The Welfare Effects of Summary Information: Taobao's Golden Seller Certification

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Abstract

Consumer-based rating systems and reputation signals have been main sources of information on product quality and seller performance in online markets. However, it is time consuming to sifting through all the information. This raises an important question: if someone has evaluated all the reviews, summarized all the available information and compiled it into a simple badge, will consumers value such easily accessible information in decision making? This paper studies the valuation of Golden Seller certification, a badge that conveys such summary information, using data collected from the smart phone markets on Taobao. We use a structural model to evaluate the overall effects of the Golden Seller certification on consumer welfare and seller profits. Our results reveal that the Golden Sellers charge a relatively lower price, but have a significant higher sales volume. Additionally, our demand estimation and counterfactual simulation suggest that consumer welfare improves because of the new information as well as the added convenience and accessibility of the existing information conveyed in the badge. Meanwhile, Golden Sellers, or high-quality sellers, benefit from the certification substantially while the other sellers are only slightly worse off. These results suggest that the certification enhances market efficiency and expands market.

1. Introduction

With the development of online platforms, consumers are able to buy a branded product from a third-party seller for a lower price. As a consequence, information about product quality and seller performance has become increasingly important. Usually consumers obtain relevant information from seller's description, customer review systems and other reputation signals. The customer review system relies mainly on consumers monitoring sellers, and sellers signal quality by accumulating good reviews and establishing a reputation. The other type of reputation signals requires platform intervention, such as platform certified sellers and buyer protection programs. However, sifting through all the information is time consuming. This raises an important question: if someone has evaluated all the reviews, summarized all the available information and compiled it into a simple badge, will consumers value such easily accessible information in decision making? If customer review system has already provided such mechanism, what additional information does platform certification provide? Does it require sellers to invest more to get certified? Does it increase price premium correspondingly? How much do consumers value the platform certification, and will it truly benefit consumers?

We shed light on these questions in this study by examining the effects of platform certified quality sellers in Taobao marketplace on demand, market equilibrium, seller surplus, as well as consumer surplus. Taobao has adopted the Golden Seller certification as a platform rating of the sellers since July 1st, 2014. Golden Seller certification is awarded by Taobao based on a range of criteria, including seller's operating duration, revenue, ratings on product quality and service quality, and consumer reviews. The effect of Golden Seller certification is not a priori obvious. On one hand, sellers who invest in acquiring Golden Seller certification may charge a price premium once the reputation certification is established. On the other hand, unlike market reputation, many fixed costs invested by the sellers for platform certification are likely to benefit sellers in the long run, leading to a lower marginal cost, and a subsequently a lower equilibrium price. For example, their investment in platform analytics helps them to understand consumers tastes and can better target and advertise, and thus saving time and financial resources on advertisement in the long run. Moreover, competition for Golden Seller certification may lead to a more competitive market outcome, leading to a lower equilibrium price. Sellers may not be able to reap a price premium given the stringent criteria of Golden Seller certification and the fear of losing the status.

By examining the smart phone market on Taobao, we find that the Taobao certified Golden Sellers set a lower price on average, and sell more compared to other sellers. We find this platform reputation certification increases both consumer and seller surplus, enhancing market efficiency. On average, consumers in smart phone markets benefit from the availability of the Golden Seller badge by ¥105540.10 per day, which is 4.53% of the average daily revenue from smart phone sales. We simulate a counterfactual hiding Golden Seller badge from consumers. The counterfactual analysis shows that the overall profits of Golden Sellers decrease by ¥101805.51 per day, which is equivalent to 12.72% of the Golden Sellers' daily sales revenue. Meanwhile, the overall profits of the other sellers increase by ¥11080.83, which is only 0.69% of those sellers' daily revenue. The total loss in daily profits is ¥90724.68 in the counterfactual, which accounts for 3.91% of the overall daily revenue from smart phone markets.

There are two implications. First, platform certification enhances market efficiency, increasing total surplus. It is important to understand more of the mechanism such as how such market efficiency is achieved, and how the certification criteria can impact the market outcomes. These questions remain for future research. Second, platform certification promotes marketplace health in the long run. It is likely to attract more sellers and buyers and increase total platform transactions.

2. Golden Seller

Taobao has implemented the Golden Seller recognition system as a platform rating of the sellers since July 1st, 2014. Golden Seller is awarded by Taobao based on a list of criteria1. The

[1] See Appendix for details.

criteria combine a wide range of characteristics including seller's operating duration, seller's revenue, ratings on product quality and service quality, and consumer reviews etc. The evaluation is entirely free, and sellers can opt-out. Sellers who meet all the criteria will be awarded an icon of Golden Medal, which appears on the searching result page, the product page, the seller's home page and the communication tool Aliwangwang.

Golden Seller is evaluated every half month. The evaluation results are announced on the 1st and 16th every month. We define a period as one evaluation cycle, which is fixed as the first 15 days for the first half of each month and the remaining days for the second half of each month. The data for the evaluation each period is extracted from 2 periods ago. For example: a seller will acquire the icon of gold medal from April 1st to 15th only if the seller's overall performance during March 1st to 15th meets all the criteria. However, the status is not fixed throughout the period. On Aug 29, 2014, Taobao announced that starting from Sep 1st, Golden Seller status can be cancelled due to several reasons, such as penalty or deposit falls below the required amount, and can be recovered after appealing and correction. In other words, the seller's status can vary within a period.

3. Data

Our dataset consists of 52 smart phone models launched in 2017 from six most popular brands in China, VIVO, Huawei, Honor, Xiaomi, OPPO and Apple. We collect data irregularly from Jan 13th, 2018 to Jun 9th, 2018, in total 102 days across 11 evaluation periods[2]. A period is defined as one evaluation cycle, roughly half a month.

An observation in our regressions is a PhoneModel-Seller-Date combination. On each date, we observe seller ID, phone model ID, each seller's posted price, sales in the past 30 days, as well as several sellers' characteristics, such as Golden Seller status, the ratings on product, service and delivery, and the seller rating score.

[2] A list of dates that we collected data is in Table A.2.

The ratings on product, service and delivery are three separate ratings. Consumers voluntarily rate sellers with a rating from 1 to 5 for each of the three dimensions within 15 days after the transaction is completed. The ratings displayed on the website are the accumulated in the past 6 months. In addition, a consumer is required to submit a seller rating based on the overall performance within 15 days after each transaction. The overall rating can be positive (+1), neutral (0), or negative (-1). The default rating is positive if the consumer does not submit the seller rating within 15 days. The seller rating score is highly correlated with the seller's total number of transactions from the start of the business as most consumers would not bother to change the default. The platform categorized the rating scores into 21 grades[3], including the new sellers without any grade level yet. Consumers observe the seller rating grade through the symbols displayed next to the seller's name.

We only observe the total number of products sold in the past 30 days. To perform analysis later, we estimate the daily sales from the 30-day moving window[4]. Table 1 displays the summary statistics.

4. Effects on Price and Sales

To estimate the price premium and consumers' reaction to the Golden Sellers, we use a 2SLS model.

$$Y_{ijd} = \alpha GS_{jd} + X'_{ijd}\beta \ + \delta_n + \gamma_i + \theta_m + \varepsilon_{ijd}, \qquad (1)$$

where Y_{ijd} is the outcome variable -- the natural log of price and the predicted daily sales of a phone model i from seller j on date d. Daily sales is the quantity of products sold rather than the sales revenue.

GS_{jd} is a dummy variable that equals to 1 if seller j is a Golden Seller on date d, thus GS_{jd} can vary within one period.

3 Table A.3 displays the 21 grades, the corresponding seller rating and the symbol for each grade.

4 Estimation details are explained in Appendix.

X_{ijd} is a vector of control variables, including a dummy variable indicating weekends and holidays, and some seller level characteristics, such as the average rating[5], dummies for seller's geographical location, and dummies for seller's rating grade.

δ_n is the day of the period fixed effects. It is calculated as the date minus the date of the announcement of evaluation results in the current period. For example, if the observation is collected on Feb 21th, 2018, then *n* is derived by Feb 21th, 2018 minus Feb 16th, 2018, which means Feb 21th, 2018 is the 5th day in current period. The range of n is from 0 to 15.

γ_i and θ_m are the fixed effects of phone model i and month m.

The key regressor GS_{jd} is endogenous as it is directly correlated with the error terms, including the product quality and the sellers' behavior that we do not observe but affect the price level and quantity sold as well as the Golden Seller status. To address the endogeneity issue, we instrument the key regressor $GS_{jd}$with the seller's Golden Seller status lagged two periods, i.e. $l2_{GS\,jd}$. This instrumental variable is correlated with the current status since the status two periods ago implies a relatively better performance of the business, which leads to a higher probability for this seller to get the badge again later. It is exogenous because the status two periods ago should not have any direct effect on current price and sales since consumers cannot observe seller's status two periods ago under the assumption that all consumers are new. For the instrumental variable to be valid, we assume the seller's overall performance depends on time-invariant behavior (fixed) and period specific behavior (random). Thus corr($GS_j,\ l2_{GS\,j}$) $\neq 0$ is due to the time-invariant behavior, and corr($\varepsilon_j,\ l2_{GS\,j}$) $= 0$ is due to the period specific behavior.

Table 2 shows the effects of Golden Seller status on prices and daily sales. In Column (2), we find that the prices of products from Golden Sellers are around 1.5% lower than the product prices from the other sellers. One might be expecting a price premium for Golden Sellers, as the badge indicates a higher product quality and seller reliability. However, the negative effect on prices can be explained by the price competition in the evaluation. According to the criteria, sellers have to

[5] The rating on product, delivery and service are highly correlated. The correlation between each two ratings is above 0.8. To avoid multicollinearity, we take the average of the three ratings.

meet the target revenue to compete for the badge, and a lower price leads to higher sales and thus means a higher chance to become a Golden Seller later. This conjecture is verified by the day of the period fixed effects. We observe a trend of the price reduction toward the next evaluation day. Starting from the 5^{th} day, we find a trend of price reduction as the coefficients are getting larger in magnitude. In Column (4), we find that the Golden Seller status has a significantly positive effect on daily sales. It is worth noting that the magnitude (0.71) is not trivial compared to the average daily sales (0.267). Moreover, more than 75% of the observations in our sample have zero daily sales. That being said, the badge can boost the business sales from zero to above average. Therefore, sellers have a strong incentive to lower price to compete for the Golden Seller badge. Particularly, Golden Sellers, with the fear of losing the certificate in the future, are also willing to engage in the price competition.

The results in Table 2 are consistent with our expectation that consumers do prefer Golden Sellers. The day of period fixed effects are also consistent with our conjecture that sellers adjust prices strategically toward the end of each period in order to compete for the badge again. To continue digging into the effects of the evaluation on consumers as well as on sellers, we use a nested logit model to estimate demand. We will use the demand estimation to construct a counterfactual hiding the Golden Seller badge to consumers. Then we can answer the ultimate question – will the evaluation of Golden Seller improve total surplus? Particularly, will consumers and sellers benefit from the evaluation? If so, who will be the big winner?

5. Demand Estimation

5.1 Demand Model

We estimate demand with a nested logit model. A market is defined as a date. By this market definition, we implicitly assume that each consumer entering the market decides first which phone model to buy and then decides which seller they are buying from. We assume consumers are myopic for simplicity. That is, consumers end up either purchasing a product or exiting the market, which is the outside good. A product is defined as a combination of phone model ID, seller ID and date. Suppressing the time subscript, consumer i's utility from choosing product j is given by:

$$u_{ij} = -\alpha P_j + X_j'\beta + \xi_j + \zeta_{ig} + (1-\sigma)\epsilon_{ij} \qquad (2)$$

$$= \delta_j + \zeta_{ig} + (1-\sigma)\epsilon_{ij}$$

where δ_j is the mean utility from purchasing product j. The vector X_j is a vector of control variables, including Golden Seller status, the average rating of product, delivery, and service, dummies for sellers' geographical location, dummies for sellers' rating grade, whether it's bought on weekends and holidays, phone model fixed effects, month fixed effects, and the day of period fixed effects. ξ_j is the unobserved quality of product j. ζ_{ig} is the common taste shock to all products within a nest, which is defined as a phone model. ϵ_{ij} are consumer i's idiosyncratic tastes of product j. σ measures the correlation of tastes across products within a nest. Assume ζ_{ig} and ϵ_{ij} follow a type I extreme value distribution, then $\zeta_{ig} + (1-\sigma)\epsilon_{ij}$ also follows type I extreme value distribution.

Following Berry (1994), the inside share and the group share are $s_{j|g} = \frac{e^{\delta_j/1-\sigma}}{D_g}$ and $s_g = \frac{{D_g}^{1-\sigma}}{1+\sum_{g'} {D_{g'}}^{1-\sigma}}$, where $D_g = \sum_{j\in J_g} e^{\delta_j/1-\sigma}$. The market share of product j is $s_j = \frac{e^{\delta_j/1-\sigma}}{{D_g}^{\sigma}\left(1+\sum_{g'} {D_{g'}}^{1-\sigma}\right)}$. Setting the mean utility from consuming the outside good to zero, we derive the regression equation of the nested logit model:

$$\ln(s_j) - \ln(s_0) = -\alpha P_j + X_j'\beta + \sigma \ln(s_{j/g}) + \xi_j \qquad (3)$$

The price elasticities predicted by the nested logit model are given by:

$$\eta_{jk} = \frac{\partial s_j}{\partial p_k}\frac{p_k}{s_j} = \begin{cases} -\alpha p_j\left(\frac{1}{1-\sigma} - \frac{\sigma}{1-\sigma}s_{j/g} - s_j\right), \; if\ j = k \\ \alpha p_k s_k\left(\frac{\sigma}{1-\sigma}\frac{s_{j/g}}{s_j} + 1\right), \; if\ j\ and\ k\ are\ in\ the\ same\ nest \\ \alpha p_k s_k, \; otherwise \end{cases} \qquad (4)$$

5.2 Estimation

To estimate equation (3), we need a measurement of market size. According to China Internet Network Information Center's report in January 2018, the number of individuals who shop online is 533 million by the end of 2017. We assume that each individual buy one smart phone only in 2018, which means, consumers enter one market only and decide to buy or exit. We derive our measurement of market size by dividing the yearly market size by 365 as we treat each day as a market.

Price and inside share are endogenous as unobservable product characteristics affect both price and the inside share as well as demand. To address the endogeneity issue, following Hausman (1996), we use the prices of the products from the seller in the other markets as instrumental variable for price. It is a valid instrument as the prices of the products from the same seller are correlated due to the common marginal cost. Given the assumption that ξ_j is the market-specific valuation of the product, the prices in the other markets are uncorrelated with ξ_j. However, we cannot simply take the average of all other products' prices. Many sellers are small sellers with only a few models of smart phones, which means the products' average price from each seller can vary substantially. Therefore, the differences in average prices do not reflect the differences in sellers' cost. In addition, many small sellers stay in the market for only a few days. A simple average cannot measure the sellers' cost shock if the average prices change is because the seller enters or exits certain markets. To better reflect the supply shock, we standardize the prices within nests by calculating the z-score[6], and then take the average of the z-scores of the seller's products on the other dates.

We instrument for the inside share with the number of sellers within the nest. It is valid because of the correlation between price and inside share, while the product characteristics ξ_j is uncorrelated with the number of sellers within a nest.

[6] Z-score of prices is derived by (price-average price within market)/standard deviation.

Results of demand estimation are reported in Table 3. Column (1) shows the results of logit model from an OLS estimation. As expected, the price coefficient is significantly negative. The magnitude gets larger in Column (2) after introducing the instrumental variable suggesting the IV can alleviate the bias. The coefficient of Golden Seller is statistically significantly positive and large in magnitude compared to the coefficient of price, suggesting that consumers have strong preference to Golden Sellers, which is consistent with the results of the 2SLS model. The coefficient of average rating is also significantly positive, indicating that consumers prefer higher-rating sellers. This logit model predicts a mean price elasticity of -5.408.

Column (3) reports the results of nested logit model defining a phone model as a nest. σ (Phone Model), the correlation of tastes for products within nest, is statistically significant, suggesting products within a nest are more substitutable. The nested logit model predicts a mean price elasticity of -5.255.

6. Supply Side and Marginal Cost

Suppose all firms are single product firms, and they set prices at Bertrand-Nash equilibrium. The profit of product j is

$$\Pi_j = \left(p_j - mc_j\right) M s_j(p) - FC_j, \qquad (5)$$

where $s_j(p)$ is the market share of product j. M is the market size, mc_j is the marginal cost of product j, and FC_j is the fixed cost.

The first-order condition is $s_j(p) + \left(p_j - mc_j\right)\frac{\partial s_j}{\partial p_j} = 0$, which implies that the marginal cost equation for the nested logit model is

$$mc_j = p_j - \frac{1-\sigma}{\alpha\left(1-\sigma s_{j|g}-(1-\sigma)s_j\right)}\ , \qquad (6)$$

With the marginal cost estimated from equation (6), we conduct a simple regression of the predicted marginal cost on Golden Seller, controlling for phone model fixed effects, month fixed effects, day of the period fixed effects, the sellers' geographical location and seller rating grade. On average, Golden Sellers have a relatively lower marginal cost by ¥18.96 relative to the other sellers. The negative effect is not counterintuitive, despite the fact that sellers, especially Golden Sellers, tend to invest more in subscribing seller services in order to compete for the badge. This type of investment as fixed costs are highly likely to benefit sellers in the long run, leading to a lower marginal cost, and subsequently a lower equilibrium price. For example, their investment in platform analytics helps them understand consumers tastes and better target and advertise, and thus save time and financial resources on advertisement; the subscription of professional webpage design helps sellers attract more potential consumers, and thus increase the click-through rate and the conversion rate.

7. Counterfactual and Welfare

Theoretically, consumers benefit from the Golden Seller certificate system for several reasons. First, consumers now can enjoy a lower price due to the increase in price competition. Second, consumers save time reading the customer reviews and comparing the ratings across sellers by looking at the badge. Third, the badge conveys more information in addition to the ratings and reviews, which help consumers make better decisions. According to the evaluation criteria, seller's score of consumer satisfaction has to be greater than 80 to be valid for the evaluation. This is an index calculated by the platform based on the repeat purchase rate, which is not released on the website.

All channels to increase consumer surplus described above result in the positive coefficients of Golden Seller in the demand estimation. Our estimation of $\alpha,$ σ and δ_j from the nested logit model and the marginal cost from the supply side allow us to construct a counterfactual hiding the Golden Seller badge from consumers. The demand estimation suggests that consumers prefer

Golden Sellers even after controlling for average rating. If the badge is no longer visible, the model predicts that the market share of Golden Sellers decreases while the share for other sellers increases.

To simulate the counterfactual, we make several assumptions. First, we assume that the ratings and reviews are unchanged, and that the only difference in the counterfactual is that the badge is no longer visible by consumers. Second, the cost structure stays the same with or without the Golden Seller certification. Third, the sellers set price equal to the Bertrand-Nash Equilibrium price given the new demands. Last, the price of the outside good is exogenous and does not change in the counterfactual.

7.1 The Counterfactual Equilibrium

We calculate the counterfactual equilibrium prices and market shares by solving the following simultaneous-equations model:

$$
\begin{cases}
\delta_j^C = -\alpha P_j^C + \mathrm{X}_j'^C \beta + \xi_j, & (7) \\
P_j^C = mc_j + \dfrac{1-\sigma}{\alpha\left(1 - \sigma s_{j|g}^C - (1-\sigma) s_j^C\right)}, & (8) \\
s_{j|g}^C = \dfrac{e^{\delta_j^C/1-\sigma}}{D_g^C}, & (9) \\
s_j^C = \dfrac{e^{\delta_j^C/1-\sigma}}{(D_g^C)^\sigma \left(1 + \sum_{g'} D_{g'}^{C\ 1-\sigma}\right)}, & (10) \\
D_g^C = \sum_{j \in J_g} e^{\delta_j^C/1-\sigma}, & (11)
\end{cases}
$$

where $\mathrm{X}_j'^C$ is derived by converting all values of variable Golden Seller to 0. $\alpha,\ \beta,\ \xi_j$ and mc_j are estimated from the nested logit model. Equation (7) – (11) are used to calculate the new shares, the new prices, and the new producer and consumer surplus. They are solved numerically with an interactive method that consistently converges.

7.2 Consumer Surplus

The compensating variation calculated with these assumptions is the lower bound of the change in consumer surplus comparing the current platform to the counterfactual, because we are assuming consumers can still enjoy the lower price caused by the competition for the badge. Following Small and Rosen (1981), and McConnell (1995), the difference in consumer surplus per phone model per day is

$$\Delta E(CS) = \frac{M}{\alpha}\left[\ln\left(1 + \left(\sum_{j \in g^C} \exp\left(\frac{\delta_j^C}{1-\sigma}\right)\right)^{1-\sigma}\right) - \ln\left(1 + \left(\sum_{j \in g} \exp\left(\frac{\delta_j}{1-\sigma}\right)\right)^{1-\sigma}\right)\right], \quad (12)$$

where g denotes the nests in current platform, and g^C denotes the nests in the counterfactual. δ_j^C is the estimated mean utility from purchasing product j using the counterfactual equilibrium price.

Table 4 shows the average change in consumers surplus by brand. We calculate the daily change in consumer surplus per phone model following Equation (12) and sum up across all the phone models within a brand. Column (3) reports that on average, consumers worse off in the counterfactual by ¥105, 540.10 each day, which is equivalent to 4.53% of the current daily revenue. Specifically, welfare of Apple customers declines most in terms of monetary value. It can be explained by the highest average price. As consumers switch to outside goods absent the certification, consumer surplus acquired from this platform decrease more relative to other products.

Meanwhile, consumers of Honor and Xiaomi lose more relative to other consumers in terms of percentage change in the counterfactual. According to Column (3) and (6), Honor generates ¥19,845.18 in consumers surplus per day, which accounts for 7.54% of the current daily revenue, while Xiaomi generates ¥21276.08 in consumer surplus per day which is 8.86% of the currently daily revenue. Column (2) shows that the average prices of Honor and Xiaomi are lower compared to the other brands. In fact, these two brands are famous for the low price, and they are the main rivals in competing for the low-income consumers. Our results imply that the low-income consumers benefit most from the Golden Seller certification[7]. One possible explanation is that these low-income consumers are more risk averse, and therefore they tend to choose the outside good (exiting the market and buying from an official website or retail store) absent the certification.

7.3 Profits

The change in profits for a seller f is given by

$$\Delta\pi_f = \pi_f^C - \pi_f$$

$$= \left(\sum_{j\in f}\left(P_j^C - mc_j\right)Ms_j^C - FC_j\right) - \left(\sum_{j\in f}\left(P_j - mc_j\right)Ms_j - FC_j\right), \qquad (13)$$

where the superscript C indicates the counterfactual.

Table 5 reports the average change in market shares and in sellers' profits per day absent the badge. Our results show that Golden sellers worse off substantially in the counterfactual while the other sellers gain tiny benefit. In column (1), we find that, on average, the total market share of Golden Sellers' products decreases by 78.66% if the badge is hidden, leading to a profit loss of ¥101,805.51, which is equivalent to 12.72% of the current revenue. Meanwhile, the other sellers do not benefit much when consumers switch away from the Golden sellers in the counterfactual. Column (2) shows that the overall market share of the other sellers increases by merely 3.73%. These sellers in total will gain ¥11,080.83 per day in the counterfactual, which is neglectable compared to the Golden Sellers' loss. Column (3) shows the overall change if the badge is no longer available to consumers. The average total market share will decrease by 23.87%, which is equivalent to a loss of ¥90,724.68 per day, accounting for roughly 3.91% of the current daily revenue.

Our findings in the counterfactual analysis show that only high-quality sellers, who are awarded the Golden Seller badge, are the big winners in the Golden Seller evaluation. The huge increase in the profits due to the badge serves as an incentive for all the sellers to compete for the

[7] Table A.5 in Appendix reports the changes in consumer surplus by phone model. In Column (6), we find that all phone models with a percentage change higher than 10% have a relatively lower price at around ¥1,000. This finding reinforces our conjecture of the possible explanation, as all products with a lower price from all brands are targeting low-income individuals.

badge. This is consistent with our previous finding that sellers are willing to lower price toward the end of each periods, as well as the finding that Golden sellers have a lower price relative to the others, as the award for the winners are significantly large. Furthermore, the result that the overall market share decreases by around 24% in the counterfactual implies that the platform level recognition has a market expanding effect, which will in turn attract more high-quality sellers to start business on the platform in the long run.

8. Conclusion

Information on product quality in online markets is an important research topic. This paper studies the effects of summary information on e-commerce platforms on consumer decisions. Golden Seller certification is evaluated by the platform based on a list of mostly observable criteria. Although the majority of the criteria are already observable to consumers, we find that the badge benefits both consumers and sellers. Using aggregated data collected from the smart phone markets on Taobao, we find that the Golden Sellers have a relatively lower price but a significant higher sales volume. We calculate the marginal cost using the demand estimation and find that Golden Sellers tend to have a relatively lower marginal cost. Furthermore, we simulated a counterfactual hiding the Golden Seller badge from consumers. We find that both consumer surplus and producer surplus in current platform are higher than those in the counterfactual. The decrease in marginal cost and increase in total surplus suggests that the platform's certificate enhances market efficiency, which is a win-win for both sellers and consumers. Particularly, Golden Sellers, or high-quality sellers, benefit from the Golden Seller certification substantially at a tiny expense of the other sellers. In the long run, the certification will attract more high-quality sellers as well as buyers to this platform. With richer dataset, future studies can focus on investigating the mechanisms that increases efficiency, such as the reduction in consumers' search cost as well as the possible channels how investment in seller services decreases the marginal cost.

Table 1: Summary Statistics

	Mean	SD	Min	Max
Price (¥)	2227.34	1625.55	499	7888
Products Sold in the Last 30 Days	7.981	30.646	0	376
Estimated Daily Sales	0.267	0.696	0	12
Golden Seller Status	0.103	0.304	0	1
Weekends and Holidays	0.440	0.496	0	1
Rating of Delivery	4.824	0.191	1	5
Rating of Product	4.816	0.195	1	5
Rating of Service	4.828	0.187	1	5
Seller Rating Grade	8.365	3.405	0	16
Number of Sellers	2036			
Number of Smartphone Models	52			
Observations	370683			

Data Source: smart phone market on Taobao, January to June, 2018.

Table 2: Effects of GS on Price and Sales - 2SLS

	(1) ln(Price): OLS	(2) ln(Price): IV	(3) Daily Sales: OLS	(4) Daily Sales: IV
Golden Seller	-0.0112***	-0.0149***	0.364***	0.710***
	(0.00100)	(0.00190)	(0.00545)	(0.00708)
Average Rating	0.0611***	0.0851***	0.101***	0.108***
	(0.00204)	(0.00220)	(0.00389)	(0.00820)
Weekends and Holidays	0.000617	0.00104	-0.0000143	0.0119***
	(0.000596)	(0.000643)	(0.00220)	(0.00240)
1st Day of Period	-0.00176	-0.00115	0.0481***	0.0313***
	(0.00165)	(0.00172)	(0.00590)	(0.00642)
2nd Day of Period	-0.00316*	-0.00346**	0.0317***	0.0346***
	(0.00173)	(0.00172)	(0.00601)	(0.00641)
3rd Day of Period	-0.00237	-0.00309*	0.00889	0.00507
	(0.00165)	(0.00167)	(0.00568)	(0.00623)
4th Day of Period	-0.00214	-0.00279*	0.00299	-0.00153
	(0.00157)	(0.00159)	(0.00551)	(0.00592)
5th Day of Period	-0.00539***	-0.00547***	0.0632***	0.0620***
	(0.00160)	(0.00161)	(0.00571)	(0.00601)
6th Day of Period	-0.00597***	-0.00552***	-0.00396	-0.00429
	(0.00158)	(0.00161)	(0.00563)	(0.00600)
7th Day of Period	-0.00687***	-0.00612***	0.0916***	0.122***
	(0.00157)	(0.00164)	(0.00566)	(0.00611)
8th Day of Period	-0.00914***	-0.00796***	0.0424***	0.0178***
	(0.00155)	(0.00162)	(0.00548)	(0.00606)
9th Day of Period	-0.00835***	-0.00770***	0.0140**	0.0295***
	(0.00173)	(0.00187)	(0.00615)	(0.00700)
10th Day of Period	-0.00708***	-0.00585***	0.0639***	0.0386***
	(0.00165)	(0.00174)	(0.00583)	(0.00650)
11th Day of Period	-0.0108***	-0.00835***	0.0259***	0.0359***
	(0.00161)	(0.00167)	(0.00559)	(0.00624)
12th Day of Period	-0.00968***	-0.00992***	0.0453***	0.0975***
	(0.00168)	(0.00186)	(0.00605)	(0.00692)
13th Day of Period	-0.0142***	-0.0130***	0.00218	-0.000456
	(0.00172)	(0.00182)	(0.00614)	(0.00680)
14th Day of Period	-0.0142***	-0.0125***	0.0909***	0.0890***
	(0.00176)	(0.00176)	(0.00622)	(0.00656)
15th Day of Period	-0.0149***	-0.0187***	0.0771***	-0.0574***
	(0.00210)	(0.00279)	(0.00771)	(0.0104)
Adjusted R_Squared	0.940	0.940	0.222	0.211
Observations	370683	305965	370683	305965

Note: * p<0.10; ** p<0.05; *** p<0.01. Robust standard errors are in parentheses. All columns control for product FEs, month FEs, day of period FEs, province FEs and seller rating grade FEs.

Table 3: Demand Estimation

	(1) Logit: OLS	(2) Logit: IV	(3) Nested Logit: IV
Price	-0.00173***	-0.00243***	-0.00203***
	(0.0000158)	(0.0000194)	(0.000179)
Golden Seller	1.689***	1.675***	1.390***
	(0.0226)	(0.0171)	(0.130)
σ (Phone Model)			0.141**
			(0.0638)
Average Rating	0.623***	0.673***	0.560***
	(0.0233)	(0.0296)	(0.0565)
Weekends and Holidays	-0.000179	0.000952	-0.000111
	(0.0108)	(0.0107)	(0.00894)
Phone Model Fes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes
Day of Period FEs	Yes	Yes	Yes
Seller Grade FEs	Yes	Yes	Yes
Province FEs	Yes	Yes	Yes
Mean Elasticity	-3.862	-5.408	-5.255
Adjusted R_Squared	0.288	0.282	0.499
Observations	370683	370581	370581

Note: * p<0.10 ** p<0.05 *** p<0.01. Robust standard errors are in parentheses. Column (1) and (2) show regular logit, and Column (3) shows the nested logit model with nests of phone model.

Table 4: Changes in Consumer Surplus by Brand

(1) Brand	(2) Price (¥)	(3) ΔE(CS) (¥)	(4) Revenue (¥)	(5) ΔE(CS) as % of Revenue	(6) % of Golden Seller	(7) Number of Models
Apple	5647.92	-31,140.86	1,503,923.63	-2.07	17.01	3
Honor	1382.00	-19,845.18	263,274.30	-7.54	10.01	9
Huawei	2183.62	-28,625.67	412,599.79	-6.94	10.47	13
Oppo	1892.24	-3,180.02	75,376.12	-4.22	7.79	7
Vivo	1774.11	-1,541.99	78,628.44	-1.96	3.79	8
Xiaomi	1243.19	-21,276.08	240,186.36	-8.86	9.84	12
Overall	2227.34	-105,540.10	2,573,989.00	-4.53	9.23	49

Note: Column (2) shows the average price within the brand. Column (3) and (4) show the total change in CS and revenue of all models in the brand. Column (6) shows the percentage of Golden Sellers averaged by number of phone models in the brand.

Table 5: Change in Market Share and Daily Profit

	(1) Golden Sellers	(2) Other Sellers	(3) Overall
Total Market Share	0.0206%	0.0459%	0.0665%
Total Market Share in Counterfactual	0.0044%	0.0475%	0.0519%
% Change in Market Share	-78.66	3.73	-23.87
Total $\Delta\pi$ (¥)	-101,805.51	11,080.83	-90,724.68
Total Revenue (¥)	807,858.04	1,766,130.61	2,573,989.00
$\Delta\pi$ as % of Revenue	-12.72	0.69	-3.91

Note: all numbers are calculated as the daily average.

Appendix

A.1 Criteria for Golden Seller

General criteria:

1. Business operating duration >=183 days
2. Credit rating >= 251
3. Deposit paid to Taobao for Buyer Protection Program [8]
4. Percentage of used product transactions <=5%
5. No virtual online products (except for sellers of online game products)
6. Accumulate score of general penalty during the past calendar year < 12
7. No grievous penalty during the past calendar year
8. No penalty due to selling counterfeit products
9. Accumulate score of penalty due to selling counterfeit products during past calendar year<=24
10. Business is in operation.
11. Score of consumer satisfaction >= 80

Category specific criteria:

1. Positive comment rate
2. Product description is consistent with the product received (max=5)
3. Rating of service (max=5)
4. Rating of shipping quality (max=5)
5. Revenue
6. Dispute rate

[8] Under the category of cell phones, the required deposit is ￥10,000 before Jan 20th, 2018 and ￥50,000 after that.

A.2 List of Dates

Date	Period	Date	Period	Date	Period	Date	Period
13-Jan-18	1	19-Mar-18	6	16-Apr-18	8	16-May-18	10
17-Jan-18	2	20-Mar-18	6	17-Apr-18	8	17-May-18	10
23-Jan-18	2	21-Mar-18	6	18-Apr-18	8	18-May-18	10
24-Jan-18	2	22-Mar-18	6	19-Apr-18	8	19-May-18	10
25-Jan-18	2	23-Mar-18	6	20-Apr-18	8	20-May-18	10
26-Jan-18	2	24-Mar-18	6	21-Apr-18	8	21-May-18	10
27-Jan-18	2	25-Mar-18	6	22-Apr-18	8	22-May-18	10
28-Jan-18	2	26-Mar-18	6	23-Apr-18	8	23-May-18	10
29-Jan-18	2	27-Mar-18	6	24-Apr-18	8	24-May-18	10
31-Jan-18	2	28-Mar-18	6	25-Apr-18	8	26-May-18	10
1-Feb-18	3	29-Mar-18	6	26-Apr-18	8	27-May-18	10
2-Feb-18	3	30-Mar-18	6	27-Apr-18	8	28-May-18	10
3-Feb-18	3	31-Mar-18	6	28-Apr-18	8	30-May-18	10
4-Feb-18	3	1-Apr-18	7	29-Apr-18	8	31-May-18	10
5-Feb-18	3	2-Apr-18	7	30-Apr-18	8	2-Jun-18	11
6-Feb-18	3	3-Apr-18	7	1-May-18	9	5-Jun-18	11
7-Feb-18	3	4-Apr-18	7	2-May-18	9	9-Jun-18	11
8-Feb-18	3	5-Apr-18	7	3-May-18	9		
9-Feb-18	3	6-Apr-18	7	4-May-18	9		
20-Feb-18	4	7-Apr-18	7	5-May-18	9		
21-Feb-18	4	8-Apr-18	7	6-May-18	9		
22-Feb-18	4	9-Apr-18	7	7-May-18	9		
23-Feb-18	4	10-Apr-18	7	8-May-18	9		
24-Feb-18	4	11-Apr-18	7	9-May-18	9		
25-Feb-18	4	12-Apr-18	7	11-May-18	9		
26-Feb-18	4	13-Apr-18	7	12-May-18	9		
27-Feb-18	4	14-Apr-18	7	13-May-18	9		
5-Mar-18	5	15-Apr-18	7	14-May-18	9		
				15-May-18	9		

Table A.3: Seller Rating Grade

Seller Rating Grade	Symbol	Seller Rating Score
0		0-3
1	1 Heart	4-10
2	2 Hearts	11-40
3	3 Hearts	41-90
4	4 Hearts	91-150
5	5 Hearts	151-250
6	1 Diamond	251-500
7	2 Diamonds	501-1,000
8	3 Diamonds	1,001-2,000
9	4 Diamonds	2,001-5,000
10	5 Diamonds	5,001-10,000
11	1 Blue Crown	10,001-20,000
12	2 Blue Crowns	20,001-50,000
13	3 Blue Crowns	50,001-100,000
14	4 Blue Crowns	100,001-200,000
15	5 Blue Crowns	200,001-500,000
16	1 Gold Crown	500,001-1,000,000
17	2 Gold Crowns	1,000,001-2,000,000
18	3 Gold Crowns	2,000,001-5,000,000
19	4 Gold Crowns	5,000,001-10,000,000
20	5 Gold Crowns	Above 10,000,001

A.4 Estimate Daily Sales from 30-day Moving Window

For any given product j from seller j on date t, we assume the quantity sold on day t depends on a series of factors on that day:

$$Daily\ Sales_t = X_t\beta + \varepsilon_t, \qquad (8)$$

Where $Daily\ Sales_t$ is the quantity sold on date t.

X_t is vector of independent variables that affect the sales on day t, including the price, Golden seller status, months the product has been in market, holidays, day of the week fixed effects, period fixed effects, product fixed effects, and seller fixed effects.

Adding up the equation from t to t-29, we derive the 30-day sales equation:

$$30_{Day}Sales_t = \sum_{t-29}^{t} Sales_t = \beta \sum_{t-29}^{t} X_t + \sum_{t-29}^{t} \varepsilon_t \quad (9)$$

Now the aggregated quantity sold on day t is a regression on independent variables from the past 30 days. Using the estimated coefficients, we can predict the daily sales using equation (9). The coefficients for the product fixed effects and seller fixed effects for prediction are $\frac{\beta}{30}$.

The missing dates in our collected data raise some issues in the prediction process. To estimate equation (9), we need data on all relevant days. Thus, it is necessary to fill in the missing dates first in the data and then fill in the values for independent variables.

However, some of the factors in vector X might vary every day, such as Golden seller status and price. In order to make the estimation accurate and reliable, before we fill in the missing values, we should carefully choose the independent variables for equation (9). The main criterion is the missing values can be derived or conjectured from existing values. We will use Golden Seller status, price and the lengths that the product has been in the market.

We follow the steps below to conjecture the Golden Seller status for every day in the relevant time span. First, check if the Golden Seller status changes within a period using existing values. For sellers whose status does not change, fill in missing values with the existing values. For sellers with different status within a period, assume that the status is the same as the previous day. If the first day of a period is missing, assume the status is the same as the first existing value within the period. If the entire period is missing for a seller, then replace the missing status with the mode across all periods using existing values. The steps to conjecture the daily price in the relevant time span is easier. We assume that the price is the same as the previous day. Lastly, the lengths that the product has been in the market is calculated from the difference between the date and the launch day.

A.5: Changes in Consumer Surplus by Phone Model

(1) Brand	(2) Model ID	(3) Price (¥)	(4) ΔE(CS) (¥)	(5) Revenue (¥)	(6) ΔE(CS) as % of Revenue	(7) % Golden Seller
Apple	1544484	4759.29	-7834.35	233591.80	-3.53	15.71
Apple	1544485	5277.86	-10197.23	391422.44	-2.78	16.98
Apple	1544486	6930.46	-13677.38	908230.25	-1.70	18.36
Honor	1484602	2116.27	-1292.99	18935.72	-8.05	10.13
Honor	1484717	1032.86	-1805.01	15463.43	-12.82	6.81
Honor	1515229	695.08	-900.30	6172.14	-14.73	7.48
Honor	1519397	2009.57	-2156.98	34961.32	-6.35	9.71
Honor	1541471	891.01	-2775.69	15133.40	-17.86	11.66
Honor	1543106	603.49	-879.38	4787.54	-17.19	11.38
Honor	1547128	1326.16	-3570.91	29257.19	-12.83	11.62
Honor	1569914	2579.46	-3339.64	108548.46	-4.28	10.78
Honor	1576149	1162.80	-3381.22	33918.95	-11.18	10.56
Huawei	1487030	2568.83	-2458.31	48087.06	-5.92	10.65
Huawei	1487036	2925.27	-1587.23	34230.32	-5.22	8.84
Huawei	1491531	1330.81	-1888.44	16242.15	-11.45	8.58
Huawei	1505651	1043.50	-2109.42	19223.96	-13.09	9.48
Huawei	1515079	1643.85	-2395.60	20290.87	-11.92	10.06
Huawei	1515081	1993.54	-1403.59	12289.15	-12.62	10.84
Huawei	1522882	755.83	-2414.75	18936.75	-16.15	8.70
Huawei	1546323	1775.47	-2895.04	24031.18	-13.18	11.04
Huawei	1547125	3422.44	-3398.47	84537.19	-4.72	12.63
Huawei	1547126	4106.89	-2507.87	61064.93	-4.80	11.23
Huawei	1547127	5016.78	-0.10	0.00	.	10.32
Huawei	1573954	2316.63	-2934.72	57127.35	-6.39	10.31
Huawei	1578094	1229.63	-3000.17	21447.76	-14.88	12.88
OPPO	1515434	2105.98	-339.67	13467.54	-2.70	3.86
OPPO	1532250	1383.80	-519.42	8144.57	-7.08	8.16
OPPO	1555303	2499.91	-594.57	17647.65	-3.77	7.60
OPPO	1555304	2760.84	-417.46	12056.39	-3.70	8.87
OPPO	1572609	1727.30	-444.87	11016.25	-4.48	9.62
OPPO	1577241	1476.08	-395.78	6101.69	-8.07	8.52
OPPO	1579411	1267.21	-523.31	8039.73	-7.56	8.11
Vivo	1516764	826.98	-66.70	1980.43	-2.53	2.15
Vivo	1522872	2179.42	-217.18	7866.26	-2.99	4.47
Vivo	1522873	1841.10	-314.48	20077.94	-1.82	3.42
Vivo	1542983	2435.34	-308.93	18799.37	-1.81	4.63
Vivo	1547120	2606.16	-178.18	7936.72	-2.52	4.28

Vivo	1552186	1888.49	-212.77	8919.22	-2.79	3.89
Vivo	1572610	1083.11	-140.15	4179.10	-3.69	4.08
Vivo	1577243	1350.01	-159.04	11980.47	-1.39	3.69
Xiaomi	1482035	850.76	-2110.37	15219.30	-16.31	8.01
Xiaomi	1486842	1186.07	-342.13	2768.01	-11.18	9.41
Xiaomi	1486846	675.33	-1376.77	6427.25	-21.18	7.40
Xiaomi	1501906	2178.08	-2138.51	45965.38	-5.01	9.07
Xiaomi	1515960	1296.56	-2811.15	31195.46	-9.69	10.96
Xiaomi	1530718	1180.39	-2671.38	24564.22	-11.16	11.00
Xiaomi	1538893	651.26	-1712.58	10783.65	-23.42	9.17
Xiaomi	1538895	2848.68	-2207.83	44962.99	-4.59	12.48
Xiaomi	1544487	1785.11	-1857.33	36699.03	-5.29	9.96
Xiaomi	1547132	584.68	-1010.44	5043.31	-20.17	9.86
Xiaomi	1547133	887.13	-2147.52	17371.92	-13.93	9.04
Xiaomi	1547138	757.60	-1636.36	6743.49	-26.61	11.95

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