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# Reputation and pricing strategies in online market

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**Abstract:**Although pricing strategy in marketing is a crucial issue, there islittle literatureon the relationship between pricing and sellers' reputation based on dynamic pricing data**.** Using data on Taobao.com, we compare pricing behaviors of two types of sellers, business sellers (T-Mall sellers) which have higher reputation and individual sellers (Tao sellers) which have relatively lower reputation. We findthat sellers with different reputation levels will choose different pricing strategies and high-reputation sellers will have advantages in pricing. More specifically, our results reveal thatwhen a T-Mall seller enters into a market as a new extant it will be more likely to sethigher initial price than a Tao seller. In addition the magnitudes of price adjustments of Tao sellers have significant correlation with price changes in T-Mall market.On contrary, prices changes of T-mall sellers are not influenced by price changes in Tao market.

**Keywords:** reputation, pricing strategy, price adjustment, premium price

## 1. INTRODUCTION

Pricing, without doubt, is a crucialissuein both traditional and online marketplaces.As a key element of marketing strategy, pricing is essential to marketing performance and is the most direct driver of revenue [1]. In online market, consumers canmake price comparisons much easier and more efficiently. Even minor fluctuations or price disparities can have a significant impact on consumers' shopping decisions, and in turn influence sellers' revenues and profitability [2,3]. The price disparities or price changes are not only visible to consumers but also transparent to competitors. In hence sellers in online market sellers may be more complicated to decide their pricing strategies. Although a handful studies have considered price dynamics in online shopping situations[4], analysis on price movements and sellers' pricing behaviorsis still a challenging issue.

In online marketplace, consumers face more risks and uncertainties relative to traditional offline market. To reduce such uncertainties, many online platforms rely on reputation systems to promote consumers' trust in transactions.Online reputation system will support consumers to identify sellers with high quality.Both researchers and marketers agree that sellers will benefit a lot from high reputation [5,6]. For instance, many researchers provide evidence thathigh reputation willpromote large sales volume[7]. They suggest that customers are more willing to trade with reputable retailers which areperceived to be of high quality [8]. Many studies suggest that consumers are willing to pay higher price to reputable sellers, however, researchers do not reach an agreement on the impact of reputation on price. There are also many studies argue that high reputable does not guarantee those sellers high prices, but negative prices [9].Motivated by these contradictory findings, this study aims to explore if reputable sellers will have advantages in pricing. The majority of previous studies based on cross-sectional data to evaluate the positive or negative effect of reputation on price. We in this study will use a dramatically price data to make an in-depth analysis of reputation and sellers' pricing decisions.

Our analyses are based on data from the largest online C2C market in China, Taobao.com, whichhandled 1.1 trillion yuan (more than $160 billion) in sales in 2012. On taobao.com, there are two types of sellers. One is labeled by "Tmall" and we in this paper namethis type of sellersas "T-Mall sellers". To open a T-Mall shop, they must have business license issued by government and pay fees to Taobao.com including a guarantee fee and a

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yearly subscription fee, etc. The other type of sellers could be any individuals which may not have any business license. Weregard this type of sellers as “Tao sellers”. Compared to Tao sellersT-mall sellers are regarded as high reputation sellers, since they have business license which presents a high economic power and high quality. In this context, we try to shed light on different pricing strategies between Tao sellers and T-Mall sellers.

In offline market, it is hard to collect all sellers’ pricing decisions. Fortunately, online platforms such as Taobao.comprovide us an opportunity to access these data. During July 19 to Oct.12 in 2013, we collecteddaily price information of a new product (Lenovo IdeaPad Yoga 11S) which began on sale in July. During the sample period, the number of sellers is changing over time. We record sellers’ daily prices and price changes, and based on that we explore if sellers with different reputation level will choose different pricing strategies.

In specific, we attemptto answer the following questions:

(1) DoTao seller and T-mall seller choose different pricing strategies when acting asa new entrant?

(2) Which type of sellers change their prices more often?

(3) Do T-Mall (or Tao) sellers adjust their prices following by the price changes of the other type of sellers?

The paper is organized as follows. In Section 2, wereview the previous literature of the impact of reputation and pricing strategies.We then present results of our empirical analysis in section 3. Finally, in section 4, we discuss our research findings.

## 2. LITERATURE REVIEW

Reputation system engenders consumers’ trust in online marketplace and itbrings positive economic benefits to online reputable sellers [10].Ye et al. (2009)find empirical evidence that reputable sellers will obtain high sales volume[7].Many researchers suggest reputable sellers will receive a premium price. However, researchers do not reach an agreement on the impact of reputation on price. The majority of research on reputation and price suggest a positive correlation between reputation and price [11,12].They argue that consumers are willing to pay a higher price to reputable sellers [13,14], and expect to receive high-quality products and service in turn.However, Liu et al. (2012) find a negative price premium effect[9]. They suggest a high-reputation seller charges a lower price than a low-reputation seller.Though prior researches have investigated the impact of reputation on price, few studies are based on dynamic pricing data. We in this paper will complementary the existing literature by analyzing the impact of reputation on dynamic pricing decisions.

In search good market, there are mainly two alternative strategies, skimming strategy and penetration strategy[15]. When using a skimming strategy, sellers will set higher initial prices. If a penetration strategy is used, they will initiallyset lower prices to attract more consumers and get more sale volume. Some studies suggest pricing strategy for a new product need take product characteristics into account[16]. If a product has higher price sensitivity, the initial price should be lower, and in hence penetration strategy is more appropriate. Obviously sellers takinga skimming strategy will face more risk, since they will lose those consumers that do not want to pay higher prices. To the extent that reputable seller will receive a premium price is true, skimming strategy is more appropriate to reputable sellers. On a contrary, penetration strategy will be a feasible strategy for lowreputation sellers which do not have large pricing power in the market. Based on these analyses, we propose that T-mall sellers will charge higher initial price than Tao sellers when enter into a new market, and they are more likely to choose skimming strategy.

In competitive pricing situation, there are three strategies to be used, leader pricing, parity pricing and low-price supplier pricing. When a seller choose parity pricing strategy, it will match price set by the market or price leader[15]. We propose that high reputable sellers will choose leader pricing strategy, and low reputable sellers will influenced by high-reputation sellers’ pricing behaviors and thus choose parity pricing strategy when adjusting their prices.

# 3. EMPIRICAL ANALYSIS

## 3.1 Data collection

We developed a Java-based crawler to retrieve online data from Taobao.com, and we collected both sellers' reputation and pricing information from July 19 to Oct.12 in 2013. The product we focused on is Lenovo IdeaPad Yoga 11S-IFI, with 1.5-GHz Intel Core i5-3339Y processor, 4GB of RAM, 256 GB SSD Capacity, and Intel HD Graphics 4000 GPU. The product began on sales in July 2013.

There are totally 4883 product items retrieved during entire data collection period, however, many of them which have similar product names, are actually not selling Yoga 11S-IFI. So we made a further check and excluded nosy data manually.Then we got our final sample which consists of 3302 valid items.There are 86 days in the sample, for an average of 38 sellers per day.At the beginning of data collection, there are only 9 sellers in the market, 3 T-mall sellers and 6 Tao sellers. The number of sellers increased over time, and during the sample period, some sellers came into the market and also some sellers quitted the market before we ended our collection. In Figure 1, we plot dynamics of the daily mean prices for the sample period. From the plots we see that large decreases in the price occurs after 5 days, and then 12 days later the mean price increases gradually. The prices are more dynamic at earlier stage and become stable at later.

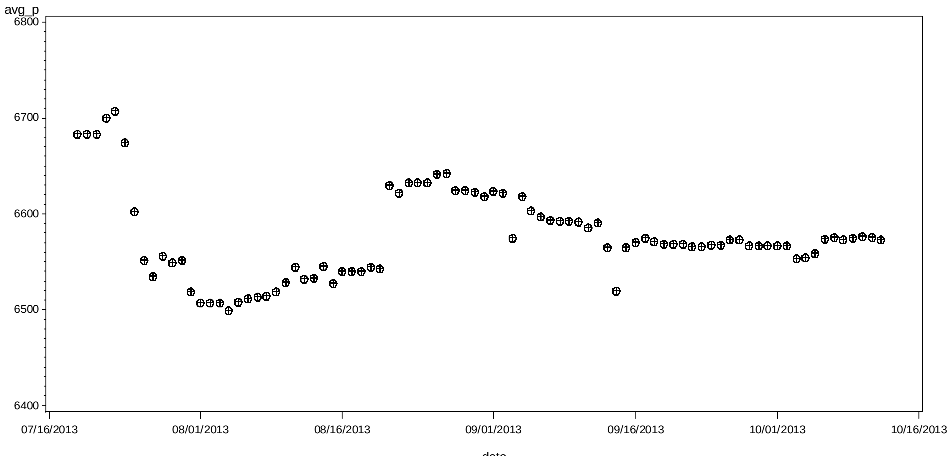


**Figure1.Mean prices over time**

## 3.2 Results

In this section, we firstly studied the pricing strategies for new entrants.Within the new product pricing situation, we explored if sellers with different reputation levels will choose different strategies when setting their initial prices.We then analyzed the frequency of price adjustments. We built a regression model toestimate factors influence sellers' price adjustments.

### 3.2.1 Pricing strategy for new entrants

During our data collection period, there are totally 63 new sellers arrive to the market (not including those 9 sellers which have already appeared at first day). In Figure 2the variable in vertical axis is relative price for a new entrant.The red plots represent data in T-mall market, and the blue onesdemonstrate initial relative price of Tao sellers. When seller *i* come into the market at date *t*, its initial relative price $p\_r\_new_{i,t}$ is defined as its initial price divided by the mean market price at date *t*.

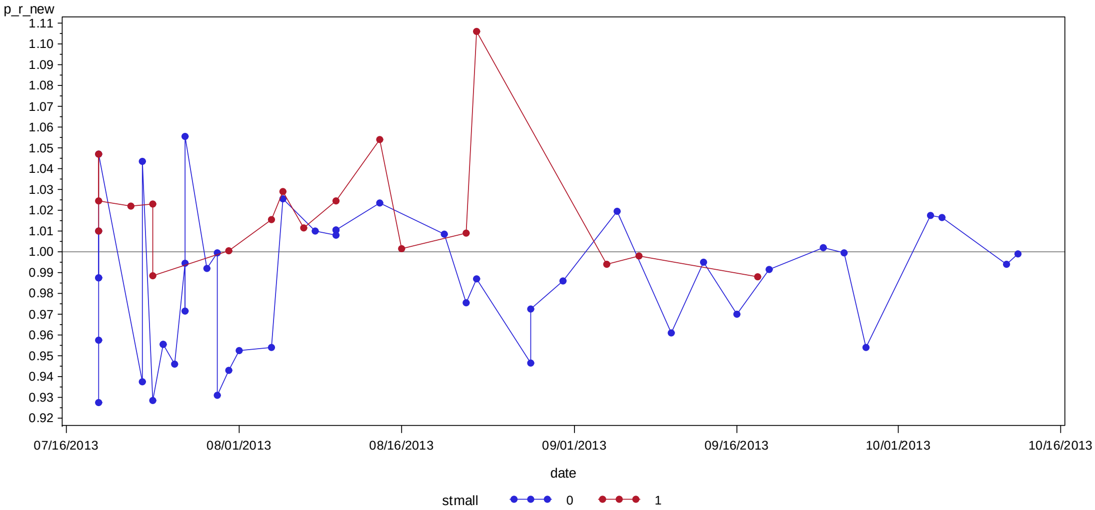


**Figure2.Relative prices for new entrants**

We conducted a t-test for these two groups (Table 1), and the results indicate thatwe can accept the null hypothesis that there is no difference in the variances between groups.Using the first method (Pooled variance estimator) for our t-test, we canreject the null hypothesis that there are no statistically significant differences between means. Our results revealed that the relative prices in Tao and T-mall market have different mean value and it is higher in T-mall market (*tmall*=1). That is to say when a T-mall seller enters into a market as a new entrant it will be more likely to set a higher initial price (use skimming strategy).

**Table 1.T-testprocedure**

(a) Statistics for variable: p_r_new

| *tmall* | N | Mean | Std Dev | Std Err | Minimum | Maximum |
|---|---|---|---|---|---|---|
| 0 | 45 | 0.9860 | 0.0326 | 0.00485 | 0.9277 | 1.0559 |
| 1 | 18 | 1.0194 | 0.0283 | 0.00668 | 0.9881 | 1.1062 |
| Diff (1-2) | | -0.0334 | 0.0314 | 0.00877 | | |

(b) T-Tests

| Method | Variances | DF | t Value | Pr > \|t\| |
|---|---|---|---|---|
| Pooled | Equal | 61 | -3.82 | 0.0003 |
| Satterthwaite | Unequal | 35.823 | -4.05 | 0.0003 |

© Equality of Variances

| Method | Num DF | Den DF | F Value | Pr > F |
|---|---|---|---|---|
| Folded F | 44 | 17 | 1.32 | 0.5447 |

### 3.2.2 Price adjustment strategy

Table 2 shows the price adjustment patterns in Tao Market and T-Mall market. Columns I, II, and III represent the total number of price changes,frequencies ofprice increases and price decreases in the subsequent period, respectively.

**Table 2.Frequency andmagnitude ofprice changes**

| Group | Frequency of price changes | | | Size of price changes | |
|---|---|---|---|---|---|
| | changes(I) | increase(II) | decrease(III) | Mean(IV) | StdDev(V) |
| Tao | 57 | 20 | 37 | -65.4736842 | 311.0506450 |
| T-Mall | 55 | 26 | 29 | 39.3485455 | 250.9686953 |

From the above table we can seesellers are more often to cut down prices than raise their prices, especially in Tao market. Though, the frequency of price increases (N = 26) was smaller than the frequency of price decreases (N = 29), the mean value of price changes of T-Mall sellers are higher than zero. The results imply that the magnitude of price increases is greater than the magnitude of price decreases in T-Mall market.

Then, we test if a seller's price adjustment has significant correlation with T-Mall sellers' price adjustments at time *t-1*, Tao sellers' price adjustments at time *t-1*, changes of T-mall market price at time *t-1*, and changes of Tao market price at time *t-1*. We built the following regression model.

$$\begin{aligned}\Delta p_{i,t} &= \alpha + \beta_1 Adj\_p_{t-1}^{Mall} + \beta_2 Adj\_p_{t-1}^{Tao} + \beta_3 Chan\_avgp_{t-1}^{Mall} + \beta_4 Chan\_avgp_{t-1}^{Taol} \\ &+ \sum \gamma Control\ variables\end{aligned} \quad (1)$$

In the above equation,

$\Delta p_{i,t}$ indicatesprice change of seller *i*attime*t*.

$Adj\_p_{t-1}^{Mall} = \sum_{j}^{J} \Delta p_{j,t-1}$ is the total sum of sellers' price adjustments in T-Mall market at time *t-1*. Similarly,

$Adj\_p_{t-1}^{Tao}$ is the total sum of sellers' price adjustments in Tao market at time *t-1*.

$Chan\_avgp_{t-1}^{Mall}$ isthe change of T-mall market price at time *t-1* which defined as T-mall market price attime*t-1* minus that at time*t-2*.Similarly, $Chan\_avgp_{t-1}^{Tao}$ is the change of Tao market price at time *t-1*.

Control variables:

$Dev\_p_{i,t-1} = price_{i,t-1} - \overline{price_{t-1}}$ , is seller *i*'s price deviation from market price attime*t-1*.

$flag\_trans_{i,t-1}$ =1, if seller *i* have sold the product at time *t-1*, and zerootherwise.

$Chan\_avgp_{t}^{Mall}$, $Chan\_avgp_{t}^{Tao}$ are defined similarly as $Chan\_avgp_{t-1}^{Mall}$ and $Chan\_avgp_{t-1}^{Tao}$.

In our full sample, totally 112 sellers adjusted their prices. We divide the sample into two groups, one is clustered by Tao sellers, and the other is grouped by T-Mall sellers.Table 3 shows descriptive statistics of variables.

**Table 3. Sample statistics**

| Variable | Group1 (Tao) | | | Group2 (T-Mall) | | |
|---|---|---|---|---|---|---|
| | N | Mean | StdDev | N | Mean | StdDev |
| $\Delta p_{i,t}$ | 57 | -65.4736842 | 311.0506450 | 55 | 39.3485455 | 250.9686953 |
| $Adj\_p_{t-1}^{Mall}$ | 57 | 83.3861404 | 234.1932528 | 55 | 41.9276364 | 280.2058130 |
| $Adj\_p_{t-1}^{Tao}$ | 57 | -95.0877193 | 275.4574300 | 55 | -130.9454545 | 274.1536078 |
| $Chan\_avgp_{t-1}^{Mall}$ | 57 | 5.0748862 | 38.4945328 | 55 | -5.0691003 | 21.7852178 |
| $Chan\_avgp_{t-1}^{Tao}$ | 57 | -1.5348233 | 29.7912814 | 55 | -4.4465385 | 29.7035721 |
| $Chan\_avgp_{t}^{Mall}$ | 57 | -10.3350089 | 36.1247670 | 55 | -8.0829396 | 27.7605549 |
| $Chan\_avgp_{t}^{Tao}$ | 57 | 2.2095761 | 35.1522540 | 55 | 2.2633319 | 27.3488121 |
| $Dev\_p_{i,t-1}$ | 57 | -104.2834933 | 237.7067618 | 55 | -31.9906223 | 126.6832652 |
| $flag\_trans_{i,t-1}$ | 57 | 0.3508772 | 0.4814868 | 55 | 0.5272727 | 0.5038572 |

Estimates for the coefficients are reported in Table 4.In Group 1, coefficient of $Chan\_avgp_{t-1}^{Mall}$ is significant. This indicates that the magnitudes of Tao sellers' price adjustments will be influenced by T_Mall market price changes. The results in Group 2 show that the magnitudes of T-Mall sellers' price adjustments will be influenced by T_Mall market price changes and T-Mall sellers' price adjustments at time *t-1*.On contrary, coefficients of $Adj\_p_{t-1}^{Tao}$ and $Chan\_avgp_{t-1}^{Tao}$ are both insignificant. It shows that Tao market price changes and Tao sellers' price adjustment will not influence seller' price adjustment decisions in the next day. The significant coefficients of $Dev\_p_{i,t-1}$ suggest that if a seller's price deviated much from market price at time *t*, it will adjust its price to reduce the deviationin the subsequent time.

**Table 4.Regression results for two groups**

| Variable | Group1 (Tao) | | | | Group2 (T-Mall) | | | |
|---|---|---|---|---|---|---|---|---|
| | ***Coef.*** | ***Std. Err.*** | p | VIF | ***Coef.*** | ***Std. Err.*** | p | VIF |
| $Adj\_p_{t-1}^{Mall}$ | -0.2740 | 0.1851 | 0.1454 | 1.96 | 0.3054** | 0.1362 | 0.0298 | 2.47 |
| $Adj\_p_{t-1}^{Tao}$ | 0.1697 | 0.1292 | 0.1952 | 1.32 | -0.0116 | 0.1092 | 0.9156 | 1.52 |
| $Chan\_avgp_{t-1}^{Mall}$ | 3.2817** | 1.2583 | 0.0121 | 2.45 | 1.6031 | 1.4378 | 0.2706 | 1.66 |
| $Chan\_avgp_{t-1}^{Tao}$ | -0.5154 | 1.2527 | 0.6826 | 1.45 | 0.1129 | 0.9205 | 0.9029 | 1.27 |
| $Chan\_avgp_{t}^{Mall}$ | 3.3969*** | 1.2645 | 0.0099 | 2.18 | 3.6900*** | 1.0220 | 0.0008 | 1.36 |
| $Chan\_avgp_{t}^{Tao}$ | 0.6940 | 1.0192 | 0.4992 | 1.34 | 1.6332 | 0.9797 | 0.1023 | 1.21 |
| $Dev\_p_{i,t-1}$ | -0.6175*** | 0.1731 | 0.0008 | 1.77 | -0.9518*** | 0.2354 | 0.0002 | 1.50 |
| $flag\_trans_{i,t-1}$ | 2.2350 | 70.9021 | 0.9750 | 1.22 | -123.7514** | 55.1899 | 0.0298 | 1.31 |
| F -Value | 6.62 | | | | 7.57 | | <.0001 | |
| Adj- R2 | 0.4452 | | | | 0.4934 | | | |

*, **, ***significance level of 0.1, 0.05, and 0.01, respectively.

## 4. CONCLUSIONS

Our results demonstrate that sellers with different reputation levels will choose different pricing strategies. Firstly, we find that initial prices set by T-Mall sellers are statistically higher than those set by Tao sellers. That is to say, high reputable sellers are more likely to choose skimming strategy when enter into a new market.

Secondly, our analyses find directional supportthatlow reputable sellers are more often to cut down their prices over time, and the magnitude of price decreases are larger than that of high reputable sellers. Moreover, it is surprising to find thatalthough the frequency of price increases is smaller than price decreases, the mean value of magnitudes of price increases is larger than price decreases in T-Mall market.

Thirdly, we find Tao sellers' price adjustments are influenced by T-Mall market price changes. On a contrary, Tao sellers' price adjustment behaviors and as well as changes of market price in Tao Market have no significant impact on the following sellers' price adjustment decisions.

Our study contributes to the understandings on the effects of seller reputation on pricing.However, our study is still preliminary in analyzing their dynamic relationships.Some other factors such as market competition still need to concern in future research.

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