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Research paper

Reducing food waste through digital platforms: A quantification of cross-side network effects

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ABSTRACT

To fight food waste, retail stores have begun selling perishable food close to the expiration date at discounted prices. To render this form of last-minute discounting effective, digital platforms have been developed with the major aim to connect local retail stores and their consumers by sharing information about these discounts. To sustain digital platforms, platform leaders need to ensure both consumers and retail stores remain active on it. To provide platform leaders with advice on how to create a sustainable digital platform, we examine how retail store activity on the digital platform affects consumer activity, and vice versa (also known as cross-side network effects). By combining a PVAR model and an impulse response function, along with data from a digital platform aimed at food waste reduction, we find that the effect of consumer activity on retail store activity is stronger and more long-lasting than the effect of retail store activity on consumer activity. We discuss the implications of our findings for both retail stores and digital platform leaders.

1. Introduction

Almost one third of all food produced globally is wasted or lost every year (FAO, 2017). Food waste has environmental, social, and economic costs (Stöckli, Niklaus, & Dorn, 2018). As retail store Tesco stated: “Food waste resulted in significant costs to our business, as well as our suppliers and our customers” (Little & Castella, 2017). Because these costs are increasing along the supply chain (Capgemini, 2017; Schanes, Dobernig, & Gözet, 2018), movements against food waste are emerging (Cicatiello et al., 2017). Especially grocery retailers are beginning to recognize the financial and reputational potential of reducing food waste in their operations (Winsight Grocery Business, 2018) and are, therefore, at the heart of initiatives to reduce food waste (Capgemini, 2017).

Industry studies find that food waste represents an $18 billion profit opportunity for grocery retailers (ReFED, 2018), with retailers able to obtain a median of five dollars in return for every dollar invested in food waste reduction (Capgemini, 2017). To tackle the food waste problem, an increasing number of different food sharing models are being developed (Michelini, Principato, & Iasevoli, 2018). The opportunity for these models mainly arises in digital technology and the emerging phenomenon of the sharing economy (Ciulli, Kolk, & Boe-Lillegraven, 2019; Michelini et al., 2018). Table 1 shows some illustrative examples of initiatives around food waste reduction that have recently been taken, by grocery retailers as well as food retailers in general.

An interesting food sharing initiative that has seen a rapid increase in adoption by grocery retailers in several Western countries is last-minute discounting of perishables (Aschemann-Witzel, 2018; Robertson & Parfitt, 2018). In last-minute discounting, grocery retail stores lower the price of perishable products close to their date of expiry. When perishables approach their expiration date, consumers perceive them as sub-optimal due to food safety and risk concerns (Stangherlin, Duarte Ribeiro, & Barcellos, 2019). However, the use of last-minute discounting motivates consumers to buy these sub-optimal products (Buisman, Haijema, & Bloemhof-Ruwaard, 2019; De Hooge et al., 2017), thereby generating revenue from perishables that would otherwise have been wasted (Adenso-Díaz, Lozano, & Palacio, 2017). Thus, last-minute discounting creates a win-win situation where (i) retail stores reduce food waste thereby mitigating the financial loss associated with it (Tsiros & Heilman, 2005; Wang & Li, 2012), and (ii) consumers are able to save money while contributing to solve the food waste problem (Aschemann-Witzel, 2018; Aschemann-Witzel et al., 2017).

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Table 1
Illustrative examples of food waste reduction platforms.

Platform name	Country	Main focus
11th hour	Singapore	Meals close to expiry date in restaurants
Chowberry	Nigeria	Products close to expiry date in supermarkets
Food cloud	Ireland	Products which are past their expiry date in supermarkets
Food for all	United States	Meals close to expiry date in restaurants
Food loop	Germany	Products close to expiry date in supermarkets
Go Mkt	United States	Meals and products close to expiry date in local restaurants
Leloca	United States	Products for which there is a food surplus
Last minute sotto Casa	Italy	Products close to expiry date in supermarkets and food retailers
My foody	Italy	Products close to expiry date in supermarkets
No food wasted	The Netherlands	Products close to expiry date in supermarkets
Optimiam	France	Food and meals close to expiry date at bakeries and in restaurants
Swipe shark	Denmark	Products close to expiry date in supermarkets
Too good to go	Belgium, Denmark, France, Germany, the Netherlands, Norway, Spain, Switzerland, United Kingdom	Meals and products close to expiry date in restaurants and supermarkets
Zéro-Gâchis	France	Products close to expiry date in supermarkets

However, information on these last-minute discounts do not always reach consumers in time (i.e., before the recommended expiry date), thereby rendering these discounts ineffective. Typically, last-minute discounts are given one or two days before the date of expiry of perishables (cf. Aschemann-Witzel, 2018; Theotokis, Pramatari, & Tsiros, 2012), leaving consumers with little time to take advantage of them. As a consequence, IT solutions in the form of digital platforms have been launched to create ties between grocery retailers and consumers, which help facilitate timely information exchange (cf. Capgemini, 2017). The importance of creating ties is recognized by the extant sustainability literature, which even argues that the absence of suitable ties between retail stores and consumers (i.e., supply chain partners) hinders a more sustainable and appreciative handling of food (Schanes et al., 2018). Digital platforms can foster food waste reduction by creating the necessary ties (Ciulli et al., 2019). Specifically, by connecting retail stores and consumers, digital platforms play a crucial role in enhancing the effectiveness of last-minute discounts, thereby also helping to reduce food waste.

Since digital platforms are a relatively recent phenomenon, research is yet to explore how ties between retail stores and consumers are created (Ciulli et al., 2019). Therefore, the objective of our study is to examine how digital platforms tie together retail stores and consumers to enhance the effectiveness of last-minute discounts. Specifically, we explore whether the effect of consumer activity on retail store activity is different from the effect of retail store activity on consumer activity. To provide a better understanding of these, possibly asymmetric, interactions, we rely on the literature of two-sided markets and dynamic cross-side network effects (CNEs). We model the retail store-consumer interactions using Panel Vector Auto Regression (PVAR) and apply it to panel data from a digital platform designed for reducing food waste of grocery retail stores. The PVAR model allows us to characterize the dynamics of CNEs in terms of both short-term and long-term effects. The results of our study will help digital platform leaders effectively market their service, thereby increasing their chances of sustaining the platform. Currently, digital platform leaders market their solutions to retail stores and consumers alike, since little is known about which party is more pivotal in sustaining digital platforms.

We contribute to the literature in two ways. First, we contribute to the literature on food waste. Previous work investigates the general impact of temporary price discounts on the sales of perishables and finds that price promotions on perishables can be effective (e.g., Donselaar, Peters, de Jong, & Broekmeulen, 2016; Nijs, Dekimpe, Steenkamp, & Hanssens, 2001). Also in the context of last-minute discounting to reduce food waste, research suggests that consumers react favorably to last-minute discounts (e.g., Aschemann-Witzel et al., 2019; Theotokis et al., 2012). However, this research focuses on consumers who have viewed these discounts in the store and are thus in a position to take advantage of them. As a consequence, they do not address the question of how these discounts can be disseminated to a wider audience in a short time span (one to two days), in order to increase their effectiveness. Given the transient nature of last-minute discounts, our study investigates how digital platforms can help enhance the effectiveness of last-minute discounts by creating ties between retail store and consumers. In addition, we make advances to the empirical literature on last-minute discounting to reduce food waste by using secondary data, since prior research in this area is primarily based on experimental studies (e.g., Aschemann-Witzel et al., 2019; Theotokis et al., 2012).

Second, our study contributes to the literature of two-sided markets and cross-side network effects. Most work in this domain has emerged in the areas of strategic management and economics (e.g., Kouris & Kleer, 2012; Rysman, 2009; Stummer, Kundisch, & Decker, 2018) and is of a theoretical nature. Thus, studies primarily use stylized analytic models (Sriram et al., 2015), leaving ample scope for empirical work. In particular, we build upon sparse empirical work on two-sided markets that quantifies cross-side network effects, i.e., the relative importance of one side over the other (e.g., Chu & Manchanda, 2016; Cong, Miao, Tang, & Xie, 2019; Song, Xue, Rai, & Zhang, 2018; Thies, Wessel, & Benlian, 2018; Voigt & Hinz, 2015). We add to the extant literature by studying how CNEs operate for digital platforms that focus on food waste reduction by connecting consumers with retail stores that sell perishable consumer products, such as fruits and vegetables, close to their expiration date. In particular, digital platforms that focus on food waste reduction need to disseminate information from retailers to consumers and generate consumer interest very quickly (within one or two days) to develop and sustain CNEs. Although our study focuses on food waste and relates closely to the grocery retail context, our findings can be generalized to other food retailers such as bakeries and restaurants and other retailers that sell consumer perishable products, such as florists and even pharmacies, since they sell products such as over-the counter food supplements and dietary aids.

This study is organized as follows. First, we provide the theoretical background for our study. Particularly, we discuss how digital platforms that focus on food waste reduction can push food waste reduction. Then, we argue that these digital platforms can be conceptualized as two-sided markets and explain the asymmetric cross-side network effects that occur within these markets. Subsequently, we describe the method and present the results. In the final section, we discuss the implications of our study and provide directions for future research.

2. Theoretical background

2.1. Tackling food waste at retail stores by last-minute discounting

Last-minute discounting in the context of food waste has been studied in the past (Buisman et al., 2019). From the perspective of the retailer, the effect of discounting on retailer performance (e.g., Adenso-Díaz et al., 2017; Gauri et al., 2017) and determining the optimal price for perishables has been the focal point of interest (e.g., Adenso-Díaz et al., 2017; Chung, 2019). From the consumer perspective, researchers have focused on the willingness to buy and the attitude (e.g., satisfaction) towards products that are discounted but suboptimal (e.g., De Hooge et al., 2017; Le Borgne, Sirieix, & Costa, 2018) and on the effects of last-minute discounting on consumer perceptions of brand quality (e.g., Theotokis et al., 2012). Although these studies provide valuable insights, they are primarily analytical or experimental in nature. We are among the first to empirically assess last-minute discounting in the context of food waste using secondary data.

Last-minute discounts are typically offered by a retail store one or two days before the product expiration date by placing discount stickers on the physical product. Consumers visiting the retail store may see them and take advantage. Research suggests that consumers react favorably to last-minute discounts (Aschemann-Witzel et al., 2019), thereby providing reassurance to retail stores that their initiative is well received. However, while valuable insights are gained from this research, we note that the study only speaks to situations where the consumer is already in the store, and thus notices the retail store's initiative to reduce food waste. But most consumers are not in the store when the discount is available and as a result remain unaware of the offer, implying an information asymmetry problem. To exploit this untapped potential, the effectiveness of retail stores' current initiatives to reduce food waste largely depend on digital platforms.

2.2. Digital platforms aimed at food waste reduction: Two-sided markets

Digital platforms play a central role in generating the interplay between its users by providing efficient and effective ways to match users who have offerings with those who want those offerings (Rangaswamy et al., 2020). Specifically, by posting last-minute discounts from grocery retail stores to the digital platform where they can be viewed by consumers, digital platforms enable these stores to alert existing traffic or even create additional traffic by connecting retail stores to local consumers and, thus, resolve the information asymmetry problem (Ciulli et al., 2019). Hence, digital platforms, which focus on food waste reduction, are conceptualized as two-sided markets with the primary function of connecting retail stores and consumers (cf. Ciulli et al., 2019; Frishammar, Cenamor, Cavalli-Björkman, Hernell, & Carlsson, 2018).

Two-sided platforms are specific multi-sided platforms composed of a platform leader and two distinct user networks that provide each other with network benefits (Eisenmann, Parker, & Van Alstyne, 2006; Landsman & Stremersch, 2011; Muzellec, Ronteau, & Lambkin, 2015; Rysman, 2009). The platform leader facilitates the user networks and tries to build and maintain the digital platform's business model (Helfat & Raubitschek, 2018). The business model should ensure that value is created and enough money is earned to keep the digital platform alive. For last-minute discounting of perishables close to expiry date, value is created (i.e., value proposition) by connecting retail stores that upload these discounts and consumers who search for these discounted perishables by using the digital platform. This allows better utilization of perishable food, a category which normally witnesses high food waste (Parfitt, Barthel, & Macnaughton, 2010). To remain sustainable, the digital platform should aim for positive cross-side network effects (Cong et al., 2019): if the digital platform leader can attract enough consumers, retail stores will be eager to join the digital platform, and vice versa. This so-called chicken and egg problem is widely prevalent in digital platforms, which operate as two-sided markets (Evans & Schmalensee, 2010; Stummer et al., 2018). Specifically, uploading a large number of perishable products to the digital platform by retail stores have a positive effect on the utility of consumers, thereby attracting more consumers to subscribe to and view discounted perishables on the digital platform and hence increasing the probability of food waste reduction. At the same time, consumers on the digital platform positively affect retail stores' decision to upload perishable products to the digital platform. The more active consumers, the larger is the market potential for retail stores to achieve food waste reduction goals (which also provide economic benefits); more retail stores in turn attract more consumers to the digital platform.

2.3. Cross-side network effects

Research on two-sided markets point out that the benefit of joining one side of a digital platform depends on the total number of users on the other side of the platform, and this is called the cross-side network effect (Chu & Manchanda, 2016). Empirical work on cross-side network effects has remained limited, but has shown rapid growth of late (Chu & Manchanda, 2016; Song et al., 2018; Sridhar, Mantrala, Naik, & Thorson, 2011; Voigt & Hinz, 2015). While past research has studied symmetric cross-side network effects in two-sided markets (see, e.g., Sriram et al., 2015 and Voigt & Hinz, 2015 for an overview), little attention has been paid to the asymmetric interactions between the two sides of a digital platform (Chu & Manchanda, 2016; Song et al., 2018; Thies et al., 2018; Voigt & Hinz, 2015). To sustain a digital platform (including the focal initiative to reduce food waste), however, both CNEs are important (Cong et al., 2019), for example, retail stores on consumers and consumers on retail stores.

We identify a few studies that empirically quantify asymmetric two-way cross-side network effects.[1,2] Chu and Manchanda (2016) quantify two-way CNEs (i.e., buyers on sellers and sellers on buyers) and their evolution over the platform's life cycle for a customer-to-customer (C2C) online platform. The findings show a large and positive cross-network effect on both sides of the platform, but also that this effect is asymmetric in that the installed base of sellers have a much larger effect on the growth of buyers than vice versa. Also, Voigt and Hinz (2015) focus on a C2C platform to investigate network effects. In particular, they investigate users' spending behavior on an online dating platform and find asymmetric CNEs, i.e., men are more likely to pay for online dating services when there is a sufficient installed user base of women than vice versa. In a business-to-business (B2B) setting, Song et al. (2018) examine how CNEs on different platform sides (application software side and user side) of Mozilla Firefox are temporally asymmetric and find a long-term CNE from the user side to the application side and a short-term CNE from the application side to the user side. Finally, Thies et al. (2018) empirically assess CNEs for a crowdfunding platform (which is classified as a business-to-consumer (B2C) context). By analyzing data on the evolution of Kickstarter, a large crowdfunding platform, they find evidence for asymmetric network effects. In particular, while an increasing number of entrepreneurial projects has a strong effect on the installed base of funders, an increased installed base of funders does not have an effect on the growth of the number of entrepreneurial projects.

Our paper is related to these studies, but with one notable difference. The two-sided market we study is unique because discounting perishables to reduce food waste is very time sensitive. Specifically, the quality of perishables deteriorates continuously until it is no longer suitable for sale or consumption (Wang & Li, 2012). Thus, when retail stores upload last-minute discounts on the digital platform, consumers have a small time window to view these discounts and act (about one or two days). If a 'mismatch' between retail stores and consumers arises, it renders last-minute discounts ineffective, and, in turn, it becomes more difficult to sustain the digital platform and to accomplish the goal of reducing food waste.

We follow previous research (e.g., Song et al., 2018; Thies et al.,

[1] Another identified study that empirically assesses CNEs is the study of Cong et al. (2019). Unlike the other identified studies and our own research context in which we focus on one specific digital platform and its users, this study examines CNEs across multiple platforms with the focus on platform failure.

[2] Please note that the identified studies may document same-side network effects and non-network factors, but because of our focus on CNEs, we only report findings on cross-side network effects.

2018; Voigt & Hinz, 2015) by adopting user activity as a measure of installed base.[3] The main reason is that user networks contribute to each other in dimensions other than membership (i.e., the size of the two user networks) (Landsman & Stremersch, 2011). In particular, retail stores and consumers who simply join the digital platform without taking any action do not create any value (i.e., they do not contribute to the overall goal of food waste reduction). Thus, the interdependency between user networks on both sides extends beyond membership and involves usage too (Rysman, 2009). In our setting, when focusing on digital platforms aimed at food waste reduction, it is not just the number of retail stores and consumers that join the platform that matters, but more important is the activity of these retail stores and consumers. The current study, therefore, focuses on the relation between the activities of retail stores and consumers and explores whether asymmetric CNEs exist between these two sides: how does retail store activity, such as the number of perishables on last-minute discount that are uploaded, impact consumer activity, such as the number of views of discounted perishables, and vice-versa?

2.4. Asymmetric interactions between retail stores and consumers

For digital platforms to survive, platform leaders must maintain positive cross-side network effects (Helfat & Raubitschek, 2018; Thies et al., 2018), which is a major challenge (Voigt & Hinz, 2015). Each side of the market has its own set of distinct features and agenda that may not align. These distinct features of each of the two sides of the market may result in asymmetric influences of CNEs between the two sides which can have important implications for sustaining the digital platform (Cong et al., 2019; Song et al., 2018). In particular, platform leaders are typically concerned with understanding the primacy of one side versus the other. By exploring whether the two cross-side network effects are asymmetric, it is possible to pinpoint the side of the digital platform that is more important in sustaining the platform (Chu & Manchanda, 2016).

2.4.1. Retail store-to-consumer effect

The main goal of retail stores participating in digital platforms aiming to reduce food waste is to sell more perishables before they expire and need to be thrown away. Thus, retail stores seek to increase their revenues by diminishing costs inherent in food waste (Tsiros & Heilman, 2005; Wang & Li, 2012). Since uploading of last-minute discounts by retail stores stimulates consumers to use the digital platform to search for discounted perishables, we refer to it as the retail store-to-consumer effect. Empirical evidence of this effect is provided by Nijs et al. (2001), who find that the short- and long-term effectivity of price promotions is greater for perishable goods than for other product categories. Moreover, since consumers are less willing to pay for perishable products close to expiry (Tsiros & Heilman, 2005), discounting them may be an effective strategy to waste less food and increase profits (Aschemann-Witzel et al., 2019; Tsiros & Heilman, 2005; Wang & Li, 2012). In addition, last-minute discounting of perishables can build trust between retail stores and consumers because it minimizes food waste and will benefit society as a whole (Tsiros & Heilman, 2005). This reputational effect further encourages retail stores to participate in a digital platform and upload discounted perishables.

On the other hand, in the long term, retail stores bear the risk of eroding their pricing power by using last-minute discounts on perishables. Research shows that when retail stores use price discounts on a regular basis, consumers' reference prices are lowered and they may wait for prices to be reduced in the future, and, as a result, postpone their purchases (van Heerde, Leeflang, & Wittink, 2000). However, Chung (2019) states that it is not clear whether consumers strategize in their purchase of perishable products as they do when purchasing seasonal goods such as fashion products. It is possible that consumers make a tradeoff between price and quality (i.e., freshness) without behaving strategically.

2.4.2. Consumer-to-retail store effect

Consumers participate in the digital platform for two reasons. First, consumers have the strong feeling that participating in digital platforms dedicated to reducing food waste is morally correct. It can make consumers feel guilty for wasting food (Van Geffen et al., 2020). By using the digital platform to identify and subsequently buy perishables on last-minute discount, consumers feel that they are helping in the fight against food waste. Second, by buying perishables on last-minute discount, consumers save money. Consumers' use of the digital platform will increase sales of perishables in retail stores which, in turn, will prompt these stores to be more active on the platform by uploading more perishables on last-minute discount. We call this the consumer-to-retail store effect. Although consumers foresee immediate moral and economic benefits of using these digital platforms that focus on food waste, their usage may dwindle in the long run. Literature finds that the reason for the decline in usage is due to the level of consumers' cooking skills and the accuracy of planning skills. Consumers with developed cooking skills who are able to prepare a wide variety of food can improvise based on the perishables available for sale (Stangherlin et al., 2019), while consumers who lack these skills are more rigid about the perishables they can use, thereby making them less proactive in using digital platforms to reduce food waste. In a similar vein, consumers with accurate planning skills are better in making decisions on the quantity to purchase, cook, and consume, but experience less freedom in making spontaneous decisions concerning what to eat (Van Geffen et al., 2020), which makes these consumers less prone to last-minute discounts.

2.4.3. Quantifying the retail store-to-consumer and consumer-to-retail store effects

We expect that the retail store-to-consumer and consumer-to-retail store effects differ in strength, i.e., they are asymmetric because of the distinct features and objectives outlined above (cf. Cong et al., 2019). Note that there are different mechanisms at work in the short and long term, for both retail stores and consumers. To summarize, while, in the short term, grocery retail stores use the digital platform as an avenue to reach consumers and thus recoup some of their costs of food that otherwise would go to waste (or be sent to local food banks such as food pantries and meal programs), in the long-term, they may hold back to some extent, to prevent stimulating opportunistic and strategic buying behavior by consumers (e.g., delaying their purchases when expecting a last-minute bargain to emerge) that may make them more price sensitive. Consumers, on the other hand, want to save money and help the environment by making use of the digital platform in the short term, but in the long term may be hesitant to change their buying patterns (e.g., consumers need flexibility and creativity in their cooking repertoire to fully benefit from the products offered on the digital platform).

Quantifying the relative importance of one side over the other of a two-sided network provides digital platform leaders with the necessary information to allocate their available resources more efficiently (Chu & Manchanda, 2016; Sridhar et al., 2011).

[3] In essence, while some papers refer to installed bases, they actually operationalize installed bases as an activity-based measure (e.g., Song et al., 2018; Thies et al., 2018; Voigt & Hinz, 2015). For example, Song et al. (2018), who study a platform with applications on one side and users on the other side, use application quantity (i.e., number of applications) as a proxy for application usage on one side and a measure of user activity (i.e., the average daily times of actual usage) on the other side. Thus, like other studies, our paper actually captures the installed base, which we operationalize as retail store and consumer activity.

3. Methodology

3.1. Research context

To study the dynamics and (a)symmetry of CNEs we use data from a company in Europe that built a digital platform in 2016 for reducing food waste. The firm managed to attract a set of grocery retail stores and their consumers that interact on the digital platform to jointly prevent waste of perishable food. The data pertain to retail store behavior (i.e., uploading of last-minute discounts on the digital platform) and consumer behavior (i.e., viewing the available last-minute discounts).

To participate in the digital platform, grocery retail stores subscribe for a year and pay a fixed yearly fee. In addition, retail stores incur some transaction cost, because perishables placed on last-minute discount are scanned by personnel at the retail store to post the items on the digital platform. Consumers can download the mobile phone app and use the digital platform for free. The app uses the consumers' geolocation to indicate nearby retail stores and the discounted perishables available. Consumers can (pre)select the retail stores they would like to receive information from. The mobile app does not send push notifications (i.e., no proactive messages are sent when new perishable products are added to the digital platform).

3.2. Data

Retail stores gradually joined the digital platform in the year following its launch in 2016, as illustrated by Fig. 1. We track the activity of retail stores for the first year since they joined the digital platform. On the grocery retail store side, we observe the perishable products that are uploaded by a retail store on the digital platform on a daily basis. Primarily perishables from categories such as vegetables, fruits, meats, and dairy were placed under last-minute discount. On the consumer side, we observe the day as well as the time at which a consumer views the perishables offered on last-minute discount by his or her preferred retail store(s). We have data on 48 grocery retail stores who uploaded 159,040 perishable products in their first year (i.e., 52 weeks) of joining the digital platform, and which are viewed by 9985 consumers. Each consumer's list of preferred retail stores is also known. For the analysis, the data were aggregated from day to week level in accordance with the fact that grocery trips in the European country where the study is based, are not made every day.

To measure retail store activity on the digital platform, we calculate the number of distinct products offered on last-minute discount by a retail store. To measure consumer activity on the digital platform, we calculate the number of distinct consumers who viewed these last-minute discounts in the same store. Table 2 provides some descriptive statistics.

Although the activity at the consumer side is measured by the number of consumers who viewed the last-minute discounts on perishables and not the actual purchases that these consumers made, it still serves as a good proxy for purchase behavior of the perishables posted on the digital platform. As the mobile app did not send push notifications, a reasonable assumption is that consumers only open the app just before or during their grocery shopping journey. Previous research shows that the level of interest in mobile apps of retailers is indeed directly associated with purchase intent (Taylor & Levin, 2014). Empirical support for this assumption is offered by our data too. Fig. 2 shows a plot confirming that consumers generally opened and thus used the app during popular times for grocery shopping, i.e., from 9 am to 9 pm.

3.3. Econometric modeling

To analyze the data and study the dynamic interactions and feedback effects over time between (i) the number of last-minute discounts uploaded on the digital platform by the retail stores, and (ii) the number of distinct consumers – linked to these stores on the digital platform – who viewed these discounts, we used a vector autoregressive (VAR) model. VAR models address the modeling needs of our study as it controls for endogeneity, reverse causality and feedback loops between variables (Granger & Newbold, 1986; Pauwels, 2004), thereby better illustrating the cross-side network effects between the two sides of the digital platform. VAR has been used to study cross-side network effects in two-sided markets in different contexts such as digital platforms (Song et al., 2018) and crowdfunding campaigns (Thies et al., 2018), and is also an established modeling technique in marketing research (e.g., Colicev, Malshe, Pauwels, & O'Connor, 2018; Dekimpe and Hanssens, 1995; Luo, Raithel, & Wiles, 2013; Yang et al., 2019).

As we have panel data which involve time-series information related to 48 grocery retail stores, we use the panel vector autoregressive model (PVAR) to estimate the relationship between the number of last-minute discounts uploaded by the retail stores and the number of distinct consumers who view these discounts (Holtz-Eakin, Newey, & Rosen, 1988). PVAR pools data across retail stores, while controlling for cross-sectional heterogeneity by using store fixed effects (for similar practice, see Borah & Tellis, 2016; Colicev, Kumar, & O'Connor, 2019; Hewett, Rand, Rust, & Van Heerde, 2016).

Before specifying our PVAR model, we need to conduct two important tests. First, we use Granger causality tests (Granger, 1969) to establish the relationship between the number of last-minute discounts uploaded and the number of distinct consumer views of these discounts. Granger causality of variable Y by variable X implies that we can better predict Y by also including the lagged value of X (along with the lagged values of Y) than by only including the lagged value of Y. This is one of the closest causality tests that can be carried out with non-experimental data (Srinivasan, Rutz, & Pauwels, 2016) and is also known as temporal causality. Specifically, we adopt the Granger causality test for panel data proposed by Dumitrescu and Hurlin (2012). This approach offers a test that takes into account heterogeneity across retail stores when estimating the causal relationship between last-minute discounts and distinct consumer views and provides an overall Granger causality statistic for the entire data set (by averaging across retail stores). The null hypothesis for the test assumes that the variables do not (Granger) cause each other. Our results show that the *p*-values are significant for last-minute discounts causing distinct consumer views ($p < 0.000$) and distinct consumer views causing last-minute discounts ($p < 0.002$),[4] and thus we can reject the null hypothesis. As the results indicate that last-minute discounts (Granger) cause distinct consumer views, both these variables are endogenous.

Second, we use unit root tests to check whether our two key variables, i.e., number of last-minute discounts and number of distinct consumer views, are stationary. This is a requirement for using PVAR. We use panel unit root tests which are unit root tests for multiple-series and can be applied to panel data (see Baltagi, 2013 for more details). These panel unit root tests build upon classical tests performed on single time series, such as the Augmented Dickey-Fuller (ADF) and Phillips-Perron tests. We use a range of panel root tests, specifically, Fisher-type panel unit root tests as indicated by both Choi (2001) and Maddala and Wu (1999). We also use the Levin-Lin-Chu (LLC) test (Levin, Lin, & Chu, 2002). These tests have been frequently used by previous research in marketing (e.g., Colicev et al., 2019; Kim & Hanssens, 2017; Kübler, Pauwels, Yildirim, & Fandrich, 2018; Rego, Morgan, & Fornell, 2013). Table 3 includes the results of these tests. These results permit us to reject the unit root hypothesis for last-minute discounts *and* distinct consumer views, and suggest that these variables can enter the PVAR model in levels.

Based on the results of the panel Granger causality tests and the unit root tests, the PVAR model is specified as follows:

[4] Reporting the minimum *p*-value across 15 lags.

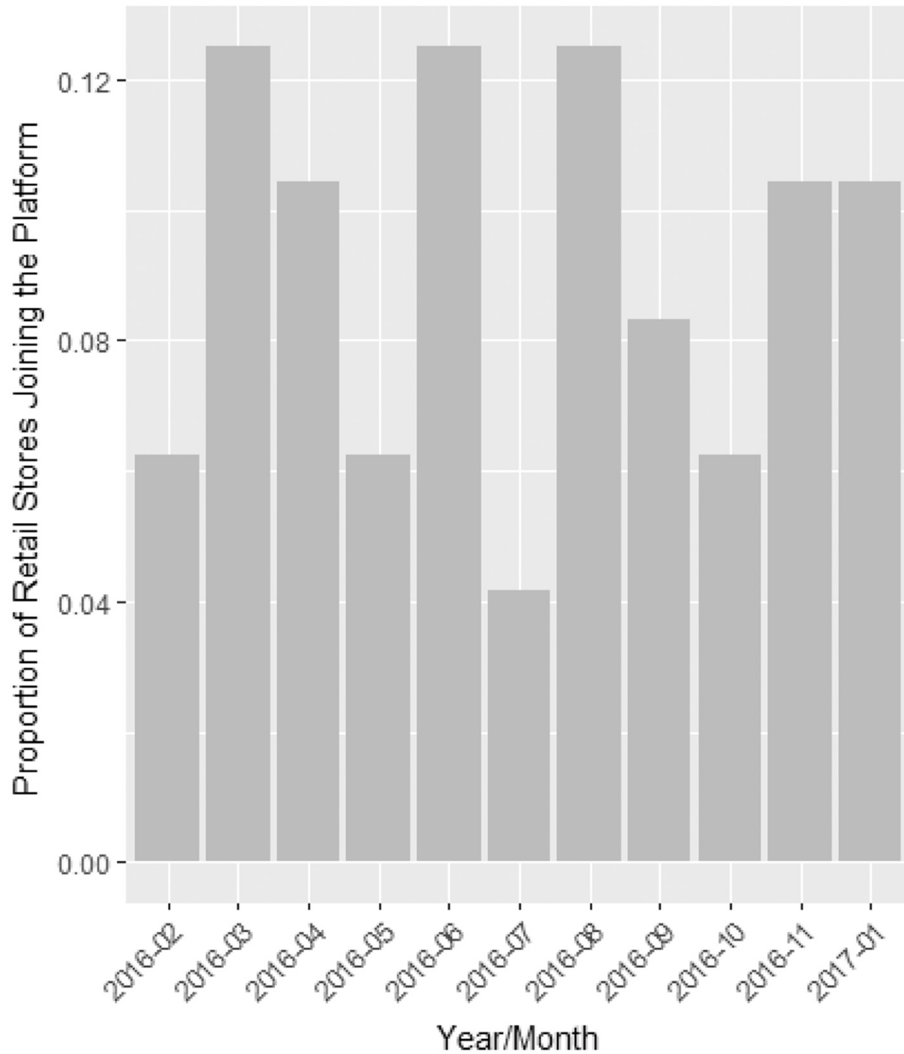

Fig. 1. Distribution of grocery retail stores joining the digital platform over time.

Table 2
Descriptive statistics.

Variables	Mean	SD	Min	Max
Number of last-minute discounts	63.718	40.325	10	161
Number of distinct consumer views	17.072	12.618	3	60

Note: Descriptive statistics are based on activity on the digital platform related to 48 retail stores. The data pertains to the activity of the first 52 weeks after these stores joined the platform.

(1)

$$\begin{bmatrix} LD_{it} \\ CV_{it} \end{bmatrix} = \sum_{n=1}^{p} \begin{bmatrix} \gamma_{1.1}^{n} & \gamma_{1.2}^{n} \\ \gamma_{2.1}^{n} & \gamma_{2.2}^{n} \end{bmatrix} \begin{bmatrix} LD_{it-n} \\ CV_{it-n} \end{bmatrix} + \begin{bmatrix} \mu_{1,i} \\ \mu_{2,i} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,it} \\ \varepsilon_{2,it} \end{bmatrix},$$

where $LD =$ last-minute discounts, $CV =$ distinct consumer views, $i = 1, \ldots S (= 48)$ retail stores and $t = 1, \ldots T (= 52)$ weekly observations since a retail store i joined the platform.

The off-diagonal terms in the matrix $\gamma_{k,\ l}^{n}$ (k≠l) represent the lagged effects of distinct consumer views on last-minute discounts, and the lagged effects of last-minute discounts on distinct consumer views. The diagonal elements in the matrix $\gamma_{k,\ l}^{n}$ (k = l) represent the autoregressive effects. Store fixed effects (μ_i) are included to control for any time-invariant store factors.[5,6] Finally, the error terms (ε_{it}) capture the contemporaneous effects between the variables.

Next, we estimate eq. (1) using Generalized Method of Moments (GMM). However, since previous research has shown that fixed effects (μ_i) are likely to be correlated with regressors due to the lags of the dependent variable (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998), we use forward orthogonal deviations (also known as Helmert transformation) to eliminate the fixed effects. As the Helmert transformation only removes the forward mean, that is the mean of all future observations for each store-month in our data, the orthogonality between the transformed variables and the lagged regressors is preserved, and thus we may use lagged instruments in our estimation (Arellano & Bover, 1995). Further, Helmert transformations do not induce autocorrelation in the error terms. To estimate our PVAR model we use the panelvar package in R (Sigmund & Ferstl, 2019), which has been used by a number of studies (e.g., Koengkan, Losekann, & Fuinhas, 2018; Liu & Kim, 2018), and permits us to calculate robust

[5] Week fixed effects are not included as the weeks in our model correspond to the weeks retail stores joined the digital platform rather than calendar weeks.

[6] By using the Hausman test on a simplified version of our PVAR model, we test whether random effects are preferred to fixed effects in our context. The results indicate that the preferred model is fixed effects (rather than random effects).

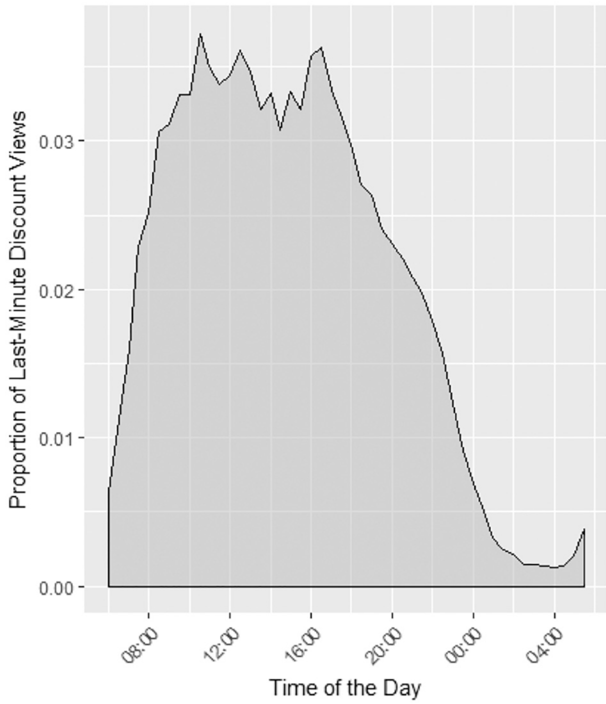

Fig. 2. Distribution of last-minute discount views by consumers over time.

Table 3
Panel unit root tests.

Panel unit root test	Levin-Lin-Chu (2002)	ADF-Fisher based test by Choi (2001)	ADF-Fisher based test by Maddala and Wu (1999)
Distinct consumer views	0.000	0.000	0.000
Last-minute discounts	0.000	0.000	0.000

Notes: Null hypotheses assumes unit root. No intercept or trend is included in the different tests.

standard errors.

To choose the optimal lag order for our PVAR model estimation using GMM, the consistent moment and model selection criteria (MMSC) proposed by Andrews and Lu (2001) are used. These criteria resemble common Maximum Likelihood based model selection criteria such as Akaike Information Criterion (AIC) (Akaike, 1969), Bayesian Information Criterion (BIC) (Schwarz, 1978), and the Hannan-Quinn Information Criterion (HQIC) (Hannan & Quinn, 1979). Based on the optimal lags, we then check for multicollinearity among the lagged variables by calculating the Variance Inflation Factor scores (VIF values). If the VIF values are below 10, multicollinearity is not a concern (Yoder & Pettigrew-Crosby, 1995). Finally, we assess model stability by checking whether the eigenvalues of the companion matrix are within the unit circle (Heij, de Boer, Franses, Kloek, & van Dijk, 2004).

Our PVAR comprises a system of equations as the endogenous variables, i.e., number of last-minute discounts uploaded by retail stores and number of distinct consumer views, depend on each other. Because of this interdependency, the coefficient estimates only provide limited information about the reaction of the system to a shock (i.e., a unit increase in one of these variables). Hence, impulse response functions are calculated to provide a better understanding of the model's dynamic behavior. To exemplify, if a shock is given to distinct consumer views this week and one would like to see its response on last-minute discounts, not just for the same week but also for a specified number of weeks in the future, impulse response functions are required. More generally, impulse response functions describe the evolution of our focal variable along a specified time horizon, after a shock is given to the system at a particular point in time. To calculate the impulse response functions, we recast our PVAR into its vector moving-average form and then derive the impact of a one-unit shock of one endogenous variable on the other. For an in-depth exposition, we direct the interested reader to Hamilton (1994).

As the impulse response function permits us to trace the impact over time of one-unit shock of an endogenous variable on other endogenous variables, we are able to examine the short-term as well as the long-term effects of a unit shock of the number of last-minute discounts uploaded by retail stores on the number of distinct consumers who view these discounts and vice versa. We use the generalized impulse response functions (GIRFs) which are robust to the causal ordering of variables (Pesaran & Shin, 1998). The standard errors are calculated by bootstrapping, using cross-sectional resampling as prior research recommends the use of this method for panel models such as PVAR (Kapetanios, 2008).

4. Results

4.1. PVAR model

The optimal lag length for the PVAR model according to all three MMSC criteria, i.e., MMSC-AIC, MMSC-BIC, and MMSC-HQIC, is one lag (see Table 4). The calculated VIF values show that multicollinearity is not a concern because all the VIF values are around 2 (VIF for lagged last-minute discounts is 1.84 and for lagged distinct consumer views it is 2.12). Our stability check finds that the PVAR model is stable as the eigenvalues of the companion matrix are 0.90 and 0.57, and are thus within the unit circle. As the parameter estimates of the PVAR model are not interpretable (Sims, 1980; Song et al., 2018), the GIRFs are used to estimate the effect of the variables.

4.2. Generalized impulse response functions (GIRFs)

The GIRFs are used to examine how a one-unit shock to distinct consumer views affects last-minute discounts and vice versa, and are depicted in Fig. 3. Panel A displays the consumer-to-retail store effect and, thus, shows how a one-unit shock to distinct consumer views affects last-minute discounts over a 15-week period. Panel B displays the retail store-to-consumer effect and, thus, shows how a one-unit shock to last-minute discounts affects distinct consumer views over a 15-week period. The dotted line represents the 95% confidence interval. Our results show that the consumer-to-retail store effect is stronger than the retail store-to-consumer effect, but both these effects dwindle over time.

To better illustrate how the effects depicted by the GIRFs dwindle over time, the short-term and long-term effects are reported in Table 5, where short-term effects refer to the immediate effects (i.e., effects at

Table 4
Model and moment selection criteria (MMSC) for lag selection of PVAR.

Lag	MMSC-BIC	MMSC-AIC	MMSC-HQIC
1	−1495	−350	−807
2	−1477	−348	−799
3	−1464	−350	−796
4	−1447	−349	−788
5	−1431	−348	−782
6	−1421	−354	−783
7	−1406	−354	−777
8	−1383	−347	−764

Note: MMSC-BIC, MMSC-AIC and MMSC-HQIC are model and moment selection criteria that resemble the common Maximum Likelihood based criteria Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC) and Hannan-Quinn Information Criterion (HQIC).

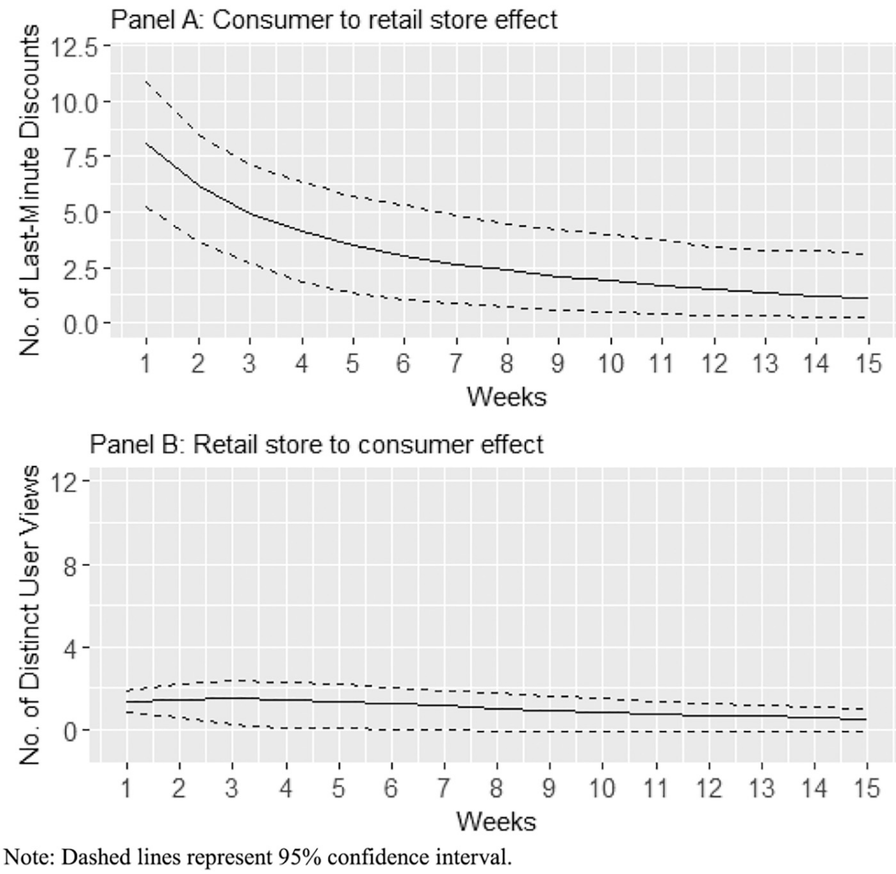

Fig. 3. Generalized impulse response function of CNE.
Note: Dashed lines represent 95% confidence interval.

Table 5
Short and long-term cross-side network effects.

	Short-term effect	Long-term effect
Retail store to consumer effect	1.29	0
Consumer to retail store effect	8.06	1.10

Note: All non-zero effects are significant ($p < 0.05$). Insignificant effects are reported as 0.

week 1), while long-term effects are effects that persist over a relatively long period of time (i.e., effects at week 15). In line with previous research using VAR type models (e.g., Dekimpe & Hanssens, 1999; Pauwels & Weiss, 2008), we report values of significant effects while assigning a value of 0 for non-significant effects. We find that although the consumer-to-retail store effect dwindles over time, it continues to have a relatively long-term impact. The retail store-to-consumer effect also decreases over time, but dwindles quickly to zero. A possible explanation for a strong short-term consumer-to-retail store effect may be that extra consumer interest leads to an important increase in sales of discounted perishables on offer which stimulates retail stores to upload more eligible products on the platform and to do this more promptly and systematically. Prior findings support this conjecture (Taylor & Levin, 2014). The effect lasts longer since an increase in sales of a product near its expiration date implies that other, alternative products - perishables with longer shelf life - will remain unsold (substitution effect). These, in turn, may become candidates for the next days' last-minute discounts. Theoretically, it could precipitate a gradual overall increase in the number of perishables, discounted last-minute, which may lead to a relatively long-term consumer-to-retail store effect that we find.

In comparison, the retail store-to-consumer effect is small in the short-term. To motivate consumers to purchase a perishable at last-minute discount, retail stores need to increase the variety of perishables. Consumers considering the extra discounted perishables are more likely to buy different than similar items. Within a particular category, the quantity they can absorb and use in a short period of time will be limited. This is further boosted by the fact that the perishable products in a certain category act as substitutes or need to be integrated in a meal, which means planning for or already having the additional meal components at home. More creative and flexible (in cooking repertoire) consumers may be able to absorb more products than more rigid counterparts. This may explain why we find the long-term retail store-to-consumer effect being zero.

4.3. Robustness checks

We perform three different robustness checks. For these robustness checks, we report the cumulative effect in Table 6 by taking the sum of significant GIRFs (Colicev et al., 2019). First, we increase the number of

Table 6
Cross-side network effects: Robustness to alternative specifications.

Robustness check	Consumer to retail store effect (Effect 1)	Retail store to consumer effect (Effect 2)
Lag 2	19.4*	1.16*
Time fixed effects	6.61*	1.14*
Log transformation of variables	0.63*	0.33*

Notes: We report the cumulative effects which are calculated by taking the sum of significant GIRF values.
* $p < 0.10$.

lags to two to check whether it affects our results. Second, we control for any variations arising due to the time *since* a retail store joined the platform by incorporating time fixed effects (where time represents the week since joining the digital platform). Third, we take the log transformation of both our variables (i.e., consumer views and last-minute discounts) before estimating the PVAR model. We find that, for all the robustness checks, the consumer-to-retail store effect remains stronger than the retail store-to-consumer effect.

5. Discussion

Food waste is a huge problem. By 2030, the total cost of food waste could be as high as $600 billion (Waste Wise Products, 2017), without factoring in environmental and social consequences. The problem is expected to increase unless efforts are made to tackle it. Grocery retailers can help reduce food waste by adopting strategies such as last-minute discounting of perishables that are close to their expiration date. Digital platforms and integrated mobile apps can help retail stores swiftly disseminate information on these discounts to consumers.

This study used data from such a digital platform to study cross-side network effects using a dynamic perspective. Drawing on two-sided market theory, we have advanced the literature on digital platforms by empirically examining the asymmetry between the cross-side network effects of the two sides of the market in the context of business-to-consumer industries (cf. Chu & Manchanda, 2016; Song et al., 2018; Thies et al., 2018; Voigt & Hinz, 2015). In our research setting, we have retail stores on one side and consumers on the other. In addition, in the context of research on food sharing models (Michelini et al., 2018), this is the first study – to the best of our knowledge - to quantify the relative importance of one side over the other side of the network. This quantification is especially relevant in our research context of food waste in which time sensitivity is high. Indeed, to increase the effectiveness of last-minute discounts, retail stores and consumers need to be connected within a short timespan (i.e., one or two days). Our study shows interesting results. Particularly, we find evidence of asymmetric cross-side network effects in that the magnitude of the effects, between both sides of the network, is different. Specifically, the consumer-to-retail store effect is stronger and more long lasting than the retail store-to-consumer effect.

5.1. Theoretical implications

Our findings contribute to recent endeavors, primarily in the area of cross-side network effects and food waste, to understand retail store-consumer interactions in the fight against food waste. First, regarding the literature on two-sided markets and cross-side network effects, our findings provide further evidence for the existence of asymmetric cross-side network effects (e.g., Chu & Manchanda, 2016; Song et al., 2018; Thies et al., 2018; Voigt & Hinz, 2015). Unlike existent studies, we focus on a digital platform that needs to connect both sides of the market (i.e., retail stores and consumers) very quickly, i.e., within one or two days, to develop and sustain CNEs. Our results provide evidence that dynamic environments, in which time sensitivity is high, ask for knowledge on the relative importance of one side over the other side of the market. Hence, our findings may apply to other retailers as well, especially those that rely on (almost) simultaneous interactions of users on both sides of the digital platform, e.g., retailers that focus on perishable products other than groceries such as bakeries, restaurants, florists, and pharmacies, but also services that rely on sharing-economy businesses such as Uber.

Second, while literature on food waste is extensive, food waste at the retail level is under-researched (Cicatiello, Franco, Pancino, Blasi, & Falasconi, 2017; Filimonau & Gherbin, 2017; Michelini et al., 2018) and studies on the use of digital platforms to mitigate the food waste problem are still largely lacking (for an exception see, e.g., Corbo & Fraticelli, 2015). By investigating how digital platforms, focused on reducing food waste, can be sustained, we respond to multiple calls related to food waste such as (i) better understanding managerial approaches to reduce food waste (Filimonau & Gherbin, 2017; Stöckli et al., 2018) and (ii) assessing the effectiveness of strategies against food waste (Cicatiello et al., 2017; Stöckli et al., 2018). Specifically, our study shows that digital platforms are able to effectively tie together retail stores and consumers within a short timespan (i.e., one or two days) by levering the different CNEs, which, in turn, enhances the effectiveness of last-minute discounts and reduces food waste. Additionally, we extend prior, often descriptive and qualitative work in this domain (e.g., Corbo & Fraticelli, 2015; Halloran, Clement, Kornum, Bucatariu, & Magid, 2014; Pirani & Arafat, 2016) by empirically assessing digital solutions to the food waste problem using secondary data.

Our findings suggest that digital platforms are able to effectively create ties between retail stores and consumers in that consumer-to-retail store and retail store-to-consumer effects are present but asymmetric. Specifically, the discounted offerings uploaded by retail stores trigger consumers to use the digital platform to identify which offers to take advantage of. Consumers thus value the option to save money and, possibly, also the thought of actively helping to prevent food waste. However, this effect is shortly lived, which implies that, while academic research and popular press urge retailers to take initiatives to tackle food waste (e.g., Capgemini, 2017; Cicatiello et al., 2017; Winsight Grocery Business, 2018), firms should find ways to keep consumers alert and active. Previous research already indicates that the reasons for household food waste are complex and not yet fully understood (Lee, 2018), which make it hard to develop successful food waste reduction strategies (Aschemann-Witzel, de Hooge, Almli, & Oostindjer, 2018). Advancing the literature on food waste in grocery retailing, our results show that the effectiveness of retail stores' food waste reduction strategies are dependent on consumer actions and behavior. Both digital platform leaders and retail stores should take this into account. They may explore the use of push messages to trigger consumers to respond and remain active, but also suggesting recipes in which the perishables on discount can be used can trigger consumer activation. In line with the product transformation salience theory (e.g., Winterich, Nenkov, & Gonzales, 2019), we expect that providing recipes will lead consumers to think how the discounted perishables could be used, thereby encouraging them to behave sustainably by increasing their purchase of perishables on discount.

5.2. Managerial implications

Our findings provide evidence to retail stores that their initiative to provide last-minute discounts on close to expiry products persuades consumers to use the digital platform, via its mobile app, to view these products. However, since the consumer-to-retail store effect is stronger than the retail store-to-consumer effect, it is advisable for the digital platform leader to intervene on the consumer side of the market (cf. Chu & Manchanda, 2016). Based on existing literature on mobile apps, we speculate that the digital platform leader should improve the perceived compatibility and interactivity of their app. These characteristics have a positive influence on affective involvement, which increases consumers' intention to use mobile apps (Kang, Mun, & Johnson, 2015). Perceived compatibility is the degree to which consumers believe the digital platform fits with their needs and preferences (Kang et al., 2015). Digital platform leaders will benefit from a detailed understanding of consumers' service needs. By providing recipes based on the perishables on discount, the digital platform leader and retail store can foster compatibility and stimulate willingness to use. It also adds to interactivity, because the provision of recipes can make using the digital platform more appealing and interesting (Kang et al., 2015). Interactivity could also be enhanced by offering consumers the option to create a digital grocery shopping list at the beginning of their journey that includes the close to expiry date products on sale. Push notifications may, as was mentioned, enhance perceived interactivity too. We encourage scholars to empirically validate these theoretical presumptions in future research.

Finally, the results may hold important information for policy makers. They can help subsidize parts of the two-sided market to help the digital platform leader to promote the platform and enhance its interconnectivity. By stimulating the overall installed base and use, the chances of such digital platforms to become sustainable will increase. Governments may also consider changing regulations regarding the quantification and transparency of food waste in order to provide retail stores more incentives to reduce the food waste problem. Indeed, in order to reduce food waste, one needs to quantify the food waste problem but also the outcome of food waste prevention strategies (such as last-minute discounting). For instance, if retail stores are encouraged to quantify their food wastage and analyze its causes, information is more readily available that can be used to take further measures to reduce food waste. Moreover, transparency about the success rates of certain food waste reduction strategies enables best practices to be shared more easily.

5.3. Limitations and future research directions

This study has several limitations, some of which provide worthwhile avenues for further research. First, while this research focuses on the asymmetric cross-side network effects between retail stores and consumers on a digital platform aimed at food waste reduction, we do not empirically investigate which strategies the digital platform owner should adopt to increase consumers' and retail stores' usage of the digital platform and its associated app. We encourage researchers to investigate the effectiveness of different intervention strategies (e.g., providing recipes, enabling grocery shopping lists, push notifications), especially on the consumer side of the market, in order to elicit a virtuous cycle of the mobile app's use and to reduce the food waste problem. In this regard, it may also worthwhile to investigate why the consumer-to-retail store effect is stronger and lasts longer than the retail store-to-consumer effect. Due to a lack of data, we only present theoretical reasons for this finding (e.g., substitution effect), but we encourage scholars to empirically test our presumptions.

Second, while literature shows that the level of interest in mobile apps of retailers is directly associated with purchase intent (Taylor & Levin, 2014), providing us with confidence that consumer views serve as a good proxy for actual purchase behavior of the perishables uploaded on the digital platform, it might be that there is a gap between what consumers aim to do (e.g., buying discounted perishables) and what they actually do (e.g., viewing the app without making purchases) (cf. Van Geffen et al., 2020). Due to the unavailability of data, we were not able to measure actual purchase behavior and compare intentional and actual consumer behavior. Future research might take up this issue and investigate whether consumer views outweigh actual purchases or vice versa, and the implications for retail stores and the objective of reducing food waste.

Third, an interesting avenue for further research is to examine the performance implications for retail stores that actively participate on a digital platform to reduce food waste. One can argue that active participation can have both a negative and positive impact, which makes the performance implications ambivalent. On the negative side, using the digital platform can make consumers more price sensitive as they may defer their purchase until these last-minute discounts appear. On the positive side, apart from an uptake in sales of the perishables on last-minute discount, retailers can expect a boost in store visits as well as basket size.

Fourth, our sample only consists of retail stores and consumers who choose to participate in the digital platform. While this sample suits the purposes of this study, it can imply that we have a sample selection bias. Retail stores and consumers who are more concerned about food waste are more likely to be active on the digital platform but are not necessarily representative of, respectively, the retailing industry and consumer population. Future work can examine what motivates retail stores and consumers to use the digital platform to reduce food waste. In addition, it is also important to examine the motivation of existing users of the digital platform. For example, does the self-interested economic reason of saving money or the altruistic and moral reason of contributing to food waste reduction dominate in the decision to use the digital platform (see e.g., Aschemann-Witzel, 2018)?

Finally, to tackle the increasing problem of food waste, different actors should initiate multiple initiatives. While our focus was on one of these initiatives, i.e., providing last-minute discounts on perishables close to their recommended expiry date, retail stores could take multiple actions at the same time. Therefore, future research can explore the synergies between different food waste reduction initiatives to see whether they complement or compete with each other. Additionally, while we focus on initiatives taken by grocery retail stores, other parties within the supply chain are also responsible for taking action. Future research could take a supply chain perspective and investigate the interrelationships between food waste reduction initiatives taken by different parties within the supply chain.

Declaration of Competing Interest

None.

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