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Price Discrimination in Online Retail

Christoph M. Hindermann^a

Abstract

Although newspapers and online blogs provide a variety of anecdotal evidence for price discrimination, they are mostly not based on a scientific and systematic approach. This survey gives a short overview of scientific price discrimination studies in online retail. At first, it contains a short methodological part which shows how price discrimination can be detected. Thereafter, the results of different price discrimination studies are presented, showing that the prevalence of price discrimination varies across studies. Studies who analyze only ‘popular’ websites find a higher rate of prevalence than studies focusing also on ‘unpopular’ websites. As far as scientific evidence is available, online prices hinge on user-based, technical, and location-based features. The dispersion of the price seems to be largest when firms discriminate between users from different countries. Finally, potential reasons why price discrimination is not applied by all retailers are given.

Keywords Price Discrimination – Online Retail – Pricing – Price Differentiation

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1 Introduction

Due to the modern internet technologies, online retailing has become a standard for shopping. Although online retailing goes along with a variety of benefits for consumers, one phenomenon also causes a lot of consumers to worry about (see Turow, 2005, 2009): Price discrimination (or ‘personalized prices’ or ‘individualized pricing’). In particular, newspapers and blogs provide a variety of anecdotal evidence that price discrimination is largely applied in the wild. To give some examples, it has been reported that Capital One offered different loan offers depending on the web browser used (Devin, 2010); Kayak provided different flights for different prices depending on the location of the device (Casanova, 2014); Hotwire seemed to offer logged-in customers a higher price than customers that were not logged in (Elliot, 2009); Asians were twice as likely as non-Asians to be offered a higher price for the Princeton online SAT tutoring packages (Angwin et al., 2015); Orbitz steered Apple users toward more expensive hotels than Windows users (Vissers et al., 2014); and Ryanair raised ticket prices based on consumers’ previous visits (Vissers et al., 2014). At a first glance, that companies – who aim at maximizing their profits by price discrimination – offer personalized prices in online retail is not surprising since customers can easily be tracked when surfing through the web by cookies, fingerprints, HTTP headers, and other tracking techniques (for an overview, see Bujlow et al., 2017 or Ermakova et al., 2018).¹

Combining both the anecdotal evidence of price discrimination and the prevalence of tracking techniques, it would be interesting to know from a scientific perspective to what degree personalized prices (in the sense of third-degree price discrimination) actually exist in online retail. This short survey gives an overview of scientific studies on price discrimination. In section 2, it surveys which approaches can be used to reveal price discrimination. Thereafter, in section 3, the results of experimental price discrimination studies are presented, in particular focusing on which consumer characteristics are most likely to cause individual differences in the offered price. In short, there is evidence that price discrimination is mainly based on user-based features (such as being logged in and having a user account, the originated site, the language settings, and browser history), technical features (such as the operating system, mobile browsing, or the browser used), and location-based features (in terms of the IP address). However, as far as scientific evidence is available, the presence of price discrimination is higher on ‘popular’ (more than 50% of the websites) than on ‘unpopular’ websites (roughly 4% of the websites). Based on these findings,

¹ For example, studies show that between 98% and 100% of the websites use HTTP cookies (Ayenson et al., 2011; McDonald & Cranor, 2011; Soltani et al., 2010) and 20% to 54% of the websites use Flash cookies (Ayenson et al., 2009; McDonald & Cranor, 2011; Soltani et al., 2009). Other studies report that the prevalence rates of fingerprinting techniques vary between 0.04% and 5% (Acar et al., 2013, 2014; Roesner et al., 2012; Nikiforakis et al., 2013).

section 4 presents ethical, legal, technical, and economic explanations why companies may (still) abstain from price discrimination. Finally, section 5 gives a summary.

2 Personalized Prices in Online Retail: General Considerations

Strongly referring to Pigou’s (1932) concept of third-degree price discrimination, one speaks about price discrimination or personalized pricing when prices for an identical good differs among customers based on their individual characteristics.² There are two approaches detect price discrimination in online retail, namely the input and the output approach (Oxera, 2017, 31). According to the input approach, an outsider investigates whether pricing algorithms themselves consist of commands that indicate price discrimination (for example, if a customer uses an Apple device, increase the price by 10 percent for this customer). On the other hand, according to the output approach, an outsider investigates whether the observed price of an identical good differs among customers (for example, users with an Apple device face a higher price for an identical product than Windows users). Since the input approach requires access to the pricing algorithms which most companies will deny, most of the empirical studies on price discrimination belong to the output approach as this survey also does.

In accordance with the output approach, studies on price discrimination analyze whether price discrimination takes place at all and (or) aim at identifying the determinants of price discrimination, i.e. it is investigated which customer features are associated with a higher or lower price. To analyze whether price discrimination occurs at all, scholars can apply crowd-sourcing techniques according to which the prices of identical products – that a set of different real-world users face while surfing through the web – were compared (Hannak et al., 2014; Iordanou et al., 2017; Mikians et al., 2013). For example, based on a sample of 300 real-world users, Hannak et al. (2014) analyze whether prices of identical goods differ when browsing on three different types of e-commerce sites (general retailers, travel retailers, and rental cars retailers). Among ‘popular websites’, they (2014, 7) find evidence for price discrimination “on four general retailers [out of ten, author’s note] and five travel sites [out of six, author’s note]”, indicating that travel sites are most likely to perform price discrimination. To give a second example, Mikians et al. (2013) use the browser plugin *\$heriff* to analyze the prices that were shown to 340 test users while surfing through the web. The authors (2013, 1) find that “there exists several retailers [such as amazon.com, hotels.com and further, author’s note] that return prices for the same product that vary by 10%-30%

² In contrast to personalized pricing, dynamic pricing means that the price of an identical good varies for all customers over time, i.e. all customers are equally affected by falling or raising prices.

whereas there also exist isolated cases that may vary up to a multiplicative factor, *e.g.*, $\times 2$.” Similarly, Iordanou et al. (2017, 2) also use the browser plugin *Sheriff* to search for price discrimination, finding that “76 out of 1994 checked [popular and unpopular, author’s note] e-commerce sites return prices that may vary depending on the country or other characteristics of the user”. The authors find that the dispersion of prices is significantly lower within countries (up to around 8%) than across countries (up to 700%).

Since the crowd-assisted search for price discrimination does not control for customer features (such as browser settings, geolocation, user-agent string, fingerprinting, and so forth), this method only provides information on whether a site performs price discrimination but cannot explain which features cause a higher or lower price. To cope with this shortcoming, a researcher has two possibilities. First, a researcher can apply multiple regression techniques to investigate which features cause differences in the price. In statistical terms, this means that the price of an individual good (dependent variable) is regressed on customer features (independent variables). For example, Iordanou et al. (2017) uses features such as the type of the operating system and the browser (independent variables) to explain price differences (dependent variable). Second, a researcher could test systematically for the impact of customer features on the price in an experimental design. Most studies choose this procedure to detect price discrimination (Hannak et al., 2014; Iordanou et al., 2017; Mikians et al., 2012, 2013; Schleusener & Hosell, 2015; Vissers et al., 2014). Since there are numerous e-commerce sites in the wild, systematic price discrimination studies typically limit their scope of analysis and decide on a specific set of customer features to be tested.

First, experimental price discrimination studies typically limit their scope of analysis. Most studies define in advance which products or branches they want to analyze. For example, Vissers et al. (2014) focus on airline ticket prices; Hannak et al. (2014) concentrate on general retailers, hotel retailers, and car rentals; and Schleusener and Hosell (2015) investigate retailers that belong to the branches tourism, consumer electronics, sports, fashion, insurances, toys, media, food, drugstores, and garden furniture. Another possibility provides Mikians et al. (2012) who simply selected product categories from Alexa (35 product categories; 200 distinct vendors). Besides the decision on a branch or a product, a researcher may also limit the scope of analysis according to the absolute price level (since the price level may be related to the customers’ search behavior) and to the size and professionalism of the company (since larger companies may have more technical competence to perform price discrimination) (see also Schleusener & Hosell, 2015, 15-17).

Second, an experimental design requires that the researcher decides which customer features may cause price discrimination. In general, it can be distinguished between consumer-based,

technical, and location-based features.³ First, consumer-based features – as provided to the (potentially) discriminatory site by the consumer’s cookie profile, the consumer’s cookie settings, its search and purchasing history, the question whether he or she owns an account, and how the user was directed to the site – may cause price discrimination since they signal a consumer’s search behavior and its willingness-to-pay (also called personal-data-induced price discrimination, see Iordanou et al., 2017). To simulate different customers, scholars construct different user profiles for experimental testing. For example, Mikians et al. (2012) apply two different profiles in their study (affluent and budget customers). Similarly, Vissers et al. (2014) train three different consumer profiles (affluent consumer, budget consumer, and flight comparer) for investigating price discrimination of airline tickets (see also Constantindis & Diercks, 2014). Schleusener and Hosell (2015) also train three customer profiles in their study (luxury, normal, and clean user profiles). Second, technical features – such as browser and OS profiles – may be another source of price discrimination since marketing analysts typically assume that, for example, Apple users have a higher willingness-to-pay than users of other brands.⁴ Most of the experimental studies consider this possibility (Mikians et al., 2012; Schleusener & Hosell, 2015; Vissers et al. 2014). Third, location-based features, such as the IP address, may cause price differentiation since they indicate whether a user lives in an affluent region or not. For example, Vissers et al. (2014) query airline tickets from New York and Leuven; Schleusener and Hosell (2015) search for products from different locations in Germany (see also Mikians et al., 2012, 2013); and Hupperich et al. (2018) checks for locations all over world. To test for different locations, scholars may use VPN clients to pretend that the user lives in a particular geographical area.

When testing for price discrimination, price differences result not only from different consumer-based, technical, or geographical features but also from noise. To ensure that price differences (that are found in experimental settings but also when applying crowd-sourcing techniques) do not result from noise, a researcher has to consider the following five aspects (Hannak et al., 2014, 3; Mikians et al., 2013; Vissers et al., 2014). First, he or she has to investigate an identical or a homogeneous product since small product differences, versioning, or bundling may impact the price (Schleusener & Hosell, 2015, 15-16). Second, one has to look for price variation at an identical time. Otherwise, when comparing prices of requests from different points in time, price changes could be due to other reasons than price discrimination (e.g. supply-sided factors, see Vissers et al., 2014). If that were the case, one would find evidence for dynamic rather than for

3 Iordanou et al. (2017) choose alternative terms to express the same classification. They speak about personal-data induced price discrimination (reflecting customer-based features) and location-based price discrimination (reflecting geographical features). Technical features are not addressed in their study.

4 Vissers et al. (2014) note that “the *User-Agent string* is the most straightforward feature for identifying the client’s Internet browser and OS.”

personalized pricing. Third, the researcher is recommended to compare the prices before taxation and without shipping costs. The reason is that taxation and shipping costs may vary due to different locations of the customers (such as different states, countries, or shipping providers). Fourth, when automatically retrieving the prices with the help of an algorithm, one has to make sure that the prices have the same format. This may be problematic since prices may be offered in different currencies or since the retailers' web template differs. Fifth, pricing differences may not only result from personalization but also from A/B testing of providers. Since customers are typically randomly assigned to a group in A/B tests, observed price differences are not due to personalization.

3 The Output Approach: Empirical Findings of Experimental Studies

Based on the considerations above, several studies analyze experimentally whether price discrimination occurs and, if yes, which features lead to different prices (table 1). Investigating highly volatile airline ticket prices, both Constantinidis and Diercks (2014) and Vissers et al. (2014) find no evidence for personalized prices. Rather, both studies conclude that price differences in airline tickets are caused by supply-sided factors and/or reasons of yield management. Vissers et al. (2014, 2) even stress that it is “difficult to establish cause and effect for airline prices”. Next, Schleusener and Hosell (2015) investigate a variety of different branches with respect to the presence of price discrimination. According to their results, systematic price discrimination only occurs in the high-cost tourism sector. In particular, customers with a luxury-user profile had to pay more than clean users and customers using an Apple device had to spend more than those using Windows. Hannak et al. (2014) test systematically for price discrimination for hotels and general retailers. They find some evidence for price discrimination on hotel websites. For example, there is evidence that some sites (*cheaptickets.com*, *orbitz.com*) offer users that have an account and are logged-in lower prices. On *travelocity.com*, customers that used a mobile device with iOS had to pay less than other customers. Similarly to *tevelocity.com*, the general retailer *homedepot.com* also offered lower prices to customers that used a mobile browser. Next, Mikians et al. (2012) searched for personalized prices in 35 product categories. They found no evidence for price discrimination based on technical (system-based) features but a few instances of price discrimination based on geographical (for example, Kindle e-books on *amazon.com* or price differences for products at *steampowered.com* of 20% when comparing users from Spain and Germany) or user-based (some pages offered different prices to customers originating from different sites) features. Similarly, Mikians et al. (2013) also checked for systematic price discrimination. They find some evidence for user-based features (prices of Kindle e-books varied depending on whether a user is logged in or

Table 1: Findings of Experimental Price Discrimination Studies

Author(s) <i>chronologically ordered</i>	Scope of Study	Evidence	Features (percentage of the variation in the price as far as explicitly indicated by the study)		
			<i>User-based</i>	<i>Technical</i>	<i>Location-based</i>
Mikians et al. (2012)	different branches ^a	limited	originated web site (up to 23%)	-	yes - (largely across country; up to 166%)
Mikians et al. (2013)	different branches ^b	limited	user account	-	yes
Hannak et al. (2014)	hotels	limited	user account	mobile browsing	-
	general retailers	limited	-	mobile browsing	-
Constantinides & Diercks (2014)	airline tickets	no	-	-	-
Visser et al. (2014)	airline tickets	no	-	-	-
Schleusener & Hosell (2015)	different branches ^c	limited (tourism sector)	luxury users payed more than clean users	operating system (Apple users payed more than Windows users)	-
Iordanou et al. (2017)	different branches ^d	limited	-	-	yes - (across countries up to 700%)
Hupperich et al. (2018)	hotels / rental car	limited	language settings	operating system / browser	yes

Notes: ^a – 35 different product categories from 200 distinct vendors; ^b – products from 600 distinct domains; ^c – tourism/traffic, consumer electronics, sports articles, fashion, insurances, toys, food, drugstores, media, garden furniture; ^d – 4800 products across 1994 e-commerce sites

not) as well as geographical features (users from Finland had to pay more than those from the UK or the US). Iordanou et al. (2017) also provide evidence for price discrimination based on geographical features, in particular when comparing prices across countries. Lastly, Hupperich et al. (2018) find some evidence for location-based price discrimination among websites offering hotel services; and some evidence that websites individualize prices according to language settings, operating systems, and/or the browser.

To sum up, systematic price discrimination studies find either no evidence at all or limited evidence, whereas price discrimination in the tourism/hotel sector seems to be most likely. Regarding the features, it turns out that (i) location-based discrimination is likely to occur across

countries, (ii) technical discrimination is mainly based on the operating system, and (iii) user-based discrimination refers to whether the user owns an account or not, the originating site, and, in one study, the browsing behavior. Although studies find evidence for price discrimination, its prevalence rate differs between studies investigating only ‘popular’ websites (roughly 50%; see Hannak et al., 2014) and those who investigate also ‘unpopular’ websites (approximately 4% of all websites (76 out of 1994) apply price discrimination activities; Iordanou et al., 2017). Of course, these estimations represent only a lower bound since experimental studies do not account for all possible features causing price discrimination.

4 Explanations for the Limited Evidence for Personalized Pricing

Although studies find evidence for personalized pricing, it is not applied by all websites. This is somewhat surprising since the technical possibilities for personalized prices are given, in particular in online retail. Thus, the question arises why not all online retailers engage in price discrimination. The literature provides ethical, legal, technical, and economic explanations (see also Haucap & Heimeshoff, 2017).

First, companies may abstain from socially unaccepted forms of price discrimination since most of the consumers find it ethically wrong.⁵ To give some numerical examples, Turow et al. (2005, 4) found that American adults “overwhelmingly object to most forms of behavioral targeting and all forms of price discrimination as ethically wrong.” And further, Turow et al. (2009, 15) also state that 78% of the respondents did not want tailored discounts based on “what you did on *other* websites you have visited”; 62% of the respondents did not want tailored discounts based on “what you do on the website you are visiting.” According to Miller (2014, 68-97), ‘ethically wrong’ expresses the view that price discrimination “harms consumers”, “is already illegal (or should be) under antitrust law”, “is deceptive”, “is unfair”, or “is socially unjust”. Similarly, Borgesius and Port (2017, 1) note that “many people regard personalized pricing as unfair or manipulative” (see also White House, 2015).

Although these objections are not new, one may question *why* people find personalized prices unfair or unjust. The literature focuses on six reasons. A first reason is that price discrimination “violates the equal treatment norm among buyers”; since prices are not uniform anymore, there is no “equal access to the goods and services on the basis of price” (Ferrell et al.,

5 Townley et al. (2017, 18-19) list a variety of socially accepted forms of price discrimination. These are status-based discounts, volume-based discounts, loyalty discounts, new customer discounts, peak pricing, and timing-based discounts.

2016). A second explanation refers to the theory of loss or regret aversion by Loomes and Sugden (1982). According to their theory, people dislike situations they could regret. Thus, Borgesius and Poort (2017) note that “people probably object to a situation in which they would have been offered a better price if they had used a different browser or computer, or deleted their cookies.” A third reason may be that personalized pricing happens surreptitiously and intransparently. Thus, customers face information asymmetries in a way that they do not know to which price category they belong (Borgesius & Poort, 2017). Fourth, online price discrimination is accompanied by collecting customer data, leading to a reduction of the customers’ privacy in general. Fifth, customers may argue that price discrimination lowers consumer welfare due to redistribution (which is not necessarily true in case of competition, see Coen & Timan, 2013 or Townley et al., 2017). Sixth, the presence of price discrimination may lead to higher search costs for the customers, which they want to avoid. All these objections show that customers may have an aversion to price discrimination. Thus, companies may fear that customers will abstain from buying their products in case of price discrimination, which would lead to a loss of reputation and lower profits.

Second, price discrimination may only take place to a limited extent due to legal reasons. Dependent on the country, different laws may restrict price discrimination. To give only one example, in the EU, the General Data Protection Legislation (GDPR) allows companies only to process those data to which a consumer gives consent to. In other words, companies are not allowed to use consumer information unless the consumers explicitly give consent that their information can be used for pricing activities. Even further, the GDPR prohibits price discrimination according to some characteristics as written in Article 9:⁶

Processing of personal data revealing racial or ethnic origin, political opinions, religious or philosophical beliefs, or trade union membership, and the processing of genetic data, biometric data for the purpose of uniquely identifying a natural person, data concerning health or data concerning a natural person's sex life or sexual orientation shall be prohibited.

Third, personalized pricing requires some technical expertise. In particular smaller companies still lack knowledge to engage in price discrimination (Haucap & Heimeshoff, 2017). In addition, personalized pricing also requires that the same price is shown to the same customer independent on the channel of distribution (multichannel-pricing). Thus, the price should be the

⁶ A more detailed discussion on price discrimination and GDPR is given by Borgesius and Poort (2017).

same when a customer browses on the website of the company, searches on comparison sites, or buys offline (Schleusener & Hosell, 2015).

Fourth, personalized pricing may still not be the standard due to economic reasons. First of all, although companies may be able to track consumers and, thus, to collect information, there is still a fundamental information problem. To perform (profitable) price discrimination, a seller needs to know the willingness-to-pay of a consumer. However, this is only possible to a limited extent since the seller can collect some information on the customer but not all (thus the seller has only a rough approximation of the willingness-to-pay). In addition, the sophisticated consumer still has the possibility to present a blank profile to the firm or to use manipulated data to pretend that he or she has a low willingness-to-pay.⁷ In the latter case, a company cannot categorize customers as price-sensitive or price-insensitive (or as high and low spenders in terms of Acquisiti and Varian (2005)). But even if firms are able to correctly identify the customer and its willingness-to-pay (whatever the efforts of the customers are to be anonymous), they also must be able to prevent resale. Otherwise, a customer with a low willingness-to-pay could buy the product and, then, sell it to another customer with a higher willingness-to-pay, circumventing personalized prices (exploit arbitrage). A second economic reason is that competition may limit the possibility for price discrimination (Haucap & Heimeshoff, 2017). As long as competition prevails, customers have the possibility to switch to a seller that offers the product for a lower price (unless all sellers have calculated exactly the same willingness-to-pay and offer the product to that price). Thus, it is unlikely that a seller can charge a higher price than the competitive price, especially not when the customers actively compare between sites. A last economic reason may be that the implementation of a price discrimination system and the collection of information causes costs.

In sum, there are a variety of challenges for sellers to perform personalized pricing. Those range from ethical reasons (in particular that customers find personalized pricing unfair) over legal to technical and economic reasons. In particular, a competitive environment and customers who compare prices across sites make it for firms almost impossible to charge the willingness-to-pay of these customers. In this situation, companies can hardly raise the price above the market price. But even if companies are able to perform price discrimination, they still fear that “customers may view this pricing tactic as inherently unfair” (White House, 2015).

⁷ Coen and Timan (2013, 74-78), however, suggest that firms may anticipate that consumers will use anonymization techniques to pretend having a low willingness-to-pay. In turn, firms may charge a higher price to those customers which use anonymization techniques (such as having a blank profile).

5 Summary

In accordance with anecdotal evidence, several studies some find evidence for individualized prices (or price discrimination). Individual price differences – as far as offered by the sites – are based on user-based features (having a user account, the originated site, the language settings, and browser history), technical features (the operating system, mobile browsing, or the browser used), and location-based features (in terms of the IP address). Although these features may be helpful to get some information on a customer’s willingness-to-pay or its price sensitivity, it is not enough information to engage in first-degree price discrimination.⁸ The survey also shows that ‘popular’ websites are more likely to perform price discrimination than ‘unpopular’ sites as one study investigating only popular websites find a higher share of websites engaging in price discrimination (Hannak, 2014) than a study investigating a sample that also contains unpopular websites (Iordanou et al., 2017). It also reveals that the price dispersion is largest when comparing prices that are offered to customers from different countries. That the dispersion within countries is lower may be due to legal reasons (no discrimination according to law) or ethical reasons (since customers within a country are more likely to compare prices among each other).

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⁸ In this sense, personalized pricing should rather be described as ‘sophisticated third-degree price discrimination’.

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