The Effect of Reputation on Performance of New vs. Established Sellers: An Empirical Study of Chinese Largest E-commerce Platform

by

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Abstract

We study the dynamic return of reputation using a panel data set selected from the largest e-commerce platform in China, Taobao.com. We distinguish new sellers from established sellers, and compare the effects of reputation on their monthly revenue, monthly transaction volume and revenue per transaction by using panel data regression model and IV controlling for seller and month fixed effects. We find a substantial reputation return for established sellers, while for new sellers, they need to actively manage their reputation. For established sellers, they have higher transaction volumes and better bargaining power as reputation grows. In contrast, for new sellers, they may need to cut the price to increase transaction volume and reputation.

Keywords: seller reputation, sales performance, reputation return, e-commerce platform, online market, life-cycle

Introduction

It has been long recognized by economists that information asymmetries can lead to market inefficiencies, and under extreme condition, it can even potentially lead to market failure (Akerlof, 1970). Nowadays, in e-commerce markets, such a problem of information asymmetry might be even worse due to the nature of online shopping, where the two sides of transactions trade anonymously. To deal with these problems, almost all of the e-commerce platforms are designed with reputation system that collects feedback and comments from buyers about their past transactions and transforms the past selling experience of the seller into observable scores or rankings for other potential buyers to see, so that the interaction between buyer and seller can improve the service and transparency for online shopping.

However, how does the reputation affect the behavior of market participants? Much of the previous literatures on reputation for both online and offline markets concentrate on buyer side instead of the seller, with a handful of studies using empirical data from online markets such as eBay and Taobao studying the relationship between reputation and price or sales volume. In order to answer the question from both sides of the transaction, we would like to focus more on the seller side of the e-commerce market in this paper.

One intrinsic dynamic feature of reputation implies that the effect of reputation may be different for sellers at different stages of their business' life-cycle. Empirically, there are existing literatures studying the static return to reputation, however, not many studies focused on the incentives for new sellers to build reputation for long-term profits. In this research, we try to bridge this gap by studying the dynamic effects of reputation using the dataset from Taobao, the largest e-commerce platform in China.

By using the panel data set including 1,322,546 Taobao Marketplace sellers during 5 months in 17 different product categories, we studied the difference between effects of reputation on seller performance separating new and established sellers. We found significant difference of reputation's effects on revenues for sellers at different life-cycle stages by using the model of panel data regressions and IV with both seller and month fixed effects. We found that for established sellers, there is a reputation premium; while for new sellers, they need to actively manage their reputation. By decomposing revenue into transaction volume and average revenue per transaction, we found that for established sellers, they have higher transaction volumes and can charge a higher price as reputation grows; while for new sellers, they may need to cut the price to increase transaction volume and reputation. By focusing on a fixed group of new sellers, we got evidence that even for new sellers who still have incentives to manage their reputation, they start to enjoy some reputation premium as they become somewhat established.

In Section 2, we provided literature reviews and discussed the findings and gaps of existing studies. In Section 3, we introduced Taobao and its reputation system, which is the source of our panel data set, and gave an introduction of the dataset and showed some descriptive statistics about the data set to give an overview. We illustrated our empirical framework in Section 4, including one important definition of new and established sellers, the panel data regression model and the instrumental variable we used in this research. In Section 5, we discussed the results of analysis and interpret the results with respect to our research questions. In the last section, we drew our conclusion, suggested some possible implications of this research and discussed some limitations of this research, which might give inspirations and suggestions for future research.

Literature Review

Previous literatures about the influence of the seller's reputation on performance were reviewed. The studies involve the relationship between reputation and performance from price to sales volume. And this is followed by a review of some empirical studies on different ecommerce platforms in different countries.

Information asymmetry has been long recognized by scholars that it would lead to market inefficiency and even market failure (Akerlof, 1970). And online markets are believed to be troubled by information asymmetry problem. In the research conducted by Ghose, Ipeirotis and Sundararajan who used text mining techniques in online electronic markets, they stated that a buyer can only evaluate the quality about products of a seller through seller's description before transaction, and the real quality of the seller can only be evaluated after transaction is done (Kauffman, 2000). Reputation mechanisms might be able to mitigate the information asymmetry problem (Ghose, Ipeirotis, & Sundararajan, 2009). As Cabral and Hortacsu states, the "… eBay reputation system gives way to noticeable strategic responses from both buyers and sellers" (Cabral and Hortacsu, 2010). As an indicator of quality, reputation of the seller provides information for buyer to know more about the seller and his products, so that it can reduce the unbalanced information between two sides of transaction and enhance the trust between them (Ba & Paul, 2002).

Most of researches related to the relationship between reputation and price shows that the reputation of seller has a significant effect on auction price. Depken and Gregorius analyzed action transactions of Apple iPhone from eBay and found that "closing prices are influenced by the level of seller reputation" (Gregorius & Depken II, 2010). To be more specific, a seller with better online reputation will be able to receive a higher final price for the auctioned product.

Since in the online auction market, it is difficult to observe and evaluate the quality of the auctioned products, while reputation may serve as a signal to product quality, so that buyers may be more willing to offer sellers with monetary incentives with the hope to get better quality, which is defined as price premium by Shapiro (Shapiro, 1983). However, as the seller reputation increases, it is not always true for sellers to receive a higher price. In other words, buyers are not always willing to pay premiums to sellers with high reputation (Jin & Kato, 2006). Therefore, a high reputation does not always lead to a price premium.

Besides above studies related to the correlation between reputation and product price, there are also plenty of scholars studied the relationship between reputation and sales volume. A significant impact of reputation on the likelihood of sales were found by Dewan and Hsu using eBay data (Dewan & Hsu, 2004). And a strong correlation between reputation and sales volume were discovered from Taobao Buy-It-Now (BIN) data (Ye, Li, Kiang, & Wu, 2009).

To sum up, empirical studies using dataset from eBay US showed a significant impact of reputation on price (price premium), while studies using dataset from Taobao revealed an important effect of reputation on sales volume. Regarding empirical studies using data from Taobao, three studies were reviewed. One of them revealed the auction price premium effect of seller's reputation (Zhao & Huang, 2008); while the other two studies based on Taobao all found the strong relationship between seller's reputation and sales volume, but no clear correlation with price premiums (Ye, Li, Kiang, & Wu, 2009). A more recent study based on Taobao found a non-linear relationship between reputation and sales volume (Zhang & Zhang, 2011). To be more specific, there exist a threshold of seller's reputation. When seller's reputation is below the threshold, sales volume decreases with the improvement of seller's reputation; while when above the threshold, there is a positive correlation between seller's increasing reputation and sales volume.

Above review of previous studies showed that there are differences between the findings of reputation effects on price and sales volume for dataset from eBay US and Taobao. Moreover, in the recent study which reveals the non-linear relationship, the authors did not specify the reason for the existence of threshold, so that it is hard to interpret the meaning of the threshold, in other words, why there are different impacts for sellers with different reputation level.

One intrinsic dynamic feature of reputation implies that the effect of reputation may be different for sellers at different stages of their business' life-cycle. For instance, some previous literature regrading reputation dynamics (Shapiro, 1983) shows that, sellers may choose to realize low or even negative profits in the beginning so that they may earn a reputation premium in the future. In other words, new sellers may be willing to sacrifice their short-term profits for long-term reputation and behave differently to change in reputation compared with established sellers. Empirically, there are existing literatures studying the static return to reputation as we discussed above, however, not many studies focused on the incentives for new sellers to build reputation for long-term profits. In this research, we try to bridge this gap by studying the dynamic effects of reputation using the dataset from Taobao, the largest e-commerce platform in China.

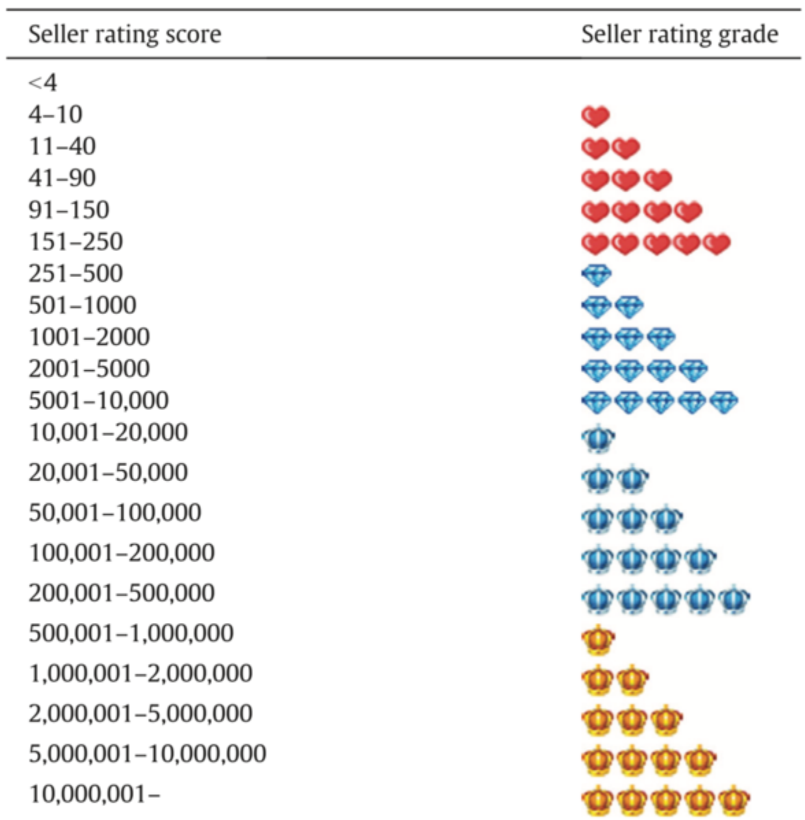
Background and data

Taobao and its online reputation system

E-commerce in China is a rapid-growing and multi-billion dollar market, where Taobao is market leader without doubt. In the Chinese e-commerce market, Taobao, founded by the Alibaba Group, Inc. in May 2003, is an indisputably leading platform, which provides an online marketplace for small businesses and individuals to trade with customers. With an innovative website service and technical support at only little cost to sellers, Taobao dominated all other Chinese e-retailers soon, including eBay China and Amazon.cn. By the end of 2016, Taobao had approximately 500 million registered users, with over 60 million regular visitors on a daily basis and an average of 48 thousand products sold every minute.

To prevent sellers from registering multiple accounts or changing their online identidy, Taobao requires that all sellers register their Taobao accounts with valid national identification cards, which contains information on name, gender, ethnicity, date of birth, address, a unique identification number and a photo of the card holder. To register a seller account, a seller must upload a scan of his national identification card as well as a picture of herself holding the card. This requirement links the online identity of the seller to her personal offline identity, which makes it difficult for an individual to open an account using others' identification cards or to have multiple accounts.

In addition to the registering requirements, Taobao also provides a reputation system to build trust between buyers and sellers in the transaction. In Taobao, a buyer can rate the seller after each transaction for each product they purchase. The default rating score is positive (+1) for each product sold, unless it is overwritten by the buyer with zero (0) or negative (-1) point. The rating score of a seller is the cumulative sum of all the feedback scores from the previous transactions. Given this nature of the calculation of rating score, the rating score is dependent on the cumulative transaction volume. A seller's rating score is then categorized into one of 20 rating grades, with each being represented by a system of hearts, diamonds, crowns and golden crowns. Please see Fig. 1 for the mapping from rating score to rating grade in Taobao. These 20 grades are well recognized by all Taobao buyers, for example, a "crown" seller is regarded as a successful and trust-worthy seller. All rating grades will be displayed on the official shop websites of the seller and will also appear together with their product in search results.



Seller rating score	Seller rating grade
<4	
4–10	
11–40	
41–90	
91–150	
151–250	
251–500	
501–1000	
1001–2000	
2001–5000	
5001–10,000	
10,001–20,000	
20,001–50,000	
50,001–100,000	
100,001–200,000	
200,001–500,000	
500,001–1,000,000	
1,000,001–2,000,000	
2,000,001–5,000,000	
5,000,001–10,000,000	
10,000,001–	

Figure 1. [The reputation system of Taobao: Seller's rating score and rating grade.]

In Taobao, a seller can also rate a buyer after each transaction. For a registered user that has both behaviors as a seller and a buyer, Taobao distinguishes his rating score as a seller from his rating score as a buyer. In another word, a seller's rating score as a seller on Taobao is based on the feedback he gets only as a seller, which means he cannot manipulate his rating score by increasing his purchasing volume.

Data

Our primary dataset used in this research is a random sample from Taobao.com, which includes over 1 billion sellers' information during 5 months in 17 different product categories. In order to get this sample, information about category was acquired from the store searching website page of Taobao, and then store searching was conducted according to the product category, so that data about store information could be acquired through analysis of JSON results. Repeated stores are deleted after crawling firstly, since a seller may sell products in multiple categories. Each month, we repeated the crawling process, and got the panel data set from October 2017 to February 2018.

For Taobao, it distinguishes Mall sellers from Marketplace sellers. Marketplace sellers are those individuals or small businesses selling online, while Mall sellers are companies, brand owners who have their Taobao official online accounts. Our random sample includes 1,322,546 Taobao Marketplace sellers and 10,474 Taobao Mall sellers. Since these Mall sellers also have offline reputation which may affect their online reputation and online performance, I excluded them from the sample, leaving only 1,322,546 Taobao Marketplace sellers in the dataset. Besides, we also drop inactive sellers who do not have any transaction records in at least one month and also sellers with obvious data errors. In the end, we are left with 1,063,167 Marketplace sellers in our final sample.

For each seller, we observed the basic account information including the unique seller id, location, store name, cumulative revenue, cumulative transaction volume, main business category of each seller, and also several measures of seller reputation, for instance, rating score, rating grade, which is determined by rating score, and percentage of positive ratings.

Fig. 2 shows the time series for the number of sellers in our sample, the average rating score and average monthly revenue in the five months of our sample period from October 2017 to February 2018. We observe a plunge in February 2018 for both average monthly revenue and the number of sellers. This might be caused by the Chinese New Year and Spring Festival, during which most of the sellers and almost all of the parcel delivery companies are on a break.

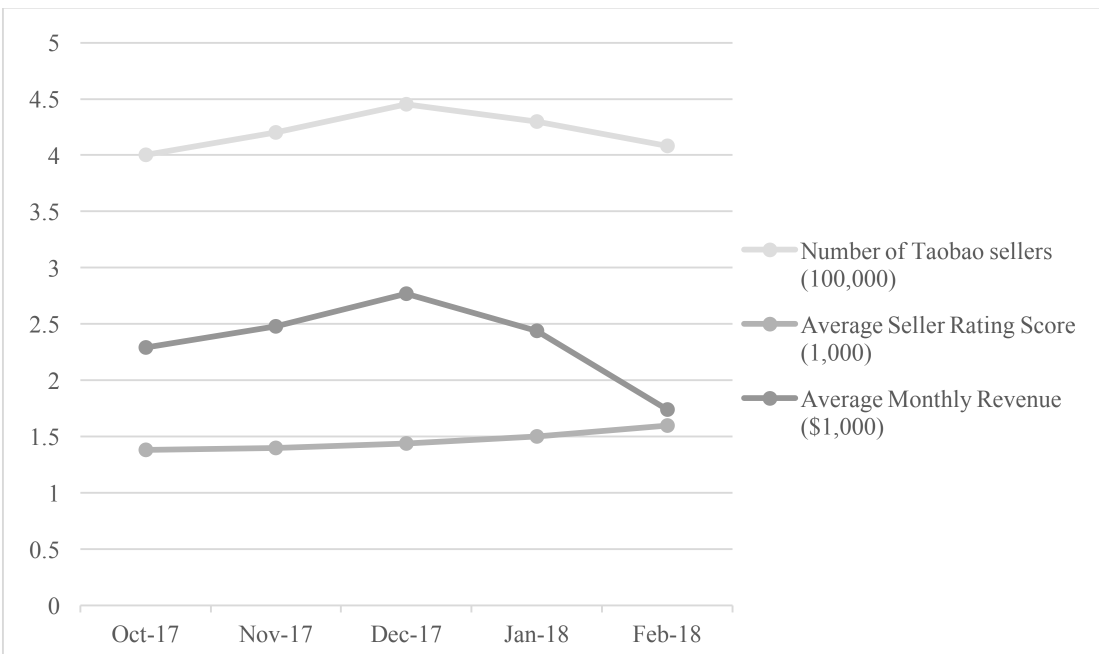


Figure 2. [Development of Taobao sellers over time in our sample.]

Fig. 3 shows the distribution of ratings of seller in our updated new random sample. For each rating grade symbol, we assign a numerical rating grade from 0 to 18. In this random sample, the highest rating grade is 18, which is 3 golden crowns equivalently. From Fig. 3 we see that approximately 40% of sellers are in or above diamond grade, while only fewer than 2.5% sellers are above crown status, and very few enter the golden crown status.

Seller rating score	Seller rating grade[a]	Frequency	Percent	Cumulative
Below 4	0	393,803	7.35	7.35
4–10	1	441,247	8.23	15.58
11–41	2	867,299	16.18	31.76
41–90	3	632,231	11.8	43.56
91–150	4	424,077	7.91	51.47
151–250	5	419,987	7.84	59.31
251–500	6	639,662	11.93	71.24
501–1000	7	535,426	9.99	81.23
1001–2000	8	404,274	7.54	88.77
2001–5000	9	338,159	6.31	95.08
5001–10,000	10	135,936	2.54	97.62
10,001–20,000	11	74,895	1.40	99.02
20,001–50,000	12	39,300	0.73	99.75
50,001–100,000	13	8,819	0.16	99.91
100,001–200,000	14	2,954	0.06	99.97
200,001–500,000	15	1,292	0.02	99.99
500,001–1,000,000	16	236	4.40e−05	100
1,000,001–2,000,000	17	101	1.89e−05	100
2,000,001–5,000,000	18	30	5.60e−06	100
Seller/months		5,359,728		

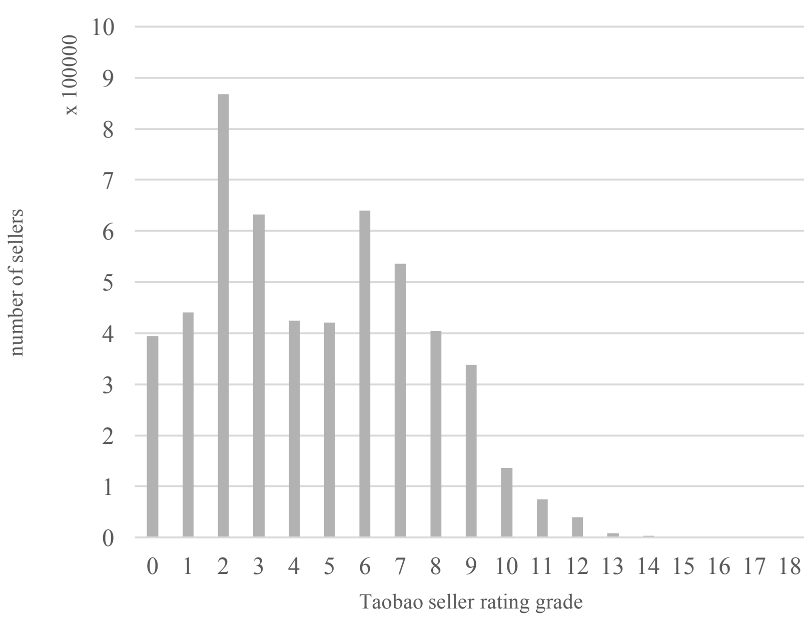


Figure 3&4. [The distribution of seller ratings in our sample.]

Empirical framework

Definitions of new and established sellers

In order to study the different impacts of reputation on seller's performance and behaviors at different stages of their life cycle, we need to separate new sellers from established sellers in our dataset. Two factors are considered when distinguishing new sellers: beginning time the seller enter the platform and the level of cumulative transaction volume. For instance, a seller who just started selling in the platform and is still at a low level of transaction volume is defined as a new seller, while an established seller is someone who has been selling on Taobao for a certain amount of time and has reached to a certain level of cumulative transaction volume. To be more specific, since we have a panel data, we define new and established sellers based on their first appearance in the data and their cumulative transaction volume at their first appearance. Table 1 shows in detail the criteria for two groups of seller. The definition has been checked by running the regression model discussed in the next part taking log(revenue) as dependent variable, the coefficients of all three rating factors are all statistically significant, which shows that our definition will generate robust regression results.

Table 1

[*Definitions of new and established sellers.*]

	First appearance	Cumulative transaction at first appearance
New seller	Later than Month 1	≤ 30
Established seller	In Month 1	> 250

According to the above definition, a seller who appears in the data in Month 1 (October 2017) and has reached a cumulative transaction volume of 250 at that time is an established seller. The reason why we choose 250 is that a score of 251 is the threshold for a seller to have a diamond status. Other the other hand, if a seller appears in the data later than the first month with a cumulative transaction volume of less than 30, it will be defined as a new seller. 30 is chosen because it was found that for sellers who first appear in data later than first month, approximate 74% of them have their transaction volume below 30. By satisfying both criteria, we avoid the conditions where some established sellers stop selling for some periods and then returned to business but still have good performance. Because in this case, even though they appear in the data set later than Month 1 but their cumulative transaction amount is above 30 at their first appearance.

Based on the definition, we reorganized the data, separated the new sellers and established sellers from the whole dataset and found that there are 329,169 new sellers and 104,138 established sellers. In Table 2, I summarize the statistics for these new and established sellers. In general, it shows that new sellers have much lower monthly revenue and monthly transactions, a lower rating score and rating grade compared with established sellers. Though the positive rating is about the same for both groups, established sellers have a much more stable one and have a lower variance.

Table 2

[*Summary statistics of new sellers vs. established sellers.]*

	New Sellers		Established Sellers	
	Mean	**Std. dev**	**Mean**	**Std. dev**
Monthly revenue ($)	876.61	8459.18	5966.28	44993.89
Monthly transactions	40.24	188.97	327.73	2386.05
Rating score	109.07	422.64	4670.87	23347.87
Rating grade	2.46	1.91	8.2	1.61
Positive rating (%)	99.496	2.682	99.267	0.8

Empirical model

To study the different effects of reputation on performance of new and established sellers in their different stage of life cycle, I would like to run regression separately for two groups of sellers. All three rating indicators will be taken into account, together with other factors including a seller fixed effect and a month fixed effect using the panel data. The proposed regression model is

$$y_{it} = \alpha_1 RatingGrade_{i,t} + \alpha_2 RatingScore_{i,t} + \alpha_3 \%PositiveRate_{i,t} + \mu_i + \omega_t + \varepsilon_{it},$$

where

$RatingGrade_{i,t}$: the numerical rating score from 0 to 18 for seller *i* in month;

$RatingScore_{i,t}$: the total rating score for seller *i* in month *t*;

$\%PositiveRate_{i,t}$: the percentage positive rate for seller *i* in month *t*;

μ_i: seller fixed effect;

ω_t: month fixed effect; and

ε_{it} : seller and month specific error term, assuming i.i.d. across sellers and over time.

In this regression model, we are able to alleviate the endogeneity concerns. By including seller fixed effects, we can reduce the effects of factors other than reputation on performance, such as a well-designed online store interface or an easy-to-remember store name, which may have potential effects on revenue and rating score of the seller. In this way, we can only focus on the effect of reputation on performance. On the other hand, the month fixed effect helps us control the differences in different months, for instance, any seasonal effects such as Double Eleven Shopping Day and Chinese Spring Festival holiday, or macroeconomic conditions, which have impacts on all sellers.

As discussed above, using seller fixed effects will alleviate most of the endogeneity concerns, however, there might still be some potential endogeneity problems when the seller and month specific error term ε_{it} is correlated with the seller's rating. For example, there might be a selection bias. In the data crawling process of each month, we only select seller who choose to continue operating their stores in the given month. Thus, we omit the sellers who choose to exit the market. If the revenue shock ε_{it} and the rating together contribute to the decision of leaving the market, in other words, the survival of the seller, ε_{it} and rating are then correlated.

To solve the potential endogeneity problems mentioned above, we introduce an instrumental variable, the cumulative transaction volume as a buyer, into the model. For this instrumental variable to work, we need the cumulative buyer transaction to be correlated with seller's rating, and to be independent with the error term conditioned on seller and time fixed effects.

On the one hand, the first requirement is fulfilled, since a seller's cumulative transaction volume as a buyer is likely to be correlated with his rating. It can be explained based on the length of time the seller use Taobao. If a seller spends more time on Taobao, it will affect his buyer transaction volume as well as his seller transaction volume, and then influence his selling rating. On the other hand, the cumulative buyer transaction volume is independent with the error term. Because we have included seller fixed effects in the model to control for the unobservable seller heterogeneity, and therefore we believe that the shock conditioned on the seller fixed effect is independent over time.

Given the above arguments on relevance and exogeneity, the cumulative seller's transaction volume as a buyer satisfies the condition to be a valid instrumental variable. In the previous regression model we built, rating grade is a function of rating score. Here, we construct a grade variable based on seller's cumulative transaction volume as a buyer following the same cutoff threshold as shown in Figure 3, and include it as an instrumental variable.

Table 3 provides the summary statistics for the instrumental variables while Table 4 presents the first-stage results. From the first-stage results, we can see that the seller's transaction behavior as a buyer are significant factors of his seller rating. All F-statistics in the first-stage regressions shown in Table 4 are far larger than 10 and therefore we can reject the null hypothesis that excluded instruments are irrelevant in the first-stage regressions.

Table 3

[*Summary statistic of instrumental variable.]*

	New Sellers		**Established Sellers**	
	Mean	**Std. dev**	**Mean**	**Std. dev**
Cumulative buyer transaction	77.28	247.531	202.537	337.984
Cumulative buyer transaction grade	2.253	1.838	3.931	1.931
Number of Sellers	329,169		104,138	

Table 4

[*First-stage regression results.]*

	New Sellers		Established Sellers	
	Rating Score	**Rating Grade**	**Rating Score**	**Rating Grade**
Buyer transaction grade	53.649***	0.559***	104.049***	0.178***
	(0.603)	(0.002)	(18.288)	(0.001)
Buyer transaction	0.081***	6.165e-5***	3.813***	6.703e-5
	(0.002)	(6.357e-6)	(0.080)	(4.588e-6)
% Positive ratings	1.514	49.583***	13.347	48.566***
	(5.060)	(14.080)	(30.706)	(17.708)
Seller fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
F-statistic	7944.26	81671.63	2025.74	43022.76
Number of Sellers	329169		104138	

Result & Discussion

Using the empirical model proposed in the previous section, we apply the data set to the panel data regression model, run regressions for new and established seller group separately and get the results accordingly. We provide three specifications, from including only one rating indicator to gradually adding more seller rating measures, and show results for both OLS and IV results. For each regression, we include both seller fixed and month fixed effects in each specification. There are three main findings from analysis of data results that answer the question in Section 1 and show the significant differences between new sellers and established sellers.

Finding 1: For established sellers, there is a reputation premium. While for new sellers, they need to actively manage their reputation.

Table 5 and 6 present the regression results when we take log monthly revenue on various rating variables for new and established sellers. We display three different results by adding more seller rating variables gradually, and use both OLS (Table 5) and IV (Table 6) model. We include seller fixed effects and month dummies in all six regressions.

Compared the results from Table 5 with Table 6, we can observe a negative bias in the OLS regression. This bias leads to the underestimation of the percentage change in a seller's monthly revenue by approximately 5% when his rating grade increases by one unit. This bias could be probably generated by the negative correlation between the rating measures and the error term, which we discussed in last section.

Table 5

[*The effect of reputation on log(revenue) with OLS method.]*

new sellers	1	2	3
rating grade	-0.079***	-0.091***	-0.092***
	(0.004)	(0.005)	(0.005)
rating score		1.030e-4***	1.057e-4***
		(1.291e-5)	(1.287e-5)
%positive ratings			2.194***
			(0.216)
seller fixed effects	Yes	Yes	Yes
month fixed effects	Yes	Yes	Yes
Established sellers	1	2	3
rating grade	0.318***	0.314***	0.324***
	(0.007)	(0.007)	(0.007)
rating score		2.228e-6***	2.455e-6***
		(4.518e-7)	(5.085e-7)
%positive ratings			27.396***
			(2.616)
seller fixed effects	Yes	Yes	Yes
month fixed effects	Yes	Yes	Yes

*** significant at 1% level

Note: [The regressions below take log(monthly revenue) as dependent variable.]

Table 6

[*The effect of reputation on log(revenue) with IV method.]*

new sellers	1	2	3
rating grade	-0.287***	-0.167***	-0.166***
	(0.011)	(0.038)	(0.038)
rating score		1.132e-3***	-1.152e-3***
		(3.396e-4)	(3.386e-4)
%positive ratings			1.858***
			(0.215)
seller fixed effects	Yes	Yes	Yes
month fixed effects	Yes	Yes	Yes
Established sellers	1	2	3
rating grade	0.427***	0.354***	0.378***
	(0.035)	(0.039)	(0.039)
rating score		4.640e-5***	4.230e-5***
		(7.750e-6)	(7.640e-6)
%positive ratings			33.695***
			(1.580)
seller fixed effects	Yes	Yes	Yes
month fixed effects	Yes	Yes	Yes

*** significant at 1% level

Note: [The regressions below take log(monthly revenue) as dependent variable.]

In IV regression 3 for established sellers in Table 6, we observe that one unit increase in rating score is associated with only very little gain in monthly revenue. However, one unit increase in rating grade will lead to approximately 38% increase in monthly revenue. This suggests that rating grade, compared with rating score, is more important in affecting the monthly revenue. This is not surprising since only the rating grade is displayed on both the homepage of the seller and each product page sold by this seller. Overall, from the regression results for established sellers, there is a reputation premium for them, meaning better reputation leads to more monthly revenues.

However, for new sellers, we can observe a different result. In all regressions, rating grade is associated with a negative coefficient, indicating a negative effect of rating grade, while even though the effect of rating score is positive for most of the regressions, it is too small that will not lead to any significant changes to monthly revenue. From IV regression 3 for new sellers, we can conclude that one unit increase in rating score will even lead to a 16.6% decrease in monthly revenue.

To understand and explore more about the result, we decompose the monthly revenue into the amount of monthly transaction and the average revenue per transaction and run regressions using monthly transaction and the average revenue per transaction as dependent variable separately for new and established seller groups. By using this method, we get our second main finding.

Finding 2: For established sellers, they have higher transaction volumes and better bargaining power as reputation grows. While for new sellers, they may need to cut the price to increase transaction volume and reputation.

In Taobao, the amount of transaction is calculated based on number of items instead of number of orders. Therefore, the term “amount of transaction” is close to the concept of “quantity”. Due to this reason, the average revenue per transaction can be considered as a measure of “price”. We then regress these two measures on the seller’s rating using the same model with instrument variable, and the results are shown in Table 7.

Table 7

[*The effect of reputation on transactions and average revenue per transaction.]*

new sellers	log(transaction+1)	Log (average revenue per transaction)
rating grade	0.053***	-0.031***
	(0.015)	(0.011)
rating score	-2.672e-3***	1.330e-3***
	(1.349e-4)	(1.024e-4)
%positive ratings	7.138e-4	0.717***
	(0.086)	(0.067)
seller fixed effects	Yes	Yes
month fixed effects	Yes	Yes
Established sellers	**log(transaction+1)**	**Log (average revenue per transaction)**
rating grade	0.263***	0.036***
	(0.016)	(0.010)
rating score	1.577e-5***	2.332e-6***
	(3.204e-6)	(2.032e-6)
%positive ratings	23.410***	1.230***
	(0.662)	(0.425)
seller fixed effects	Yes	Yes
month fixed effects	Yes	Yes

*** significant at 1% level

Note: [This table reports the IV regression results.]

The results show that for established sellers, a higher rating grade is associated with a higher transaction volume and a higher average revenue per transaction. Specifically, one unit increase in rating grade will cause a 26.3% increase in transaction volume and 3.6% increase in average revenue per transaction. Both of effects pf “quantity” and “price” contribute the total effect of reputation on revenue for established sellers. However, for new sellers, a higher rating grade is associated with a higher transaction volume but lower average revenue per transaction. Particularly, one unit increase in rating grade leads to a 5.3% increase in monthly transaction volume, but a 3.1% decrease in the average revenue per transaction. These results indicate that for new seller, as their rating grade grows, they may cut the prices to enhance transaction volume and ratings.

To sum up, the results above indicate that the effect of reputation measured by rating grade is different for new and established sellers. For an established seller, the increase in his rating grade leads to the increase of price, transaction volume, and therefore, his monthly revenue. For a new seller, however, an increase in his rating grade leads to a decrease of price and monthly revenue, but an increase in transaction volume. This is intuitively correct. A rational and forward-looking seller has incentives to lower prices in the beginning to exchange for a higher rating and higher returns in the longer term.

Finding 3: Even for new sellers who still have incentives to manage their reputation, they start to enjoy some reputation premium as they become somewhat established.

The above findings suggest that established sellers enjoy a reputation premium, while new sellers need to manage their reputation. However, one potential concern to this interpretation is that new and established sellers might be distinctively different. In our model, we include seller-fixed effect to control for seller differences within the new and established seller group. However, these two groups may also differ in how they react to higher ratings. In other words, the different estimates of effects of rating on revenue, transaction, and average revenue per transaction might not be explained by the heterogeneous effect of reputation for sellers at different stages of their life cycle. In order to solve this concern, we focus on one fixed group of sellers to study the effect of ratings changes when a seller transits from a new to an established one.

The group we focus on is a subgroup of new sellers: 32443 new sellers who first appear in our data set in Month 2 (November 2017). We define a new dummy variable to indicate whether the seller is "established" in a given month. This dummy variable equals to 1 if the rating grade is no smaller than 6 (a one-diamond status or rating score of 250 equivalently), and 0 otherwise. Then we add the interaction term of the newly introduced dummy variable and the seller rating grade to the regression model used previously.

The results are displayed in Fig. 12. The estimated coefficient of rating grade indicates that a higher rating grade increases transaction volume, decreases average revenue per transaction, and has no significant effect on monthly revenue. This is consistent with the previous results for different groups of new and established sellers. One more important result from Fig. 12 is that the coefficients of interaction term for three regressions are all positive, indicating that the effect of reputation on price, quantity, and month revenue changes when they become established. As they become gradually established, they cut less price, sell more products and earn more monthly revenue. This implies that, though increasing reputation still gives new sellers incentives to manage his reputation, he will start to enjoy some reputation return as he become somewhat established.

Table 8

[*IV regression results for new subgroup.]*

	log(revenue)	log(transaction+1)	log(revenue/transaction)
rating grade	-0.072	0.556***	-0.266***
	(0.181)	(0.087)	(0.055)
rating score	-1.167e-3	-3.352e-3***	1.239e-3***
	(9.403e-4)	(4.528e-4)	(2.641e-4)
%positive ratings	0.015	-0.025***	0.020***
	(0.011)	(0.005)	(0.003)
rating grade * Estab.	0.133***	0.063***	0.031***
	(0.029)	(0.014)	(0.008)
seller fixed effects	Yes	Yes	Yes
month fixed effects	Yes	Yes	Yes

*** significant at 1% level

Conclusion

Our research contributed to the previous literature by exploring the dynamic effects of reputation from the seller side using an extensive dataset of the largest e-commerce platform in China. Guided by the empirical models and definitions, we distinguished new sellers from established sellers in our data set and found significant difference of reputation effects for the two groups. Specifically, we found that established sellers receive higher returns on reputation, while for new sellers, they need to actively manage the reputation to increase transaction and sales by cutting down the short-term price.

The result of the research narrows the gap in previous literature and provides empirical analysis and evidence on dynamic returns of seller reputation. Besides, it is consistent with the result with and offers one possible solution to the non-linear relationship proposed in one of the previous research "*Does E-commerce Reputation Mechanism Matter?*".

The findings of this research also have some real-life implications. For example, for sellers on e-commerce platform, this research suggests them to actively adjust their pricing strategy according to their current life-cycle stage and rating grades. And for e-commerce platform, this research may also give them some inspirations on how to design a better reputation system to more accurately solve the potential information asymmetry problem. For example, whether the current setting of rating grade is reasonable and fully reflect the information of seller, which maximizes the information transformation and communication between buyer and seller.

However, there is no denying that this research still has some limitations, but it provides future research some possible alternatives to study. On the one hand, since we mentioned about survival situation of sellers in Section 4, we should have studied the effect of reputation on survival of sellers in the research, which might also be correlated with reputation. However, since we only have a five-month dataset, which is hard to identify whether a seller truly leave the market. Hence, if one could collect data for a longer period, whether reputation has an impact on the survival of seller could also be studied in future research. On the other hand, we also noticed that category plays an important role in the effect of reputation, for instance, for experience or search based products, rating may be a very important factor; while for some standard products, such as prepaid top-up card for mobile phone or game, reputation might be less significant. But in our research, we did not control for the product categories when studying the effects of reputation, and therefore the result we get is just an average over all the product categories. For future research, a category fixed effect could be included to the regression model, or regressions could be run for different product category separately to explore and control for the category effect.

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