Investigating the Price Discrimination on User Portraits in Online New Retail Case study on JD.com

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Abstract: With the emergence of online new retail platforms and pricing strategies boosted by Big Data, price discrimination has triggered extensive attention in the business field, from the legal, commercial and ethical perspectives. This study adopts JD.com, one of the pioneering online new retail platforms, as a case study to investigate the relationship between user portrait, sales volume and discounted price to show the degree of price discrimination. Results show that gender, age and marital status are critical factors in price discrimination of online new retail platforms. Instead of price discrimination, dynamic pricing is a more accurate word in describing behaviours of online retailers. This paper offer suggestions for online new platform to legally design dynamic pricing, such as targeted coupons and festival promotion, based on different user portraits. For further studies, comparative studies on dynamic pricing on different online new retail platforms, both in China and Foreign countries, are suggested.

1. Introduction

In recent years, firms are increasingly deploying pricing approaches with the help of big data driven algorithms to determine the dynamic prices for their goods and services. Based on different user portrait features and time of purchase behaviors, sellers may discriminate customers on product price. The online new retail constitutes a platform where a suggested revolutionary trend in how human capitals and data-driven strategies interact commercially, online as well as offline, is performing.

In China, there are detailed rules on anti-monopoly and price discrimination. The 14th clause in the Price Law claims that sellers price discriminating their customers with the same trading conditions and same goods is inappropriate. The Chinese government only prohibits price discrimination with no proper reasons, under the 6th item under the 17th clause. Anti-monopoly laws are divided into three categories including anti-competitive agreements among corporations, abusing dominant power, and merging that will eliminate competition. The anti-monopoly committee is responsible for devising the laws and policy while the enforcement is responsible for supervising companies for carrying them out. It is not counted as a monopoly if the competition was not reduced significantly in the market or consumers will get benefits in return.

There have been numerous cases of price discrimination in recent years in China and they all have undergone serious punishment. Six LCD manufacturers were found in 2012 holding secret meetings on price-fixing and discussion of market information. They were fined 353 million RMB. Typical penalties for violating anti-monopoly laws include fines up to 10% of turnover in that fiscal year, confiscation of illegal income, etc. The ethic and business issues aroused by price discrimination are worth more research investigation.

1.1. Definitions

(1) Price Discrimination

The current literature varies on the definition of price discrimination. But the majority seem to agree that price discrimination is to set different prices for different customers, sometimes for the same product. This concept emphasizes that the same product charges different prices to different customers as price discrimination. But it did not answer whether charging different prices for the same consumer for different quantities is price discrimination. From the perspective of microeconomics, price discrimination is the action that a monopolist can sell the same unit of products at different prices. This definition does not limit that price discrimination must occur when different prices must be charged to different consumers, but it does not answer whether charging different prices for different units purchased by the same consumer is considered price discrimination.

This paper followed the definition stated in Taylor's "Industrial Organization Theory": "It is very difficult to come up with a satisfactory definition of price discrimination. Roughly speaking, as for two units of the same commodity, if their prices are different for the same consumer and different consumers, it can be concluded that producers have implemented price discrimination." First, the perpetrator of price discrimination must be the same seller, and different sellers of the same product request different prices, which is called price dispersion; second, it must be the same product (same quality, same cost). Third, when asking for different prices, the object may be different consumers or the same consumer.

(2) User Portrait

User portrait is a method of labelling user information in a big data environment that provides a sufficient data foundation. By abstracting label information, the user can be perfectly presented with a full picture of the virtual user, which is the user portrait. First, the user portrait is the virtual representation of the user's real data. The set of common features is presented. Secondly, the user portrait focuses on the "typical users" obtained after refining static and dynamic attributes, which is a conceptual model of a user group with some distinctive characteristics. Finally, the user portrait puts more emphasis on the user's dominant position and highlights the user's specific needs.

Regarding the constituent elements of user portrait, D. Travis gave seven basic conditions when proposing the concept of user portraits: basicity, empathy, authenticity, uniqueness, goal, quantity, and applicability, The first letters of the seven characteristics constitute the word Persona. The constituent elements of user portraits can be summarized as the user's basic literacy, educational level, social relationship, work status, location, time information, etc. These characteristics can be classified into stable factors and variable information (such as the search environment, search targets and other factors that may change).

(3) Online New Retail

Drove by factors as IT, consumption upgrade and competition trend, China's retail industry is facing the new opportunity of transformation, namely the “new retail” with profound integration of “online + offline + logistics". "New retail" is the return of the essence of retail; it is the comprehensive type of retail business that can better meet the consumers' multidimensional and integrated requirement with all-channel and extensive type of retail business. The basic concept of "new retail" includes the following main aspects: First, the in-depth integration of "online + offline + logistics" aims to provide consumers with omnichannel and comprehensive services; second, data technology-driven, Data technology connects retail, connects online and offline, and optimizes retail efficiency; third, the essence of retailing with consumption as its core is highlighted, and it strives to provide consumers with efficient and satisfactory services that exceed expectations. It can be seen that "new retail" is a return to the essence of retail, and it is a comprehensive retail format that better meets consumers' multi-dimensional needs for shopping, entertainment, and social interaction with omnichannel and pan-retail in the era of data-driven and consumption upgrades. JD.com is one of the pioneers in new retail practice.

2. Literature Review

In terms of multi-channel products selling, Cui et al. investigated the price discrimination among wholesale prices in a sourcing marketplace globally. The research observed the behaviors where suppliers quote prices and price discrimination in business-to-business (B2B) markets. They collaborated with an international trade company and ran a field experiment on its sourcing platform. The results found that there is no significant difference in the wholesale prices quoted to buyers selling in U.S. and South African markets. In addition, suppliers quoted significantly higher wholesale prices to white buyers than to Asian and black buyers regardless of country. However, price discrimination disappeared when buyers presented market information to suppliers, providing the lowest wholesale price offered by other suppliers in the market, whereas price discrimination remained when buyers present social information to suppliers, thereby indicating the buyer was referred by a previous customer. Market information could help buyers obtain a lower wholesale price because it signaled a lower willingness to pay. Social information, however, could reduce price quotes for only black and white buyers but not for Asian (particularly Chinese) buyers [1].

Further, Narwal and Nayak explore the applicability of Pay-What-You-Want (PWYW) pricing multi-channel retailing. It revealed that when consumers treat price differentiation negatively, this perception interacted with their rooted beliefs about the multi-channeled cost of retailers' products. PWYW acceptance could be fostered in multi-channel by communication of additional value generated in offline selling [3]. Similarly, Geng and Zhang investigated the pricing strategies of online trading platforms with indirect network externalities using game theory, optimization, and comparative statics, considering heterogeneous trading behavior and long-tail effects in downstream markets. It is found that the transaction-based model is more profitable than the subscription-based model under heterogeneous trading behavior due to the feasibility of "price discrimination". However, due to certain advantages of subscription fees, such as the avoidance of offline transactions, the subscription-based model is better in the case of a concentrated distribution of sellers' revenues with smaller number of Gini coefficient. In the case of a lucrative long tail, the platform should set a low price to attract small sellers in the long tail. Moreover, if the Gini coefficient is large, the market entry barrier for sellers may have an opposite effect on the optimal price under each model. This means that the choice of revenue model and pricing strategy can be influenced by the Gini coefficient or the long tail [4].

When it comes to the advantages of price differentiation, Esteves and Resende, in the context of a duopoly market in which firms simultaneously competed in prices and advertising decisions, explored the competitive and welfare effects of personalized pricing with targeted advertising by comparing equilibrium outcomes under customized pricing decisions to the results arising under mass advertising and uniform pricing. The results showed that, when both firms compete in both market segments, all segment consumers were expected to pay higher average prices under the personalized pricing strategy [5]. As for the online and offline stores, Cebollada et al. used a household scanner panel dataset to reveal that across different product categories, customers are less sensitive to prices when shopping online instead of offline. In addition, price sensitivity was negatively related to the physical easiness to purchase products. A retailer may substantially optimize its profits mode by upgrading its stagnant pricing policy into a dynamic one [6].

Under the background where the advent of big data analytics has favored the emergence of forms of price discrimination based on consumers' profiles and their online behavior, Botta and Wiedemann analyzed this practice as possible exploitative abuse by dominant online platforms. The paper argued that, because of its "mixed" effect on consumers' welfare, personalized pricing required a case-by-case assessment under EU competition law and thus it should not be banned a priority. Due to the case-by-case approach, competition law seemed more suitable than omnibus regulation to tackle the negative effects that personalized pricing could have on consumers' welfare. In particular, the authority could negotiate with online platforms different kinds of behavioral commitments: transparency requirements, limits on data collection or user profiling, rights to optimize out of personalized pricing and the obligation to share customers' data with competitors could significantly relieve the risks of personalized pricing [7]. On the contrary, Wang et al. also conclude that from the perspective of consumers, the increased sensitivity in consumer price setting might not bring benefits to sellers [8].

Choe et al. propose a model of dynamic competition between two firms in which the firm collects customer information through purchases in the first period. This generates asymmetric information in the second period, where the firm knows more about its past customers than its competitors. The study examines on the basis of customer information attained in two different periods; how do companies provide differentiated prices. When product differentiation is exogenously fixed, asymmetric information leads to two asymmetric equilibria in which one firm chooses to price more aggressively to secure a larger first-period market share. When product differentiation is also endogenously selected, two asymmetric equilibria continue to exist, with one of the firms choosing to position itself more aggressively. The more aggressive firm, either through pricing or positioning, can force the game in its favor [9].

Chen examined the welfare implications of input price discrimination in a vertically-related market, which was composed of a monopolistic upstream market and a duopolistic downstream market. The downstream duopolies produced quality-differentiated products at different marginal costs. The results showed that the equilibrium input prices are closely related to the downstream quality gap and cost difference. When the monopolist simply charged a unit wholesale price for its input product, discriminatory pricing could be socially desirable even though the aggregate output remains unchanged. Nevertheless, if a two-part tariff was feasible, then banning price discrimination could increase the aggregate output and social welfare [10].

Based on current literature, the researchers mainly focus on the relationship between online users' previous behavior and data-driven differentiated pricing methods. However, few studies linked users' portraits and previous purchase behaviors together. Further, the object of investigation was mainly on western platforms. Thus, this paper attempts to investigate the price discrimination on Chinese platforms from the perspective of user portrait. This paper attempts to evaluate in terms of online new retail, how do user portraits affect online sales volume? And Based on the interrelationship, how do online retailers discriminate against customers with their portraits?

3. Research Design

3.1. Data Collection

The data are recorded during 2018 and 2019. The records are made under the column of home-used electrical applicants. In this research, the purchase behaviors of 457,298 current JD.com consumers are observed where they ordered over 31,867 products. Their data has gone through data masking and is stored in four datasets: 1) "SKUs" table: It stores the overall information related to products including its brand, its attributes, and entry/sold date; 2) "users" table: It shows relevant information to user portrait such as age, education, living city, user level, and etc.; 3) "clicks" table: It shows every the channel where customer get exposed to certain products; 4) "orders" table: It performs the price information from original to discounted price.

3.2. Data Pre-processing

After data pre-processing within all of the current data, in the analysis of sales distribution, the sales of JD.com tends to be highly skewed. The proportion of sold products with 1000+ records formed only 1 percentage of the total sales, while the number rose to 8.0 when the products whose selling record above 100 are counted. Greatly skewed to the right, JD.com's sales distribution is composed of certain goods with enormous sales volume. Based on the highly skewed sales distribution, this essay continued to investigate the relationship between different consumers' characteristics and product sales. Linear regression is adopted. Before analyzing with the data, the author gives special codes to the data. For example, the recorded online users in the users table are given numbers to represent their user portrait. For the "user_level", the degree of user level is ranged from 1 to 4. The higher number indicates the fact that this user has accumulated larger amounts of previous purchase behaviors. If a user is under the membership of JD.com, they will be given the number of 1 within the column of "Plus_Member". If not, the code will be given as 0. Similarly, the education level of the users is examined through numbers 1 to 5 with the higher number showing the higher education level. For the living city of different users, the coding with numbers is used to show the city level relevant to industrial development. The code is from one to five to show the difference. The coding in purchasing power is also applied with the same standard.

4. Results

After processed with linear regression, the correlation between the sales of individual purchased goods and the user portraits features is showed in Table one. The dependent variable is the total sales volume of certain products ordered by different online users, while the independent variable is the features of different user portraits. The results show that the user portrait of "user_level", "city_level", and "purchase_power" are not statistically significant (p>0.05). It also shows that membership of JD.com, age and educational level have no distinct relationship with product sales with p value less than 0.05, and have limited impact on sales. With p value >0.05, the user portraits of "Marital_status" and "Gender" has correlation with product sales volume. Female customers prefer shopping on online new retail than male customers do. When it comes to the marital status of customers, those who are not married tend to buy more than married ones. Based on this result, the essay hypothesizes that JD.com may discriminate customers on their gender and marital status. To examine this hypothesis, the linear regression continues to be used.

Table 1. Linear regression results between user portrait and product sales volume

Variables	Coef	Std Err	t	P>|t|
User_level	20.8349	0.377	55.205	0.165
Plus_Member	0.8692	0.911	0.955	0.800
Education	0.2536	0.333	0.762	0.508
City_level	-0.8834	0.247	-3.580	0.280
Purchase_power	-2.5657	0.493	-5.199	0.124
Gender_Female	12.9252	2.419	5.342	0.000
Gender_Male	-1.4812	2.456	-0.603	0.000
Gender_Unknown	41.1100	5.095	2.852	0.004
Age_16-25	17.5876	5.702	0.974	0.330
Age_26-35	18.3902	5.691	1.348	0.178
Age_36-45	19.8418	5.711	1.299	0.194
Age_46-55	17.8047	5.813	1.705	0.088
Age_<15	17.6498	36.623	-0.345	0.730
Age_>56	16.7091	5.856	0.518	0.605
Age_Unknown	18.5677	8.198	0.612	0.541
Marital_status_Married	43.0995	1.481	4.925	0.000
Marital_status_Single	42.7529	1.490	10.570	0.000
Marital_status_Unknown	2.9388	1.787	1.645	0.000

The Table 2 shows the linear regression results between user portrait and individual discounted price. The dependent variable is classified as the price offered to customers' purchasing behavior while the user portraits are treated as the independent variable. User portraits features with P values less than 0.05 are statistically significant. Only these features are taken into consideration. It can be inferred that the final price of certain product of JD.com are closely related to the features of age, gender and marital status. This correlation supports the probable existence of price discrimination to a certain extent. In terms of age (p=0.000<0.05), the increase in customers' age may reflect as a decrease in the discounted price of certain products. When it comes to gender (p=0.000<0.05), female customers may come across different prices with male customers. Further, the married customers also suffer from price discrimination to certain degree.

Table 2. Linear regression results between user portrait and individual discounted price

Variables	Coef	Std Err	t	P>|t|
User_level	-0.1911	0.138	-1.388	0.165
Plus_Member	-0.0985	0.388	-0.254	0.800
Education	0.1348	0.204	0.662	0.508
City_level	-0.1470	0.136	-1.081	0.280
Purchase_power	-0.4686	0.305	-1.537	0.124
Gender_Female	43.2887	1.371	31.570	0.000
Gender_Male	42.1524	1.382	30.511	0.000
Gender_Unknown	41.1100	2.857	14.390	0.000
Age_16-25	17.5876	3.325	5.289	0.000
Age_26-35	18.3902	3.317	5.545	0.000
Age_36-45	19.8418	3.330	5.959	0.000
Age_46-55	17.8047	3.388	5.256	0.000
Age_<15	17.6498	21.393	0.825	0.409
Age_>56	16.7091	3.418	4.888	0.000
Age_Unknown	18.5677	4.706	3.945	0.000
Marital_status_Married	43.0995	0.881	48.908	0.000
Marital_status_Single	42.7529	0.876	48.820	0.000
Marital_status_Unknown	40.6986	1.105	36.821	0.000

5. Conclusions

Membership and user level are a form of price differentiation instead of price discrimination. It is publicly informed instead of conducted secretly like many of the illegal price discrimination. Instead of price discrimination, dynamic pricing is a more accurate word in describing the behaviors of online retailers. Online retailers consider the age of people primarily because senior citizens have lower financial ability to afford daily necessities. Lowering the price can attract more senior citizens. Moreover, if the user is married, they might need more items in their daily life. According to this research, JD can accordingly make more creative strategies based on the findings. There could be stronger promotions on festivals that are related to the factors that this paper discussed, such as on Women's Day. JD.com can open the pop-up stores in less industrialized cities to show locals samples of the products they sell and attract this demographic group. Consumption rewards could be created where people get higher value coupons they spent more on the website. Coupons with higher values can be handed to senior citizens to stimulate their spending. Family package is another one to encourage an entire family to purchase more. For future studies, researchers could investigate how the type of products link with the factors mentioned above. Also, more factors can be considered as the factors mentioned above are not the only ones influencing sales and user activity. Screen time, income and many more could be taken into account. A comparative study can also be conducted looking at both China and foreign online retail platforms to see how these two platforms differ from each other in terms of price discrimination.

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