Consumer Privacy and Product Steering versus Price Discrimination in the Online Market

Daniella Daae

Master thesis

This thesis will complete my degree.

Master thesis in Economics

University of Bergen, Institute of Economics

[June 2023]

UNIVERSITETET I BERGEN

Preface

I want to thank my supervisor Eeva Mauring, for all the help and guidance with my thesis. Thank you to my family for always being there for me and helping me remember to take breaks. Thank you to my fellow colleagues for the constant support, and all the good memories throughout the years.

Summary

The following master thesis aims to study consumer privacy, where I focus on price discrimination and steering in the online market. I look closer at whether consumers will benefit from revealing their preferences or not to the seller. The consumer will need to consider the benefits of more accurate recommendations and possible consequences of higher product prices. **My topic question is as follows:** *Will consumers benefit from voluntarily disclosing their information to the seller?*

I present two models by Hidir and Vellodi (2021) and Ichihashi (2020). The models study the price implications of consumers' privacy and welfare in the online market. Hidir and Vellodi (2021) focus on price discrimination and introduce incentive-compatible market segmentation. To ensure trade over relevant products, Hidir and Vellodi (2021) state that the consumer needs to partially reveal their information with pooling segments wide enough to keep the prices low and narrow enough to get trade with relevant products. Ichihashi (2020), with a focus on steering, studies a multi-product seller either with a commitment or no-commitment pricing regimes. A consumer discloses information to the seller, which learns the consumer's preferences, set prices, and makes product recommendations.

With relevant theoretical work on steering and price discrimination, I present a study on how the consequences of disclosure can be both negative and positive for the consumer. Empirical work by Hannak et al. (2014) has proven that both steering and price discrimination are present in the online market. Consumers experienced receiving personalised search results, as e-commerce sites personalised them depending on previous purchases and searches. Protecting consumers' online privacy has led to regulations on how firms can collect users' data. The European Union passed the General Data Protection Regulation (GDPR) in 2016, a privacy and security law that gives consumers more control over their information. The consumer must consent for the firm to collect and process their personal data (Ali et al., 2021).

I have used Scientific Workplace for graphs and figures.

Contents

Table of figures and functions

Overview of figures:

Functions:

0.1 Introduction

The focus on consumer privacy has risen as firms have increasing access to consumer data. Firms use the consumer data to personalise advertising and possibly use price discrimination. In response, policymakers have argued that consumers should be given more control over their personal data, such that consumers could choose when and what they share (Ali et al., 2021). This thesis will follow up on the debate of product steering versus price discrimination in the online market. I study the incentives for the consumers to reveal their information voluntarily to the seller or if they should withhold some information.

E-commerce sites use personalisation algorithms to implement price discrimination and steering, as personalisation has become an essential feature in many web services. Hannak et al. (2014) found that 9 out 10 e-commerce sites in their study engaged in either product steering or price discrimination based on the consumer specific information they had. The prices would, in some instances, differ by hundreds of dollars. Amazon tested out briefly an algorithm that personalised prices for their frequent shoppers. Many consumers believe that online price discrimination is illegal and against practices; however, consumers frequently accept real-world price discrimination through student discounts, coupons, and members-only prices (Hannak et al., 2014).

Consumer outrage can result from buyers being met with different prices online for the same product. Amazon experienced irritation from their shoppers, when it was discovered that they were setting different prices for the same DVD. Amazon CEO Jeff Bezos said in 2000 that they never tested and never will test prices based on their customer demographics. Bezos said that they performed a random price test, which was a mistake. The price test created uncertainty for the consumer and did not simplify their lives (Enos, 2000). If the seller thinks price discrimination will infuriate consumers, they might refrain from personalised pricing (Ichihashi, 2020).

Facebook and Google are internet companies that can access information and gather knowledge about users’ tendencies in order to help sellers make sales. Steering is one of the primary ways companies do this: by influencing which products the consumer considers for purchase (Heidues et al., 2022). The Wall Street Journal reported in 2012 an example of price steering, where they revealed how travel retailer Orbitz showed more expensive hotels to Mac users compared to PC users (Mattioli, 2012). Reports of price discrimination and steering have led to negative publicity for the involved companies. In this case, it is the lack of transparency that raises questions. How are the e-commerce practices manipulating the prices and search results (Wilson, 2014)?

After finding proof of steering and price discrimination in the online market from the empirical study by Hannak et al. (2014), I wanted to explore how this affects consumer privacy and welfare. At the same time, it is interesting to explore how firms are reluctant to vary prices for fear of antagonizing the consumer (Anderson & Simester, 2010). In this thesis, I focus on the consumer side. I want to uncover if consumers will benefit or be disadvantaged from disclosing their information to the seller. My topic question for the master thesis is: *will consumers benefit from voluntarily disclosing their information to the seller?*

I will present two models, which will be compared and discussed later in the text. Both models consider situations where the buyer will communicate their preference to the seller and get tailored prices and product offerings. Whether the seller will use the information depends on the model and the situation. In order to answer my topic question, I use the two models to understand if consumers will benefit or not from disclosing their information to the seller. A price discrimination model is from the article "Privacy, Personalization and Price Discriminations" by Hidir and Vellodi (2021). For product "steering", I am describing a model from the article "Online Privacy and Information Disclosure by Consumers" written by Ichihashi (2020). Both models share a similar result that shows that consumers can benefit from accurate recommendations; however, the disclosed information given to the seller could lead to higher product prices.

The disposition of the thesis will be as follows: Chapter 1, I will cover the theoretical background of steering and price discrimination. In Chapter 2, I will present relevant previous work on the topic and discuss their results. The literature will also be relevant to the model and the analysis in the later chapters. In Chapter 3, I present the framework of the analysis, such as which variables I am studying and the relevant functions for both models. Following is Chapter 2, which will be a comparison of the two models. Further, Chapter 5 will discuss the models and their results and link the answers with relevant literature. There will also be presented examples of firms breaking regulations connected to consumer privacy. In the end, I present a conclusion and summary.

CHAPTER 1

Theoretical background

1 Introducing the concepts

This section will present the concepts of price discrimination and product steering. The main theoretical background of price discrimination is mainly based on Tirole (1988), Varian (1989), and the classical work of Pigou (1932). There are three types of price discrimination: first-, second-, and third-degree. As well as price discrimination, I will introduce the concept of product steering. This introduction of the theoretical background will help understand what is needed for a seller to use price discrimination or product steering to sell more goods.

1.1 Definition of price discrimination

A satisfactory definition of price discrimination takes a lot of work to come up with. The producer price discriminates when two units of the same good are sold at different prices, and this could be to either different consumers or the same consumer. The definition just mentioned explains what price discrimination roughly is; however, it is unsatisfactory. Therefore, it needs to be extended or modified (Tirole, 1988). The definition fails on two counts because the different prices charged to different consumers could mean transportation costs or other costs of selling the good. Price discrimination could also present when all the consumers are charged the same price (Varian, 1989). Varian (1989) explains a preferred definition from Stigler (1987), where price discrimination would be present if two or more similar goods were sold at prices that are different ratios to the marginal costs.

1.2 Different degrees of price discrimination

The classic work of Pigou (1932) distinguishes between the three degrees of price discrimination that the monopolist may take part in. In the following subsections, I will present each of the degrees from first to third.

1.2.1 First-degree price discrimination

The simplest one is perfect price discrimination when a single consumer or more than one identical consumer has unit demand. First-degree price discrimination also works with more than one consumer, that differs in their willingness to pay. Tirole (1988) supposes that each consumer has v as their valuation (willingness to pay) for a good. To illustrate, a monopolist can extract the whole consumer surplus by charging a price p = v. (Tirole, 1988). The seller gives a single take-it-or-leave-it offer to each of the consumers that would extract the maximum amount possible to achieve from the market (Varian, 1989). At first degree, all the different units of an article of trade are sold at different prices. In this case, each product price is equal to its demand price, and therefore there is no consumer surplus left for the buyers (Pigou, 1932).

1.2.2 Second-degree price discrimination

For second-degree price discrimination, personal arbitrage, and screening, we can look at a situation where a monopolist faces a demand composed of heterogeneous consumers. For a monopolist that knows the consumers' tastes, they can offer personalised bundles or packages. A bundle means a price and quantity or price and quality pair. This way, perfect discrimination can be achieved. When there are no exogenous signals from each of the consumer's demand functions, the monopolist can offer menus of bundles for the consumers to select from. In this case, consumers may choose bundles directed at other consumers. Here "self-selection" and "incentive-compatibility" constraints become relevant, and in general, this makes perfect discrimination impossible (Tirole, 1988). At the second degree, a monopolist can make n separate prices so that all units with a demand price greater than x are sold at the price x. All units with a demand price that is less than x and greater than y is sold at a price y, and so on (Pigou, 1932).

1.2.3 Third-degree price discrimination

Third-degree multimarket price discrimination can be described through, for example, a monopolist that produces a single product with a total cost of C(q). The monopolist can divide the aggregate demand into m "groups" or "markets", which they can do because of some "exogenous" information, such as consumers' age or occupation. There are m distinct downward-sloping demand curves for the product, one for each m groups. The monopolist is aware of the demand curves. Here we assume that arbitrage cannot occur between groups and that the monopolist cannot discriminate within the group. The monopolist will charge a linear tariff for each group (Tirole, 1988).

In the third-degree, the monopolist can distinguish among all their customers with different groups by separating them by some practicable mark. The monopolist can charge a separate monopoly price to the members of each group. Third-degree price discrimination is the one that is most realistic and made use for in everyday life. The third-degree differs fundamentally from the other degrees, as it may be a refusal to meet the demands of one market. This is when the demand prices in that market have higher prices than when the demands are satisfied in another market (Pigou, 1932).

1.3 Conditions for price discrimination

For price discrimination to be a viable solution for a firm's pricing problem, three conditions must be followed. Firstly, market power is needed for the firm. Secondly, there must be a way for the firm to sort the customers. Lastly, the firm must be able to prevent resale (Varian, 1989).

I first look at the issue of **market power**. In the theory of monopoly and oligopoly, price discrimination arises naturally. There is an incentive to engage in price discrimination whenever a good is sold for a price that exceeds the marginal cost. The price of the good exceeds the marginal cost, meaning that someone is willing to pay more than the production cost is for one extra unit of the good. Lowering the price for all consumers would be unprofitable. However, lowering the price of the marginal consumer could be profitable (Varian, 1989).

Varian (1989) claims that, in order to only lower the price for the marginal consumer or for a specific class of consumers, there must be a way for the firm to **sort the consumers**. With some respect to exogenous categories such as age, the firm can efficiently sort the consumers. A more complex analysis is needed when a firm must price discriminate on the premises of an endogenous category, such as time of purchase. In such situations, the monopolist encounters the problem of structuring their pricing so that the consumer "self-selects" into the appropriate categories.

For the firm to sell at different prices to different consumers, it must be able to **prevent the resale of the goods**. The firm needs to prevent consumers that buy at a discount price from reselling to other consumers. In order to prevent resale, a mechanism such as a firm legally restricting resale could be an option. Tariffs, taxes, and transportation costs can also hinder resale (Varian, 1989).

1.4 Steering

A form of steering will occur when users receive different results for the same inquiry. Alternatively, the same products will be shown in a different order for the same search. For example, if Best Buy offers a more expensive product to user A than user B when they are both looking for “laptops”. Personalisation in the web search is similar to price steering. The e-commerce providers may give more relevant products or try to extract more money from the user. Steering is possible for e-commerce sites because they often do not sort search results by an objective metric by default. The objective metric can be a price or a user review. Therefore, the results can be sorted using ambiguous metrics like “Most Relevant” or “Best Match” (Hannak et al., 2014).

Online intermediaries that have information about the consumers’ tendencies will often “steer” the consumer towards a specific product they are more likely to purchase. A way for internet companies like Google and Facebook to use their knowledge about their users’ tendencies to help sellers to make more sales is through steering. Internet companies influence consumers by directing them toward specific products they should consider for purchase. Previous research about steering assumes that consumers are rational, and that steering is based on information about the consumers’ preferences (Heidhues et al., 2022). The practice of steering would benefit consumers by helping them get product recommendations that are more relevant to their preferences. Therefore, consumers will allow sites to access their detailed information (Hidir & Vellodi, 2021).

1.5 Bayesian Persuasion

Bayesian persuasion (Kamenica & Gentzkow, 2011) assumes that the consumer discloses information without observing their values. Kamenica and Gentzkow (2011) ask when one person can persuade another to change their action. They consider a symmetric information model where a sender chooses a signal to reveal to a receiver. The receiver will then take a non-contractible action that will affect the welfare of both players. The necessary and sufficient conditions for the existence of a signal that strictly benefits the sender are derived.

They also characterise the sender-optimal signals and examine the comparative statics with respect to the alignment of the sender's and receiver's preferences.

CHAPTER 2

2 Literature

This section will give an overview of the related work written about product steering and price discrimination in the online market. Most of the literature follows the classic theoretical work of Pigou (1920), as presented in the introduction of the concepts. Bergmann, Brooks, and Morris (2015) have continued with the theoretical literature on the topic of market segmentation and third-degree price discrimination. In recent years multiple articles have been published that present the debate of price discrimination and product steering. The question of consumer privacy in the online market is increasingly important as we use the Internet on an everyday basis, and there is more accessible access to information about consumers' preferences and willingness to pay.

2.1 Bergmann, Brooks, and Morris (2015)

Bergmann, Brooks, and Morris (2015), in the article "The Limits of Price Discrimination", consider single product pricing, where the seller has additional information about a consumer's value. The authors analyse the consequences on the welfare of a monopolist, having more information about consumers' tastes beyond the prior distribution. This situation can carry out as third-degree price discrimination, as the additional information can be used to charge different prices to different market segments. Bergmann et al. (2015) characterise what could happen to the producer and consumer surplus for all the possible segmentations of the market. There will be no segmentations if the monopolist has no information beyond the prior distribution of valuations. The producer will charge the uniform monopoly price and get the associated monopoly profit, which will always be a lower bound on producer surplus. The consumers receive a positive surplus, which is the standard information rent. On the other hand, if the monopolist has complete information about the valuations of the buyers, then the monopolist can charge each buyer at the accurate valuation.

Bergmann et al. (2015) have shown that consumer segmentation and price discrimination can prompt a wide range of welfare outcomes. It can be used to increase social surplus by creating segments with prices that make it possible for more consumers to buy. Consumer segmentation and price discrimination can be performed to ensure that the surplus created would go to the consumers, which would mean that consumer surplus would be maximised (Baretto et al., 2022).

2.3 Ali, Lewis, and Vasserman (2021)

Ali, Lewis, and Vasserman (2021) studied in the working paper "Voluntary Disclosure and Personalized Pricing" the effect of letting the consumer have more control over their own data. The consumers themselves can choose what to share and when. The results of the study show that consumer control relative to both perfect discrimination and uniform pricing improves consumer welfare. Firstly, consumers can use disclosure to amplify the competitive forces. Secondly, consumers can induce a monopolist to lower prices by disclosing their information. The improvement of welfare through consumer control depends on the technology of disclosure and market competitiveness. Simple disclosure technologies will be sufficient in competitive markets. When consumers face a monopolist, they need partial disclosure possibilities to obtain any form of welfare gains.

Ali et al. (2021) studied disclosure incentives as they are applied to consumer privacy. They ask the question in their study: Will consumers benefit from personalised pricing when they have control over their data? It depends on both competition and disclosure technology. Under a monopoly, disclosure benefits the consumers only when the disclosure technology allows low-valuation consumers to pool together and then receive a group price. They present a contrasting result under a duopoly, where the disclosure intensifies competition and would be generally beneficial.

2.4 Heidhues, Köster, and Kőszegi (2023)

Heidhues et al. (2023) analyse in the article "Steering Fallible Consumers" the welfare implications of the practice of product steering for "fallible" consumers that make strategic and statistical mistakes while evaluating offers. Heidhues et al. (2023) assume that consumers are rational, and that steering will base on the information companies have on the consumers' preferences. Steering based on high-quality information about the mistakes of the consumers would be harmful to the consumer. Heidhues et al. (2023) raise the possibility of broader regulations on steering practices. At the same time, it is shown that any type of steering could benefit the consumer if they do not refrain reasonably.

Heidhues et al. (2023) conclude that their results imply that restricting mistake-based steering is beneficial. Another part that would be beneficial is restricting steering to base on the self-initiated search and self-declared interests. Regulators could also direct steering towards value-based steering.

2.5 De Corniere and De Nijs (2016)

De Corniere and De Nijs (2016) study in the article "Online advertising and privacy" an online platform that auctions advertising slots. Several advertisers compete in this auction, and the consumers differ in their preferences. Before the auction, the platform will decide whether they allow advertisers to access the information about consumers (disclosure) or not (privacy). With disclosure, the authors improve the match between consumers and advertisers. However, this could increase product prices, even without price discrimination. De Corniere and De Nijs (2016) provide conditions under which disclosure or privacy will be optimal privately and/or socially. In the case where advertisers compete on the downstream market, a disclosure could lead to a decrease or increase in the product price. This case depends on the nature of the information.

De Corniere and De Nijs's (2016) article studies the decision by a platform of whether they should use the information gathered about consumers to increase the revenue from advertising. De Corniere and De Nijs (2016) ask who will benefit most from these practices and if they have social value. This article contributes to the literature on targeted advertising. Disclosing information about the consumer can make the platform able to ensure that a consumer will see the most relevant advertisement. On the other hand, the platform will display ads randomly if no information is disclosed to them.

De Corniere and De Nijs (2016) say that disclosure can lead to higher prices even without price discrimination. Without the standard literature on information disclosure in auctions, this effect opens the possibility that the platform will disclose too much information. Too much disclosing happens especially when the demand function has an intermediate (constant) price elasticity. However, disclosure improves the quality of the match between consumers and advertisers, and the trade increase can compensate for the price effect. When the advertisers compete downstream, the equilibrium price can go either up or down. In the latter case, the trade-off between price effect and match effect will disappear so that disclosure will be socially optimal, but the platform may prefer privacy.

2.6 Barreto, Ghersengorin, and Augias (2022)

Barreto et al. (2022), in the article "Price discrimination with redistributive concerns", show how consumers continuously leave traces of their identities on the Internet. Consumers share information through social media activity, search-engine utilization, online purchasing and so on. The amount of consumer data is then generated and collected and has acquired the status of a highly valued good, allowing the firms to tailor the prices and advertisements to different consumers. In practice, the availability of consumer data will segment the consumers. The data collector observes that a given consumer has a specific characteristic that allows firms to fine-tune how they interact with people that share those characteristics.

Barreto et al. (2022) present that consumer data can be used to sort consumers into different market segments. Sorting into various market segments allows the monopolist to charge different prices at each segment. Barreto et al. (2022) study consumer-optimal segmentations with redistributive concerns, that is for example prioritising of poorer consumers. Different consumers pay different prices. The surplus is distributed across all consumers, which raises the question if it benefits poorer consumers relative to wealthy consumers. If the willingness to pay and wealth are correlated positively, segmentation that maximizes the total surplus will tend to benefit the richer more than the poor. These segmentation types are efficient; however, they may grant additional profits to the monopolist. This is compared to the consumer-optimal segmentations with no redistributive concerns. Barreto et al. (2022) show that the optimal segmentation is surprisingly simple for the remaining markets. It will generate one segment with a discount price and another segment with the same price that would be charged if there were no segmentation.

2.6 Hidir and Vellodi (2021)

Hidir and Vellodi (2021), in the article "Privacy, Personalization and Discrimination", analyse consumer privacy and the debate on product steering versus price discrimination in online retail. The authors ask to what extent the consumer has incentives to voluntarily reveal their information to the seller before they perform a trade. The situation leads to a trade-off where the precise information will give the consumer the preferred item in the trade; however, the seller will be able to extract surplus by setting higher personalised prices. Hidir and Vellodi (2021) use incentive-compatible market segmentation (IC-MS), a market segmentation compatible with the buyer's incentive to reveal their preferences voluntarily. Characterisation of the buyer-optimal IC-MS is the main result of this analysis. The buyer-optimal IC-MS is partially revealing, as it mainly contains pooling segments wide enough to keep the prices low and narrow enough to provide a trade with relevant products.

2.7 Ichihashi (2020)

Ichihashi (2020) studies in the paper "Online Privacy and Information Disclosure by Consumers" the price and welfare implications of consumer privacy in the online market. The author has investigated how a consumer discloses information to a seller of multiple products, which then leads to knowing the consumer's preferences. In this way, the seller can set prices and make product recommendations. The consumer could get more benefits from accurate product recommendations. However, this makes it possible for the seller to use this information to price discriminate.

Ichihashi (2020) shows how the seller prefers refraining from using consumer information for pricing to encourage more information disclosure. The study discovered that the commitment regime could hurt the consumer, as they could be better off by pre-committing to withhold some of their information. The consumer could be better off if the seller had less information and would only be able to give noisy recommendations. There is a contrast between a multi-product and single product model, as the single product models could lower the total surplus if the seller can base prices on the information provided to them. In the single product model, the seller's commitment will possibly enhance the total welfare at the expanse of the consumer's welfare.

2.8 Hannak et al. (2014)

Hannak et al. (2014), in the article "Measuring Price Discrimination and Steering on E-commerce Web Sites", take on a study of price discrimination and steering on e-commerce sites, such as Walmart, and various travel sites like Expedia and Orbitz. E-commerce sites can manipulate the products shown or customize the price of the products on their site. The study uncovered that 9 out 10 e-commerce sites Hannak et al. (2014) studied performed some sort of price discrimination or steering. Personalisation could provide advantages for the users, as it is easier to provide the product or search the user wants. However, personalisation on e-commerce sites could also disadvantage users as the sites can manipulate the products shown.

The manipulation of products offered is an example of price steering. It could also lead to customizing the prices of the products, which is an example of price discrimination.

Hannak et al. (2014) reveal with their analysis that hotel sites Hotels.com and Expedia use the same personalisation strategy. Both sites use randomised A/B tests on users, which tell them by comparing two webpages against each other in order to determine the page that performs better. Hannak et al. (2014) discovered that two travel sites would steer users toward more expensive hotel reservations. Travel site Orbitz is shown to implement price discrimination by offering reduced hotel prices for "members". Home Depot personalised search results for users using their mobile devices. Priceline would personalise the search results based on the user's previous clicks and purchases. The empirical study made by Hannak et al. (2014) contributes to addressing the problem of whether personalisation is an advantage or a disadvantage for the users of e-commerce sites.

2.9 Discussion of the literature

The articles mentioned in subsections 2.1 to 2.8 speak on either price discrimination or product steering in the online market and continue the discussion of online privacy. In this subsection, I will summarise the findings and discuss how the authors contribute to a better understanding of price discrimination and steering in the online market. Do the authors get similar results? I focus on how consumer welfare is affected by online sites using either steering or price discrimination.

Hidir and Vellodi's (2021) main finding is the buyer-optimal IC-MS, where buyers reveal as little as possible about their tastes to ensure low prices. At the same time, the consumer will provide enough information to get the seller to offer relevant products. Bergmann et al. (2015) are pioneers in the theoretical literature on market segmentation, and further work on the topic has been continued by Hidir and Vellodi (2021). Barreto et al. (2022) studied consumer-optimal segmentations with redistributive concerns, where the segmentations are efficient. However, additional profits may occur compared to the consumer-optimal segmentations with no redistributive concerns.

De Corniere and De Nijs (2016) absents from the standard literature on information disclosure in auctions, as disclosure can lead to higher prices even without price discrimination. The effect on pricing decisions opens the possibility that the platform could disclose too much information. Another result is Ichihashi (2020) discovering that the seller prefers to commit not to use the information for pricing, as this could encourage the consumer to disclose information. The commitment could hurt the consumer, and they will be better off by withholding some information.

Ali et al. (2021) try to answer whether consumers benefit from personalised pricing when they control their own data. Ali et al. (2021) argue that the answer will depend on both competition and disclosure technology. Disclosure will only benefit under a monopoly when the disclosure technology allows low-valuation consumers to pool together. The result will be to receive a group price. Heidues et al. (2023) results say that steering can sometimes lower consumer welfare in possibly relevant situations. Restricting steering to be based on self-declared interests and self-initiated search would be beneficial. The welfare effect will depend on the nature and quality of the intermediary's information and the properties of the consumer's mistakes.

Based on these theoretical results presented above, indicate that the price discrimination found in Hannak's et al. (2014) study could both hurt and benefit consumers. Hannak et al. (2014) proved with their data that four general retailers and five travel sites used personalisation, and showed cases where the sites altered the prices by hundreds of dollars. Consumers could also be affected negatively by being steered towards more expensive hotel rooms, as the results on the travel sites were tailored to factors such as which computer the buyer was browsing from. At the same time, searches and recommendations could lead to better matches for consumers, which would benefit them. Hannak et al. (2014) conducted a controlled experiment to investigate what features the e-commerce personalisation algorithm considers when shaping consumer content. The experiment led to cases where sites were altering the results based on the user's OS/browser, account on the sites, and the history of previously purchased/clicked products.

The literature contributes to the debate on consumer privacy in the online market. Hidir and Vellodi (2021) speak directly about whether control over their own information will benefit the consumers. A few of the articles focus on targeted advertising, such as De Corniere and De Nijs (2016), which considers an online platform auctioning advertising slots to competing firms. If the consumers disclose their information, it will improve the match between consumers and advertisers. However, the disclosure can lead to an increase in product prices. Disclosure can have both positive and negative consequences. Positive sides for the consumers are offers with better matches, while a negative side is higher marginal revenues increasing for advertisers leading to higher prices for consumers.

The literature presented above all contributes to research on how consumers can benefit or get disadvantages from sharing their information with e-commerce sites. Considering the different results of each study, disclosing some information could be beneficial. At the same time, withholding some information can ensure lower prices and relevant product offers for the consumer. I think the literature paints a coherent picture of how consumers prefer to receive better recommendations and prevent the prices from getting too high. The question of how much information the consumer should disclose depends on the nature of the information and the surrounding conditions. It is also a question of whether the seller will use the information at all. Surprisingly results such as Ichihashi (2020) show that the seller would prefer to commit not to use the information for pricing to encourage information disclosure. However, Hannak et al. (2014) revealed from their study that 9 out of 10 e-commerce sites performed either price discrimination or steering. I will mention further discussions and additional comments in Chapter 5 and discuss the topic of regulations to protect consumer privacy in the online market.

CHAPTER 3

3 Framework of the analysis

In this section, I will introduce the two models. In the following sub-sections, there is first an introduction to why I choose the specific models. Then, I present the model of price discrimination. Following, I present the model of product steering.

3.1 Choosing the models

In order to answer my topic question of if the consumer should reveal their information or not the seller, I needed to choose which models could be relevant. I chose models from two articles that dive into the debate of price discrimination versus product steering in the online market, which Hidir and Vellodi's (2021) analysis does. Hidir and Vellodi (2021) study a bilateral trade setting, where the buyer has private valuations over the seller's multi-product inventory. Ichihashi (2020) studies the price and welfare implications of consumer privacy. I will introduce these models in order to answer the question of how consumers will either benefit or have a disadvantage by disclosing their information. Could disclosing their information increase or decrease the welfare of the buyer? The consumer can benefit from having correct product recommendations; however, the seller may use the information provided to them for price discrimination. These models will help me study whether the consumer should disclose their information or not and dive more into the study of consumer privacy.

3.2 Model of price discrimination

Hidir and Vellodi (2021) present the model in terms of price discrimination. A buyer faces a seller of multiple, heterogeneous goods over which the buyer has valuations that are private. The seller gives an offer of take-it-or-leave-it price from their stock. The seller will be interested in incentivising the buyers to voluntarily reveal their preferences. Hidir and Vellodi (2021) introduce the notion of incentive-compatible market segmentation (IC-MS), where they ask to what extent the buyer has incentives to reveal their information to the seller before trading voluntarily. The answer makes them turn on a fundamental trade-off. Precise information leads to trade over the preferred item, allowing the seller to extract trade surplus through personalised prices.

3.2.1 Model of Hidir and Vellodi (2021)

Hidir and Vellodi (2021) look at a situation where a buyer and a seller interact, which is their introduction to incentive-compatible market segmentation (IC-MS). The seller has a stock of indivisible, heterogeneous goods indexed by $v \in V \triangleq [0,1]$. The buyer has a known valuation for a good v that is determined by their type $\theta \in \Theta \triangleq [0,1]$. Type θ buyer has the willingness to pay for good v given by utility u(v,θ). The seller believes that the type Θ is uniform, which is common knowledge. Here they employ a model with pure horizontal differentiation, where they introduce the utility function:

$$\boldsymbol{u(v,\theta)} = \bar{u} - \boldsymbol{a(v-\theta)^2}$$

Where ū, *a* > 0. The buyer's type will represent the preferred good. From the inferior products, it will suffer a quadratic loss.

The utility function from Hidir and Vellodi (2021) shows the utility that the consumer gets from consuming the good. The parameter ū is a constant term that represents the baseline level of satisfaction for the consumer or the utility when they do not consume the good. Parameter *a* shows the curvature of the utility function. The parameter *a* reflects how fast the consumer's utility declines as the quality of the good deviates from the ideal level of the type θ. A higher *a* would mean a steeper decline in the utility, as this would mean the quality of the good would move away from θ. Further, parameter *a* indicates how much the consumer care about getting this value close to their type. Term v is the good and represents the quality level of the good that the consumer receives. Lastly, there is θ that denotes the ideal or taste of the consumer. The consumer's ideal can be the performance or the highest value the consumer wants, i.e., the preferred quality for the good.

3.2.2 IC-MS

Hidir and Vellodi (2021) present incentive-compatible market segmentation with extended and revised definitions used in Bergmann et al. (2015). Hidir and Vellodi (2021) look at a market that is a distribution over the types $x \in X \triangleq \Delta(\Theta)$. The aggregated market is shown by $\tilde{x} = U[0,1]$. An offer is then presented by a combination of good v and at the price p,

$$(v, p) \in V \cdot \mathbb{R}_+$$

A set of types that would buy good v at the price p is $\Theta(\mathrm{v},\mathrm{p}) \triangleq \{\theta \in \Theta \mid \mathrm{u}(\mathrm{v},\theta) \geq \mathrm{p}\}$. For this offer (v, p) to be optimal for the market x and would maximize the seller's expected revenue, they choose offers (v.p) that solve the following:

$$\int_{\Theta(v,p)} px(d\theta) \geqslant \int_{\Theta(v',p')} p'x(d\theta)$$

This is for all $(\mathrm{v}',\mathrm{p}') \in \mathrm{V} \cdot \mathbb{R}_{+}$. Hidir and Vellodi (2021) further denote the set of markets for the optimal offer (v, p) with $X(v,p) \triangleq \{\mathrm{x} \in \mathrm{X} \mid (v,p)\ optimal\ for\ x\}$.

Hidir and Vellodi (2021) say a segmentation will split the aggregate market into sub-markets, and each $\mathrm{x} \in \mathrm{supp}\sigma$ is a segment. For the segmentation σ, an offer rule ϕ gives a specific offer for each segment. The offer rule would be the function ϕ: suppσ → $\Delta(\mathrm{V} \cdot \mathbb{R}_{+})$. For ϕ to be optimal for σ, each offer must be optimal in its own respective segment. For σ to be a complete market segmentation where each type forms its own segment, they need $\mathrm{x} \in \mathrm{supp}\sigma \Rightarrow \mathrm{x} = \delta(\theta)$. The $\delta(\theta)$ is the Dirac-delta function.

3.2.3 Producer surplus and consumer surplus

Hidir and Vellodi (2021) present the producer (interim) seller surplus and consumer surplus as the following, where there is a fixed segmentation and offer pair (σ,ϕ).

$$PS(\sigma,\phi;x) = \iint_{\Theta(v,p)} px(d\theta)\phi(x)(dv,dp)$$

$$CS(\sigma,\phi;x) = \iint_{\Theta(v,p)} (u(v,\theta)-p)x(d\theta)\phi(x)(dv,dp)$$

The total interim surplus (TS) is given by:

$$TS(\sigma,\phi;x) \triangleq \mathrm{CS}(\sigma,\phi;x) + \mathrm{PS}(\sigma,\phi;x)$$

It is possible to simplify the expressions presented above. The idea in Hidir and Vellodi's (2021) model is that the offer rule ϕ specifies the set of types θ that buy the good v at the price p. Suppose I look at a situation where θ could only consist of three different types of buyers. The valuation of the buyer can either be θ_1, θ_2 or θ_3, i.e., $\Theta = \{\theta_1, \theta_2, \theta_3\}$. I choose three levels of θ because it accommodates total separation, full pooling, and partial pooling. When there is total separation, every θ gets a separate offer of the good v and price p. With fully pooling, θ_1, θ_2, and θ_3 are in one block. Lastly, there can be partial pooling, where θ_1 and θ_2 could be together, and θ_3 is separate.

Further, the offer rule ϕ; says which types should get which price and value at the offer the buyers receives. An example could be segmenting the market, such that types 1 and 2 are in the first segment x_1. Types 1 and 2 are supposed to buy good v_1 at the price p_1. Type 3 is in the second segment x_2, where they are supposed to purchase good v_2 at the price p_2.

$$x_1 = \{\theta_1, \theta_2\} \text{ and } x_2 = \theta_3.$$

The offer rule, ϕ, specifies which type gets which pair of values and price. The pairing of price and values can be expressed in the following way:

$$\phi = \{\theta_1, \theta_2\}\ gets\ (v_1, p_1)$$

$$\phi = \{\theta_3\}\ gets\ (v_2, p_2)$$

Producer surplus is how likely I will get the price p_2, which depends on the probability of the type being type 3. Both the other types are supposed to buy at the price p_1 and then depend on the probability of it being either type 1 or 2.

$$\boldsymbol{PS} = \mathrm{p}_2 \cdot P(\theta = \theta_3) + \mathrm{p}_1 \cdot P(\theta = \theta_1 or\ \theta = \theta_2)$$

Similarly, in this example, is the consumer surplus. I need to split θ_1 and θ_2 in the consumer surplus expression, as the utilities will differ in these cases.

$$\mathbf{CS} = \mathrm{P}(\theta = \theta_3)[\mathrm{u}(\mathrm{v}_2, \theta_3) - \mathrm{p}_2] + \mathrm{P}(\theta = \theta_1)[\mathrm{u}(\mathrm{v}_1, \theta_1) - \mathrm{p}_1] + \mathrm{P}(\theta = \theta_2)[\mathrm{u}(\mathrm{v}_1, \theta_2) - \mathrm{p}_1]$$

Total surplus sums the producer surplus with the consumer surplus.

$$\boldsymbol{TS} = PS + CS$$

3.2.4 Optimal IC-MS – testing of N and CS**

Hidir and Vellodi (2021) introduce a **Least Separating Clearing IC-MS** structure and the unique seller-optimal segmentation. Buyers want wide segments that will induce the sellers to offer price discounts, however not too wide because it can undermine trade. Segments with the width $\Lambda(a, \bar{u})$ will balance this trade-off perfectly. Conversely, the seller prefers narrow segments, increasing the total surplus by giving well-targeted offers and allowing the seller to capture the gains through higher markups.

The unique seller-optimal segmentation is full market segmentation, which means the seller will offer each buyer their ideal good at their maximum willingness-to-pay of ū. The seller is perfectly informed about the type of buyer they are facing. Further, the seller will then offer the good the consumer is willing to pay the most for. They continue by introducing **Theorem 1:**

Let N = $\left\lceil \frac{1}{\Lambda(a,\bar{u})} \right\rceil$, where $\lceil y \rceil$ maps $y \in \mathbb{R}$ to the smallest integer greater than y. Then σ_{LSC} is buyer-IC-optimal if and only if $\sigma_{LSC} \in \Sigma_P^{N^*}$ consist of N*-1 segments with width $\Lambda(a,\bar{u})$, and one segment with width 1- $\Lambda(a,\bar{u})$(N*-1).* (Hidir & Vellodi, 2021, p. 1350).

This theorem is essential for the main findings of Hidir and Vellodi's (2021) article.

Further, in this section, I will test how this LSC IC-MS will look like. I focus on how the market is divided into segments, which is shown by the function of N*:

$$\boldsymbol{N}^* = \left\lceil \frac{1}{\Lambda(a,\bar{u})} \right\rceil$$

Function 1: The submarkets the market is split into (Hidir & Vellodi, 2021).

The market is segmented into as many intervals as possible of width $\Lambda(a,\bar{u})$. The economic interpretation of the critical width $\Lambda(a,\bar{u})$ brings up the discussion that a segment wider than $\Lambda(a,\bar{u})$ would lead to the seller setting a monopoly price that would force some types to reject (Hidir & Vellodi, 2021). The width is presented as the following:

$$\boldsymbol{\Lambda(a,\bar{u})} = 2\sqrt{\frac{\bar{u}}{3a}}$$

Function 2: Critical width (Hidir & Vellodi, 2021).

I complete N* by placing the $\Lambda(a,\bar{u})$ into the function and will test the effect with different values of a and $\bar{u}$.

$$\boldsymbol{N}^* = \left\lceil \frac{1}{2\sqrt{\frac{\bar{u}}{3a}}} \right\rceil$$

Function 3: Placing function 2 ($\Lambda(a,\bar{u})$) into function 1(N) (Hidir & Vellodi, 2021).*

Hidir and Vellodi (2021) show that if a good is sufficiently substitutable, this will make the buyer willing to fully accept the choice of the good in favor of a price discount. On the contrary, the preferred segmentation of the buyer becomes increasingly informative as the buyer becomes less willing to be offered mismatched products. If the buyer only wants a specific product, there will be in their best interest to reveal their preference.

Corollary 1: *N* is (weakly) increasing in a* (Hidir & Vellodi, 2021).

I start with the question of how *a* is affecting N*. I have placed N* into the program Scientific Workplace to see graphically the difference when ū is set at different values. I will treat N* as a continuous variable and ignore the ceiling operator.

Values set at: (line) ū=1, (dotted) ū=2 and (xxx) ū=3.

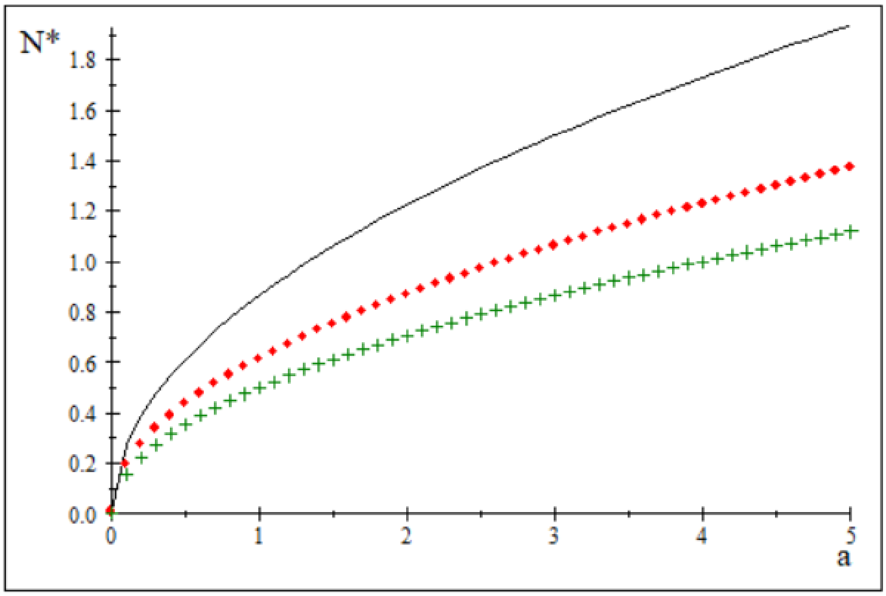

*Figure 1: Effect of a on N**

Figure 1 illustrates corollary 1, i.e., N* is (weakly) increasing in a. The top line, with the value set at ū=1, illustrates that if the consumer cares a lot about which product they get, the incentive-compatible market segmentation will involve a lot of small segments. A larger *a* represents that the consumer cares about getting something close to their preferences.

Further, I study the effect of ū on N* with different values of *a*.

Values set at: (line) a=1, (dotted) a=2 and (xxx) a=3.

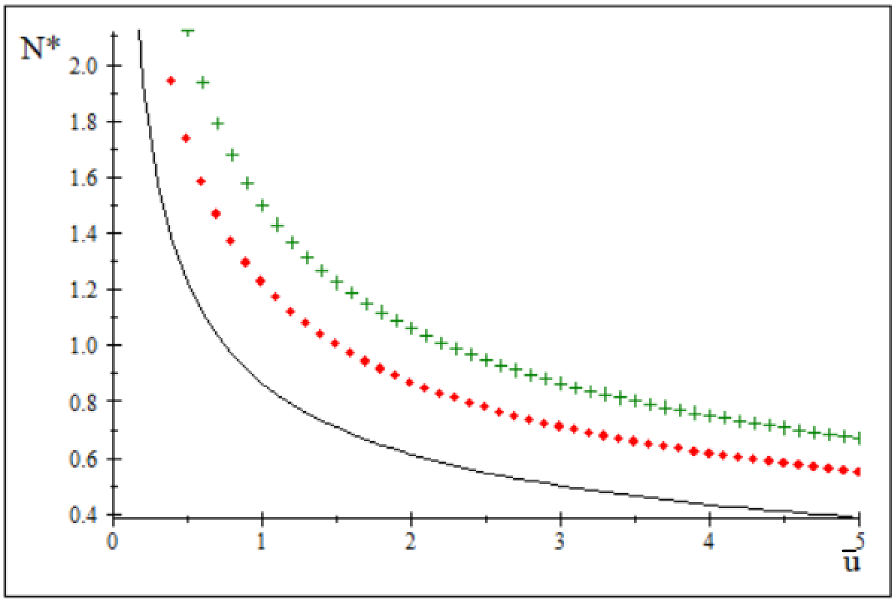

*Figure 2: Effect of ū on N**

The graph in Figure 2 shows that N* decreases with a larger ū. The parameter ū represents the consumer's baseline valuation for the product, and is independent of the taste parameter θ. As the baseline valuation increases, the segmentation decreases. Intuition for ū increasing, which leads to the number of submarkets (N*) decreasing, is that the market adapts to the demands and preferences of buyers with higher valuations. Furthermore, product matching will be more precise and customised with fewer submarkets. The market will be able to cater to specific tastes. The value $a = 3$ shows the highest amount of N* as ū gets a larger value. With a lower value of a, e.g., $a = 1$ or 2, there will be fewer segmentations of submarkets in the market.

Hidir and Vellodi (2021) test the LSC IC-MS by presenting the consumer surplus function below, which also is the corollary 2.

$$\boldsymbol{CS}^* = \frac{a}{6}[(N^* - 1)\Lambda(a, \bar{u})^3 + (1 - (N^* - 1)\Lambda(a, \bar{u}))^3]$$

Corollary 2: *Consumer Surplus**. (Hidir & Vellodi, 2021).

I will continue by testing the effect on consumer surplus, exploring both the effect of a and $\bar{u}$. I have placed CS* in Scientific Workplace, which I did with N* previously. I aim to study the effect with different values of a and ū. Figure 3 illustrates the effect of a on CS*.

Values set at: (line) ū=1, (dotted) ū=2 and (xxx) ū=3.

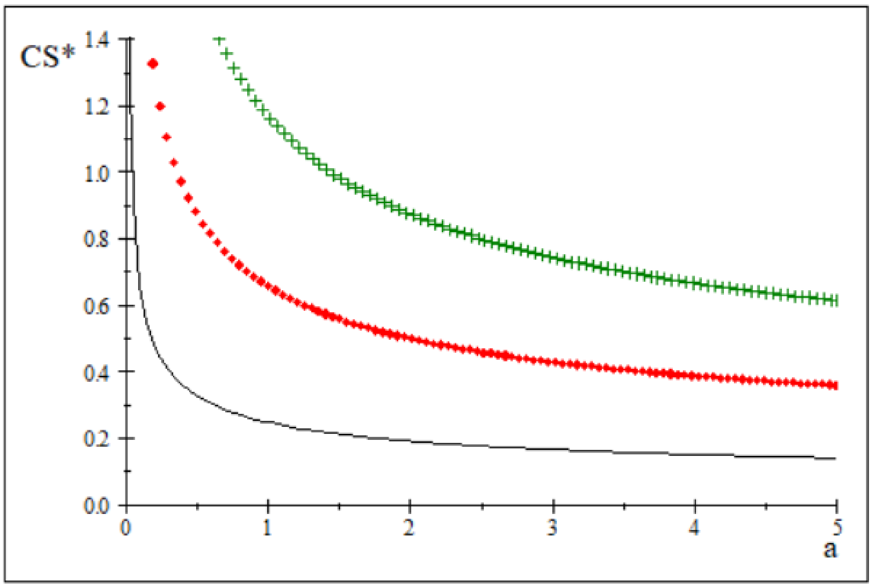

*Figure 3: Effect of a on CS**

The graphs in Figure 3 illustrate that the consumer surplus decreases as parameter *a* increases. It corresponds with the figure of N* as this shows that consumers cannot hide their preferences if they want something close to their taste.

I study the effect with ū, which differs from the effect with *a*. The effect varies as *a* depends on the taste parameter θ, which makes it interesting to study the effect *a* has on the consumer surplus. On the other hand, ū does not depend on θ at all. Parameter ū somehow affects everybody the same. Therefore, I decided to illustrate how ū affects CS* as well.

Values set at: (line) a=1, (dotted) a=2 and (xxx) a=3.

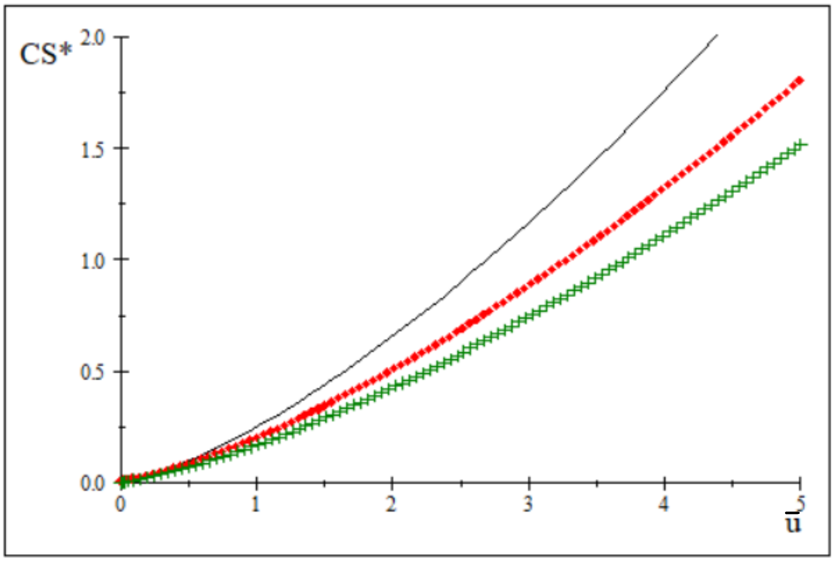

*Figure 4: Effect of ū on CS**

Consumer surplus increases as the parameter $\bar{u}$ increases. As mentioned earlier, ū is not dependent on the consumer's taste and somehow affects everybody the same. The consumer surplus rises with an increasing baseline valuation that the consumers have for the product. The increase in baseline valuation indicates that the consumers have a high willingness to pay for the good. The overall effect is illustrated in Figure 4.

3.2.5 Results and discussion

Theorem 1 (Least Separating Clearing IC-MS) constitutes the main results of the paper of Hidir and Vellodi (2021). The construction is subtle; however, the segmentation admits a simple description; it is the least informative segmentation that guarantees trade. The intuition relies on the buyer's mixed incentives to pool. The gain of the buyers from pooling comes through price discounts. Suppose the types pool, the seller's optimal price offer decreases as she attempts to trade with a wider segment. If these discounts are sufficiently large, this gain outweighs the buyer's loss from being offered a sub-optimal good. On the other hand, if the price the seller offers is not discounted enough, the buyer's loss from being mismatched outweighs the price gain. This results in a breakdown in trade. In online retail, this would be the buyer seeking to balance the gains from steering against the losses from price discrimination. This simple characteristic extends to richer menus of offers and more general preferences.

The results connected to testing N* and CS* from the model by Hidir and Vellodi (2021), give insight in how the trade in the market is affected. As goods become less substitutable, the buyer's preferred IC-MS involves increased information revelation, Corollary 1, as there is little point in buying a worthless good. It is pointless to buy a worthless good even at a discount. Corollary 1 is shown in the test of N*, where *a* decreases as it becomes larger. The parameter *a* represents how much the consumer cares about getting something close to their preferences. On the other hand, testing CS* shows that a larger value of *a* would lead to less consumer surplus. In this case, CS* was shown to be decreasing in a (figure 3). With a larger value of *a*, consumers will be left with less surplus. The effect of an increasing *a* on CS* reveals if consumers care about what type of product they should consume, the firm can use this against them to get consumer surplus out of them. The lambda Λ(a,u) is the width of the segments. If consumers care a lot about which product type they get, the market needs to be segmented finely. The case of a finely segmented market means that the consumers need to give up much information to the seller to get something close to their preferences.

3.2.6 Summary

Hidir and Vellodi (2021) present a model of bilateral trade, which is between a multi-product seller and a privately informed buyer. The notion of an incentive-compatible segmentation is presented, which is a splitting of the market consistent with the voluntary incentives for the buyers to reveal their type. Hidir and Vellodi's (2021) main result is the characterisation of the buyer-optimal IC-MS. The buyers will disclose as little information as possible about their taste to ensure lower prices. At the same time, the buyers provide enough information to ensure that the seller will offer relevant products to the buyer. These conflicting objectives are mapping directly into the consumer privacy debate through price discrimination and steering.

The results of testing the number of segmentations the market is split into (N*) shows that as goods become less substitutable, the buyer's preferred IC-MS involves an increased information revelation. The results refer to Corollary 1, which proves that it is unnecessary to buy a worthless good, even if it is given at a discount. Corollary 1 said that a is weakly increasing in N*. For the consumer surplus (CS*) in the case of a larger a, it would decrease. Consumers cannot hide their preferences at the same time as getting something close to their tastes.

3.3 Model of product steering

Ichihashi (2020) studies the welfare and price implications of consumer privacy. A consumer will disclose information to a multi-product seller, the seller learns about the consumer's preferences, sets prices, and makes product recommendations. The consumer will benefit from accurate recommendations, and then the seller could use the information to price discriminate. He shows that the seller would prefer to commit to not using the information for pricing to encourage information disclosure. However, this commitment will hurt the consumer, who could be better off by pre-committing to withhold some information. In contrast to single product models, the total surplus may be lower if the seller can base the prices on the information.

3.3.1 The baseline model of Ichihashi (2020)

Ichihashi (2020) presents the baseline model with a monopolistic seller of K $\in \mathbb{N}$ products, which contains a set of products denoted by $K = \{1, \ldots, K\}$. Ichihashi (2020) follows a single consumer with unit demand, in that they eventually will consume one of the K products or nothing. The value towards a product k for the consumer, is denoted by u_k. The value u_k is drawn identically and independently across k $\in K$, which is according to some nondegenerate probability distribution supported on a compact set $V \subset \mathbb{R}_+$, which means that V is a subset of the non-negative real numbers. The vector of values is denoted by:

$$\boldsymbol{u} \coloneqq (u_{1,\dots,}u_K)$$

The preferences of the consumer are quasilinear. If consumers buy product k at price p, their ex-post payoff is $u_k - p$. In other occurrences, the payoff would be zero. The payoff for the seller would be their revenue. Both the seller and the consumer are risk neutral.

At the start of the game, before u is observed, the consumer will choose a disclosure rule (M, ϕ) from an exogenously given set, *D*. Each element of D is s set of a finite message space M and a function ϕ:

$$\phi: V^K \to \Delta(M)$$

$\Delta(M)$ represents the set of all probability distributions over M.

Further, the consumer chooses a disclosure rule, where nature draws $\boldsymbol{u} \in V^K$ and a message $m \in M$. This is according to $\phi(\cdot\,|\mathbf{u}) \in \Delta(M)$. In the case of online disclosure, *D* corresponds to the set of the consumer's privacy choices. These privacy choices can be whether the consumer shares their own browsing history. If *D* comprises all disclosure rules, information disclosure will be Bayesian persuasion (Ichihashi, 2020).

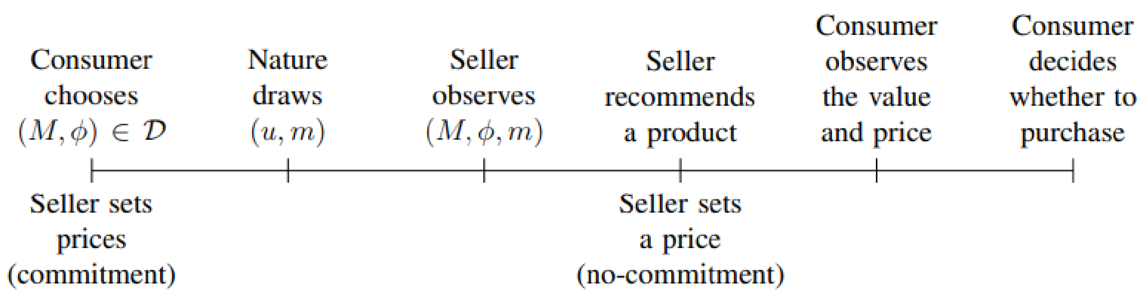

Figure 1: timing of moves under each pricing regime (Ichihashi, 2020).

Figure 1, made by Ichihashi (2020), illustrates the timing of moves under each pricing regime. From the first step, where the consumer chooses the disclosure rule and under the commitment regime, the seller sets prices. The finishing move is the consumer deciding whether to purchase or not.

3.3.2 Disclosure rule

The disclosure rule presented in the model by Ichihashi (2020) makes it possible for the consumer to reveal their preferences to the seller about different products. A disclosure rule is a pair from (M, ϕ). M is the message space, while ϕ is a function that shows the value of the consumer's preferences towards a probability distribution over the messages. M, the message space, is a set of messages that the consumer can send to the seller. Each message has a particular signal that the consumer wants to communicate to the seller about their personal preferences. In the context of online privacy choices, this can be the message of whether the consumer has visited a specific website before.

The function ϕ maps the consumer's preferences to a probability distribution over the messages. ϕ specify how likely the consumer will send each message, given their value for the different products. In a situation where a consumer values product 1 high, and product 2 low, the function ϕ will assign a higher probability to the message corresponding to product 1 than to product 2. After the consumer has chosen a disclosure rule (M, ϕ), nature will draw the consumer's values for the different products u and draw a message m from the probability distribution $\phi(u)$. The seller receives the message that the consumer sends, and the seller will use this message to recommend a specific product to the said consumer. The seller can also use this information from the message to set the price of the recommended product (Ichihashi, 2020).

3.3.3 Restricted model of Ichihashi (2020)

Ichihashi (2020) present the restricted model by assuming that the seller has two products (K=2) that they sell. Disclosure rule, D is [1/2, 1]. Each $\delta \in [\frac{1}{2}, 1]$ is called a disclosure level. The disclosure level represents the amount of information the consumer shares about which product they find more valuable.

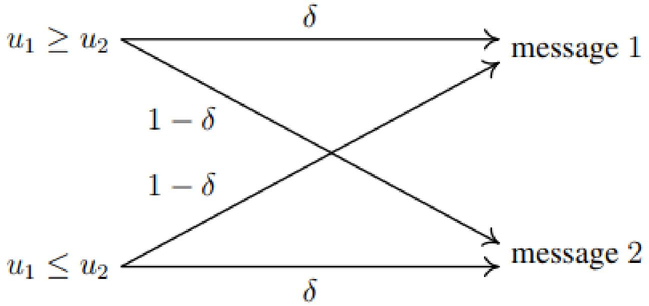

Figure 1: Disclosure rule (Ichihashi, 2020).

In Figure 1, Ichihashi (2020) illustrates that message 1 or 2 is drawn from each δ representing a disclosure rule. Message $m \in \{1, 2\}$ is drawn with probability δ if product m is more valuable than the other product. The disclosure rule will draw messages 1 and 2 with equal probability if products 1 and 2 have the same value. If the seller observes message m, the seller assumes that the consumer has a higher value for product m with probability δ. A larger δ implies that the seller can more accurately learn which product has a higher value.

Ichihashi (2020) considers first the seller's recommendation strategy. For a given price, the seller prefers to recommend the product more likely to have a higher value. The seller prefers this because it will maximize the probability of purchase. The following lemma is made from this:

LEMMA 1: *Fix a pricing regime and take any equilibrium. Suppose that the consumer chooses a disclosure level $\delta > 1/2$. After observing message $k \in \{1, 2\}$, the seller recommends product k. (Ichihashi, 2020, p.577).*

Lemma 1 implies that in equilibrium, a disclosure level δ equals the probability of the seller recommending the most valuable product (this refers to Figure 1). The greater the disclosure, the more likely the consumer is to see their preferred product.

Further, Ichihashi (2020) considers equilibrium pricing. Ichihashi (2020) considers the case where the consumer chooses a disclosure level δ, and message $k \in \{1, 2\}$ is realised. The consumer's value for the recommended product, which is product k by Lemma 1, is then drawn from:

$$\delta F^{max} + (1 - \delta)F^{min}$$

F^{max} and F^{min}, denote the cumulative distribution functions (CDFs) of max (u_1, u_2) and min (u_1, u_2), respectively. The following lemma is made:

LEMMA 2: *Consider the no-commitment regime and take any equilibrium. Suppose that the consumer has chosen a disclosure level of δ. Then the sellers set a price of*

$$\textbf{(1)}\ \boldsymbol{p}(\boldsymbol{\delta}) \coloneqq \mathbf{min}\ \Big(\underset{\boldsymbol{p} \epsilon \mathbb{R}}{\mathbf{arg\,max}}\quad \boldsymbol{p}[\mathbf{1} - \boldsymbol{\delta} \boldsymbol{F}^{\boldsymbol{max}} + (\mathbf{1} - \boldsymbol{\delta})\boldsymbol{F}^{\boldsymbol{min}}(\boldsymbol{p})]\Big)$$

for the recommended product. Moreover, $p(\delta)$ is also the optimal price under the commitment regime when the seller anticipates the equilibrium choice of δ. (Ichihashi, 2020, p. 578).

Because the price of product k affects the revenue only when the seller recommends product k, the last sentence of Lemma 2 is added. The product k only affects the revenue when message k is realized, which refers to Lemma 1. Equivalently, product k will only affect revenue when the seller recommends product k. Under the commitment regime, the seller will choose the product k's price to maximize the expected revenue conditional on message k. When given a disclosure level δ, this maximation problem is identical to the one on the right-hand side of (1).

Lemmas 1 and 2 lead to the first main result, which is Theorem 1:

Theorem 1: *In any equilibrium, the seller obtains a higher payoff, and the consumer obtains a lower payoff under the commitment regime than under the no-commitment regime. (Ichihashi, 2020, p. 578).*

The intuition for this is that under the commitment regime, more disclosure will lead to better recommendations without affecting the prices. The consumer will then prefer the highest disclosure level $\delta = 1$. If the choice of $\delta = 1$ is anticipated, the seller will set the price of p(1) for each product up front. Under the no-commitment regime, the consumer will instead consider the effect of disclosure on prices. In particular, the consumer can always choose $\delta = 1$ to induce the equilibrium outcome of the commitment regime. This is because p(·) in (1) describes the optimal pricing under both regimes. The consumer is (weakly) better off under the no-commitment pricing regime (Ichihashi, 2020).

The seller prefers to commit to prices upfront. Firstly, the optimal price p(δ) depends on δ but not on a realized message. The seller would then be indifferent between the two pricing regimes if the consumer chose the same disclosure level δ. Further, the revenue would increase in δ because higher disclosure leads to a more accurate recommendation. With more accurate recommendations, the consumer's demand shifts up. Therefore, the seller will prefer the commitment regime, where the buyer would choose $\delta = 1$ (Ichihashi, 2020).

3.3.4 Price and disclosure level

In this subsection, I will find an expression for $F^{MIN} and\ F^{MAX}$, to plot the seller price into Scientific Workplace. By doing so, I will prove and further investigate what Ichihashi (2020) has studied in his research. Ichihashi (2020) presents the function for the price, and I will test how the price changes with different disclosure levels $\delta \in [\frac{1}{2}, 1]$. I assume $u_{1,}, u_2$ is independent and identically distributed (iid).

$$u_1 \sim F = u[0,1]$$

$$u_2 \sim F = u[0,1]$$

F^{MAX}: how max $\{u_{1,}, u_2\}$ is distributed CDF of maximum two uniformly distributed random variables.

$$F_{u_1}(x) = P(u_1 < x) = x \; for \; x \in [0,1]$$

In terms of the maximum, it makes out this expression:

$$F^{MAX}(x) = P(u_1 < x)P(u_2 < x) = x * x = x^2$$

$$F^{MAX}\,(p) = \; p^2$$

In terms of the minimum, it makes out this expression:

$$F^{MIN}(p) = 1 - (1 - P(u_1 < p)\,)(1 - P(u_2 < p)\,)$$
$$= 1 - (1-p)(1-p)$$
$$= 1 - (1-p)^2$$
$$= 1 - (1 - 2p + p^2)$$
$$= \mathbf{2p - p^2}$$

Ichihashi (2020) present in Lemma 2, the price the seller sets when the consumer chooses a disclosure level of δ as:

$$\boldsymbol{p(\delta) \coloneqq \min\,(\underset{p\epsilon\mathbb{R}}{\arg\max} \quad p[1 - \delta F^{max} + (1-\delta)F^{min}(p)]})$$

Further, I find p that maximises by placing the F^{MIN} and F^{MAX} found above in the expression of $p(\delta)$ and take the partial derivative of the expression:

$$p(\delta) = p[1 - \delta * p^2 - (1-\delta)(2p - p^2)$$

$$\frac{\partial p(\delta)}{\partial p} = 0$$

$$(\partial p(\delta))/\partial p = p(1 - \delta p^2 - 2p + p^2 + 2\delta p - \delta p^2)$$

$$= p(-2\delta p + 2\delta p + p^2 - 2p + 1)$$

Apply the product rule:

$$= 1(-2\delta p + 2\delta p + p^2 - 2p + 1) + p(2p - 4\delta p + 2\delta - 2)$$

$$= -6\delta p^2 + 4\delta p + 3p^2 - 4p + 1$$

Further, solving for p, where I start by writing the equation in standard form:

$$(-6\delta + 3)p^2 + (4\delta - 4)p + 1 = 0$$

And then place it in the quadratic formula:

$$p = \frac{-(4\delta - 4) - \sqrt{(4\delta - 4)^2 - 4(-6\delta + 3) * 1}}{2(-6\delta + 3)}$$

Simplify the expression (calculations in appendix):

$$p = \frac{-2\delta + 2 - \sqrt{4\delta^2 - 2\delta + 1}}{3(-2\delta + 1)}$$

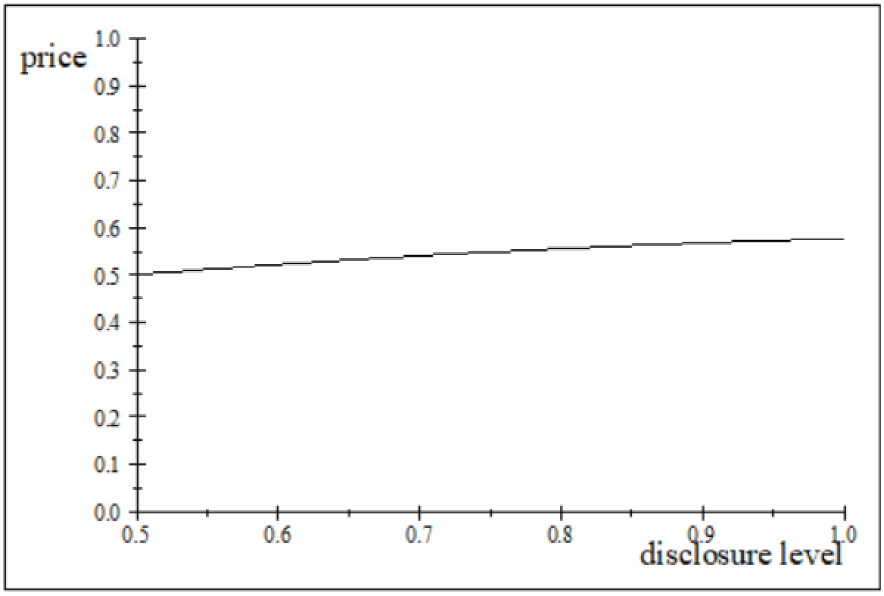

Figure 3: Price and the disclosure level $\delta \in [\frac{1}{2}, 1]$.

Figure 3 illustrates how the price changes when the disclosure level moves between the values of ½ and 1. The graph illustrates that the price does not change drastically when δ increases. The result is connected to Theorem 1 presented in the restricted model of Ichihashi (2020). The seller will obtain a higher payoff under the commitment regime, while the consumer receives a lower payoff in the commitment regime than in the no-commitment regime (Ichihashi, 2020).

Ichihashi (2020) considers the seller in a commitment or no-commitment pricing regime. Under the commitment regime, the seller sets the price of each product at the same time as the consumer chooses a disclosure rule. Therefore, the consumer prefers to set a higher disclosure level of $\delta = 1$ to get better recommendations. The price function made by Ichihashi (2020) considers the no-commitment regime, so the consumer will consider the effect disclosure has on prices. Under the no-commitment regime, the seller sets prices after observing a disclosure rule and a realized message m. The price depends on δ, but not on the realized message. If the consumer chooses the same disclosure level δ, the seller will be indifferent between the pricing regimes. With an increasing δ, the revenue increases because with more disclosure, the recommendations are more accurate, and the demand of the consumer shifts up. The seller prefers the commitment regime, which can explain why the price does not change drastically when the disclosure level increases (Ichihashi, 2020).

3.3.5 Results and discussion

Ichihashi's (2020) Theorem 1 gives an economic explanation of how online sellers seem to refrain from using individual data to price discriminate. Consumers also casually share their information, despite growing concern about personalised pricing. Considering Theorem 1, it is possible to view this case as the sellers' strategic commitment and the consumer's best response. Further, the theorem shows that this outcome could be less desirable for the consumer. The result says that the consumer is better off under the no-commitment regime, which suggests that the consumer could be better off where the sellers are less than fully informed about the most relevant product.

Theorem 1 also has policy implications; it implies that the consumer may benefit from regulations restricting the amount of information the seller can expect to acquire. In order to see this, Ichihashi (2020) considers the equilibrium under the commitment regime, where the consumer chooses $\delta = 1$. Further, suppose a regulator restricts the available disclosure levels to [1/2, δ^*], where δ^* is the equilibrium choice under a no-commitment regime. The consumer will choose the disclosure level δ^* regardless of the pricing regime, leading to a higher payoff than without the regulation (Ichihashi, 2020).

It is partly true that the restriction on set D of available disclosure rules drives Theorem 1. The result shows that if the consumer's endogenous disclosure is crucial for the seller to give accurate recommendations. In this case, the sellers can be better off by committing and not to use the information for pricing. If the focus is on disclosure rules, those parameterized by δ are an easy way to capture these situations. In a different case, if the consumer's endogenous disclosure is not vital for accurate recommendations, the seller may prefer the no-commitment regime (Ichihashi, 2020).

The model of Ichihashi (2020) generates different predictions. In terms of the classical theory of third-degree discrimination, it will be profitable for a seller to set the prices based on the information they have on the consumer's willingness to pay. The consumer will also be worse off if the seller can tailor the prices to precise information about the consumer's values. The first main findings are that the seller would be better off by committing not to use the consumer's information for pricing. The consumer's endogenous disclosure is the key. The seller can prompt the consumer to disclose more information by making such a commitment, which makes the seller make more accurate recommendations. Consumer demand will shift up due to recommended products and increased revenue. An apparent downside to the commitment regime is that the seller cannot base prices on the information. Ichihashi (2020) provides conditions on the available disclosure rules under which the seller's benefits from accurate recommendations dominate the potential loss.

The second main finding by Ichihashi (2020) is that the consumer is worse off if the seller commits not to use the information for pricing. A key observation is that, under the no-commitment regime, the consumer can induce the seller to set lower prices by withholding information about the most valuable product. Although this would lead to less accurate product recommendations, the consumer's gain from low prices can exceed the loss from potential product mismatch. In contrast, the consumer loses their chance to influence prices by strategically concealing information if the seller commits to prices beforehand. **Consequently, the consumer is worse off under commitment** (Ichihashi, 2020).

3.3.6 Summary

Ichihashi's (2020) model consists of a monopolistic seller of K products and a consumer with unit demand. The consumer also has identically and independently distributed values for the products. At the beginning of the game, the consumer will choose a disclosure rule, which will determine the information the seller learns about the consumer's values. The seller will recommend one of the K products after learning about the values of the consumer. Ultimately, the consumer will observe the value of the recommended product and decide if they want to buy it (Ichihashi, 2020).

Ichihashi (2020) illustrates the seller's price when considering it is a no-commitment regime and testing how the price depends on the disclosure level. The result shows that the price remains relatively close to the same in all instances. Under a commitment regime, more disclosure will lead to better recommendations without affecting price. The seller will set the price of p(1) for each product up front when anticipating the choice of $\delta=1$. The two main findings were, firstly, the seller is better off by committing not to use the information of the consumer for pricing. Secondly, the consumer is worse off if the seller commits not to use the information for pricing.

CHAPTER 4

4 Comparison

Following the introduction of the models in Chapter 3, I present a comparison of the two models. There are some key distinctions between Hidir and Vellodi (2021) and Ichihashi (2020). Firstly, Ichihashi (2020) studies a persuasion model, which means he abstracts from the incentive-compatibility property, which is central in the analysis of Hidir and Vellodi (2021). Secondly, the valuations are independently distributed over products in Ichihashi's (2020) setting, compared to Hidir and Vellodi's (2021), having perfectly correlated valuations. Hidir and Vellodi (2021) use their key parameter lambda $\Lambda(a,\bar{u})$, which has no counterpart in Ichihashi's (2020) analysis. The parameter $\Lambda(a,\bar{u})$ refers to the width of the segments that the market is divided into (Hidir & Vellodi, 2021).

Hidir and Vellodi (2021) consider a model in which the buyer communicates their preferences to the seller, who then use the information to tailor product offerings and prices. The focus and formulation differ from Ichihashi's (2020) in at least two ways. Firstly, Hidir and Vellodi (2021) focus on understanding the consumer's trade-off between better product matches and prices. In contrast, on top of this trade-off, Ichihashi (2020) asks what could lead sellers to commit not to use consumer data for price discrimination. Thus, Hidir and Vellodi (2021) focus on the no-commitment regime, whereas Ichihashi (2020) compares two pricing regimes. Secondly, there is a different intended application.

The main application of Hidir and Vellodi (2021) is a situation where a consumer looks for a product knowing which product they want to buy. E.g., when a consumer performs a search query on an e-commerce website, it is suitable that the consumer knows which product they want to buy. In contrast, Ichihashi (2020) considers a situation where a consumer makes privacy choices without knowing precisely the desired product. For example, when we look at a consumer that decides whether to reveal his browsing activities (by accepting cookies), he may not have a particular product in mind. However, the consumer will expect that by sharing more data, he will likely see more relevant product recommendations and targeted ads.

In the article of Hidir and Vellodi (2021) looking at the exogenous variables is natural. Their main result is the buyer-optimal IC-MS, where buyers will reveal as little information as possible about their tastes to get lower prices. At the same time, the consumer provides just enough information for the seller to offer them relevant products. In Ichihashi's (2020) article, the disclosure level, δ, is not exogenous. The disclosure level is part of the equilibrium. To get the result of Ichihashi (2020), the consumer must choose a disclosure rule before observing their values. The consumer doing so is suitable if the consumer is not informed of the existence or characterisation of the products. The consumer understands that their personal data will inform the seller how they value each product.

CHAPTER 5

5 Discussion and comments

Here I discuss the contributions of Hidir and Vellodi (2021) and Ichihashi (2020) and connect how the two models corroborate or contradict the findings of the other theoretical papers mentioned in Chapter 2. I will also be commenting on how consumers are affected by firms using price discrimination and steering in practice. How has the consumers reacted to these practices in the past? What measures have been taken to give consumers more control over how their personal data is used?

5.1 Discussion and connection to previous literature

I start with the two main theoretical articles I presented in Chapter 3. Hidir and Vellodi (2021) assume that consumers know their tastes before searching for products. Their notion of the IC-MS makes their model of costless communication and affordable signalling. Hidir and Vellodi's (2021) model aims to understand how the information alone affects allocative efficiency. Ichihashi (2020) follows the line of Bayesian persuasion (Kemenica & Gentzkow, 2011). Ichihashi (2020) assumes that the consumer will disclose their information without observing their own values. The commitment is shown to make the consumer worse off.

Hannak et al. (2014) illustrate with their empirical studies that personalisation has become an essential feature of many web services. There is evidence that shows that e-commerce sites are using these personalisation algorithms to implement price discrimination and steering. As a result of Hannak's et al. (2014) methodology, they can only identify the positive instances of price discrimination and steering. Because of only receiving positive results, it is part of the incompleteness of their empirical study. The study led to observations of two travel sites, Expedia and Hotels.com, which used A/B tests to steer users toward more expensive hotel reservations. In contrast, Heidues et al. (2023) say that firms will likely not use A/B testing for value-based steering. For A/B testing to happen, a consumer's choices must reflect their actual values. Heidues et al. (2023) say that probably the most important use of A/B testing is not by comparing different products, but by testing different ways of selling the same product.

Ali et al. (2021) question if consumers benefit from personalised pricing when they have control over their data, and they argue that it depends on the disclosure technology and the competition. Under a monopoly, consumers only benefit from it when disclosure technology would allow low-valuation consumers to pool together. The consumers then receive a group price. Ali et al. (2021) study focuses on hard evidence of disclosure, looking at disclosure incentives applied to consumer privacy. Hidir and Velldi (2021) have complementary work in studying the communication of soft information to the monopolist, which is when multiple potential products can be sold. Ali et al. (2021) study a single product setting and show the benefits that result from personalised pricing when the consumer can disclose hard rather than soft information.

Heidhues et al. (2023) show that steering while using a rational model would be misleading. Their setting is a contrast through showing that steering a rational consumer, would tend to be beneficial if the prices do not respond much. Furthermore, the harm of endogenous prices is limited as it would reduce consumer surplus to zero. However, steering a fallible consumer is often harmful, even if the prices are endogenous or not. In the case where consumers make no statistical errors, then they both reasonably buy and refrains. The consumer would be considered rational; therefore, they will benefit from value-based and perceived-value-based steering. Hidir and Vellodi (2021) could argue that steering could benefit consumers when prices are held fixed. However, Heidues et al. (2023) say this conclusion is incorrect in the case of fallible consumers. Research has focused on two primary sources of harm caused by steering. Firstly, it may lead to prices being changed, and the effect would be complex and uncertain. De Corniere and De Nijs (2016) have also researched this source of harm caused by steering. Secondly, Heidues et al. (2023) examine the intermediary's incentives and recommendations. The intermediary may not be aligned with the consumer's preferences.

De Corniere and De Nijs (2016) show that disclosure has positive and negative consequences. The positive sides are when the advertisers can condition their bids on information about consumers. In equilibrium, the highest bidder will be the firm that offers the best match. Therefore, the equilibrium will be efficient. However, in a situation when the good matches correspond with higher marginal revenues for the advertisers, they show that the disclosure of personal information will lead to higher prices for the consumers. In contrast, Ichihashi (2020) contemplates a situation where the seller commits to not using information for pricing and considering a broad set of disclosure rules. De Corniere and De Nisj (2016) assume that disclosure decisions would be binary.

5.2 Consumer outrage and more control over their own data

De Corniere and De Nijs (2016) say that firms could be reluctant to use first- or third-degree price discrimination as they are afraid of the backlash from the public and causing the consumers to make fewer purchases. The backlash was connected to what happened with Amazon in 2000, when the company was caught setting different prices for the same DVD. Setting different prices for the same product caused consumer outrage, and the company backed down and admitted they had made a mistake (Enos, 2000). Anderson and Simester (2010) performed an empirical study on how firms are sometimes reluctant to vary prices for fear of antagonising consumers. Consumers' response to a downward price adjustment revealed that many consumers stopped purchasing if the firm charged a lower price than what they previously paid for the same item. Anderson and Simester (2010) characterised the consumer demand loss as the consumers boycotting the firm. Consumers could be less antagonized by lower prices on items they had purchased before if they could take advantage of the discounts. From Anderson and Simester's (2010) study stopping the consumer from abusing this discount was impossible.

Ali et al. (2021) bring up how consumers advocate for how consumer data is shared, and this takes a prominent role in the ongoing international debate on consumer privacy. The increased focus on consumer privacy led to the General Data Protection Regulation (GDPR), passed by the European Union in 2016. The GDPR requires the firm to obtain consent from the consumers before they can collect and process their personal data. The private sector has also made steps towards giving more control to the consumer. Apple had an update in April 2021, where it is default asking users whether they want to allow an app to track them. With requirements connected to consumer privacy, it still needs to be assured that firms and companies follow these laws. Satariano (2023) from The New York Times reported on the 22nd of May 2023 that Meta had been fined 1.3 billion dollars, a record under the GDPR law. The ruling is connected to Facebook, as collected data about their European users have been transferred to the United States. Meta was previously a target of regulators under the GDPR, as Meta forced users to accept personalised ads as a condition for using Facebook. Meta went under a data leak in November, which they were also fined for.

The model of Ali et al. (2021) is designed to analyse a broad class of disclosure technologies. The disclosure technology of track/do-not-track is part of GDPR. In this system the consumer can report the group or the range they belong to, similar to the privacy control menus that Google and Facebook offer. With these available technologies, giving consumers control over their own data can generate substantial gains for their welfare. The gains depend on which equilibrium is selected.

5.3 Ending remarks of discussion

Ichihashi (2020) illustrates how the price stays relatively close to the same even when the disclosure level increases. The consumer is shown to be worse off if the seller commits not to use the information for pricing. Under the no-commitment, the consumer can prompt the seller to set lower prices by withholding information about the more valuable product. For the consumer, withholding information could lead to less accurate product recommendations; however, the loss could be compensated by getting lower prices instead.

Hidir and Vellodi (2021) show how consumer surplus will decrease when the parameter *a* increases. The parameter *a* measures how sensitive the consumer is to getting something far away from their tastes. The main result of Hidir and Vellodi (2021) is shown through a characterisation of the buyer-optimal IC-MS. It will be partially revealing, and it contains pooling segments wide enough that the prices are low but narrow enough to get trade with relevant products.

Ali et al. (2021) mention the international debate on consumer privacy and how consumer data is shared and used in the online market. Consumer privacy in the online market was in focus when regulation laws such as GDPR got passed in the European Union. Regulation laws protect consumers and give them more control over how their private information is used. There are multiple cases of these regulations not being followed, and consumers' privacy is taken advantage of. As recent as May 2023 Meta was fined under the GDPR for sharing information of European data on Facebook with the United States (Satariano, 2023). Firms want to prevent consumer outrage, which Amazon experienced when they set a different price for the same DVD in 2000 (Enos, 2000).

CHAPTER 6

6 Conclusion

The goal of my thesis has been to study the consumers' incentive to disclose their private information to the sellers. The seller can use this information to give product recommendations or price discriminate. Theoretical studies have shown different ways of researching this question. I focused on the models of Hidir and Vellodi (2021) and Ichihashi (2020), where they research whether the consumer would benefit from disclosing their information to the seller. Hidir and Vellodi (2021) give a result with a partially revealing buyer optimal IC-MS in a pooling segment wide enough to keep prices low. And at the same time, narrow enough to create a trade of relevant products. Ichihashi (2020) reveal a situation where the consumer is worse off if the seller commits not to use the information disclosed to them. Under the no-commitment pricing regime, the consumer can urge the seller to set lower prices by withholding information about their higher value products. The consumer will get less accurate product recommendations, but the loss is compensated by lower prices instead.

Will consumers benefit from voluntarily disclosing their information to the seller? The consumers disclosing their information could lead to both negative and positive consequences. Whether the consumer should disclose their preferences depends on how steering and price discrimination are used. Firms can even be reluctant to use price discrimination for fear of backlash from consumers (De Corniere & De Nijs, 2016).

Protecting consumers' privacy has also been a focus in recent years, as GDPR was passed in Europe by the European Union in 2016 (Ali et al., 2016). There are examples of companies and firms not following the regulations, where the data collected from the consumer has been used and sent to the United States (Satariano, 2023). Protecting the consumers' private information still has a long way to go. Therefore, it is important to keep researching the consequences followed from the increasing access to consumer information online. Stricter regulations on steering and price discrimination could be necessary for consumer privacy and welfare.

7 Bibliography

Ali, S. N., Lewis, G., & Vasserman, S. (2021). Voluntary Disclosure and Personalized Pricing. *NBER Working Paper*. http://www.nber.org/papers/w26592

Anderson, E.T & Simester, D.I (2010). Price Stickiness and Customer Antagonism. *The Quarterly Journal of Economics, 125*(2), 729-765. https://doi.org/10.1162/qjec.2010.125.2.729

Barreto, D.M, Ghersengorin, A. & Augias, V. (2022). Price Discrimination with Redistributive Concerns. *SciencePo Working papers, HAL*. https://hal-sciencespo.archives-ouvertes.fr/hal-04067226

Bergmann, D., Brooks, B. & Morris, S. (2015). The Limits of Price Discrimination. *American Economic Review, 105*(3), 921-957. http://dx.doi.org/10.1257/aer.20130848

De Corniere, A. & De Nijs, R. (2016) Online Advertising and Privacy. *RAND Journal of Economics*, *47*(1), 48-72. https://www.jstor.org/stable/43895634

Enos, L. (2000, 28. September) Amazon Apologizes for Pricing Blunder. *E-Commerce Times.* https://www.ecommercetimes.com/story/amazon-apologizes-for-pricing-blunder-4411.html

Hannak, A., Soeller, G., Lazer, D., Mislove, A., & Wilson, C. (2014). Measuring price discrimination and steering on e-commerce web sites. *In Proceedings of the 2014 conference on internet measurement conference*, 305-318. http://dx.doi.org/10.1145/2663716.2663744

Heidhues, P., M. Koster & B. Koszegi (2023). Steering fallible consumers. *The Economic Journal*, *133*, 1430-1465. https://doi.org/10.1093/ej/ueac093

Hidir, S., & Vellodi, N. (2021). Privacy, personalization, and price discrimination. *Journal of the European Economic Association*, *19*(2), 1342-1363. https://doi.org/10.1093/jeea/jvaa027

Ichihashi, S. (2020). Online privacy and information disclosure by consumers. *American Economic Review*, *110*(2), 569-95 https://www.aeaweb.org/articles?id=10.1257/aer.20181052 DOI: 10.1257/aer.20181052

Kamenica, E. & Gentzkow, M. (2011). *Bayesian Persuasion. American Economic Review 101*, 2590–2615. http://www.aeaweb.org/articles.php?doi=10.1257/aer.101.6.2590

Mattioli, D. (2012, 23. August). On Orbitz, Mac Users Steered to Pricier Hotels. *The Wall Street Journal.* https://www.wsj.com/articles/SB10001424052702304458604577488822667325882

Pigou, A. C. (1932). *The Economics of Welfare* (4th edition). 1920. Macmillan&Co.

Satariano, A. (2023, 22. May). Meta Fined $1.3 Billion for Violating E.U. Data Privacy Rules. *The New York Times.* https://www.nytimes.com/2023/05/22/business/meta-facebook-eu-privacy-fine.html

Stigler, G. (1987). *The Theory of Price.* Macmillan.

Tirole, J. (1988). *The Theory of Industrial Organization*. MIT Press.

Varian, H.R (1989). Handbook of Industrial Organizations, *Elsevier Science Publishers B.V*, *1*, 598-647. https://doi.org/10.1016/S1573-448X(89)01013-7

Wilson, C. (2014, 3. November). If you use a Mac or an Android, e-commerce sites may be charging you more. *The Washington Post.* https://www.washingtonpost.com/posteverything/wp/2014/11/03/if-you-use-a-mac-or-an-android-e-commerce-sites-may-be-charging-you-more/

8 Appendix

The calculations presented in the appendix are connected to the expressions for $F^{MIN} and\ F^{MAX}$, in order to plot the seller price into Scientific Workplace.

Calculations to section 3.3.4

Assuming that $u_{1,}, u_2$ is independent and identically distributed:

$$u_1 \sim F = u[0,1]$$

$$u_2 \sim F = u[0,1]$$

F^{MAX}: how max $\{u_{1,}, u_2\}$ is distributed CDF of maximum 2 uniformly distributed random variables.

$$F_{u_1}(x) = P(u_1 < x) = x\ for\ x \in [0,1]$$

In terms of the maximum, it makes out this expression:

$$F^{MAX}(x) = P(u_1 < x)P(u_2 < x) = x * x = x^2$$

$$F^{MAX}\,(p) = \ p^2$$

In terms of the minimum, it makes out this expression:

$$F^{MIN}(p) = 1 - (1 - P(u_1 < p)\,)(1 - P(u_2 < p)\,)$$

$$= 1 - (1 - p)(1 - p)$$

$$= 1 - (1 - p)^2$$

$$= 1 - (1 - 2p + p^2)$$

$$= \mathbf{2}\boldsymbol{p} - \boldsymbol{p}^{\mathbf{2}}$$

Ichihashi (2020) present in Lemma 2, the price the seller sets, when the consumer chooses a disclosure level of δ as:

$$\boldsymbol{p}(\boldsymbol{\delta}) \coloneqq \mathbf{min}\ (\ \underset{\boldsymbol{p}\epsilon\mathbb{R}}{\mathbf{arg\,max}}\quad \boldsymbol{p}[\mathbf{1} - \boldsymbol{\delta}\boldsymbol{F}^{\boldsymbol{max}} + (\mathbf{1} - \boldsymbol{\delta})\boldsymbol{F}^{\boldsymbol{min}}(\boldsymbol{p})])$$

Further, I will find p that maximises, by placing the $F^{MIN}\ and\ F^{MAX}$ found above in the expression of $p(\delta)$ and take the partial derivative of the expression:

$$p(\delta) = p[1 - \delta * p^2 - (1 - \delta)(2p - p^2)$$

$$\frac{\partial p(\delta)}{\partial p} = 0$$

$$\partial p(\delta)/\partial p = p(1 - \delta p^2 - 2p + p^2 + 2\delta p - \delta p^2)$$

$$= p(-2\delta p + 2\delta p + p^2 - 2p + 1)$$

Apply the product rule:

$$= 1(-2\delta p + 2\delta p + p^2 - 2p + 1) + p(2p - 4\delta p + 2\delta - 2)$$

$$= -2\delta p^2 + 2\delta p + p^2 - 2p + 1 + 2p^2 - 4\delta p^2 + 2\delta p - 2p$$

$$= \boldsymbol{-6\delta p^2 + 4\delta p + 3p^2 - 4p + 1}$$

Further, solving for p, where I start by writing the equation in standard form:

$$(-6\delta + 3)p^2 + (4\delta - 4)p + 1 = 0$$

And then place it in the quadratic formula:

$$p = \frac{-(4\delta - 4) - \sqrt{(4\delta - 4)^2 - 4(-6\delta + 3) * 1}}{2(-6\delta + 3)}$$

Simplify the expression:

Starting with: $\sqrt{(4\delta - 4)^2 - 4(-6\delta + 3) * 1}$

$$\sqrt{16\delta^2 - 32\delta + 16 + 24\delta - 12}$$

$$\sqrt{16\delta^2 - 8\delta + 4}$$

Factor:

$$\sqrt{4(4\delta^2 - 2\delta + 1)}$$

Applying the radical rule:

$$\sqrt{4}\sqrt{4\delta^2 - 2\delta + 1}$$

$$\boldsymbol{2\sqrt{4\delta^2 - 2\delta + 1}}$$

Placing it with the quadratic formula:

$$p = \frac{-(4\delta + 4) - 2\sqrt{4\delta^2 - 2\delta + 1}}{2(-6\delta + 3)}$$

Focusing on the numerator:

$$-(4\delta + 4) - 2\sqrt{4\delta^2 - 2\delta + 1}$$

$$-2 * 2\delta + 2 * 2 - 2\sqrt{1 + \delta^2 * 4 - 2\delta}$$

Factoring out the common term 2:

$$2(-2\delta + 2 - \sqrt{1 + \delta^2 * 4 - 2\delta})$$

Back to the quadratic formula:

$$p = \frac{2(-2\delta + 2 - \sqrt{1 + \delta^2 * 4 - 2\delta})}{2(-6\delta + 3)}$$

Focusing on the dominator, factor:

$$2(-6\delta + 3)$$

$$2 * 3(-2\delta + 1)$$

$$\mathbf{6}(-\mathbf{2}\boldsymbol{\delta} + \mathbf{1})$$

Back to the quadratic formula:

$$p = \frac{2(-2\delta + 2 - \sqrt{1 + \delta^2 * 4 - 2\delta})}{6(-2\delta + 1)}$$

Cancelling the common factor 2, and getting the final expression of p as:

$$p = \frac{-2\delta + 2 - \sqrt{4\delta^2 - 2\delta + 1}}{3(-2\delta + 1)}$$