# Costly Signaling in E-Commerce Markets: Empirical Evidence from A Quasi-Experiment on Taobao.com

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**Abstract**

Reputation systems in e-commerce markets are widely adopted to mitigate information asymmetries, but instead they undermine market competition because new sellers are unlikely to sell their products. In this paper we study how signaling mechanisms can be employed by e-commerce markets to fix the drawback of reputation systems. Guided by a dynamic signaling theory, we compile data from the largest e-commerce market in China to examine the treatment effects of signaling programs on transactions under three scenarios: different signaling costs, different product values and different reputation ratings. The theoretical and empirical findings of the paper indicate the following requirements for an efficient signaling mechanism which can facilitate transactions of new sellers in an e-commerce market: 1. the reputation system of the market can generate reliable customer reviews; 2. the product value is high; 3. the signaling cost is high, especially for low-reputation sellers; and 4. the signaling cost and the status of taking signaling actions are factored in ranking the display order of sellers.

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## 1. Introduction

In this paper we use data from Taobao.com (Taobao), the largest e-commerce platform in China,[1] to study the effectiveness of signaling mechanisms in mitigating information asymmetries in e-commerce markets (e-markets). We restrict the analysis to Taobao's consumer-to-consumer (C2C) markets, the equivalent of Amazon.com's marketplace that enables third-party sellers to sell new and used products at fixed prices. The data contain all transactions of two types of new products with very different values – Nokia 5230XM cell phone (Nokia) and new Kingston Micro SD card (Kingston) within the half year between July 1st and December 31st of 2010, during which the sellers experiment various signaling actions on the e-market.

In a C2C market, information asymmetry has been a severe issue because buyers and sellers usually trade anonymously and buyers cannot see and feel a product before purchasing. To mitigate information asymmetries, E-markets including that of Taobao usually adopt a reputation system in which ratings of trustworthiness are assigned to a seller on the basis of buyers' reviews of their previous transactions. The major drawback of the reputation system, however, is that new sellers with few previous sales are unlikely to close a deal. In our data there are only about 6% of bottom half sellers in terms of reputation ratings achieved positive sales in the half year. Fan, Ju and Xiao (2016) document that new sellers at Taobao, in hopes of improving their reputation in the long run, tend to lower prices to boost transaction volumes; but doing so decreases their survival likelihood. Reputation systems actually undermine competition in e-markets.

Both economics theories and empirical findings suggest that it is possible to use costly signaling such as money-burning advertising, quality claims, third-party certifications, warrantees and charity to fix the drawback of the reputation system in an e-market.[2] In 2010, Taobao experimented various signaling programs including charity in its C2C markets. A seller in a product market has the option to pay certain costs to participate in these programs, and both the participation status and participation costs of the programs are displayed on the seller's website. Data from Taobao allow us to examine the following three questions not yet addressed by the

[1] As of December 2014, more than seven million merchants sell more than 800 million products at Taobao. Taobao's total gross merchandise volume (GMV) in the first quarter of 2015 amounted to 381 billion Yuan (US$ 62 billion), which was almost three times as much as Amazon's worldwide revenue in the same period.

[2] Theoretical papers include Nelson (1974), Klein and Leffler (1981), Kihlstrom and Riordan (1984), Milgrom and Roberts (1986) and Bagwell and Riordan (1991). Empirical studies by Thomas et al. (1998), Horstmann and MacDonald (2003), Jin and Kato (2006), Boulding and Kirmani (1993), Roberts (2010), Choi and Ishii (2010), Elfenbein et al. (2012) and Bate et al. (2013) have examined the role of advertising, quality claims, third-party certifications, warrantees and charity in siganling product quality.

literature: i) what signaling actions can be effective quality signals in a product market; ii) which product markets benefit more from signaling in mitigating information asymmetries; and iii) what is the interaction between signaling and reputation in a product market.

The first question is important because the classical signaling theory demonstrates the essential role of participation costs in signaling quality. Sellers' participation cost is therefore an important factor to consider when designing signaling programs in an e-market. In this paper, we examine how signaling equilibrium outcomes in a product market vary across programs with different participation costs. The second question is important because sellers in an e-market normally sell a large number of products with different values and of various categories. The seminal paper by Stigler (1961) points out that consumers put more effort into searching information when the benefits of doing so are bigger. One implication of the search theory for the e-market under our investigation is that buyers would make an effort to search relevant information when they purchase expensive products. [3] Therefore, signals sent by sellers are better received by buyers in the market of expensive products than in that of cheaper products. In this paper we also examine how signaling equilibrium outcomes from a signaling program differ across markets with different product values. Finally, the importance of the third question is demonstrated by the theory in Daley and Green (2014), which explains the situation under which buyers can infer a seller's type through two channels – signaling and noisy public information such as reputation ratings. The paper suggests that in equilibrium a seller resolves the trade-off between using the costly signal and allowing the ratings to distinguish him. In this paper we examine the effect of reputation ratings on signaling equilibrium outcomes in different product markets.

We investigate the three questions by first developing a stylized dynamic signaling model to capture the key features of transactions in e-markets and the key elements in three strands of literature – the classical signaling theory in industrial organization, the information search of buyers and the theory of signaling with incomplete public information as in Daley and Green (2014). We are thus able to draw several insights regarding our research questions from the theoretical model. With these insights, we compile the data set containing all weekly transactions of all sellers of the two products – Nokia and Kingston - over the half year during which the sellers

[3] Lewis and Marvell (2011) document that consumers in gasoline market search more as prices rise than they do when prices fall. Such an empirical evidence confirms theoretical predictions in Cabral and Fishman (2008), Yang and Ye (2008) and Tappata (2009) on asymmetric responses to price adjustments in consumers' search behavior.

were allowed to participate in various signaling programs. The data set allows us to investigate both the effects of signaling programs with different signaling costs on transactions of a large number of sellers who sell a homogeneous product, and the effect of one signaling program on transactions of a large number of sellers who sell products of different values.

We design a difference-in-differences (DID) matching approach with regression adjustments to identify the treatment effects of signaling programs on transactions under three scenarios: different signaling costs, different product values, and different reputation ratings. The novelties of our empirical approach are the following. First, the DID comparison between a treated and a controlled seller of a signaling program is on the same time window in our matching approach. A traditional regression implementation of the DID identification would compare treated and controlled sellers across time because treated sellers participate in a signaling program at different times during the sampling period. Second, we exploit the variation in sellers' time of participation in a signaling program to address the self-selection in participation in the matching step; sellers who have similar observed characteristics and participate in a signaling program before the sampling period are used as the control group of treated sellers who participate in the signaling program during the sampling period. A traditional DID matching approach would compare treated sellers of a signaling program with sellers who never participate in the program, but doing so fails to control for unobserved factors that affect both the participation decision and outcome of comparison. Finally, we design a regression adjustment approach to remove the impacts of various factors on outcome dynamics in the time window of the DID comparison. A traditional DID matching approach would assume that the matched treated and controlled sellers have the same outcome dynamics during the time window of comparison given that the sellers have similar observed characteristics at treatment time; this assumption, however, ignores the possibility that the observed characteristics of a matched pair can follow different dynamics which affect the outcome dynamics.

Consistent with the insights drawn from the dynamic signaling theory, signaling actions with zero or little cost cannot signal product quality efficiently in our findings. A costly signaling program has significantly positive effects on participants' sales and revenue and such effects are more notable in the market of expensive products (Nokia) than in that of cheap products (Kingston). Moreover, the higher the participation cost, the stronger the positive impact of signaling is on sales and revenue of participants. We also find interesting interactive effects of signaling and reputation

ratings on sellers' sales and revenue. The interactive effects, however, cannot be clearly explained by standard signaling theories. First, we find that the positive effects on sales and revenue of a costly signaling program are much larger for high-reputation participants than for low-reputation ones. It is therefore unlikely for low-reputation sellers to rely on costly signaling programs to facilitate transactions. We argue that such small impact can be attributed to business practices adopted by e-markets. Most e-markets use algorithms to rank the display order of sellers, and reputation ratings are of a heavy weight in those algorithms. Consistent with the cited information search theory, buyers pay little attention to sellers that are not displayed in the first several pages. Therefore, signals sent by low-reputation sellers will be poorly received by buyers. Second, we find that taking signaling actions with zero cost ("cheap talk") not only is useless for low-reputation sellers but also generates negative impact on high-reputation sellers' transaction outcomes. Buyers would render a seller's high reputation rating implausible if the seller engages in "cheap talk".

The findings of the paper have important implications for designing efficient signaling mechanisms in e-markets. First, signaling mechanisms will never replace the reputation system in terms of mitigating information asymmetries. In fact, both our theoretical model and empirical findings indicate that an efficient signaling program is built on a potent reputation system which encourages credible customer reviews on transactions. Second, signaling programs are likely to be ineffective in the market of cheap products. Finally, a signaling program that can fix the drawback of a reputation system and facilitate transactions for low-reputation sellers could be priced discriminately – charging low-reputation sellers a high participation fee and high-reputation sellers a low participation fee. Algorithms widely used to rank the display order of sellers in e-markets should be improved to incorporate the participation status of signaling programs and reflect differences in participation costs, and thus assign a higher score to participants paying a higher cost.

This paper contributes to the broad literature of signaling in industrial organization through the following practices: testing empirically the predictions of the signaling theory regarding the importance of signaling costs, offering new insights and evidence on the connections between the theory of signaling and the theory of consumers' information search, and examining the role of signaling when other channels of information asymmetry mitigation are available. This paper contributes also to the emerging studies on mechanism design in e-markets. This stream of

literature has empirically investigated the role of reputation (Houser and Wooders 2006; Cabral and Hortacsu 2010; Ye et al. 2013; Jullien and Park 2014; Hui et al. 2016; Elfenbein et al. 2016; and Fan et al. 2016), charity (Elfenbein et al. 2012) and information disclosure (Lewis 2011) in mitigating information asymmetries in e-markets. Finally, the empirical approach developed in this paper can be applied to identify treatment effects under the DID framework in various fields.

## 2. A Dynamic Signaling Model

In this section we present a dynamic signaling game in an e-market and use the model to show how signaling equilibrium outcomes are affected by signaling costs, product value and reputation ratings.

*Model set-up*

Formally we consider a competitive electronic market where a large number of sellers sell a durable good to a large number of buyers in multiple periods. Time is discrete and indexed by $t = 0,1,\cdots$. At the beginning of the initial period ($t = 0$), a seller is endowed with a reputation rating $r$, which is public information, and a batch (with size $K$) of the good to sell. The seller has a probability $(\lambda_t)$ to sell one unit of the good to a buyer in a period. The quality of the good, which is privately known to the seller, is either good ($G$) or bad ($B$). The value of a good-quality good to a buyer is $v$, and without loss of generality, the value of a bad-quality good is normalized to zero. In the rest of the paper we use the type of the good and the type of the seller interchangeably and use $\theta \in \{G, B\}$ to denote the type.

The existence of a signaling mechanism implies that the seller can choose to pay a cost $\tau$ to join a program at $t = 0$; both the cost and the seller's status of participating the program are publicly known. Let $\alpha = \{S, NS\}$ denote the seller's signaling action – signaling $(S)$ *vs.* not signaling $(NS)$, a $\theta$-type seller's strategy is to assign a probability, which is denoted by $w_\theta$, to signal. Observing both $r$ and $\alpha$, a buyer forms her initial belief about the seller's type $\mu_0 = \mu(r, \alpha) \equiv \Pr(\theta = G | r, \alpha)$. The formation of the initial belief follows the Bayes updating process. Without any information, a buyer has the prior belief $\Pr(\theta = G) = \frac{1}{2}$; observing the seller's reputation rating, the buyer updates her prior belief according to the Bayes rule

$$\mu(r) = \frac{1}{1+R(r)}, \tag{1}$$

where $R(r) = f_L(r)/f_H(r)$, with $f_\theta(r)$ denoting the probability density of the reputation rating of a $\theta$-type seller. If the reputation system is effective such that the reputation rating is informative, we have $R(r) < 1$. Observing further the signaling action of the seller, the buyer updates her belief again according to the Bayes rule

$$\mu_0 \equiv \mu(r,\alpha) = \frac{\mu(r)}{\mu(r) + (1-\mu(r)) \times \Phi(\alpha)}, \tag{2}$$

where in equilibrium $\Phi(\alpha = S) = \frac{\Pr(\alpha = S | \theta = B, r)}{\Pr(\alpha = S | \theta = G, r)} = \frac{w_{rB}}{w_{rG}}$ and $\Phi(\alpha = NS) = \frac{1-w_{rB}}{1-w_{rG}}$. $\mu_0$ is then the market belief about the seller's type in the initial period.

Starting from $\mu_0$, the type of the seller is revealed to the market gradually through transactions. A transaction occurring in period $t$ generates a customer review $(\delta_t)$ which is either positive $(P)$ or negative $(N)$. The probability that the seller has a positive review is type dependent. Let $\eta_\theta$ denote the probability that a $\theta$-type seller has a good review from a transaction, we have $\eta_G > \eta_B$. Market belief in period $t+1$ is updated by observing the customer review from the transaction in period $t$. Again, the updating follows the Bayes rule:

$$\mu_{t+1}^{\delta_t} = \frac{\mu_t}{\mu_t + (1-\mu_t) \times \Gamma(\delta_t)}, \tag{3}$$

where $\Gamma(\delta_t = P) = \frac{\eta_B}{\eta_G}$ and $\Gamma(\delta_t = N) = \frac{1-\eta_B}{1-\eta_G}$. Given the updating process in equation (3), the transition of market belief on the seller's type is

$$\mu_{t+1} | \mu_t = \begin{cases} \mu_t & \text{with probability} \quad 1-\lambda_t \\ \mu_{t+1}^P & \text{with probability} \quad \lambda_t \times \eta_\theta \\ \mu_{t+1}^N & \text{with probability} \quad \lambda_t \times (1-\eta_\theta) \end{cases}. \tag{4}$$

The probability that the seller can sell one unit of the good to a buyer in a period is determined by the buyer's search, that is, the buyer reviews information of sellers and chooses a seller to purchase from. We do not model buyers' search behavior explicitly but simply presume that buyers always search for high-quality products in the e-market. The transaction probability

thus depends positively on the credibility of the seller ( $\mu_t$ ). Moreover, since information search is costly to buyers, a buyer can only review a subset of sellers and will only review more sellers when the benefit of doing so is larger. This assumption is consistent with the evidence in Dinerstein et al. (2014). When buyers are willing to review more sellers, the seller's probability to sell one unit of the good depends more on his credibility. Intuitively, the more expensive the good is, the larger benefit of information searching is. We therefore denote the probability for the seller to have a buyer in a period as $\lambda_t = \lambda(\mu_t, v)$, which has the following properties:

$$\partial\lambda(\mu_t, v)/\partial\mu_t > 0 \text{ and } \partial\lambda(\mu_t, v)/\partial\mu_t > \partial\lambda(\mu_t, v')/\partial\mu_t \text{ if } v > v'. \tag{5}$$

The transaction probability determines the number of periods that the seller needs to sell all the $K$ units. Let $T_\theta(r,\alpha)$ denote the number of periods for a $\theta$-type seller to sell all the $K$ units, it can be defined as

$$T_\theta(r,\alpha) := \sup\left\{T = 1,2,...: \sum_{t=0}^{T} \lambda_t \le K\right\}. \tag{6}$$

Market competitiveness implies that the transaction price of a seller in a period equals the market expected evaluation for his product. The expected pay-off of the seller is therefore $E\left(\sum_{t=0}^{T_\theta(r,\alpha)} \beta^t \pi_t\right)$, where $\beta \in (0,1)$ is a discounting factor and $\pi_t \equiv \lambda_t \times \mu_t \times v$ is the expected profit of the seller in period $t$. The profit maximizing problem of a $\theta$–type seller in a recursive form is formally

$$V_0^\theta(r) \equiv \max_{w_\theta} \left(\pi_0^S - \tau\right) \times w_\theta + \pi_0^{NS} \times (1 - w_\theta) + \beta \times EV_1^\theta(\mu_1 | \mu_0, w_\theta), \tag{7}$$

where $\pi_0^a = \lambda_0 \times \mu_0^a \times v, a = S, NS$; $\mu_0^S = \mu(r, S)$ and $\mu_0^{NS} = \mu(r, NS)$, that is, the initial market belief on the seller's type when the seller signals and does not signal respectively; and

$$EV_1^\theta(\mu_1 | \mu_0, w_\theta) = w_\theta \times E\left(V_1^\theta(\mu_1 | \mu_0^S)\right) + (1 - w_\theta) \times E\left(V_1^\theta(\mu_1 | \mu_0^{NS})\right), \tag{8}$$

in which

$$E\left(V_1^\theta(\mu_1 | \mu_0^\alpha)\right) = (1 - \lambda_0) \times E\left(V_1^\theta(\mu_0^\alpha)\right) + \lambda_0 \times \eta_\theta \times E\left(V_1^\theta(\mu_1^G)\right) + \lambda_0 \times (1 - \eta_\theta) \times E\left(V_1^\theta(\mu_1^B)\right), \tag{9}$$

where $\mu_1^G$ and $\mu_1^B$ are determined by equation (4) given that $\mu_t = u_0^\alpha$.

In sum, the dynamic signaling game has the following features. First, the seller's signaling action taken in the initial period determines the initial state of the dynamics of market belief.

Therefore, the signaling action affects not only the expected profits of initial period but also those of future periods through affecting both future prices and the time to sell ($T_\theta(r,\alpha)$). Second, good and bad quality sellers benefit differently from signaling because they have different transitions of market belief as shown in equation (4); compared with a bad-quality seller, a good-quality seller has a higher probability to get a positive review regarding a transaction and has therefore a higher probability to improve his credibility in the next period given a $\mu_t$. Finally, the benefits of having a larger initial market belief ($\mu_0$) for a good-quality seller are larger when the transaction probability ($\lambda_t$) depends more on market belief.

The equilibrium of the signaling game given a reputation rating $r$ is characterized by solving the profit-maximizing problem in (7) for both good and bad quality sellers subject to the constraint that the process of market belief $\{\mu_t\}_{t=0}^{T_\theta(r,a)}$ is determined by equations (1) – (4). The solutions are the two best-response functions – $w_{rG}(w_{rB})$ and $w_{rB}(w_{rG})$, and the intersections of the best-response functions are the equilibria of the dynamic signaling game denoted by $(w_{rG}^*, w_{rB}^*)$. The equilibrium market belief of a seller with reputation rating $r$ and taking signaling action $\alpha$, denoted by $\mu^*(r,\alpha)$, is obtained by evaluating equation (2) at the signaling equilibrium. The signaling is effective if $\Delta_r \equiv \mu^*(r,S) - \mu^*(r,NS) > 0$ and is more effective when $\Delta_r$ is larger. When the signaling is effective, a seller can take the action to increase both the probability of having a transaction and the price.

*Theoretical insights*

We use the dynamic signaling model to obtain insights regarding the empirical research questions in this paper. Because characterizing analytically the equilibria of the dynamic signaling game is no simple task, we use numerical simulations to draw insights. In simulations we parameterize the transaction probability function as simple linear form:

$$\lambda_t = \kappa_0 + \kappa_1 \times \mu_t \,. \tag{10}$$

As shown by equation (5), the effect of product value on signaling equilibrium is investigated by varying the parameters in the transaction probability function; the dependence of transaction probability on $\mu_t$ is weaker in the market of a cheaper product. Table 1 presents the parameter values used in the base-line simulation. In all simulations, we use Monte-Carlo integration to evaluate the expectations in equation (8) and the number of random draws is chosen to be large

(1000). To save space, we present the details of simulation results in the appendix and summarize the key insights from the simulation results in this section.

Figure 1 presents signaling equilibria under different signaling costs among sellers with the same reputation rating $(\mu(r) = 0.3)$. The simulation results imply that a program could play the role of quality signal only when the sellers incur certain cost to participate in the program. If the cost is too high, as shown by Figure 1e, the participation rate of the program is zero because no one can benefit from taking the action. If the cost is positive but too low, as shown by Figure 1b, good-quality sellers cannot distinguish themselves from bad-quality ones, thus the participation rate of the program is again zero. In the extreme case of zero signaling cost, as shown by Figure 1a, the only equilibrium is the fully pooling outcome, in which good and bad quality sellers have equal participation rates and participating in the program does not affect sales and revenue of sellers. If a program plays the role of product quality signal, the equilibrium outcome is either fully separating of partial pooling; at either of the equilibrium cases, joining a signaling program leads to a higher market belief for a seller as long as the intermediate market belief given the seller's reputation rating is between 0 and 1, as shown by equations (1) – (2). The increase in market belief from participating in a signaling program is larger when the equilibrium is closer to the fully separating case. Figure 1c and 1d indicate that when we increase the signaling cost of a program within a range in which the program is effective in signaling quality, the partial-pooling equilibrium shifts toward the fully separating equilibrium. A higher market belief leads to a larger transaction probability and a higher product price as suggested by the dynamic signaling model.

Holding signaling cost constant and varying reputation rating leads to different signaling equilibria, as shown by Figure 2. A good-quality seller with a higher reputation rating relies less heavily on costly signaling in conveying information about his type. On the other hand, a bad-quality seller with a higher reputation rating has a stronger incentive to imitate the strategy of good-quality sellers with the same reputation rating. If a bad-quality seller with a high reputation rating adopts a different strategy from good-quality ones with the same reputation rating, buyer would infer that the high reputation rating of the bad-quality seller is implausible. Thus, a signaling program is expected to better separate the two quality types among sellers with a low reputation rating than among those with a high reputation rating.

Figure 3 presents the equilibrium market beliefs from taking a signaling action for sellers with different reputation ratings and under different signaling costs. When the signaling cost is

low $(\tau = 5)$, a partial-pooling signaling equilibrium exists only among sellers with a low reputation rating $(\mu(r) = 0.1 \text{ or } \mu(r) = 0.3)$. As a result, buyers would consider action taken by the low-reputation sellers a signal and adjust their belief about the low-reputation sellers who take the signaling action upward. A signaling action can separate good and bad quality sellers with a higher reputation rating when the signaling cost is higher.

The impacts of signaling on sales and revenue are also different for sellers who sell products of different values, as demonstrated by simulation results in Figure 4. In this scenario we re-parameterize the transaction probability as a constant $\lambda_t = 0.30$, which equals the average transaction probability in the baseline cases when $\mu_t = 0.5$. A costly signaling program is unlikely to signal quality in markets of cheap products because buyers in these markets make little effort to search relevant information. Therefore, signals sent by sellers are poorly received by buyers in these markets. Figure 4 shows that a signaling program is unlikely to result in a partial pooling equilibrium in a market of cheap products. In such a market, a costly signaling program can only signal quality for sellers with a low reputation rating.

## 3. Empirical strategy

In this section, we use data from Taobao to test empirically the effects on sellers' sales and revenue of participating in signaling programs with different participation costs and in different product markets under the guidance of insights drawn from the simulations.

*Data and overall research design*

We selected two products – Nokia 5230XM and Kingston Micro SD card, which were popular items traded on Taobao.com in 2010 and have very different values,a new Nokia is about US$ 160 and a new Kingston is only about US$ 6. With the help from the engineering team of Taobao, we observe the transactions of all sellers of the two products from July 1st to December 31st of 2010.

In order to facilitate transactions and build trustworthiness between sellers and buyers, Taobao offered 20 programs, which are shown in Table 2, for sellers to participate. The first 14 programs are mainly for marketing promotion and the last 5 programs are for quality assurance. Program 15 – Donation is similar to the charity program discussed in Elfenbein, Fisman and Mcmanus (2012). Participating in each program incurs cost, which can be either sellers' cost of participating in marketing promotion programs and donations to charities in each transaction, or up-front cost paid

by sellers to Taobao (the cost of participating in quality assurance programs). Therefore, each of these programs can play the role of signal if the participation status of sellers varies systematically with product quality of the sellers.

We include three programs in the empirical analysis, Donation and two quality assurance programs – the Authentic Description and the 30-days Repair Warranty. Participation costs of the three programs are transparent and very different. Taobao requires Nokia sellers to deposit USD1700 and Kingston sellers USD170 to participate in the Authentic Description program which acts as a prerequisite for joining in other quality insurance programs, including the 30-days Repair Warranty which requires an extra deposit of USD330. Such deposits cannot be withdrawn until the seller exits the business. As for Donation, a seller has the option to donate US$ 0.163, 0.02 or 0.003 in each transaction to a charitable organization. The sellers' opportunity cost of participating in the two quality assurance programs occurs whether or not a sale is achieved; on the other hand, the cost of participating in Donation occurs only when the seller has transactions. Therefore, the Authentic Description and the 30-days Repair Warranty are signaling programs charging equal prices for individual seller while Donation is the one charging higher prices for sellers with larger transactions; between the two chosen quality assurance programs, the 30-days Repair Warranty is the one with a higher signaling cost.

We then compare the three costly signaling programs with "cheap talk", a signaling action with zero cost. We use word-capturing technique to identify whether or not a seller engages in "cheap talk" from the seller's product description. A seller engages in "cheap talk" when the following keywords occurred in his product descriptions: *genuine product, quality guarantee, original product, refund 10 times value of the product if the product is a counterfeit, limited edition* and *absolutely.*

We assembled weekly transaction data of the sellers over the half year. For each seller in a week, we have his number of sales and sale revenue, and other information displayed on his website at the beginning of the week, such as prices, product descriptions, transaction histories, participation status of the 20 programs, cumulative reputation ratings and historical customer reviews. From registration data we also obtained sellers' length of time (in weeks) in the business and location. Figure 5 shows the interface of a Nokia's seller who participates in the Authentic Description program (5a) and a Nokia's seller who participates in Donation (5b) in 2016.[4]

[4] Taobao no longer includes the 30-days repair warranty in the signaling programs in 2016.

Although sellers in our data are from 2010, the information displayed on sellers' interfaces in 2010 and 2016 is basically the same. In Figure 1a, the seller's participation status and the amount of program deposits are displayed on the right-side of the interface. In Figure 1b, the bottom of the interface shows that the seller commits to donate US$ 0.003 to the healthcare charities in rural areas for each transaction. Buyers can also find the reputation ratings of the two sellers – 4 diamonds for the first and 5 hearts for the second.[5] Other important information shown on the interfaces includes cumulative number of transactions and buyer's comments on the transactions.

We examine the effects on sales and revenue of participating in the three signaling programs and engaging in "cheap talk" by Nokia and Kingston sellers in different categories of reputation ratings. Specifically, we divide sellers of one product into two categories – high reputation sellers with a reputation rating 5 (one diamond) or above and low reputation sellers with a rating less than 5.[6] Donation as a signaling mechanism in e-markets has been documented in literature. However, one major concern about the empirical research design is that if the two quality assurance programs – the Authentic Description and the 30-days Repair Warranty, do affect sales and sale revenue, such effects may come from other channels instead of signaling. Lewis (2011) points out that in an e-market, product descriptions and photos displayed on a seller's website define an enforceable contract between a seller and a buyer. Contract enforcement at Taobao is through Alipay – a third-party online payment system (like Paypal of the US) owned by Alibaba (the owner of Taobao）. Most transactions at Taobao go through Alipay and every seller at Taobao must have an Alipay account. Taobao reimburses a buyer directly from a seller's Alipay account if it favors the buyer in a seller-buyer conflict. Therefore, a seller's decision to participate in quality assurance programs does not improve the enforceability of the contract – information disclosed by the seller on his website.

*Identifying the effects of signaling on sales and revenue*

We develop a Difference-in-Differences (DID) matching with regression adjustment approach to identify the causal effects on sales and revenue of sellers in markets of Nokia and Kingston of participating in one of the three signaling programs – the Authentic Description, the 30-days Repair Warranty and Donation. Because a seller's status of engaging in "cheap talk" remains

[5] Figure A2 in the appendix of the paper lists reputation ratings implemented at Taobao.
[6] About 30% of Nokia sellers and about 45% of Kingston sellers have a high reputation rating.

unchanged in the sampling period, we rely on a cross-sectional regression to identify the effects on sales and revenue of engaging in "cheap talk".

In the DID matching with regression adjustment approach, the treatment group of a signaling program in a market contains participants who joined in the program during the sampling period. We separate a treatment group into two types: type I treatment group consists of treated sellers who cannot sell a single product before treatment and type II treatment group contains those who have positive sales before treatment. This partition is for the purpose of using pre-treatment sales to control for unobserved factors affecting a seller's credibility, which affects the seller's sales and revenue.

We match a treated seller, denoted by $i$, who is from a market and starts to participate in a program of research interest in week $t$, to a set of controlled sellers who are from the same market and whose status of participation in the signaling program do not change. Because a seller's participation decision is likely to be affected by unobserved factors which influence also the outcome of research interests, matching a treated seller to those who have never participated in the program (never-in sellers) leads to a self-selection bias in estimation. We address this identification issue by matching a treated seller to always-in sellers who already are in the program before the sampling period. The identification assumption of such matching is that the time of participating in a program is exogenous, which is a weaker assumption than the one assuming participation is exogenous.

An always-in seller who is matched to a treated seller satisfies the following conditions:

**C1.** The matched seller has the same type (type 1 and 2 defined by pre-treatment transactions) and reputation rating as the treated one at the treatment time.

**C2**. The matched seller is from the same location and have the same experience (years in the business) as the treated seller.

**C3**. The matched seller has similar numbers of positive reviews from last week and last month to the treated seller at the treatment time. [7]

Intuitively, the matching process is to match the treated seller to controlled sellers who have similar credibility captured by reputation ratings, customer reviews and pre-treatment sales at the

[7] On average, more than half of sellers in a week in both the two markets have zero recent positive reviews. We categorize the number of reviews in to 0, (0, 90%-ile] and >90%-ile. The numbers of recent positive reviews (in last week and month) of a treated seller and matched controlled sellers must be in the same category.

treatment time. A more credible seller is expected to sell more products at higher prices, as suggested by the theoretical results. Another requirement for the validity of these matching variables is that these variables affect the participation decision of sellers in the program. We estimate the conditional probability $\Pr(s_{it} = 1 | \mathbf{z}_{it})$, where $s_{it}$ is a binary indicator if seller $i$ starts to participate in the program in week $t$ and $\mathbf{z}_{it}$ is a vector of covariates containing the matching variables, as a probit model. The estimation results, which are shown in Table A1 of the appendix, demonstrate that these matching variables affect sellers' decisions to participate in the signaling programs significantly.

The matched sample allows us to compute the difference-in-differences of outcome of research interests (weekly sales or sale revenue). Let $y_i^{pre}$ and $y_i^{post}$ denote the average outcome of the treated seller before and after the treatment respectively, for each controlled seller $i' \in \Gamma_i$, where $\Gamma_i$ denotes the set of controlled sellers matched to treated seller $i$, we calculate

$$\tau_{ii'} = \left(y_i^{post} - y_i^{pre}\right) - \left(y_{i'}^{post} - y_{i'}^{pre}\right). \tag{11}$$

In the traditional DID matching approach, $\tau_{ii'}$ gives us one observation on the net impact of the treatment on $y_i$ and a point estimate of the average treatment effect on treated can be constructed by averaging the observations from the matched pairs. However, such a DID matching estimator has the concern that $y_{it}$ and $y_{i't}$ may follow different dynamics in the time-window of comparison. Although the matching process ensures that the treated seller and a controlled seller have similar credibility captured by the matching variables at the treatment time, it cannot rule out the possibility that the matching variables of the treated and the matched seller follow different dynamics. Moreover, either the treated or the matched seller may change his status of participation in other 19 programs listed in Table 2 in the time window of comparison and such changes affect the outcome of DID comparison.

We use a regression adjustment approach to remove the factors (the time-varying matching variables and participation status of other programs) causing $y_{it}$ and $y_{i't}$ to have different dynamics. Let $\mathbf{x}_{it}$ denote the vector of variables affecting $y_{it}$, we do the DID computation for each of the variables in $\mathbf{x}_{it}$ to obtain

$$\Delta\mathbf{x}_{ii'} = \left(\mathbf{x}_i^{post} - \mathbf{x}_i^{pre}\right) - \left(\mathbf{x}_{i'}^{post} - \mathbf{x}_{i'}^{pre}\right) \tag{12}$$

where $\mathbf{x}_i^{post}$ and $\mathbf{x}_i^{pre}$ are average values of $\mathbf{x}_{it}$ in pre- and post-treatment period respectively. We then formulate the following regression equation without a constant:

$$\tau_{ii'} = \Delta\mathbf{x}_{ii'}\mathbf{B} + e_{ii'} \tag{13}$$

The OLS residual of the regression equation – $\hat{e}_{ii'}$, measure then the net effect of the treatment variable on the outcome of the treated seller when we compare the treated seller with a matched one. Our estimator to the average treatment effects on treated is constructed as

$$\delta = \|\Psi\|^{-1} \sum_{i \in \Psi} \left( \|\Gamma_i\|^{-1} \sum_{i' \in \Gamma_i} \hat{e}_{ii'} \right) \tag{14}$$

where $\Psi$ denotes the set of treated sellers.

The confidence interval of the estimator is constructed using bootstrap in which we randomly sample with replacement the block of matched pairs of treated sellers to obtain the bootstrap sample of DID computation and calculate $\delta$ on the bootstrap sample, which has the same panel structure as the original matched pairs (one treated seller could be matched to multiple controlled sellers); repeating the process by many times and the empirical distribution of $\delta$ over the bootstrap samples is used to construct the confidence interval of the estimator.

Because the status of engaging in "cheap talk" is time-invariant in the sample, we use the following cross-sectional regression equation to identify the treatment effects of "cheap talk" on sales and revenue.

$$y_i = \alpha \cdot \text{CheapTalk}_i + \theta \cdot \text{CheapTalk}_i \cdot \text{Reputation}_i + \mathbf{X}_i\mathbf{B} + \varepsilon_i \tag{15}$$

where $y_i$ is the sales or revenue of seller $i$; $\text{CheapTalk}_i$ is a dummy of engaging-in "cheap talk"; $\text{Reputation}_i$ is the seller's reputation rating; and $\mathbf{X}_i$ is a vector of control variables including dummies of participating in the 20 signaling programs listed in Table 1, reputation rating, experience and location dummies. Because the decision to participate in the 20 programs is likely to be driven by sales and revenue, in regression we keep only sellers who did not change the status of participating in the programs in the sampling period. Therefore, the participating status of sellers in the 20 signaling programs is pre-determined in the regression.

*From theory to empirics*

The theoretical insights drawn from simulations allow us to make several predictions for empirical findings and we will compare empirical results with the predictions in the next section. Prediction 1 is made from simulation results presented in Figure 1.

**Prediction 1:**

(a) Participating in the three costly signaling programs has positive effects on both sales and revenue of the participants.

(b) Engaging in "cheap talk" has no impacts on sales and revenue.

(c) Compared with the Authentic Description, the 30-Days Repair Warranty has larger effects on sales and revenue of the participants.

For point (a), positive participation in a signaling program with a positive cost imply the existence of partial or fully separating equilibria that leads to a higher market belief for the participants; a seller would not be willing to pay the cost to participate in the program if he cannot benefit from the program. For point (b), at the pooling equilibrium under a signaling action with zero cost such as "cheap talk", buyers do not update their belief according to sellers' status of taking the action. Point (c) comes from the fact that the participation cost of the 30-Days Repair Warranty is higher than that of the Authentic Description.

Prediction 2 is made from simulation results presented in Figure 2, 3 and 4.

**Prediction 2:**

(a) Participating in a costly signaling program has larger impacts on sales and revenue for low-reputation sellers than for high-reputation sellers, especially in the market of cheap product (Kingston).

(b) A costly signaling program is more effective to signal quality in the market of expensive products (Nokia) than in that of cheap products (Kingston).

## 4. Empirical Results

Herein we present main empirical findings and interpret the findings through comparing the empirical findings to the theoretical predictions presented in previous section. The DID identification requires that the matched treated and controlled sellers have similar patterns in outcomes under investigation before treatment. In Figure 6a-6e we plot the time series of average sales of treated and controlled sellers before and after participating in different signaling programs. The treated and controlled sellers are indeed homogeneous in pre-treatment sales pattern in our DID comparison.

*The findings*

The first set of findings is about Nokia and Kingston sellers' participation in the three signaling programs and "cheap talk". Table 3 summarizes the findings. The number of participants in a signaling program is the sum of always-in participants who joined the program before the sampling period and new participants who started during the sampling period. In the two product markets, the number of sellers who engage in "cheap talk" is much larger than that in the three signaling programs. The highest rate of participation in the Authentic Description among the three signaling programs can be partly attributed to the fact that the Authentic Description is a prerequisite to participate in other quality assurance programs including the 30-days Repair Warranty which requires extra deposits. The rate of participation of high-reputation sellers in the three costly signaling programs in both markets is much higher than that of low-reputation sellers; on the other hand, high-reputation and low-reputation sellers have similar rates of participation in "cheap talk" in both markets.

We select treated sellers of signaling programs from the new participants of the program with enough observations in both pre- and post-treatment periods. Table 4 presents the number of treated sellers for the signaling programs in the two product markets. Table 3 indicates the number of participants in Donation among Kingston sellers is very small; hence it is not surprise that we do not have enough treated Kingston sellers for Donation to make meaningful statistical analyses. In the market of Nokia, we obtain 379 treated sellers for the Authentic Description, 188 treated sellers for the 30-days Repair Warranty and 117 treated sellers for Donation. In the market of Kingston, we obtain respectively 378 and 318 treated sellers for the Authentic Description and the 30-days Repair Warranty. Majority of the treated sellers of the signaling programs in both markets are type 1 sellers, i.e., those who did not have sales in pre-treatment periods. Except for the treated sellers of the Authentic Description, majority of treated sellers with other signaling programs are high-reputation sellers.

Table 5 presents the estimated effects of the three signaling programs on participants' sales and revenue in the market of Nokia. Overall, we identify significant treatment effects of the signaling programs on participants' sales and revenue and we are able to draw three observations from the results. The first observation is that the three programs play the role of signaling product quality only for sellers with a high reputation rating. As shown by Table 4, except for the Authentic Description, very few sellers with a low reputation rating participate in other two signaling

programs during the sampling period. As a result, we are not able to estimate separately the treatment effects on sales and revenue of low-reputation participants of the two signaling programs – the 30-days Repair Warranty and the Donation. The very low rate of participation in the signaling programs among low-reputation sellers clearly suggests the ineffectiveness of the programs in signaling quality among low-reputation sellers. Estimation results in Table5 indicate also that the treatment effects of the Authentic Description on sales and revenue for low-reputation participants are much weaker than those for high-reputation sellers with the same pre-treatment sales. Moreover, although we cannot estimate separately the treatment effects of the signaling programs on sales and revenue of low-reputation participants in other cases, excluding the few low-reputation participants in these estimations normally leads to larger estimates of the treatment effects.

The second observation drawn from estimation results in Table 5 is that among high-reputation participants in the signaling programs, those with positive sales in pre-treatment periods (type 2 participants) obtain much greater benefits from the signaling programs than those with zero pre-treatment sale (type 1 participants). The two observations indicate that the treatment effects on sales and revenue of costly signaling are stronger for participants with higher credibility at the treatment time.

The third observation drawn from the estimation results in Table 5 is that signaling programs with higher participation costs have larger treatment effects on participants' sales and revenue. Between the two quality assurance programs, the 30-days Repair Warranty has a higher participation cost because a participant pays additional deposit to join it and has to be in the Authentic Description first. Therefore, the identified treatment effects of the 30-days Repair Warranty on participants' sales and revenue are the add-ons to that of the Authentic Description. Results in table 5 show that by joining in the 30-days Repair Warranty, high-reputation participants of the Authentic Description achieve higher sales and revenue and such results are statistically significant and are especially large for type 2 participants.

Signaling programs are in general unsuccessful in signaling product quality in the market of Kingston, as shown by estimation results in Table 6. The two quality assurance programs, successful in the market of Nokia, have only negligible impacts on Kingston's sellers' sales and revenue; in most cases, such impacts are statistically insignificant. The Donation program is also useless in signaling quality because few Kingston sellers participate in it. Finally, low-cost

signaling actions cannot signal product quality, as demonstrated by the regression results presented in Table 7. Engaging in "cheap talk" has no significant effects on sellers' sales and revenue in the market of Kingston. The regression results indicate that in the market of Nokia, engaging in "cheap talk" actually hurts sellers with a high reputation rating.

The baseline DID matching estimation results presented in Table 5 and Table 6 are obtained by matching a treated seller to a set of always-in sellers. As a sensitivity check, we change the matching approach to match a treated seller to a set of never-in sellers holding other matching criteria unchanged, and re-run the DID matching estimations. As we pointed out before, using never-in sellers to construct the control group is subject to the endogeneity concern caused by self-selection in participating in the signaling programs. As expected, the estimation results, presented in Table A2 and A3 of the appendix, are different from the baseline results to certain degree. The basic conclusions drawn from the baseline estimates, however, are unchanged.

*Interpretation*

Our empirical findings confirm the theoretical insights summarized in Prediction 1 on the importance of signaling cost to the effectiveness of a signaling action. All three costly signaling programs can play the role of signaling product quality in the market of Nokia and the one with a higher participation cost has a larger effect. In contrast, engaging in "cheap talk" is useless. The empirical findings confirm also the theoretical insights summarized in point (b) of Prediction 2 on the impacts of product value on the effectiveness of a signaling program. All three signaling programs are in general unsuccessful in signaling quality in the market of Kingston.

However, there is an inconsistency between theoretical insights and empirical findings. In our stylized theoretical model, a costly signaling action separates better the two types of sellers (good vs. bad) among low-reputation sellers than among high-reputation ones. Therefore, as long as the signaling cost is the same for every participant, the benefits of signaling are expected to be higher for low-reputation participants than for high-reputation ones. The empirical results tell a different story. In the market of Nokia, the participation rates of low-reputation sellers in the Donation and the 30-days Repair Warrantee are very low although high-reputation participants can obtain benefits from these two programs. Participating in the Authentic Description has much stronger impacts on sales and revenue for high-reputation participants than for low-reputation ones. Moreover, among high-reputation participants in these signaling programs, those with positive pre-treatment sales derive more benefits from the programs than ones with zero pre-treatment sales

do. Larger pre-treatment sales imply higher credibility of sellers at treatment time holding reputation rating constant.

What are the possible causes to the ineffectiveness of costly signaling programs among low-reputation sellers? We offer two explanations based on both the developed theory and observations on business practices of e-marketers. In our theory, a seller's transaction probability and selling prices are determined by his credibility at a signaling equilibrium – $\mu^*(r,\alpha)$, which is determined by the Bayesian updating process in equations (1) and (2). A simplification of our theoretical model is that the transaction probability of a seller is a continuous increasing function of $\mu^*(r,\alpha)$. However, because a large number of sellers compete for a finite number of buyers in each period, the ranking of a seller's credibility at the equilibrium matters the most for the seller's transaction probability. Sellers with a low reputation rating and without recent transactions have a low rank in the intermediate market belief $\mu(r)$. Signaling can facilitate the transactions of these sellers only when the strength of the signal is strong such that the signaling action dominates the prior $\mu(r)$ in the Bayesian updating in equation (2) to boost the ranking of the sellers' credibility significantly. In other words, the dependence of transaction probability on the market belief for low-reputation sellers is weaker than what the theory implies. As we have demonstrated for the market of a cheap product, signaling is ineffective when transaction probability depends on the market belief weakly.

When is a signal strong enough to boost the ranking of low-reputation sellers' credibility? The answer is a signal with a high signaling cost as demonstrated by Figure 3. When signaling cost is low $(\tau = 5)$, our theory suggests the existence of a partial-pooling signaling equilibrium among sellers with a low reputation rating $(r = 0.1 \text{ or } 0.3)$. At the equilibrium, taking the signaling action leads to a higher market belief. However, because of the low signaling cost, buyers do not see the action as a strong signal such that Bayesian updating in equation (2) cannot boost the ranking of the signal senders' credibility significantly. If the increase in credibility cannot facilitate transaction, the partial-pooling equilibrium is unlikely to exist. When signaling cost is high $(\tau = 20)$, the strong signal from taking the action dominates the prior $(\mu(r))$ in the Bayesian updating process and low-reputation sellers can rely on the signaling action to boost the ranking of their credibility.

Another possible reason for the ineffectiveness of signaling programs among low-reputation sellers is the default algorithm used by e-marketers to rank the display order of sellers. Cumulative reputation rating and recent sales are normally assigned heavy weights in the ranking algorithm; sellers with a high reputation rating and a large amount of recent sales tend to be ranked at the top of the display order. The information search cost of buyers to find relevant information of a seller is lower if the seller is displayed close to the top. As a result, signaling actions taken by front-page sellers are more likely to be seen than those taken by sellers who are displayed in subsequent pages. Hence, the puzzling empirical findings on the interactive effects of costly signaling and reputation on transactions can be explained by the information search theory cited in the paper.

Another empirical finding that cannot be explained well by the stylized theory is the negative effects of engaging-in "cheap talk" on high reputation sellers' sales and revenue in the market of Nokia. "Cheap talk" is expected to have no impacts on a seller's transactions, no matter what reputation rating the seller has. The empirical results suggest that when a seller with a high-reputation rating engages in "cheap talk", buyers would discount his reputation rating.

## 5. Discussions

In this paper, we conduct an empirical study on how signaling works in e-markets under the guidance of a dynamic signaling model. On one hand, empirical findings from this paper suggest that costly signaling cannot fix the drawback of a reputation system in mitigating information asymmetries in the case of our investigation; new sellers with a low reputation rating cannot rely on costly signaling programs to facilitate transactions. On the other hand, findings from both theoretical and empirical analysis make possible the design of an efficient signaling mechanism which will fix the drawback of reputation systems.

The first implication drawn from the findings of the paper is that an efficient signaling mechanism should be based on an efficient reputation system. As shown by the theoretical model, an action can signal product quality only when the reputation system can generate reliable customer reviews such that high-quality sellers are differentially advantageous in taking the action. Second, only the market of expensive products can benefit from signaling mechanism in mitigating information asymmetries because only in these markets sellers' signals can be well-received by buyers. Third, an efficient signaling mechanism must have a high enough signaling cost to separate

low and high quality sellers. Finally, a signaling mechanism that can facilitate transactions of new sellers should price differentially by charging a higher price for sellers with a lower reputation rating. Moreover, the algorithm of ranking display order of sellers should reflect the cost differences by assigning a higher score to sellers who pay higher.

One important feature of the market under our examination is that the number of sellers is large. As a result, searching the information of a seller is costly, especially when the seller is ranked low in display order. Findings of the paper imply that signaling can work better in a more concentrated market where the number of sellers is smaller.

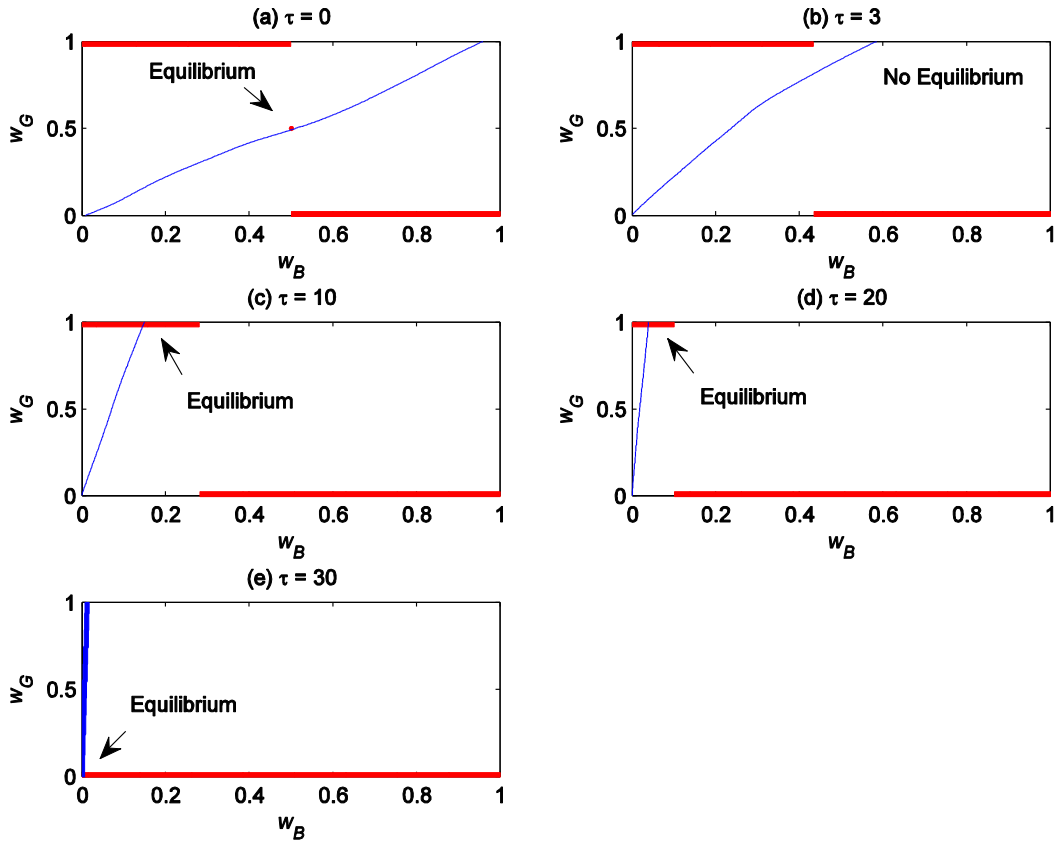



**Figure 1. The effect of signaling cost on signaling equilibrium**. Blue line is the best-response curve of a bad-quality seller and red line is the best-response curve of a good-quality seller. A partial-pooling signaling equilibrium exists when signaling cost is not too small and too large. When a partial-pooling equilibrium exists, an increase in signaling cost shifts the partial-pooling equilibrium to be closer to the fully-separating equilibrium.

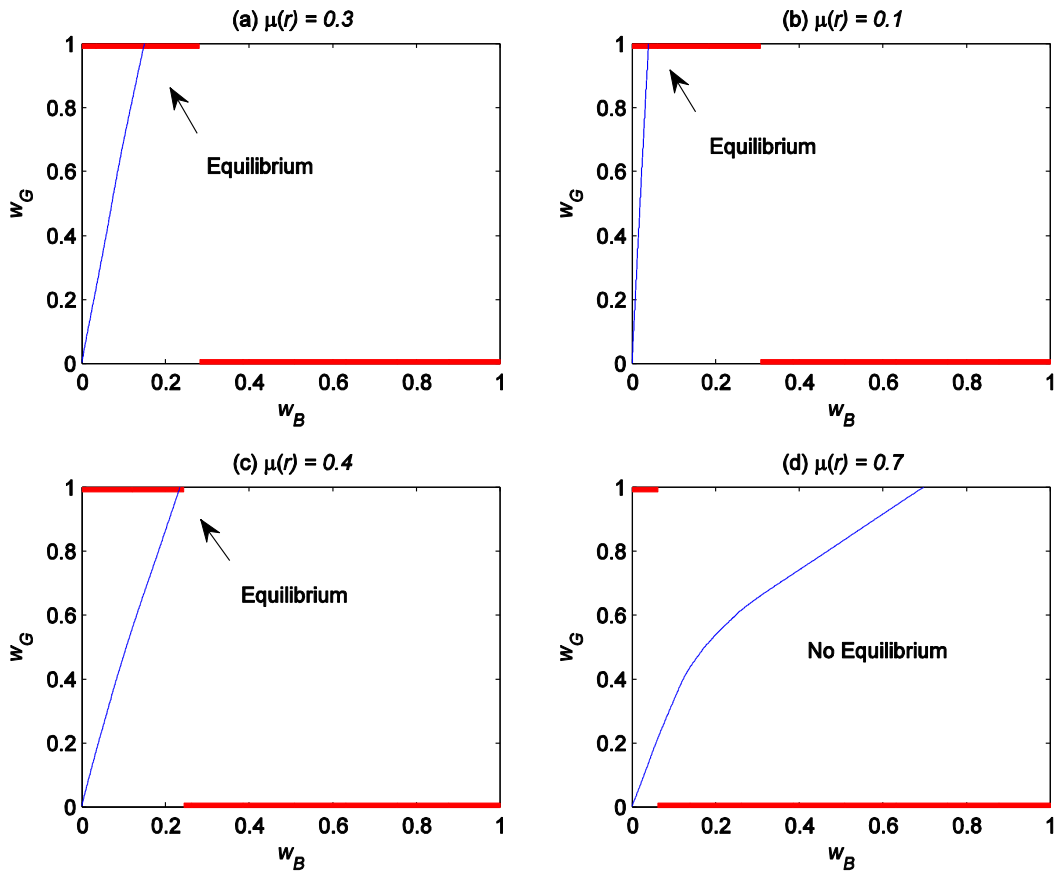



**Figure 2. The effect of reputation rating on signaling equilibrium.** Blue line and red line are the best response curves of bad-quality and good-quality sellers respectively. For a given signaling cost, a partial-pooling signaling equilibrium is more likely to exist among sellers with a lower reputation rating. Moreover, the partial-pooling signaling equilibrium is closer to the fully-separating equilibrium when the sellers' reputation rating is lower.

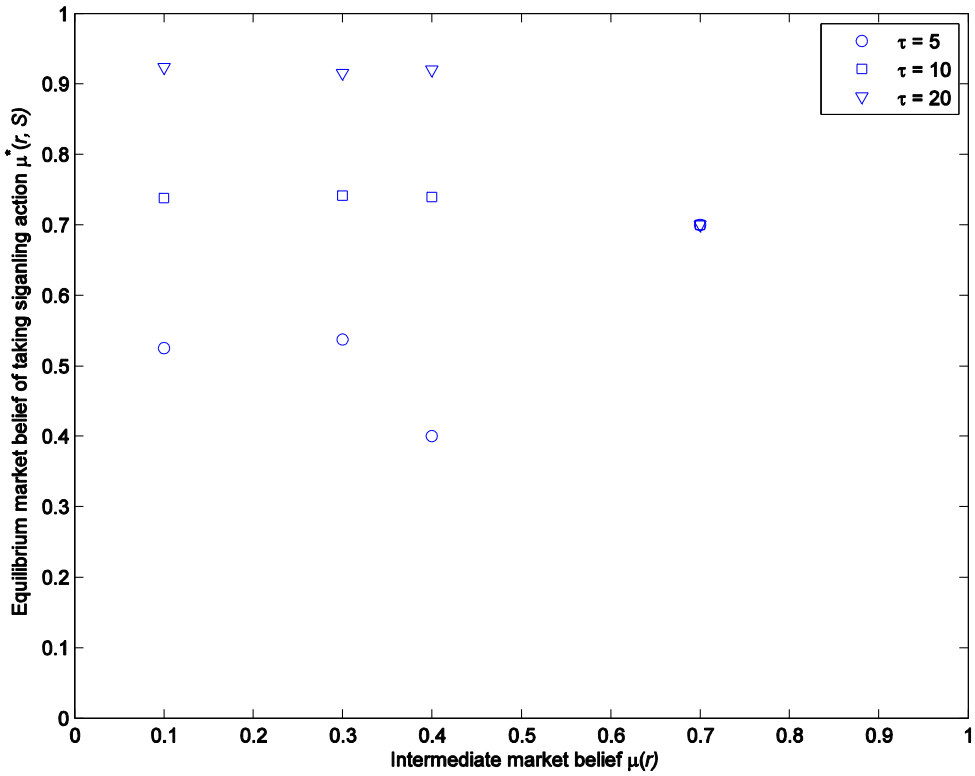



**Figure 3. Bayesian updating from taking a signaling action at signaling equilibria among sellers with different reputation ratings and with different signaling costs.** When signaling cost is low, Bayesian updating applies only for participants with a low reputation rating because a partial pooling signaling equilibrium exists among these sellers. However, the strength of the signal is low when the signaling cost is low. As a result, the Bayesian updating for the low-reputation participants is not big enough to facilitate transactions. A signaling program is more likely to facilitate transactions of low-reputation participants when the signaling cost is higher.

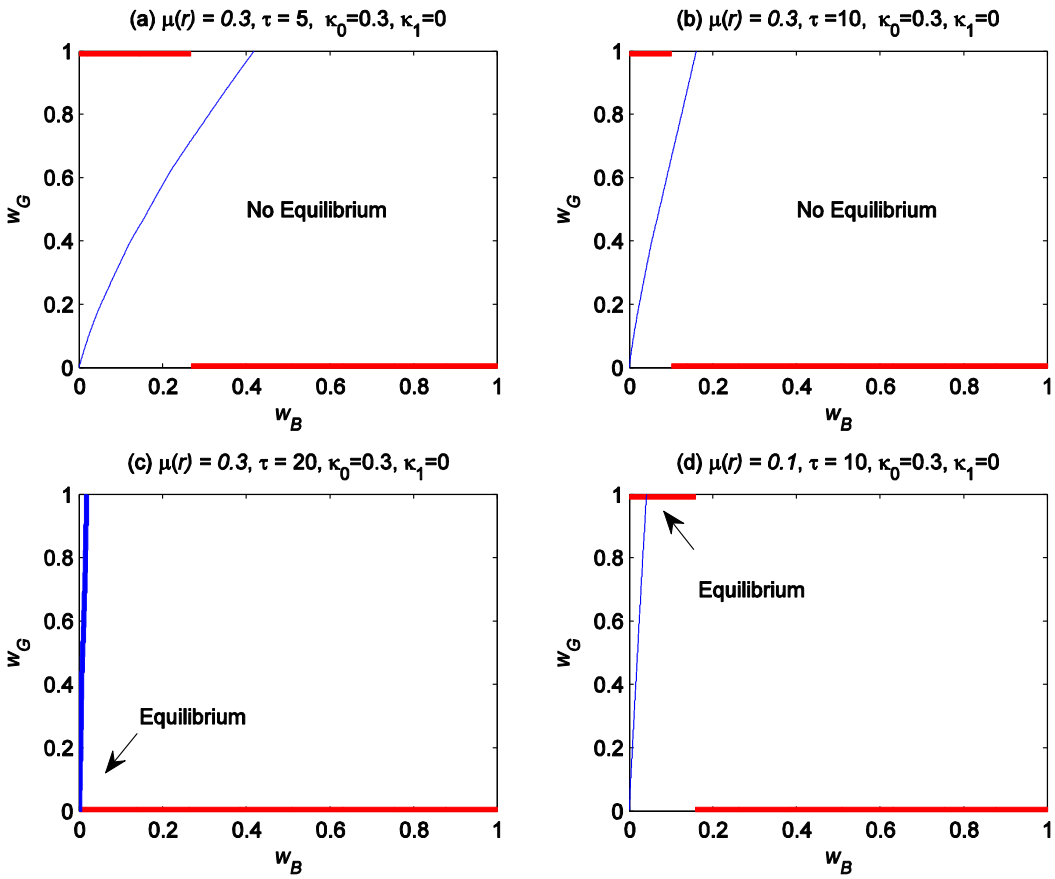



**Figure 4. The effect of product value on signaling equilibrium**. Blue line and red line are best response curves of bad and good quality sellers respectively. When transaction probability does not depend on market belief, as in a non-expensive product market, a partial-pooling signaling equilibrium can only exist among sellers with a very low reputation rating.

**Figure 5a. The Authentic Description Program**

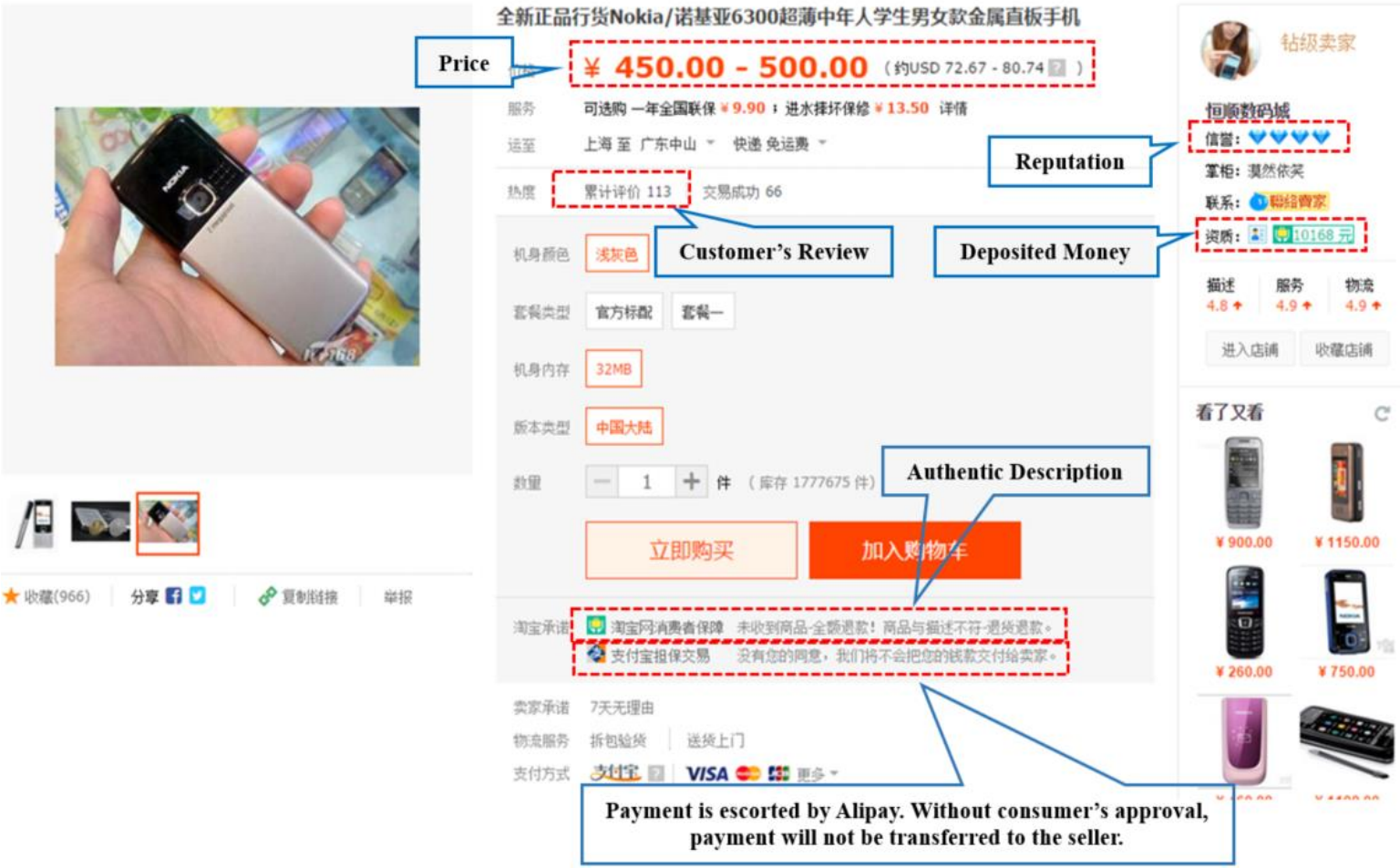


**Figure 5b. The Donation Program**

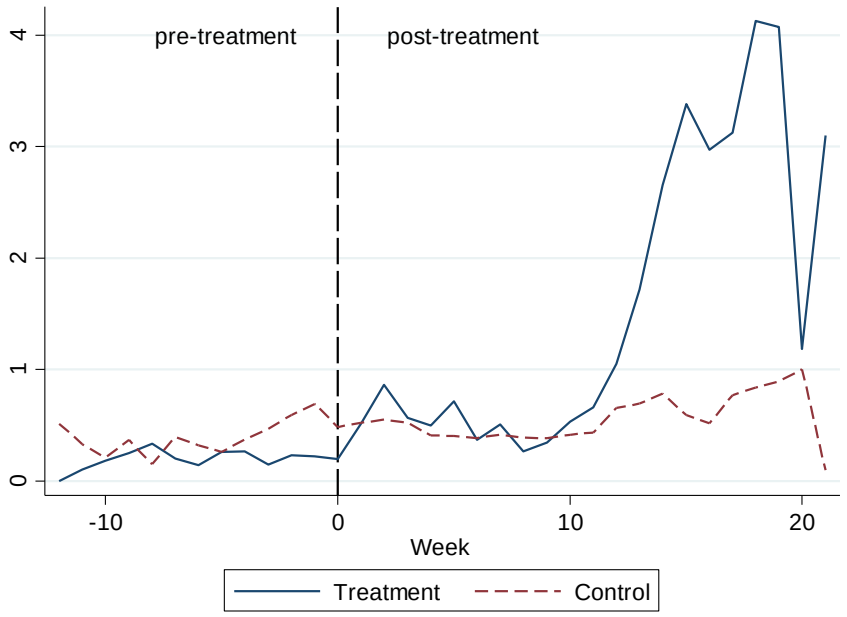



**Figure 6a. Sales before and after treatment for Nokia Authentic Description Program.** The time when a seller participates in a program is defined as week 0. Periods before week 0 is defined as pre-treatment and after week 0 is defined as post-treatment. The average sales per week are calculated by averaging sales of all sellers in each week.

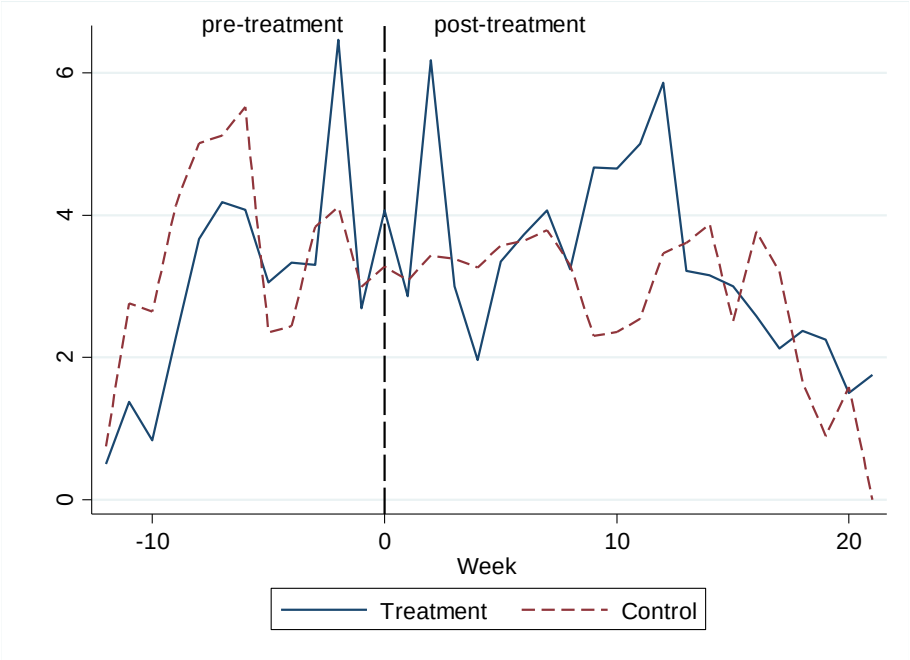



**Figure 6b. Sales before and after treatment for Nokia Donation Program.** The time when a seller participates in a program is defined as week 0. Periods before week 0 is defined as pre-treatment and after week 0 is defined as post-treatment. The average sales per week are calculated by averaging sales of all sellers in each week.

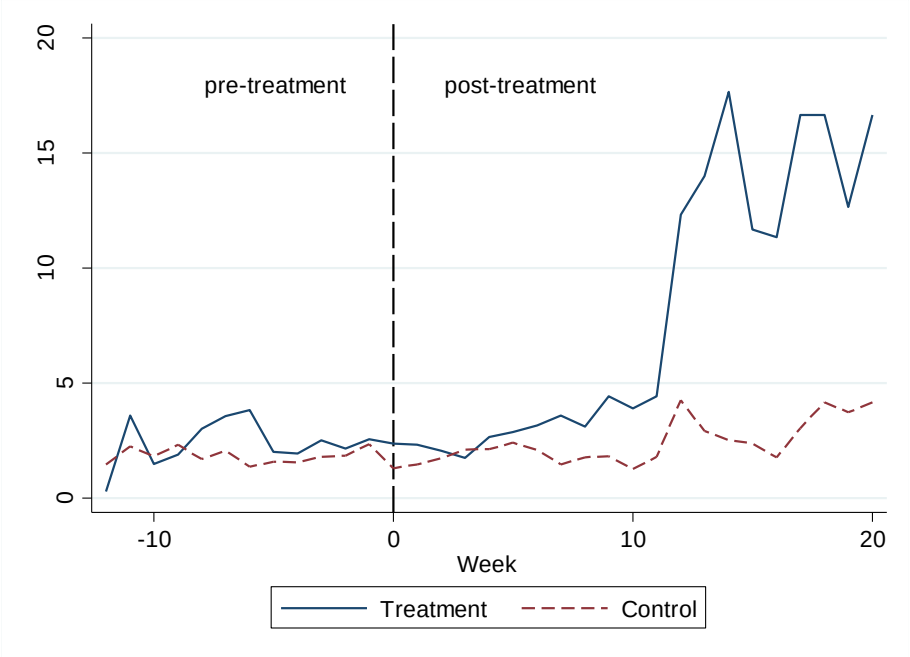



**Figure 6c. Sales before and after treatment for Nokia 30-Day Repair Warranty Program.** The time when a seller participates in a program is defined as week 0. Periods before week 0 is defined as pre-treatment and after week 0 is defined as post-treatment. The average sales per week are calculated by averaging sales of all sellers in each week.

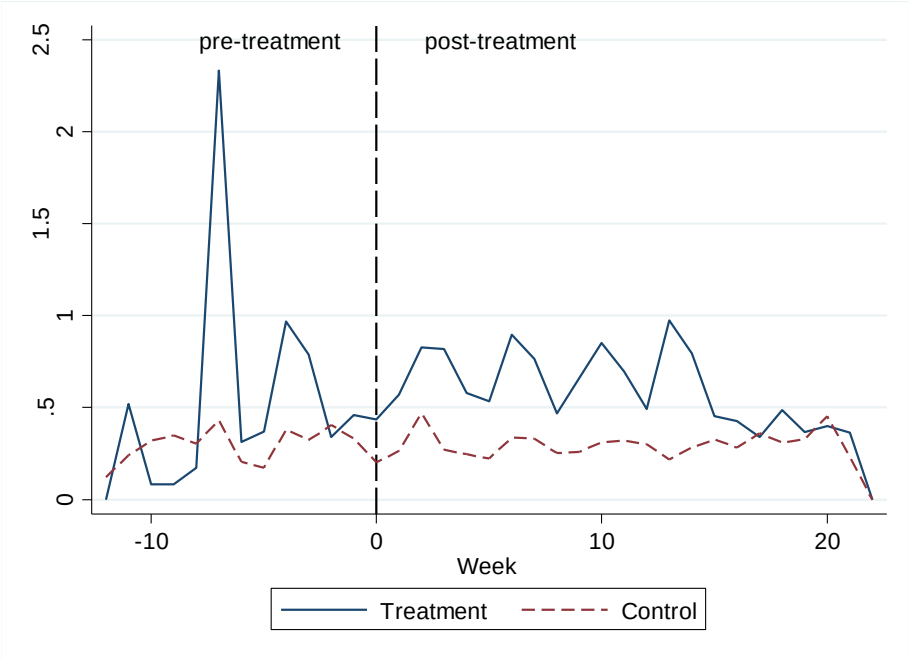



**Figure 6d. Sales before and after treatment for Kingston Authentic Description Program.** The time when a seller participates in a program is defined as week 0. Periods before week 0 is defined as pre-treatment and after week 0 is defined as post-treatment. The average sales per week are calculated by averaging sales of all sellers in each week.

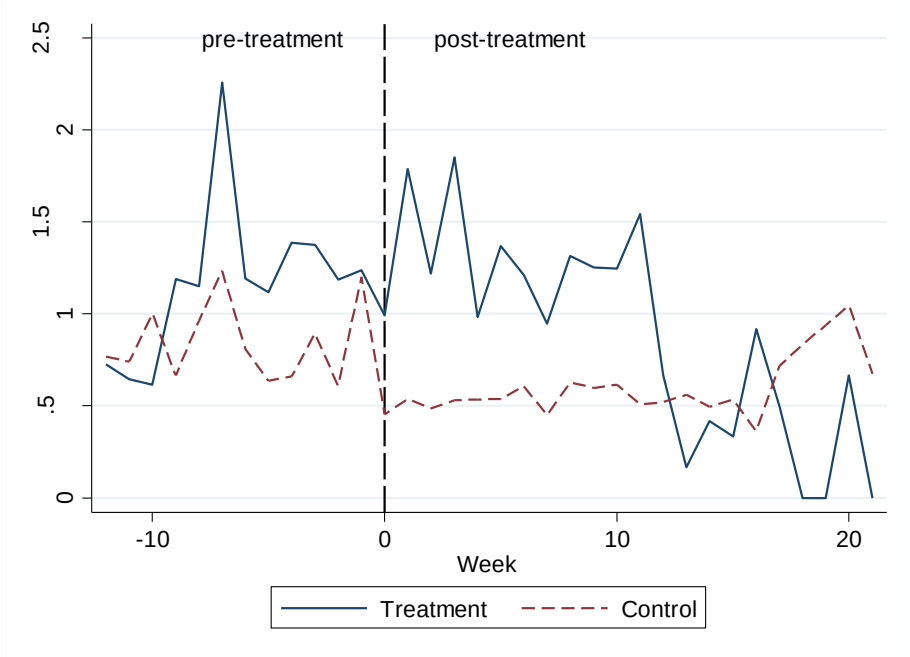



**Figure 6e. Sales before and after treatment for Kingston 30-Day Repair Warranty Program.** The time when a seller participates in a program is defined as week 0. Periods before week 0 is defined as pre-treatment and after week 0 is defined as post-treatment. The average sales per week are calculated by averaging sales of all sellers in each week.

**Table 1: Base-line parameter values in numerical simulations**

| Parameters | Explanation for the parameters | Parameter value |
|---|---|---|
| $K$ | Number of units of products | 100 |
| $v$ | Product value | 1 |
| $\eta_G$ | Probability of good-quality seller to obtain a positive review from a transaction | 0.65 |
| $\eta_B$ | Probability of bad-quality seller to obtain a positive review from a transaction | 0.45 |
| $\tau$ | Signaling cost | 10 |
| $\mu(r)$ | Intermediate market belief based on reputation rating | 0.3 |
| $\kappa_0$ | Intercept of the linear transaction probability function, which is a function of market belief | 0.05 |
| $\kappa_1$ | Slope of the linear transaction probability function | 0.50 |
| $\beta$ | Discount rate | 0.995 |

**Table 2 Description of Programs**

| Number | Program Name | Definition |
|---|---|---|
| 1 | **Coupon** | Coupon is acceptable to pay |
| 2 | **VIP** | Deals only for VIP |
| 3 | **Discount** | Discount with bundling sales |
| 4 | **Limited-Time Discount** | Discount within a specific period |
| 5 | **Flash Sale** | Promotional sales |
| 6 | **Final payment discount** | Discount if the spent is higher than a required amount |
| 7 | **Free shipping** | Free shipping |
| 8 | **Gifts** | Seller gives gifts to customers |
| 9 | **Cumulating Credit** | Buyer accumulate credit scores from buying |
| 10 | **Cash on Delivery** | Payment is made on delivery |
| 11 | **Credit Card** | Seller accepts credit card payment |
| 12 | **Imported Product** | The product is imported |
| 13 | **Purchasing Agent** | The seller is a purchasing agent |
| 14 | **Flash Delivery** | Guaranteed delivery date |
| 15 | **Donation** | Part of the payment will be donated to charitable organizations |
| 16 | **Authentic Description** | Descriptions and photos are guaranteed to match the real product |
| 17 | **Refund** | Fully refund within 7 days |
| 18 | **Quality Guaranteed** | Quality of the product is assured |
| 19 | **Penalty** | Seller will refund the customers triple times of the value of the product if the product is fake |
| 20 | **30-day Repair Warranty** | 30-day repair warranty |

**Table 3 Participation of signaling actions**

| | Nokia | Kingston |
|---|---|---|
| Total number of sellers | 17876 | 13035 |
| High reputation | 6144 | 6430 |
| Low reputation | 11732 | 6605 |
| | | |
| Number of participants of authentic description | 6544 | 6040 |
| High reputation | 4854 | 4884 |
| Low reputation | 1690 | 1156 |
| | | |
| Number of participants of free return within 30 days | 784 | 1583 |
| High reputation | 630 | 1419 |
| Low reputation | 154 | 164 |
| | | |
| Number of participants of donation | 667 | 297 |
| High reputation | 476 | 219 |
| Low reputation | 191 | 78 |
| | | |
| Number of participants in “cheap talk” | 8890 | 9278 |
| High reputation | 3971 | 4831 |
| Low reputation | 4979 | 4447 |

**Table 4. Sellers in the Treatment Group**

| ` | Nokia | | | Kingston | |
|---|---|---|---|---|---|
| | **Authentic Description** | **Donation** | **Repair Warranty** | **Authentic Description** | **Repair Warranty** |
| **Total number of the treatment** | 379 | 117 | 188 | 378 | 318 |
| High reputation | 187 | 91 | 153 | 215 | 271 |
| Low reputation[1] | 192 | 26 | 35 | 163 | 47 |
| **Type I:** Sellers with zero sale in pre-treatment periods | 319 | 79 | 113 | 287 | 173 |
| High reputation | 172 | 57 | 89 | 149 | 131 |
| Low reputation | 147 | 22 | 24 | 138 | 42 |
| **Type II:** Sellers with positive sales in pre-treatment periods | 60 | 38 | 75 | 91 | 145 |
| High reputation | 40 | 34 | 64 | 66 | 140 |
| Low reputation | 20 | 4 | 11 | 25 | 5 |

Note: *Low reputation includes sellers whose reputation rating is at most 5. High reputation contains sellers whose reputation rating is greater than 5.*

**Table 5. The Effects of Signaling Programs on Outcomes of Nokia Sellers**

| | Number of Treated | Observations | Revenue | Sale |
|---|---|---|---|---|
| **Authentic Description** | | | | |
| **Type I: Zero Pre-treatment Sale** | **319** | **942** | 49.431* | 0.268* |
| | | | [3.911; 103.685] | [0.025; 0.561] |
| **High Reputation** | **147** | **575** | 51.919** | 0.345* |
| | | | [11.013; 119.692] | [0.063; 0.655] |
| **Low Reputation** | **172** | **367** | 1.68 | 0.009* |
| | | | [-0.025; 3.464] | [0.001; 0.021] |
| **Type II: Positive Pre-treatment Sales** | **60** | **333** | 79.141*** | 0.522*** |
| | | | [27.468; 155.318] | [0.241; 1.066] |
| **High Reputation** | **40** | **304** | 109.961** | 0.784*** |
| | | | [44.683; 214.531] | [0.345; 1.328] |
| **30-day Repair Warranty** | | | | |
| **Type I: Zero Pre-treatment Sale** | **113** | **110** | 2.395*** | 0.014*** |
| | | | [1.339; 4.128] | [0.008; 0.023] |
| **High Reputation** | **89** | **90** | 2.663*** | 0.017*** |
| | | | [1.439; 4.846] | [0.01; 0.028] |
| **Type II: Positive Pre-treatment Sales** | **75** | **106** | 132.243* | 0.911** |
| | | | [4.488; 251.359] | [0.198; 1.622] |
| **High Reputation** | **64** | **97** | 150.414 | 0.962* |
| | | | [-0.937; 325.829] | [0.145; 1.848] |
| **Donation** | | | | |
| **Type I: Zero Pre-treatment Sale** | **79** | **74** | 2.964 | 0.01 |
| | | | [-8.556; 35.505] | [-0.059; 0.165] |
| **High Reputation** | **57** | **55** | 7.533 | 0.037 |
| | | | [-15.64; 48.194] | [-0.023; 0.302] |
| **Type II: Positive Pre-treatment Sales** | **38** | **48** | 144.071 | 0.877 |
| | | | [-44.688; 343.753] | [-0.178; 2.024] |
| **High Reputation** | **34** | **48** | 137.39 | 0.932 |
| | | | [-58.17; 349.739] | [-0.376; 1.995] |

*Note: Type I are sellers with zero sale in pre-treatment periods. Type II are sellers with positive sale in pre-treatment periods. Low reputation includes sellers whose reputation rating is at most 5. High reputation contains sellers whose reputation rating is greater than 5. We obtain the results by 200 bootstrap repetitions and report median alone with 10$^{th}$ percentile and 90$^{th}$ percentile in parentheses. ***, **, * denotes 1%, 5% and 10% significant level, respectively. Sales are measured in units of product. Revenue is measured in US Dollar.*

**Table 6. The Effects of Signaling Programs on Outcomes of Kingston Sellers**

| | Number of Treated | Observations | Revenue | Sale |
|---|---|---|---|---|
| **Authentic Description** | | | | |
| **Type I: Zero Pre-treatment Sale** | **287** | **1407** | 0.257** | 0.046*** |
| | | | [0.099; 0.425] | [0.018; 0.088] |
| **High Reputation** | **149** | **1106** | 0.329*** | 0.071*** |
| | | | [0.139; 0.691] | [0.021; 0.134] |
| **Low Reputation** | **138** | **301** | -0.048 | -0.006 |
| | | | [-0.172; 0.121] | [-0.042; 0.033] |
| **Type II: Positive Pre-treatment Sales** | **91** | **654** | -0.011 | 0.011 |
| | | | [-1.105; 0.883] | [-0.182; 0.203] |
| **High Reputation** | **66** | **632** | 0.277 | 0.097 |
| | | | [-0.689; 1.174] | [-0.105; 0.292] |
| **30-day Repair Warranty** | | | | |
| **Type I: Zero Pre-treatment Sale** | **173** | **307** | 0.068 | 0.011 |
| | | | [-0.033; 0.202] | [-0.006; 0.039] |
| **High Reputation** | **131** | **270** | 0.103 | 0.015 |
| | | | [-0.024; 0.24] | [-0.006; 0.045] |
| **Type II: Positive Pre-treatment Sales** | **145** | **561** | 0.286 | 0.065 |
| | | | [-0.617; 1.151] | [-0.099; 0.281] |
| **High Reputation** | **140** | **558** | 0.172 | 0.059 |
| | | | [-0.655; 1.067] | [-0.123; 0.237] |

*Note: Type I are sellers with zero sale in pre-treatment periods. Type II are sellers with positive sale in pre-treatment periods. Low reputation includes sellers whose reputation rating is at most 5. High reputation contains sellers whose reputation rating is greater than 5.*

*We obtain the results by 200 bootstrap repetitions and report median alone with 10$^{th}$ percentile and 90$^{th}$ percentile in parentheses. ***, **, * denotes 1%, 5% and 10% significant level, respectively. Sales are measured in units of product. Revenue is measured in US Dollar. The average exchange rate in second half 2010 for US Dollar to Chinese Yuan is 6.7178. Data source is International Monetary Fund.*

**Table 7. The Effects of Cheap Talk on Outcomes of Nokia Sellers**

| | Nokia | | Kingston | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Variables** | **REVENUE** | **SALE** | **REVENUE** | **SALE** |
| **Cheap talk** | 5.876 | 0.036 | 0.269 | 0.042 |
| | (4.102) | (0.024) | (0.182) | (0.045) |
| **Seller's Reputation Rating (From 1 to 12)** | 3.742*** | 0.022*** | 0.100*** | 0.017** |
| | (0.711) | (0.004) | (0.027) | (0.007) |
| **Age of seller's Shop (Month)** | 0.007 | 0.000 | -0.007** | -0.002** |
| | (0.082) | (0.000) | (0.003) | (0.001) |
| **Cheap talk * Reputation Rating (From 1 to 12)** | -3.029*** | -0.018*** | -0.048 | -0.009 |
| | (0.845) | (0.005) | (0.032) | (0.008) |
| **Seller's Location** | ✓ | ✓ | ✓ | ✓ |
| **Seller's Participating Status on 20 programs** | ✓ | ✓ | ✓ | ✓ |
| **Constant** | -5.092* | -0.031* | 0.039 | 0.022 |
| | (2.789) | (0.017) | (0.137) | (0.034) |
| **Observation** | 10,407 | 10,407 | 7,533 | 7,533 |

*Note: We define these key words as Cheap Talk: "imported product", "genuine product", "original product" and they are time-invariant. For Observations of Nokia and Kingston contain the three key words account for 49.2% and 69.5% of the sample, respectively. We average all variables across individual sellers to transform our sample into cross-section data. Reputation rating ranges from 1 to 12. Age of seller's shop starts from 1 to 87 months.*

*Standard errors in parentheses. ***, **, * denotes 1%, 5% and 10% significant level, respectively. Sales are measured in units of product. Revenue is measured in USD. The average exchange rate in second half 2010 for US Dollar to Chinese Yuan is 6.7178. Data source is International Monetary Fund.*

## *Appendix*

In this appendix, we first describe in detail the numerical simulations used to draw the theoretical insights in the text. We then present results from robustness checks in which a treated seller is matched to a set of never-in sellers.

### Numerical Simulations

Results presented in Figure 1 of the text are obtained by varying the value of $\tau$ while fix other parameters at their base-line values. When there is no signaling cost, a bad-quality seller tries to imitate the strategy of good-quality sellers who have the same reputation rating as him. As such, the best response curve of a bad-quality seller is the diagonal line.[8] On the other hand, in the case of zero signaling cost, a good-quality seller always tries to distinguish himself from bad-quality sellers by choosing probability 1 to take the signaling action when the strategy of bad-quality sellers is less than 0.5, and switching the probability to 0 when the strategy of bad-quality sellers is greater than 0.5. The only signaling equilibrium is the fully pooling equilibrium (0.5, 0.5).

Increase in signaling cost causes a good-quality seller to reduce his switching threshold of signaling probability between zero and one. In another word, as signaling cost increases, a good-quality seller signals only when the signaling becomes informative. As for a bad-quality seller, the increase in signaling cost causes the net benefits for him to imitate the strategy of good-quality sellers to decrease. As such, the slope of the best-response curve of a bad-quality seller increases with the increase in signaling cost.

Figure 1 of the text suggests that we can find $\bar{\tau} > \underline{\tau} > 0$ and when $\tau \in [\underline{\tau}, \bar{\tau}]$, there exists uniquely a stable partial-pooling equilibrium in which good-quality sellers take the signaling action with probability 1 and bad-quality sellers mix signaling and not signaling with a probability $w_B^* \in (0,0.5)$. Moreover, increase in signaling cost shifts the equilibrium to be closer to the fully separating case. When signaling cost is greater than $\bar{\tau}$, the equilibrium becomes a case of fully pooling (0, 0).

Results presented in Figure 2 of the text are obtained by changing the value of $\mu(r)$ while fix other parameters at the base-line values. Graph (a) in the Figure is the base case presented in

[8] The best-response curve of a low-type seller (blue line) in (a) of Figure 1 is not exactly the same as the 45-degree line because of numerical error in simulation.

graph (c) of Figure 1 of the text. We compare the base case with cases with both a lower $\mu(r)$ (graph (b)) and a higher $\mu(r)$ (graph (c) and (d)). A good-quality seller with a larger $\mu(r)$ relies less on costly signaling to convey information about his type. As we can see in Figure 2 of the text, given a signaling cost, the threshold of a good-quality seller switching signaling probability between zero and one decreases when $\mu(r)$ increases. On the other hand, a bad-quality seller with a larger $\mu(r)$ has a stronger incentive to imitate the strategy of good-quality sellers with the same reputation rating; the best response curve of a bad-quality seller becomes flatter when $\mu(r)$ increases. The economic intuition for this result is that if a bad-quality seller with a high reputation rating adopts a different strategy from good-quality sellers with the same reputation rating, buyer would infer that the high reputation rating of the bad-quality seller is incredible.

Combining the effects of changing $\mu(r)$ on the best responses of both good-quality and bad-quality sellers, we can conclude that when $\mu(r)$ is small, increase in $\mu(r)$ shifts the signaling equilibrium from less pooling to more pooling; when $\mu(r)$ is greater than a threshold, there is no longer a signaling equilibrium. [9]

In our model, product value affects signaling equilibrium through affecting the dependence of transaction probability on market belief. Results presented in Figure 4 of the text are obtained by re-parameterizing the transaction probability as a constant $\lambda_t = 0.30$, which equals the average transaction probability in the baseline cases when $\mu_t = 0.5$ .Given the constant transaction probability function, we first re-compute the signaling equilibria in the baseline cases presented in graphs (b) – (d) of Figure 1 of the text and the results are presented in graphs (a) – (c) of Figure 4 of the text.

As expected, compared with the baseline cases, good-quality sellers rely less on signaling to convey information when market belief cannot affect transaction probability. The economic intuition for this result is simple. In current scenario with a constant transaction probability, a costly signaling taken by a good-quality seller can only boost the initial market belief, which benefits the seller through increasing current and future prices. However, when an increase in market belief leads also to a larger transaction probability as in baseline cases, a higher initial market belief can also benefit a good-quality seller through speeding up the process of revealing

[9] In our numerical experiments, we cannot find signaling equilibrium when $\mu(r)$ is increased to be greater than 0.5.

his type to the market (thus shorten the time to sell the products). The change in the transaction probability function does not affect the best response function of a bad-quality seller very much because a bad-quality seller cannot benefit from speeding up the process of revealing his type.

In sum, when an increase in market belief cannot facilitate transaction, the difference in benefits from signaling between a good-quality and a bad-quality seller reduces. As such, a costly signaling can hardly separate the two types of sellers. As shown by comparing graphs (a) – (c) in Figure 4 of the text with graphs (b) – (d) in Figure 1 of the text, signaling equilibrium no longer exists when signaling cost is 5 and 10 and only a fully pooling equilibrium (0,0) exists when signaling cost is 20 if transaction probability does not depend on market belief. Graph (d) of Figure 4 of the text shows that a partial pooling equilibrium exists in this scenario only when the intermediate belief induced by reputation rating assigns a very low probability for sellers to be high type. This result can be attributed to two mechanisms. First, as demonstrated in Figure A1 of the appendix, the expected value-to-go of a good-quality seller $E\left(V_1^H\left(\mu_1|\mu_0\right)\right)$ is a concave function of initial market belief $\mu_0$. Second, as we argued in previous scenario, a bad-quality seller has small incentive to imitate the strategy of a good-quality seller when $\mu(r)$ is small.

**Results of matching to never-in sellers**

The validity of a difference-in-difference estimator rests on the assumption that a seller who participate in a signaling program (treated seller) and sellers who do not participate (controlled seller) follow the same time trend. In other words, treated sellers should not fundamentally different from controlled sellers. Our identification strategy is to match a treated seller of a signaling program with control sellers who are always in the signaling program in order to control for unobserved factors which affect the participation decision and the outcome of interest.

Table A2 presents the estimated effects of the three signaling programs on participants' sales and revenue in the market of Nokia using never-in sellers as the control group. The treated sellers of a signaling program are the same as in the baseline estimations, but the controlled sellers are changed to those who never participated in the signaling program. Results in Table A2 are mostly consistent with what we have found in Table 5 of the text.

Table A3 presents the results of two signaling programs, the Authentic Description and the 30-days Repair Warranty, in the market of Kingston. The findings parallel, and deviate somewhat

from what we have found in Table 6 of the text. The parallel result is that the Authentic Description has negligible effects on Kingston sellers' sales and revenue. However, the 30-days Repair Warranty affects significantly sellers' outcomes.

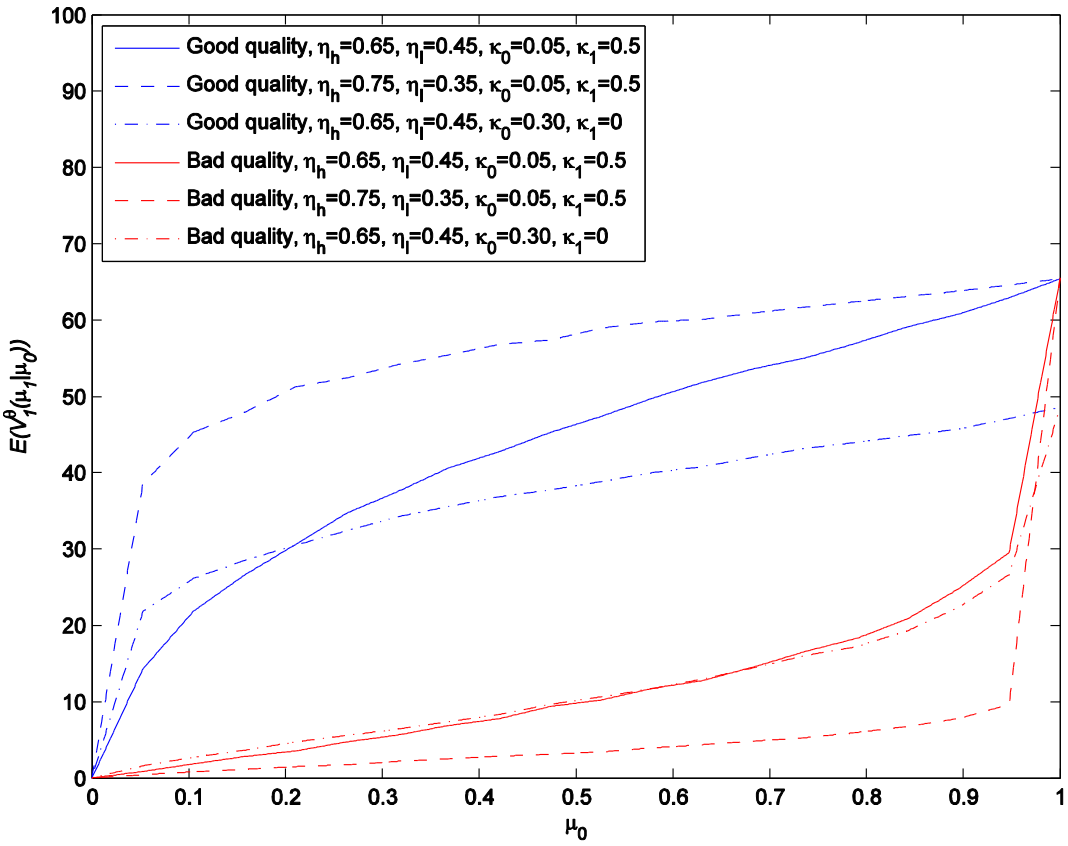
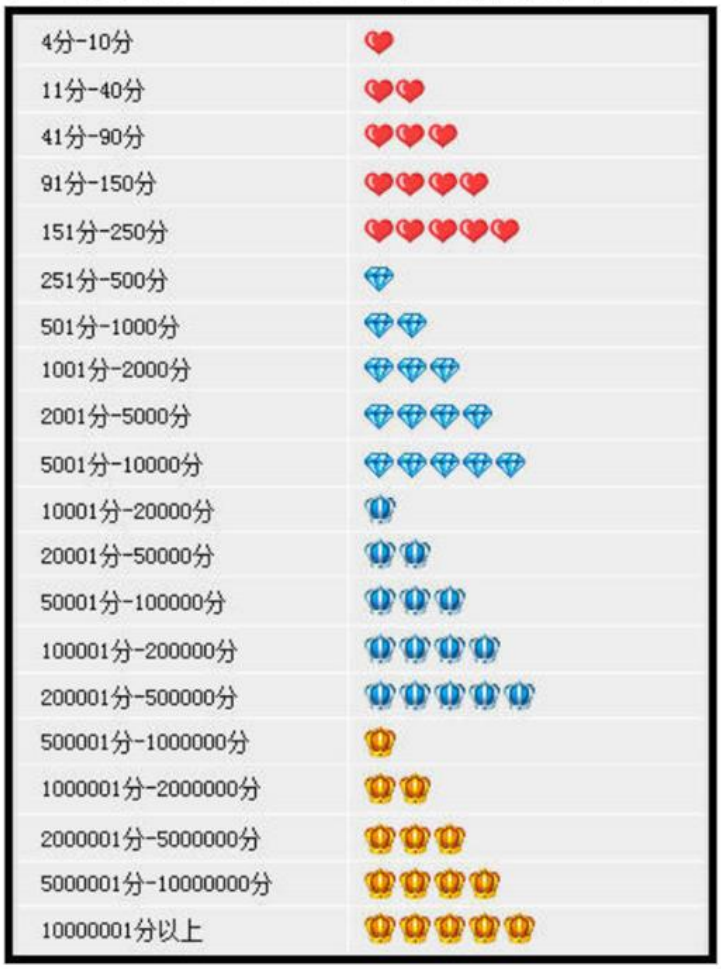



**Figure A1.** Expected value-to-go as a function of initial market belief $\mu_0$



| | |
|---|---|
| 4分-10分 | ❤ |
| 11分-40分 | ❤❤ |
| 41分-90分 | ❤❤❤ |
| 91分-150分 | ❤❤❤❤ |
| 151分-250分 | ❤❤❤❤❤ |
| 251分-500分 | 💎 |
| 501分-1000分 | 💎💎 |
| 1001分-2000分 | 💎💎💎 |
| 2001分-5000分 | 💎💎💎💎 |
| 5001分-10000分 | 💎💎💎💎💎 |
| 10001分-20000分 | 👑 |
| 20001分-50000分 | 👑👑 |
| 50001分-100000分 | 👑👑👑 |
| 100001分-200000分 | 👑👑👑👑 |
| 200001分-500000分 | 👑👑👑👑👑 |
| 500001分-1000000分 | 🏆 |
| 1000001分-2000000分 | 🏆🏆 |
| 2000001分-5000000分 | 🏆🏆🏆 |
| 5000001分-10000000分 | 🏆🏆🏆🏆 |
| 10000001分以上 | 🏆🏆🏆🏆🏆 |

**Figure A2.** Reputation ratings at Taobao

**Note:** Seller's reputation rating is decided by the summation of customer's review that equals 1 if positive, 0 if neural, and -1 if negative. If the total score lies between 4 and 10, the seller's reputation rating is 1 heart. Analogous notation applies to other reputation levels. High-reputation sellers in our analysis are those with at least 5.

**Table A1. Probit Regression of Seller's Participating in programs[1]**

| | Nokia | | Kingston | |
|---|---|---|---|---|
| | **Authentic Description** | **Donation** | **Authentic Description** | **Donation** |
| **Seller's Credit Level (From 1 to 12)** | 0.139*** | 0.075*** | 0.102*** | 0.069*** |
| | (0.009) | (0.014) | (0.010) | (0.024) |
| **Age of seller's Shop (Month)** | -0.009*** | -0.005*** | -0.008*** | -0.014*** |
| | (0.001) | (0.002) | (0.001) | (0.004) |
| **Dummy: Positive reviews of last week** $\in (\mathbf{0}, \mathbf{90}^{th}]$ | 0.123*** | 0.129 | 0.190*** | 0.009 |
| | (0.046) | (0.089) | (0.052) | (0.154) |
| **Dummy: Positive reviews of last week** $> \mathbf{90}^{th}$ | 0.139 | 0.028 | 0.330** | -0.378 |
| | (0.091) | (0.128) | (0.131) | (0.246) |
| **Dummy: Positive reviews of last month** $\in (\mathbf{0}, \mathbf{90}^{th}]$ | 0.410*** | 0.175 | 0.256*** | 0.076 |
| | (0.052) | (0.111) | (0.067) | (0.188) |
| **Dummy: Positive reviews of last month** $> \mathbf{90}^{th}$ | 0.442*** | 0.351** | 0.314** | 0.388 |
| | (0.097) | (0.150) | (0.145) | (0.267) |
| **Seller's Location[2]: Central China** | -0.156** | -0.029 | -0.070 | 0.048 |
| | (0.070) | (0.120) | (0.067) | (0.141) |
| **Seller's Location: Western China** | 0.003 | 0.025 | 0.018 | ---[3] |
| | (0.060) | (0.114) | (0.083) | --- |
| **Seller's Location: Northeast China** | 0.067 | --- | 0.077 | --- |
| | (0.134) | --- | (0.145) | --- |
| **Seller's Location: Hong Kong or Macau** | -0.499 | 0.169 | --- | --- |
| | (0.336) | (0.230) | --- | --- |
| **Constant** | -3.335*** | -3.773*** | -3.213*** | -3.705*** |
| | (0.047) | (0.091) | (0.057) | (0.146) |
| **Observations** | 114,710 | 191,661 | 80,856 | 153,140 |
| **Number of Sellers** | 9,408 | 14,566 | 6,191 | 11,127 |
| **pseudo R-Sq.** | 0.138 | 0.066 | 0.085 | 0.039 |

*Note: 1.In these regressions, we discard a seller's remaining periods' observation once we observe the seller participates in the signaling program because those observations are not informative once the decision of participating is made.*
*2. The baseline case is Eastern Coast. 3. Variables are omitted due to multicollinearity*
****, **, * denotes 1%, 5% and 10% significant level, respectively.*

**Table A2. The Effects of Signaling Programs on Outcomes of Nokia Sellers Using Never-in Sellers as the Control Group**

| | Number of Treated | Matched Pairs | Revenue | Sale |
|---|---|---|---|---|
| **Authentic Description** | | | | |
| **Type I: None to Positive** | **319** | **1066** | 37.496*** | 0.197*** |
| | | | [9.603; 83.045] | [0.056; 0.385] |
| **High Reputation** | **147** | **180** | 72.598*** | 0.398*** |
| | | | [11.348; 152.603] | [0.063; 0.832] |
| **Low Reputation** | **172** | **886** | 3.554*** | 0.022*** |
| | | | [2.21; 4.962] | [0.014; 0.03] |
| **Type II: Positive to Positive** | **60** | **58** | 1.047 | 0.004 |
| | | | [-12.689; 18.093] | [-0.084; 0.117] |
| **High Reputation** | **40** | **38** | 23.091* | 0.141* |
| | | | [2.441; 40.453] | [0.025; 0.286] |
| **30-day Repair Warranty** | | | | |
| **Type I: None to Positive** | **113** | **396** | 2.628* | 0.016** |
| | | | [0.211; 4.867] | [0.003; 0.026] |
| **High Reputation** | **89** | **338** | 3.824** | 0.023* |
| | | | [0.754; 7.038] | [0.005; 0.036] |
| **Type II: Positive to Positive** | **75** | **513** | 65.623 | 0.374 |
| | | | [-0.253; 143.177] | [-0.059; 0.854] |
| **High Reputation** | **64** | **486** | 80.275 | 0.42 |
| | | | [-0.189; 177.583] | [-0.042; 1.002] |
| **Donation** | | | | |
| **Type I: None to Positive** | **79** | **553** | 25.003 | 0.201 |
| | | | [-14.308; 74.887] | [-0.029; 0.475] |
| **High Reputation** | **57** | **489** | 49.32 | 0.319* |
| | | | [-5.438; 112.057] | [0.013; 0.675] |
| **Type II: Positive to Positive** | **38** | **270** | 142.072* | 1.007 |
| | | | [20.366; 326.084] | [-0.071; 2.053] |
| **High Reputation** | **34** | **259** | 161.888* | 0.895* |
| | | | [41.825; 316.387] | [0.106; 2] |

*Note: We obtain the results by 200 bootstrap repetitions and report median alone with 10th percentile and 90th percentile in parentheses. ***, **, * denotes 1%, 5% and 10% significant level, respectively. Sales are measured in units of product. Revenue is measured in US Dollar.*

**Table A3. The Effects of Signaling Programs on Outcomes of Kingston Sellers**

**Using Never-in Sellers as the Control Group**

| | Number of Treated | Matched Pairs | Revenue | Sale |
|---|---|---|---|---|
| **Authentic Description** | | | | |
| **Type I: None to Positive** | **287** | **1460** | 0.027 | 0.001 |
| | | | [-0.241; 0.334] | [-0.06; 0.063] |
| **High Reputation** | **149** | **466** | 0.449*** | 0.096*** |
| | | | [0.219; 0.713] | [0.045; 0.156] |
| **Low Reputation** | **138** | **994** | -0.338 | -0.065 |
| | | | [-0.645; -0.005] | [-0.163; 0.007] |
| **Type II: Positive to Positive** | **91** | **173** | -0.9 | -0.177 |
| | | | [-2.171; 0.091] | [-0.369; 0.025] |
| **High Reputation** | **66** | **127** | -0.951 | -0.175 |
| | | | [-2.075; 0.234] | [-0.429; 0.099] |
| **Low Reputation** | **25** | **46** | -0.742 | -0.121 |
| | | | [-3.087; 0.678] | [-0.603; 0.275] |
| **30-day Repair Warranty** | | | | |
| **Type I: None to Positive** | **173** | **1378** | 0.119** | 0.025** |
| | | | [0.028; 0.255] | [0.006; 0.044] |
| **High Reputation** | **131** | **1189** | 0.171*** | 0.03*** |
| | | | [0.069; 0.328] | [0.008; 0.058] |
| **Type II: Positive to Positive** | **145** | **1856** | 1.117** | 0.254** |
| | | | [0.257; 1.849] | [0.11; 0.397] |
| **High Reputation** | **140** | **1843** | 1.22** | 0.243*** |
| | | | [0.41; 1.908] | [0.104; 0.413] |

*Note: Type I are sellers with zero sale in pre-treatment periods and positive sale in post-treatment periods. Type II are sellers with positive sale in both pre-treatment and post-treatment periods. Low reputation includes sellers whose credit level is at most 5. High reputation contains sellers whose credit level is greater than 5.*

*We obtain the results by 200 bootstrap repetitions and report median alone with 10$^{th}$ percentile and 90$^{th}$ percentile in parentheses. ***, **, * denotes 1%, 5% and 10% significant level, respectively. Sales are measured in units of product. Revenue is measured in US Dollar. The average exchange rate in second half 2010 for US Dollar to Chinese Yuan is 6.7178. Data source is International Monetary Fund.*

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