YU, HUIJIE. Essays on Reputation Mechanisms in E-Commerce. (Under the direction of Robert Hammond and Xiaoyong Zheng.)

Founded by Alibaba Group in 2003, Taobao Marketplace has become the dominant online retailer in China. In Chapter 1, I utilize a unique dataset of iPhone5 posted-price transactions from Taobao Marketplace to study expected consumer welfare gain due to increased quality provision. Departing from product specific reputation measures constructed by counting cumulative past sales, I introduce a more accurate measure by counting the amount of positive and negative feedback given to products directly. I find that consumers respond positively to good reputation: utility from purchasing an iPhone5 increases when feedback ratings increase, and thus products that have better reputation enjoy greater market share. Reputation has a significant effect on consumer willingness to pay. For a one standard deviation increase in the iPhone5 specific positive feedback ratio, the consumer willingness to pay is 3 percent of the price of an iPhone5. I also find compelling empirical evidence in support of the positive relationship between good reputation and consumer welfare. Counterfactual analysis suggests that if every seller of the iPhone5 in Taobao Marketplace provides satisfactory service, consumer welfare would increase by 11.1 USD, about 2 percent of the price of an iPhone5.

Chapter 2 quantifies the welfare effects of reputation in this online marketplace. On the demand side, I employ a nested logit model and estimate consumer willingness to pay for reputation. On the supply side, reputation is modeled as an endogenous variable and cost parameters are estimated. Good reputation is found costly to maintain. My results suggest that it costs an average seller 123 USD per day to maintain his positive feedback ratio at 99.1 rather than 98.6 percent, a half standard deviation difference. Two counterfactual analyses are conducted to study the welfare effects of reputation.

Chapter 3 uses a laboratory experiment to study the effects of reputation systems. This is achieved by varying the information that short-run players receive concerning the past actions of long-run players. In particular, I compare the equilibrium behavior and payoffs of these two types of players under two different reputation monitoring systems. The first system mimics a classic reputation framework that allows short-run players to observe the long-run player’s past choices in chronological order. Under the second reputation system, only the aggregate frequencies of the long-run player’s past choices are observable to short-run players. Results show that efficient outcomes are reached more frequently under the second system than the first. These experimental results have strong implications for the design of feedback systems in online marketplaces.
Essays on Reputation Mechanisms in E-Commerce

by
Huijie Yu

A dissertation submitted to the Graduate Faculty of North Carolina State University in partial fulfillment of the requirements for the Degree of Doctor of Philosophy

Economics

Raleigh, North Carolina
2015

APPROVED BY:

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Stephen Margolis        Thayer Morrill

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Robert Hammond          Xiaoyong Zheng
Co-chair of Advisory Committee
Co-chair of Advisory Committee
DEDICATION

This dissertation is dedicated to my parents for their love and endless support.
BIOGRAPHY

Huijie (Alice) Yu was born in Jiangmen, China. She holds a bachelor’s degree in biology from the University of Science and Technology of China and a master’s degree in applied economics from the City University of Hong Kong. During her graduate study at North Carolina State University, Huijie was inducted into the Honor Society of Phi Kappa Phi and awarded with the BB & T Dissertation Fellowship.
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CHAPTER 1

REPUTATION AS A SUBSTITUTE FOR PRODUCT QUALITY: EVIDENCE FROM ALIBABA’S TAOBAO.COM

1.1 INTRODUCTION

The phenomenon of reputation in Internet commerce has attracted a lot of attention for at least two important reasons. First, the Internet provides systematic and formal feedback systems while traditional markets typically do not. Second, online markets have been growing rapidly and globally. eBay reported a total revenue of 14.1 billion US Dollars (USD) and a gross merchandise volume (GMV) of 67.8 billion USD in 2012. Taobao.com, the dominant Internet retailer in China, will soon become the biggest e-commerce market in the world. In 2012, when the site had more than 250 million active users, its total revenue was higher than 4.1 billion USD and its GMV was greater than 170 billion USD.

Parties to transactions in the online marketplace have asymmetric information about the goods being traded. Buyers do not know the quality of the product or service provided by the seller until they actually receive it. A buyer may leave good feedback with respect to a seller if he receives a...
satisfactory product. On the contrary, the buyer will be disappointed if he receives a product of bad quality and thus may choose to leave bad feedback. Feedback not only reveals quality, it also contains information about consumer welfare.

There is a large empirical literature that studies reputation related issues. Papers that focus on the effects of online feedback characteristics on transaction outcomes include Houser and Wooders (2006), Resnick et al. (2006), Jin and Kato (2006), Cabral and Hortaçsu (2010), Lei (2011), Elfenbein, Fisman and McManus (2012), and Jolivet, Jullien and Postel-Vinay (2014). Although different data are used, the results of these papers are similar: reputable sellers enjoy better transaction outcomes, such as higher price and higher probability of sales. Another class of literature focuses on “social learning.” Luca (2011), Cai, Chen and Fang (2009), and Anderson and Magruder (2012) study how social learning affects individuals’ dining choices. Reinstein and Snyder (2005) and Moretti (2009) investigate the effects of social learning in the movie industry. Hilger, Rafert and Vilas-Boas (2011) conduct a field experiment to investigate how consumers respond to expert opinion labels for wine. Although different methodologies are applied in these papers, they agree that individuals tend to follow other people’s decisions. However, none of these papers has examined how consumer welfare is affected by sellers’ reputation, in particular, whether a seller delivers good quality in online marketplaces.

This paper considers the problem of estimating demand in the online marketplace and studies the effects of reputation on consumer welfare. Specifically, I develop and estimate a discrete choice demand model where consumers make purchasing decisions based on product characteristics. The estimation focuses on one product, iPhone5, in Taobao Marketplace. The quality of the iPhone5 may vary in two aspects: the quality of the actual product and the quality of the service provided by sellers. The quality of an iPhone5 is relatively easy to define: whether it functions normally, or whether it comes with the original packaging and parts. When it comes to the quality of the services provided, things are often not as straightforward. For instance, a buyer may enjoy his purchasing experience if the seller is able to solve problems and communicate effectively. Although quality is not fully revealed in online marketplaces, feedback left by consumers is an informative proxy for quality. By leaving feedback ratings and comments, consumers are able to express their thoughts about the products and the service they receive from the seller, for instance, whether the products are as described, whether the shipping service is fast, etc. Hence, the feedback score discloses quality and can be considered as a product characteristic. In particular, my reputation measures include iPhone5 specific feedback scores and seller-specific feedback ratings. The utility derived from purchasing an iPhone5 depends on product quality; feedback, as a good proxy for reputation, reveals quality.

I find that online feedback reveals product quality and consumer demand responds positively to good reputation. When everything else is held constant, consumer WTP for a one standard deviation
increase in the iPhone5 specific positive ratio is 20.6 USD, which is about 3.4 percent of the price of an iPhone5. If all sellers deliver perfect services in Taobao Marketplace, the expected consumer welfare from purchasing an iPhone5 would increase by 11.1 USD, about 2 percent of the product price. When every seller has a perfect feedback score, without re-optimization of prices, competition among sellers becomes more fierce and low-priced products would gain market share while high-priced products lose market share. For a single product in Taobao Marketplace, sales go up by 1.36 units and revenue goes up by 320 USD on average. For Taobao Marketplace as a whole, sales increase by 161 units and revenue increases by 38 thousand USD.

My article is distinguished from previous studies in the following ways. It is the first empirical work that investigates consumer welfare in the online marketplace. Specifically, it is the first to estimate a structural model of demand for online products with a focus on reputation of the sellers. Previous literature examines the effects of online feedback on transaction price and sales within the reduced form framework. With an estimated structural demand model, I am able to quantify the welfare effects of reputation.

Second, my dataset of iPhone5 posted-price transactions from Taobao Marketplace is unique. Lei (2011) addresses the importance of controlling for the product specific dimension of reputation. He constructs a product specific reputation measure for Gmail invitations by counting the cumulative sales volume of Gmail invitations. Taobao displays both the numbers and the contents of all positive, neutral, and negative feedback ratings towards a specific product sold by a specific seller. I calculate a ratio constructed from the number of positive ratings and the total number of ratings, which should be a more accurate measure of product specific reputation than cumulative past sales.

This chapter is structured as follows. Section 1.2 reviews literature. In Section 1.3, I introduce the institutional setup of Taobao. In Section 1.4, I construct a discrete choice demand model. Details of the dataset are provided in Section 1.5. Section 1.6 reports summary statistics. The main empirical results are presented in Section 1.7. Counterfactual analysis is conducted in Section 1.8. Section 1.9 concludes the paper.

### 1.2 LITERATURE REVIEW

There are two strands of empirical papers that study the phenomenon of reputation. The first studies reputation mechanisms in online marketplaces. Almost all of these studies focus on the effects of online feedback on price and sales on eBay.com: Lucking et al. (2007), Houser and Wooders (2006), Resnick et al. (2006), and Jin and Kato (2006). Lei (2011) uses a collection of auctions of Gmail invitations on eBay to study the influence of seller reputation on auction outcomes. He finds that sellers who improve their reputation by one quintile from the lowest experience a 6.2 percent higher proba-
CHAPTER 1. REPUTATION AS A SUBSTITUTE FOR PRODUCT QUALITY: EVIDENCE FROM ALIBABA’S TAOBRO.COM

1.2. LITERATURE REVIEW

Elfenbein, Fisman and McManus (2012) develop a two-period signaling model to show that charity is an effective quality signal and yields a price premium. There are three types of sellers in this model: good sellers who get utility from charity and always invest effort (by paying a cost) to make sure that the product works, opportunistic sellers who get no utility from charity and only invest effort when doing so is financially profitable, and ethical sellers who get no utility from charity and always invest effort to ensure the quality of products. The crucial assumption of this model is a positive correlation between a seller’s utility from charity and his disutility from behaving opportunistically towards consumers. There are two key predictions. First, in a separating equilibrium, charity is a quality signal. Second, when the cost of investing effort is not too low, the charity premium declines when feedback reveals opportunistic sellers. The empirical evidence of this paper shows that consumers respond positively to products tied to charity, particularly for sellers that are relatively new and hence have limited alternative means of assuring quality. The paper also finds fewer customer complaints for charity-intensive sellers. Jolivet, Jullien and Postel-Vinay (2014) find that reputation of sellers influences transaction outcomes in a French Internet marketplace.

The second group of literature focuses on the effects of “social learning” or “Word-of-Mouth” on consumers’ decisions. Sorensen (2006) uses data from the University of California to examine how social learning influences employees’ choices of health plans. The effect of social learning is found to be large and significant, and the strength of it depends on factors such as the department’s size or the employee’s demographic distance from her coworkers. For the movie industry, both expert critics (Reinstein and Snyder 2005) and information received from peers (Moretti, 2009) have significant effects on individuals’ consumption decisions. Hilger, Rafert and Vilas-Boas (2011) conduct a field experiment to investigate how consumers respond to expert opinion labels for wine. They find that demand decreases for low-scoring wines and increases for high-scoring wines. There are papers that examine dining choices. Both Luca (2011) and Anderson and Magruder (2012) use regression discontinuity designs to estimate the effects of online reviews from Yelp.com on demand for dining. Cai,
Chen and Fang (2009) conduct a field experiment and find that customers who receive information about a restaurant's most popular dishes tend to order those dishes. Although different approaches are applied in these papers, all of them address the issue of omitted variables and attempt to overcome the hurdle of endogeneity.

Other empirical papers specifically study reputation mechanisms in Chinese online marketplaces. Cai et al. (2014) show that before the introduction of a centralized feedback system, sellers on Eachnet.com (an eBay equivalent in China) with a longer successful selling record enjoyed more repeat business, reached more buyer regions, sold in more product categories and had a higher completion sale rate. After the introduction of the centralized feedback system, reputable sellers enjoyed even larger market expansion into new buyer regions and new product categories compared to non-reputable sellers. Fan, Ju and Xiao (2013) use data from Taobao.com to study how reputation affects revenue, price, transaction volume, and survival likelihood for new and established sellers. They also investigate sellers' activity in managing reputation at different stages. Their paper concludes that when new sellers reach a certain level of reputation, they engage in active reputation management, such as cutting prices to generate more sales. But these activities can reduce the survival likelihood of new sellers.

1.3 THE TAOBAO REPUTATION MECHANISM

1.3.1 The History of Taobao Marketplace

China's e-commerce market has been growing rapidly since 2003 as shown in Figure 1.1. In 2012, it surpassed America's in value, with a total value of 238 billion USD. In the same year, the number of Chinese online shoppers surged to 250 million. However, there is substantial room for growth. Online penetration in China was 43 percent in 2012, well below the 70 percent or higher seen in developed economies. 1

Taobao Marketplace (Taobao.com) was established in 2003 and is operated by China's Alibaba Group. Taobao Marketplace facilitates consumer-to-consumer (C2C) retail by providing a platform for small businesses and individual entrepreneurs to open online retail stores that mainly cater to consumers in China, Hong Kong, Macau, and Taiwan. For the fiscal year ending on March 31, 2013, the combined GMV of Taobao Marketplace and Tian Mao (an affiliated website owned by Alibaba)

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1"The World's Greatest Bazaar.”
Source: *The Economist*
Accessed: 08/19/2014
1.3. THE TAOBAO REPUTATION MECHANISM

CHAPTER 1. REPUTATION AS A SUBSTITUTE FOR PRODUCT QUALITY: EVIDENCE FROM ALIBABA'S TAOBAO.COM

Figure 1.1 Growth of Internet Penetration and E-commerce Sales in China

exceeded 170 billion USD, which is about 2.3 percent of China's 2012 GDP.

Developed as an eBay equivalent in China, sellers in Taobao Marketplace are able to list new and used goods for sale either through an auction format or a posted-price format. Unlike eBay, the overwhelming majority of the products sold in Taobao Marketplace are brand new items with a posted-price; auctions make up a very small percentage (less than 2 percent) of transactions. The way that Taobao generates revenue also differs from eBay. eBay charges a listing fee when a seller lists an item on eBay and a final value fee when an item sells, while Taobao Marketplace does not charge any fee for listing (either new or used items). Taobao allows sellers to advertise their products by paying to be listed as featured products on the home page or as recommended products on the search page. Prices to advertise in the center of Taobao Marketplace's home page can be as high as 25,000 USD per day. Taobao also generates revenue from selling various tools to sellers. One of the common tools is the Display Helper, which improves the layout of a seller's store page. Another one is the Promotion Helper, which facilitates promotions (see Section 1.3.2).

In 2008, Tian Mao (formerly Tmall.com and Taobao Mall), a business-to-consumer (B2C) platform was launched by Alibaba. In 2010, an independent web domain, Tmall.com, was created for Tian Mao to differentiate listings by its merchants, who are either brand owners or authorized distributors, from Taobao's C2C merchants. Although Taobao Marketplace was established as a C2C

2“Alibaba Group to Split Taobao Online Retail Unit into Three.”
Source: Bloomberg L.P.
Accessed: 09/02/2014
platform and Tian Mao was launched as a B2C platform, products from both Taobao Marketplace and Tian Mao display on the Taobao search page.

Figure 1.2 Financial Report of Alibaba from 2009 - 2012

Taobao has come to dominate Internet retailing in China and it will likely become the biggest e-commerce market in the world. As shown in Figure 1.2, Taobao.com accounted for a 90 percent share of China’s C2C online retail market in 2011, while Tian Mao accounted for a 51 percent share of the B2C online retail market. Both the revenue and profit of Alibaba have grown rapidly since 2008. Revenue increased from 2.3 to 4.1 billion USD and net profit grew from 0.2 to roughly 0.5 billion USD between 2011 to 2012.

Table 1.1 2012 Financial Reports of Alibaba, Amazon and eBay

<table>
<thead>
<tr>
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<th>Revenue</th>
<th>Net Profit/Loss</th>
<th>GMV</th>
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<td>Alibaba</td>
<td>4.1</td>
<td>0.5</td>
<td></td>
<td>171.2*</td>
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<tr>
<td>Amazon</td>
<td>61.1*</td>
<td>-0.04</td>
<td></td>
<td>87.8</td>
</tr>
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<td>eBay</td>
<td>14.1</td>
<td>2.6*</td>
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<td>67.8</td>
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*leader in each category

Table 1.1 compares the revenue, net profit and GMV of Alibaba, Amazon, and eBay. In 2012 Amazon obtained the highest revenue, eBay had the highest profit, and Alibaba (including Taobao Mar-
ketplace and Tian Mao) enjoyed the highest GMV among the three.

![Price Cut](image)

**Figure 1.3** Price Cut

### 1.3.2 Sales Format of Taobao Marketplace

Although Taobao Marketplace is similar to eBay in many ways, the major sales format in Taobao differs from eBay. Sellers on eBay offer their goods brand new or used through listings that may be: true auctions in which bids are collected until a specified ending time (usually 7 days after the auction begins); posted-price listings in which the seller specifies a price and ending date, often 30 days or more later; or a hybrid form in which a true auction also includes a “buy-it-now”. For auction-style listings with the Buy-it-Now option, a buyer has the chance to purchase an item immediately before bidding starts. Once someone bids, the Buy-it-Now option disappears and bidding continues until the listing ends, with the item going to the highest bidder.

Sellers on Taobao Marketplace can sell a brand new or used product by using an auction or a posted-price format. Taobao offers free listings to sellers and sellers can select 7 or 14 days as the listing period for either format. Taobao automatically renews the listings so that they never expire unless a seller manually removes them. Auctions account for less than 2 percent of total transaction volume, and thus this study only focuses on brand new merchandise sold at a posted-price.

In order to attract consumers and promote sales, sellers in Taobao Marketplace have promotions from time to time. Common promotions include price cuts, vouchers with purchase, or gifts with purchase.
During the price cut promotion, sellers usually claim that the price cut is temporary in order to attract more buyers. In order to make the price cut visible and noticeable to consumers, a seller may use a tool developed by Taobao called Promotion Helper. Taobao charges a small fee from the seller who purchases this tool. This fee is usually a monthly flat-rate fee and the tool can be applied to several products up to a limit. When the seller uses this tool to establish a price cut promotion, both the original price and the actual price display on the product page. It is important to point out that the original price displayed oftentimes may not be the actual original price and sellers tend to claim a very high original price to make the price cut “significant.” Price cuts in Taobao resemble marketing strategies in traditional markets: a seller increases the original price before having a price cut in order to make the discount appear significant. Hence, this type of promotional activity in Taobao can be considered advertisement and the service fee charged by Taobao can be interpreted as advertisement cost.

Figure 1.3 is an example of the price cut of an iPhone 5. The seller sets 6,000 RMB (1,000 USD) as the claimed original price and 3,000 RMB (500 USD) as the actual price. Thus the claimed original price is not informative to the researcher. The actual price is reflected by transaction records and thus recorded by the researcher.

Voucher with purchase is also a common promotion in Taobao Marketplace. A money voucher is issued when a buyer purchases a certain item from the seller or his order exceeds a certain value. Vouchers can be used with the same seller in current or subsequent purchases. When the voucher is applied, the value (of the voucher) will be subtracted from the total at checkout. The value of the voucher is usually small (about 1-10 percent of the total value of the order).
Figure 1.4 is a promotion banner for voucher with purchase. When the value of an order is above 50 RMB (8.5 USD), 198 RMB (33 USD), or 398 RMB (66 USD), a voucher that is worth 5 RMB (0.85 USD), 10 RMB (1.7 USD), or 20 RMB (3.5 USD), respectively, will be issued to the buyer and can be applied to the current purchase.

It is worth pointing out that this promotion is unobserved by the researcher because (1) the promotion banners are in terms of pictures on a product page and (2) the transaction record only shows the price before vouchers are applied. Promotions of voucher with purchase only last for a short period of time, usually no longer than a week. When the promotion ends, the seller simply removes the promotion banner from the product page.

Another promotion in Taobao Marketplace is gift with purchase. A buyer gets a free gift when he purchases a specific product or his order exceeds a certain value. Figure 1.5 is a promotion banner...
1.3. THE TAOBAO REPUTATION MECHANISM

1.3.1 Feedback System of Taobao

Both Taobao and eBay have well-established rating systems so that buyers can track how sellers performed in previous transactions. The biggest difference in the rating systems of Taobao and eBay is that Taobao displays both product specific feedback ratings and comments on the product page. Buyers on Taobao can track not only the performance of a seller, they can also track specific products sold by specific sellers.

On each seller profile page on Taobao, one can see a seller’s ID, location, the date when the ID was created, a seller’s total feedback score, and crowns (or hearts) as shown in Figure 1.6. A feedback score of at least 4 earns a seller a heart. As feedback score increases, the icon will change to a diamond, then a blue crown, and eventually transform all the way to five yellow crowns for a score above 10,000,000.
1.3. THE TAOBAO REPUTATION MECHANISM

CHAPTER 1. REPUTATION AS A SUBSTITUTE FOR PRODUCT QUALITY: EVIDENCE FROM ALIBABA'S TAOBAO.COM

as shown in Figure 1.7.

Figure 1.8 Seller Feedback on Taobao

Similar to eBay, Taobao displays recent feedback ratings, including feedback that a seller has received in the last 1 week, 1 month, 6 months, and prior to the last 6 months as shown in Figure 1.8. The positive feedback rating ratio is displayed as the percentage of positive ratings left by members. It is calculated by dividing the number of positive ratings by the total number of ratings.

Detailed seller ratings (Figure 1.9) on Taobao include three components: item as described, attitude of the seller, and shipping speed. Buyers are asked to rate the seller in each of these categories with a score of one to five stars, with five being the highest rating and one the lowest. These ratings do not count toward the overall feedback score and they are anonymous. The seller cannot trace detailed seller ratings back to the buyer who left them. When the seller's score is above or equal to the average score on Taobao Marketplace, the score is labeled in red. Otherwise it is labeled in green.

Lei (2011) addresses the importance of controlling the product specific dimension of reputation. One important advantage of using Taobao data is the direct product specific reputation measure displayed on a product page. Product specific feedback contains information with respect to the seller's performance in the sale of a specific product, including the quality of the product sold and the service provided by the seller.

Figure 1.10 shows the layout of product specific ratings on Taobao. On the product feedback page, one can read off the number of buyers that leave a positive, neutral, and negative comment with respect to the entire history of a product. A buyer can read all the comments that are displayed in reverse chronological order. One can also choose to read only the positive, neutral, or negative comments by selecting “positive,” “neutral,” or “negative” tabs respectively. Next to each comment
given to a seller, the ID of the buyer giving the comment is shown. It also shows what product is purchased by this buyer, the date of purchase, and the transaction price.

Figure 1.9 Detailed Seller Ratings on Taobao

Figure 1.10 Product Specific Ratings on Taobao
1.4 EMPIRICAL STRATEGY

1.4.1 Basic Model

The setup of the demand model follows Berry (1994) and Klier and Linn (2012). Begin with the utility function of consumer $i$ for product $j$ at time $t$:

$$U_{ijt} = X_{jt} \beta - \alpha P_{jt} + \eta_j + \xi_{jt} + \epsilon_{ijt}$$  \hspace{1cm} (1.1)

Assume there are no random coefficients in the model. Note that a seller may sell more than one product. $X_{jt}$ is a vector of characteristics of product $j$ at time $t$, where $j = 0, 1, 2, ..., J_t$ and $t = 1, ..., 81$ (Day 1 to Day 81 throughout the observation period). Specifically, $X_{jt}$ includes seller specific reputation measures and iPhone5 specific reputation measures. $\beta$ is a vector of regression coefficients of the reputation measures, $X_{jt}$. $P_{jt}$ is the price of product $j$ at time $t$ and $\alpha$ is the regression coefficient of price. Unobserved time-invariant product characteristics are denoted by $\eta_j$. $\xi_{jt}$ can be thought of as the mean of the consumers’ valuation of the time-varying unobserved product characteristics of product $j$ at time $t$. $\epsilon_{ijt}$ is i.i.d. across products and consumers, and it follows the extreme value distribution. The market share of product $j$ is then given by the logit formula:

$$s_{jt} = \frac{e^{\delta_{jt}}}{\sum_{j=0}^{J} e^{\delta_{jt}}}$$  \hspace{1cm} (1.2)

where $s_{jt}$ is the market share of product $j$ at time $t$. With the mean utility of the outside good normalized to zero,

$$\ln(s_{jt}) - \ln(s_{0t}) = \delta_{jt} = X_{jt} \beta - \alpha P_{jt} + \eta_j + \xi_{jt}$$  \hspace{1cm} (1.3)

where $s_{0t}$ is the market share of the outside option: product 0. Product 0 is an iPhone5 sold in Tian Mao.

1.4.2 Nested Logit Model

Building on the basic logit model, a nested logit model is developed. This model assumes that consumer taste follows an extreme value distribution. It allows for more flexible substitution patterns as compared to the simple logit model. Products are grouped into $G + 1$ exhaustive and mutually exclusive sets, where $g = 0, 1, ..., G$. Products are categorized into different groups based on essential characteristics (with details provided below). The outside good, $j = 0$, is assumed to be the only member of group 0.
CHAPTER 1. REPUTATION AS A SUBSTITUTE FOR PRODUCT QUALITY: EVIDENCE FROM ALIBABA’S TAobao.COM

1.4. EMPIRICAL STRATEGY

Under the nested logit structure, the error term includes a common shock for all products within a group, and an idiosyncratic term (Klier and Linn, 2012),

$$\epsilon_{ijt} = \omega_{igt} + (1 - \sigma)\phi_{ijt},$$

(1.4)

where $\omega_{igt}$ is the shock for iPhone5 in group $g$ at time $t$; $\sigma$ is the similarity coefficient, which represents the extent to which consumers receive similar shocks within a group at time $t$, and $\phi_{ijt}$ is the idiosyncratic shock for consumer $i$ and product $j$ at time $t$. The class shock for consumer $i$ is the same for all products within a nest. Intuitively, a consumer first selects a group and then a product. As $\sigma$ approaches 1, the within group correlation of utility goes to one. As $\sigma$ approaches zero, the within group correlation goes to zero and the nested logit model collapses to the simple logit model.

Products are divided into 11 different groups based on version and memory size (see Section 1.6 for more details). They are 16 Gigabyte (G) Chinese (CHN), 16 G European (EUR), 16 G Hong Kong (HK), 16 G Japanese (JP), 16 G United States (US), 32 G CHN, 32 G HK, 32 G JP, 32 G US, 64 G CHN, and 64 G JP.

Following Berry (1994), I combine Eq.(1.1) and (1.4) to obtain the nested logit specification,

$$\ln(s_{jt}) - \ln(s_{0t}) = X_{jt}\beta - \alpha P_{jt} + \eta_j + \sigma \ln(\tilde{s}_{jt/g}) + \tilde{\epsilon}_{jt},$$

(1.5)

Eq.(1.5) can be estimated by linear regression and the nesting structure partially relaxes the independence of irrelevant alternatives (IIA) assumption of the basic logit model. However, Eq.(1.5) imposes restrictions on cross price demand elasticities, and IIA assumption is maintained within a nest.

1.4.3 Model Identification

The difficulty in estimating demand models lies in endogeneity. Some of the time-varying promotions in Taobao Marketplace are unobserved (to the researcher) and these promotions may be correlated with the independent variables in both Eq.(1.3) and Eq.(1.5). Therefore, estimating these two equations by ordinary least squares (OLS) would yield biased estimates.

One approach to tackle endogeneity is to include product fixed effects. If one assumes that unobserved characteristics do not change over time, fixed effects models would yield unbiased estimates. For instance, some sellers have better writing skills or communication skills. Some sellers are better at designing web pages. These unobserved factors are unlikely to change over time and would be eliminated by fixed effects. However, I suggest that this assumption is not appropriate in this demand model because some of the unobserved characteristics may change over time.
1.4 EMPIRICAL STRATEGY

As discussed in Section 1.2.4, there are several types of time-varying promotions in Taobao Marketplace. Both the promotions of voucher with purchase and gift with purchase can vary over time. A seller can easily change the gift or the value of the money voucher. When a promotion ends, he simply removes the promotion banner on the product page. Although the value of the gift or the money voucher is small, these promotional activities become confounding factors in the error term, and thus the error term is correlated with one or more explanatory variables in the demand estimation. In order to further control for endogeneity, an instrumental variable (IV) strategy is proposed.

There are two endogenous variables in the nested logit model: $P_{jt}$ and $\bar{s}_{jt/g}$. The unobserved time-varying promotions are captured by the error term $\xi_{jt}$. Intuitively, promotional activities affect sellers’ pricing decisions and thus $\xi_{jt}$ and $P_{jt}$ would not be mean independent.

An example to consider is the time-varying free gift with purchase. When a buyer purchases an iPhone5 from the seller, he gets a free iPhone5 case for free. The buyer’s willingness to pay for this iPhone5 may increase because the purchase comes with a free iPhone5 case. Thus it is possible that the seller charges a slightly higher price. Another time-varying unobserved promotional activity is the money voucher with purchase. When a buyer gets a money voucher with purchase, the seller may increase the price of the product and thus price would be correlated with the error term.

The second endogenous variable is $\bar{s}_{jt/g}$. Imagine there are two phones that belong to the same group but are sold by two different sellers. One may be more popular than the other and thus have a higher within-group share if the purchase comes with a free gift. This promotion is unobserved to the researcher but correlated with within-group share. Therefore, it suggests the need for additional exogenous variables that are correlated with $\bar{s}_{jt/g}$.

Two classes of instrumental variables are used to control for endogeneity. The standard approach would be to follow Berry (1994) and use characteristics of products sold by other sellers in the same nest. $Ave_{Pos\_Mon\_Nest}jt$ is the average of the seller specific positive ratio for all other sellers in the same group over the past month. This variable is likely to be correlated with both endogenous variables. The better the reputation of all other sellers, the smaller the within-group share one enjoys. If all other sellers have higher reputation, one is very likely to set a lower price to compete with other sellers and attract more customers. Therefore, $Ave_{Pos\_Mon\_Nest}jt$ should be negatively correlated with both price and within-group share. $Ave_{Pos\_Mon\_Nest}jt$ would be a valid instrument if a seller’s promotion decision is not affected by the average reputation of all other sellers in the same group.

The second class of instrumental variables includes two lagged variables. $past\_sales_{jt-7}$ is the cumulative 30-day sales of iPhone5s before time $t - 7$, i.e. $past\_sales_{jt-7} = sales_{jt-8} + sales_{jt-9} + ... + sales_{jt-37}$. The social learning literature suggests that one tends to follow other people’s choices. If that is the case, a buyer tends to buy from a seller who has had strong sales in the past. Thus the lag
of past sales is likely to be positively correlated with the current within-group share. What is more, this lagged variable is likely to be correlated with price. A seller may set a higher price if he has had strong sales and developed a good reputation.

While being correlated with two endogenous variables, $\text{past sales}_{jt-7}$ is unlikely to be correlated with $\xi_{jt}$. Recall that the error term consists of unobserved time-varying promotions. A promotion in general lasts no longer than a week and thus errors that are at least a week apart are unlikely to be correlated. The closest component of $\text{past sales}_{jt-7}$ to the error term is $\text{sales}_{jt-8}$, the sales 8 days ago. This variable is not likely to be correlated with the error term if the unobserved promotion lasts no longer than a week. Even for the very rare case where an unobserved promotion lasts longer than a week, the structure of this lagged variable (being the sum of 30-day sales) would attenuate its correlation with the error term.

Another instrumental variable is $P_{jt-10}$, which is the price of product $j$ 10 days ago. Since the price of an iPhone5 fluctuates within a small range in a relatively short period, $P_{jt-10}$ is very likely positively correlated with the current price, $P_{jt}$. And since the unobserved promotional activities do not last more than a week, $P_{jt-10}$ is not likely correlated with $\xi_{jt}$. The reason why $P_{jt-7}$ is not selected as an instrument is that if a promotion lasts a little longer than a week, $P_{jt-7}$ might be correlated with the error term. In order to be conservative, $P_{jt-10}$, instead of $P_{jt-7}$, is used as an IV.

In the simple logit model of Eq.(1.3), $P_{jt}$ is endogenous. To control for endogeneity, one or more instruments is required. As discussed above, $P_{jt-10}$ is likely to be correlated with $P_{jt}$ but orthogonal to $\xi_{jt}$, and thus is used as an instrument. The second instrument is $\text{Ave_Pos_Mon_All}_{jt}$ defined as the average positive ratio of all other sellers of the iPhone5. $\text{Ave_Pos_Mon_All}_{jt}$ should be negatively correlated with $P_{jt}$: when all other sellers have a better reputation, one would set a lower price. $\text{Ave_Pos_Mon_All}_{jt}$ would be orthogonal to the error term if a seller’s decision to have promotions is not influenced by the average reputation of all other sellers in the market for iPhone5s.

1.5 DATA

Data on iPhone5, is collected for the following reasons: (1) the transaction volume of the brand new iPhone5 is high; (2) iPhone5 is a relatively expensive product and consumers care about its quality and the purchasing experience; (3) it is a homogenous good in the sense that there is not much variation among products.

The data sample covers transactions of the iPhone5 between May 10, 2013 and July 29, 2013 in Taobao Marketplace. The number of observations used in the estimation is 8,046 and the number of products is 158. The data extraction involves three steps. First, transactions related to iPhone5 are identified through the search results on Taobao.com with keyword “iPhone5”. Second, used items
### Table 1.2 Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Mean</th>
<th>STD</th>
<th>Min</th>
<th>Max</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Q_{jt}$</td>
<td>Quantity Sold</td>
<td>5.8222</td>
<td>9.88</td>
<td>0</td>
<td>83</td>
<td>8,046</td>
</tr>
<tr>
<td>$Q_{0t}$</td>
<td>Quantity Sold in Tian Mao</td>
<td>65.7636</td>
<td>32.82</td>
<td>9</td>
<td>162</td>
<td>81</td>
</tr>
<tr>
<td>$s_{jt}$</td>
<td>Market Share</td>
<td>0.0070</td>
<td>0.01</td>
<td>0.0906</td>
<td>0.1084</td>
<td>8,046</td>
</tr>
<tr>
<td>$s_{jt/g}$</td>
<td>Within Group Market Share</td>
<td>0.0751</td>
<td>0.16</td>
<td>0.0242</td>
<td>0.0992</td>
<td>8,046</td>
</tr>
<tr>
<td>$s_{0t}$</td>
<td>Market Share of Tian Mao</td>
<td>0.0772</td>
<td>0.04</td>
<td>0.0108</td>
<td>0.1655</td>
<td>81</td>
</tr>
<tr>
<td>$positive_{jt}$</td>
<td>No. of iPhone5 Specific Positive Feedback with Comments</td>
<td>1,286.5580</td>
<td>1,894.7514</td>
<td>14</td>
<td>8,875</td>
<td>8,046</td>
</tr>
<tr>
<td>$positive_{woj}t$</td>
<td>No. of iPhone5 Specific Positive Feedback without Comments</td>
<td>2,095.5220</td>
<td>2,998.1321</td>
<td>21</td>
<td>16,090</td>
<td>8,046</td>
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<tr>
<td>$neutral_{jt}$</td>
<td>No. of iPhone5 Specific Neutral Feedback</td>
<td>7.0199</td>
<td>20.56</td>
<td>0</td>
<td>138</td>
<td>81</td>
</tr>
<tr>
<td>$negative_{jt}$</td>
<td>No. of iPhone5 Specific Negative Feedback</td>
<td>7.0969</td>
<td>20.23</td>
<td>0</td>
<td>181</td>
<td>8,046</td>
</tr>
<tr>
<td>$posratio_{jt}$</td>
<td>No. of Seller Specific Positive Feedback</td>
<td>0.9911</td>
<td>0.01</td>
<td>0.8750</td>
<td>1</td>
<td>8,046</td>
</tr>
<tr>
<td>$D_{1j}t$</td>
<td>Item as Described</td>
<td>0.7940</td>
<td>0.40</td>
<td>0</td>
<td>1</td>
<td>8,046</td>
</tr>
<tr>
<td>$D_{2j}t$</td>
<td>Seller Attitude</td>
<td>0.6923</td>
<td>0.46</td>
<td>0</td>
<td>1</td>
<td>8,046</td>
</tr>
<tr>
<td>$D_{3j}t$</td>
<td>Shipment Speed</td>
<td>0.7172</td>
<td>0.45</td>
<td>0</td>
<td>1</td>
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<tr>
<td>$Ave_{Djt}$</td>
<td>No. of Seller Specific Positive Feedback</td>
<td>0.7345</td>
<td>0.40</td>
<td>0</td>
<td>1</td>
<td>8,046</td>
</tr>
<tr>
<td>$posmon_{jt}$</td>
<td>No. of Seller Specific Positive Feedback</td>
<td>932.8577</td>
<td>1,357.55</td>
<td>11</td>
<td>14,011</td>
<td>8,046</td>
</tr>
<tr>
<td>$neumon_{jt}$</td>
<td>No. of Seller Specific Neutral Feedback</td>
<td>3.2586</td>
<td>5.99</td>
<td>0</td>
<td>73</td>
<td>8,046</td>
</tr>
<tr>
<td>$negmon_{jt}$</td>
<td>No. of Seller Specific Negative Feedback</td>
<td>2.9305</td>
<td>4.86</td>
<td>0</td>
<td>35</td>
<td>8,046</td>
</tr>
<tr>
<td>$posratio_{monjt}$</td>
<td></td>
<td>0.9934</td>
<td>0.01</td>
<td>0.8796</td>
<td>1</td>
<td>8,046</td>
</tr>
<tr>
<td>$pastsales_{jt}$</td>
<td>Cumulative Sales in the Past 30 Days</td>
<td>515.9979</td>
<td>647.46</td>
<td>20</td>
<td>3,175</td>
<td>8,046</td>
</tr>
<tr>
<td>$logpastsales_{jt}$</td>
<td>Log of Cumulative Sales in the Past 30 Days</td>
<td>5.5504</td>
<td>1.20</td>
<td>2.9957</td>
<td>8.0631</td>
<td>8,046</td>
</tr>
<tr>
<td>$P_{jt}$</td>
<td>Price (USD)</td>
<td>693.3588</td>
<td>80.28</td>
<td>501</td>
<td>1,003.1670</td>
<td>8,046</td>
</tr>
</tbody>
</table>

are excluded from the search. Lastly I filter to ensure that the data sample includes no products aside from the iPhone5. The product of concern is thus as homogenous as possible.

### 1.6 SUMMARY STATISTICS

Table 1.2 reports summary statistics for the key variables of the model. The dependent variable in the demand estimation is defined as $ln(s_{jt}) - ln(s_{0t})$. $s_{jt}$ is the market share of product $j$ at time $t$, defined as the ratio of quantity sold of product $j$ to the total quantity sold in Taobao and TianMao at time $t$. Note that if the quantity sold of a listed product is zero at time $t$, 0.01 unit instead of zero, is used to calculate $s_{jt}$. $\bar{s}_{jt/g}$ is the within group share of product $j$ at time $t$ in group $g$ and is calculated by dividing the quantity sold of product $j$ at time $t$ by the total quantity sold of group $g$ at time $t$. If the actual quantity sold at time $t$ is zero, 0.01 is used as the quantity to calculate $\bar{s}_{jt/g}$. $s_{0t}$ is the market share of the outside option, in this case, the iPhone5 sold in TianMao. $positive_{jt}$, $neutral_{jt}$, and $negative_{jt}$ are the quantities of iPhone5 specific positive feedback (with comments left), neutral feedback, and negative feedback, respectively. $positive_{woj}t$ is the quantity of all iPhone5 specific positive feedback, which includes both with and without comments. $posratio_{jt}$ is calculated as $\frac{positive_{jt}}{positive_{jt}+neutral_{jt}+negative_{jt}}$ over the entire transaction history of iPhone5 sold by
Table 1.3 Frequency Counts of Products

<table>
<thead>
<tr>
<th>GROUP</th>
<th>Freq</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>16G CHN</td>
<td>1,702</td>
<td>21.50</td>
</tr>
<tr>
<td>16G EUR</td>
<td>49</td>
<td>0.61</td>
</tr>
<tr>
<td>16G HK</td>
<td>2,962</td>
<td>36.81</td>
</tr>
<tr>
<td>16G JP</td>
<td>721</td>
<td>8.96</td>
</tr>
<tr>
<td>16G USA</td>
<td>1,445</td>
<td>17.96</td>
</tr>
<tr>
<td>32G CHN</td>
<td>397</td>
<td>4.90</td>
</tr>
<tr>
<td>32G HK</td>
<td>134</td>
<td>1.67</td>
</tr>
<tr>
<td>32G JP</td>
<td>267</td>
<td>3.37</td>
</tr>
<tr>
<td>32G USA</td>
<td>94</td>
<td>1.17</td>
</tr>
<tr>
<td>64G CHN</td>
<td>136</td>
<td>1.69</td>
</tr>
<tr>
<td>64G JP</td>
<td>139</td>
<td>1.73</td>
</tr>
</tbody>
</table>

No. of Observations: 8,046

seller $s$ until time $t$. Note that iPhone5 specific feedback does not vary across products that are sold by the same seller. The mean, minimum, and standard deviation of $posratio_{jt}$ are 0.9911, 0.8750, and 0.01, respectively. I construct three dummy variables, $D_{jt}^1$, $D_{jt}^2$, and $D_{jt}^3$, which take the value one if the scores for item as described, attitude of the seller, and shipping time, are respectively above the average score on Taobao. They take a value of zero otherwise. $Ave_{D_{jt}}$ is the average of these three dummy variables. $P_{jt}$ is the transaction price of the iPhone5 adjusted by shipping cost. $posmon_{jt}$, $neumon_{jt}$, and $negmon_{jt}$ are the quantities of seller specific positive, neutral, and negative feedback in the recent 1 month. $posratio_{mon_{jt}}$ is defined as $\frac{posmon_{jt}}{posmon_{jt} + neumon_{jt} + negmon_{jt}}$. The price of an iPhone5 varies according to the version and memory size. Chinese consumers realize additional costs when they purchase iPhone5 that is not specifically manufactured for the Chinese market. For instance, the Japanese version is the cheapest because it is exclusively designed for the Japanese market. The Chinese version costs the most because it is specifically designed for the Chinese market.

Table 1.3 summarizes the frequency counts of products in each group. The most popular products are from the following three groups: 16G CHN, 16G HK, and 16G US.
1.7 ESTIMATION RESULTS

1.7.1 Demand Estimates

This subsection presents the results of the reduced form model, the simple logit estimation, and the nested logit estimation. Keep in mind that the estimates reported do not reflect the magnitude of the marginal effects of the independent variables on market share. I firstly replicate the previous reputation literature and use OLS to estimate the effects of feedback ratings on the market share of product j. Column (2) reports the estimates of the simple logit model (Eq.(1.3)). The coefficient of $P_{jt}$ is negative but not statistically significant. The coefficient of $posrat i o_{j t}$ indicates that an iPhone5 yields a higher market share when it has a better iPhone5 specific reputation. The coefficient of $Ave_{Dj t}$ suggests that a seller who provides better services enjoys higher market share for his products. Column (3) reports the estimates of the nested logit model (Eq.(1.5)). In this model, the coefficient of $P_{jt}$ becomes statistically significant. Demand of an iPhone5 decreases when its price increases. The coefficient of log of $\bar{s}_{jt/g}$ is 0.4416, which lies between 0 and 1. This suggests that consumers receive both idiosyncratic shocks and similar shocks to products within a class.

The hierarchical structure of the nested logit model may present a more realistic depiction of how consumers shop in the online marketplace. From a statistical perspective, the magnitude of
### Table 1.5 First-Stage Estimates

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( P_{jt} ) Logit</td>
<td>-130.8732***</td>
<td>-134.5323***</td>
<td>31.2256***</td>
</tr>
<tr>
<td>( P_{jt} ) Nested Logit</td>
<td>-134.5323***</td>
<td>8.7424***</td>
<td>12.5622***</td>
</tr>
<tr>
<td>( \log(s_{jt} = g) )</td>
<td>31.2256***</td>
<td>1.1710***</td>
<td>0.1357***</td>
</tr>
<tr>
<td>( \text{Ave}<em>{-} \text{Pos}</em>{-} \text{Mon}<em>{-} \text{All}</em>{jt} )</td>
<td>-325.9366***</td>
<td>-299.1641*</td>
<td>8.1246</td>
</tr>
<tr>
<td>( \text{Ave}<em>{-} \text{Pos}</em>{-} \text{Mon}<em>{-} \text{Nest}</em>{jt} )</td>
<td>-299.1641*</td>
<td>(115.44)</td>
<td>(14.45)</td>
</tr>
<tr>
<td>( \log\text{sales}_{jt-7} )</td>
<td>0.4759</td>
<td>0.0762</td>
<td>0.6821***</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>F statistic</td>
<td>90.02</td>
<td>46.32</td>
<td>26.49</td>
</tr>
</tbody>
</table>

Standard Errors in Parentheses; ***p<0.01, **p<0.05, *p<0.1; No. of Observations: 8,046.

\( R^2 \) provides further evidence that the nested logit model may have advantages over the alternative simple logit model in estimating the demand of iPhone5 in Taobao Marketplace. The adjusted \( R^2 \) of the nested logit model is 0.56, which is much greater than the adjusted \( R^2 \) of the simple logit model.

Table 1.4 also reports underidentification and over identification tests for both models. The p-values for underidentification test are smaller than 0.01 for both models. The p-values for the overidentification test for both models suggest that it fails to reject the null hypothesis that the model is over identified. This suggests that the IVs used in the estimations are not correlated with the error terms.

Table 1.5 reports the first-stage estimates of the simple logit model and the nested logit model. \( P_{jt} \) is the only endogenous variable in the simple logit estimation. \( \text{Ave}_{-} \text{Pos}_{-} \text{Mon}_{-} \text{All}_{jt} \) and \( P_{jt-10} \) are used as the instruments. As shown in Column (1), \( P_{jt-10} \) and \( P_{jt} \) are positively correlated. The coefficient of \( \text{Ave}_{-} \text{Pos}_{-} \text{Mon}_{-} \text{All}_{jt} \) is negative and significant, which indicates that a seller is more likely to lower the price when the average feedback score of all other sellers increases. Columns (2) and (3) report the first-stage estimates of the nested logit model. Column (2) shows that the coefficient of \( P_{jt-10} \) is positive and significant. The coefficient of \( \text{Ave}_{-} \text{Pos}_{-} \text{Mon}_{-} \text{Nest}_{jt} \) is negative and significant, which implies that when the average reputation of all other sellers in the same group increases, a seller tends to set a lower price. Column (3) shows that \( \log\text{sales}_{jt-7} \) has a positive and significant effect on \( \log(\hat{s}_{jt/g}) \). All F statistics are significantly larger than 10, indicating that the IVs
are highly correlated with the endogenous variables in the first-stage estimation.

One might find the negative coefficients of $posratio_{jt}$ in Columns (1) and (2) counterintuitive. A possible explanation for this sign lies in the correlation between $posratio_{jt}$ and $Ave\_D_{jt}$. In fact, when I only include $posratio_{jt}$ as the exogenous variable in the estimation, the sign becomes positive, which suggests a positive correlation between $posratio_{jt}$ and $P_{jt}$.

In sum, after endogeneity is controlled for, several estimation results are interesting. First, consumers respond negatively to price in the online marketplace. This is consistent with consumer theory and consumer behavior in traditional markets. Second, it is well documented that better quality yields higher utility. Results suggest that better feedback score yields higher utility and reputation on the Internet reveals product and seller quality.

### 1.7.2 Willingness to Pay for Reputation

WTP for an increase in reputation can be calculated as

$$WTP_{reputation} = \frac{\beta_r}{\alpha} \Delta X_r$$  \hspace{1cm} (1.6)

where $\alpha$ is the marginal utility of price, $\beta_r$ is the marginal utility derived from iPhone5 specific reputation, and $X_r$ is iPhone5 specific reputation ($posratio$). The total derivative of the indirect utility function is set to zero. WTP is interpreted as the amount of money that would have to be added to the price of the iPhone5 to keep the consumer’s utility level constant if the iPhone5 specific positive ratio goes up by a certain amount.

According to Eq.(1.6), for a one standard deviation increase in the iPhone5 specific positive ratio, i.e. $\Delta X_r = 0.01$, the amount of money added to the price would be $\frac{34.2332}{0.0166} \times 0.01 = 20.6224$ USD. For a seller who has 433 positive and 2 negative feedback ratings, the iPhone5 specific positive ratio is equal to 0.9954.\(^3\) If this seller could remove his negative feedback and thus has 435 positive and 0 negative feedback ratings, the iPhone5 specific positive ratio would become 1. The amount of money added to the price would then be $\frac{34.2332}{0.0166} \times (1 - 0.9954) = 9.4863$ USD. In contrast, if this seller has 431 positive and 4 negative feedback ratings, in order to keep the consumer’s utility level constant, the price would need to be decreased by 9.4863 USD. The above results suggest a significant effect of reputation on WTP. For a seller who has accumulated a good amount of positive feedback ratings, receiving one more positive feedback would not greatly change consumer’s WTP. However, receiving one extra negative feedback would result in significant decrease in WTP.

\(^3\)The sample median of the number of positive, neutral, and negative feedback are 433, 1, and 1, respectively.
1.8 COUNTERFACTUAL ANALYSIS

Although the relationship between seller reputation and transaction outcomes on the Internet is well studied, few efforts exploit the influence of seller reputation on consumer welfare in online marketplaces. In this section, counterfactual analysis is conducted to answer the following questions: (1) how is consumer’s welfare influenced by reputation? (2) how does reputation affect a single product’s sales and revenue? (3) how does reputation affect Taobao Marketplace as a whole with respect to sales and revenue?

Counterfactual analysis is conducted by using estimates from the nested logit model. I focus on the case where the product dimension reputation measure, $posratio$, is set to 1 for all sellers. An investigation is conducted into the change in the expected consumer welfare, the changes in sales quantity and revenue of a product, and the changes in total sales quantity and revenue of Taobao Marketplace. Before going through more details, it is important to point out that the supply side is assumed to remain constant, which means sellers do not re-optimize prices (or any other decisions).

1.8.1 Change in Consumer Welfare

The equation for consumer welfare change is given by

$$ E(CS_i^1) - E(CS_i^0) = \frac{1}{\alpha} \left[ \ln \left( \sum_{j=0}^{J} e^{V_{j|i}} \right) - \ln \left( \sum_{j=0}^{J} e^{V_{j|i}^0} \right) \right] $$

(1.7)

where $E(CS_i^1) - E(CS_i^0)$ is the expected consumer welfare change at time $t$. $V_{j|i}^0$ is the predicted indirect utility obtained from product $j$ at time $t$. $V_{j|i}^1$ is the counterfactual indirect utility where $posratio$ is set to 1 for all products.

Table 1.6 reports the summary statistics for the estimated expected consumer welfare change during the period of 81 days. The interpretation of Table 1.6 is that, if all sellers of iPhone5 are perfect, the expected consumer welfare gain (in terms of money) on average would be about 11.1 USD (2

### Table 1.6 Change in Expected Consumer Welfare

<table>
<thead>
<tr>
<th>VARIABLES (USD)</th>
<th>Mean</th>
<th>STD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E(CS_i^1) - E(CS_i^0)$</td>
<td>11.0778</td>
<td>2.24</td>
<td>5.4529</td>
<td>16.4820</td>
</tr>
</tbody>
</table>

No. of Observations: 81
percent of the price of an iPhone5. The result implies that, if everything else is fixed, good reputation is favored by consumers in online marketplaces. The maximum expected consumer welfare gain is 16.5 USD, which is about 3 percent of the price of an iPhone5.

1.8.2 Change in Sales and Revenue for a Product

In this subsection, I compare the actual sales volume and revenue with the counterfactual sales and revenue of a single product. Note that the counterfactual analysis only focuses on positive. It is set to 1 for all sellers in Taobao Marketplace.

The counterfactual market share of product \( j \) at time \( t \) is calculated by

\[
s^1_{jt} = \frac{e^{V^1_{jt}}}{\sum_j e^{V^1_{jt}}} \quad (1.8)
\]

where \( s^1_{jt} \) is the counterfactual market share of product \( j \) at time \( t \). \( V^1_{jt} \) is the counterfactual indirect utility obtained from product \( j \) at time \( t \).

Assuming that the total combined sales of Taobao and Tian Mao are held constant, the counterfactual sales quantity is given by

\[
Q^1_{jt} = TQ_t \times s^1_{jt} \quad (1.9)
\]

where \( Q^1_{jt} \) is the counterfactual sales volume of product \( j \) at time \( t \). \( TQ_t \) is the total combined sales volume of Taobao and Tian Mao. The difference between the counterfactual and actual sales of product \( j \) at time \( t \) is then given by

\[
\Delta Q_{jt} = Q^1_{jt} - Q^0_{jt} \quad (1.10)
\]

where \( Q^0_{jt} \) is the actual sales volume of product \( j \) at time \( t \). The counterfactual revenue of product \( j \) at time \( t \) is calculated by

\[
R^1_{jt} = P_{jt} \times Q^1_{jt} \quad (1.11)
\]

where \( P_{jt} \) is the price of product \( j \) at time \( t \). I calculate the difference between the counterfactual revenue and the actual revenue of product \( j \) at time \( t \), \( \Delta R_{jt} \), by

\[
\Delta R_{jt} = R^1_{jt} - R^0_{jt} \quad (1.12)
\]

where \( R^0_{jt} \) is the actual revenue of product \( j \) at time \( t \).
CHAPTER 1. REPUTATION AS A SUBSTITUTE FOR PRODUCT QUALITY. EVIDENCE FROM ALIBABA'S TAOBAO.COM

1.8. COUNTERFACTUAL ANALYSIS

Table 1.7 Changes in Sales

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Mean</th>
<th>STD</th>
<th>Min</th>
<th>Max</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔSales</td>
<td>1.3605</td>
<td>17.21</td>
<td>-75.8924</td>
<td>164.2316</td>
<td>8,046</td>
</tr>
<tr>
<td>ΔSales (price &lt;= $653)</td>
<td>17.8748</td>
<td>24.52</td>
<td>-45.0621</td>
<td>164.2316</td>
<td>1,948</td>
</tr>
<tr>
<td>ΔSales ($653 &lt; price &lt;= $708)</td>
<td>-4.0832</td>
<td>9.91</td>
<td>-73.7922</td>
<td>28.3714</td>
<td>1,844</td>
</tr>
<tr>
<td>ΔSales ($708 &lt; price &lt;= $726)</td>
<td>-5.5630</td>
<td>11.50</td>
<td>-75.8924</td>
<td>9.7746</td>
<td>2,173</td>
</tr>
<tr>
<td>ΔSales ($726 &lt; price)</td>
<td>-2.0424</td>
<td>3.77</td>
<td>-44.1024</td>
<td>8.2484</td>
<td>2,081</td>
</tr>
</tbody>
</table>

No. of Observations: 8,046

Table 1.8 Changes in Revenue

<table>
<thead>
<tr>
<th>VARIABLES (Thousand USD)</th>
<th>Mean</th>
<th>STD</th>
<th>Min</th>
<th>Max</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔRevenue</td>
<td>0.3209</td>
<td>10.45</td>
<td>-54.6763</td>
<td>86.6595</td>
<td>8,046</td>
</tr>
<tr>
<td>ΔRevenue (price &lt;= $653)</td>
<td>10.1516</td>
<td>13.82</td>
<td>-25.6792</td>
<td>86.6595</td>
<td>1,948</td>
</tr>
<tr>
<td>ΔRevenue ($653 &lt; price &lt;= $708)</td>
<td>-2.8576</td>
<td>6.90</td>
<td>-52.1794</td>
<td>18.6778</td>
<td>1,844</td>
</tr>
<tr>
<td>ΔRevenue ($708 &lt; price &lt;= $726)</td>
<td>-3.9907</td>
<td>8.26</td>
<td>-54.6763</td>
<td>7.0052</td>
<td>2,173</td>
</tr>
<tr>
<td>ΔRevenue ($726 &lt; price)</td>
<td>-1.5610</td>
<td>2.82</td>
<td>-32.0674</td>
<td>6.1368</td>
<td>2,081</td>
</tr>
</tbody>
</table>

No. of Observations: 8,046

Table 1.7 reports the gain (or loss) in terms of sales for a single product. The 25, 50, and 75 percentile cutoff prices are 653 USD, 708 USD, and 726 USD, respectively. Intuitively, if all sellers have a perfect feedback score, consumer’s utility would heavily depend on the product price. Since price is held constant, low price would become a big advantage and thus products that are sold at lower prices would gain sales. On the contrary, high-priced products would lose market share. The results in Table 1.7 confirm this story. On average, each product would gain sales at a rate of 1.36 units per day. When I take a closer look at products that are categorized based on price, I find that low-priced products gain sales while those with higher prices lose sales.

Table 1.8 reports the gain (or loss) of revenue of a single product. The mean of ΔRevenue is about 320 USD, indicating that on average, revenue of a single product would go up.

The results of Table 1.8 are consistent with Table 1.7. Products sold with low prices (below or equal to the 25 percentile cutoff) gain and those with high prices (above the 25 percentile cutoff) lose sales and revenue. The sales volume and revenue of products with price below the 25 percentile
1.8. COUNTERFACTUAL ANALYSIS

CHAPTER 1. REPUTATION AS A SUBSTITUTE FOR PRODUCT QUALITY: EVIDENCE FROM
ALIBABA’S TAOBAO.COM

Table 1.9 Change in Sales in Taobao Marketplace

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Mean</th>
<th>STD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>∆Taobao Sales</td>
<td>161.4787</td>
<td>63.34</td>
<td>42</td>
<td>304.0001</td>
</tr>
</tbody>
</table>

No. of Observations: 81

cutoff go up by more than 17 units and 10 thousand USD, respectively. For products that are sold
with price above the 25 percentile cutoff, the means of change in sales volume and revenue become
negative.

1.8.3 Market Expansion of Taobao Marketplace

This subsection compares the actual and counterfactual sales and revenue of Taobao Marketplace
as a whole. Recall that the iPhone5 sold in Tian Mao is defined as the outside option. The market
of Taobao expands if Taobao “steals” sales from Tian Mao. The purpose of this section is to examine
whether the market of Taobao would generate higher sales volume and greater revenue if all sellers
in Taobao Marketplace deliver satisfactory quality.

The change in total sales quantity of Taobao at time t, ∆TQ_t, is calculated by

\[ \Delta TQ_t = \sum_{j=1}^{J} (Q_{jt}^1 - Q_{jt}^0) \]  (1.13)

where \( Q_{jt}^1 \) is the counterfactual sales quantity of product \( j \) at time \( t \) and \( Q_{jt}^0 \) is the actual sales quan-
tity of product \( j \) at time \( t \). The change in total revenue of Taobao at time \( t \), ∆TR_t, is given by

\[ \Delta TR_t = \sum_{j=1}^{J} (R_{jt}^1 - R_{jt}^0) \]  (1.14)

where \( R_{jt}^1 \) is the counterfactual revenue of product \( j \) at time \( t \) and \( R_{jt}^0 \) is the actual revenue of prod-
uct \( j \) at time \( t \).

Results in Table 1.9 suggest that, if all sellers deliver perfectly satisfactory services when selling an
iPhone5, the total sales of iPhone5 in Taobao Marketplace would go up by 161 units on average. Keep
in mind that, behind the scenes, there is substitution between low-priced products and high-priced
products.

Table 1.10 shows that the counterfactual total revenue of Taobao would go up by more than 38
1.9 CONCLUSION

This chapter studies the effects of reputation on consumer welfare in the online marketplace. Particularly, I use a unique dataset of posted-price transactions of iPhone5 in a major Chinese online platform, Taobao.com, to study the expected consumer welfare gain due to better quality provided. Departing from the product specific reputation measure constructed by counting the cumulative past sales, a more accurate measure is established by counting the number of positive and negative feedback given directly toward a specific product.

Consumers respond positively to good reputation: utility from purchasing an iPhone5 increases when feedback rating increases, and thus products with better reputation obtain greater market shares. Consumers are willing to pay 20.6 USD (3.4 percent of the price of an iPhone5) for a one standard deviation increase in iPhone5 specific positive feedback ratio. Empirical evidence is also found in support of the positive relation between good reputation and consumer welfare. Counterfactual analysis indicates that if every seller of iPhone5 provides satisfactory service in Taobao Marketplace, consumer welfare would go up by 11.1 USD, about 2 percent of the price of an iPhone5.

Counterfactual analysis is also conducted to examine sales and revenue of iPhone5 on the supply side. If all sellers of iPhone5 provide good services, sellers would re-optimize prices. However, my paper does not consider re-optimization and thus price is held fixed. Because every seller delivers equally good service in the counterfactual scenario, consumers’ utility would be heavily dependent upon price. Low-priced products would gain market shares and revenue while high-priced products would lose sales and revenue. Both total sales and revenue of iPhone5 in Taobao Marketplace would go up on average.
	hundred USD. It is important to note that there is no re-optimization of prices on the supply side. Since all sellers have equally perfect ratings, the low-priced products would gain market share. Therefore, it is possible that the counterfactual revenue of Taobao Marketplace as a whole is lower than the actual revenue if the gain mainly comes from iPhone5s sold at low prices.

### Table 1.10 Change in Taobao Revenue

<table>
<thead>
<tr>
<th>VARIABLES (Thousand USD)</th>
<th>Mean</th>
<th>STD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta )Taobao Revenue</td>
<td>38.6183</td>
<td>35.39</td>
<td>-35.3858</td>
<td>127.8382</td>
</tr>
<tr>
<td>No. of Observations: 81</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

thousand USD. It is important to note that there is no re-optimization of prices on the supply side. Since all sellers have equally perfect ratings, the low-priced products would gain market share. Therefore, it is possible that the counterfactual revenue of Taobao Marketplace as a whole is lower than the actual revenue if the gain mainly comes from iPhone5s sold at low prices.
An improvement would be to allow re-optimization of prices on the supply side. More importantly, in the current chapter, iPhone5 specific reputation is modeled as an exogenous variable, rather than an endogenous variable decided by sellers. Both issues will be addressed in Chapter 2.
BIBLIOGRAPHY


CHAPTER 2

QUANTIFYING THE WELFARE EFFECTS OF REPUTATION IN E-COMMERCE: EVIDENCE FROM ALIBABA’S TAOBAO MARKET

2.1 INTRODUCTION

Reputation mechanisms in Internet commerce have attracted a lot of attention for at least two important reasons. First, online markets have been growing rapidly and globally. eBay reported a total revenue of 14.1 billion US Dollars (USD) and a gross merchandise volume (GMV) of 67.8 billion USD in 2012. Taobao.com, the dominant Internet retailer in China, had more than 250 million active users in 2012. Its total revenue was higher than 4.1 billion USD and its GMV was greater than 170 billion USD in the same year. Second, the Internet provides systematic and formal feedback systems while traditional markets typically do not.

Parties to transactions in the online marketplace have asymmetric information about the goods and services being traded. Buyers do not know the quality of the product or service provided by the
2.1. INTRODUCTION

EVIDENCE FROM ALIBABA’S TAOBAO MARKET

seller until they actually receive it. A buyer may leave good feedback with respect to a seller if he
receives a satisfactory product. On the contrary, the buyer will be disappointed if he receives a prod-
uct of bad quality and thus may choose to leave bad feedback. Thus, feedback left by consumers is
considered a good proxy for sellers reputation. On the supply side of the market, each seller chooses
to provide a certain quality of service, which directly affects the nature of feedback they receive for
their products. Sellers are aware of the consequences of providing high (low) quality, that is, con-
sumers would leave positive (negative) feedback and he builds a good (bad) reputation. In this sense,
reputation can be viewed as an endogenous variable that is chosen by sellers.

In order to increase economic efficiency, feedback systems in online marketplaces have been
continously improved. eBay classic reputation mechanisms allow buyers and sellers to mutually eval-
uate their performance in completed transactions. In order to reduce seller retaliation and improve
market transparency, in May 2007, eBay added a new system, called Detailed Seller Ratings, which
allows buyers to unilaterally rate seller performance. Similarly, Taobao Marketplace added Detailed
Seller Ratings to its feedback systems in 2008. Online marketplaces also provide trainings for sellers
to improve their performance. For example, Taobao University, an affiliation of Taobao Marketplace,
offers courses that cover a wide range of topics to sellers.

There is a vast empirical literature that studies reputation related issues. Papers that focus on
the effects of online feedback characteristics on transaction outcomes include Houser and Wooders
Postel-Vinay (2014), and Elfenbein, Fisman and McManus (2012), to name just a few. Although dif-
ferent data are used, the results of these papers are similar: reputable sellers enjoy better transaction
outcomes, such as higher prices and higher probability of sales. Another literature focuses on “social
learning.” Luca (2011), Cai, Chen and Fang (2009), and Anderson and Magruder (2012) study how
social learning affects individuals’ dining choices. Reinstein and Snyder (2005) and Moretti (2009)
investigate the effects of social learning in the movie industry. Hilger, Rafert and Vilas-Boas (2011)
conduct a field experiment to investigate how consumers respond to expert opinion labels for wine.
Although different methodologies are applied in these papers, they agree that individuals tend to
follow other people’s decisions.

The idea that better reputation leads to more sales is fairly intuitive, but it induces a very inter-
esting question: why don’t all sellers try to build a good reputation by providing satisfactory quality
to buyers? A few papers have attempted to examine seller behavior with regard to reputation mainte-
nance. Fan, Ju and Xiao (2013) use Taobao data to investigate sellers’ activity in managing reputation
at different stages. Cabral and Hortaçsu (2010) find that when a seller’s reputation is high, the in-
centive to invest in maintaining reputation is also high. When a perfect record is stained by the first
negative feedback, sellers are less motivated to deliver satisfactory services.
2.1. INTRODUCTION

There are several important questions that are not addressed in the existing literature. First, how much is sellers’ cost of maintaining reputation at different levels? Second, how much is consumer willingness to pay (WTP) for reputation? Finally, what are the welfare effects of reputation? Particularly, would profits increase when sellers increase their reputation? Also, would consumers be better off when sellers deliver better quality but charge higher prices at the same time? To address these questions, it would require me to develop a model where consumers and sellers interact and simultaneously make their optimal decisions.

This paper considers the problem of estimating demand and supply in the online marketplace and studies the welfare effects of reputation. The estimation focuses on one product, iPhone5, in Taobao Marketplace. On the demand side, consumers make purchasing decisions based on product characteristics. One of the important product characteristics is quality. Quality consists of two aspects in this case: quality of the actual product and quality of the services provided by sellers. The former is easy to measure and does not vary much across sellers due to the nature of the products in my sample. In contrast, quality of the services provided varies across sellers and is difficult to measure. For instance, a buyer may enjoy his purchasing experience if the seller is able to solve problems and communicate effectively. Although quality is not fully revealed in online marketplaces, feedback left by consumers is an informative proxy for quality. By leaving feedback ratings and comments, consumers are able to express their thoughts about the service they receive from the seller, for instance, whether the products are as described, whether the shipping service is fast, etc. Hence, feedback scores disclose quality and is an important dimension of product characteristics. My reputation measures include iPhone5 specific feedback scores and seller specific feedback ratings.

The supply side is an oligopoly model, where each seller maximizes profits by choosing optimal prices and quality provision. Since sellers know that they will receive feedback ratings based on the quality they provide, sellers indirectly choose optimal reputation. Sellers’ cost of selling iPhone5s includes two pieces: cost of the products and cost of reputation maintenance.

I find compelling empirical evidence in support of the positive relationship between good reputation and consumer demand: utility from purchasing an iPhone5 increases when feedback ratings increase, and thus products that have better reputation enjoy greater market share. Reputation has a positive effect on consumer willingness to pay. For a half standard deviation increase in the iPhone5 specific positive feedback ratio, the consumer willingness to pay is 1.5 percent of the price of an iPhone5. Results of supply estimation show that it would cost an average seller 123 USD per day more to maintain his reputation at 99.1 rather than 98.6 percent, a half standard deviation difference.

I conduct two counterfactual analyses to examine the welfare effects of increase in seller reputation. In the first simulation, the slope of the marginal cost of reputation maintenance decreases by 20 percent. The results show that the mean of iPhone5 specific positive ratios increases from 99.1 to 99.3
percent. The average increase in prices equals 19 USD. Seller profits significantly increase, driven by the decrease in cost of reputation maintenance. Consumer welfare slightly increases due to the increase in seller reputation, despite the increase in prices. The effort of reducing cost of reputation maintenance pay for itself: social welfare increases by 23 thousand USD per day.

The second simulation assumes that any negative feedback can be revised. I find that the mean of iPhone5 specific positive ratios slightly increases. Seller profits slightly increase due to the increase in prices and quantity sold. Consumer welfare decreases by a small amount, mainly driven by the increase in product prices. Social welfare as a whole increases by 12 thousand USD per day.

My article is distinguished from previous studies in the following ways. It is the first empirical work that quantifies the effects of reputation mechanisms on consumer and seller welfare in the online marketplace. Specifically, it is the first to estimate a structural market equilibrium model for online products with a focus on reputation of the sellers. My results will hopefully shed light on optimal reputation mechanism design in online marketplaces. Klein, Lambertz and Stahl (2013) find that an increase in market transparency leads to higher quality provision. Nonetheless, they do not quantify the welfare effects of reputation. Market equilibrium analysis has been applied in a variety of industries with product differentiation, from groceries and packaged goods to automobiles. In general, these models attempt to uncover cost and demand information from market data. However, there has been comparatively little investigation into the online retail industry, an industry that has been growing rapidly throughout the world.

Second, my dataset of iPhone5 posted-price transactions from Taobao Marketplace is unique. Lei (2011) addresses the importance of controlling for the product specific dimension of reputation. He constructs a product specific reputation measure for Gmail invitations by counting the cumulative sales volume of Gmail invitations. Taobao displays both the numbers and the contents of all positive, neutral, and negative feedback ratings towards a specific product sold by a specific seller. I calculate a ratio constructed from the number of positive ratings and the total number of ratings, which should be a more accurate measure of product specific reputation than cumulative past sales.

### 2.2 LITERATURE REVIEW

There is abundance of empirical literature that studies the phenomenon of reputation in online marketplaces. These papers mainly focus on the effects of online feedback on price and sales on eBay.com: Lucking et al. (2007), Houser and Wooders (2006), Resnick et al. (2006), Jin and Kato (2006), and Melnik and Alm (2002). Lei (2011) uses a collection of auctions of Gmail invitations on eBay to study the influence of seller reputation on auction outcomes. He finds that sellers who improve their reputation by one quintile from the lowest experience a 6.2 percent higher probability of sale. He
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also finds a 6.1 percent increase in valuation after adjusting for truncation bias from failed auctions and controlling for unobserved seller heterogeneity. Cabral and Hortaçsu (2010) find that, following the first negative feedback received by a seller, the sales growth rate drops from positive 5 percent to negative 8 percent.

There are also papers that study reputation mechanisms in Chinese online marketplaces. Cai et al. (2014) show that before the introduction of a centralized feedback system, sellers on Eachnet.com (an eBay equivalent in China) with a longer successful selling record enjoyed more repeat business, reached more buyer regions, sold in more product categories and had a higher sale completion rate. After the introduction of the centralized feedback system, reputable sellers enjoyed even larger market expansion into new buyer regions and new product categories compared to non-reputable sellers. Fan, Ju and Xiao (2013) use data from Taobao.com to study how reputation affects revenue, price, transaction volume, and survival likelihood for new and established sellers. Jolivet, Jullien and Postel-Vinay (2014) find that reputation of sellers influences transaction outcomes in a French Internet marketplace.

Literature that studies reputation mechanisms in the offline markets focuses on the effects of expert or peer reviews or Word-of-Mouth on consumers’ decisions. For the movie industry, both expert critics (Reinstein and Snyder, 2005) and information received from peers (Moretti, 2009) have significant effects on individuals’ consumption decisions. Hilger, Rafert and Vilas-Boas (2011) conduct a field experiment to investigate how consumers respond to expert opinion labels for wine. They find that demand decreases for low-scoring wines and increases for high-scoring wines. There are papers that examine dining choices. Both Luca (2011) and Anderson and Magruder (2012) use regression discontinuity designs to estimate the effects of online reviews from Yelp.com on demand for dining. Cai, Chen and Fang (2009) conduct a field experiment and find that customers who receive information about a restaurant’s most popular dishes tend to order those dishes. Hubbard (2002) examines how reputational incentives work in the California vehicle emission inspection market. He finds that a consumer’s choice of firm for vehicle inspection is negatively correlated with (1) his previous inspection failure with this firm and (2) firms’ failure rates across all consumers.

Although the effects of reputation on consumer behavior has been well studied, only a few works attempt to investigate seller behavior with regard to maintaining reputation. Cabral and Hortaçsu (2010) show that subsequent negative feedback ratings arrive 25 percent more frequently following the first negative feedback the seller receives. They argue that when a seller’s reputation is high, the incentive to invest in maintaining reputation is also high. By contrast, when a perfect record is stained by the first negative feedback, sellers are less motivated to deliver satisfactory services. They also find that sellers invest in building a reputation as a buyer and then use that reputation as a seller. Moreover, a seller is more likely to exit the market the lower his reputation. Right before
exiting, sellers receive more negative feedback than their lifetime average. Fan, Ju and Xiao (2013) investigate sellers’ activity in managing reputation at different stages. They conclude that when new sellers reach a certain level of reputation, they engage in active reputation management, such as cutting prices to generate more sales. But these activities can reduce the survival likelihood of new sellers.

Elfenbein, Fisman and McManus (2012) develop a two-period signaling model to show that charity is an effective quality signal and yields a price premium. There are three types of sellers in this model: good sellers who get utility from charity and always exert effort (by paying a cost) to make sure that the product works; opportunistic sellers who get no utility from charity and only exert effort when doing so is financially profitable; ethical sellers who get no utility from charity and always exert effort to ensure the quality of products. The crucial assumption of this model is a positive correlation between a seller’s utility from charity and his disutility from behaving opportunistically towards consumers. There are two key predictions. First, in a separating equilibrium, charity is a quality signal. Second, when the cost of exerting effort is not too low, the charity premium declines when feedback reveals opportunistic sellers. The empirical evidence of this paper shows that consumers respond positively to products tied to charity, particularly for sellers that are relatively new and hence have limited alternative means of assuring quality.

Empirical literature that investigates reputation mechanism design is sparse. Klein, Lambertz and Konrad (2013) apply eBay data and conduct a natural experiment to study the effects of improvements in market transparency on seller behavior. The paper finds that consumer satisfaction increases when market transparency increases. The authors conclude that a reduction in informational asymmetry improves seller performance through a reduction in moral hazard.

## 2.3 TAobao Reputation Mechanism

### 2.3.1 The History of Taobao Marketplace

China’s e-commerce market has been growing rapidly since 2003 as shown in Figure 2.1. In 2012, it surpassed America’s in value, with a total value of 238 billion USD. In the same year, the number of Chinese online shoppers surged to 250 million. However, there is substantial room for growth. Online penetration in China was 43 percent in 2012, well below the 70 percent or higher seen in developed economies. ¹

¹“The World’s Greatest Bazaar.” Source: The Economist
Accessed: 08/19/2014

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Taobao Marketplace (Taobao.com) was established in 2003 and is operated by China’s Alibaba Group. Taobao Marketplace facilitates consumer-to-consumer (C2C) retail by providing a platform for small businesses and individual entrepreneurs to open online retail stores that mainly cater to consumers in China, Hong Kong, Macau, and Taiwan. For the fiscal year ending on March 31, 2013, the combined GMV of Taobao Marketplace and Tian Mao (an affiliated website owned by Alibaba) exceeded 170 billion USD, which is about 2.3 percent of China's 2012 GDP.

Developed as an eBay equivalent in China, sellers in Taobao Marketplace are able to list new and used goods for sale either through an auction format or a posted-price format. Unlike eBay, the overwhelming majority of the products sold in Taobao Marketplace are brand new items with a posted-price; auctions make up a very small percentage (less than 2 percent) of transactions. The way that Taobao generates revenue also differs from eBay. eBay charges a listing fee when a seller lists an item on eBay and a final value fee when an item sells, while Taobao Marketplace does not charge any fee for listing (either new or used items). Taobao allows sellers to advertise their products by paying to be listed as featured products on the home page or as recommended products on the search page. Prices to advertise in the center of Taobao Marketplace's home page can be as high as 25,000 USD per day. Taobao also generates revenue from selling various tools to sellers. One of the common tools is the Display Helper, which improves the layout of a seller's store page. Another one is the Promotion Helper, which facilitates promotions (see Section 2.3.2).

In 2008, Tian Mao (Tmall.com), a business-to-consumer (B2C) platform was launched by Alibaba. In 2010, an independent web domain, Tmall.com, was created for Tian Mao to differentiate listings by its merchants, who are either brand owners or authorized distributors, from Taobao's C2C
merchants. Although Taobao Marketplace was established as a C2C platform and Tian Mao was launched as a B2C platform, products from both Taobao Marketplace and Tian Mao display on the Taobao search page.

Taobao has come to dominate Internet retailing in China and it will likely become the biggest e-commerce market in the world. As shown in Figure 2.2, Taobao.com accounted for a 90 percent share of China’s C2C online retail market in 2011, while Tian Mao accounted for a 51 percent share of the B2C online retail market. Both the revenue and profit of Alibaba have grown rapidly since 2008. Revenue increased from 2.3 to 4.1 billion USD and net profit grew from 0.2 to roughly 0.5 billion USD between 2011 and 2012.

Table 2.1 compares the revenue, net profit and GMV of Alibaba, Amazon, and eBay. In 2012 Amazon obtained the highest revenue, eBay had the highest profit, and Alibaba (including Taobao Marketplace and Tian Mao) enjoyed the highest GMV among the three.

**2.3.2 Sales Format of Taobao Marketplace**

Although Taobao Marketplace is similar to eBay in many ways, the major sales format in Taobao differs from eBay. Sellers on eBay offer their goods brand new or used through listings that may be: true auctions in which bids are collected until a specified ending time (usually 7 days after the

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2“Alibaba Group to Split Taobao Online Retail Unit into Three.”
Source: Bloomberg L.P.
Accessed: 09/02/2014
Table 2.1 2012 Financial Reports of Alibaba, Amazon and eBay

<table>
<thead>
<tr>
<th></th>
<th>Revenue</th>
<th>Net Profit/Loss</th>
<th>GMV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alibaba</td>
<td>4.1</td>
<td>0.5</td>
<td>171.2*</td>
</tr>
<tr>
<td>Amazon</td>
<td>61.1*</td>
<td>-0.04</td>
<td>87.8</td>
</tr>
<tr>
<td>eBay</td>
<td>14.1</td>
<td>2.6*</td>
<td>67.8</td>
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</tbody>
</table>

*leader in each category

auction begins); posted-price listings in which the seller specifies a price and ending date, often 30 days or more later; or a hybrid form in which a true auction also includes a “buy-it-now”. For auction-style listings with the Buy-it-Now option, a buyer has the chance to purchase an item immediately before bidding starts. Once someone bids, the Buy-it-Now option disappears and bidding continues until the listing ends, with the item going to the highest bidder.

Sellers on Taobao Marketplace can sell a brand new or used product by using an auction or a posted-price format. Taobao offers free listings to sellers and sellers can select 7 or 14 days as the listing period for either format. Taobao automatically renews the listings so that they never expire unless a seller manually removes them. Auctions account for less than 2 percent of total transaction volume, and thus this study only focuses on brand new merchandise sold at a posted-price.

In order to attract consumers and promote sales, sellers in Taobao Marketplace have promotions from time to time. Common promotions include price cuts, vouchers with purchase, or gifts with purchase.

During the price cut promotion, sellers usually claim that the price cut is temporary in order to attract more buyers. In order to make the price cut visible and noticeable to consumers, a seller may use a tool developed by Taobao called Promotion Helper. Taobao charges a small fee from the seller who purchases this tool. This fee is usually a monthly flat-rate fee and the tool can be applied to several products up to a limit. When the seller uses this tool to establish a price cut promotion, both the original price and the actual price display on the product page. It is important to point out that the original price displayed oftentimes may not be the actual original price and sellers tend to claim a very high original price to make the price cut “significant.” Price cuts in Taobao resemble marketing strategies in traditional markets: a seller increases the original price before having a price cut in order to make the discount appear significant. Hence, this type of promotional activity in Taobao can be considered advertisement and the service fee charged by Taobao can be interpreted as advertisement cost.

Figure 2.3 is an example of the price cut of an iPhone5. The seller sets 6,000 RMB (1,000 USD) as the claimed original price and 3,000 RMB (500 USD) as the actual price. Thus the claimed original
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Price is not informative to the researcher. The actual price is reflected by transaction records and thus recorded by the researcher.

Voucher with purchase is also a common promotion in Taobao Marketplace. A money voucher is issued when a buyer purchases a certain item from the seller or his order exceeds a certain value. Vouchers can be used with the same seller in current or subsequent purchases. When the voucher is applied, the value (of the voucher) will be subtracted from the total at checkout. The value of the voucher is usually small (about 1-10 percent of the total value of the order).

Figure 2.4 is a promotion banner for voucher with purchase. When the value of an order is above 50 RMB (8.5 USD), 198 RMB (33 USD), or 398 RMB (66 USD), a voucher that is worth 5 RMB (0.85 USD), 10 RMB (1.7 USD), or 20 RMB (3.5 USD), respectively, will be issued to the buyer and can be applied to the current purchase.

It is worth pointing out that this promotion is unobserved by the researcher because (1) the promotion banners are in terms of pictures on a product page and (2) the transaction record only shows the price before vouchers are applied. Promotions of voucher with purchase only last for a short period of time, usually no longer than a week. When the promotion ends, the seller simply removes the promotion banner from the product page.

Another promotion in Taobao Marketplace is gift with purchase. A buyer gets a free gift when he purchases a specific product or his order exceeds a certain value. Figure 2.5 is a promotion banner for gift with purchase. In this example, purchase of an iPhone5 comes with a free portable iPhone5 charger, a pair of ear buds, an iPhone5 case and a screen protector. Similar to voucher with purchase, gift with purchase is unobserved to the researcher because the promotion banners are displayed as
pictures, which makes it difficult to record. Besides, these promotions are not reflected by transac-
tion records. Gift with purchase changes over time because sellers tend to constantly change the
contents of the gifts.

2.3.3 Feedback System of Taobao

Both Taobao and eBay have well-established rating systems so that buyers can track how sellers per-
formed in previous transactions. The biggest difference between the rating systems of Taobao and
eBay is that Taobao displays both product specific feedback ratings and comments on the product
page. Buyers on Taobao can track not only the overall performance of a seller, they can also track his
performance for each product he sells.

On each seller profile page on Taobao, one can see a seller’s ID, location, the date when the ID was
created, a seller’s total feedback score, and crowns (or hearts) as shown in Figure 2.6. A feedback score
of at least 4 earns a seller a heart. As feedback score increases, the icon will change to a diamond, then
a blue crown, and eventually transform all the way to five yellow crowns for a score above 10,000,000
as shown in Figure 2.7.

Similar to eBay, Taobao displays recent feedback ratings, including feedback that a seller has
received in the last 1 week, 1 month, 6 months, and prior to the last 6 months as shown in Figure 2.8.
The positive feedback rating ratio is displayed as the percentage of positive ratings left by members.
It is calculated by dividing the number of positive ratings by the total number of ratings.

Detailed seller ratings (Figure 2.9) on Taobao include three components: item as described, atti-
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Figure 2.5 Gift with Purchase

Figure 2.6 Seller Profile on Taobao

tude of the seller, and shipping speed. Buyers are asked to rate the seller in each of these categories with a score of one to five stars, with five being the highest rating and one the lowest. These ratings do not count toward the overall feedback score and they are anonymous. The seller cannot trace detailed seller ratings back to the buyer who left them. When the seller’s score is above or equal to the average score on Taobao Marketplace, the score is labeled in red. Otherwise it is labeled in green.

Lei (2011) addresses the importance of controlling for the product specific dimension of reputation. One important advantage of using Taobao data is the direct observation of the product specific reputation measure. Product specific feedback contains information with respect to the seller’s performance in the sale of a specific product, including the quality of the product sold and the service provided by the seller.
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Figure 2.7 Seller Rating on Taobao

Figure 2.10 shows the layout of product specific ratings on Taobao. On the product feedback page, one can read off the number of buyers that left a positive, neutral, and negative comment from the date the seller started to sell a product. A buyer can read all the comments that are displayed in reverse chronological order. One can also choose to read only the positive, neutral, or negative comments by selecting “positive,” “neutral,” or “negative” tabs respectively. Next to each comment given to a seller, the ID of the buyer giving the comment is shown. It also shows what product is purchased by this buyer, the date of purchase, and the transaction price.

2.3.3.1 Feedback Revisions on Taobao

Feedback ratings and comments on Taobao can be revised in some cases. A seller may ask a buyer to revise the negative feedback that he left. If the buyer agrees to do so, he can either change his negative (or neutral) feedback to positive or delete the feedback as long as the feedback is less than 30 days old. Once a feedback has been left for more than 30 days, it cannot be revised or deleted. A positive feedback cannot be changed. Only neutral or negative feedback can be revised or deleted. Unlike eBay, detailed seller ratings on Taobao cannot be revised.
2.3.4 Taobao University

Taobao University is an affiliation of Taobao marketplace that offers trainings in order to improve sellers’ business on Taobao. The training courses, either taught locally or online, target a broad range of sellers. For beginners, trainings may focus on the basics of selling process on Taobao, including payment methods, how to create listings and complete transactions, and so on. For advanced sellers, trainings may address inventory and logistics, promotions, advertisement, and other marketing issues. Similarly, eBay offers trainings for sellers through eBay University.

2.4 THE MODEL

Consumers and sellers of iPhone5 interact in Taobao Marketplace. Consumers choose a product that maximizes utility. Sellers choose optimal prices and reputation to maximize profits. A seller can
choose to build and maintain reputation at different levels. A buyer who receives services of good quality would leave positive feedback. On the contrary, if a seller provides a product of bad quality, the buyer would be very likely to leave negative feedback. Therefore, feedback should be a good measure for seller reputation. In this section, I first specify the demand model, followed by the supply side setup.

2.4.1 The Demand

The setup of the demand model follows Berry (1994). I begin with the utility function of consumer $i$ for product $j$ at time $t$:

$$U_{ijt} = X_{jt}\beta - \alpha p_{jt} + \eta_j + \xi_{jt} + \epsilon_{ijt}$$  \hspace{1cm} (2.1)

$X_{jt}$ is a vector of characteristics of product $j$ at time $t$, where $j = 0, 1, 2, ..., J_t$ and $t = 1, ..., 79$ (Day 1 to Day 79 throughout the sample period). Specifically, $X_{jt}$ includes seller specific reputation measures and iPhone5 specific reputation measures. $\beta$ is a vector of regression coefficients of the reputation measures, $X_{jt}$. $p_{jt}$ is the price of product $j$ at time $t$ and $\alpha$ is the regression coefficient of price. Unobserved time-invariant product characteristics are denoted by $\eta_j$. $\xi_{jt}$ can be thought of as the mean of the consumers’ valuation of the time-varying unobserved product characteristics of product $j$ at time $t$. $\epsilon_{ijt}$ is i.i.d. across products and consumers, and it follows the extreme value distribution. $\epsilon_{ijt}$ captures the unobserved characteristics that vary across products, individual con-
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consumers, and time.

Demand follows a nesting structure, with the outside good defined as the purchase of an iPhone5 on Tian Mao. Products are grouped into \( L \) exhaustive and mutually exclusive sets based on essential characteristics (with details provided below). The outside good, \( j = 0 \), is assumed to be the only member of group 0.

Under the nested logit structure, the error term is comprised of a common shock for all products within a group, and an idiosyncratic term. Assuming that product \( j \) belongs group \( k \), i.e., \( j \in B_k \), the error term can be written as

\[
\epsilon_{ijt} = \omega_{ikt} + (1 - \sigma)\phi_{ijt},
\]

where \( \omega_{ikt} \) is the shock for an iPhone5 in group \( k \) at time \( t \); \( \sigma \) is the similarity coefficient, which represents the extent to which consumers receive similar shocks within a group at time \( t \), and \( \phi_{ijt} \) is the idiosyncratic shock for consumer \( i \) and product \( j \) at time \( t \). The class shock for consumer \( i \) is the same for all products within a nest. Intuitively, a consumer first selects a group and then a product. As \( \sigma \) approaches 1, the within group correlation of utility goes to one. As \( \sigma \) approaches zero, the within group correlation goes to zero and the nested logit model collapses to the simple logit model.

Products are divided into 11 different groups based on version and memory size (see Section 2.6 for more details). They are 16 Gigabyte (G) Chinese (CHN), 16 G European (EUR), 16 G Hong Kong (HK), 16 G Japanese (JP), 16 G United States (US), 32 G CHN, 32 G HK, 32 G JP, 32 G US, 64 G CHN, and 64 G JP.

E.q.(2.1) and (2.2) lead to (2.3). See Appendix for derivation.

\[
\ln(s_{jt}) - \ln(s_{0t}) = X_{jt}\beta - \alpha p_{jt} + \eta_j + \sigma \ln(s_{j|B_k}) + \xi_{jt}.
\]

2.4.2 The Supply

Sellers compete in a Bertrand-Nash manner, choosing optimal prices and reputation while taking as given the prices and reputation of iPhone5 sold by other sellers.

The profit maximization problem for seller \( s \) at time \( t \) is written as

\[
\begin{align*}
\max_{\bar{p}_{st}, q_{st}} & \quad \sum_{n \in S_t} (p_{nt} - mc_{nt})M_t s_{nt}(p_{nt}, q_{st}) - FC_{st} - C(q_{st}) \\
\text{subject to} & \quad q_{st}^{LB} \leq q_{st} \leq q_{st}^{UB}, \ s = 1, \ldots, S_t, \ n = 1, \ldots, N_t,
\end{align*}
\]

where seller \( s \) chooses \( \bar{p}_{st} \) and \( q_{st} \) to maximize his profit at time \( t \) when he takes other sellers’ decisions as given. \( \bar{p}_{st} \) is a vector of prices of products sold by seller \( s \) at time \( t \), i.e., \( \bar{p}_{st} = (p_{1st}, p_{2st}, \ldots, p_{Nst}) \).
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A seller may sell multiple products. So the number of sellers at time $t$, $S_t$, is larger than (or equal to) the number of products, $N_t$. $q_{st}$ is the optimal reputation chosen by seller $s$ at time $t$. $mc_{nt}$ is the marginal cost for product $n$. $M_t$ is the market size at time $t$. $FC_{st}$ is the fixed cost for seller $s$ at time $t$. $q_{st}^{LB}$ and $q_{st}^{UB}$ are the lower bound and upper bound, respectively, of the reputation chosen by seller $s$ at time $t$. Details of these bounds will be discussed later.

$C(q_{st})$ can be interpreted as the cost of the value added to the raw product. It is more costly, in terms of money and time, for a seller who invests efforts to ensure the quality of products and services than those who do not. For instance, a reputable seller may carefully pack his goods, ship them out promptly, and offer exchange if products fail to work. On the contrary, a mediocre seller is more likely to pack his products carelessly, delay shipment, or fail to resolve problems. In fact, consumers have almost identical expectation and perception about the quality of the actual iPhone5. The variation of consumer satisfaction mainly comes from these additional services provided by sellers.

The Lagrangian can be written as

$$
\mathcal{L}(p_{st}, q_{st}) = \sum_{n \in S_t} (p_{nt} - mc_{nt}) s_{nt}(p_{nt}, q_{st}) - FC_{st} - C(q_{st}) \\
- \lambda_{1st}(q_{st} - q_{st}^{UB}) - \lambda_{2st}(-q_{st} + q_{st}^{LB})
$$

The Kuhn Tucker conditions are as follows.

$$
s_jt(p_{jt}, q_{st}) + \sum_{n \in S_t} (p_{nt} - mc_{nt}) \frac{\partial s_{nt}}{\partial p_{jt}} = 0, j = 1, \ldots, J_t
$$

$$
\sum_{n \in S_t} (p_{nt} - mc_{nt}) M_t \frac{\partial s_{nt}}{\partial q_{st}} - C'(q_{st}) - \lambda_{1st} + \lambda_{2st} = 0
$$

$$
\lambda_{1st} \geq 0, q_{st} - q_{st}^{UB} \leq 0, \lambda_{1st}(q_{st} - q_{st}^{UB}) = 0
$$

$$
\lambda_{2st} \geq 0, q_{st} - q_{st}^{LB} \geq 0, \lambda_{2st}(q_{st} - q_{st}^{LB}) = 0, s = 1, \ldots, S_t
$$

2.5 ESTIMATION

2.5.1 Demand Estimation

The difficulty in estimating demand models lies in endogeneity. Some of the time-varying promotions in Taobao Marketplace are unobserved (to the researcher) and these promotions may be correlated with the independent variables in (2.3), particularly the price variable. Therefore, estimating
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this equation by ordinary least squares (OLS) would yield biased estimates.

One approach to tackle endogeneity is to include product fixed effects. If one assumes that unobserved characteristics do not change over time, fixed effects models would yield unbiased estimates. For instance, some sellers have better writing skills or communication skills. Some sellers are better at designing web pages. These unobserved factors are unlikely to change over time and would be eliminated by fixed effects. However, I suggest that this assumption is not appropriate in my demand model because some of the unobserved characteristics may change over time.

As discussed in Section 2.3.2, there are several types of time-varying promotions in Taobao Marketplace. Both the promotions of voucher with purchase and gift with purchase can vary over time. A seller can easily change the gift or the value of the money voucher. When a promotion ends, he simply removes the promotion banner on the product page. Although the value of the gift or the money voucher is small, these promotional activities become confounding factors in the error term. Intuitively, promotional activities affect sellers’ pricing decisions and thus $\xi_{jt}$ and $p_{jt}$ would not be mean independent.

An example to consider is the time-varying free gift with purchase. When a buyer purchases an iPhone5 from the seller, he gets a free iPhone5 case for free. The buyer’s willingness to pay for this iPhone5 may increase because the purchase comes with a free iPhone5 case. Thus it is possible that the seller charges a slightly higher price. Another time-varying unobserved promotional activity is the money voucher with purchase. When a buyer gets a money voucher with purchase, the seller may increase the price of the product and thus price would be correlated with the error term.

The second endogenous variable is $s_{j|B_t}$. Imagine there are two phones that belong to the same group but are sold by two different sellers. One may be more popular than the other and thus have a higher within-group share if the purchase comes with a free gift. This promotion is unobserved to the researcher but correlated with the within-group share. Therefore, it suggests the need for additional exogenous variables that are correlated with $s_{j|B_t}$.

Two classes of IVs are used to control for endogeneity. The standard approach would be to follow Berry, Levinsohn and Pakes (1995) and use characteristics of products sold by other sellers in the same nest. $Ave_{Pos_{Mon_{Nest}st}}$ is the average seller specific positive ratio for all other sellers in the same group over the past month. This variable is likely to be correlated with both endogenous variables. The better the reputation of all other sellers, the smaller the within-group share one enjoys. If all other sellers have higher reputation, one is very likely to set a lower price to compete with other sellers and attract more customers. Therefore, $Ave_{Pos_{Mon_{Nest}st}}$ should be negatively correlated with both price and within-group share. $Ave_{Pos_{Mon_{Nest}st}}$ would be a valid instrument if a seller’s promotion decision is not affected by the average reputation of all other sellers in the same group.
The second class of instrumental variables includes two lagged variables. \( past sales_{st-7} \) is the cumulative 30-day sales of iPhone5s before time \( t-7 \), i.e., \( past sales_{st-7} = sales_{st-8} + sales_{st-9} + \ldots + sales_{st-37} \). The social learning literature suggests that one tends to follow other people’s choices. If that is the case, a buyer tends to buy from a seller who has had strong sales in the past. Thus the lag of past sales is likely to be positively correlated with the current within-group share. What is more, this lagged variable is likely to be correlated with price. A seller may set a higher price if he has had strong sales and developed a good reputation.

While being correlated with two endogenous variables, \( past sales_{st-7} \) is unlikely to be correlated with \( \xi_{jt} \). Recall that the error term consists of unobserved time-varying promotions. A promotion in general lasts no longer than a week and thus errors that are at least a week apart are unlikely to be correlated. The closest component of \( past sales_{st-7} \) to the error term is \( sales_{st-8} \), the sales 8 days ago. This variable is not likely to be correlated with the error term if the unobserved promotion lasts no longer than a week. Even for the very rare case where an unobserved promotion lasts longer than a week, the structure of this lagged variable (being the sum of 30-day sales) would attenuate its correlation with the error term.

Another instrumental variable is \( p_{jt-10} \), the price of product \( j \) 10 days ago. Since the price of an iPhone5 fluctuates within a small range in a relatively short period, \( p_{jt-10} \) is very likely to be positively correlated with the current price, \( p_{jt} \). And since the unobserved promotional activities do not last more than a week, \( p_{jt-10} \) is unlikely to be correlated with \( \xi_{jt} \). The reason why \( p_{jt-7} \) is not selected as an instrument is that if a promotion lasts a little longer than a week, \( p_{jt-7} \) might be correlated with the error term. In order to be conservative, \( p_{jt-10} \), instead of \( p_{jt-7} \), is used as an IV.

### 2.5.2 Supply Estimation

The goal of supply estimation is to obtain estimates of the marginal cost of a product of iPhone5 and marginal cost of reputation maintenance. The cost of reputation maintenance is assumed to take the following form

\[
C(q_{st}) = \frac{1}{2} m_{st} q_{st}^2 - Z_{st},
\]

where \( m_{st} \) and \( Z_{st} \) are seller and time specific constants and both positive. Marginal cost of reputation maintenance, \( C'(q_{st}) \), is increasing with \( q_{st} \).

Without any constraint, the highest reputation a seller can choose at time \( t \) is 1 and the lowest reputation is 0. In fact, a seller’s positive feedback ratio at time \( t \) is restricted by (1) accumulated ratings up to time \( t-1 \) and (2) the maximum quantity that can be potentially sold at time \( t \).

Let us look at a simple example. A seller has had 100 positive ratings and 1 negative rating at time
2.5. ESTIMATION

CHAPTER 2. QUANTIFYING THE WELFARE EFFECTS OF REPUTATION IN E-COMMERCE: EVIDENCE FROM ALIBABA’S TAOBAO MARKET

$t-1$. Suppose this seller can sell up to 10 units per day. Then the upper bound of reputation at time $t$ is calculated as $\frac{100+10}{100+1+10} = 0.991$, meaning that the seller provides satisfactory quality to buyers for all 10 units sold. The lower bound would then be $\frac{100}{100+1+10} = 0.901$, which means he provides low quality for all the 10 units.

Recall that Taobao allows buyers to revise or delete negative feedback when the feedback is less than 30 days old. For instance, suppose a seller has 100 positive ratings and 1 negative rating which is less than 30 days old at time $t-1$. Then at time $t$ the upper bound of his quality constraint is 1 because the negative rating could be removed.

Next, I find the maximum possible quantity sold by seller $s$ at time $t$. The maximum quantity sold during a 1 week period is used to proxy for the maximum possible quantity sold at time $t$.

$$Q_{st} = \max \{Q_{st-3}, Q_{st-2}, Q_{st-1}, Q_{st}, Q_{st+1}, Q_{st+2}, Q_{st+3}\}$$ (2.11)

where $Q_{st}$ is the maximum possible quantity sold at time $t$. Therefore, the reputation constraint for seller $s$ at time $t$ is calculated as

$$q_{st}^{LB} = \frac{G_{st-1}}{G_{st-1} + N_{st-1} + Q_{st}}$$ (2.12)

$$q_{st}^{UB} = \frac{G_{st-1} + Q_{st} + N_{st-1}^{R}}{G_{st-1} + N_{st-1} + Q_{st}}$$ (2.13)

where $G_{st-1}$ and $N_{st-1}$ are the numbers of accumulated positive and negative ratings of seller $s$, respectively, at time $t-1$. $N_{st-1}^{R}$ is the number of negative feedback that can be revised at time $t$. $N_{st-1}^{R} \leq N_{st-1}$.

I assume that, in the estimation of the supply model, the constraints are strictly not binding in equilibrium. I relax this assumption in the counterfactual analyses. Next, I recover $mc$ using Eq.(2.6). It can be written in vector form as:

$$s_{i}(p_{t}, q_{t}) + \Omega_{i}(p_{t} - mc_{i}) = 0,$$ (2.14)

where $s_{i}$, $p_{t}$ and $q_{t}$ are $J_{t}$ by 1 vectors. $\Omega_{i}$ is a $J_{t}$ by $J_{t}$ matrix. Each element of $\Omega_{i}$ can be written as $\Omega_{jrt} = \Omega_{jrt}^{r} \frac{\partial \Omega_{jrt}}{\partial p_{r}}$. The indicator, $\Omega_{jrt}^{r}$, equals 1 if alternative $r$ and alternative $j$ are sold by the same seller, and equals 0 otherwise.

For example, there are five alternatives sold by two sellers. Alternative 1, 2 and 3 are sold by Seller 1. Alternative 4 and 5 are sold by Seller 2. Then Eq.(2.14) will take the following form:
2.5. ESTIMATION

The own elasticities of price and reputation on market shares can be written as (see Appendix for derivations)

\[
\frac{\partial s_{jt}}{\partial p_{jt}} = \frac{\partial V_{jt}}{\partial p_{jt}} \cdot s_{jt} \cdot \left[ \frac{1}{1-\sigma} - \frac{\sigma}{1-\sigma} \cdot s_{jt} B_{k,t} - s_{jt} \right] 
\]  

(2.17)
2.6 DATA AND SUMMARY STATISTICS

EVIDENCE FROM ALIBABA’S TAOBAO MARKET

\[
\frac{\partial s_{jt}}{\partial q_{st}} = \frac{\partial V_{jt}}{\partial q_{st}} \cdot \left[ \frac{1}{1-\sigma} - \frac{\sigma}{1-\sigma} \cdot s_{j|B_k t - s_{jt}} \right]
\]

(2.18)

\[
\frac{\partial s_{rt}}{\partial q_{st}} = \frac{\partial V_{rt}}{\partial q_{st}} \cdot \left[ \frac{1}{1-\sigma} - \frac{\sigma}{1-\sigma} \cdot s_{r|B_h t - s_{rt}} \right]
\]

(2.19)

where product $j$ and $r$ are sold by the same seller $s$. Product $j$ belongs to nest $k$, i.e., $j \in B_k$. Product $r$ belongs to nest $h$, i.e., $r \in B_h$. E.q.(2.19) holds when $k = h$ or $k \neq h$. $\frac{\partial V_{jt}}{\partial p_{jt}}$ and $\frac{\partial V_{rt}}{\partial q_{st}}$ (or $\frac{\partial V_{rt}}{\partial q_{st}}$) denote the demand coefficients of price and the iPhone5 specific positive feedback ratio, respectively.

Now turn to the cross derivatives, $\frac{\partial s_{rt}}{\partial p_{jt}}$, where alternative $j$ and alternative $r$ belong to two different nests ($k \neq h$), we have

\[
\frac{\partial s_{rt}}{\partial p_{jt}} = -\frac{\partial V_{jt}}{\partial p_{jt}} \cdot s_{rt} \cdot s_{jt}
\]

(2.20)

If alternative $j$ and alternative $r$ belong to the same nest, i.e., $k = h$, the cross derivatives, $\frac{\partial s_{rt}}{\partial p_{jt}}$, become

\[
\frac{\partial s_{rt}}{\partial p_{jt}} = \frac{\partial V_{jt}}{\partial p_{jt}} \cdot s_{rt} \left[ \frac{-\sigma}{1-\sigma} \cdot s_{j|B_k t - s_{jt}} \right]
\]

(2.21)

2.6 DATA AND SUMMARY STATISTICS

I focus on the products of iPhone5 because of the following reasons. (1) the transaction volume of the brand new iPhone5 on Taobao is high; (2) the iPhone5 is a relatively expensive product and consumers care about its quality; (3) the iPhone5 is almost homogenous in the sense that there is not much variation among individual units. The heterogeneity of the product is mainly the quality of the service delivered by the sellers.

The data sample covers the history of transactions of the iPhone5 between May 12, 2013 and July 29, 2013 on Taobao Marketplace. The number of observations is 11,941 and the number of sellers is 161. The data collection involves the following steps. The transactions related to the iPhone5 are identified through the search results on Taobao.com with the keyword “iPhone5”. I then excluded used items. Lastly I made sure the data sample includes no other model of iPhone aside from the iPhone5. This is done to make the product in my study as homogenous as possible.

Table 2.2 reports the summary statistics for the key variables of the model. The dependent variable in the demand estimation is defined as $ln(s_{jt}) - ln(s_{0t})$. $s_{jt}$ is the market share of product $j$ at time $t$, defined as the ratio of quantity sold of product $j$ to the combined total quantity sold in Taobao and Tian Mao at time $t$. Note that if the quantity sold of a listed product is zero at time $t$, 0.01
2.6. DATA AND SUMMARY STATISTICS

CHAPTER 2. QUANTIFYING THE WELFARE EFFECTS OF REPUTATION IN E-COMMERCE: EVIDENCE FROM ALIBABA’S TAOBAO MARKET

Table 2.2 Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Mean</th>
<th>STD</th>
<th>Min</th>
<th>Max</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Q_{jt} )</td>
<td>Quantity Sold</td>
<td>5.8222</td>
<td>9.89</td>
<td>0</td>
<td>83</td>
<td>8,047</td>
</tr>
<tr>
<td>( Q_{0t} )</td>
<td>Quantity Sold in Tian Mao</td>
<td>65.7636</td>
<td>32.82</td>
<td>9</td>
<td>162</td>
<td>69</td>
</tr>
<tr>
<td>( s_jt )</td>
<td>Market Share</td>
<td>0.0670</td>
<td>0.01</td>
<td>0.0906</td>
<td>0.1084</td>
<td>8,047</td>
</tr>
<tr>
<td>( s_jB_kt )</td>
<td>Within Group Market Share</td>
<td>0.0751</td>
<td>0.16</td>
<td>0.0242</td>
<td>0.0992</td>
<td>8,047</td>
</tr>
<tr>
<td>( s_{0t} )</td>
<td>Market Share of Tian Mao</td>
<td>0.0772</td>
<td>0.04</td>
<td>0.0108</td>
<td>0.1655</td>
<td>69</td>
</tr>
<tr>
<td>( positive_{st} )</td>
<td>No. of iPhone5 Specific Positive Feedback with Comments</td>
<td>1,286.5580</td>
<td>1,894.7514</td>
<td>14</td>
<td>8,875</td>
<td>4,934</td>
</tr>
<tr>
<td>( neutral_{st} )</td>
<td>No. of iPhone5 Specific Neutral Feedback</td>
<td>7.0199</td>
<td>20.56</td>
<td>0</td>
<td>138</td>
<td>4,934</td>
</tr>
<tr>
<td>( negative_{st} )</td>
<td>No. of iPhone5 Specific Negative Feedback</td>
<td>7.0969</td>
<td>20.23</td>
<td>0</td>
<td>181</td>
<td>4,934</td>
</tr>
<tr>
<td>( posratio_{st} )</td>
<td>No. of Seller Specific Positive Feedback</td>
<td>0.9914</td>
<td>0.01</td>
<td>0.8750</td>
<td>1</td>
<td>4,934</td>
</tr>
<tr>
<td>( posmon_{st} )</td>
<td>Cumulative Sales in the Past 30 Days</td>
<td>515.9979</td>
<td>647.46</td>
<td>20</td>
<td>3,175</td>
<td>4,934</td>
</tr>
<tr>
<td>( logpastsales_{st} )</td>
<td>Log of Cumulative Sales in the Past 30 Days</td>
<td>5.5504</td>
<td>1.20</td>
<td>2.9957</td>
<td>8.0631</td>
<td>4,934</td>
</tr>
<tr>
<td>( P_{jt} )</td>
<td>Price (USD)</td>
<td>693.3588</td>
<td>80.28</td>
<td>501</td>
<td>1,003.167</td>
<td>8,047</td>
</tr>
</tbody>
</table>

unit instead of zero, is used to calculate \( s_{jt} \). \( s_{jB_kt} \) is the within group share of product \( j \) at time \( t \) in group \( k \) and is calculated by dividing the quantity sold of product \( j \) at time \( t \) by the total quantity sold of group \( k \) at time \( t \). If the actual quantity sold at time \( t \) is zero, 0.01 is used as the quantity to calculate \( s_{jB_kt} \). \( s_{0t} \) is the market share of the outside option, in this case, the iPhone5 sold in Tian Mao. \( positive_{st} \), \( neutral_{st} \), and \( negative_{st} \) are the quantities of iPhone5 specific positive feedback with comments left, neutral feedback, and negative feedback, respectively. \( posratio_{st} \) is calculated as \( \frac{positive_{st}}{positive_{st}+neutral_{st}+negative_{st}} \) over the entire transaction history of iPhone5 sold by seller \( s \) up to \( t \). Note that iPhone5 specific feedback does not vary across products that are sold by the same seller. The mean of \( posratio_{st} \) is 0.9914, indicating that the iPhone5 specific positive feedback ratio on Taobao marketplace is high. I construct three dummy variables, \( D_{st}^1 \), \( D_{st}^2 \), and \( D_{st}^3 \), which take the value one if the scores for item as described, attitude of the seller, and shipping time, are respectively above the average score on Taobao. They take a value of zero otherwise. \( Ave_{-}D_{st} \) is the average of these three dummy variables. \( P_{jt} \) is the transaction price of the iPhone5 adjusted by shipping cost. \( posmon_{st} \), \( neumon_{st} \), and \( negmon_{st} \) are the quantities of seller specific positive, neutral, and negative feedback with comments in the recent 1 month and these variables are displayed on each seller’s page. \( posratio_{mon_{st}} \) is defined as \( \frac{posmon_{st}}{posmon_{st}+neumon_{st}+negmon_{st}} \). Although Taobao also displays the entire history of the seller specific ratings, most of the iPhone5 sellers have a very long selling history (3 - 5 years) on Taobao and thus ratings of the entire history are not accurate measures.
2.7. ESTIMATION RESULTS

CHAPTER 2. QUANTIFYING THE WELFARE EFFECTS OF REPUTATION IN E-COMMERCE:
EVIDENCE FROM ALIBABA’S TAOBAO MARKET

Table 2.3 Frequency Counts of Products

<table>
<thead>
<tr>
<th>GROUP</th>
<th>Freq</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>16G CHN</td>
<td>1,702</td>
<td>21.50</td>
</tr>
<tr>
<td>16G EUR</td>
<td>49</td>
<td>0.61</td>
</tr>
<tr>
<td>16G HK</td>
<td>2,962</td>
<td>36.81</td>
</tr>
<tr>
<td>16G JP</td>
<td>721</td>
<td>8.96</td>
</tr>
<tr>
<td>16G USA</td>
<td>1,445</td>
<td>17.96</td>
</tr>
<tr>
<td>32G CHN</td>
<td>397</td>
<td>4.90</td>
</tr>
<tr>
<td>32G HK</td>
<td>134</td>
<td>1.67</td>
</tr>
<tr>
<td>32G JP</td>
<td>267</td>
<td>3.37</td>
</tr>
<tr>
<td>32G USA</td>
<td>94</td>
<td>1.17</td>
</tr>
<tr>
<td>64G CHN</td>
<td>136</td>
<td>1.69</td>
</tr>
<tr>
<td>64G JP</td>
<td>139</td>
<td>1.73</td>
</tr>
</tbody>
</table>

No. of Observations: 8,047

for sellers’ performance in recent times. I also include only the ratings left with comments in the regression because they show up by default on Taobao's product pages. The price of an iPhone5 varies according to the version and memory size. Chinese consumers realize additional costs when they purchase an iPhone5 that is not specifically manufactured for the Chinese market. For instance, the Japanese version is the cheapest because it is exclusively designed for the Japanese market. The Chinese version costs the most because it is specifically designed for the Chinese market. pastsales$st$ is the amount of the iPhone5 that have been sold in the past 30 days since $t - 30$ by seller $s$. Taobao displays this variable on each product page which buyers easily observe.

Table 2.3 summarizes the frequency counts of the products in each group. The most popular products are from the following three groups: 16G CHN, 16G HK, and 16G US.

2.7 ESTIMATION RESULTS

2.7.1 Demand Estimates

This subsection presents the results of the nested logit estimation as shown in Table 2.4. The estimates reported do not reflect the magnitude of the marginal effects of the independent variables on market share. Note that the two seller specific reputation measures, Ave_D$st$ and posratio_mon$st$, are highly correlated. I only include Ave_D$st$ as the seller specific reputation measure in the regression because this variable captures most information of the seller specific reputation. Both seller
specific and iPhone5 specific reputation measures have significant and positive effects on consumer utility. This is consistent with the findings of previous literature that reputation has positive effects on transaction outcomes in online markets. The coefficient of log of $s_{j|Bk_t}$ is 0.4416, which lies between 0 and 1. This suggests that consumers receive both idiosyncratic shocks and similar shocks to products within a class.

Table 2.4 also reports underidentification and over identification tests for the estimation. The p-values for underidentification test is smaller than 0.01. The p-values for the overidentification test suggests that it fails to reject the null hypothesis that the model is over identified. These results provide evidence that the IVs are not correlated with the error term.

Table 2.5 reports the first-stage estimates of the nested logit model. Column (1) shows that the coefficient of $p_{jt}$ is positive and significant. The coefficient of $Ave_{Pos\_Mon\_Nest_{st}}$ is negative and significant, which implies that when the average reputation of all other sellers in the same group increases, a seller tends to set a lower price. Column (2) shows that $log psales_{jt-7}$ has a positive and significant effect on $log(s_{j|Bk_t})$. All F statistics are significantly larger than 10, indicating that the IVs are highly correlated with the endogenous variables in the first-stage estimation.

One might find the negative coefficient of $posratio_{st}$ in Columns (1) counterintuitive. A possi-
Table 2.5 First-Stage Estimates

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_{jt}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\log(s_{jt}b_{jt})$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>posratio$_{st}$</td>
<td>-134.5323***</td>
<td>31.2256***</td>
</tr>
<tr>
<td></td>
<td>(44.14)</td>
<td>(5.52)</td>
</tr>
<tr>
<td>Ave_D$_{st}$</td>
<td>12.5622***</td>
<td>1.1710***</td>
</tr>
<tr>
<td></td>
<td>(1.99)</td>
<td>(0.30)</td>
</tr>
<tr>
<td>$p_{jt-10}$</td>
<td>0.1241***</td>
<td>0.0043***</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.01 × 10$^{-1}$)</td>
</tr>
<tr>
<td>Ave_Pos_Mon_Nest$_{st}$</td>
<td>-299.1641*</td>
<td>8.1246</td>
</tr>
<tr>
<td></td>
<td>(115.44)</td>
<td>(14.45)</td>
</tr>
<tr>
<td>logpsales$_{st-7}$</td>
<td>0.4759</td>
<td>0.6821***</td>
</tr>
<tr>
<td></td>
<td>(0.64)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>F statistic</td>
<td>46.32</td>
<td>26.49</td>
</tr>
</tbody>
</table>

Standard Errors in Parentheses; ***p<0.01, **p<0.05, *p<0.1; No. of Observations: 8,047.

...ble explanation for this lies in the correlation between posratio$_{st}$ and Ave_D$_{st}$. In fact, when I only include posratio$_{st}$ as the exogenous variable in the estimation, its sign becomes positive, which suggests a positive correlation between posratio$_{st}$ and $p_{jt}$.

In sum, after endogeneity is controlled for, several estimation results are interesting. First, consumers respond negatively to price in the online marketplace. This is consistent with consumer theory and consumer behavior in traditional markets. Second, it is well documented that better quality yields higher utility. Results suggest that better feedback score yields higher utility and reputation on the Internet reveals product and seller quality.

2.7.2 Willingness to Pay for Reputation

WTP for an increase in reputation can be calculated as

$$WTP_{\text{reputation}} = -\frac{\beta_r}{\alpha} \Delta X_r$$

(2.22)

where $\alpha$ is the marginal utility of price, $\beta_r$ is the marginal utility derived from iPhone5 specific reputation, and $X_r$ is iPhone5 specific reputation, posratio. The total derivative of the indirect utility
function is set to zero. WTP is interpreted as the amount of money that would have to be added to
the price of the iPhone5 to keep the consumer's utility level constant if the iPhone5 specific positive
ratio goes up by a certain amount.

According to E.q.(2.22), for a one standard deviation increase in the iPhone5 specific positive
ratio, i.e., $\Delta X_r = 0.01$, the amount of money added to the price would be $\frac{34.2332}{0.0166} \times 0.01 = 20.6224$
USD. For a seller who has 433 positive and 2 negative feedback ratings, the iPhone5 specific positive
ratio is equal to 0.9954. If this seller removes his negative feedback and thus has 435 positive and 0
negative feedback ratings, the iPhone5 specific positive ratio would become 1. The amount of money
added to the price would then be $\frac{34.2332}{0.0166} \times (1 - 0.9954) = 9.4863$ USD. In contrast, if this seller has
431 positive and 4 negative feedback ratings, in order to keep the consumer's utility level constant,
the price would need to be decreased by $\frac{34.2332}{0.0166} \times (0.9954 - 0.9908) = 9.4863$ USD. The above results
suggest a significant effect of reputation on WTP. For a seller who has accumulated a good amount of
positive feedback ratings, receiving one more positive feedback would not greatly change consumer
WTP. However, receiving one extra negative feedback would result in significant decrease in WTP. In
the above example, prices of the iPhone5 will drop by about 9 USD when the seller's negative ratings
increase by 2.

2.7.3 Supply Estimates

Finally, the cost parameters are estimated. Estimates of marginal cost of an actual product are re-
ported in Table 2.6. Table 2.7 reports the marginal cost of reputation maintenance.

To estimate the cost parameter of reputation, $m_{st}$, I use E.q.(2.10) which imposes a parametric
structure on $C_{st}$. $m_{st}$ is then calculated as

$$m_{st} = \frac{C'_{st}(q_{st})}{q_{st}}$$

Table 2.8 shows the estimation results of $m_{st}$. Cost of maintaining reputation is expensive: for an

---

The sample median of the number of positive, neutral, and negative feedback are 433, 1, and 1, respectively.
### Table 2.7 Marginal Cost of Reputation Maintenance

<table>
<thead>
<tr>
<th>VARIABLES (Thousand USD)</th>
<th>Mean</th>
<th>STD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C'(q_{st})$</td>
<td>24.52</td>
<td>43.88</td>
<td>0.02</td>
<td>340.27</td>
</tr>
</tbody>
</table>

No. of Observations: 4,934

### Table 2.8 Cost Parameter of Reputation

<table>
<thead>
<tr>
<th>VARIABLES (Thousand USD)</th>
<th>Mean</th>
<th>STD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>$m_{st}$</td>
<td>24.89</td>
<td>44.29</td>
<td>0.02</td>
<td>341.39</td>
</tr>
</tbody>
</table>

No. of Observations: 4,934

average seller to increase his positive feedback ratio by a half standard deviation, the cost of reputation maintenance increases by $0.5 \times 24,889 \times (0.996^2 - 0.991^2) = 123$ USD.

### 2.8 COUNTERFACTUAL ANALYSIS

This section investigates the effects of reputation on consumer welfare and seller profits. The first counterfactual focuses on sellers’ cost of reputation maintenance. Taobao provides courses and trainings to help sellers to build business. These courses mainly focus on how to create compelling listings, how to use the listing and promotion tools to promote sales, and knowledge about inventory. If Taobao provides more trainings that help sellers to deliver satisfactory services to buyers, it would potentially lower sellers’ cost of maintaining good reputation. The first counterfactual is to examine the effects of reduction in cost of reputation maintenance.

The second counterfactual studies Taobao’s rule of feedback revision. Buyers are allowed to revise negative (or neutral) feedback that they leave towards sellers within a 30-day period. When a buyer leaves a negative rating, the seller can communicate with the buyer and try to fix the problem. Then the buyer may agree to change the negative rating to positive. However, once the negative rating has been left for more than 30 days, it can not be revised. The feedback revision mechanism encourages sellers to provide good services in a transaction, but also gives sellers a chance to resolve problems after. The second counterfactual focuses on the effects of removing the time limit on feedback revision.

E.q. (2.6) to (2.9) are the main equilibrium equations used in the counterfactual analyses. I use
2.8. COUNTERFACTUAL ANALYSIS

CHAPTER 2. QUANTIFYING THE WELFARE EFFECTS OF REPUTATION IN E-COMMERCE: EVIDENCE FROM ALIBABA’S TAOBAO MARKET

the MATLAB optimization toolbox, ‘fmincon’, to solve for the following unknown variables: \( p_{jt}, q_{st}, \lambda_{1st} \) and \( \lambda_{2st} \). I then compare seller profits and consumer welfare before and after the change.

Change in prices is calculated as

\[
\Delta p_{jt} = p_{jt}^1 - p_{jt}^0
\]

where \( p_{jt}^0 \) and \( p_{jt}^1 \) are the price of product \( j \) before and after the change, respectively. Change in sales is given by

\[
\Delta Q_{jt} = Q_{jt}^1 - Q_{jt}^0 = M_t s_{jt}^1 - M_t s_{jt}^0
\]

where \( Q_{jt}^0 \) and \( Q_{jt}^1 \) are the actual and counterfactual quantity sold, respectively. \( M_t \) is assumed to remain constant. \( s_{jt}^0 \) and \( s_{jt}^1 \) are the market share of product \( j \) before and after the change, respectively.

E.q. (2.25) calculates the change in revenue for seller \( s \) at time \( t \). \( \Delta C(q_{st}) \) in E.q. (2.27) is defined as the change in cost of the product. E.q. (2.27) calculates the change in cost of reputation for seller \( s \) at time \( t \). Change in seller profits can be written as E.q. (2.28).

\[
\Delta R_{st} = \sum_{n \in S_s} p_{nt}^1 Q_{nt}^1 - \sum_{n \in S_s} p_{nt}^0 Q_{nt}^0
\]

\[
\Delta CP_{st} = M_t \sum_{n \in S_s} (mc_{nt}s_{nt}^1 - mc_{nt}s_{nt}^0)
\]

\[
\Delta C(q_{st}) = C^1(q_{st}^1) - C^0(q_{st}^0)
\]

\[
= \frac{1}{2} m_{st}^1 q_{st}^{12} - Z_{st} - (\frac{1}{2} m_{st}^0 q_{st}^{02} - Z_{st})
\]

\[
= \frac{1}{2} m_{st}^1 q_{st}^{12} - \frac{1}{2} m_{st}^0 q_{st}^{02}
\]

\[
\Delta Profit_{st} = \sum_{n \in S_s} (p_{nt}^1 - mc_{nt}^1) M_t s_{nt}^1 - FC_{st} - C^1_{st}(q_{st}^1) - \left( \sum_{n \in S_s} (p_{nt}^0 - mc_{nt}^0) M_t s_{nt}^0 - FC_{st} - C^0_{st}(q_{st}^0) \right)
\]

\[
= \sum_{n \in S_s} [(p_{nt}^1 - mc_{nt}^1) M_t s_{nt}^1 - (p_{nt}^0 - mc_{nt}^0) M_t s_{nt}^0] - C^1_{st}(q_{st}^1) + C^0_{st}(q_{st}^0)
\]

where \( q_{st}^0 \) is the actual reputation, and \( q_{st}^1 \) is the counterfactual reputation chosen by seller \( s \) at time \( t \).
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CHAPTER 2. QUANTIFYING THE WELFARE EFFECTS OF REPUTATION IN E-COMMERCE: EVIDENCE FROM ALIBABA’S TAobao MARKET

Change in total profits of Taobao iPhone5 market at time $t$ is calculated by

$$\Delta T BProfit_t = \sum_{s=1}^{S_t} \Delta Profit_{st}$$

(2.29)

Change in consumer welfare (for a representative consumer) can be written as

$$\Delta CW_t = E(CW^1_t) - E(CW^0_t) = \frac{1}{\alpha} \left[ \ln \left( \sum_{j=0}^{I} e^{V_{jt}^1} \right) - \ln \left( \sum_{j=0}^{I} e^{V_{jt}^0} \right) \right]$$

(2.30)

where $E(CW^0_t)$ and $E(CW^1_t)$ are the expected welfare before and after the change, respectively. $V_{jt}^0$ and $V_{jt}^1$ are the indirect utility derived from product $j$ before and after the change, respectively. ($V_{jt}$ is defined in (2.31) in Appendix.)

$$\Delta T BCW_t = \Delta CW_t \times M_t$$

where $\Delta T BCW_t$ is the change in total consumer welfare at time $t$.

2.8.1 Reduction in Cost of Reputation

Since maintaining good reputation comes with a high cost, it is natural to ask the following question: would sellers choose better reputation if cost of reputation maintenance decreases, if so, by how much? In this subsection, I simulate the equilibrium with a lower cost of reputation. Specifically, I reduce the slope of marginal cost of reputation maintenance, $m$, by 20 percent for all observations, i.e., $m_{1st} = 0.8m_{0st}$. While the magnitude of reduction does not exactly reflect the change in sellers’ cost resulted from training provision, it helps us to understand the direction of change in profits and consumer welfare. Table 2.9 reports the change in prices, reputation, seller profits, and total profits of Taobao iPhone5 market as a whole.

As shown in Table 2.9, when the cost parameter, $m$, is decreased by 20 percent, sellers choose higher reputation on average. The mean of iPhone5 specific positive feedback ratios increases from 99.14 to 99.31 percent. Sellers increase their prices by 19 USD per product per day. Quantity sold of a product increases by 0.9 unit per day. Sellers’ cost of maintaining reputation significantly decreases even the average reputation is higher. The mean of seller profits increases by about 5 thousand USD, mainly driven by the reduction in cost of reputation. The total profit of Taobao iPhone5 market increases by 364 thousand USD per day. The above results suggest that if Taobao provides sellers with trainings that effectively reduce cost of reputation maintenance, sellers would be better off. Seller profits alone pay for the efforts of reducing cost of reputation maintenance because the increase in
2.8. COUNTERFACTUAL ANALYSIS

EVIDENCE FROM ALIBABA’S TAOBAO MARKET

Table 2.9 Effects of Reduction in Cost of Reputation

<table>
<thead>
<tr>
<th>VARIABLES</th>
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<th>STD</th>
<th>Min</th>
<th>Max</th>
<th>No. Obs</th>
</tr>
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<td>291.5323</td>
<td>478.5594</td>
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</tr>
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</table>

Numbers smaller than $10 \times e^{-6}$ are considered 0.
CHAPTER 2. QUANTIFYING THE WELFARE EFFECTS OF REPUTATION IN E-COMMERCE:
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seller profits is larger than the decrease in cost of reputation maintenance.

A representative consumer’s welfare increases by about 5 USD and the total consumer welfare increases by 4.2 thousand USD per day. Change in social welfare at time \( t \) is calculated by Eq. (2.32). \[ \sum_{s=1}^{S} \Delta C(q_{st}) \] can be viewed as the total efforts of reducing cost at time \( t \). Table 2.9 shows that the social welfare at time \( t \) increases by 364 thousand USD per day.

\[ \Delta SocialWF_{t} = \Delta TB CW_{t} + \Delta TB Profit_{t} \] (2.31)

The results of this simulation indicate that, when cost of reputation is decreased, sellers would choose higher reputation. At the same time, sellers would increase the prices of their products. When the positive effects of increase in seller reputation dominate the negative effects of increase in prices on consumer welfare, consumers would be better off.

2.8.2 Removal of Feedback Revision Limit

When Taobao removes the time limit on feedback revision, each seller would face the same upper bound of reputation, i.e., \( U_{B} = 1 \). Table 2.10 reports the effects of the change of the upper bound of reputation. The mean of iPhone5 specific positive feedback ratios increases by a small amount, from 0.9914 to 0.9916. Sellers choose higher prices on average: the average price increases by 11.5 USD. The average quantity sold increases by 0.76 unit for a product per day. Although reputation chosen increases on average, the mean of cost of reputation decreases by 98 USD. It suggests that sellers with lower cost of reputation maintenance would choose a higher reputation while those with higher cost would tend to choose a lower reputation in counterfactual. The mean of profits for each seller increases by about 260 USD, and the profit of Taobao iPhone5 market increases by 18 thousand USD per day. The welfare of a representative consumer decreases by 7 USD per day, due to the increase in prices. Social welfare increases by 12 thousand USD per day, driven by the increase in seller profits.

Results of the second exercise suggest that, when Taobao removes its time limit on feedback revision, sellers with lower cost of reputation may choose higher reputation. On the contrary, sellers with higher cost of reputation may choose lower reputation. When the negative effects of increase in prices exceed the positive effects of increase in seller reputation, consumer welfare decreases. Since the increase in total seller profits is larger than the decrease in total consumer welfare, social welfare increases.
### Table 2.10 Effects of Removal of Time Limit on Feedback Revision

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<th>VARIABLES</th>
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<th>STD</th>
<th>Min</th>
<th>Max</th>
<th>No. Obs</th>
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Numbers smaller than $10 \times e^{-6}$ are considered 0.
2.9 CONCLUSION

Reputation mechanisms play an important role in online marketplaces. In this article, I use a unique dataset of posted-price transactions of iPhone5 in a major Chinese online platform, Taobao.com, to study the welfare effects of reputation. By modeling reputation as a choice variable on the supply side, I am able to estimate the cost of reputation maintenance in the online market. More importantly, I quantify the welfare effects of reputation.

Results of demand estimation show that consumers respond positively to good reputation. Products with better reputation obtain greater market shares. Consumers are willing to pay 10.3 USD (1.5 percent of the price of an iPhone5) for a half standard deviation increase in iPhone5 specific positive feedback ratio. Supply estimation suggests that reputation maintenance is costly. For a seller to maintain his iPhone5 specific positive feedback ratio at 99.1 rather than 98.6 percent, his cost increases by 123 USD per day.

Evidence is also found in support of the positive relationship between good reputation and seller profits. When the cost of reputation maintenance decreases, sellers provide better quality and accordingly maintain a better reputation. When all negative feedback ratings are allowed to be revised, sellers choose a slightly higher reputation. In these two cases, both seller profits and social welfare as whole increase. It is ambiguous whether consumers would be better off when seller reputation increases because sellers with better reputation charge higher prices. When the positive effects of increase in reputation exceeds the negative effects of increase in prices, consumer welfare goes up. Otherwise, consumers would be worse off.

A few limitations of the analysis should be noted. First, it is assumed that feedback ratings are left without noise, that is, sellers providing good quality would for sure receive positive feedback while providing bad quality would result in receiving negative feedback. Second, the parametric cost function of reputation may be too restrictive. Finally, I assume that the reputation measures consumers face can be chosen by the sellers on the same day consumers make their purchases. In reality, there is a lag between seller’s reputation maintenance effort and the change in their reputation measures. Addressing this issue would require the use of a dynamic model. These could be the subjects of future research.
BIBLIOGRAPHY


3.1 INTRODUCTION

Parties to transactions in online marketplaces have asymmetric information about the goods being traded. Buyers do not know the quality of a product or service provided by a seller until they actually receive it. Some examples of online shopping markets are websites such as eBay and Alibaba's Taobao.com. In order to facilitate trade, these websites allow buyers to leave feedback about a seller in order to reduce the complications of information asymmetry.

Public records often include information concerning all the past choices of a seller. For example, buyers on eBay can observe all the feedback about a seller since the first day of business. In this case, buyers are informed of all the past actions taken by the seller. In other cases, public records include only the frequencies of the various actions taken by a seller, but need not identify their order. It is relatively easy to find product reviews, rating services, or consumer reports that give a good idea of the average performance of a product, firm, or service. It is more difficult to identify the
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precise stream of actions. For example, one can find travel guides reporting that a certain airport has legitimate taxis that provide good value per dollar with high probability, as well as pirate taxis that routinely provide poor value per dollar.

Economic theory (Ekmekci 2010, Jehiel and Samuelson 2012, Liu and Skrzypacz 2014, etc.) shows that economic efficiencies differ under various reputation monitoring systems. The goal of this paper is to compare the economic efficiencies of two reputation systems in a laboratory setting. This is achieved by varying the information available to short-run players. In the first scenario, short-run players can observe all the past actions chosen by a long-run player in chronological order. In the second scenario, only the aggregate frequencies of actions chosen by the long-run player are available to the short-run players. Jehiel and Samuelson (2012) assume that short-run players use analogical reasoning for inference. Short-run players correctly identify the average strategy of long-run players, but do not recognize how this play varies across histories. In this chapter, I design an experiment that compares the payoffs and behavior of both the long-run and short-run players in these two scenarios.

The theoretical literature on reputation has shown that uncertainty about a player's preference has significant implications for equilibrium play in repeated games. Fundenberg and Levine (1989, 1992) design a repeated game where a long-run player faces a sequence of short-run players. The long-run player is either a rational player who is interested in maximizing her payoffs or a mechanical type who plays the same stage game in every period. The reputation monitoring system in this chapter is a classic reputation framework, where short-run players can see all the past choices of the long-run player. The authors show that the rational long-run player can guarantee a payoff arbitrarily close to the payoff she would obtain by always playing like the mechanical type. Short-run players play a best response to this choice. An important assumption of this paper is that short-run players have a perfect understanding of the equilibrium strategies of various types of long-run players. This payoff bound is called the Stackelberg bound.

This classic reputation model assumes that short-run players have a perfect understanding of the equilibrium strategies of various types of long-run player. Jehiel and Samuelson (2012) depart from the classic model and assume that the short-run players mistakenly believe that the long-run player plays in a stationary fashion. The authors show that long-run players earn higher payoffs than the Stackelberg bound. They also provide a characterization of equilibrium behavior. The long-run players start in either a reputation building or reputation spending stage, followed by a reputation manipulation stage.

Table 3.1 illustrates how the short-run players interpret the ratings of the long-run player in Jehiel and Samuelson (2012). The long-run player can be considered a seller and the short-run players can be viewed as consumers. For instance, a consumer is told that the seller provided good quality 5 times
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and bad quality 5 times in the previous 10 transactions. The consumer may process the information as the seller playing the mixed strategy (50% chance of good quality and 50% chance of bad quality) in every stage. The truth is that the seller played strategically: he built his reputation by providing good quality in the first 5 transactions and exploited his reputation by providing bad quality in the next 5 transactions. When the buyer only observes the aggregate frequencies of actions played by the seller, he may mistakenly believe that the strategic seller plays the same strategy in every stage.

Table 3.1 Analogical Reasoning

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<tr>
<th>Stage</th>
<th>Exact History</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>GOOD</td>
<td>50%B,50%G</td>
</tr>
<tr>
<td>2</td>
<td>GOOD</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>GOOD</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>GOOD</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>GOOD</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>BAD</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>BAD</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>BAD</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>BAD</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>BAD</td>
<td></td>
</tr>
</tbody>
</table>

Camerer and Weigelt (1988) is the first study to design an experiment where a long-run player interacts with a sequence of short-run players who have incomplete information about the long-run player's preferences but observe past choices. This design varies the probability of a long-run player's type but does not vary the information available to short-run players. This work suggests that the ability to manipulate reputation could allow the long-run player to obtain higher payoffs. This paper and its follow-up studies of Neral and Ochs (1992) and Brandts and Figueras (2003) focus on how sequential equilibrium predicts behavior. None of these papers varies the observability of the past choices of a long-run player.

Bolton, Katok and Ockenfels (2004) vary the availability of information regarding a long-run player's past choices in their experiment. Short-run players may or may not observe the long-run player's past choices. Long-run players yield higher payoffs when there is reputation. Grosskope and Sarin (2010) vary whether the past choices of a long-run player are observable to short-run players. They allow for reputation to have either a beneficial or a harmful effect on the long-run player. They find that reputation is seldom harmful but its beneficial effects are not as strong as theory pre-
3.2 EXPERIMENTAL DESIGN

There are two roles in my experiment. I think of the long-run player as a firm that chooses to provide either high quality ($H$) or low quality ($L$). The short-run player is a buyer who chooses to purchase either a branded product ($P$) or generic product ($G$) from the firm. There are eight rounds in the experiment. Each round consists of eight stages.

Every stage game is a coordination game and based on the Product Choice Game (Jehiel and Samuelson 2012). A firm and a buyer make decision simultaneously in each stage. Stage payoffs are shown in the table below. Given that the firm chooses low, the buyer receives 0 playing branded and 1 playing generic. Given that the firm chooses high, the buyer earns 3 playing branded and 2 playing generic. Low quality is the one shot dominant strategy for the firm. The firm would like the buyer to purchase the branded product, which is the best response for the buyer if the firm chooses high quality.

Table 3.2 Stage Payoff

<table>
<thead>
<tr>
<th>LR / SR</th>
<th>$P$</th>
<th>$G$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L$</td>
<td>3, 0</td>
<td>1, 1</td>
</tr>
<tr>
<td>$H$</td>
<td>2, 3</td>
<td>0, 2</td>
</tr>
</tbody>
</table>

The objective of my experiment is to compare economic efficiencies under two reputation sys-
3.2 EXPERIMENTAL DESIGN

In System 1, buyers are informed of the exact order of actions taken by the seller in previous stages. System 2 more closely mimics reality in the sense that most reputation systems only disclose aggregate frequencies and not the precise order of a seller’s past actions. Therefore, buyers in System 2 only observe the frequencies of actions played by the seller.

I use a between subject design where each subject participates only once in my experiment. Twenty subjects participate in my experiment. Ten of them play in the following order: 2 rounds of System 1, 4 rounds of System 2, and 2 rounds of System 1. The rest play in a different order: 2 rounds of System 2, 4 rounds of System 1, and 2 rounds of System 2.

Roles of subjects are randomly determined by computer before each round. Therefore, roles of each subject may switch between rounds. There are five subjects who play in a round. In a round, one subject plays the role of long-run player (firm), and the other four subjects play the roles of short-run players (buyers). The long-run subjects play every stage of a round. For administration purposes, each short-run subject plays two stages of a round. Specifically, one subject plays the role of buyer in Stage 1 and 5, one plays the role of buyer in Stage 2 and 6, one plays the role of buyer in Stage 3 and 7, and one plays the role of buyer in Stage 4 and 8.

All sessions were conducted at the computer lab at Poole College of Management at North Carolina State University in May 2015. Participants in the experiment were NC State students. The computer interface was programmed using z-Tree (Fischbacher 2007). The participants were not allowed to communicate with one another and were separated on individual computer terminals. Subjects were given 15 minutes to read the instructions and any questions were answered in private. Then play of the experiment started and typically lasted about one hour. Participants were asked to fill out a questionnaire after they finished the experiment. Then they were told their total earnings for the entire experiment. Payoffs in points were converted to dollars at the rate of 10 points = 2.5 dollars. Average earnings were 14.4 dollars including an additional 5 dollars paid for showing up to the experiment. The instructions did not mention any frame or context. The firm-buyer frame I provide in this paper seeks to make my discussion easy to understand.

3.2.1 Hypothesis

Since each round of experiment is a finite game, the firm should always choose low quality and buyers should always choose generic in equilibrium. This is not an efficient outcome because both the firm and buyers can earn higher payoffs if the firm chooses high and a buyer chooses branded. Literature shows that if reputation monitoring systems exist, trust may be established and the firm and buyers coordinate to reach a more efficient outcome. The objective of this experiment is to examine the behavior and payoffs of the firm and buyers under two different reputation frameworks.
nomic efficiencies of these two systems are also compared.

Fudenberg and Levine (1989, 1992) derive the Stackelberg bound when buyers observe the exact history of past actions played by the firm. One of the important assumptions in this model is that buyers have a correct understanding of the equilibrium strategy of the firm throughout the entire course of the game. This model predicts that the more information concerning the firm’s past behavior is available, the more efficient an outcome would be.

Apart from the classic model, Jehiel and Samuelson (2012) assume that buyers reason as if the firm behaves in a stationary fashion in the analogical game. This formulation can be viewed as capturing a setting in which it is difficult for buyers, who appear in the game just once, to obtain a detailed description of the actions of the firms over every possible history. Under System 2, only aggregate frequencies of actions of the firm are revealed. Buyers mistakenly believe that the firm is playing the same (possibly mixed) strategy in every stage when the firm is actually playing strategically. This reasoning reduces the cost to manipulate buyers’ beliefs and results in a boost in the firm’s payoffs.

Jehiel and Samuelson (2012) predict that players’ behavior and payoffs under System 2 differ from those of System 1. They show that buyers tend to choose more branded under System 2 than System 1. The predictions of the firm’s play under System 2 are not as clear because the dynamics of the firm’s actions depend on the parameters of the model, history of the firm’s actions, and buyers’ past actions. They also show that the firm’s payoff bound under System 2 is strictly higher than the Stackelberg bound.

The purpose of my experiment is to compare players’ behavior and efficiencies under these two systems. The hypotheses are shown in the table below. If buyers choose more branded and the firm chooses more high, it is likely that efficient outcomes can be reached more frequently.

| Table 3.3 Hypotheses of Buyer Behavior, Firm Behavior, and Efficiency |
|-------------------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|
| Buyer | $H_0$: Buyers choose more branded under System 1. |
|      | $H_1$: Buyers choose more branded under System 2. |
| Firm  | $H_0$: A firm chooses more high under System 1.   |
|       | $H_1$: A firm chooses more high under System 2.   |
| Efficiency | $H_0$: More efficient outcomes are reached under System 1. |
|          | $H_1$: More efficient outcomes are reached under System 2. |
3.3 RESULTS

3.3.1 Buyers’ Behavior

Buyers’ choices are shown in Table 3.4. In the first four stages, buyers chose more action $P$ (branded) in the analogical game than in the classic game. The difference increased when more stages were played: buyers chose action $P$ 10 times more than action $G$ in the second four stages.

Table 3.4 Frequency Count of Buyers’ Actions

<table>
<thead>
<tr>
<th>Stage</th>
<th>Action</th>
<th>Analogical (System 2)</th>
<th>Classic (System 1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stage 1 to 4</td>
<td>Branded</td>
<td>25</td>
<td>22</td>
</tr>
<tr>
<td></td>
<td>Generic</td>
<td>39</td>
<td>42</td>
</tr>
<tr>
<td>Stage 5 to 8</td>
<td>Branded</td>
<td>34</td>
<td>24</td>
</tr>
<tr>
<td></td>
<td>Generic</td>
<td>30</td>
<td>40</td>
</tr>
</tbody>
</table>

These results are consistent with the theoretical prediction of Jehiel and Samuelson (2012): buyers play more $P$ under System 2 than System 1. When buyers are informed of every past action taken by the firm, they may correctly understand the firm’s equilibrium strategy. When buyers only observe the frequencies of a firm’s past actions, it is possible that they are confused about the firm’s equilibrium strategy. They falsely reason as if the firm plays in a stationary fashion. Therefore, it may be easier for a firm to manipulate buyers’ beliefs and induce buyers to choose action $P$ under System 2.

A nonparametric test (Wilcoxon rank-sum test) is performed to examine statistical significance of the difference in buyers’ behavior between System 1 and 2. I construct a dummy variable for a buyer’s choice. It has a value of 0 when branded is chosen and 1 when generic is chosen. Number of observation for each system is $8(\text{rounds}) \times 4(\text{stages}) \times 2(\text{groups}) = 64$ for the first four stages. Number of observation for the second four stages is also 64 for each system.

Results of the nonparametric test are shown in 3.5. The difference in the first four stages is not statistically significant, but the difference in the second four stages is significant at a ten percent level.

3.3.2 Sellers’ Behavior

Table 3.6 shows the firms’ behavior in the experiment. In the first four stages, sellers played action $H$ 8 times more under System 2 than System 1. In the second four stages, sellers chose more $H$ under
CHAPTER 3. ANALOGICAL REASONING IN THE PRODUCT CHOICE GAME: EVIDENCE FROM
THE LAB

3.3. RESULTS

Table 3.5 Nonparametric Test of Buyers’ Behavior

<table>
<thead>
<tr>
<th>Stage</th>
<th>System</th>
<th>N</th>
<th>Z</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stage 1 to 4</td>
<td>2 1</td>
<td>64</td>
<td>-0.548</td>
<td>0.5837</td>
</tr>
<tr>
<td>Stage 5 to 8</td>
<td>2 1</td>
<td>64</td>
<td>-1.769</td>
<td>0.0770*</td>
</tr>
</tbody>
</table>

System 2 than System 1 as well, but the difference decreased to 2 times.

Table 3.6 Frequency Count of Sellers’ Actions

<table>
<thead>
<tr>
<th>Stage</th>
<th>Action</th>
<th>Analogical (System 2)</th>
<th>Classic (System 1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stage 1 to 4</td>
<td>High</td>
<td>31</td>
<td>23</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>33</td>
<td>41</td>
</tr>
<tr>
<td>Stage 5 to 8</td>
<td>High</td>
<td>23</td>
<td>21</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>41</td>
<td>45</td>
</tr>
</tbody>
</table>

Under System 1, actions of both types of players did not change much when the game moved forward. Under System 2, firms chose high quality for 31 times in the first half of the game and then decreased to 23 times in the second half. In contrast, buyers chose branded for 25 times in the first half and then increased to 34 times in the second half of the game. These results confirm the story of Jehiel and Samuelson (2012). The analogical game starts with an initial phase where a firm builds up his reputation to a certain level. The game then enters a reputation manipulation phase where a firm induces buyers to play in the firm’s favor. Even the firm chooses fewer high when the game moves on, buyers still believe that there is a good probability the firm would play high.

A nonparametric test is also performed for sellers’ behavior under these two systems. I calculate the fraction of L being played by each seller. For example, if a seller chooses H once and L three times, this fraction variable is equal to \(\frac{3}{4}\). The number of observation for each system is \(8(\text{rounds}) \times 2(\text{groups}) = 16\). As shown in 3.7, L (H) is played more (less) frequently under System 1 than System 2 although results are not statistically significant.
### Table 3.7 Nonparametric Test of Sellers’ Behavior

<table>
<thead>
<tr>
<th>Stage</th>
<th>System</th>
<th>N</th>
<th>Z</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stage 1 to 4</td>
<td>2</td>
<td>16</td>
<td>-1.045</td>
<td>0.2961</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>16</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stage 5 to 8</td>
<td>2</td>
<td>16</td>
<td>-0.742</td>
<td>0.4581</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>16</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### 3.3.3 Payoffs and Efficiency

Outcomes of two games are shown in 3.8 and 3.9. In the analogical game, the efficient outcome was played with a probability of 23%, while it was played with a probability of 16% in the classic game. Both results depart from the one-shot equilibrium where buyers always choose $G$ and sellers always choose $L$. When there exists a reputation system, efficient outcomes could be supported.

### Table 3.8 Outcomes of the Analogical Game

<table>
<thead>
<tr>
<th>SR / LR</th>
<th>$H$</th>
<th>$L$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P$</td>
<td>30 (23.4%)</td>
<td>29 (22.7%)</td>
</tr>
<tr>
<td>$G$</td>
<td>24 (18.8%)</td>
<td>45 (35.2%)</td>
</tr>
</tbody>
</table>

### Table 3.9 Outcomes of the Classic Game

<table>
<thead>
<tr>
<th>SR / LR</th>
<th>$H$</th>
<th>$L$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P$</td>
<td>20 (15.6%)</td>
<td>26 (20.3%)</td>
</tr>
<tr>
<td>$G$</td>
<td>22 (17.2%)</td>
<td>60 (46.9%)</td>
</tr>
</tbody>
</table>

As shown in 3.8 and 3.9, efficient outcomes were played more frequently under System 2 than System 1. This is mainly driven by buyers’ willingness to play more $P$ when only the aggregate strategy of a firm is revealed. The firm is also willing to choose more $H$ under System 2, especially at the beginning of the game, in order to build up her reputation and induce buyers to play $P$ in later staggers.
A variable is constructed to calculate the fraction of efficient outcomes being played under these two systems. For example, if there is one efficient outcome in the first four stages in a specific round, the fraction is calculated as \( \frac{1}{4} \). The number of observation for each system is \( 8 \times 2 = 16 \). The results of nonparametric test are shown in 3.10. Efficient outcomes are played more frequently under System 2 but results are not significant.

### Table 3.10 Nonparametric Test of Efficiency

<table>
<thead>
<tr>
<th>Stage</th>
<th>System</th>
<th>N</th>
<th>Z</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stage 1 to 4</td>
<td>2/1</td>
<td>16</td>
<td>0.778</td>
<td>0.4309</td>
</tr>
<tr>
<td>Stage 5 to 8</td>
<td>2/1</td>
<td>16</td>
<td>0.994</td>
<td>0.3201</td>
</tr>
</tbody>
</table>

Table 3.11 shows the average earnings per round for a firm and buyer. Both types of players earned higher average payoffs in System 2 than System 1. This is consistent with the prediction of Jehiel and Samuelson (2012): profit of the long-run player is higher in the analogical game than the classic game.

### Table 3.11 Average Payoffs Per Round

<table>
<thead>
<tr>
<th>Player</th>
<th>Analogue</th>
<th>Classic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm</td>
<td>12</td>
<td>11.125</td>
</tr>
<tr>
<td>Buyer</td>
<td>1.43</td>
<td>1.28</td>
</tr>
</tbody>
</table>

A nonparametric test is conducted to examine the difference in profits between two systems. The number of observation for each system is \( 8 \times 2 = 16 \). Results are presented in 3.12.

### 3.4 CONCLUSION

Reputation plays a crucial role in various markets, for instance, credit markets and E-commerce. Almost every online shopping site has its reputation systems. Different reputation monitoring systems are often compared theoretically but not empirically. Since field experiments are very costly to con-


**Table 3.12** Nonparametric Test of Profits

<table>
<thead>
<tr>
<th>Player</th>
<th>Stage</th>
<th>System</th>
<th>N</th>
<th>Z</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buyer</td>
<td>Stage 1 to 4</td>
<td>2</td>
<td>16</td>
<td>0.873</td>
<td>0.3812</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1</td>
<td>16</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Buyer</td>
<td>Stage 5 to 8</td>
<td>2</td>
<td>16</td>
<td>0.613</td>
<td>0.5399</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1</td>
<td>16</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Seller</td>
<td>Stage 1 to 4</td>
<td>2</td>
<td>16</td>
<td>-0.288</td>
<td>0.7732</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1</td>
<td>16</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Seller</td>
<td>Stage 5 to 8</td>
<td>2</td>
<td>16</td>
<td>1.395</td>
<td>0.1631</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1</td>
<td>16</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

...duct, lab experiments become good tools for investigating these topics. The results of my experiment imply that the classic reputation system may not be as efficient as the system under which information regarding a long-run player’s past choices is not fully revealed to short-run players.

Another interesting reputation mechanism to be studied in the future is limited record keeping (Liu and Skrzypacz 2014). Economic efficiency and players’ behavior under this reputation system can be examined by using a lab experiment. The experimental results will also cast light on the optimal design of reputation mechanisms in the real world.
BIBLIOGRAPHY


APPENDICES
APPENDIX

A

APPENDIX FOR CHAPTER 2

A.1 MATHEMATICAL DERIVATION

A.1.0.1 Derivation of E.q.(2.3)

I begin with the derivation of E.q.(2.3), following Train (2012),

\[ U_{ijt} = W_{kt} + Y_{jt} + \epsilon_{ijt} = V_{jt} + \epsilon_{ijt} \]  

(A.1)

where \( U_{ijt} \) is the indirect utility of individual \( i \) obtained from choosing alternative \( j \) at time \( t \). Alternative \( j \) belongs to nest \( k \). \( W_{kt} \) depends only on variables that describe nest \( k \) at time \( t \). These variables differ over nests but not over alternatives within each nest. \( Y_{jt} \) depends on variables that describe alternative \( j \) at time \( t \).

Note that the decomposition is fully general, since for any \( W_{kt} \), \( Y_{jt} \) is defined as \( V_{jt} - W_{kt} \). Market share of product \( j \) at time \( t \) can be written as
\[ s_{jt} = s_{j|B_k t} s_{B_k t} = \frac{e^{V_{jt}/(1-\sigma_k)} \left( \sum_{f \in B_k} e^{V_{ft}/(1-\sigma_k)} \right)^{-\sigma_k}}{\sum_{l=1}^{K} \left( \sum_{f \in B_l} e^{V_{ft}/(1-\sigma_l)} \right)^{1-\sigma_l}} \]

\[ = \frac{e^{V_{jt}/(1-\sigma_k)} \left( \sum_{f \in B_k} e^{V_{ft}/(1-\sigma_k)} \right)^{1-\sigma_k}}{\sum_{l=1}^{K} \left( \sum_{f \in B_l} e^{V_{ft}/(1-\sigma_l)} \right)^{1-\sigma_l}} \]

\[ = \frac{e^{V_{jt}/(1-\sigma_k)} \left( \sum_{f \in B_k} e^{V_{ft}/(1-\sigma_k)} \right)^{1-\sigma_k}}{\sum_{l=1}^{K} \left(e^{W_{kl}/(1-\sigma_k)}\right)^{1-\sigma_l}} \] (A.2)

where

\[ I_{kt} = \ln \sum_{f \in B_k} e^{Y_{ft}/(1-\sigma_k)} \]

For the outside option, I assume good 0 is the only good in its group 0. \( V_{0t} \) is normalized to be zero.

\[ s_{0t} = s_{i|B_0 t} s_{B_0 t} = \frac{1}{1} \cdot \frac{1}{\sum_{l=1}^{K} \left( \sum_{f \in B_l} e^{V_{ft}/(1-\sigma_l)} \right)^{1-\sigma_l}} \] (A.3)

Dividing E.q.(A.2) by (A.3), we obtain

\[ \frac{s_{jt}}{s_{0t}} = \frac{e^{V_{jt}/(1-\sigma_k)} \left( \sum_{f \in B_k} e^{V_{ft}/(1-\sigma_k)} \right)^{1-\sigma_k}}{\sum_{f \in B_k} e^{V_{ft}/(1-\sigma_k)}} \] (A.4)

Take log of E.q.(A.4), we get the following equation,

\[ \ln(s_{jt}) - \ln(s_{0t}) = \frac{V_{jt}}{1-\sigma_k} + (-\sigma_k) \ln \sum_{f \in B_k} e^{V_{ft}/(1-\sigma_k)} \]

\[ = \frac{V_{jt}}{1-\sigma_k} + (-\sigma_k) \ln(e^{W_{kt}/(1-\sigma_k)} \sum_{f \in B_k} e^{Y_{ft}/(1-\sigma_k)}) \]

\[ = \frac{V_{jt}}{1-\sigma_k} + (-\sigma_k) \frac{W_{kt}}{1-\sigma_k} + (-\sigma_k) \ln \sum_{f \in B_k} e^{Y_{ft}/(1-\sigma_k)} \] (A.5)

And we know

\[ \ln(s_{j|B_k t}) = Y_{jt}/(1-\sigma_k) - \ln \sum_{f \in B_k} e^{Y_{ft}/(1-\sigma_k)} \] (A.6)
A.1. MATHEMATICAL DERIVATION

Next, I calculate the derivatives that are present in the first order conditions. They are \( \frac{\partial s_{jt}}{\partial p_{jt}} \), \( \frac{\partial s_{jt}}{\partial q_{it}} \), and \( \frac{\partial s_{jt}}{\partial r_{it}} \). Note that alternative \( r \) and alternative \( j \) are sold by seller \( s \) at time \( t \).

The derivation of \( \frac{\partial s_{jt}}{\partial p_{jt}} \) is as follows. \( \frac{\partial s_{jt}}{\partial q_{it}} \) and \( \frac{\partial s_{jt}}{\partial r_{it}} \) follow similar proofs.

\[
\frac{\partial s_{jt}}{\partial p_{jt}} = \frac{\partial}{\partial p_{jt}} \left[ \frac{e^{V_{jt}/1-\sigma_k} \left( \sum_{f \in B_k} e^{V_{ft}/1-\sigma_k} \right)^{1-\sigma_k}}{\sum_{l=1}^{K} \left( \sum_{f \in B_l} e^{V_{ft}/1-\sigma_l} \right)^{1-\sigma_l}} \right] = \frac{\sum_{l=1}^{K} \left( \sum_{f \in B_l} e^{V_{ft}/1-\sigma_l} \right)^{1-\sigma_l}}{\left( \sum_{l=1}^{K} \left( \sum_{f \in B_l} e^{V_{ft}/1-\sigma_l} \right)^{1-\sigma_l} \right)^2} \cdot \frac{\partial V_{jt}}{\partial p_{jt}}
\]

Now let us turn to the cross derivatives, \( \frac{\partial s_{jt}}{\partial p_{jt}} \). There are two cases. In the first case, alternative \( j \) and alternative \( r \) belong to two different nests, particularly, \( j \in B_k \) and \( r \in B_h \). We obtain

\[
\frac{\partial V_{jt}}{\partial p_{jt}} \cdot s_{jt} = \left[ \frac{1}{1-\sigma_k} + \frac{-\sigma_k}{1-\sigma_k} \cdot s_{jt} \right] \cdot \frac{\partial V_{jt}}{\partial p_{jt}}
\]
\[
\frac{\partial s_{rt}}{\partial p_{jt}} = \frac{\partial}{\partial p_{jt}} \left[ \frac{e^{V_{jr}/(1-\sigma_k)\left( \sum_{f \in B_k} e^{V_{jr}/(1-\sigma_k)} \right)^{-\sigma_h}}}{\sum_{i=1}^{K} \left( \sum_{f \in B_i} e^{V_{jr}/(1-\sigma_i)} \right)^{-\sigma_i}} \right]
\]

\[
= \frac{e^{V_{jr}/(1-\sigma_k)\left( \sum_{f \in B_k} e^{V_{jr}/(1-\sigma_k)} \right)^{-\sigma_h}}}{\sum_{i=1}^{K} \left( \sum_{f \in B_i} e^{V_{jr}/(1-\sigma_i)} \right)^{-\sigma_i}} \cdot \left( \sum_{f \in B_k} e^{V_{jr}/(1-\sigma_k)} \right)^{-\sigma_k} - \frac{e^{V_{jr}/(1-\sigma_k)\left( \sum_{f \in B_k} e^{V_{jr}/(1-\sigma_k)} \right)^{-\sigma_h}}}{\sum_{i=1}^{K} \left( \sum_{f \in B_i} e^{V_{jr}/(1-\sigma_i)} \right)^{-\sigma_i}} \cdot \left( \sum_{f \in B_k} e^{V_{jr}/(1-\sigma_k)} \right)^{-\sigma_k} \cdot \frac{\partial V_{jr}}{\partial p_{jt}}
\]

When alternative \( j \) and alternative \( r \) belong to the same nest \( B_k \), the cross derivatives become

\[
\frac{\partial s_{rt}}{\partial p_{jt}} = \frac{\partial}{\partial p_{jt}} \left[ \frac{e^{V_{jr}/(1-\sigma_k)\left( \sum_{f \in B_k} e^{V_{jr}/(1-\sigma_k)} \right)^{-\sigma_k}}}{\sum_{i=1}^{K} \left( \sum_{f \in B_i} e^{V_{jr}/(1-\sigma_i)} \right)^{-\sigma_i}} \right]
\]

\[
= \frac{e^{V_{jr}/(1-\sigma_k)\left( \sum_{f \in B_k} e^{V_{jr}/(1-\sigma_k)} \right)^{-\sigma_k}}}{\sum_{i=1}^{K} \left( \sum_{f \in B_i} e^{V_{jr}/(1-\sigma_i)} \right)^{-\sigma_i}} \cdot \left( \sum_{f \in B_k} e^{V_{jr}/(1-\sigma_k)} \right)^{-\sigma_k} \cdot \frac{\partial V_{jr}}{\partial p_{jt}}
\]

\[
= \frac{\partial V_{jt}}{\partial p_{jt}} \cdot s_{rt} \cdot s_{jt}
\]
B.1 EXPERIMENTAL INSTRUCTIONS

Welcome!

Today you will be participating in an experiment composed of two games: Game 1 and Game 2. There are 4 rounds of Game 1 and 4 rounds of Game 2. Each round consists of 8 stages. Half of you will play in the following order: Game 1 for 2 rounds, Game 2 for 4 rounds, and Game 1 for 2 rounds. The other half will play in a different order – Game 2 for 2 rounds, Game 1 for 4 rounds, and Game 2 for 2 rounds. At the beginning of Round 1, Round 3, Round 5, and Round 7, you will see a message on your screen that tells you what game to play in the following 2 rounds. For example, you will play Game 1 in the following 2 rounds and you will see

You will play Game 1 in the following 2 rounds.

There are 2 roles in this experiment, the long-run player (LR) and the short-run player (SR). In each round some of you will play LR and the rest will play SR. 8 SRs play against 1 LR in each round. There are four SR participants and each participant plays two of the eight stages in each round. One SR participant plays the 1st (Stage 1) and 5th SR (Stage 5), one plays the 2nd (Stage 2) and 6th SR (Stage 6), one plays the 3rd (Stage 3) and 7th SR (Stage 7), and one plays the 4th (Stage 4) and 8th SR (Stage 8). LR plays all eight stages in each round. Your role will be assigned at the beginning of each round and on your screen you will see what role you will play in the following round. For example,
if you are the SR playing in Stage 3 and 7 in the following round, you will see this message on your screen:

**In the current round, you are the 3rd and 7th short-run player.**

If you are LR in the following round then on your screen you will see

**In the current round, you are the long-run player.**

Your role does not change throughout each round but may switch between rounds. Both LR and SR must make decisions within 30 seconds in every stage.

In each stage, both LR and SR see which stage they are in on their screens. For example, in Stage 3 of a round in Game 2, LR will see

**You are LR in Stage 3 in the current round, Game 2**

SR will see

**You are the 3rd SR in the current round, Game 2.**

All dollar values in these instructions and during the experiment are expressed in terms of experimental currency. Experimental dollars will be converted into U.S. dollars at the end of the experiment and your take-home earnings will be paid in cash. This includes a $5 show-up payment for arriving on time.

The payoff depends on the actions of both LR and SR. At each stage, LR and SR take actions simultaneously. LR chooses between action L and action H. SR chooses between action P and action G. Please see Page 3 if you are LR and see Page 4 if you are SR for more details about the actions and payoffs of the game.

In each round of Game 1, SR will observe the number of actions played by the LR in the previous stages in that round. In Game 2, SR can observe the order of LR's actions taken in previous stages in that round. Please see Page 3 and 4 for more details about Game 1 and Game 2.

**How You Get Paid**

In a particular round, you will earn experimental dollars based on your own actions and other players’ actions. The LR subject's payoff for each round is the sum of his payoffs in each of eight stages. The SR subject's payoff for each round is the sum of his payoffs from the two stages in which he participated.

Your total reward for this experiment is the sum of your earnings in each round. Experimental currency will be converted into U.S dollars at the rate of 10 experimental dollar equal to $2.5 U.S. dollars.

Do you have any questions about the process?
Instructions for Long Run Players

If you are LR for a round, you will decide what actions to take in the eight stages in a round. The payoff depends on the actions of both LR and SR. At each stage, LR and SR take actions simultaneously. LR chooses between action L and action H.

Below is the payoff table for LR. Given SR choosing action P, your payoff is 3 when you choose L and 2 when you choose H. If SR chooses action G, you get 1 by choosing L and 0 by choosing H.

<table>
<thead>
<tr>
<th>LR / SR</th>
<th>P</th>
<th>G</th>
</tr>
</thead>
<tbody>
<tr>
<td>L</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>H</td>
<td>2</td>
<td>0</td>
</tr>
</tbody>
</table>

You will also see the following message on your screen when it is your turn to choose an action.

Your decision: (1=H, 2=L).

If you choose H, input 1 to your screen by using your keyboard and then use your mouse to click the OK button. If you choose L, input 2 and then click OK.

Game 1

In each round of Game 1, 8 SRs play against 1 LR. In Game 1, SR will observe the number of actions played by the LR in the previous stages in that round. LR will observe SR's action taken in the last stage. For example, the game is in Stage 4 and SR chose P in Stage 3.

Then LR will see the following message on his screen:

Third SR's decision: P

Game 2

In each round of Game 2, 8 SRs play against 1 LR. SR can observe the order of LR's actions taken in previous stages. LR can observe SR's action taken in the last stage. For example, the game is currently in Stage 4 and SR chose P in Stage 3.

LR will see SR's action chosen in the previous stage:

Third SR's decision: P
Instructions for Short Run Players

If you are SR for a round, you will decide what action to take in your stages. Your payoff depends on the your action and LR's action. At each stage, LR and SR take actions simultaneously. SR chooses between action P and action G.

Below is the payoff table for SR. Given LR choosing action L, your payoff is 0 when you choose P and 1 if you choose G. If LR chooses action H, you get 3 by choosing P and 2 by choosing G.

<table>
<thead>
<tr>
<th></th>
<th>L</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>P</strong></td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td><strong>G</strong></td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

Each SR participant plays two stages in each round. Thus each SR subject receives the payoffs from the stages in which they participate. You will also see the following message on your screen when it is your turn to choose an action.

Your decision: (1=P, 2=G).

If you choose P, input 1 to your screen by using your keyboard and then use your mouse to click the OK button. Input 2 if you choose G and then click OK.

**Game 1**

In each round of Game 1, 8 SRs play against an LR. In Game 1, SR will observe the number of actions played by the LR in the previous stages in that round. For example, the game is currently at Stage 4 in a round. Suppose LR chose H in Stage 1, H in Stage 2, and L in Stage 3. Then the 4th SR will see the following message on his screen:

Number of L being played: 1
Number of H being played: 2

The above information tells the 4th SR that LR chose action H twice and action L once in the previous three stages. Note that it does not tell you anything about the order of the actions taken.

**Game 2**

In each round of Game 2, 8 SRs play against an LR. An SR can observe the order of LR's actions taken in previous stages. For example, the game is in Stage 4. LR chose H in Stage 1, H in Stage 2, and L in Stage 3.

Then the 4th SR will see the following on his screen:

In Stage 1, LR played H.
In Stage 2, LR played H.
In Stage 3, LR played L.