weighting matrix.

[Insert Table 8]

Figure 12 shows the moment match of the timing of becoming GS given age cohorts. The moment is defined in Equation (8). The left panel shows the data moments and the right panel shows the corresponding model moments. As is clear in the graph, major patterns in the data are well captured by our simulated moments.

[Insert Figure 12]

Figure 13 shows the relative sales moment match. As is clear in the graph, both model and data moments shows that relative sales increase with GS year.

[Insert Figure 13]

Figure 14 shows the corresponding decision rules. The implication is that higher-quality firms signal immediately after birth, while lower quality firms need to invest in quality upgrading and signal their quality when they pass the quality threshold. It coincides with our static model prediction that higher-quality firms choose to signal.

[Insert Figure 14]

Table 9 shows that the estimated total signaling costs (a combination of fixed and differential costs) for the lowest quality bin are 17 times higher than that for the highest quality bin. Moreover, in our simulated model, the differential signaling cost constitutes an average of 1.4% of export revenue for firms with 8 GS years, while it substantially increases to 58.6% for firms with only 1 GS year. This finding underscores the significance of taking the differential signaling cost into account when analyzing firms' export behavior.

6.3.1 Model Validations

We validate our model using an untargeted moment in our data: the aggregate share of GS firms within each GS year. It is defined as:

$$AggregateShare(G = k) = \frac{Frequency(G = k)}{\sum_{k>0} Frequency(G = k)} \tag{21}$$

We plot the untargeted model moment and data moment in Figure 16. It is clear that the untargeted model moment captures the general trend of the data moment very well.

[Insert Figure 16]

6.3.2 Discussion and Robustness Checks

Alternative Theory

An alternative explanation for higher GS year having higher sales could be that firms with higher GS years are those firms that survive exit shocks for consecutive years and thus, they are naturally stronger firms. One may concern that it does not necessarily attribute the pattern to the signaling channel. However, when we plot our data moments within each age cohort in Figure 18, we still find that online sales generally rise with GS year. Thus, the pattern can not solely be explained by firm age.

[Insert Figure 18]

Signaling vs Online Review It is important to differentiate signaling from online review, an important reputation building channel. Reputation building by reviews usually does not have a single crossing property. Reviews are initiated by the consumer, but signaling is initiated by firms.

Robustness Checks Our parameter estimates does not change significantly when we consider alternative values of elasticity, alternative number of quality bins. Moreover, the pattern for the timing of GS does not change significantly when we consider specific industries. First, adopting elasticy 4 as in Melitz and Redding (2015), or 5 as in Fan et al. (2018), does not significantly alter our parameter estimates, as shown in Table 10. Second, using different quality grids, such as 8 or 12, as shown in Table 11 does not affect our estimates significantly either. Third, different industries exhibit similar trends regarding the timing of GS as shown in Figure 17.

[Insert Table 10, Table 11 and Figure 17]

In the next section, with the estimated parameters in hand, we conduct counterfactual analyses and quantify the significance of the signaling cost.

6.4 Counterfactual

We consider two counterfactuals to quantify the significance of the signaling mechanism: first, changing the differential signaling cost; second, changing the fixed signaling cost. For each counterfactual, we consider changes in average investment and total trade flows in our model.

6.4.1 Change the Differential Cost of Signaling

How would a change in the differential cost of signaling affect firm outcomes? An increase in the differential cost of signaling means that the cost difference between higher- and lower-quality firms to signal quality is greater, and it is easier for buyers to distinguish between them.

We found that the relationship between exports, investments and the differential signaling cost is not monotonic. When the differential cost of signaling is too high, that is, an increase of 4.4 times in our model, only the highest quality firm (those at the 10th quality grade) will find it profitable to signal. This is because they face the lowest differential signaling cost.

By contrast, in our simulated model, when the differential cost of signaling shifts to zero, given the current fixed cost of signaling, certification does not bring extra benefits to firms because it can not help distinguish firm quality. In this case, the economy falls into a pooling equilibrium where no firms signal and total trade flows fall by 8.51%. Note that total trade does not fall to zero because even though quality is indistinguishable, trade still happens under CES demand: higher- and lower-quality firms have the same market share. Specifically, a 1% reduction in the differential signaling cost will raise average investment by 18.2% and increases total trade flows by 1.50%.

6.4.2 Change the Fixed Cost of Signaling

How would a change in the fixed cost affect the equilibrium outcomes? In our model, if the fixed cost of signaling increases 2.65 times, the equilibrium will become pooling where no firms choose to signal because the cost of signaling is too high. In this case, total trade plummets by 8.51%. The representation consumer forms an expectation of firm quality based on the market average and we can not distinguish higher-quality firms from lower-quality ones. In less extreme cases, a 1% reduction in the fixed signaling cost will raise total investment by 7.24% and boost total trade by 0.58%.

In summary, these counterfactuals highlight the significance of signaling costs. First, a 1% reduction in the differential cost of signaling raises total investment in quality by 18.2% and increases total trade by 1.50%, and a 1% reduction in the fixed cost of signaling raises total investment in quality by 7.24% and total trade by 0.58%. Second, when the differential cost decreases to zero or when the fixed cost increases 2.65 times, we fall into a pooling equilibrium where no firms signal, and total trade plummets by 8.51%.

7 Conclusion

In this study, we documented how Alibaba.com, a global B2B platform, helps firms overcome information friction through its certification policy. We argue that certification policy, as a signaling technology, distinguishes higher-quality from lower-quality firms, thus incentivizing quality upgrading.

This study provides a new perspective for understanding information friction: the cost of signaling quality. We showed that the various signals that firms send online are positively associated with firm sales, and that certification boosts firm export revenue, the number of export varieties, the number of export destinations, and firm export quality. We also documented the signaling behavior during a firm's lifecycle. We estimated the cost of signaling quality and quantified how changes in both differential and fixed signaling costs can affect firm investment and total trade, and even shift the market equilibrium.

Empowering SMEs is a global mission emphasized by many countries.[56] This is particularly important for developing countries plagued by information frictions. Fortunately, in the digital economy, e-commerce certification policies provide valuable opportunities for SMEs to signal their quality online. This finding has significant implications for helping SMEs grow in global markets. Our study is subject to a few caveats. First, we did not observe firms' online prices, thus we cannot speak much about signaling through prices. Second, we abstract away the consumer search and matching process from our model because we could not directly observe it in the data. Future research could seek to enhance our understanding of how the different online signals interact with each other and their impact on firms' online matching outcomes and their entry into new markets.

[56] See UNCTAD news: `https://unctad.org/en/pages/newsdetails.aspx?OriginalVersionID=1350`, accessed July 2023.

Appendices

A Figures

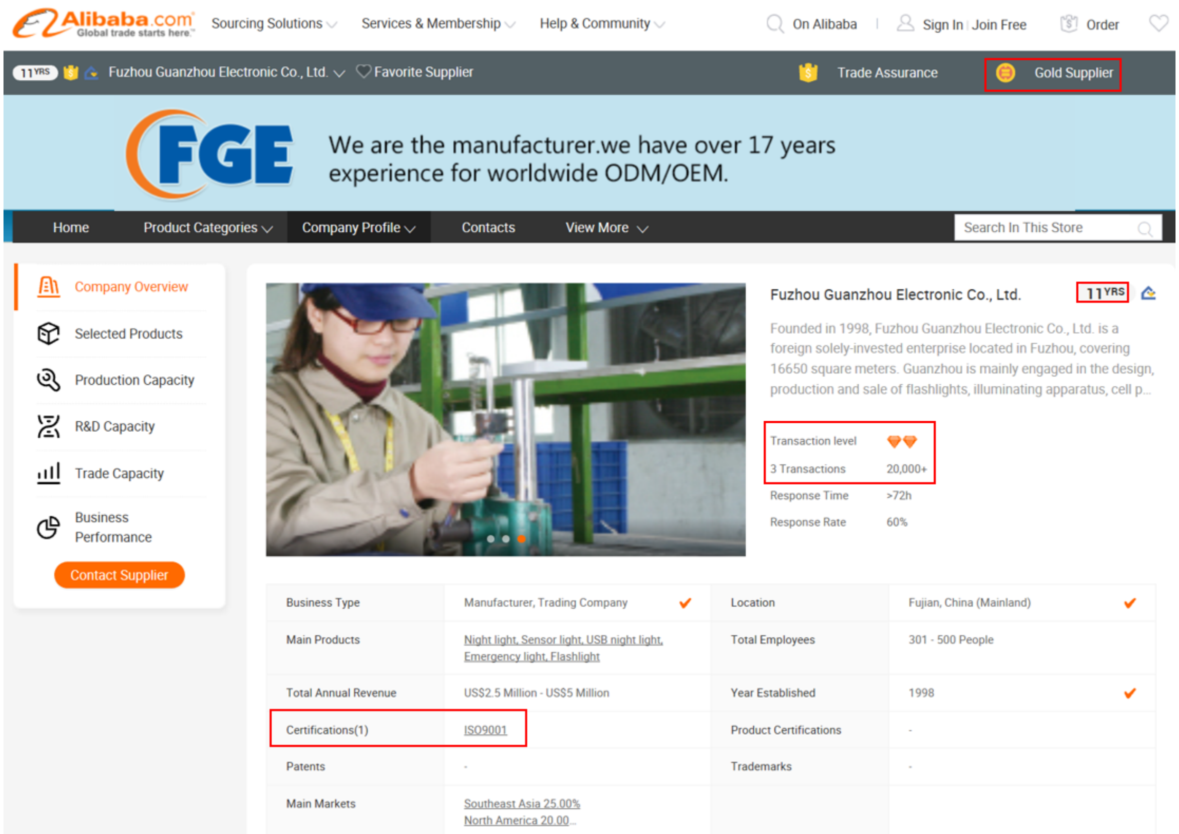

Figure 1: An Overview of a Gold Supplier

Notes: The company profile of a Gold Supplier shows that the company has 11 years of GS certification, over 20,000 USD transaction value in the past six months, has an ISO9001 certificate. The company is a manufacturer and a trading company, located in Fujian, China. Information with a tick means that this information is verified by a third-party verification agency.

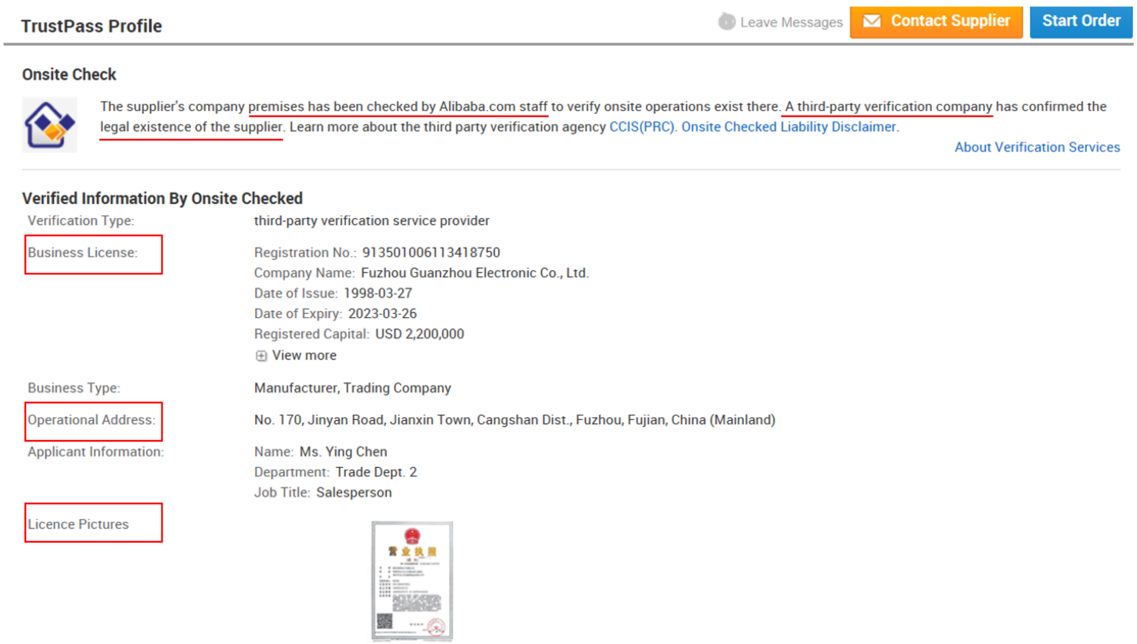

Figure 2: TrustPass Profile of a Gold Supplier

Notes: The TrustPass Profile of the Gold Supplier shows that the company's premises have been checked by Alibaba.com staff and a third-party verification company has confirmed the legal existence of the supplier. The company's business license, operational address, and the license picture are shown too. This is how certification helps companies overcome information frictions online.

Figure 3: Geographic Distribution of New Gold Suppliers in 2017

Notes: This figure shows the top 10 locations for new GS in 2017. Higher bar indicates larger number of new GS in this city. Shenzhen, Guangzhou, Dongguan, the top 3 cities are famous manufacturing and trade hubs in China.

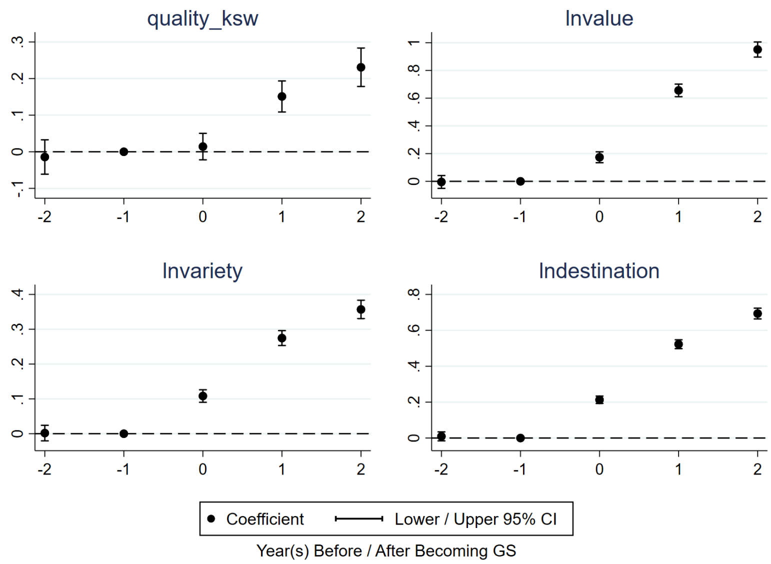

Figure 4: Event Study Estimates

Notes: This figure shows the coefficients, β_k, estimated from equation (7) and their 95% confidence intervals (CI). The sample is GS firms. $k = -1$ is excluded and serves as the default category. The coefficients show the change in outcome variables at event time t relative to those at one period before becoming GS. The results show that all β_{-2} are insignificant, suggesting that firms before becoming GS have little rising or falling pre-trends. Firms one period after becoming GS witness 0.15 unit increase in export quality, 65.6% increase in export revenue, 27.5% in the number of varieties, 52.3% increase in the number of destinations.

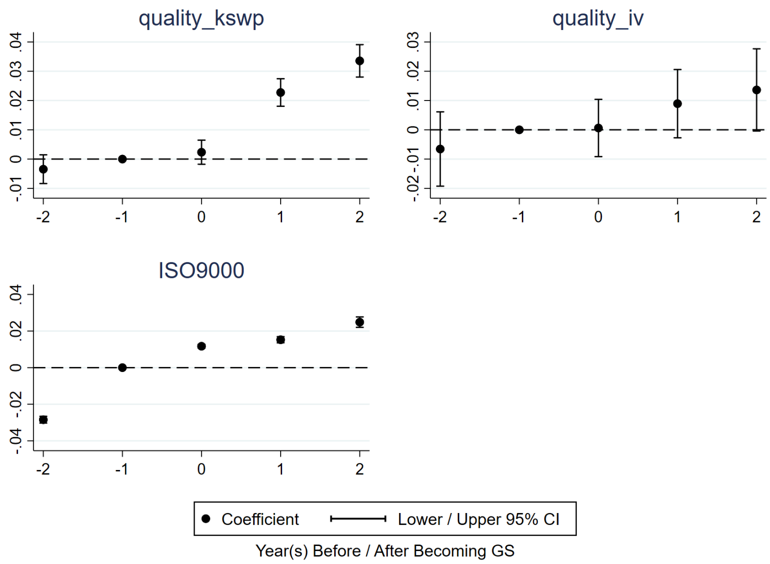

Figure 5: Event Study Estimates: Alternative Quality Measures

Notes: This figure shows the coefficients, β_k, estimated from equation (7) and their 95% confidence intervals (CI). The sample is GS firms. $k = -1$ is excluded and serves as the default category. The coefficients show the change in outcome variables at event time t relative to those at one period before becoming GS. The figures shows that firm export quality increases after becoming GS when considering alternative measures of quality.

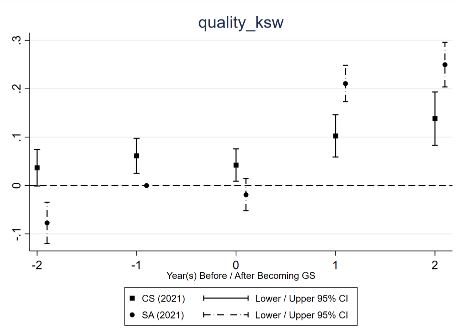

Figure 6: Event Study Estimates: CS (2021) and SA (2021) approach

Notes: This figure shows that the rising trend of our event-study estimates remained robust after adopting the adjustments in Callaway and Sant'Anna (2021) and Sun and Abraham (2021). CS refers to Callaway and Sant'Anna and SA refers to Sun and Abraham in the figure.

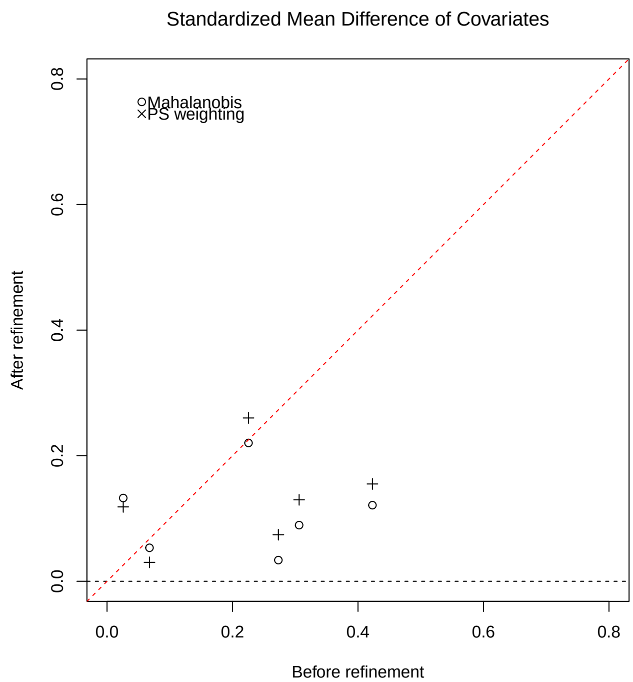

Figure 7: Mean Difference before and after Refinement

Notes: The x-axis represents the balance of each matching variable in the unrefined matching set in the past periods, and the y-axis represents the balance of the refined matching set. Both are in absolute values. The red dashed line is a 45-degree line, the dots represent the balance of Mahalanobis distance matching, and × represents that of the propensity score weighting method. The point at the lower right of the red line indicates that the balance of the matching set has been improved after refinement. This figure shows that most of the points are located at the lower right of the red line, and the balance is improved after refinement. The average difference after refining and matching does not exceed 0.25. In general, the two matching methods have exhibited high matching quality.

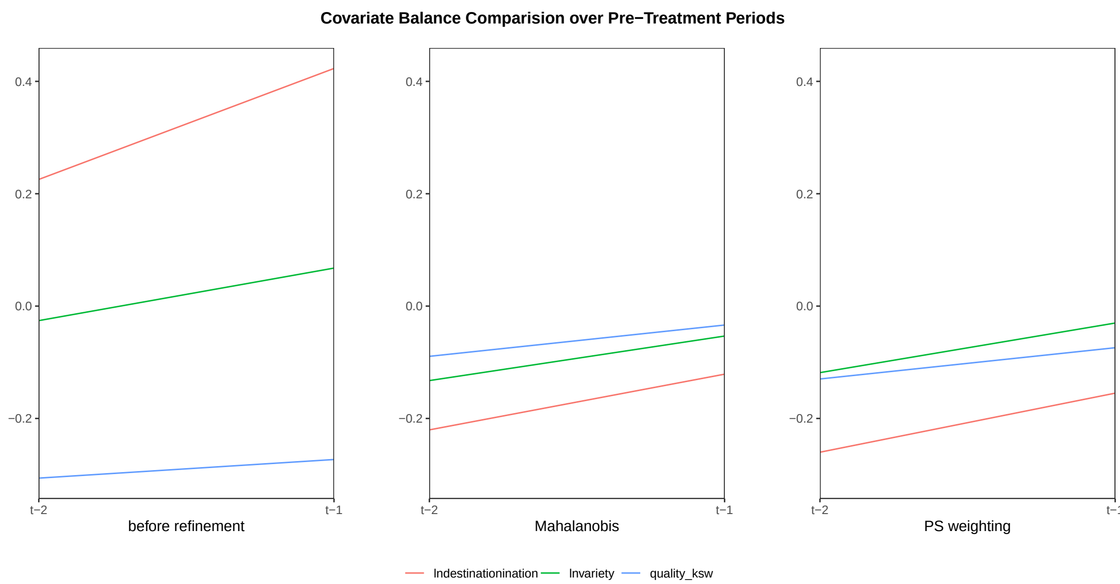

Figure 8: Covariate Balance

Notes: We examine the parallel assumption by drawing the balance changes in the matching covariates following Imai, Kim and Wang (2021). The blue line is our most concerned export quality. It is clear from the figure that the balance of export quality remains stable and close to zero, indicating that the parallel trend assumption is satisfied.

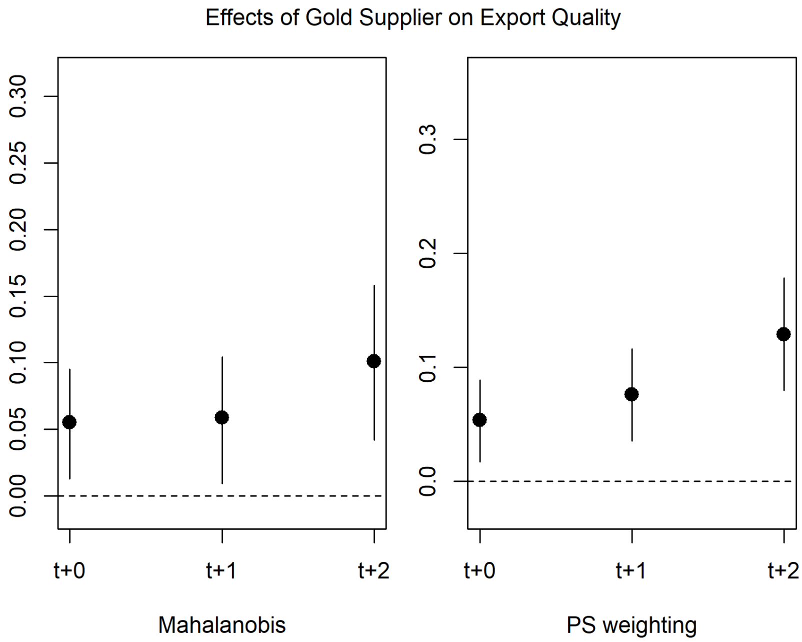

Figure 9: Average Treated Effect

Notes: This figure shows the ATT of GS after Mahalanobis and PS weighting matching respectively. The results show that, using Mahalanobis matching, after one year of becoming GS, firm export quality increases by 0.058 unit. Using PS weighting matching, the estimate is 0.076.

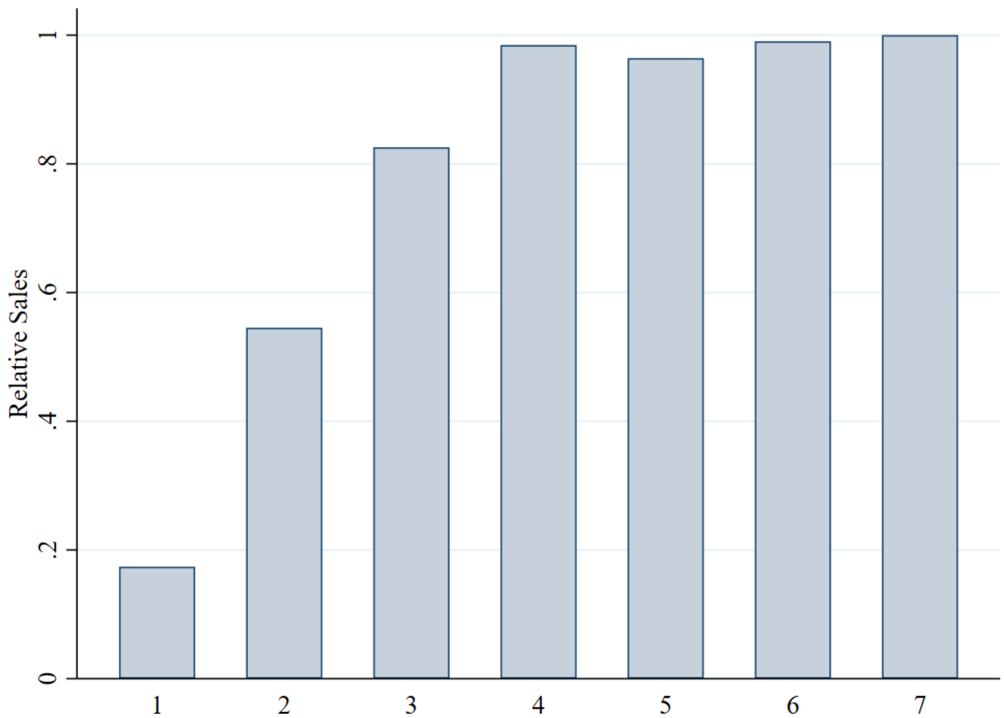

Figure 10: Relative Sales

Notes: This figure shows that online sales (measured by mid-point value) relative to the cohort with 7 GS Year by each GS Year cohort.

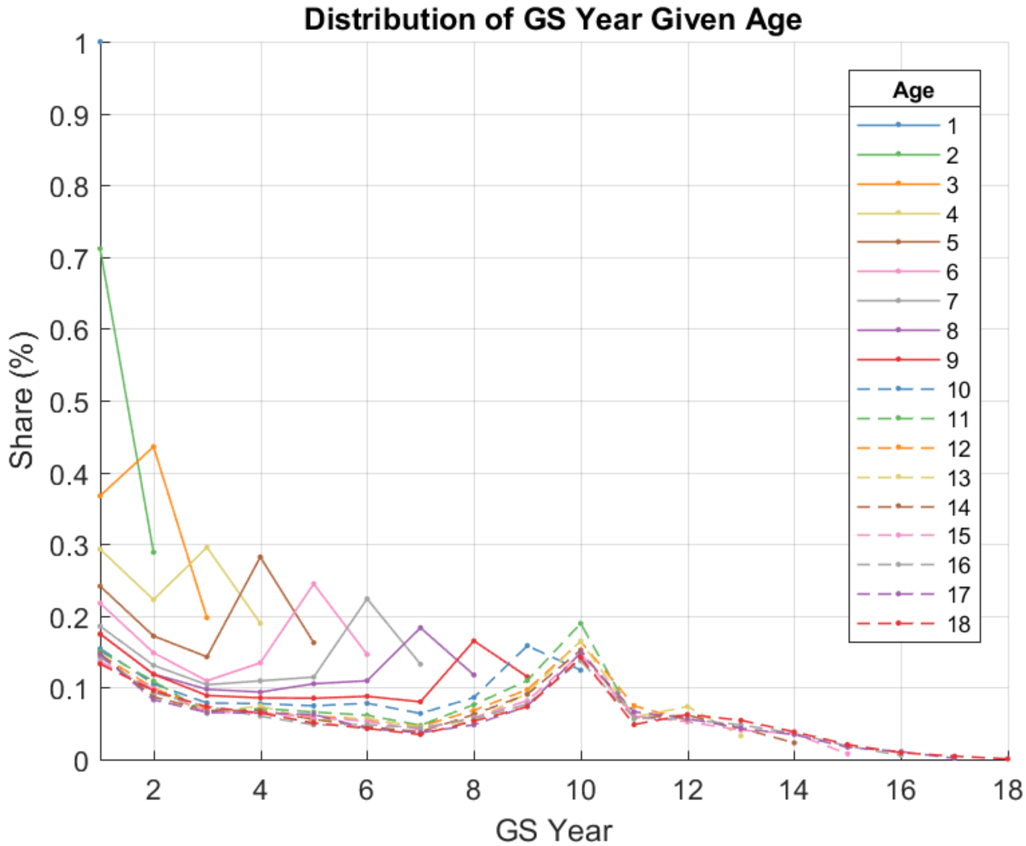

Figure 11: Distribution of GS Year Given Age

Notes: This figure plots the conditional distribution of G given age defined as $Share(G = j|Age = k) = \frac{Frequency(G=j,Age=k)}{\sum_{j>0} Frequency(G=j,Age=k)}, j > 0$ where $Frequency(G = j, Age = k)$ is the number of firms with GS year j and age k. For k=1, due to how we collected the data, 1-year-old firms should all be GS so that they can be observed in the data. Among 2 years-old firms in the data, 71% choose to signal only in the second year after their birth, 29% choose to signal right after they were born and continue signaling for two periods. Note that firms that quit GS before 2018 are not observed in the data. For k=4 to 9 cohorts, the data show a clear U-shape: for each age cohort, firms that just became GS and firms that waited for one period after birth and then continuously signaled both accounted for a large share. In Nov 2008, in the wake of the financial crisis, Alibaba.com introduced a 2,900 USD GS plan to supplement the previous 7,300 USD plan. This explains the large share of firms registered as GS at GS Year 10 (2009).

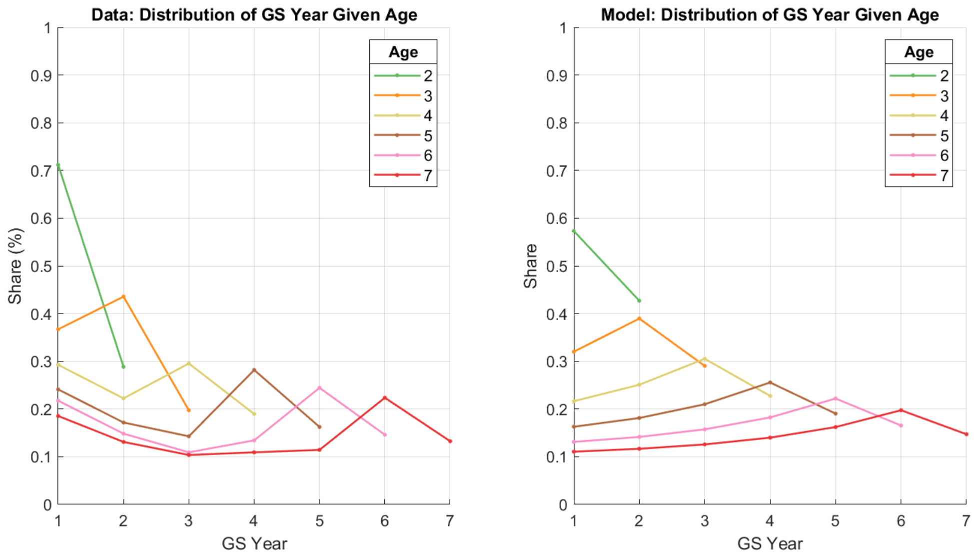

Figure 12: Moment Match

Notes: This figure illustrates the distribution of the timing of becoming GS after birth given age cohorts. As is clear in the graph, major patterns in the data are very well captured by our simulated moments.

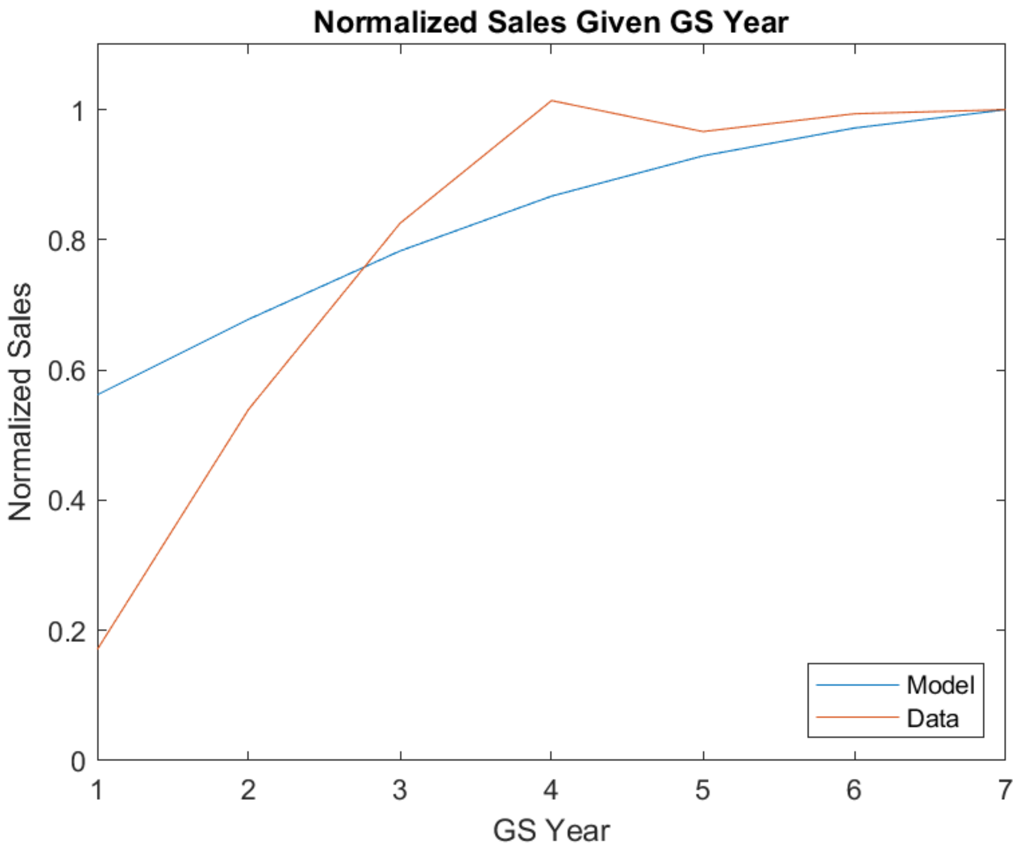

Figure 13: Relative Sales Moment Match

Notes: This figure shows that relative sales are well matched by the simulated moments.

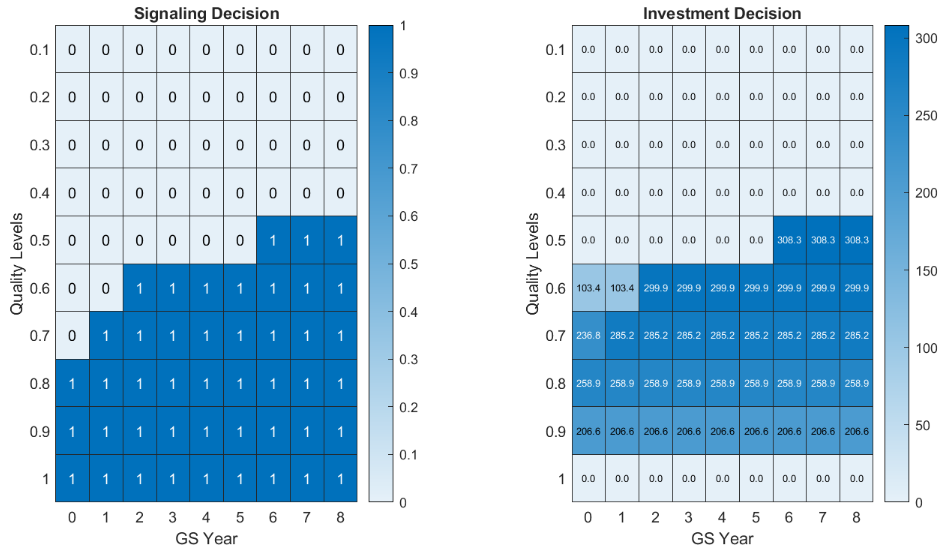

Figure 14: Signaling and Upgrading Decisions

Notes: This figure shows the corresponding decision rules. The implication is that higher-quality firms signal immediately after birth, while lower quality firms need to invest in quality upgrading and signal their quality when they pass the quality threshold.

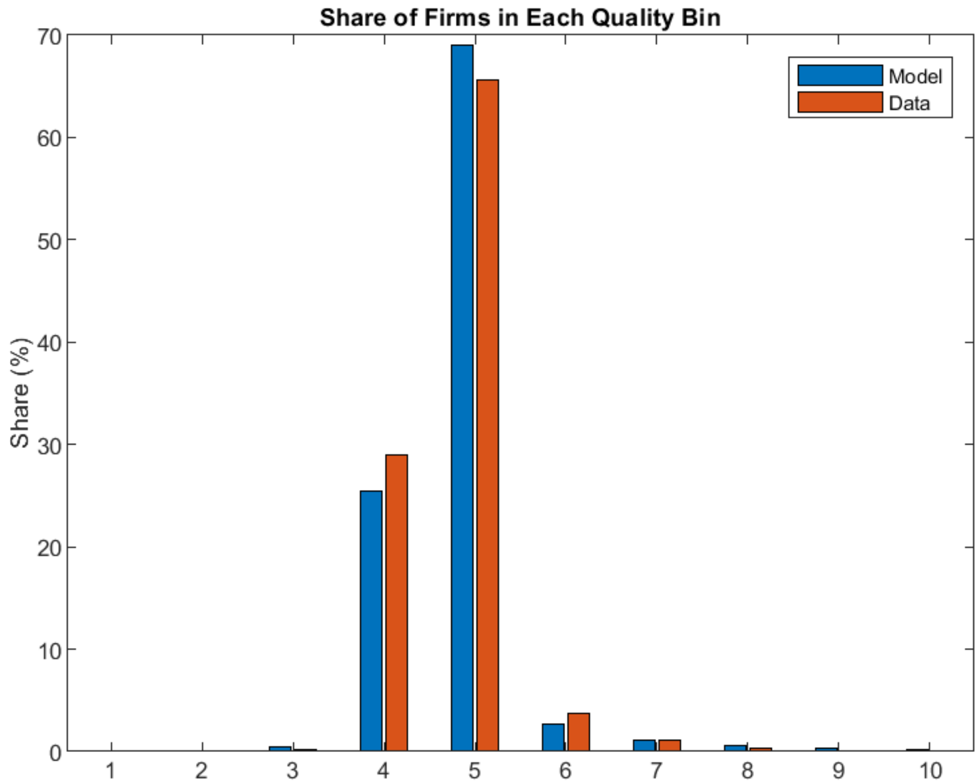

Figure 15: Signaling and Upgrading Decisions

Notes: This figure shows the moment match for aggregate quality distribution.

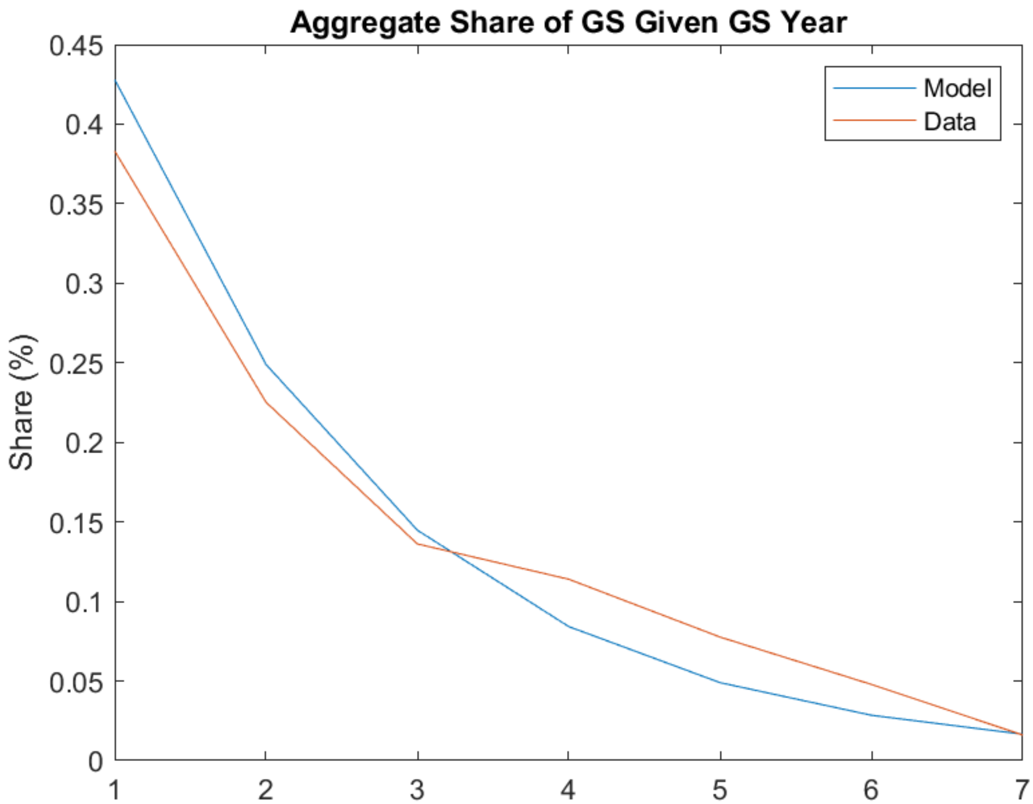

Figure 16: The Untargeted Moment: Aggregate Share of GS in Each GS Year

Notes: This figure shows that model moment match the untargeted data moment: the aggregate share of GS firms in each GS year.

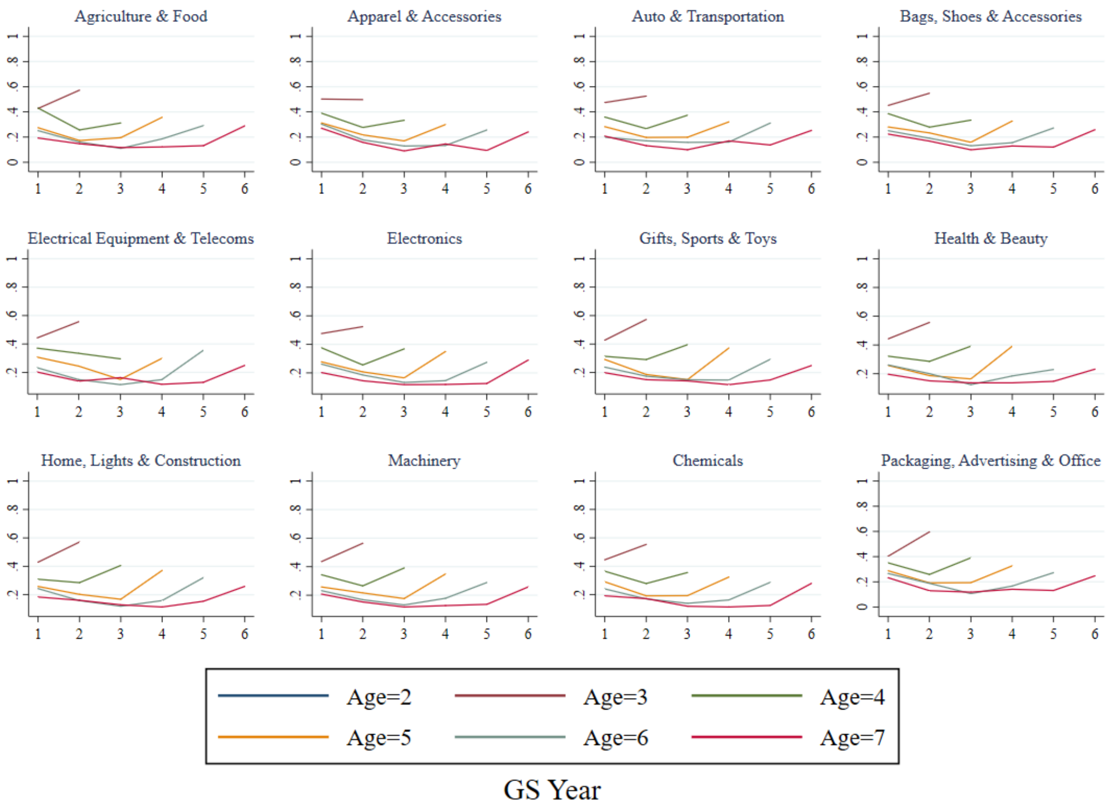

Figure 17: Distribution of GS Year Given Age by Industry

Notes: This figure shows that the timing of becoming GS has a consistent pattern across all 12 industries.

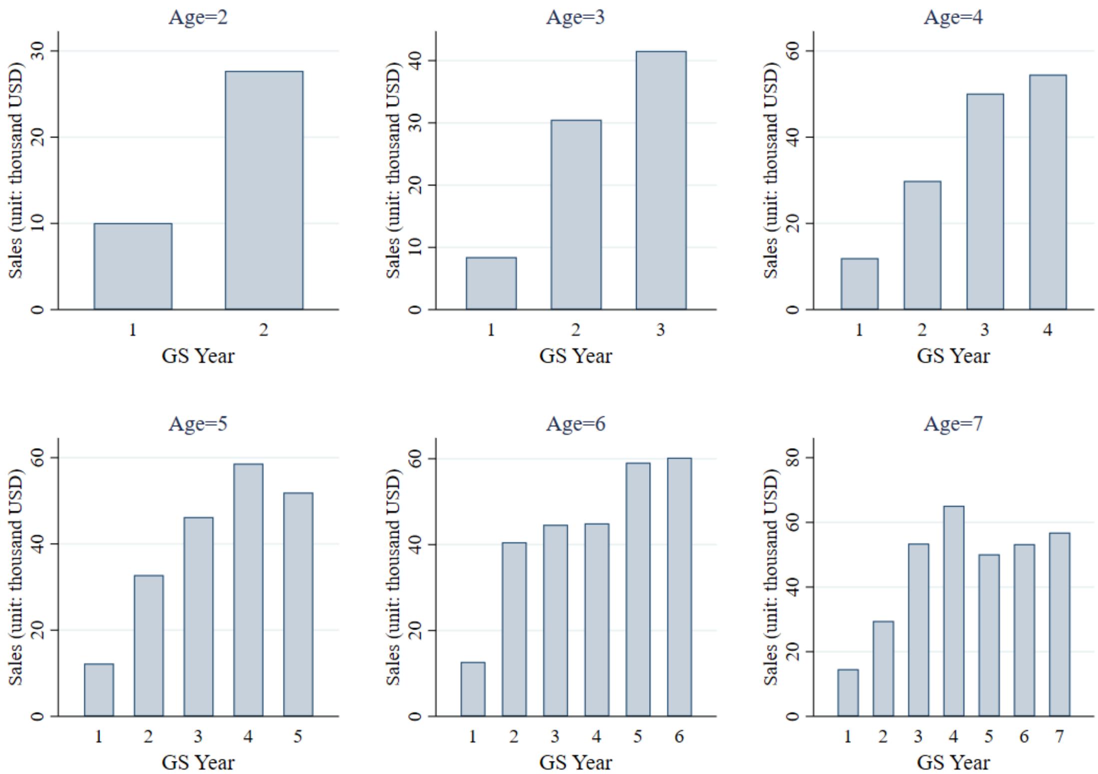

Figure 18: Average Sales by GS Year for Each Age Cohort

Notes: This figure shows that generally, online sales increase with GS year regardless of firm age. This pattern suggests that GS year can signal firm quality controlling for firm age.

B Tables

Table 1: Industry Description

Industry	Revenue (million USD)	Revenue Share (%)	No. of firms	Firm Share (%)
Home, Lights & Construction	644.0	15.88	15796	13.98
Machinery, Industrial Parts & Tools	601.9	14.84	16735	14.81
Electronics	445.9	10.99	11456	10.14
Packaging, Advertising & Office	405.4	9.993	10099	8.938
Apparel,Textiles & Accessories	402.9	9.932	11307	10.01
Metallurgy, Chemicals, Rubber & Plastics	330.4	8.143	10808	9.565
Gifts, Sports & Toys	306.7	7.560	9138	8.087
Electrical Equipment, Components & Telecoms	214.0	5.275	6030	5.337
Auto & Transportation	211.0	5.201	6617	5.856
Bags, Shoes & Accessories	189.4	4.668	4689	4.150
Health & Beauty	178.7	4.406	5286	4.678
Agriculture & Food	119.3	2.941	3598	3.184
N.A.	7.242	0.179	1431	1.266
Total	4057	100	112990	100

Notes: This table show the main industries that a firm operates in, the share of revenue in each industry and the share of the number of firms in each industry. N.A indicates that the main industry can not be determined due to lack of data of the main products that the firm sells online.

Table 2: Summary Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
lnsale_1	53,720	9.239	2.343	0	16.07
lnsale_2	53,720	9.542	2.249	0	16.08
ln(sale+1)_1	112,982	4.394	4.888	0	16.07
ln(sale+1)_2	112,982	4.538	5.011	0	16.08
year_gs	112,982	1.118	0.853	0	2.890
assess	112,982	0.104	0.305	0	1
age	112,982	1.870	0.746	0	4.220
certificate	112,982	1.397	1.431	1	41
patent	112,982	1.139	1.346	1	175
trademark	112,982	1.075	0.448	1	48
customer	112,982	0.0505	0.219	0	1
private	112,982	0.704	0.457	0	1
small	112,982	0.641	0.480	0	1
rating	6,352	4.779	0.472	1	5

Notes: lnsale_1 and lnsale_2 are the lower and upper bounds for log sales, while ln(sale+1)_1 and ln(sale+1)_2 are the lower and upper bound for ln(sales+1). The number of observations reduced to 112,982 from 112,990 after dropping firms with missing establishment year.

Table 3: Correlation

	year_gs	assess	lnage	certificate	patent	trademark	customer	private	small	rating
year_gs	1									
assess	0.0935	1								
age	0.561	0.135	1							
certificate	0.0813	0.511	0.134	1						
patent	0.0188	0.0755	0.0522	0.181	1					
trademark	0.00970	0.107	0.0506	0.183	0.235	1				
customer	0.0905	0.0485	0.0461	0.0338	0.0222	0.0436	1			
private	-0.0774	0.183	-0.148	0.0703	0.00850	0.0121	-0.000600	1		
small	-0.0870	-0.0194	-0.217	-0.0823	-0.0367	-0.0169	-0.00720	0.0630	1	
rating	-0.0219	.	0.0232	0.00830	0.0209	0.0202	0.0292	-0.0126	-0.0271	1

Notes: variables *rating* and *access* has missing correlation because they are perfectly colinear: only Assessed Suppliers have ratings in the data.

Table 4: Total GS Years and Online Sales

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(sales)				ln(sales+1)			
	All Suppliers		Assessed Suppliers		All Suppliers		Assessed Suppliers	
year_gs	0.099***	0.177***	0.224***	0.350***	0.982***	1.285***	1.381***	1.487***
	(0.014)	(0.017)	(0.039)	(0.048)	(0.016)	(0.019)	(0.062)	(0.069)
assess		1.030***				2.113***		
		(0.031)				(0.053)		
age		-0.285***		-0.452***		-0.704***		-0.447***
		(0.019)		(0.068)		(0.021)		(0.097)
certificate		0.063***		0.044***		0.183***		0.050***
		(0.006)		(0.010)		(0.012)		(0.013)
patent		0.010		0.010		0.055***		0.010
		(0.007)		(0.012)		(0.015)		(0.016)
trademark		0.170***		0.140***		0.664***		0.205***
		(0.024)		(0.046)		(0.093)		(0.066)
customer		0.418***		0.413***		1.294***		0.826***
		(0.036)		(0.062)		(0.062)		(0.106)
private		-0.013		0.109		0.073**		0.027
		(0.023)		(0.197)		(0.030)		(0.245)
small		0.041*		-0.026		0.598***		0.126
		(0.022)		(0.070)		(0.028)		(0.099)
rating				0.169***				0.182**
				(0.057)				(0.088)
Observations	53,720	53,720	5,768	5,768	112,982	112,982	6,352	6,352
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the firm level. The result shows that controlling for firm age, size, other firm certifications and other firm characteristics observed in the Alibaba Data, years of certification is associated with a significant and positive increase in firm online sales. Consumer rating data are only available for Assessed Suppliers. Column 4 and 8 of this table suggests that, apart from reputation which is discussed in existing literature (Chen and Wu, 2021), the years of being certified is positively associated with firm online sales. Standard errors are in the parentheses. *** indicates significance at the 0.01 level, ** at 0.05, * at 0.1.

Table 5: Event Study Estimates

	Baseline				Alternative Quality Measures		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	quality_ksw	lnvalue	lnvariety	lndestination	quality_kswp	quality_iv	ISO9000
l2	-0.014	-0.004	0.002	0.009	-0.003	-0.007	-0.028***
	(0.024)	(0.024)	(0.011)	(0.013)	(0.002)	(0.006)	(0.001)
f0	0.014	0.174***	0.108***	0.213***	0.002	0.001	0.012***
	(0.018)	(0.020)	(0.009)	(0.011)	(0.002)	(0.005)	(0.001)
f1	0.151***	0.656***	0.275***	0.523***	0.023***	0.009	0.015***
	(0.022)	(0.023)	(0.011)	(0.013)	(0.002)	(0.006)	(0.001)
f2	0.231***	0.951***	0.357***	0.694***	0.034***	0.014*	0.025***
	(0.027)	(0.028)	(0.013)	(0.015)	(0.003)	(0.007)	(0.001)
Observations	102,232	103,144	103,144	103,144	102,232	102,574	873,004
Adjusted R-squared	0.686	0.740	0.714	0.712	0.614	0.921	0.602
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The event study estimates show that GS certification positively affects firm export quality, export revenue, the number of export variety and the number of export destination. The results are robust when we consider alternative quality measures including the percentile approach, the IV quality estimate and the number of ISO certification (in logs) the firms reported online. Standard errors are in the parentheses. *** indicates significance at the 0.01 level, ** at 0.05, * at 0.1.

Table 6: Event Study Estimates: Small and Large Firms

	Small firms			
	(1)	(2)	(3)	(4)
VARIABLES	quality_ksw	lnvalue	lnvariety	lndestination
l2	-0.007	0.005	-0.008	0.014
	(0.043)	(0.046)	(0.019)	(0.022)
f0	0.036	0.334***	0.145***	0.296***
	(0.034)	(0.039)	(0.016)	(0.019)
f1	0.257***	1.030***	0.359***	0.688***
	(0.038)	(0.045)	(0.018)	(0.022)
f2	0.402***	1.413***	0.458***	0.893***
	(0.047)	(0.053)	(0.022)	(0.027)
Observations	45,122	45,747	45,747	45,747
Adjusted R-squared	0.575	0.635	0.606	0.639
Firm FE	Yes	Yes	Yes	Yes
Prov-Industry-Year FE	Yes	Yes	Yes	Yes
	Large firms			
	(5)	(6)	(7)	(8)
VARIABLES	quality_ksw	lnvalue	lnvariety	lndestination
l2	-0.010	0.006	0.006	0.008
	(0.029)	(0.022)	(0.014)	(0.015)
f0	0.002	0.064***	0.080***	0.153***
	(0.020)	(0.018)	(0.011)	(0.012)
f1	0.067**	0.349***	0.201***	0.386***
	(0.026)	(0.021)	(0.014)	(0.015)
f2	0.093***	0.555***	0.269***	0.525***
	(0.034)	(0.027)	(0.018)	(0.018)
Observations	54,349	54,622	54,622	54,622
Adjusted R-squared	0.773	0.748	0.763	0.734
Firm FE	Yes	Yes	Yes	Yes
Prov-Industry-Year FE	Yes	Yes	Yes	Yes

Notes: We estimate the event study specification seperately for initially small and large firms. We split the GS sample into smaller and larger firms by the median of firm initial export revenue. The results show that smaller firms experience larger increases in their export outcomes after becoming GS. Standard errors are in the parentheses. *** indicates significance at the 0.01 level, ** at 0.05, * at 0.1.

Table 7: Verifying Prediction from the Static Model

	All Sample		GS Sample	
	(1)	(2)	(3)	(4)
VARIABLES	gs	gs	gs	gs
quality_ksw	0.001***		0.005***	
	(0.000)		(0.001)	
quality_kswp		0.009***		0.054***
		(0.001)		(0.009)
Observations	2,147,573	2,147,573	126,466	126,466
R-squared	0.867	0.867	0.785	0.785
Firm FE	Yes	Yes	Yes	Yes
Industry-Prov-Year FE	Yes	Yes	Yes	Yes

Notes: This table verifies that higher quality firms are more likely to become GS firms no matter in all Customs sample or in GS sample only. Standard errors are in the parentheses. *** indicates significance at the 0.01 level, ** at 0.05, * at 0.1.

Table 8: Parameter Estimates

Parameter	Estimates	Standard Error
Signaling cost a_2	1.35	1.29
Investment cost c	0.00029	0.0064
Upgrading Parameter b	0.0040	0.094

Notes: This table shows the SMM estimator for the parameters by minimizing the distance between the data moments and the model moments.

Table 9: Signaling Cost for Different Qualities

Quality Bin	Signaling Cost	Times
1	1.29	17.48
2	1.16	15.65
3	1.02	13.82
4	0.89	11.99
5	0.75	10.16
6	0.62	8.33
7	0.48	6.49
8	0.35	4.66
9	0.21	2.83
10	0.074	1.00

Notes: This table shows the signaling cost in the model, including fixed cost and differential cost, as well as the times of the signaling cost in each quality bin relative to the 10th quanlity bin.

Table 10: Robustness: Parameter Estimates Under Alternative Values of Elasticity

Panel A: Elasticity = 4		
	Estimate	Standard error
Signaling Cost a_2	1.40	0.85
Investment Cost c	0.00033	0.00042
Upgrading Parameter b	0.0039	0.0046
Panel B: Elasticity = 5		
	Estimate	Standard error
Signaling Cost a_2	1.32	1.04
Investment Cost c	0.00031	0.00037
Upgrading Parameter b	0.0036	0.0066

Notes: This table shows the SMM estimator for alternative values of elasticity used in the literature.

Table 11: Robustness: Parameter Estimates Under Alternative Number of Quality Bins

Panel A: Number of Quality Bins = 8		
	Estimate	Standard error
Signaling Cost a_2	1.59	0.94
Investment Cost c	0.00033	0.00076
Upgrading Parameter b	0.0016	0.0046
Panel B: Number of Quality Bins = 12		
	Estimate	Standard error
Signaling Cost a_2	1.60	1.56
Investment Cost c	0.00023	0.00031
Upgrading Parameter b	0.0043	0.0084

Notes: This table shows the SMM estimator for alternative number of quality bins.

C Difference-in-Difference Estimator

The panel matching method is implemented in two steps. First, establish a matching set for each treated observation ensuring they have the same treated history. Second, refine the matching set based on covariates up to L periods before the shock and reducing the difference between the treated group and the control group. Then, we can construct an ATT at F period(s) after the shock.

In this paper, we aim to examine the effect of GS on firm export quality. Consistent with the event-study analysis, we choose $F = L = 2$, which means we adjust the variables at $t = -1, -2$ (2 periods before GS) and examine the impact of GS on the export quality at $t = 0, 1, 2$ (0-2 periods after the firm becomes a GS).

Now, our sample is all customs firms from 2000 to 2015. The treated group are firms that became GS before 2015, and the control group are selected from the remaining companies. We use the Mahalanobis distance approach and the Propensity Score Weighting approach to refine our matching set[57] and examine the robustness of the results. The matching covariates include the number of export varieties, the number of destinations and the export quality history. Moreover, we match firms within each HS2 industry defined by the largest HS2 industry in which the firm exported from 2000 to 2015.

[Insert Figure 7 and 8]

We first examine the balance between the treated group and the control group following Imai, Kim and Wang (2021).[58] In Figure 7, the x-axis represents the balance of each matching variable in the unrefined matching set in the past periods, and the y-axis represents the balance of the refined matching set.[59] The red dashed line is a 45-degree line, the dots represent the balance of Mahalanobis distance matching, and $\times$ represents that of the propensity score weighting method. The point at the lower right of the red line indicates that the balance of the matching set has been improved after refinement. Figure 7 shows that most of the points are located at the lower right of the red line, and the balance is improved after refinement. The average difference after refining and matching does not exceed 0.25. In general, the two matching methods have exhibited high matching quality.

[57] Please see their introduction in Imai, Kim and Wang (2021).

[58] For each treated observation (i, t), the balance of variable j in period t is defined as $B_{it}(j, l)$, which represents the average difference in standard deviation. Please refer to Imai, Kim and Wang (2021) for its detailed expression. The closer $B_{it}(j, l)$ is to 0, the smaller the difference between the treated group and the control group, and the higher the matching quality. Cochran (1968) proposed a rough rule of no more than 0.25 standard deviations.

[59] Both are in absolute values.

Then, we can examine the parallel trend assumption by drawing the balance changes in the matching covariates. The blue line is our most concerned export quality. It is clear from Figure 8 that the balance of export quality remains stable and close to zero, indicating that the parallel trend assumption is satisfied.

[Insert Figure 9]

Here we only briefly introduce the panel matching method proposed by Imai, Kim and Wang (2021). Please refer to their paper for details.

Suppose there are N individuals and T periods in the balanced panel (this method is also applicable to the unbalanced panel). Let i and t denote each individual and each period, where $i = 1, 2, 3, ...N$, $t = 1, 2, 3..., T$. Let Y_{it} denote the dependent variable, and TR_{it} denote the dummy variable for whether individual i receives the shock at period t. Z_{it} represents K other matching variables. Let F denote F periods after the shock and L denote the L period before the shock. To find the control group, they use a matching method to adjust for covariates up to L periods before the shock. Then, the Average Treated Effect (ATT) is expressed as:

$$\begin{aligned}\delta(F, L) = \mathbb{E}\{Y_{i,t+F}(TR_{it} = 1, TR_{i,t-1} = 0, \{TR_{i,t-\ell}\}_{\ell=2}^{L})- \\ Y_{i,t+F}(TR_{it} = 0, TR_{i,t-1} = 0, \{TR_{i,t-\ell}\}_{\ell=2}^{L})|TR_{it} = 1, TR_{i,t-1} = 0\}\end{aligned} \tag{22}$$

The key assumption of the DiD approach is the parallel trend assumption, that is, given the shock history, the history of the dependent variable (excluding the past period t-1) and the history of the control variable, the trend of the dependent variable after the shock and its hypothetical unaffected trend are the same, that is:

$$\begin{aligned}&\mathbb{E}[Y_{i,t+F}(TR_{it} = 1, TR_{i,t-1} = 0, \{TR_{i,t-\ell}\}_{\rho=0}^{L}) - Y_{i,t-1}| \\ .\quad &TR_{it} = 1, TR_{i,t-1} = 0, \{TR_{i,t-\ell}, Y_{i,t-\ell}\}_{\ell=2}^{L}\{\mathbf{Z}_{i,t-\ell}\}_{\ell=0}^{L}] = \\ &\mathbb{E}[Y_{i,t+F}(TR_{it} = 0, TR_{i,t-1} = 0, \{TR_{i,t-\ell}\}_{\ell=2}^{L}) - Y_{i,t-1}| \\ &TR_{it} = 0, TR_{i,t-1} = 0, \{TR_{i,t-\ell}, Y_{i,t-\ell}\}_{\ell=2}^{L}, \{\mathbf{Z}_{i,t-\ell}\}_{\ell=0}^{L}]\end{aligned} \tag{23}$$

D Proofs

Proposition 1 (A partially separating equilibrium): Consider the class of partially separating equilibria where higher-quality firms signal and lower-quality firms do not. An equilibrium in this class is defined by a cutoff θ^* such that $g(\theta) = 1$ for $\theta > \theta^*$ and $g(\theta) = 0$ for $\theta < \theta^*$. The type θ^* is indifferent between signaling and not signaling.

Proof. Denote $\pi_1(\theta)$ as the profit for signaling firms with quality θ and π_0 as the profit for non-signaling firms with quality θ. In this equilibrium, the incentive constraints should be satisfied. In other words, firms of different quality types would not deviate. High types should find signaling more profitable than not signaling, low types should prefer not signaling, and the type θ^* is indifferent between signaling and not signaling. Thus, we have:

$$\pi_1(\theta) > \pi_0(\theta) \; for \; \theta > \theta^* \tag{24}$$

$$\pi_1(\theta) < \pi_0(\theta) \; for \; \theta < \theta^* \tag{25}$$

$$\pi_1(\theta^*) = \pi_0(\theta^*) \tag{26}$$

Moreover, the participation constraints should be satisfied: no matter signaling or not, all firms should have non-negative profits.[60] First, when firms signal, they should have non-negative profits. As the lowest-quality firm has the highest cost of signaling and signaling firms have the same sales in a static model, this condition holds when the lowest-quality firm has non-negative profit:

$$\pi_1(\underline{\theta}) \geq 0 \tag{27}$$

Second, when firms do not signal, they should also have non-negative profits:

$$\forall \, \theta, \pi_0(\theta) \geq 0 \tag{28}$$

In this partially separating equilibrium, the consumer's belief is a function of the cut-off quality θ^*. For simplicity, denote $E_1 \equiv E(\theta|g = 1)$, $E_0 \equiv E(\theta|g = 0)$. Based on the Bayes' rule, the consumer's expectation of quality conditional on seeing signals is the expectation of quality for signaling firms, i.e. for $\theta > \theta^*$:

$$E_1(\theta^*) = \int_{\theta^*}^{\overline{\theta}} \theta f(\theta) d\theta \tag{29}$$

[60] I assume the outside option is zero for firms.

Similarly, we have consumer expectation conditional on not seeing any signals:

$$E_0(\theta^*) = \int_{\underline{\theta}}^{\theta^*} \theta f(\theta) d\theta \tag{30}$$

Substitute equations (12), (29) and (30) into equation (26), we have $BE_1(\theta^*)^\sigma - s(\theta^*) = BE_0(\theta^*)^\sigma$. Thus, the cutoff quality θ^* is solved from:

$$B[E_1(\theta^*)^\sigma - E_0(\theta^*)^\sigma] = s(\theta^*) \tag{31}$$

Equation (31) shows that when the benefit of signaling equals the cost of signaling, the firm is indifferent between signaling and not signaling. It can be further written as:

$$E_1(\theta^*)^\sigma - E_0(\theta^*)^\sigma - \frac{s(\theta^*)}{B} = 0 \tag{32}$$

Denote $h(\theta') \equiv E_1(\theta')^\sigma - E_0(\theta')^\sigma - \frac{s(\theta')}{B}$. Equation (32) means $h(\theta' = \theta^*) = 0$. Then a sufficient condition for the existence of θ^* is: $h(\theta' = \overline{\theta}) \cdot h(\theta' = \underline{\theta}) < 0$.

Define $\overline{E} \equiv \int_{\underline{\theta}}^{\overline{\theta}} \theta f(\theta) d\theta$, we have:

$$h(\overline{\theta}) = -\overline{E}^\sigma - \frac{s(\overline{\theta})}{B} \tag{33}$$

$$h(\underline{\theta}) = \overline{E}^\sigma - \frac{s(\underline{\theta})}{B}. \tag{34}$$

Thus, the sufficient condition for the existence of θ^* is:

$$h(\overline{\theta}) \cdot h(\underline{\theta}) = [-\overline{E}^\sigma - \frac{s(\overline{\theta})}{B}] \cdot [\overline{E}^\sigma - \frac{s(\underline{\theta})}{B}] < 0 \tag{35}$$

Since $\overline{E}^\sigma > 0$ and $\frac{s(\overline{\theta})}{B} > 0$, $[-\overline{E}^\sigma - \frac{s(\overline{\theta})}{B}] < 0$ is guaranteed. Equation (35) reduces to

$$\overline{E}^\sigma - \frac{s(\underline{\theta})}{B} > 0 \tag{36}$$

This means that the average revenue is higher than the largest signaling cost. And this is the sufficient condition for having a partially seperating equilibrium. □

Proposition 2 (Pooling equilibria): We can find two types of pooling equilibria. One where no firms signal and the otehr where all firms signal.

Proof. First, a pooling equilibrium where firms do not signal exists if $\pi_1 < \pi_0$ and $\pi_1 > 0, \forall\, \theta$. Since $s'(\theta) < 0$, this class of pooling equilibrium exists for any beliefs and cost function that satisfy:

$$B(E_1^\sigma - E_0^\sigma) < s(\overline{\theta}) \tag{37}$$

where $E_0 = \int_{\underline{\theta}}^{\overline{\theta}} \theta f(\theta) d\theta$ since all firms do not signal and E_1 can be any off-equilibrium path belief that satisfy this equation.

Second, a pooling equilibrium where firms all signal exists if $\pi_1 > \pi_0$ and $\pi_0 > 0$, $\forall\, \theta$.

Similarly, since $s'(\theta) < 0$, this class of pooling equilibrium exists for any beliefs and cost function that satisfy:

$$B(E_1^\sigma - E_0^\sigma) > s(\underline{\theta}) \tag{38}$$

where $E_1 = \int_{\underline{\theta}}^{\overline{\theta}} \theta f(\theta) d\theta$ since all firms signal and E_0 can be any off-equilibrium path belief that satisfy this equation.

□

Proposition 3 (Constant Expectation): A sufficient condition for a constant conditional expectation $E(\theta|G)$ across different periods is that the total mass of entrants grow at a constant rate of λ and exit at a rate of δ, where λ^{n-T} is limited and $\delta^T \to 0$.

Proof. The economy starts from period 1 and the initial mass of firm is m. Given decision rules under a rational expectation equilibrium, consider $G = k$, $r_n(j, k)$ represents the share of firms at state $\theta = j$ and $G = k$ at the beginning of period n for entrants that enter at period 1.

Let $\mu_t(\theta = j|G = k)$ denote at the beginning of period t, the share of firms with states $(\theta = j, G = k)$ in the total number of firms with $G = k$.

When we have a long enough period T, at period n ($n > T$), we can always only aggregate firms entering since period $n - T + 1$, i.e. the most recent T periods, given that the earlier entrants all die out in the long run. Under the same rationale, at period $n+1$, we can still consider the most recent T periods. Through this reasoning, we find that the realized conditional expectation is constant in our dynamic model if we can assume that firms entering before $n-T+1$ die out in the long run. And at each period, firms behave under the same decision rule under constant expectation. Therefore, our assumption is self-consistent.

We can think of a simple case where there are 10 periods in total and 5 periods away firms all die. At period 10, the distribution of firms consists of firms entering from period 6 to 10. At period 9, the distribution of firms consists of firms entering from period 5 to 9. The stacked distribution of firms remains constant given they behave under the same decision rule.

When we stand at period n, $m\lambda^{n-1}r_1(j,k)$ is the number of firms that just entered at periold n, $m\delta^{n-1}r_n(j,k)$ is the number of firms that entered at period 1 and they have experienced $n-1$ periods of exit shocks indicated by δ^{n-1}. To fomalize the idea, at period n, the share of firms with state $(\theta = j, G = k)$ in the total number of firms with state $G = k$ consists of entrants from period 1 to n. Because we assume $\delta^T \to 0$, firms T periods away, i.e. firms that enter before period $n - T + 1$ all die out. Thus we sum firms entering since period $n - T + 1$ when calculating the share at period n. Thus we have:

$$
\begin{aligned}
&\mu_n(\theta = j|G = k) \\
&= \frac{m[\delta^{n-1}r_n(j,k) + \lambda\delta^{n-2}r_{n-1}(j,k) + \cdots + \lambda^{n-1}r_1(j,k)]}{m[\delta^{n-1}\sum_{j'} r_n(j',k) + \lambda\delta^{n-2}\sum_{j'} r_{n-1}(j',k) + \cdots + \lambda^{n-1}\sum_{j'} r_1(j',k)]} \\
&= \frac{m[\lambda^{n-T}\delta^{T-1}r_T(j,k) + \lambda^{n-T+1}\delta^{T-2}r_{T-1}(j,k) + \cdots + \lambda^{n-1}r_1(j,k)]}{m[\lambda^{n-T}\delta^{T-1}\sum_{j'} r_T(j',k) + \lambda^{n-T+1}\delta^{T-2}\sum_{j'} r_{T-1}(j'a,k) + \cdots + \lambda^{n-1}\sum_{j'} r_1(j',k)]}
\end{aligned}
\tag{39}
$$

Similarly, at period $n+1$ we have the share of firms with state $(\theta = j, G = k)$ in the total number of firms with state $G = k$ as follows:

$$
\begin{aligned}
&\mu_{n+1}(\theta = j|G = k) \\
&= \frac{m[\lambda^{n-T+1}\delta^{T-1}r_T(j,k) + \lambda^{n-T+2}\delta^{T-2}r_{T-1}(j,k) + \cdots + \lambda^{n}r_1(j,k)]}{m[\lambda^{n-T+1}\delta^{T-1}\sum_{j'} r_T(j',k) + \lambda^{n-T+2}\delta^{T-2}\sum_{j'} r_{T-1}(j',k) + \cdots + \lambda^{n}\sum_{j'} r_1(j',k)]} \\
&= \frac{m[\lambda^{n-T}\delta^{T-1}r_T(j,k) + \lambda^{n-T+1}\delta^{T-2}r_{T-1}(j,k) + \cdots + \lambda^{n-1}r_1(j,k)]}{m[\lambda^{n-T}\delta^{T-1}\sum_{j'} r_T(j',k) + \lambda^{n-T+1}\delta^{T-2}\sum_{j'} r_{T-1}(j'a,k) + \cdots + \lambda^{n-1}\sum_{j'} r_1(j',k)]}
\end{aligned}
\tag{40}
$$

Thus, $\mu_n(\theta|G = k) = \mu_{n+1}(\theta|G = k)$. The conditional expectation of quality is constant under our assumptions that λ^{n-T} is limited and $\delta^T \to 0$. $\square$

E Computation Procedures

For the ease of computation, there exists a maximum of G and θ that the firm can reach as explained in the text. To compute the equilibrium, we take the following procedures:

1. Guess an initial expectation vector for different years of GS.

2. Generate the decision rule and value function through value function iteration until the value function converges. Note that the distribution of firms does not matter in step 2.

3. Given the distribution of entrants, the growth rate of the entrants and the exit rate, apply the decision rule obtained from step 2, At period n, generate the distribution of firms for firms entering at period $n-T$ to period n. Note that firms T periods away die out according to Proposition 3. Aggregate them up and generate accumulated distribution of firms at period n ($freq$ hereafter).

4. Generate the conditional expectation of quality based on $freq$.

5. Use the expectation from step 4 to update the expectation and go through steps 2-4 until the expectation converges.

Due to the discrete nature of our quality grids, when our program fluctuates between multiple expectations, we choose the expectation where fewer firms choose to signal based on the least cost rule. The off-path equilibrium is assigned as follows: if no firms signal at a certain year of GS, then intuitively, the corresponding expectation of quality is set to zero.

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