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DISCUSSION PAPER

Societal Implications of Personalized Pricing in Online Grocery Shopping

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Abstract
Attention to big data analytics is ubiquitous and growing given the online shopping revolution and its potential to generate individual-specific actionable datasets which were previously unavailable or cumbersome to cultivate. However, the food industry has not drawn much attention to discussions of individualized pricing strategies using online grocery datasets. Considering growth of the online grocery market and consumers data abundance to grocers, this brief viewpoint article focuses on potentials of incorporating big data analytics into pricing strategies in online grocery markets. This discussion informs of various practices of big data analytics and ultimately calls to attention the potential for personalized pricing in online food markets. This article proposes the need for empirical analysis and developing research agendas investigating impacts of personalized pricing on market efficiencies, which is not as unambiguous in practices as it is theoretically. In addition, the status of online groceries, concepts of price differentiation, societal, economic, and regulatory implications of personalized pricing are discussed.

Keywords Big data · Data analytics · Economics · Food prices · Online shopping · Technology

JEL Classification C8 · D40 · L11 · L15 · Q18 · Z13

Introduction

Interest and investment in 'big data' and associated data analytics has grown rapidly and become a critical input to decision making in businesses, academia, government policies, and political campaigns. Big data can be characterized by its large scale, the

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ever- accelerating pace of its generation and collection, and variety of its formats such as structured and unstructured (Laney 2001; IBM 2017; Oracle 2022a, b; SAS; University of Wisconsin Data Science 2015). With big data amassed, big data analytics (BDA) introduces more individualized service, marketing, and products, often through the use of machine learning and artificial intelligence.

BDA has been applied to nearly every field encompassing healthcare, media and entertainment, e-commerce, financial services, telecommunications, government, and even manufacturing industries. The food/agricultural industry is no exception, and big data has emerged along the whole food supply chain from farmers' production activities to retailers' inventory management and marketing strategies to government's food safety risk management. Considering the ubiquitous uncertainty and its related risks along the food supply chain, such as difficulties in forecasting weather conditions for farming, managing disruptions in agricultural and food supply chain system, predict consumers' demand for short-lived perishable fresh food, and food safety risk management, there remains substantial potential in agricultural and food industries to which BDA can contribute for mitigating negative impact of the uncertainty and improve productivity and efficiency. Food safety risks and food waste management along the supply chain take the lead to apply BDA and AI (Donaghy et al. 2021; Kayikci et al. 2022; Ciccullo et al. 2022).

Despite the advancements in the field, agricultural and food industries have not yet drawn much attention in BDA compared to other industries. Although freshness, the most important characteristic of agricultural commodity and food items, already emphasized an importance of well managing inventories, grocery industry has been excluded even when BDA and Artificial Intelligence (AI) is discussed for more efficient warehouse management and/or supply chain. In particular, the discussion of BDA used for individualized marketing, pricing, and promotion of food products to individual customers is nearly absent from market, economic, and data use conversations, although the potential is ever-present and growing rapidly with the recent rise in online grocery shopping.

Given a constant online grocery buying behavior that 19% of consumers on average use grocery online from January to October of 2022 (Lusk and Polzin 2022) even post pandemic, this brief viewpoint article focuses on incorporating BDA strategies into online grocery shopping with a focus on economic and societal perspectives. There are clear changes in online versus brick-and-mortar food retailing including business processes innovation, improved shopping experiences, and distributional impacts of pricing strategies. These topics are explored for the purpose of informing the discussion on various practices of BDA and ultimately to motivate the call to attention to a topic of personalized pricing which this study argues is critical due to the possibly huge impact on consumers, producers, and market as a whole in food markets.

Digital Transformation of Food Industries/Businesses

Food represents an essential and necessary good for all people. The food retail industry has a significant economic impact on federal, state, and local economies. Supermarket and grocery stores accounted for $756 billion in revenue in 2021 (IBIS World 2021). In fact, the grocery industry dwarfs other industries, including the automobile industry at $82 billion and smartphone industry with $84 billion in 2021 (IBIS World 2021). Market size of the grocery industry increased at the average growth rate of 2.7% from 2017 to 2022 (IBIS World 2021). According to 2021 Consumer Expenditure Survey by US BLS (2021), a household on average spent $8,169 annually in 2019 for food ($4,643 for food at home and $3,526 for food away from home), accounting for 13% of the total annual expenditure. According to more recent monthly survey by Lusk and Polzin (2022), consumers report spending $177 ($119 for food at home and $58 for food away from home) per week in October 2022 (CFDAS 2022).

The COVID-19 pandemic brought more people to online grocery shopping (Aull et al. 2021; Jensen et al., 2021). Etumnu and Widmar (2020) conducted a survey on consumers' online grocery shopping behavior pre-pandemic and reported that 31% of all respondents had grocery shopped online. Jensen et al. (2021) found nearly 55% of US households shopped online during the COVID-19 pandemic; 20% of those respondents with online grocery shopping experience were first time users. Compared to pre-pandemic when online penetration to grocery sectors was 3–4%, grocers watched 9–12% of their business shift into online, with some high-density urban areas reaching 20% (Aull et al. 2021). From there, it is projected to expand to 20.5% in 2026 (Mercātus 2021).

Despite consumers' potential desire to head back to brick-and-mortar grocery stores post-pandemic, the ingrained experience of online grocery shopping during the pandemic and added convenience may keep some consumers online. Moreover, federal rules on use of funds from the Supplemental Nutrition Assistance Program (SNAP) have relaxed and allow more online food buying. Consumers' willingness to purchase groceries online reaches beyond shelf-stable products such as household care, snacks, packaged foods, to include also fresh food which has traditionally been less popular in online grocery platforms, such as meats, dairy, and frozen food (Aull et al. 2021). According to Etumnu and Widmar (2020), the most frequently purchased grocery category over the past week was snacks and sweets (31%) followed by such fresh items as vegetables (29%), fruits (28%), and milk and dairy (28%). Online grocery markets will be pertinent to BDA in several ways, (1) technical management of warehouses and inventory, (2) logistics and (3) strategic marketing approaches based on individualized, and potentially real-time updated, consumer analyses.

The grocery/supermarket industry has remained largely immune to digital transformation compared to manufactured goods industries such as electronics and clothing mainly due to difficulties and cost inefficiencies in managing warehouse and logistics to keep perishables fresh. In the past, customers have hesitated to shop groceries online due to fear of receiving inferior quality items (Ramus and Nielson 2005). The high cost of managing storage and logistics for fresh items, in combination with limited demand for online groceries, led to failures of the most prominent and early-stage internet-based supermarkets in the US such as Webvan, Streamline, Homegrocer, Homerun and Shoplink in the early 2000 (Tanskanen et al. 2002).

However, recent technological advances in BDA, Artificial Intelligence (AI), and machine learning (ML) help overcome the past difficulties that online grocers faced. For inventory and logistics management of grocers, challenges are to manage highly perishable products, differing temperature regimes (chilled, frozen, and ambient), keeping proper stock levels, food waste minimization, wide variation in consumers tastes, accurate item picking for orders placed in a basket, and last mile delivery (Mason 2019). For example, Ocado, one leading online grocer from the UK, successfully overcame the challenges[1] with its innovative central fulfillment centers (CFC) exploiting AI, BDA, ML, and robots, enhancing cost efficiencies in proper stock-holding level with forecasting, accurate basket

[1] Successful cases can also be seen in Amazon, Zalando, etc. selling universal goods. However, only Ocado is briefly mentioned because this discussion is mainly about grocery industry.

picking, deliveries, and food waste reduction. Furthermore, Ocado expand its business realm from retailers to platform providers of its innovative CFC, recently collaborating with Kroger, Inc. in the US, Coles in Australia, AEON I Japan, and other renowned EU grocers (Ocado Group 2022; Kroger 2022).

Big Data Uses in the Grocery Industry

Despite common use in everyday parlance, "big data" is not well defined. Big data is often characterized by 3 Vs: Volume, Velocity, and Variety (Laney 2001; IBM 2017; Oracle 2022a, b; SAS; University of Wisconsin Data Science 2015). First, volume features the amount of data, which exploded in size. Individuals around the world are generating 2.5 quintillion bytes of data every day just by living (Shah 2020; Marr 2018). Second, velocity means that data is being generated, sent, and received at an ever-accelerating pace. These real-time generated datasets often require real-time evaluation to be used effectively. Lastly, variety refers to the various forms of data from traditional types of numeric data that can be fit easily and neatly into database to new and unstructured types such as social media posts, emails, audio/video files, webpages, etc. (Oracle 2022a, b; University of Wisconsin Data Science 2015).

Pearls are worthless in their shell. Challenges with big data are not so much issues of the 3 Vs, but more in its use or implementation. How are these datasets used in our daily lives? And, by whom, or for who's gain? In the field, BDA allows personalized services and offers to customers and improves management efficiency[2] for businesses with highly probable predictions and optimized operations. In the e-commerce, analyzing shoppers' behavior and transaction data enables companies to predict user preferences, propose personalized product recommendations, charge personalized prices (Oracle 2022a, b; Akter and Wamba 2016).[3]

Most innovative stories about uses of AI, BDA, and ML in the grocery industry are about improving management efficiencies, logistics, and inventory processes (Rajeb et al. 2022), but analyzing consumer's behavior in a marketing context with economic insights potentially involved[4] has been underappreciated. The value of utilizing BDA for businesses success lies in increased revenues, cost reductions, personalized service, and detection and solution for supply chain problems. Other issues such as collection and ownership of personalized data, pricing strategies, economic interpretation of pricing strategies have not been widely addressed.

[2] We use a term "management efficiency" defined by Spacey (2018) as the output that a management teams can create in relative to capital and expenses. Examples are allocative efficiency, return on capital, productivity, resource efficiency, process efficiency, and cost efficiency (Spacey 2018).

[3] Only e-commerce is described in the main texts. There are other industries which utilize BDA for personalized services. In healthcare, BDA allows healthcare providers to design personalized treatment and genomic research to identify diseases genes and biomarkers informing patients of health issues that they may face in the future (Tulane University 2021; Dash et al. 2019). Media and entertainment companies try to understand what content their customers like to watch at what time and what device they use for viewing content, then suggest a certain content at a certain time to an individual customer (Lippell, 2016). In the telecommunications industry, companies now can predict overall customer satisfaction; if telecoms face a risk of customers churning, they take actions such as proactive offers to retain customers (Oracle 2022a, b; Al_Janabi and Razaq 2019). In sum, BDA improves customer satisfaction with personalized services as well as management efficiency.

[4] For this study is mainly interested in marketing in on/offline grocery industries, a main topic described in this study is limited in marketing context.

Among those, for retailers, pricing is the most important factor that has the biggest impact on profits by far (McKinsey 2019). For consumers, price is still the first factor considered for purchases (Bir et al. 2019; Deloitte 2019; Lusk, 2017; Wolf and Tonsor 2013; Lusk and Briggeman 2009). Prices might have been determined or set to satisfy not only retailers' needs, but also customers' needs. Glimpsing into the history of pricing strategies may provide an understanding/idea of how prices are to be set for achieving both consumers' satisfaction and retailers' maximizing profits.

Until the mid-19th century, individual sales people and customers discussed prices that each wanted to pay and receive until the negotiation comes to an end with a fixed price that both agreed on (Aifora 2020; Wallheimer 2018). These negotiations implied that shopkeepers had to know product details such as cost of the product to stores, inventory levels, market demand, how much different customers wanted it and competitors' prices for the same/similar products. However, finding out that it is inefficient to train every sales clerk in the art of price haggling and each negotiation takes long time, John Wanamaker[5] started put tags with fixed prices that every customer pays equally in his department store in Philadelphia from 1861 (Aifora 2020; Wallheimer 2018).

With the advent of the Internet and mobile devices, it became easy and cheaper to collect information from customers and it is not necessary to train sales clerks. BDA, ML, and AI enhance analytic quality of the large amount of data, offering personalized advertising and services for customers. According to Sanjog Misra from the Chicago Booth School of Business, the next step will be personalized pricing and the information-based pricing and advertising is right way to go albeit concern on privacy and data ownership (Wallheimer 2018).

Understanding Consumers' Grocery Shopping Behavior with Big Data

Car buyers likely encounter a sales person asking for personal information in negotiating process. For example, when a customer starts a conversation with a dealer for buying a new vehicle, that conversation might have begun with one of the following questions such as "What vehicle/model are you driving today?" or "Are you renting that vehicle?". Knowing more about customers, their job, lifestyle, preferences, and potentially customer's willingness to spend is helpful in the sales process. On top of prices determined in the market, this adds margin that dealers can seek to absorb from individual consumers. This conversational approach is a traditional form of collecting and utilizing personal data to customize products/service and deliver more value to individual customers.

Loyalty cards provided for customers use to identify themselves and collect points or qualify for discounts also collect detailed information about individual customers and their purchases. Such information includes demographic information, purchasing behaviors like shopping frequency or preference among product varieties or brands. With the data collected, retailers offer personalized promotions and coupons or suggest customized products (Forbes 2012). This type of data can be collected when customers willingly swipe or scan the loyalty cards in-store. On the other hand, it can now be more easily amassed in online

[5] There is still an unsettled argument surrounding who first introduced the fixed pricing. Some argue that it originated from the Quaker merchants in Philadelphia who believed that everyone is equal before God and everyone should be charged the same price (Aifora 2020). Others say that Alexzander Turney Stewart, an Irish-American merchants, opened a store in Brooklyn earlier in 1846 with posted price for more efficient purchasing process (Optimus price 2018).

spaces when all customer activity, including browsing and not just ultimate purchases, can be logged in an app or on a website.

In the era of big data and individual electronic devices, methods of collecting data about consumers are advancing and data sources are diversifying. Detailed data on individual consumers is being collected by online retailers for customer's purchasing behaviors such as how much each customer usually pays for a certain item, how frequently each customer purchases the same items, what specific products or options each prefers. With all the data for individuals on hand, retailers can better understand preferences, suggest customized products for individuals and potentially estimate the maximum willingness-to-pay (WTP) for various items. With WTP estimated for individual customers, it is technically possible for retailers to charge different prices to each customer for the same products. This is called first-degree price discrimination or personalized pricing in economics while called customer segmentation in business marketing (Perloff 2017; Woodcock 2017; McDonald and Dunbar 2012; Tirole 1988).

Conversations about BDA and the implications are arguably more critical in grocery markets than other industries because food is essential, grocery items are non-durable and consumers repeating shopping visits regularly[6], which provides continuous and regular database updates for grocers to analyze consumers' tastes, product preferences, differentiate products accordingly and estimate demand with more accuracy. Horizontal and vertical product differentiation[7] is apparent in modern food markets, from product characteristics such as tastes, appearances, brand, or healthfulness to broader dimensions such as production process including animal confinement conditions, use of chemicals, and implications for environment and sustainability.

As there is growth of online grocery shopping (Widmar and Bir 2022), more shoppers will create online accounts. Thus, online grocers will have readily accessible data for their online customers, such as demographic information, addresses for stores shopped, and an easy accounting of past purchases, shopping behaviors, products requested, substitution products offered and rejected versus accepted, etc. The growth in use of personalized accounts to conduct online shopping for groceries facilitates the potential to use BDA to suggest personalized grocery items, promotional offers, and technically possible, although not yet offered to our knowledge, personalized prices. While online shopping is not necessary to facilitate this use of BDA in grocery retail, the aggregation of data in a single online account for a given supermarket facilitates these activities much more so than when shoppers can buy products anonymously in brick-and-mortar stores. Notably, shopper's loyalty cards amass purchase data and history in a similar way to the use of online accounts, but they rely on the shopper to scan their card at point of purchase whereas ordering in one's

[6] A typical household made 1.6 trip per week on average in 2019 in the US (Tighe 2020).

[7] Horizontal differentiation means goods that are different in regards to customers' preference, but not associated with products' quality. Examples that would fit horizontal differentiation include a variety of products in response to different consumer tastes, sugar content of breakfast cereals, fat content of fluid milk, lean composition of ground beef, competing national brands of the same products, and, with recent online grocery shopping, diversification in the final mile delivery methods such as in-store pickup, curbside pickup, delivery by retailers, by a third-party, and/or delivery via mail. Vertically differentiated products are different in quality. Consumers prefer one to the other if they are sold at the same price. Examples of vertical differentiation, offering different qualities of the same product in response to consumers' demands, include organic versus conventionally grown, prime versus choice beef, and national brands versus private brands of the same product.

account ensures a record of the purchase is tied to the account/shopper without this additional step.

Purchasing vehicles and electronics happens intermittently over several years with updated personal background information such as income, educational level, and preferences. Without adequate datasets for estimating demand, sellers may need to ask customers those questions to find out information of individual consumers. On the other hand, the more data grocery stores collect about its existing customers by its regularity in purchases, the more accurate its estimates of consumers' demands and WTP will be. Aggregation of one's shopping behaviors easily into an online account, in combination with the regularity of grocery shopping is why grocery industries needs to be considered as one of important sectors for BDA discussions.

Personalized Pricing in Applied Economics

Personalized Pricing

Differential pricing that has already been utilized in many forms such as senior citizen discounts at movie theaters or tiered pricing for air fares[8]. On the grocery stores, there already exists differential pricing strategy conducted by on/offline grocery retailers. A single grocery store charges different prices on the same items based both on cross-sectional property (across locations) (González and Miles-Touya 2018; Anania and Nisticò 2013; Lan et al. 2012; Lloyd et al., 2012) and time-series property (over time) (Aparicio, Metzman, and Rigobon, 2021; González and Miles-Touya 2018). Recently, a technology called algorithmic pricing in which computer algorithms constantly tracks market conditions such as supply and demand and/or competitors' pricing, helping firms determine optimal prices on a nearly real-time basis appeared in grocery markets as well as others (Aparicio, Metzman, and Rigobon, 2021).

Although it is possible to charge different prices on individual consumers, which is called first-degree price discrimination in economics or personalized pricing in this article, with individual customer data, it has not been implemented or observed much in the U.S. retail grocery industry thus far. There would undoubtedly be public resistance to individualized pricing. In the U.S. in 2000, a customer complained that after erasing cookies from his/her computer s/he was provided with a lower price for a particular DVD at Amazon.com and Jeff Bezos, a CEC of Amazon, admitted and promised the company would never set prices based on customer demographics (Salkowski 2000). Amazon's failed attempt to charge different prices to different customers is evidence of consumers' resistance to being charged differently from their neighbors for identical items (Professional Pricing Society 2002). In South Korea, individual customers of Market Kurly, the leading online grocery firm, have faced different prices for exactly the same product on their individual online accounts at the same point in time and quickly reported it to the media. Coupang, Amazon in South Korea, tried the same personalized pricing and confronted consumers resistance (Hani 2022; SBS News 2021; Teller Report 2021).

While they are less likely to be first-degree price discrimination, there are several methods which circumvent customer resistance such as personalized or account exclusive

[8] This is called third-degree price discrimination that occurs when sellers charge different prices to different groups, not individuals.

promotions or coupon provision, which is equivalent to personalized pricing without upsetting customers. Or, firms can engage in 'search discrimination' or 'steering', which show different products to customer in different groups based on available information on consumers. For example, OrbitzWorldwide was showing more expensive hotel offer to Mac users or Staples.com displaying different prices to customers with their location data identified (Mikians et al. 2013: Mikians et al. 2012; Wall Street Journal 2012a, b).

The benefit of personalized pricing to sellers is simple; maximize profits. Compared to uniform pricing under which optimal price is somewhere in the middle of prices high enough to generate profits and low enough to entice more customers, personalized pricing would allow sellers to raise price to some customers without pricing others out of the markets, ultimately maximizing profits. A seller can gain more revenue by charging higher prices to customers with higher WTP than a uniform price that would have been charged without personalized pricing. A seller would not lose customers with lower WTP by offering them prices close to their WTP, which is still slightly higher than the uniform price. Furthermore, a seller can expand market by attracting more customers with even lower WTP than the uniform price with price offers close to the WTP. Before personalized pricing, the customer with lower WTP than the uniform pricing would have not afforded to purchase the item. A seller can earn higher revenue than beforehand if higher prices can support the lower revenue or even cost from selling at lower prices, sometimes leading to an increase in total market surplus.[9]

Several studies have simulated impacts of price discrimination on profit. Cebollada et al. (2019) adopted zone pricing in the online store based on the information of proximity of individual consumers addresses to their closest brick-and-mortar-retail grocery retail stores and simulation results suggested that zone specific pricing will increase retailers' profit by 7% for pizza, 4% for liquid dish detergent, and 14% for oranges. Shiller (2014) conducted a personalized pricing simulation that would bring 15% higher profits to Netflix compared to its current status quo with constant pricing strategies if the personalized pricing is based on individual customers' web browsing activities. When using demographic data only for personalized pricing, the extra profit would be 0.30%, which is much lower than based on web browsing data.

While it is well understood that firms benefit from price discrimination, there is no common understanding when consumer welfare and overall market surplus are considered. In theory, the extra revenue earned is not necessarily a newly produced surplus from the market growth by the pricing strategy. Rather, it originates from the surplus that consumer would have enjoyed under a uniform pricing. That being said, personalized pricing may make consumers worse off in this case. On the other hand, there is also a potential benefit of the personalized pricing, which is that it may expand the size of market (Woodcock 2017; Borreau et al. 2017; Executive Office of the Obama administration 2015). Woodcock (2017) describes that price discrimination expands the market and as a result increases total market surplus by bringing a subset of customers who would have not been able to afford to buy at higher uniform price.

If personalized pricing is well managed, BDA may provide a tool for distributing wealth by subsidizing prices for the poor with charging higher prices to wealthier shoppers so that sellers cover the cost of the subsidy while increasing its profits and the total market surplus. Personalized pricing simulation for Netflix customers conducted by Shiller (2014)

[9] A graphical description of personalized pricing is provided in Appendix.

suggests that the 75th percentile of consumers gets about 1% discount and the median customer would get 4% discount, while consumers estimated to have the highest willingness to pay would face prices about 63% higher (Shiller 2014). Furthermore, reduction of aggregate consumers surplus caused by the personalized pricing is 1.79% (Shiller, 2014). While Cebollada et al. (2019) and Shiller (2014) run simulations based on demand estimates, Dubé and Misra (2022) conduct a field experiment of personalized pricing on clients in collaboration with Ziprecruiter.com. They find personalized pricing based on consumers' observable features could improve firm's profitability with relatively small loss of aggregate consumer surplus while redistributing surplus from larger clients to smaller clients in company size (Dubé and Misra 2022). 70% of consumers exposed to personalized pricing face personalized prices below the optimal uniform prices under monopoly scheme at the expense of the consumers with highest WTP and redistributive benefits could outweigh the loss in total consumer surplus. Kehoe et al. (2020) also found that personalized pricing may increase consumer welfare in a dynamic durable-goods duopoly markets.

With all that being said, effect of personalized pricing is ambiguous depending on different market aspects such as characteristics of goods or consumers price elasticity of demand. Therefore, this cannot be completely defined with a single proposition (Widmar 2020; Batie 2008). Rather, this is more likely to be an open empirical question that deserved to be answered depending on a variety of settings on markets, consumer characteristics, and/or consumer segments.

Societal, Economic, and Regulatory Implications of Personalized Pricing

The appearance of BDA and ambiguity on its effects on society if and when implemented into marketplaces for life-sustaining necessities like food and water necessitates new and profound debates in social, economics- or law-related antitrust perspectives. From a social viewpoint, there are concerns that BDA ushers in the era of Big Brother. On the other hand, there are also hopes of efficiency improvements BDA can bring to society, thereby creating value. Fukuyama (2018) stated - "*successful democracy depends not on extreme of freedom and equality, but balance between a capable state exercising legitimate power and the institutions of law and accountability that seek to constrain* it" – thus, successful BDA on personalized pricing depends on balance between the hope on efficiency improvement with personalized service and the concerns on a distributional impact on surplus between seller and consumers.

In economics and antitrust perspective, Woodcock (2017) contemplates how to address the BDA based personalized pricing by comparing two standards – a total welfare standard versus a consumer welfare standard – that antitrust has long debated. Personalized pricing is also characterized by multiple stakeholders' viewpoints with respect to the desirable outcomes (Batie 2008; Kreuter et al., 2004). On a total welfare standard, producers are allowed to take surplus from consumers unless they cause a reduction in a total welfare by doing so. Using a consumer welfare standard, producers are not allowed to increase their surplus at the expense of consumers. As Woodcock (2017) points out, producers prefer the total welfare standard to keep the ability to take surplus from consumers albeit a certain level of burden of not destroying a total welfare. Woodcock (2017) goes further describing that BDA for price discrimination will end up reducing consumer welfare unless antitrust changes law appropriately to preserve overall market surplus and compromise distribution of wealth between producer and consumers. As Baker (2012) argues a compromise of allowing big business the redistribution but not as radically as consumer rebel.

In the grocery industry, known for thin margins, any new methods that potentially improves retail margins will be welcomed. BDA for personalized service and personalized pricing may facilitate improved margins, yet personalized pricing may both benefit and harm consumers and sellers and final outcome remains *a priori* ambiguous from both standards of a total welfare and a consumer welfare.

Woodcock (2017) and Baker (2012) in the area of law that also concerns this issue suggests revision of the current antitrust laws so that price discrimination based on BDA can be appropriately addressed. Woodcock (2017) suggested three options as (1) reducing the level of pricing power by deconcentration, (2) price regulations by imposing a redistribution requirement, and (3) an outright ban on price discrimination based on BDA. Borreau et al. (2017) recommends monitoring of online prices on a regular basis not as much as discouraging firms to be less innovative and transparent about the pricing strategies should be guaranteed so that consumers stay informed its impact on them as well as on the overall markets (Bourreau et al., ; Executive Office of the President of the United States 2015). Big data and its related techniques may also be used to lower information asymmetry and search costs of consumers. Collecting prices data from online grocery stores and sharing with consumers more frequently may be helpful to render online grocery markets more competitive by lowering information asymmetry and/search costs of consumers. (Jung et al. 2021).

However, regulations many times bring unintended consequences such as slowing innovation (McLaughlin 2018). Again, consequences of personalized pricing are not as clear as theoretic description and some studies presented results that oppose the negative impacts of the pricing strategies on the overall markets and consumers. Therefore, it is not recommended to put regulations in place without adequate empirical evidence, in particular with the ambiguity and variations in outcomes of BDA as described in Dubé and Misra (2022), Kehoe et al. (2020), Cebollada et al. (2019), and Shiller (2014).

Proposition of Research Agendas

Personalized pricing has been extensively investigated in prior studies. Associated topics such as its benefits (Liu and Zhang 2006), fairness (Richards et al., 2016), quality differentiation (Choudhary et al. 2005), target market strategic behavior (Chen et al., 2023) or entry deterrence (Liu and Zhang 2006) have been explored. As more personalized information becomes available due to technological advances and big data analytics, others are introducing related opportunities and challenges that emerge from the ongoing big data evolution (Dekimpe 2020; Bradlow et al. 2017) and proposing important roles that big data could or should play in retailing business (Dekimpe 2020; Bradlow et al. 2017).

While information on consumers' purchasing behavior is extensively collected by retailers and/or grocery stores, data collection technology is also evolving. Data collection technologies are becoming user friendly so that non-computer scientists can collect previously unavailable data from online spaces. If information in online spaces is available and can be complementary to existing datasets, there is potential for a variety of exploratory studies that merge novel and existing data to develop previously unavailable insights. Web scraping, for example, is a rapidly developing online data collection technology. Exploiting web scraping, product's information can be collected from online retailers' websites more frequently, more geographically disaggregated, more individual store level, and more customized that ever (Jung et al. 2021).

Table 1 An illustrative research questions/agenda with big data on food products

Topics	Research questions
Marketing	
• Price optimization	- How to develop dynamic and best-response pricing strategies in reaction to competitors' actions, consumers' demand responses and supply response.
• Understanding consumers and segmentation	- How to understand consumers' preferences and provide more personalized recommendation. - Estimation of customers' willingness to pay for homogeneous and/or differentiated products and charge differentiated prices for individual products and customers.
Information transparency	
• More frequent price index	- Collect food prices for grocery items and develop more frequently updated price indices, such as a daily price index.
• Publishing price information to the public	- Publishing prices and price indices to the public, enhancing price transparency and supporting purchasing decisions.
• Price comparison	- Collect food prices across more aggregated regional levels such as at zip codes level and compare such prices across regions. - Estimating price premiums for higher-quality products.
Pricing strategies	
• Investigating price strategies	- How retailers or restaurants react to their competitors' prices, including includes spatial pricing games, dynamic price adjustments upon competitors' actions on pricing, and/or breadth and width of promotions. - Price dispersion across regions or stores owned by the same store chain.
Consumers sentiment	
• Monitor customers' reactions	- Monitor online communities such as social media, review pages, blogs, etc. to find out what consumers talk about products, pricing strategies, service, or campaigns.
• Enhance customers' satisfaction	- Based on what is found from online media monitoring, retailers can react quickly to consumers conversations on personalized pricing in particular.

The Billion Prices Project (https://thebillionpricesproject.com/) collects micro price data from online retailers by utilizing web scraping technique and conducted diverse research. The project developed daily price indices (Cavallo and Rigobon 2016) and examined retail pricing behaviors such as price stickiness (Cavallo 2018), dynamic/algorithmic pricing (Aparacio et al. 2023; Aparacio and Misra 2022; Calvano et al. 2020), online-offline price comparison (Cavallo 2017), and trade policy (Cavallo et al. 2021).

The food and grocery industry remains behind albeit its importance in price index, market size and its impacts on grocers' profit, consumers' welfare, and market efficiencies. With the advanced data collection techniques available, more detailed data can now be collected from food and grocery related websites. Through exploiting web scraping, for example, nearly information of all the products registered on websites for sale can be collected in more disaggregated levels of observation in terms of regions, categories, frequency, and/

or characteristics. Additions of such rich online dataset to the existing available datasets would allow for new research in food and grocery industries and relevant research questions are listed here in this study (Table 1). Topics listed in table are limited to personalized pricing and alleviation of information asymmetry with big data available from online spaces. Dekimpe (2019) lists more extensive research topics covering but not limited to operations, supply chain management, etc.

One type of data that is challenging to collect from online retailers or grocery stores is quantity sold. Considering the importance of big data analytics and its impact on market efficiency and sustainability, collaborations among academia, industry, or government would be helpful to conduct more integrated research on food and related industries.

Conclusions/Summary

Popular media largely indicates a belief of the negative impact of the use of BDA for activities such as personalized pricing on consumer welfare and positive impact on firm profitability. However, under certain circumstances, it could not only increase firms' profits, but also benefits consumers and improve overall market efficiency. Therefore, the topic of BDA and potential for personalized pricing in grocery markets is arguably better be examined empirically and debated publicly with societal input.

The topic of personalized pricing has not been addressed in agriculture and food industries even as the ease of collecting customer data on grocery shopping behaviors on a regular basis, which then allows firms to analyze customers and estimate their willingness to spend more accurately, has grown in the online grocery shopping era. Considering that food is a necessity and food insecurity critically important societally, discussions on what are appropriate and societally acceptable uses of BDA in food markets are needed. For example, the simulation work of applying zone pricing (Cebollada et al. 2019) may or may not exacerbate food insecurity situation in food desert areas. On the other hand, potential wealth redistribution from the rich to the poor in the market scheme with personalized pricing strategy beyond the benefits of expanding market size may alleviate the food insecurity in food desert area.

Acquisti et al. (2016) pointed out, determining the extent to which the combination of sophisticated analytics and massive amounts of data leads to an increase in aggregate welfare versus mere changes in the allocation of wealth would be a fruitful direction for future-research on BDA in the grocery industry. However, data availability, which is the heart of empirical research, is limiting the depth of research. Having said that, collaboration among government agencies, academia, and industries may facilitate progress otherwise untenable given data ownership and privacy concerns and the data analytics required to develop actionable insights.

Appendix

When a seller has some market power charging a uniform price, P_m in Fig. 1, revenue that the seller earns is area of a rectangular OP_mmQ_m. If the seller utilizes big data they collect from customers for successfully estimating demand curve and conducts personalized pricing such as P_1, P_2, P_3, P_4, there will be additional revenue as much as shaded area above the line $\overline{P_mm}$ and below P_1. In Appendix Fig. 1, the market may expand from Q_m to Q_{pc} and

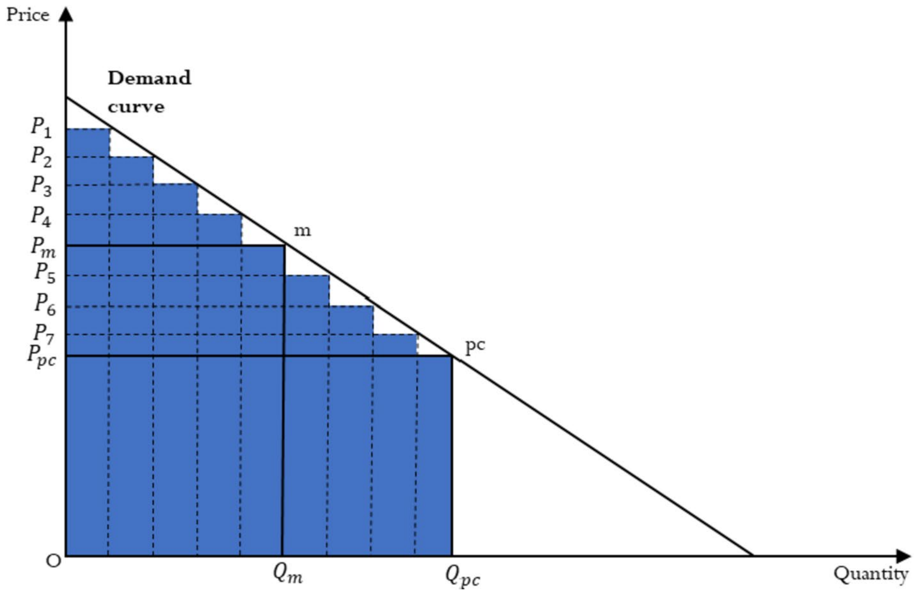

Fig. 1 Uniform prices and personalized prices and related seller's revenue

customer with such WTP lower than P_m as P_5, P_6, P_7, and P_{pc} become able to enjoy a certain product. The amount lost from consumers with lower willingness to pay compared to the uniform price level, P_m, can be compensated with extra amount earned from consumers with higher willingness to pay. Furthermore, this will draw the market closer to perfect competition with P_{pc} and Q_{pc} with the improved overall surplus of the market. Under a variety of conditions on the shape of demand curve, price discrimination could increase social welfare (Cowan and Vickers 2010; Varian 1989; Pigou 1920) as well as consumer welfare (Cowan 2012).

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