

Personalized Pricing on Digital Platforms: Evidence and Implications

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Abstract. Personalized pricing has become increasingly relevant on digital platforms because firms can use consumer information to estimate differences in willingness to pay and adjust prices accordingly. This review examines how personalized pricing operates, what evidence exists on its effects, and what these findings imply for firms, consumers, and platform governance. The paper first explains the main mechanisms linking consumer information, profiling, demand estimation, and pricing decisions. It then synthesizes evidence from theoretical models, field experiments, consumer experiments, and observations of e-commerce platforms. The reviewed evidence indicates that personalized pricing can improve firm profitability, but its effects on consumers are not uniform. Some consumers may benefit from lower prices, while aggregate consumer surplus may decline. Consumer responses also depend on perceived fairness, privacy concerns, and the degree of price individualization. The review further shows that observed online price differences should be interpreted carefully because differences may arise from factors other than personalized pricing. Overall, personalized pricing should not be understood simply as charging different consumers different prices. Its effects depend on the quality of information, the competitive environment, the degree of personalization, and how consumers perceive the pricing process. The review concludes that future research should place greater emphasis on transaction-level evidence, heterogeneous consumer effects, privacy, and methods that can distinguish genuine personalization from other sources of price variation.

Keywords: Personalized pricing, digital platforms, consumer welfare, price discrimination, algorithmic pricing

1. Introduction

Personalized pricing is a way of setting prices in which firms use information about particular consumers when deciding what to charge for the same or similar products. Digital technologies have made this approach much easier to implement. Platforms can record information such as previous purchases and other forms of user behavior and can feed that information into later pricing decisions [1]. Instead of treating all buyers as identical, firms can use these signals to estimate differences in willingness to pay and adjust their offers. For this reason, examining how consumer information enters pricing decisions is central to understanding personalized pricing on digital platforms.

Personalized pricing has been studied from both theoretical and empirical angles. On the theoretical side, researchers have considered how firms obtain consumer information, how differences between consumers can be incorporated into pricing, and how information sharing can change competition and consumer outcomes [1]. Empirical work has looked more directly at profitability, consumer welfare, and consumers' reactions to personalized prices [2, 3]. These strands of research are useful for different reasons: some explain how personalization can be implemented, while others show what may happen after it is used. Consumer reactions are especially relevant here. Hufnagel et al. examine personalized price discrimination in e-commerce in three online experiments [3]. They find negative attitudinal and behavioral responses not only among consumers who received less favorable prices, but also among some consumers who received favorable prices. Perceptions of fairness help explain these reactions [3]. Thus, the effects of personalized pricing cannot be captured by looking only at the amount paid or the profit earned by a firm.

At the same time, the existing literature is spread across several related questions. Some studies emphasize consumer information, others focus on profits or welfare, and another group examines fairness and consumer responses. The evidence also comes from different settings and research designs, which makes the overall picture less straightforward. A review that places these findings next to one another can therefore help clarify how the pricing process works and how its consequences vary across firms and consumers. This paper takes that approach. It first considers the mechanisms behind personalized pricing and then brings together evidence on its effects on firms and consumers. The discussion then turns to the implications for platform pricing, consumer welfare, and platform governance. The aim is not to estimate a new pricing relationship or to study one particular platform, but to connect findings from theoretical and empirical studies and use them to identify questions that remain open.

2. Evidence from existing studies

2.1. The mechanics of personalized pricing

Personalized pricing depends on several steps that occur between the collection of consumer information and the final price. The basic economic idea comes from price discrimination: if a firm can form a reasonable view of how much different consumers are willing to pay, it can take those differences into account rather than posting exactly the same price for everyone. Digital platforms make this process more detailed because they can collect many signals over time, including purchase history, search activity, location, device information, browsing behavior, and other interactions. Choe et al. describe a related form of behavior-based personalized pricing in which information from earlier interactions is used in later periods [1]. In practical terms, the process can be viewed as a chain: information is gathered, consumers are profiled, willingness to pay is estimated, and the resulting information is used to set prices for individuals or relatively narrow groups. This subsection focuses on that process; the evidence on outcomes is discussed later in Section 2.2. Shiller [4], for example, used web-browsing data in a simulation and estimated a profit increase of about 1.4% when browsing information was incorporated into personalized pricing, compared with 0.14% when only demographic information was used. Because this result comes from a simulation, it is better treated as an illustration of the value of richer information than as direct evidence from a platform.

The quality of the information matters throughout this process. Liu and Serfes show that the value of price discrimination depends on how well firms can identify differences between consumers [5]. More detailed information may improve this identification, but its effect also

depends on the market in which the firm is competing. Shiller [4] reaches a similar point from a data-driven perspective: large behavioral datasets, combined with flexible econometric or machine-learning methods, can reveal differences in demand that would be difficult to see from simple demographic categories. Better data therefore does not mean that every consumer will be charged more. Instead, it gives a firm more scope to make the price depend on its estimate of willingness to pay. Some consumers may consequently receive a lower price, while others may receive a higher one.

Competition adds another layer to the mechanism. Fudenberg and Tirole show how firms can use purchase histories to recognize customers and target them in later periods, and Fudenberg and Villas-Boas review the wider literature on behavior-based price discrimination and customer recognition [6]. Rhodes and Zhou likewise show that the consequences for profit and welfare vary with market coverage and competitive conditions [7]. Once a firm knows which customers are already attached to it, for instance, it can use tailored offers either to keep those customers or to compete for customers currently buying from rivals. Choe et al. consider information sharing between competing firms and show that sharing can soften competition during the information-gathering stage, even when the information is later used for more intensive personalized pricing [1]. This is useful for understanding why the effect of consumer information cannot be judged at only one point in the pricing process: the same information can influence competition differently before and after it is used to personalize prices.

Personalization can also differ in how finely consumers are divided. A platform might work with relatively broad groups, such as membership levels, or move toward prices tailored to individual consumers. Priester et al. separate the basis used for segmentation from the degree of price individualization and find that consumers do not evaluate these forms of pricing in the same way [8]. This distinction is particularly relevant online because the technical cost of moving from group-based targeting to individual targeting is relatively small. Personalized pricing is therefore better understood as a range of approaches, with uniform pricing at one end and highly individualized pricing at the other, rather than as a simple choice between two categories.

2.2. Evidence from existing studies

2.2.1. Evidence on firm profit and consumer welfare

A useful quantitative benchmark comes from Dubé and Misra [2]. They combine a randomized field experiment with a demand model to examine what happens when prices are personalized. In their setting, expected profit was 19% higher than under an optimized uniform price and 86% higher than under the firm's unoptimized status quo price. The increase in firm profit was accompanied by a 23% reduction in aggregate consumer surplus relative to the optimized uniform price. Yet this did not mean that every consumer lost: more than 60% of consumers benefited in their setting. These results are important because they separate three outcomes that are sometimes treated as if they were the same—firm profit, total consumer surplus, and the experience of an individual consumer. The main quantitative results are summarized in Table 1.

Theoretical work on information sharing gives a different but related perspective. Choe et al. find that firms can gain from sharing customer information when the sharing softens competition during the information-gathering stage [1]. Consumers may then be worse off, even though total surplus can rise because improved information may lead to better matching between consumers and firms. Dubus also shows that algorithmic pricing can change the way firms treat previous customers [9]. A firm may personalize prices for consumers it expects to have a high willingness to pay while leaving

others on a common price, which can soften competition and raise industry profits. Taken together, these findings make it difficult to judge personalized pricing from firm profit alone. Consumer surplus, total surplus, the intensity of competition, and the way gains and losses are distributed across consumers all matter.

Table 1. Selected evidence on the effects and consumer responses to personalized pricing

Study	Evidence type	Key finding	Main implication
Dubé & Misra [2]	Field experiment + demand model	Expected profit +19% vs. optimized uniform price; aggregate consumer surplus -23%; >60% of consumers benefit.	Profit gains can coexist with lower aggregate consumer surplus and uneven consumer outcomes.
Priester et al. [8]	Consumer experiments	Fairness perception was lower for individual pricing (2.54) than segment pricing (3.07) in Study 1.	Greater price individualization can reduce perceived fairness.

2.2.2. Evidence on consumer fairness and behavioral responses

Consumers' reactions provide another way to assess personalized pricing. Hufnagel et al. use three online experiments and report negative attitudinal and behavioral reactions among both price-disadvantaged and price-favored consumers [3]. Their results link these reactions to perceived price fairness. In other words, receiving a relatively good price does not necessarily make a consumer comfortable with personalization if the way that price was determined feels unfair or intrusive. This point broadens the welfare discussion beyond the immediate monetary outcome of a single purchase. Priester et al. provide quantitative evidence on the role of personalization granularity [8]. In Study 1, 91 participants rated individual pricing as less fair than segment pricing, with mean fairness scores of 2.54 and 3.07, respectively, on a seven-point scale. Study 2, which involved 257 participants, considered purchase history and location as bases for personalization. Together, these results suggest that both the level of individualization and the information used to set a price can shape consumer responses.

Richards et al. report a similar connection between personalized price differences, perceptions of inequity, and the probability of purchase [10]. Pizzi et al. show that the type of information used for personalization also makes a difference: in their two experiments [11], behavioral data produced more favorable fairness perceptions and lower privacy concerns than biometric data. Priester et al. [8] further find that individual prices are viewed less favorably than segment prices, while location-based personalization can be judged less positively than personalization based on purchase history. More recent evidence from Heidary and Pluut points to both distributive and procedural fairness [12]. This suggests that consumers care not only about whether the final price seems fair, but also about whether the process leading to that price appears legitimate.

2.2.3. Evidence on market observation and algorithmic pricing

There is also evidence from attempts to observe pricing practices directly on online platforms. Hannak et al. examine price discrimination and steering across e-commerce websites and find systematic differences in prices or in the products shown to different users [13]. Their findings

demonstrate that online platforms have the technical capacity to personalize commercial decisions, but a price difference by itself is not enough to identify a particular personalization algorithm. Other factors can produce differences as well. Consumer behavior may also change once users realize that the information they provide can affect the price. Bó et al. show experimentally that participants altered their survey answers when they knew the answers would be used in personalized pricing [14], and the manipulation was more successful when the survey was more closely connected to the product. This means that observed prices can reflect both the platform's information system and the way consumers respond to it.

3. Implications

3.1. Implications for platform pricing strategy

The studies reviewed above suggest that personalized pricing offers platforms a way to make use of differences in demand, but the business value is not limited to the price charged in one transaction. Better demand estimates can improve the match between a price and a consumer's willingness to pay. At the same time, Dubé and Misra show that higher profits can occur alongside lower aggregate consumer surplus [2], while Choe et al. show that information sharing can change competitive conditions [1]. For platforms, this makes the longer-term effects relevant as well. Customer retention, switching between platforms, trust, and incentives to collect more information may all matter after a personalized price has been offered. In Dubé and Misra's setting, expected profit increased by 19% relative to the optimized uniform price while aggregate consumer surplus decreased by 23%. The figures illustrate why a short-run profit measure is not sufficient on its own when assessing a pricing strategy.

One possible response is to use personalization in a more limited form, for example through customer segments rather than unrestricted individual pricing. Priester et al. find that the degree of individualization affects how fair consumers perceive the price to be [8]. The findings of Hufnagel et al. also suggest that negative reactions can reduce the value of a pricing strategy that looks attractive from a short-term revenue perspective [3]. Firms therefore have to weigh the additional revenue from learning willingness to pay against the longer-term value of maintaining customer relationships.

3.2. Implications for consumers and consumer welfare

The consumer consequences are not the same for everyone. A consumer whom the firm identifies as relatively price-sensitive may receive a lower price, while a consumer estimated to have a higher willingness to pay may face a higher one. Dubé and Misra provide a clear example of this distributional pattern: in their setting, aggregate consumer surplus fell, yet more than 60% of consumers benefited from personalized pricing [2]. This difference matters when results are interpreted. An average change in consumer surplus can hide substantial variation across individuals, so assessments of personalized pricing should consider both overall welfare and who gains or loses.

The price itself is only part of the consumer response. Studies of fairness and privacy indicate that consumers can react negatively to opaque or highly individualized pricing even when the price they receive is relatively favorable [3, 8, 10-12]. Pizzi et al. also find that privacy concerns vary with the type of information collected for personalization [11]. The data-collection process therefore affects how acceptable the practice appears to consumers. For digital platforms, this points to a

practical role for transparency. Firms may not need to disclose the full details of a pricing algorithm, but explaining the general basis on which personalization occurs, providing meaningful choices about data use, and presenting pricing rules in understandable terms could make the process easier for consumers to evaluate.

3.3. Implications for regulation and platform governance

The literature points toward regulation of the information and decision process rather than a blanket ban on price differences. Personalized pricing can create efficiency gains and can lower prices for a substantial group of consumers, but it may also reduce aggregate consumer surplus, damage trust, or produce unequal outcomes. Choe et al. illustrate the broader issue: information sharing can improve firms' positions while leaving consumers worse off, so rules about access to and sharing of data can affect both competition and privacy [1]. The experiment by Bó et al. adds another consideration [14]. Once consumers understand that the information they provide can influence their prices, they may change what they report. Clearer disclosure of data use is therefore relevant not only to privacy but also to the reliability of the information on which personalization is based.

A balanced approach could concentrate on three areas: telling consumers the main categories of data used for personalization, placing limits on particularly sensitive forms of targeting, and checking outcomes across different consumer groups. This follows a recurring point in the literature: the concern is not simply that prices differ, but that data, market power, and unequal treatment can interact. It is also important to separate personalized pricing from ordinary dynamic pricing. A price that changes because demand or timing changes does not necessarily depend on an individual consumer profile. The evidence from Hannak et al. reinforces this caution. Although they found personalization across a substantial subset of the sites studied, their analysis used controls to distinguish it from other sources of price variation [13]. Regulation should therefore ask not only whether prices differ, but also what produces the difference.

3.4. Implications for future research

Several gaps remain in the existing research. One is the limited amount of transaction-level evidence from real markets. Controlled experiments make causal relationships easier to identify, while observational studies show what can happen at platform scale, but the two types of evidence are not easy to connect. Another gap concerns differences between consumer groups. Future work could examine these heterogeneous effects rather than relying mainly on average changes in price or welfare. Privacy is another open issue because information that improves a firm's predictions may also make consumers less willing to participate [8, 11]. Finally, future studies need to separate genuine personalization from other reasons why prices may differ. Product characteristics, timing, demand, location, device, promotions, and similar factors should be controlled for before a price gap is interpreted as evidence of personalization. Addressing these issues would make it easier to tell when personalized pricing reflects an efficiency improvement and when it mainly shifts surplus from consumers to platforms.

4. Conclusion

This review has examined personalized pricing on digital platforms by bringing together three connected questions: how personalized pricing operates, what evidence exists on its effects, and what these findings imply for firms, consumers, and platform governance. The review shows that

personalized pricing is not simply a practice of charging different consumers different prices. It is a data-driven process involving information collection, consumer profiling, demand estimation, and pricing decisions, with its effects shaped by information quality, competitive conditions, and the degree of individualization.

The evidence reviewed indicates that the consequences are mixed. Personalized pricing can improve firm profitability and can benefit a substantial share of consumers, but aggregate consumer surplus may decline and the distribution of gains and losses can be uneven. Consumer responses also depend on how prices are generated. Perceptions of fairness, privacy, and transparency can affect whether consumers accept or reject personalized pricing, meaning that economic outcomes alone are not sufficient to evaluate the practice.

For digital platforms, the main implication is that personalization should be treated as a balance between better demand prediction and responsible use of consumer information. More controlled or segment-based approaches may be more sustainable than unrestricted individual-level pricing, while governance should pay attention to data use, pricing transparency, and outcomes across consumer groups.

A limitation of the existing literature is that theoretical models, controlled experiments, and observational studies answer different questions and are not always directly comparable. Future research should therefore obtain more transaction-level evidence, examine heterogeneous consumer effects, and develop stronger methods for distinguishing genuine personalization from price differences caused by product, timing, demand, location, device, or promotion. These directions would provide a clearer basis for determining when personalized pricing creates efficiency gains and when it mainly redistributes surplus from consumers to platforms.

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