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The Impacts of Widespread Personalized Pricing in Digital Markets

Sicheng Yuan

NLCS Singapore, Singapore, Singapore
sichengyuan7@gmail.com

Abstract. Digital technologies can help platforms to develop a personalised pricing model, which involves gathering and analysing multidimensional data about consumers. This paper explores the economic, ethical and social implications of the implementation of personalised pricing in digital markets. The research is based on a number of examples of commercial platforms, including Ctrip, Amazon, Target and Pinduoduo, and recent empirical and theoretical research, to examine the theoretical efficiency gains from neoclassical economic concepts and the actual market outcomes. The analysis is carried out on four aspects: procedural unfairness because of price discrimination, risk of privacy violations because of the intensive monitoring of consumers' data, psychological manipulation of consumer preferences by algorithms, and allocative efficiency in theory versus reality. The results show that while in theory personalised pricing can remove the deadweight loss and enhance the allocation of resources, widespread information asymmetry and opaque algorithmic systems and mass data extraction reduce the potential benefits. The widespread adoption will further increase market inequality, reduce consumer privacy, affect consumer choice, and allow for further concentration of market power by large digital platforms. Finally, such pricing policies are at odds with the desire to promote general social welfare.

Keywords: personalised pricing, price discrimination, consumer privacy, algorithmic manipulation, social welfare

1. Introduction

The collection and analysis of consumer data has picked up pace with the continuous evolution of digital technology. The data collected and analyzed are well-established data on the consumption habits, geographic location information and historical navigation data of people [1]. These data can be leveraged for businesses to develop their own pricing strategy. The other approach is through standardized price-setting procedures [2]. This issue has become crucial in the digital platform economy, since enterprises need to formulate rational pricing strategies to ensure competitiveness. This pricing policy is an example of price discrimination, a pricing policy that seeks to charge the price that consumers are willing to pay. This process is significant for each and every consumer [3].

In more traditional markets, businesses don't have a lot of information about their customers, and they focus mainly on the same pricing policies to draw in customers. Proponents of personalized pricing argue that it can be more efficient in the use of resources, as it allows for prices to be

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adjusted to reflect consumer willingness to pay. Such value-based pricing has been identified as very effective to improve the efficiency of resource allocation through mechanisms. The so called "ineffective cost" factors optimize the efficiency of resource utilization and reduce operation losses and costs [4]. However, the processes that can undermine the effectiveness of such strategies are more than procedural justice issues; they impact the process of collecting a significant amount of data. This is a serious violation of consumers' privacy rights, since companies can subtly influence consumers' behavior [5].

This article suggests that the personalized pricing mechanism has the potential to improve efficiency, in theory. However, in the real market the effectiveness of this pricing method is often less than satisfactory due to limited information resources and the information asymmetry in the real market. This practice is not only hard to do, but often fails to produce good results. Furthermore, the imbalance of fairness generated has a negative effect on data protection rights and contributes to further strengthening the power imbalance between stakeholders. Consequently, this new way of allocation is contrary to the overall goal of social welfare.

2. Personalised pricing and procedural unfairness

One of the main problems is the lack of market fairness because of personalised pricing [6]. The price consumers pay for a product can vary depending on a number of factors. The biggest Chinese online travel agency, Ctrip (Xiecheng), has been called out on its method. It was found that the same room in the same hotel can be very different in cost to different users, and sometimes the difference is quite large [7]. In this instance, one guest paid 899 yuan per person, while another paid 1,564 yuan, but the reasons for the difference are not clearly explained, so consumers cannot determine whether they have been treated unfairly. A good allocation mechanism should be transparent in the allocation process and should distribute the allocation in a fair manner, not an unequal distribution as in this case, but this is not always the case [8].

Personalised pricing not only involves unfair treatment, but also allows for the exploitation of vulnerable groups. Data can be used to find consumers who will pay more, and those who can be charged more. This pricing is done on a basis other than supply and demand, namely, by individual characteristics [9]. The Princeton Review case is a good example of how geographic data can be used to create social inequality. ProPublica reports that the cost of online tutoring was based on the student's ZIP code [10]. Consumer surveys corroborate these concerns. The Digital Economics Team at Fudan University found that over 60% of online travel platform users felt they were discriminated against by these platforms based on their "big data".

Similarly, Amazon has a recommendation system and pricing mechanism that changes prices for each consumer to maximise consumer surplus [11]. It leverages its algorithms to understand purchase history and price sensitivity, increasing prices or premium listings towards less price-sensitive customers [12]. This has the effect of reducing consumer information and clarity to make it more difficult for consumers to make informed and clear choices, which consequently leads to an increase in social inequalities [13].

3. Data collection and consumer surveillance

Personalised pricing also relies on a lot of data collection and thus poses significant privacy concerns. Personal information, including browsing history, transaction records, and other data, is used in different ways by companies to estimate willingness to pay. This leaves a large information gap. There are a lot of things companies need to know about consumers. Minimal information is

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provided about data collection, analysis and pricing decisions by consumers [14]. For instance, an independent security lab test found that it was collecting over 120 dimensions of user behaviour data, more than necessary to complete a transaction.

This imbalance can make it challenging for consumers to make informed decisions. Thus, consumers are no longer able to make rational consumption decisions [15]. This is not only a market transaction, but a continuous monitoring and evaluation of consumers.

A good example of using consumer privacy for commercial purposes is the "Pregnancy prediction" case at Target. Target's algorithm was able to make predictions about the pregnancy of a customer based on the ordinary purchase information which was aggregated. Pregnant consumers are less price sensitive and more likely to purchase high-priced products. The algorithm not only takes advantage of the information gap but also consumers' "path dependence". The "convenience illusion" is the effect of accurate targeting and personalised recommendations over years that ensnare long-term users. In such a situation, the price is set according to systematic rent-extraction, which is based on consumers' cognitive inertia and misplaced trust.

Companies can control purchase recommendations and maximize profits by violating personal privacy [16]. Companies that have more consumer information and advanced algorithmic technologies can anticipate consumer behavior and use effective pricing strategies [17]. On the other hand, smaller companies with similar data resources may find it more difficult to compete, resulting in growing market concentration and further strengthening the position of the large technology firms.

4. Psychological manipulation in digital markets

The other issue is that in digital markets, personalized pricing is no longer a reactive phenomenon in response to consumers' preferences. Platforms are increasingly not only observing behavior, but also influencing and changing consumer behavior, which leads to a greater willingness to pay [18].

Personalised pricing is a violation of the rational individual hypothesis, which states that people make rational decisions in a transparent information environment [19]. However, this is a standard economic assumption, which is reversed with personalised pricing. The preferences of consumers are no longer fixed, but are affected by the platform [20]. Consumer behaviour is not always rational, as they are affected by emotions, framing effects and psychological pressure [21]. Digital platforms take advantage of these biases to influence consumer choices and increase willingness to pay.

This manipulation is usually done by 'loss aversion' and 'fear of missing out' [22]. For example, if a customer is told "only one left" or shown a countdown timer, they will be forced to make a quick decision without taking the time to think about other options or prices. In this context, it is not consumers' willingness to pay for the utility of the product, but rather for passive consumption. The pricing mechanism that Pinduoduo has taken is a good example of how behavioural pressure plays into pricing. Social participation is structurally linked to discounts via group buying and "Cut a Slice" mechanisms instead of market dynamics. Obligation and time pressure are not only the power of the discount, but also of mechanisms like 'Cut a Slice '. Here, the consumer is not just comparing the cost with the utility of the product. It means that personalised pricing might be employed as a way of behavioural control, instead of being an efficient market coordination.

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5. Allocative efficiency under personalized pricing

In the context of neoclassical economics, personalised pricing is an important price-setting policy, and it is essentially price discrimination. This theory suggests that the purpose of a company is to find out the price that each consumer is willing to pay and then set the price [23]. This is achieved by charging more to less price-sensitive consumers and less to more price-sensitive consumers, theoretically, maximising the extraction of the market and improving the overall effectiveness of the marketing. Resources are planned to be and are used in a mathematically optimal way in this idealised case. If the price discrimination is perfect or first degree, the total market output will be expanded to the competitive level as illustrated in the left panel of Figure 1, where the price charged to each individual is equal to his or her willingness to pay. The complete elimination of the deadweight loss (DWL, Figure 1) is the basis of the neoclassical efficiency narrative that is commonly linked to uniform monopoly pricing (right panel in Figure 1).

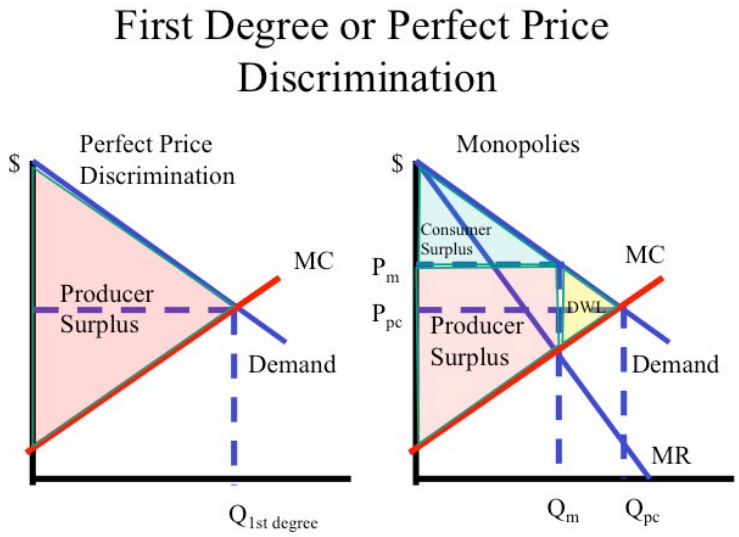


Figure 1. First degree or perfect price discrimination

Source: [23]

But the allocative efficiency that the neoclassical economists champion is mostly an algorithmic mirage. There are plenty of real-world facts that systematically refute this rosy view. This efficiency story is sold with a great deal of force as a means of hiding the psychological subversion of consumer autonomy. Indeed, personalised pricing relies on monopolies over platform data and black-box algorithms, and exacerbates information asymmetries and structural inequality. The collection and use of data is frequently not done ethically, and informed consent is a formality. Algorithms use cognitive biases in a systematic way. Thus, the willingness to pay becomes an extremely controlled, endogenous variable, as the consumer's willingness to pay will be determined by the product's characteristics.

6. Conclusion

A neoclassical view is that personalised pricing enables prices to be set according to the willingness to pay of individual customers, and so the company can minimise losses, including losses that might

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result in business failure. This is to attract more individuals to the system, and there is a certain economic justification for this. But this initiative is based on a series of idealised assumptions. This is not always the case in the digital platform economy. In many cases, there is no personalisation when it comes to pricing. They rely on a vast amount of data gathering, complex algorithms and technologies that are specific to their influence on consumer behaviour, rather than on its reflection.

The idea of widespread adoption of the different fee structures in all scenarios is difficult to imagine in terms of economic benefits. These practices have a significant impact on the fairness of the market and deprive users of all the advantages of data privacy. As far as access to data, there are relevant regulations that effectively consolidate power in the hands of a few. The whole market has been taken over by these platforms.

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