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Invisible Hand or Visible Hand: Collaborative Recommendation vs. Paying to be Prominent

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Abstract

This paper collects data from meilishuo.com, which combines consumer collaborative recommendation and paying to be prominent into their website operation. Two groups of commodities are distinguished: group one is filtered by consumers and the other is paid to be prominent. This paper analyzes what product features would motive a seller present the commodity and what factors which influence sells volume of these two groups. We find good commodity rating and bad commodity rating significantly influence the "choice" variable, namely, the choice to pay to be prominent, while the size of sellers does not affect seller's choice. Compared with high level sellers, low level sellers are more willing to purchase prominent positions. The analysis also finds out "like" and "comment" numbers as well as bad rating of the commodity have negative relation with the sells volume. The good rating of the commodity and the size of the sellers both have positive relation with the sells volume. The analysis result, to some extent, confirms that consumers search for useful information to judge the real quality of the commodity rather than just rely on the position. Results of this paper could provide some hints for sellers of these two kinds of commodities.

Keywords

Collaborative Filtering; Paying to be Prominent; Commodity Rating.

1. Introduction

Internet has changed people's life. The conventional wisdom holds that unique characteristics of the internet, like easy search, low barrier to entry, instantaneous information dissemination, will promise us a nearly perfect market and frictionless world. The e-commerce has developed for almost two decades and the volume of transaction on internet has been witnessing a lasting upsurge. The almost perfect market on the internet does not appear. Nowadays, every consumer has to use search engines and search continuously in the large amounts of commodities.

Search cost online is not as insignificant as many people once presume and in many cases, the search cost on the internet could be much larger than it is in the offline business (Xiaoli Ren et al., 2013). One important reason, we believe, why the online search cost is large is due to the tremendously large number of commodities as well as sellers. As aforementioned, the entry barrier on the internet is relatively low（Nurski, L., & Verboven, F. ,2014）; Many moderate and small sizes of sellers take advantage of this convenience and begin their businesses online. Based on a rough statistics, there are at least 1000001 sellers on the famous taobao.com.Among all these sellers, 71790 sellers are branded; only accounting for 0.72% of all sellers. In other word, many consumers who use taobao should spend much time and effort to search among many unknown sellers and commodities. So it is reasonable that the search cost for just one

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commodity is relatively low on the internet, the total search cost which is heavily influenced by the amount of commodity is quite large.

Since the number of commodity online is so large, the position of the commodity becomes vital. Good positions on the internet have become scarce resources(Wenxing Hong et al.,2010) For example, almost every large search engine, including Google and YAHOO!, has its own keyword auction (Varian, 2007; Shi, S. W., and Dong, X.,2015). It is not surprising that each e-commerce website has search engine and keyword auction into its own website. And the mechanism of keyword auction and bidding rank is studied by many researchers.

The second reason is that reputation mechanism online does not effectively help consumers to find out most qualified commodity. Almost every commercial website on the internet has its own-designed reputation system, which according to Bhardwaj, Chen and Godes (2008), contains buyer-initiated information. Current reputation system has two notable defects: one is manipulation of reputation, which is very pervasive on Chinese e-commerce websites (Siqiang Liu et al., 2014). The other drawback is the position of one commodity is not related with its reputation on most large e-commerce website. Consider a typical purchase process on taobao.com: enter the keyword in taobao’s search engine; get a list of commodities which is mainly determined by keyword auction and sales volume; consumers scan these commodities until they get satisfying goods. Reputation of one commodity works only when consumers come into the page of the commodity and assess the commodity.For those sellers who has limited budget to participate position auction, their commodities, even of very good-quality, have little chance to be a best-seller because few people would be patient enough to come into these end-in-list commodities.

Some e-commerce websites have innovated their commodity-ranking method. One remarkable innovation is positions of commodities are mainly determined by its popularity rather than position auction. The website Pinterest.com is the very first to adopt this new ranking mechanism. On Pinterest.com, Whether one commodity is ranked at the notable position of first page is determined by commodity’s “like”, “comment”, “share” and other consumer-generated information. The commodities on this website are mainly linked to small e-commercial or personal website, on which consumers could purchase the commodities. In this mechanism, if one commodity has attractive design and good quality, it is possible to get prominent by consumers adding “like” tag, “comment” tag or “Pin” tag. The cost of adding these tags to a commodity is neglectable and sometimes, it is a pleasure of surfing the Pinterest.com. So every consumer easily click a mouse, following consumers would readily find good commodities. This process is called collaborative recommendation (M O'Mahony et al., 2004).

Some Chinese website also adopt the Pinterest.com mechanism, like www.meilishuo.com and mogujie.com.This paper is based on the data of www.meilishuo.com. On the first page of these two websites, consumers could easily see that some commodities get their prominent position by position auction and others get their noticeable positions by collaborative recommendation. For those commodities which are collaboratively recommended by consumers, their product attributes is trust- worthy; consumers would hold controversial opinions for those commodities which are paid to be prominent. They may hesitate to buy these commodities. We believe consumers would continue to find more information to support their purchase decisions on these controversial commodities.

This paper wants to answer the following two questions. The first one is what characteristics make sellers choose to pay to list on the prominent pages. The second question is for these commodities which get their prominent positions by different methods, would consumers behave differently on their search and purchase process.

ISSN: 2688-9323

2. The Website Meilishuo.com and Data Capture

Meilishuo.com is a commercial website of female fashion clothes and accessories. This website does not sell commodities, and its main function is to exhibit pictures of commodities. If consumers want to buy some clothes on meilishuo.com, meilishuo provides the links to www.taobao.com.The target consumer of meilishuo.com is young females, and the price of most commodities is under 500 RMB. Commodities are classified into several categories, including shoes, bags, clothes and many other categories. Each category has its own main page and there are about one hundred commodity pictures on every page. Every commodity picture has its own main page, including “like”, “comment”, “sharer name”, “price”, and the link to www.taobao.com. Commodities on meilishuo.com are recommended by the so-called taobaoke who make living by recommend commodities in taobao community or recommend commodities to other commercial website.

The typical processes of how one commodity is presented on meilishuo.com have four steps: 1.the seller on www.taobao.com hire one taobaoke to share one of his/her commodity to meilishuo.com;2.The seller has to choose whether to pay some money to make its product prominent instaneously.Otherwise,its commodity has to be rely on consumers to get prominence. 3. The fans of the taobaoke on meilishuo would know the new shared commodity when they log in their meilishuo account; 4. Fans of the taobaoke and other consumers who know this commodity could add “like” tag or comment on this commodity. 5. The commodities who do not take part in the position selling should depend on their number of “like” and “comment” to get promoted to good position.

Why some sellers would want to present their commodities on www.meilishuo.com? Firstly, making advertisement, no matter the keyword auction and simple flash or picture advertisements on www.taobao.com is more expensive than it is on www.meilishuo.com and the advertisement positions on taobao are also very limited. Secondly, www.meilishuo.com is a special websites for girls to have access beautiful clothes and accessories; moreover, the commodities on it are specially recommended or shared by some professional taobaoke, who are experts on the girls’ fashion. So for sellers who mostly sell girls’ clothes and accessories, www.meilishuo.com is a very perfect place to make advertisements at a relatively low price. More importantly, the mechanism www.meilishuo.com adopts which combines position auction and collaborative recommendation, is a valuable plae for us to conduct appropriate data because it is more easily and credibly distinguish two kinds of sellers.

We use a web crawler to get the data of commodities on the main page of clothes category. The variables on meilishuo.com contain number of “like”, number of “comment”, “price”, “sharer’s fans”; other variables about the commodity could be fetched on its www.taobao.com webpage, including “extent of seller’s commodity accord with its description”(“sellersimilarity” in the statistics), “extent of seller’s commodity accord with its description compared with other sellers”(“sellersimilarityrelative” in the statistics), “seller’s attitude”(“sellerattitude” in statistics), “seller’s attitude compared with other sellers”(“sellerattituderelative” in statistics), “seller’s delivery speed”(“sellerdelivery” in statistics), “seller’s delivery speed compared with other sellers”(“sellerdeliveryrelative” in statistics), “the good rating of the commodity”(“commoditygoodrating” in statistics), “the moderate rating of the commodity”(“commoditymedoraterating” in statistics), “the bad rating of the commodity”(“commoditybadrating” in statistics). These variables show different aspects of the commodity.

In the clothes category, clothes could be separated into four small categories based on their prices, namely the price intervals [0, 100], [101, 200], [201, 500], [501, 10000]. Each small category has their own first page. We collect data of each small category’s first page respectively. We have run the web crawler for eight times and each data capture lasts almost 4 hours. To

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avoid unnecessary duplication of sample point, each data collection is at least 12 hours apart from the former one. The total sample point we get is over 3000. 2321 sample points are effective. Since the sample in price interval 500 10000 is relatively small and there are many mistakes in this sample, we abandon the sample in this price interval. The final effective population sample contains about 1835 points.

One important work in this paper is to distinguish which commodities are paid to be prominent and which are recommended by collaborative recommendation. It is known that many commodities are paid to be on the first page and only a few clothes are recommended by consumers. In each price interval, we set the commodities whose number of “like” and number of “comment” is below the 0.2 quantile points of “like” and “comment” of that price interval as commodities paid to be prominent. In a similar way, we set the commodities whose number of “like” and number of “comment” is greater than 0.9 quantile points of “like” and “comment” as commodities of collaborative filtered by consumers. The commodities which are collaborative filtered by consumers are called group1, and the commodities paying to be prominent are contained in group2. The number of effective sample points in group1 is 97 and the number of effective sample points in group2 is 318. The following tables are the basic statistics of the two groups.

Table 1. Basic Data in Group1

Statistic	N	Mean	St. Dev.	Min	Max
allbuyamounton	97	122.773	179.564	0	1,197
allbuyamountbefore	97	11.990	34.413	0	200
onprice	97	195.492	172.173	26.000	999.000
like	97	3,023.340	1,387.833	843	7,406
comment	97	25.876	14.851	4	67
sharerfans	97	2,473.134	6,707.987	30	53,452
sellercommoditynumber	97	808.134	3,114.587	33	18,131
selleremployee	97	3.402	3.807	1	14

The variable “allbuyamounton” means all amount sell out since the commodity is on meilishuo.com. Similarly, the variable “allbuyamounton” means all amount sell out in a month before the commodity is on meilishuo.com. “Onprice” is the price of the commodity on meilishuo.com. “Like” and “comment” respectively means the number of like and the number of comment of the commodity. “Sharerfans” indicates the fans of the commodity’s sharer. “Commoditygoodrating” and “commoditybadrating” means the good rating and bad rating of the commodity on www.taobao.com.

Table 2. Basic Data in Group2

Statistic	N	Mean	St. Dev.	Min	Max
allbuyamounton	318	19.204	61.685	0	736
allbuyamountbefore	318	18.928	50.467	0	367
onprice	318	65.003	35.155	3	117
like	318	53.969	64.931	0	374
comment	318	0.038	0.191	0	1
sharerfans	318	104.472	62.419	2	210
selleremployee	318	5.289	4.198	2	14

ISSN: 2688-9323

The names and their meaning are the same as them in table one. From the comparison of the two table, we can easily see that the all the variables in group1 and group2 have huge differences.

3. Model and Regression

3.1. Test on Influential Factors of Presenting on Www.Meilishuo.Com

Firstly, we want to analyze what kind of commodities would be chosen to presented on meilishuo.com. We name a variable “choice”. For those commodities in group2 which we believe are paid to be prominent, choice = 1; for those commodities in group1, choice = 0. If a commodity is presented on the prominent position, it should possess satisfying attributes. So we expect a good commodity rating would contribute to its presence on the first page; bad commodity ratings would function on the contrary. If a commodity is very popular, sellers would also consider put it in the spotlight. We are not sure whether seller levels and sellers’ size would positively affect the “choice” variable.

Table 3. Choice Regression with Probit

	dependent variable						
	choice probit						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
grating	4.10 (139.66)	4.26 (131.71)	4.27 (107.17)	4.09 (135.79)	4.22 (89.76)	4.54 (88.14)	4.22 (88.56)
brating	-6.63 (258.12)	-7.03 (246.46)	-34.41 (420.96)	-6.53 (245.97)	-35.90 (416.61)	-36.29 (408.40)	-35.96 (419.38)
lnprice		-0.25 (0.18)			-0.29 (0.25)	-0.27 (0.26)	-0.29 (0.25)
sellbef			4.23 (52.44)		4.42 (51.72)	4.46 (50.65)	4.42 (52.07)
slevel				-0.02 (0.08)	-0.13 (0.12)	-0.15 (0.12)	-0.14 (0.12)
semploy						-0.07 (0.07)	
scomnum							0.0001 (0.0004)
constant	1.44*** (0.15)	2.67*** (0.91)	0.94*** (0.18)	1.72* (0.93)	3.91* (2.15)	4.17* (2.20)	3.87* (2.15)
observations	410	410	410	410	410	410	410
log likelihood	-42.54	-41.49	-31.88	-42.50	-30.87	-30.33	-30.81

Note: ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01

Since the reputation manipulation on www.taobao.com is widespread, the absolute value of seller’s reputation rating is not a good indicator. In this paper, seller’s reputation is control by relative reputation, namely “sellersimilarityrelative” (“sesimre” in the regression), “sellerattituderelative” (“seattre” in the regression) and “sellerdeliveryrelative” (“sedelre” in the regression). We use “like” variable to represent the design of the commodity, and “comment”, “commoditygoodrating” (“grating” in regression equation), “commoditybadrating” (“brating” in regression equation) to indicate the quality of the commodity. “allbuyamountbefore” (“sellbef” in the regression) indicates the sell history of the commodity before it is presented on meilishuo.com. “sellercommoditynumber” (“scomnum” in regression) and “selleremployee” (“semploy” in regression) are two variables to represent the size of the seller. However, in www.taobao.com, we think the “selleremployee” variable would be much more reasonable to indicate the seller size because it is highly possible that one small seller still have many number of commodities and each commodity is of small amount. “onprice” (“lnprice”, which is the logarithmic form of “onprice”) is certainly introduced into the regression. The dependent variable is “allbuyamounton” (“sellamount” in regression).

Based on the probit regress, we want to analyze what products features would motivate sellers to present their products on meilishuo.com. Results are shown in table 3. The results are kind of odd since we get warning messages from R software when running this probit regression. The warning messages are 1:glm.fit: algorithm did not converge; 2: glm.fit: fitted probabilities numerically 0 or 1 occurred. With the linear possibility model, we run this choice decision regression, and the results are shown in table 4.

Alternatively, we use the Bayesian analysis.Results are presented in table five.

The regression indicates good commodity rating would positively motive a seller put the commodity on www.meilishuo.com and bad commodity rating functions on the contrary, just as we predicted.

Table 4. Choice Regression with Linear Probability Model

	Dependent variable					
	choice					
OLS						
	(1)	(2)	(3)	(4)	(5)	(6)
grating	0.0004*** (0.0002)	0.0004*** (0.0002)	0.0004*** (0.0002)	0.0004*** (0.0002)	0.0004*** (0.0002)	0.0004*** (0.0002)
brating	-0.01*** (0.001)	-0.01*** (0.001)	-0.01*** (0.001)	-0.01*** (0.001)	-0.01*** (0.001)	-0.01*** (0.001)
lnprice		-0.001 (0.02)			-0.03 (0.03)	-0.03 (0.03)
sellbef			0.0001 (0.0004)		0.0001 (0.0004)	0.0001 (0.0004)
slevel				-0.03*** (0.01)	-0.03*** (0.01)	-0.03*** (0.01)
semploy						-0.01** (0.01)
scomnum						
constant	0.79*** (0.02)	0.80*** (0.12)	0.79*** (0.02)	1.13*** (0.11)	1.29*** (0.20)	1.37*** (0.20)
observations	410	410	410	410	410	410
R^2	0.19	0.19	0.19	0.21	0.21	0.22
F Statistic	46.63*** (df=2;407)	31.01*** (df=3;406)	31.05*** (df=3;406)	34.93*** (df=3;406)	21.13*** (df=5;404)	18.58*** (df=6;403)

Note: ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01

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We could also find commodity prices and size of sellers do not influence the “choice” variable. Compared with big sellers, small sellers are more willing to present their commodity in the spotlight, namely, www.meilishuo.com. As far as we know, price of a prominent position on www.taobao.com is much more expensive, especially the positions on the main page. So it is reasonable for small sellers who do not possess enough resource to present themselves on the first page of other related, but cheaper websites.

Table 5. Choice Regression with Bayesian Analysis

	Dependent variable						
	choice						
constant	1.480*** (0.140)	2.280*** (0.841)	1.335*** (0.147)	2.131** (0.865)	3.693** (1.435)	3.841*** (1.441)	3.684** (1.438)
grating	0.419*** (0.147)	0.528*** (0.178)	0.073*** (0.018)	0.364*** (0.134)	0.064*** (0.017)	0.061*** (0.016)	0.065*** (0.017)
brating	-1.987*** (0.557)	-2.418*** (0.700)	-2.108*** (0.407)	-1.775*** (0.496)	-1.793*** (0.367)	-1.674*** (0.348)	-1.797*** (0.368)
lnprice		-0.165 (0.169)			-0.147 (0.173)	-0.155 (0.173)	-0.146 (0.173)
sellbef			0.210*** (0.062)		0.187*** (0.051)	0.173*** (0.047)	0.188*** (0.051)
sleve				-0.056 (0.073)	-0.142* (0.081)	-0.141* (0.080)	-0.143* (0.081)
semploy						-0.036 (0.043)	
scomnum							0.000 (0.001)

Note: ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01

3.2. Test on Influential Factors of Sale

As aforementioned, consumers who scan commodities should follow the link to www.taobao.com to purchase commodities. We could get the commodity’s sale amount from www.taobao.com, but the problem is we could not distinguish which commodity is purchased from the link to www.meilishuo.com and which commodity is purchased directly from www.taobao.com. We use the following method to deal with this problem. Suppose the commodity is presented on www.meilishuo.com from day t_0, and the commodity information is grapped on day t. amountbefore represents the sale amount in the time interval $[t_0 - 30, t]$, and amounton represents the sale amount in the time interval $[t_0, t]$. The sell amount from www.meilishuo.com in the time interval $[t_0, t]$ is

$$\text{sellamount} = \left[\frac{amounton}{t-t_0} - \frac{amountbefore}{30}\right] \cdot (t - t_0)$$

Since fans of the sharer would help the sharer’s commodity to increase “like” and “comment” when the commodity enter the meilishuo.com, so we bring “sharerfans” (“lnshfans”,which is

ISSN: 2688-9323

the logarithmic form of “sharerfans”) into the regression to control the beginning endowment of the commodity. The regression model is

$$sellamount = \alpha_0 + \alpha_1 * like + \alpha_2 * comment + \alpha_3 * lnprice + \alpha_4 * lnshfans + \alpha_5 * sesimre + \alpha_6 * seattre + \alpha_7 * sedelre + \alpha_8 * grating + \alpha_9 * brating + \alpha_{10} * sellbef$$

Consumers could judge whether one commodity is paid to be prominent by the number of “like” and “comment”. That is so-called “observational learning of consumers”.For the commodities in group2, “like” and “comment” numbers always be much smaller than those of collaborative filtered goods. So the “like” and “comment” would act negatively for sells volume because consumers is reluctant to buy those commodities when they could distinguish them out of all commodities.

When deciding whether to buy a commodity in group2, consumers need much further information. The commodity rating on www.taobao.com of the commodity and the reputation of the seller could help consumers to judge the quality of the commodity. So we propose these variables should have positive relations with the sells volume. For the sellers in group2, the seller’s size is also good signal of its good reputation. So in group2, we propose there is a positive relation between sells volume and seller size.

We believe for commodities which are collaborative filtered by consumers, whether the seller is a big one or a small one matters little; all matters is whether the commodity is of attractive design and good quality. So we propose that the “like” and “comment” numbers should be positively significant for sells volume in group1.

The reputation of the seller as well as commodity ratings also would be positively related with the sells volume, but not as strong as the commodities in group2 because the like and comment on meilishuo have provide many information for consumers.

As aforementioned, collaborative recommendation provide small sellers chances to be in the spotlight. Since paying to be prominent requires extra money, it is a reasonable reasoning that the smaller the seller, the more possible it would depend on collaborative recommendation to gain consumers’ attention. Since all the commodities in group1 are these which successfully filtered by consumers, so we propose there is a negative relation between the seller size and sells volume for the commodities in group1.The sells volume before the commodity is on meilishuo.com is a good signal of its sell history, so we propose it is positively related with commodities in both group.

With the help of R 3.0.1, we run four simple OLS regressions. Regression results are listed in table 6.

From the table, we could easily see that the coefficients of two OLS regression of group1 is not so significant no matter whether we control the size of the seller or not. Moreover, maybe due to the limited number of samples, the regression as a whole is not significant, neither.

The regression on group2 is relatively satisfying. Almost all the variables, except the “sellbef”, are as we expected. Coefficients of three variables which indicates the seller’s reputation are all zero (actually they are so small as to be rounded to be zero).

From the regression results, we can tell the like and comment of those commodities whose position is apparently purchased plays negative role in its sells volume because consumers could easily tell these commodities and become reluctant to buy it. When the consumers lack enough information from the position of commodity and other information from meilishuo.com, the goodrating of the commodity plays a significant but inconspicuous role in deciding whether to buy this product. The badrating of the commodity is in negative relation with sells volume but not in a significant way. The results indicates the seller size holds a significant positive relation with the sells volume which in our opinion, is that seller size could act as extra signal of the seller's reputation.

Table 6. Regression Results

	dependent variable			
	sellamount			
	OLS			
	(1)	(2)	(3)	(4)
like	0.001 (0.02)	-0.001 (0.02)	-0.16*** (0.05)	-0.16*** (0.05)
comment	1.97 (1.93)	2.10 (2.10)	-4.22 (18.20)	-3.89 (18.11)
lnprice	-22.49 (28.10)	-22.61 (28.27)	-10.62*** (4.07)	-12.32*** (4.13)
lnshfans	-28.06* (14.16)	-27.32* (14.98)	0.84 (3.59)	0.49 (3.58)
sesimre	0.002 (0.01)	0.002 (0.01)	0.00 (0.0000)	0.00 (0.0000)
seattre	0.01 (0.01)	0.01 (0.01)	0.00 (0.0000)	0.00 (0.0000)
sedelre	-0.02 (0.01)	-0.02 (0.01)	0.00 (0.0000)	0.00 (0.0000)
semploy		-1.02 (6.42)		1.70** (0.83)
grating	14.04 (73.24)	12.95 (73.98)	0.08** (0.04)	0.08** (0.04)
brating	-0.42 (0.41)	-0.42 (0.41)	-5.03 (4.65)	-4.59 (4.63)
sellbef	0.55 (0.57)	0.58 (0.60)	-0.12 (0.08)	-0.13* (0.07)
constant	404.84** (185.48)	404.62** (186.55)	63.10*** (23.55)	60.72** (23.46)
observation	97	97	318	318
R^2	0.12	0.12	0.08	0.10
F-statistic	1.21 (df=10;86)	1.09 (df=11;85)	2.77*** (df=10;307)	2.93*** (df=11;306)

Note: ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01

4. Conclusion

Paying to be prominent and consumer collaborative recommendation have become two main mechanisms to determine the position of one commodity on e-commercial website. However, the first method requires the seller to have extra money to purchase the position, and thus many small sellers would lose their opportunities to be in the spotlight. Consumer collaborative recommendation provides almost equal chances to sellers of different sizes, as long as the product is of good design and quality. Some Chinese e-commercial websites have combines

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these two mechanisms into their operation. The data of this paper is collected from such a website called meilishuo.com. This paper distinguishes two groups of commodities: one is paid to be prominent and the other is filtered by consumers.

This paper examines what product characteristics would motivate a seller to purchase a position to present the commodity on www.meilishuo.com. Moreover, factors influencing sells volume of these two groups of commodities are examined. We find good commodity rating and bad commodity rating significantly influence the "choice" variable, namely, the choice to pay to be prominent, while the size of sellers does not affect seller's choice. Compared with high level sellers, low level sellers are more willing to purchase prominent positions on www.meilishuo.com.

Due to the limited sample size, the empirical analysis of the consumer-filtered commodities does not work out well. The empirical analysis of the other group indicates that "like" and "comment" numbers on meilishuo.com as well as badrating of the commodity on www.taobao.com have negative relation with the sells volume. The goodrating of the commodity and the size of the sellers both have positive relation with the sells volume. The analysis results, to some extent, confirm that consumers seek for useful information to judge the real quality of the commodity rather than only rely on the position.

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