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# Identifying Drivers of Food Waste in Grocery Retail: Empirical Research Insights

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# 1 Introduction

Food waste is a significant issue with substantial environmental, economic, and social impacts. This doctoral thesis aims to empirically investigate root causes for food waste, thereby shedding light on areas previously overlooked in the context of food waste in operations management. In particular, this thesis studies store attributes and operations, promotions, and weather conditions as food waste drivers of perishable goods in the retail stage. The ultimate goal of this thesis is to identify food waste reduction opportunities and, hence, contribute to solving one of the pressing global sustainability issues.

The thesis is structured as follows: The first chapter introduces food waste as a global sustainability issue along the entire supply chain (see Section 1.1). The second chapter presents the motivation for and relevance of studying food waste drivers in grocery retail (see Section 1.2). Chapter 1.3 provides the purpose, methodology, and findings of each of the three papers that are the foundation of this doctoral thesis. The full versions of these three papers are provided in Chapters 2, 3, and 4. Chapter 5 summarizes the findings from this thesis and shares an outlook on future avenues of research.

## 1.1 Food waste as a global sustainability issue

The Food and Agriculture Organization (FAO) estimates that about one-third of all food produced for human consumption is wasted, amounting to approximately 1.3 billion tons annually (FAO, 2013). Food waste is a multifaceted global problem with far-reaching environmental, economic, and social impact. This wastage occurs at various stages of the food supply chain, including production, post-harvest handling, processing, distribution, and consumption, each presenting unique challenges and opportunities for reducing food waste.

Environmentally, food waste contributes significantly to greenhouse gas emissions, accounting for about 8-10% of global emissions (UNEP, 2021). When food is wasted, all the resources used in its production, such as water, land, and energy, are also wasted. Reducing food waste is thus essential for mitigating climate change and promoting environmental sustainability. The economic cost of food waste is staggering. Globally, the economic cost is estimated to be around USD 1 trillion annually, considering the direct economic losses and the broader impacts of resource waste and environmental degradation (WEF, 2021). Food waste translates to lost income and higher production costs for farmers, producers and retailers. In developing countries, a significant portion of food waste occurs at the post-harvest and processing stages due to inadequate infrastructure, lack of modern storage facilities, and inefficient supply chains. Investments in these areas could dramatically reduce food losses, enhancing economic stability for farmers and contributing to food security.

Socially, the issue of food waste is deeply intertwined with global food security. While approximately 1.3 billion tons of food are wasted annually, as mentioned above, about 821 million people globally suffer from chronic hunger (FAO, 2021). This paradox of simultaneous food wastage and food insecurity highlights significant inefficiencies and inequities within the global food system. Reducing food waste can thus play a crucial role in addressing hunger and improving food distribution. With a further increasing world population and growing resource scarcity, how food is produced and distributed needs to change.

Economically, adding economic costs of $ 1 trillion, environmental costs of $ 700 billion, and social costs of $ 900 billion, food waste globally costs a total of $ 2.6 trillion per year (FAO, 2013). The economic impact of retailing is also significant. At European grocers, the costs associated with food waste are around 1.6% of net sales on average, and almost 4% for the worst retailers (Klingler et al., 2016). In Germany, this amounts to food waste costs of around EUR 2 billion p.a. for the grocery retail sector, which even exceed the total transportation costs (Glatzel et al., 2012; Klingler et al., 2016). Given that the margins of grocery retailers are usually 2-3%, reducing food waste can double their profit margins (Glatzel et al., 2012).

Finally, reducing food waste is essential for mitigating climate change, improving food security, and promoting sustainable resource use. Understanding the root causes and drivers of food waste is required to tackle this pressing sustainability issue effectively. Organizations such as the FAO and the United Nations Environment Programme (UNEP) are actively working to raise awareness and implement strategies to combat food waste. The United Nations' Sustainable Development Goal 12.3 aims to halve per capita global food waste at the retail and consumer levels and reduce food losses along production and supply chains by 2030 (UNEP, 2021).

## 1.2 Food waste in grocery retail

The retail stage of the food supply chain is particularly relevant in combatting food waste for several reasons. Retailers have direct control over inventory, display, and handling practices that significantly impact food waste levels. According to Buzby et al. (2015), approximately 10% of the total food supply is wasted at the retail level in the United States alone, highlighting the substantial role retailers play in the food waste equation. Additionally, the retail stage represents the direct link to the consumer, which is crucial for several reasons. Retailers influence consumer purchasing decisions through marketing, promotions, and product placement, all of which can encourage either responsible consumption or lead to excess purchases that increase the likelihood of waste. By adopting strategies that promote sustainable consumption, such as offering smaller portion sizes or clearer labeling about product shelf life, retailers can help educate consumers and reduce food waste both in-store and in households. This link to the consumer also provides an opportunity for retailers to engage in awareness campaigns and offer incentives for waste reduction, further amplifying their impact in the fight against food waste. This makes the retail stage a strategic focal point for interventions to reduce food waste. Furthermore, the retail environment involves complex interactions between suppliers, store operations, and consumer behavior. These interactions create unique challenges and opportunities for reducing waste not present in other supply chain stages. For instance, overstocking, improper handling, and marketing practices can lead to significant waste, and these issues require tailored strategies specific to the retail context. Such a setting becomes especially relevant during promotions, where suppliers and retailers agree on certain promotional events and volumes in advance. At the same time, it is hard to predict how much demand will increase due to promotions.

Additionally, grocery retail is a low-margin business (see above). Therefore, food waste reduction dramatically strikes positively on the bottom line of sustainability in grocery retail. Therefore, identifying and understanding the drivers of food waste in this competitive sector is important and socially and environmentally vital. This can result in effective strategies for reduction. Several factors influence the level of food waste in grocery stores.

Research on food waste in grocery stores identifies several root causes for food waste and strategies for effective reduction. Pertinent literature like Akkaş et al. (2019) emphasize the importance of logistics and supply chain management, highlighting key areas such as case size covers and minimum order rules to reduce waste. Akkaş and Honhon (2022) focus on the impact of operational inefficiencies and propose several avenues for future research on food waste in grocery retail to optimize store operations and reduce waste. In another example, Wu and Honhon (2023) suggest that Buy-one-get-one-free promotions can reduce food waste by creating win-win situations for customers and retailers. Belavina (2021) analyzes the influence of grocery store density on food waste. Riesenegger and Hübner (2022) provide a comprehensive overview of proactive operational planning, including tailored demand forecasts and enhanced ordering processes to minimize food waste.

Various factors influencing food waste have not been studied empirically yet, including store attributes, weather conditions, and promotional activity. Empirical studies analyzing those impacts are the basis for drawing conclusions and determining adequate measurement, reduction, and control strategies for food waste. Drawing these relationships through empirical studies and data-driven approaches can bring retailers closer to better managing their inventory, fine-tuning their supply chains, and ultimately help direct efforts toward sustainability.

This thesis provides evidence on the specific mechanisms within grocery retail that lead to food waste by applying an empirical approach. This investigation is crucial for practical applications that can drive more sustainable operations in the retail sector.

The paper "Uncovering Waste: How Store Characteristics Impact Food Waste in Grocery Retail" in Chapter 2 explores how various store-specific attributes influence food waste levels. The study uses transaction and geo-data from a European retail chain, applying double machine learning techniques to determine the impact of store operations and characteristics on waste. The findings indicate that factors such as organizational ownership, kitchens and inventory policies affect food waste levels. This research highlights the need for retailers to consider these attributes when planning store operations and locations to reduce food waste effectively.

The paper "From deals to dumps: The effect of promotions on food waste in retail" in Chapter 3 examines how promotional activities in grocery retail stores affect food waste levels. Promotions are directly linked to increased sales and higher levels of unsold perishable products. As a result, food might go to waste, especially if the demand has been over-forecasted. The highlighted research emphasizes the necessity of reevaluating the supply operations behind promotions to be able to balance the increase of sales under promotion with minimal wastage of food.

The paper "Stormy skies, spoiled supplies? The impact of weather on food waste in grocery retail" in Chapter 4 explores how weather conditions impact food waste. This paper combines retail and weather data to explore how temperature, precipitation, and snow impact food waste in-store. There are significant statistical differences in the levels of waste due to inclement weather. Thus, retailers have to make their operations weather-sensitive in inventory strategies to mitigate the impact of weather on food perishability to cut waste.

A more detailed overview of the three contributions is presented below.

## 1.3 Contributions

In this section, an overview of the three papers forming the core of this thesis is presented. First, Table 1.1 presents information about the co-authors and the current publication status. Next, each of the three papers is summarized, including its purpose, methodology, and findings (see Sections 1.3.1-1.3.3).

| Paper | | Co-authors | Status |
|---|---|---|---|
| 1 | Uncovering Waste: How Store Characteristics Impact Food Waste in Grocery Retail | Fabian Schäfer, Santiago Gallino and Alexander Hübner | Working paper to be submitted to M&SOM |
| 2 | From deals to dumps: The effect of promotions on food waste in retail | Fabian Schäfer, Sebastian Goerg and Alexander Hübner | Submitted to Management Science |
| 3 | Stormy skies, spoiled supplies? The impact of weather on food waste in grocery retail | Fabian Schäfer and Alexander Hübner | Working Paper |

**Table 1.1:** Status of publication

### 1.3.1 Uncovering Waste: How Store Characteristics Impact Food Waste in Grocery Retail

**Purpose** The study's purpose is to explore how different characteristics of grocery retail stores impact food waste levels. The research aims to fill the gap in the existing literature by providing empirical evidence on the specific store attributes that lead to higher food waste levels. Understanding these relationships is crucial for developing actionable measures to minimize food waste and improve overall store performance.

**Methodology** The study uses proprietary transaction data from 2022 and geo-data from a European grocery retail chain covering 315 stores. By applying the Double Machine Learning algorithm XGBoost for causal inference, the research investigates the relationship between store-specific characteristics and in-store waste levels. The study focuses on the chilled assortment due to its high level of standardization and significant contribution to food waste.

**Findings** The findings indicate that store organization and operations significantly impact food waste levels. Merchant-owned stores demonstrate lower waste rates compared to retailer-owned stores, suggesting that individual business owners are more efficient in waste management. Additionally, double stock and double placement of products due to fresh-cut products also increase food waste. Finally, operational decisions such as inventory parameters or backroom operations increase food waste rates. The study highlights the importance of operational decisions in reducing food waste and provides data-driven insights and practical recommendations for retailers to enhance store performance and sustainability.

### 1.3.2 From deals to dumps: The effect of promotions on food waste in retail

**Purpose** The aim of this study is to examine how promotional activities in grocery retail influence food waste levels. Promotions are commonly used to boost sales, but they can also lead to increased food waste if not managed properly. This research ultimately targets identifying the relationship between promotional strategies and food waste, providing insights into more sustainable retail practices.

**Methodology** The study analyzes the effect of promotions using a panel dataset from 2019 from a German grocery retail chain. The dataset includes information on sales, promotions, shipment volumes, and spoilage for various product categories. The research employs linear models to investigate promotions and substitutions as drivers for food waste. The analysis focuses on the impact of different types of promotions, particularly sales lift and no sales lift promotions, on food waste levels.

**Findings** The findings reveal that promotions significantly impact food waste levels. Specifically, promotions often lead to overstocking and subsequent waste if the increased inventory is not sold before its expiration date. Additionally, we find that the cannibalization effects of promotions on non-focal products also lead to increased waste. This study emphasizes the need for retailers to carefully manage promotions to balance sales goals with sustainability objectives.

### 1.3.3 Stormy skies, spoiled supplies? The impact of weather on food waste in grocery retail

**Purpose** The purpose of this study is to explore how weather conditions influence food waste levels in grocery retail. Weather can affect consumer behavior and supply chain operations, leading to variations in food waste. This research aims to identify the specific weather-related factors contributing to food waste and provide strategies for mitigating their impact.

**Methodology** The study uses weather data from meteorological sources and the same panel data from a German grocery retail chain. The weather dataset includes variables such as temperature, precipitation, and snow depth and is complemented by proprietary retailer data about sales, shipment volumes, and spoilage records. Fixed effects models are applied to investigate the causal effects of weather on food waste. The study also considers interaction effects between weather variables and store-specific characteristics.

**Findings** The findings indicate that weather conditions significantly affect food waste levels. We find that temperature, precipitation, and snow depth increase the risk of food spoilage due to changes in consumer purchasing patterns. Stores located in regions with frequent weather fluctuations are more prone to food waste. The findings suggest that retailers can reduce weather-related food waste by proactively managing inventory levels on store and warehouse levels based on weather forecasts. These strategies can help retailers better manage the impact of weather on food waste and enable more sustainable operations.

# 2 Uncovering Waste: How Store Characteristics Impact Food Waste in Grocery Retail

**Co-authors:** Fabian Schäfer, Santiago Gallino and Alexander Hübner
In the submission process as of August 20, 2024

**Abstract** Food waste is a significant sustainability challenge for retailers, leading to higher carbon emissions and increased costs, yet empirical evidence on its root causes remains limited. Although the influence of internal and socio-economic factors in brick-and-mortar retail, such as store physical characteristics, basket sizes, or competitive intensity, is well-documented, the effect of various store attributes on food waste remains largely unexplored. Thus, our research uses proprietary transaction data and socio-economic data from a European grocery chain to investigate the relationship between store-specific attributes and in-store waste levels. The data covers 315 retail stores in urban and non-urban areas. By applying the Double Machine Learning algorithm XGBoost for causal inference, our findings indicate that store-specific attributes, operations, and organization substantially and significantly impact food waste levels. We estimate the potential for reducing food waste through counterfactual analysis up to 5.2%. Our study fills a gap in the literature on food waste in retail by providing empirical evidence on the store attributes that lead to higher waste levels beyond the existing body of literature that mainly focuses on other store performance metrics like sales or profit. Furthermore, this study creates awareness and offers novel managerial insights for practitioners considering food waste when optimizing store organization and operations, thus driving more sustainable practices in the retail sector.

## 2.1 Introduction

Reducing food waste has become a significant social challenge of our time, crucial for environmental protection and combating climate change. According to a United Nations report, if food waste were considered a country, it would be the third largest emitter of greenhouse gases globally. Annually, 1.3 billion tons of food are discarded worldwide, representing one-third of all food still suitable for human consumption (FAO, 2022). Food waste is not only an environmental issue but also an ethical one, as globally, one in seven people suffers from hunger and malnutrition (FAO, 2019). With the world's population continually increasing and resources becoming scarcer, transforming our food production and distribution systems is imperative.

Retail plays a pivotal role in addressing this global challenge. In Western countries, the consumer sector (incl. retail, food services and households) contributes almost two-thirds of total food waste (FAO, 2022). Avoiding overstock and food waste is becoming more and more relevant for retail stores due to several critical reasons that span environmental, social, regulatory, and economic dimensions (see, e.g., Akkaş et al., 2019; Lim et al., 2023). Reducing food waste enhances the environmental footprint of retail operations by cutting emissions, conserving resources such as water, energy, and land, and promoting more sustainable agricultural and consumption practices. Retailers are increasingly compelled to actively manage food waste and boost corporate social responsibility. Committing to reducing food waste can improve a retailer's reputation and strengthen its relationships with customers and communities. Many countries already have regulations and policies regarding the waste issue on the retail level. With increasing environmental awareness, future legislation will likely become more stringent. For example, in 2015, the United Nations already included the goal of halving per capita global food waste by 2030 in their agenda for sustainable development (United Nations, 2015). Last but not least, effective food waste management can significantly reduce costs. Stores can save money by minimizing the amount of expired food that goes to waste.

As margins of grocery retailers are around 2%, reducing food waste in the same magnitude can double retailers' margins (see e.g. Hübner et al., 2016; Akkaş and Honhon, 2022).

However, retailers are in a dilemma. Due to strong competition and the necessity of realizing sales, grocery retailers emphasize availability. Retailers tend to overstock their displays as full shelves usually drive sales (Hübner et al., 2020). Additionally, retailers expand assortments to meet customer expectations of a wide variety of goods to have a large choice (Gaur and Honhon, 2006; Honhon et al., 2010; Kök et al., 2015). Retailers face the trade-off between increasing the store's attractiveness with higher varieties and higher inventories on the one hand and minimizing the environmental, social, and financial impact of food waste on the other hand. Addressing this trade-off requires a comprehensive approach to optimize the store's performance. In general, retail store performance depends on several external and internal attributes. Socioeconomic and macroeconomic factors like store location (urban vs. rural), income levels, or customer preferences (e.g., to-go options or weekend shopping), play a significant role in this regard (see e.g., Reinartz and Kumar, 1999; Kumar and Karande, 2000; Fisher et al., 2006). By defining store attributes, the retailer can influence the customer behavior and economic success of a store. For example, innovations like offering online shopping, pickup, and delivery services can attract customers who prefer to shop remotely (see, e.g., Gallino and Moreno, 2014). The motivation and qualification of store employees and managers play crucial roles in determining store performance (see, e.g., Perdikaki et al., 2012; DeHoratius et al., 2023). Furthermore, the assortment variety and availability of fresh products can enhance customer satisfaction and loyalty (see, e.g., Kök et al., 2015). Stores can have different replenishment processes, for example, on how full the shelves should be, how backrooms are used, or when reorders are released (Fisher et al., 2006). These examples show that a variety of external and internal store attributes influence demand, execution and store performance.

Despite the well-established influence of certain store settings and practices on customer behavior, demand, and revenues, little is known about the effect of store attributes on food waste Akkaş and Gaur (2022); Hübner et al. (2024). Only Belavina (2021) and Amorim et al. (2024) analyzed so far the food waste impact in relation to store settings. Belavina (2021) show analytically that a greater store density and competition increases food waste on the retail level. Amorim et al. (2024) empirically study the influence of offering omnichannel services on food waste. However, research about the impact of multiple store attributes and their interdependencies on food waste in retail constitutes an open research gap. Akkaş and Gaur (2022) find a lack of empirical research in identifying food waste drivers. There is a need for empirical research to explore how store attributes, operations, and organizational practices contribute to food waste (see e.g., Akkaş and Honhon, 2022; Riesenegger et al., 2023). Our research aims to study the relationship between various store-specific attributes and waste levels. By pinpointing the store attributes contributing to higher food waste, this research aims to offer data-driven insights and practical recommendations to reduce waste, save costs and reduce environmental footprint across stores.

To achieve this research goal, we investigate the panel dataset on a store-product-day level of a leading European retail chain from January 2022 to December 2022 after the aggregation to a store-product group level as the unit of analysis. We apply an exploratory approach to a variety of store-related variables. As we need to deal with a large set of influencing factors that may determine store performance, we will use the Double Machine Learning (DML) algorithm XGBoost, which is capable of dealing with a broad set of variables. We enrich the data set with sociodemographic and competition data on a street level. We explore the direct effect of different store parameters on food waste, including but not limited to store organization (like self-employed vs. employed managers), store type (like urban stores, omnichannel offers, freshly prepared food), and store operations (like inventory practices and replenishment parameters). We use Partially Linear Regression (PLR) models to avoid multi-collinearity issues from studying multiple store features simultaneously.

We find empirical evidence that certain store attributes act as drivers of food waste. Specifically, we identify two major effects: first, the impact of double stocking and double placement, and second, the role of more efficient operations in merchant-owned stores. Additional effects that increase food waste are backroom operations and a greater reach of maximum shelf levels. We estimate the potential for reducing food waste through counterfactual analysis up to 5.2%. Materializing this potential in reducing waste can save the retailer up to 14mn consumer units, 35mn EUR costs, and an increase of the profit margin by 14%. We ensure the robustness of our results by employing a linear model, incorporating variations in control variables, and train-test split variation. Our contribution to research is twofold. First, we contribute to the literature stream about how store organization and type, and operations affect store performance. Second, we extend the list of empirically identified food waste drivers (see, e.g., Akkaş et al., 2019), enabling deriving effective reduction measures. Our study offers novel insights for practitioners looking to optimize store operations. This study also sets the cornerstone for future research about store-related effects on food waste, such as the effect of in-store inventory optimization or determining replenishment frequencies.

The remainder is structured as follows. Related literature is reviewed in Section 2.2. Section 2.3 provides the background of the study and describes the available datasets. The description of the models to conduct the exploratory analysis is presented in Section 2.4, which also outlines the regression results and the robustness checks. Our estimation results, limitations, and future avenues for research are discussed in Section 2.5. Finally, our conclusion is presented in Section 2.6.

## 2.2 Related Literature

Previous studies have examined the impact of various store attributes on general performance metrics such as sales and customer satisfaction. For instance, Kumar and Karande (2000) found that store characteristics significantly influence sales performance. Fisher et al. (2006) hypothesized that store-internal factors such as physical store characteristics, advertising, and the qualities of store employees and managers play crucial roles in determining store performance. Further empirical findings support that execution issues significantly influence store performance regarding customer satisfaction and sales Fisher et al. (2006); Perdikaki et al. (2012). Amongst others, Reinartz and Kumar (1999); Kumar and Karande (2000); Gauri et al. (2008) identify key internal store attributes, including types of shop, non-food revenue share, basket size, store area, number of years in operation, renovation, car parking facilities, and the existence of pick-up service. Also external factors such as key competitors, number of competitors (Talukdar et al., 2010; Trivedi et al., 2017), customer's buying power (Reinartz and Kumar, 1999; Lanfranchi et al., 2014), and population density (Reinartz and Kumar, 1999; Gauri et al., 2008, 2009) have been studied extensively in this context.

Food waste in retail stores is an emerging area, but still at the beginning. Gruber et al. (2016) show that store ownership, whether franchised or retail-chain-owned, can be a differentiator in how store managers perceive food waste. Through qualitative interviews with managers, it was found that the increased independence of store managers, stemming from store ownership by merchants, causes them to perceive food waste differently. Belavina (2021) develop a stylized model to theoretically analyze the impact of grocery store density on food waste. An increase in store density reduces consumer waste by improving access to groceries, but it also increases retail waste due to the decentralization of inventory, which amplifies variability in the supply chain and lowers customer demand. Additionally, higher store density intensifies competition, leading to more waste when stores compete on service levels. Despite some first theoretical insights, the relationship between specific store attributes and food waste remains underexplored as the study focuses on a macroeconomic view. The first empirical study in this area is the paper of Amorim et al. (2024). They show that offering BOPS can reduce waste by pooling inventories across channels. One of their findings is that food waste levels after the introduction of omnichannel services vary significantly between stores, depending on characteristics such as location (urban vs. local) and store size. Stores in local, non-urban areas experience greater reductions in food waste with higher online channel penetration compared to urban stores. Additionally, the authors observe that food waste levels differ among product categories, with fresh products particularly benefiting from increased online sales penetration.

Beyond store attributes based on the physical store and the environment, store operations are another factor to consider that influences food waste (Huang et al., 2021; Riesenegger et al., 2023). Key operational practices include demand forecasting, inventory management, shelf management, and more (Hübner et al., 2024). Proper demand forecasting helps align stock levels with customer demand, reducing the risk of overstocking and subsequent waste.

**Research gap** Although extensive research exists on the general impact of store attributes and socio- and macroeconomic factors on customer behavior and financial impact, the influence of store-related variables on food waste constitutes an open area of research. Current literature highlights the need for empirical research to examine how store attributes and operations practices contribute to food waste (see, e.g., Akkaş et al., 2019; Belavina, 2021; Akkaş and Gaur, 2022). Understanding these connections is essential for creating effective strategies to reduce food waste in stores and enhance overall store performance. This study aims, therefore, to examine the impact of store attributes on food waste.

## 2.3 Empirical setting

To address the research objective of examining the impact of store attributes on waste, we collaborated with a retailer. This section outlines the background of the study (Section 2.3.1), describes the available datasets (Section 2.3.2) and defines the variables used in the regression models (Section 2.3.3).

### 2.3.1 Study background

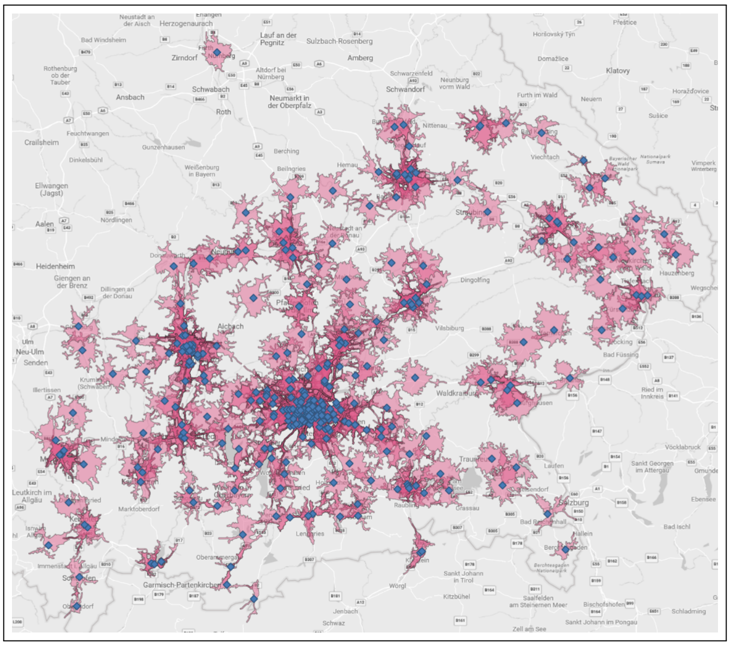
This paper is based on a cooperation with a multi-billion and multi-format grocer, denoted as RetailCo for confidentiality reasons. This retailer operates over 3,500 stores across Europe and offers a full grocery product range. The joint project is based on a larger initiative with senior management's attention to reducing food waste by investigating the differences in food waste across stores. The retailer's management wants to understand store differences and identify opportunities to reduce waste. The diverse range of store attributes, such as organizational structures, store types, and store operations, could contribute to waste, which is the management expectation at the beginning of the project. Throughout the study, we have regularly discussed our results with several members of RetailCo, including middle management, data analysts, and supply chain managers, gaining valuable insights from these interactions.

**Geographical scope** The retailer is organized in regions. To some extent, the regions have different assortments (e.g., regional suppliers and products), and the stores are supplied from regional warehouses with slightly different operations (e.g., warehouse automation and transportation processes). Since our focus is on the stores, we want to exclude variations in upstream processes caused by varying warehouse operations or supplier interactions. Therefore, we concentrate on one homogenous region. This ensures that identical supply and order processes for all stores are investigated. We identified one region in Southeast Germany where all stores can access the assortments from one regional warehouse, and reorder processes are standardized. The region is representative for the retailer because it encompasses various store formats, including both rural and urban locations in large and small cities, different types of store organization, and a range of store operations procedures. It accounts for approximately one-twelfth of RetailCo's stores and sales.

Germany has one of Europe's highest densities of grocery stores per capita. This density results from the competitive market landscape, the dominance of major players such as Aldi, Edeka, Lidl, Kaufland, and Rewe and the diverse range of store formats available. This intense competition fosters the development of advanced retail concepts and operations. Discount chains engage in aggressive price wars, forcing other retailers to follow suit. The fierce competition in the German market creates an ideal environment for studying food waste levels across stores, as Belavina (2021) demonstrated analytically that store density is a key factor contributing to food waste. The extensive presence of discount retailers, along with super- and hypermarkets, guarantees that consumers in both urban and rural areas have convenient access to grocery stores. Consequently, the German market boasts a highly dense store network. The driving range around each store can indicate the competition level. This range is exemplarily shown in Figure 2.1. Based on the competitor data provided by RetailCo, we identified an average of approximately eight competitors within a 5-minute driving range. The data also reveals that urban stores tend to face more competition, as indicated by a correlation coefficient of 0.54 compared to non-urban stores.

**Cooperative organization** RetailCo is organized as a cooperative. Cooperative retailers are often guided by principles such as democratic control and member economic participation. Cooperative retailers are significant players in many European markets, particularly in sectors such as food retailing. For instance, cooperative retailers represent nearly half of the

**Figure 2.1:** Illustration of the regional scope, stores, and 10-minute car driving range around each retail store



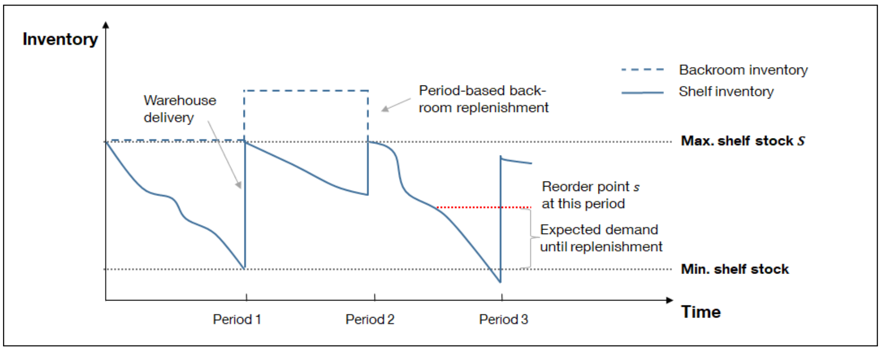
market share in Germany. RetailCo operates the store in two different ways. Approximately half of the stores function as *retailer-owned stores*, where the outlets are fully controlled and coordinated by regional and central levels and managed by RetailCo employees. The remaining half of the outlets operate as *merchant-owned stores*, where store managers are self-employed, assuming full profit and loss responsibility for their businesses. This extends beyond a typical franchising model, as these self-employed merchants are self-responsible business persons with broader decision-making authority. They are entrepreneurs who run their own retail enterprises, assuming responsibility for all facets of store operations, such as assortment selection, ordering, restocking, and customer service. Unlike franchises or employed managers, merchant-owned stores enjoy greater independence and flexibility in running their businesses. Nevertheless, central corporate management is responsible for setting the strategy, policies, and guardrails for the operational procedures applicable to both store types. Uniformity is maintained across all outlets, amongst others, through shared IT infrastructure, common operational and sales processes determined by the RetailCo headquarters, and utilization of products sourced from the same warehouse. Products are purchased centrally. RetailCo also provides various support functions for both types of stores, including employee training, sales development, and administrative assistance.

**Store formats** RetailCo operates a heterogeneous set of store formats to cater to different customer needs and market situations. The main formats are supermarkets (with a comprehensive range of grocery and household goods, typically ranging usually from 800 to 2,500 sqm in size) and hypermarkets (above 2,500 sqm, offering a very wide range of grocery and non-food items). Additionally, they operate smaller stores (with less than 800 sqm, mainly located in city centers and tailored for quick shopping trips) and convenience stores at high-traffic locations (with convenience products for quick purchases on the go). These various formats allow RetailCo to flexibly respond to different location requirements and customer needs, whether in urban areas, rural regions, or high-traffic hubs. The different formats also mean the stores are not standardized in sales areas, assortment sizes, etc., and are heterogeneous, for example, in customer type (family weekend shoppers vs. convenience on the go) or basket sizes. However, urban stores show a higher number of competitors, a greater buying power of customers, more households close by, and a greater day population in the adjacent areas compared to non-urban stores. Interestingly, large and small stores can be found in both urban and rural areas.

**Service offers** Certain stores offer an omnichannel service in the form of BOPS. Here, customers place a purchase order online, e.g., through the RetailCo mobile app or website, and physically go to the selected store to collect the ordered items. Selected stores offer additional home delivery as another sales channel. Some stores offer a counter displaying freshly prepared food at the entrance, e.g., ready-to-eat salads, yogurt bowls, or wraps. The meal prepping happens in a kitchen in the store, where products from a separate stock are used for preparation.

**Inventory policies and replenishment processes** The replenishment process is standardized at RetailCo and based on an automated ordering system, which is representative of industry standards. Figure 2.2 illustrates the inventory policy and parameters applied. The retailer applies a continuous inventory review policy. Whenever the inventory meets the reorder point, an order that ensures a refill to at least the order-up-to level is released. Each store can independently set the two inventory parameters for each product that influence the timing (when?) and the volume (how much?) of replenishment, namely minimum shelf stock and maximum shelf stock. The order-up-to level, denoted at RetailCo as *maximum shelf stock*, is the number of consumer units of one SKU that fit onto the shelf to max out the available shelf space. The maximum shelf level can exceed the expected demand during the replenishment period. Retailers' rationale behind this is to improve the appearance of the shelf through high shelf availability ("high availability leads to sales"). When even more units are delivered to the store than available space on the shelf, the excess units are stored in the backroom. They are moved from the backroom to the shelf as space becomes available. Each store operates a backroom. The storage area in the backroom is intentionally kept open and adaptable to enhance flexibility.

**Figure 2.2:** Replenishment and inventory policy applied



Furthermore, the stores determine by themselves a *minimum shelf stock*, which resembles a minimum representation quantity. This refers to the smallest amount of a particular product that must be kept on display to maintain a visually appealing and well-stocked appearance. This quantity ensures that the product is sufficiently represented on the shelves, which can help attract customers and drive sales. It also prevents the shelves from looking empty, which might negatively impact the perceived availability and popularity of the product. It also includes the safety stock to mitigate the risk of stockouts caused by uncertainties in supply and demand. The size of the minimum shelf stock is typically determined based on sales-driven expectations (e.g., products of everyday essentials), technical shelf restrictions, and operational factors such as the variability of demand, lead time for replenishment, and the desired level of service. The reorder point is ultimately derived from minimum shelf stock and calculated exogenously by the centrally-provided and standardized automated replenishment system. It is the minimum shelf stock plus the expected demand during the replenishment period. Hence, the reorder point depends on the forecasts and the store-determined minimum shelf stock and may vary from period to period. Higher minimum shelf stock settings, determined by the store, trigger earlier and more frequent orders.

**Upstream operations** Stores can order only in case packs (i.e., the outer package of consumer units), and the order volume is always a multiple of the case pack size. The minimum order quantity is one case pack. Store managers can manually increase order volumes, e.g., during promotions or to fulfill specific customer orders. Store managers, however, cannot reduce order volumes proposed by the automated ordering system. All stores order daily and are replenished within less than 24 hours after the order release. The stores are supplied either on a morning or afternoon tour from the warehouse. One set of stores is always supplied during morning hours between 4 and 9 a.m. These stores are called “morning delivery stores” and need to place their orders by 11 a.m. of the preceding day. The other stores, so-called “afternoon delivery stores”, are supplied during the afternoon between 12–8 p.m. and need to place orders by 2 am of the day of the delivery.

Stores can also be supplied through inventory allocations from the warehouse, which are delivery quantities that are not based on a store order and the automated replenishment process. These allocation quantities result from bulk stock at the warehouse that is pushed downstream to the stores for two reasons. First, a high inventory with a low remaining shelf life is pushed to the stores, i.e., products close to the ED at the warehouse. Intuitively, the retailer avoids product spoilage on the warehouse level and aspires to sell the products off at the edge of expiration. Second, supply volumes for promotional weeks are allocated to stores. These promotion weeks take place from Monday to Saturday.

### 2.3.2 Data description

We received a proprietary panel data set on a store-product-day level for the months from January to December 2022 from RetailCo. These daily data include the sales volume, the shipment volume to the stores, the end-of-day inventory at the store, demand forecasts, the unit price of each SKU, the remaining shelf life, and the supply quantity of the delivered items. The data encompass all types of loss and spoilage, categorized into breakage, theft, and expiration. Our dataset records all units not sold before their ED, resulting in financial loss for the retailer. We refer to this as food waste, although a very small portion is repurposed, such as being donated to food banks. We aggregate the data into cross-sectional store-product data to eliminate controlling for seasonal effects. Our initial data set covers 323 stores. Since some store-specific information was not available for all stores, the final dataset includes 315 stores in 260 distinct ZIP code areas supplied by a single warehouse. The stores operate in different sizes. The sales areas are, on average, 1,403 sqm, with 59 small and convenience stores that have less than 800 sqm, 245 stores with 800 to 2,500 sqm (supermarkets), and 11 stores with more than 2.500 sqm (hypermarkets).

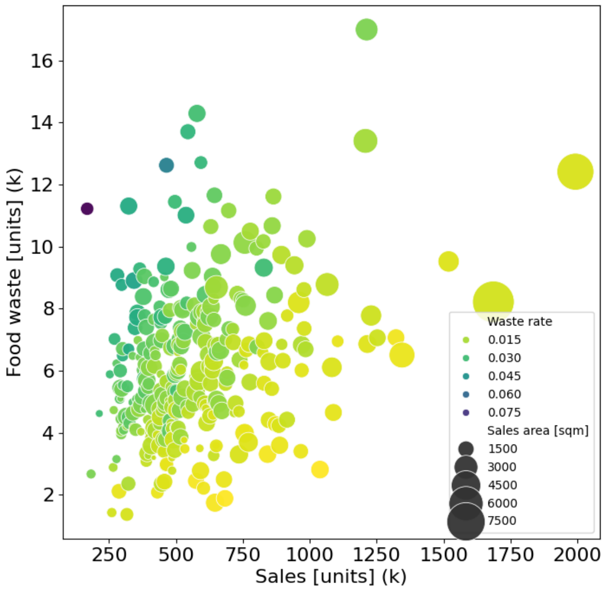
In the following, we will focus on the self-service chilled assortment for two reasons. First, the risk of spoilage is higher for perishable products. Other categories, such as ambient (e.g., canned food, rice, drinks), have a longer shelf life (e.g., more than 12 months) and are less susceptible to turning into food waste. Second, chilled products are standardized and carry printed expiration date (ED) labels. This is important as the freshness level is less prone to a subjective quality assessment than categories that do not carry ED labels (e.g., fruits & vegetables). The retailer distinguishes five chilled categories (Milk/Dairy products, Convenience, Delicacies, Cheese, and Butter), subdivided into up to 80 product groups. An overview of the available main data on store- and store-categories-level is given in Table 2.1.

**Table 2.1:** Overview of main sales and waste data obtained from retailer (full data set)

| | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|
| **Store level data (total assortment)** | | | | |
| Total sales area per store (in sqm) | 1,403 | 750 | 328 | 8,828 |
| Average basket size (in consumer units) | 7.19 | 1.51 | 3.34 | 11.38 |
| Average basket size (in EUR) | 17.9 | 4.6 | 7.4 | 29.2 |
| **Store-category level data (chilled assortment)** | | | | |
| Number of product groups of category per store | 75.4 | 2.6 | 61 | 80 |
| Number of products (SKU) of category per store | 789 | 123 | 473 | 1,151 |
| Total annual sales of category per store (in units) | 574,089 | 242,931 | 168,858 | 1,992,765 |
| Total annual revenue of category per store (in EUR) | 860,860 | 375,392 | 239,926 | 3,081,244 |
| Revenue share of category (in %) | 3.2 | 0.4 | 2.0 | 4.3 |
| Total food waste per store (in consumer units) | 6,147 | 2,377 | 1,363 | 16,999 |
| Waste rate of category (in % of sales) | 1.8 | 0.8 | 0.4 | 8.8 |

We only included products with nonzero sales to exclude discontinued or nonrelevant products. The final sample comprises 295,848 observations on the store-SKU level. The highest number of SKU in one store is 1,151. In our data set, the stores have, on average, 75.4 product groups and 789 SKU in the chilled assortment at hand. The average annual sales per store are 861k EUR within chilled assortments. The chilled assortment revenues are, on average, about 3.2% of the total revenues of a store. The average food waste rate in our sample and the target categories is 1.8%. The total sum of food waste units of the relevant products in our sample summed up across all 315 stores is around 3.2m EUR based on 1.94m consumer units of waste. Food waste varies largely between stores in terms of absolute and relative factors. Figure 2.3 further highlights the heterogeneity across stores. It shows the absolute food waste over sales for each store during the observation period. Each bubble represents one store. Here, a brighter shading of the bubble corresponds to lower relative food waste, while a darker shading conversely means a higher waste rate. The size of the bubble represents the sales area of the store.

**Figure 2.3:** Food waste over sales per store




We further enrich the panel dataset with additional information about, for example, warehouse allocations, additional manual orders by store managers, price levels, case pack sizes, sociodemographic and competition data, and many others that will be detailed when specifying the variables.

### 2.3.3 Variables

This section develops the dependent, treatment, and control variables for the regression models based on the raw data and study background. Table

4.1 summarizes all variables considered and provides a definition of them. The unit of analysis is the cross-sectional store-product-group level with the set of stores $S, s \in S$ and the set of product groups $P, p \in P$. The summary statistics of all variables is presented in Table 2.3.

**Table 2.2:** Overview and definition of variables in main analysis

| | |
|---|---|
| **Dependent variable** | |
| $\text{FoodWasteRate}_{p,s}$ | Ratio of food waste caused by product expiration to sum of sales and food waste of a product group $p$ in store $s$ |
| **Treatment variables** | |
| **(i) Store organization and type** | |
| $\text{BOPS}_s$ ($\text{BOPSDelivery}_s$) | Binary variable; indicating if store $s$ offers a BOPS service (and home delivery service) |
| $\text{MerchantOwned}_s$ | Binary variable; indicating if store $s$ is operated by a self-employed merchant |
| **(ii) Store operations** | |
| $\text{BackroomDelivery}_{p,s}$ ($\text{BackroomInventory}_{p,s}$) | Share of deliveries (inventory) of product group $p$ to store $s$, where delivered volume exceeds maximum available space on shelf leading to intermediate storage in backroom |
| $\text{Kitchen}_s$ | Binary variable; indicating if store $s$ offers freshly self-prepared products |
| $\text{MinShelfStockCover}_{p,s}$ ($\text{MaxShelfStockCover}_{p,s}$) | Minimum (Maximum) quantity of product group $p$ to be kept on shelf at store $s$ divided by its average daily demand |
| **Control variables** | |
| **Store level** | |
| $\text{DeliveryType}_s$ | Binary variable; indicating if store $s$ receives deliveries in the morning or afternoon |
| $\text{SalesArea}_s$ | Size of the store based on the area accessible for customers for product placement in sqm of store $s$ |
| $\text{SCO}_s$ | Binary variable; indicating if store $s$ offers sqm in addition to serviced check-out counters |
| $\text{StoreAge}_s$ | Years since the start of operations of store $s$ |
| $\text{StoreUrban}_s$ | Binary variable; indicating if store $s$ is located in an urban area or not |
| **Product level** | |
| $\text{CasePackSize}_p$ | Average number of consumer units in one case pack in product group $p$ |
| $\text{ProductCategory}_p$ | Product category of product group $p$ |
| **Product-store level** | |
| $\text{CaseSizeCover}_{p,s}$ | Average number of days until all consumer units in one case pack in product group $p$ are sold in store $s$ based on average daily demand of the store |
| $\text{DemandVariability}_{p,s}$ | Continuous; Daily demand variability of product group $p$ in store $s$ across the week calculated by dividing the standard deviation of daily demand by weekly sales average |
| $\text{DeliveryDays}_{p,s}$ | Number of deliveries of product group $p$ to store $s$ |
| $\text{DeliveryQuantity}_{p,s}$ | Average delivery quantity of product group $p$ per delivery to store $s$ |
| $\text{ForecastError}_{p,s}$ | MAPE for product group $p$ at store $s$, measured as the mean absolute percentage difference between the predictions and the actual sales |
| $\text{ManualOrder}_{p,s}$ | Manual order quantity (i.e., overruling the automated ordering system) of product group $p$ at store $s$ divided by the total delivery quantity of product group $p$ at store $s$ |
| $\text{PromotionWeek}_{p,s}$ | Number of weeks, in which product group $p$ was discounted in store $s$ |
| $\text{RSL}_{p,s}$ | Average days of remaining shelf life until the product group $p$ expires upon delivery to store $s$ |
| $\text{SalesPrice}_{p,s}$ | Average price of product group $p$ in store $s$ |
| $\text{StockAllocation}_{p,s}$ | Delivery quantity of product group $p$ centrally allocated by the distribution center to store $s$ divided by the total delivery quantity of product group $p$ at store $s$ |

## Dependent variable

The target variable $\text{WasteRate}_{p,s}$ denotes the fraction of wasted consumer units of a product group $p$, in store $s$ over the entire year. It is the relation of the absolute amount of food waste (denoted $\text{FoodWaste}_{p,s}$) to sales (denoted $\text{Sales}_{p,s}$) and calculated as follows:

$$\text{WasteRate}_{p,s} = \frac{\text{FoodWaste}_{p,s}}{\text{Sales}_{p,s} + \text{FoodWaste}_{p,s}} \tag{2.1}$$

### Treatment variables

In our main model, we consider in total eigth treatment variables that are organized around (i) store organization and type and (ii) store operations.

**(i) Store organisation and type** The variable $\text{MerchantOwned}_s$ determines the organizational form of a store $s$, either as *merchant-owned* or as a branch of the retailer. This is particularly interesting since in merchant-owned set-ups, store owners with profit responsibility suffer personal losses from extra costs, lost sales, high inventory levels, or unsold products directly. In our data set, almost 40% of the stores are owned and run by merchants (see Table 2.3). Second, offering additional sales channels can generate extra demand for the stores, thereby increasing the inventory efficiency of the existing stocks. We will address this with two omnichannel-related variables. The first binary variable ($\text{BOPS}_s$) indicates whether a store offers the *BOPS* service during the observation period, while the second type of store additionally offers *home delivery services*, denoted by $\text{BOPSDelivery}_s$. In our sample, almost half of the stores offer BOPS and only about 4% also home delivery.

**(ii) Store operations** Here, we will identify the variables that describe stores' options to impact waste with store operations. These are the inventory levels and the operations practices. First, in the inventory-related areas, stores can set the minimum and maximum shelf stock levels (see above in Section 2.3.1). The higher the values of these two inventory parameters, the longer the inventory will reach and, hence, the higher the potential risk for expiry. To account for the relation of these parameters to the demand, we introduce the variable *maximum shelf stock cover* ($\text{MaxShelfStockCover}_{p,s}$) and *minimum shelf stock cover* ($\text{MinShelfStockCover}_{p,s}$) in days as the relation of the inventory level to average daily demand. The stores have on average a minimum level of 2 units and maximum level of 8 units.

The second area concerns operations practices and the need to use a backroom and secondary storage locations. Storing inventory in the backroom extends the inventory reach of delivery and hence leads to a higher age of the inventory in the store. Furthermore, storing the products in the backroom may cause further operational issues (e.g., inventory is overlooked in the backroom), as the backrooms in grocery stores are usually not very organized. To account for these facts, we will introduce two backroom-related treatment variables to analyze the effect of backroom storage operations on food waste. First, the variable *backroom delivery share* ($\text{BackroomDelivery}_{p,s}$) denotes the minimum share of deliveries, which at least partly need to be stored in the backroom compared to all deliveries. We conservatively estimate this share based on the delivery volume and the maximum shelf capacity. We do not consider existing stock on the shelves as we do not know when the deliveries will be put into the shelves, so we would otherwise bear the risk of falsely allocating delivery volumes as backroom storage. In our sample, an average of 6.6% of the deliveries did not fit into the shelves. Second, we are interested in the *inventory share stored in the backroom* ($\text{BackroomInventory}_{p,s}$). This variable indicates the backroom storage volume compared to the maximum shelf capacity. For example, if the maximum shelf capacity is 6 and 18 units are delivered, the value for the variable $\text{BackroomDelivery}_{p,s}$ is 200% under the assumption that 6 units can be directly placed on the shelf and 12 are stocked temporarily in the backroom. For the products that did not fit into the shelves, an average of 55% of the inventory needed to be stored in the backroom. Third, we will introduce the variable *kitchen* ($\text{Kitchen}_{s}$) to indicate the availability and in-store preparation of ultra-fresh products. It indicates whether a store operates a kitchen and offers freshly prepared products (e.g., sandwiches). The inventory for these products is stored separately, and no products from the shelves are consumed for meal preparation. In our data set, 90% of the stores operate a kitchen. Note that it does not explicitly indicate the share of sales of these freshly prepared products.

**Table 2.3:** Descriptive statistics of all treatment and control variables

| **Treatment variables** | **Mean** | **St.Dev.** | **Min** | **Max** |
|---|---|---|---|---|
| $\text{BOPS}_\text{s}$ (binary) | 0.477 | 0.499 | 0 | 1 |
| $\text{BOPSDelivery}_\text{s}$ (binary) | 0.044 | 0.204 | 0 | 1 |
| $\text{MerchantOwned}_s$ (binary) | 0.379 | 0.485 | 0 | 1 |
| $\text{BackroomDelivery}_{p,s}$ (in %) | 6.6 | 7.3 | 0.0 | 80.6 |
| $\text{BackroomInventory}_{p,s}$ (in %) | 55.2 | 49.2 | 0.0 | 591 |
| $\text{Kitchen}_\text{s}$ (binary) | 0.90 | 0.30 | 0 | 1 |
| $\text{MinShelfStockCover}_{p,s}$ (in days) | 2.05 | 1.78 | 0.00 | 32.95 |
| $\text{MaxShelfStockCover}_{p,s}$ (in days) | 8.32 | 7.19 | 0.41 | 303.44 |
| **Control variables** | | | | |
| $\text{CasePackSize}_p$ (in units) | 9.1 | 4.4 | 3.0 | 27.8 |
| $\text{CaseSizeCover}_{p,s}$ (in days) | 10.3 | 14.5 | 0.2 | 761.4 |
| $\text{DeliveryDays}_{p,s}$ (in days) | 53.9 | 29.5 | 2.0 | 260.0 |
| $\text{DeliveryQuantity}_{p,s}$ (in units) | 11.5 | 8.3 | 3.0 | 171.7 |
| $\text{DeliveryType}_s$ (binary) | 0.429 | 0.495 | 0.000 | 1.000 |
| $\text{DemandVariability}_{p,s}$ (in %) | 1.360 | 0.30 | 0.624 | 2.646 |
| $\text{ForecastError}_{p,s}$ (in %) | -2.81 | 1.07 | -37.69 | 0.000 |
| $\text{ManualOrder}_{p,s}$ (in %) | 2.0 | 2.7 | 0.0 | 18.2 |
| $\text{PromotionWeek}_{p,s}$ (in weeks) | 21.9 | 14.7 | 0.000 | 83.7 |
| $\text{RSL}_{p,s}$ (in days) | 51.0 | 47.4 | 7.3 | 627.5 |
| $\text{SalesArea}_s$ (in sqm) | 1,406 | 760 | 328 | 8,828 |
| $\text{SalesPrice}_{p,s}$ (in EUR) | 1.95 | 0.75 | 0.15 | 4.67 |
| $\text{SCO}_s$ (binary) | 0.112 | 0.316 | 0 | 1 |
| $\text{StoreAge}_s$ (in years) | 16.9 | 11.2 | 2.0 | 46.0 |
| $\text{StockAllocation}_{p,s}$ (in %) | 13.6 | 3.5 | 0.09 | 23.8 |
| $\text{StoreUrban}_s$ (binary) | 0.468 | 0.499 | 0 | 1 |

## Control variables

A store is subject to many influences and variations. We introduce multiple control variables to isolate the relationship between the target and treatment variables. We apply multiple empirical tests to obtain more accurate and robust estimates of the effect of the treatment variables, as it is important to strike a balance. Including too many control variables, especially irrelevant ones, can introduce noise and multicollinearity, making the model less interpretable and potentially leading to other issues like overfitting. Thus, we select appropriate control variables based on previous research, logical arguments from discussions with retailers, and empirical testing. We apply only variables as controls that cannot be directly influenced by the stores but are attributed to potentially impacting demand and inventories and, hence, ultimately, food waste. We use a large set of control variables for our model development, including multiple store-, product- and store-product-related variables. To justify the selection of variables and excluding correlated variables, we completed additionally a correlation analysis (see Figure A1 in the Appendix) and used the VIF to avoid redundancy and overfitting due to multicollinearity. It highlights that the selected treatment and control variables are not correlated. We refer again to Tables 4.1 and 2.3 for definition and statistics for all variables.

**Location, size and age of store** Our first set of control variables is used to isolate the effect of store location, size, and age. First, we differentiate between urban and rural stores with the control $\text{StoreUrban}_s$. Secondly, we use $\text{SalesArea}_s$ as an indicator for the total size of the store, which influences the assortment size and the type of customer visiting the store and purchasing patterns. The demand needed for a product and by store is also indicated by the average quantity delivered ($\text{DeliveryQuantity}_{p,s}$). The total sales ($\text{Sales}_{p,s}$) is a further indicator for the store size but goes as a denominator into the dependent variable. We will use it only as a control in a robustness check. Furthermore, $\text{StoreAge}_s$ as the years since the start of operations of store $s$ determines the age of the stores. In a similar vein, $\text{SCO}_s$ determines if store $s$ offers the recently introduced sqm to indicate the degree of innovation in this store.

**Upstream operations** Further control variables account for the potential influence of upstream operations that are not under the direct control of the store. First, we control for the number of delivery days ($\text{DeliveryDays}_{p,s}$) and $\text{DeliveryType}_s$ that indicates if a store receives deliveries in the morning or afternoon slot. The warehouse and transportation planning units of RetailCo determine both when making the tour plans for all stores. To factor out the central allocation by the warehouses, we introduce $\text{StockAllocation}_{p,s}$ that defines the delivery quantity that the stores have not ordered.

**Demand-related factors** A third set of control variables is applied to account for demand variations that may cause inventory disruptions and are not under the store's control. Demand forecasting and inventory planning are simpler when demand is stable. Large deviations between sales periods can complicate demand forecasting, leading to challenging inventory planning. There are multiple factors influencing the expected demand. First, we capture the weekly seasonality through the variable $\text{DemandVariability}_{p,s}$, which denotes the weekly sales standard deviation divided by the weekly mean per product. Promotions, such as "buy one, get one free" offers, along with price discounts, influence customer demand. To control for the influence of promotions and prices that may also cause inventory disruption, we use the control variable $\text{PromotionWeek}_{p,s}$ that defines the number of weeks in which a product $p$ was discounted in store $s$ and control also for the sales price ($\text{SalesPrice}_{p,s}$). Moreover, we also use $\text{ForecastError}_{p,s}$ to control for forecasting errors, as the forecasts are not done by the stores but by the central planning department. Lastly, stores usually apply manual orders for customers' advanced orders (e.g., large orders for events or festivals). We apply $\text{ManualOrder}_{p,s}$ that isolates these extra orders and overrules the automated ordering system by the store manager.

**Product-related influences** The final set of control variables neutralizes the effect of the product categories and supplier-determined facts. We use controls on a product level to account for the product category ($\text{ProductCategory}_p$) and the product perishability with the average remaining shelf life of products in a store $\text{RSL}_{p,s}$. To control for the influence of case pack sizes, we use $\text{CasePackSize}_p$ and $\text{CaseSizeCover}_{p,s}$.

## 2.4 Methodology and estimation results

This section develops the estimation model (Section 2.4.1), summarizes the main estimation results for the effects of store attributes on food waste (Section 2.4.2), and the robustness checks to validate our results (Section 2.4.3).

### 2.4.1 Model development

This section outlines the estimation method based on a PLR. We use the DML algorithm XGBoost for our exploratory analysis of the effect of store attributes on food waste. DML algorithm XGBoost is an appropriate approach for causal inference studies with high-dimensional covariates like in our data setting (Chernozhukov et al., 2018; Berrevoets et al., 2024). It is, therefore, an appropriate tool to control for confounding variables and accurately estimate causal effects (see e.g., Ferreira et al., 2016; Glaeser et al., 2019; Ketzenberg et al., 2020; Chou et al., 2023). We also investigate a causal inference problem with many potential confounding variables. DML combined with XGBoost can effectively control these confounders (Chernozhukov et al., 2018; Berrevoets et al., 2024). XGBoost is designed to be computationally efficient and can handle large datasets quickly. When dealing with datasets with many features, XGBoost can effectively handle and model high-dimensional feature spaces. Given that our dataset includes a large set of various store-related features, both treatment and control variables, this method is highly suitable for answering our research question. Additionally, using a PLR approach helps to consider non-linear effects, which improves the accuracy of the effect estimate of the treatment variable on the target variable. Lastly, DML applies feature selection, a powerful technique where the algorithm automatically chooses the variables estimated to have a true effect on the dependent variable (Berrevoets et al., 2024). By using cross-validation, we avoid overfitting the model parameters to the data at hand. In our case, this is helpful in achieving a higher level of generalizability to other stores beyond the ones in our dataset. When estimating the effect of each treatment variable individually on the dependent variable $\text{FoodWasteRate}_{p,s}$, we use all other treatment variables as covariates and control variables. Both equations of the PLR model are presented in Equations (2.2) and (2.3).

$$\text{FoodWasteRate}_{p,s} = D \cdot \theta_0 + g_0 \cdot (Z) + U \tag{2.2}$$

$$D = m_0 \cdot (Z) + V \tag{2.3}$$

The specific treatment variable is denoted with $D$, $\theta_0$ denotes the parameter of interest, and $Z$ is a high-dimensional vector of the covariates. The unit of observation of the treatment variables is two-fold: store-related treatment variables, which are common for each product group in one store $s$, and product-store-related treatment variables, which differ on the product-group and store level $p, s$. Since each treatment variable is estimated individually based on the simultaneous inference approach, we include the other treatments as covariates. The other covariates are either store-related or product-store-related control variables. As we aim for simultaneous inference of multiple treatment variables on the target variable $\text{FoodWasteRate}_{p,s}$, we include each variable of interest as a covariate for estimating the parameter of the current treatment. $U$ and $V$ are the error terms. By partialling out the effects $m_0$ and $g_0$ on the target variable $\text{FoodWasteRate}_{p,s}$, we can isolate the true effect of the treatment variable on the target variable, denoted $\theta$. This is done by regressing the residuals of Equation (2.2) on the residuals of Equation (2.3).

In our study, we are interested in isolating the effect of one store's variable on food waste while controlling for many further store variables. We achieve this by partialling out the effects of the other variables on the target variable when regressing food waste on the variable of interest. We use the ensemble learner XGBoost based on gradient-boosted decision trees to train our DML models (Berrevoets et al., 2024). Additionally, we apply 3-fold cross-fitting to avoid an estimation bias due to overfitting. To optimize the hyperparameters of our DML model, we divide our data into train and test sets (70/30), define a parameter grid with different parameter values for the individual hyperparameters, and use the RandomizedSearchCV method to identify the best parameter setup for each treatment variable. RandomizedSearchCV performs cross-validation on each sampled parameter setting. Cross-validation is a technique to evaluate model performance by dividing the dataset into a set of training and validation sets multiple times. Averaging over these values gives an overall model performance estimate. This estimate is used to get the best-performing set of hyperparameter values used for the regression analysis. Afterward, we run the regression analysis using the derived set of optimized hyperparameters.

### 2.4.2 Main findings on the effect of store variables on food waste

Table 2.4 summarizes the estimation results of the main model. It shows that food waste reduction is driven by the variables that the store controls. We find empirical evidence for the effects of store organization/types and operations on food waste of perishables in grocery retail. Generally, we find that the retailer can improve food waste levels by setting the correct replenishment parameters. Store operations are major food waste reduction levers, including maximum shelf stock and the existence of separate stock in the backroom and kitchens. Merchant-owned stores perform better in avoiding waste than retail chain-owned stores. Below, we will detail the findings and store organization/types and operations.

**(i) Impact of store organization and type** The treatment variable related to the form of ownership is highly statistically significant. Merchant-

**Table 2.4:** Main results: Parameter estimates of store attributes on food waste rate using DML

| **Variables** | **Est.** | **Std.Err.** |
|---|---|---|
| $\text{MerchantOwned}_s$ | -0.016 | 0.03*** |
| $\text{BOPS}_s$ | 0.004 | 0.003 |
| $\text{BOPSDelivery}_s$ | 0.012 | 0.012 |
| $\text{MinShelfStockCover}_{p,s}$ | 0.001 | 0.0004 |
| $\text{MaxShelfStockCover}_{p,s}$ | 0.001 | 0.0002*** |
| $\text{BackroomDelivery}_{p,s}$ | 0.017 | 0.005** |
| $\text{BackroomInventory}_{p,s}$ | 0.00002 | 0.00001* |
| $\text{Kitchen}_s$ | 0.046 | 0.014*** |
| Controls | Yes | |
| $MSE$ | 0.014 | |
| $MAE$ | 0.007 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$;

owned stores have lower waste rates than retail chain-managed stores. Discussions with RetailCo and further complementary data analyses help interpret the store organization's effect on food waste. Multiple reasons can explain it. First and foremost, the managers receive bonuses solely based on sales, while the owner's incentive is tied to profitability, meaning food waste directly affects their personal finances. These different incentive structures may be the main driver in explaining the different waste rates related to store ownership and overall management. Moreover, the assortment selection and product availability are usually controlled by the highest management level of a store at RetailCo because the selection and sale of inventory is the raison d'etre of all merchandise retailing. The related decisions and processes are, therefore, owned by managers in retail-chained-owned stores and owners in the merchant-owned type. That also means that the organization form ultimately defines who makes assortment and inventory decisions (employed managers or self-employed owners). We see that the merchant-owned stores have, on average, a 5% smaller assortment size (on average 809 SKUs at merchant-owned vs. 848 SKUs at the other; strongly statistically different means (p-value < 0.001) based on a t-statistic of -26.61). Smaller assortments mean that less slow-moving products are listed in stores that are particularly prone to turning into waste. However, retailer-owned stores are more forced to list more products than the other ones, as the retailer often makes commitments during negotiations with suppliers to list certain products in a certain number of stores. Furthermore, the inventory levels are generally lower at merchant-owned stores. The OOS-ratio[1] across all products (4.19% vs. 3.28%; t-statistic 23.84 with a p-value $< 0.001$) is on average higher and the StockEndOfDay (9.95 vs 11.39; t-statistic -14.47 with a p-value $< 0.001$) lower when self-employed store managers make the decisions. This indicates, in general, a lower inventory level at merchant-owned stores and that self-employed store managers may trade off more between accepting OOS situations vs. food waste.

The offering of BOPS and home delivery has interestingly no significant effect on food waste. This can be attributed to two opposing effects. On one hand, omnichannel sales can increase demand, potentially leading to higher inventory efficiency and lower waste. On the other hand, RetailCo enforces stricter product selection rules for BOPS and home delivery to minimize product returns. Customers can choose products in stores based on their preferred freshness level, but the retailer selects the units for BOPS and home delivery. The retailer uses the freshest product units for these services to avoid customer complaints and returns, which would require additional picking and shipping. Consequently, units with closer ED are left in the store, increasing the risk of perishing. Although we anticipated that these policies might impact food waste in both directions, we must recognize the limitation that our data only indicates whether a store offers omnichannel services, not the proportion of sales through these channels.

**(ii) Impact of store operations** Our analysis highlights that multiple features of store operations significantly and substantially impact food waste. Based on our estimations, different areas related to inventory

[1] Defined as the number of days where the stock of a certain product was recorded as 0 at the end of opening hours divided by the number of sales days

management, storage policies, and reorder volumes that affect food waste are presented below. The variable MaxShelfStockCover$_{p,s}$ is significant. Stores use the maximum shelf stock for operational reasons (e.g., to leverage the available shelf space) and sales reasons (e.g., to improve the availability and appearance of the shelf). A higher maximum shelf stock leads to higher order volumes and increases average inventory level and age. The store has the final vote on the maximum shelf stock. It can be set so high that it may even exceed the expected demand. A larger maximum shelf stock triggers higher delivery quantities. Those are at risk of expiring if the demand is over-forecasted and the product's remaining shelf life is significantly greater than the maximum shelf stock cover. As expected, waste clearly depends on the stores' replenishment volumes and their alignment with the average daily demand. The complimentary analysis (see Table 2.5) of inventory reach reveals the same effect. A higher reach of the average delivery quantity, denoted DeliveryQTYReach$_{p,s}$, corresponds to a higher waste rate for that item. This finding aligns with expectations, as larger average delivery quantities (e.g., due to case pack sizes or maximum shelf stock parameters) are more challenging to sell if the delivered volume does not perfectly match the average daily demand. The result is either overstock or a mix of multiple ED on the shelves when fresher deliveries arrive. This situation can prompt customers to selectively pick items based on ED (see Hübner et al., 2024), ultimately leading to increased food waste. However, the minimum representation quantity (i.e., MinShelfStockCover) does not significantly increase the waste rate. This is noteworthy, given that higher minimum levels result in earlier reorders and higher average inventories. However, it appears that the representation quantity is set so low that it gets sold before expiration and fulfills its core target – namely, ensuring a minimum number of units visible on the shelves.

Backroom storage becomes necessary when the delivery quantity exceeds the available space on the shelf. Storing inventory in the backroom increases the total inventory in the store, which can improve flexibility and availability but significantly complicates inventory management since stock is kept at shelf and backroom locations. Our regression shows that the higher the

**Table 2.5:** Parameter estimates of $\text{DeliveryQTYReach}_{p,s}$ on food waste rate using DML

| **Variables** | **Est.** | **Std.Err.** |
|---|---|---|
| $\text{DeliveryQTYReach}_{p,s}$ | 0.002 | 0.003*** |
| Controls | Yes | |
| $MSE$ | 0.014 | |
| $MAE$ | 0.007 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$;
The dependent variable is WasteRate.

need to use the backroom for intermediate storage, the higher the food waste rate. This is based on two effects: First, the more shipments need to be stored in the backroom (indicated by $\text{BackroomDelivery}_{p,s}$), the greater the waste rate at this store. In our data set, the average share of deliveries that do not fit into the shelf is 6.6%. Second, the volume that is stored for such shipments in the backroom (indicated by $\text{BackroomInventory}_{p,s}$, in our data set 55% on average) also significantly drives food waste, i.e., the higher the volume stored in the backroom compared to the shelf capacity, the greater the food waste. The negative effect of backroom storage on food waste can be explained with two facts. Firstly, inventory reach and age increase. Secondly, backrooms are not as organized as warehouses or showroom shelves, leading to products being forgotten or not replenished on the shelves in time to be sold before expiry, especially if demand does not materialize. For example, different products mixed in one box are often stored, storage location is not tracked with inventory systems, location selection is more on an "as needed basis" and does not follow clear stocking rules like in a warehouse or store shelves. This exacerbates the issues of managing dual inventories. It also highlights the need for shelf parameters to align with demand and for effective replenishment policies for backroom activities.

Similarly, double inventory increases food waste significantly due to in-store kitchens. Those stores use separate stocks instead of inventory pooling for the kitchen and store shelves. This leads to the double placement of products and double stock. Each kitchen has a dedicated refrigerator to streamline food preparation processes. This reduces walking distances for employees, eliminating the need for them to pick items from store shelves. Moreover, restocking the kitchen counter relies on additional orders beyond the regular operations for the shelves in the showroom. This additional ordering source can result in a surplus of products, ultimately leading to increased food waste.

### 2.4.3 Robustness checks

We prove the robustness of our results with (i) alternative approaches and train/test data splits by a variety of model specifications with changes in the (ii) control and (iii) treatment variables.

**(i) Alternative estimation methods** We test the robustness of our results using a simple linear model (more specifically, an OLS). Table 2.6 confirms our findings from the main model. The OLS regression obtains directionally similar results with also significance for the variables of the merchant-owned stores, the maximum shelf stock cover and backroom delivery and inventory, and kitchen. The direction of the effects is identical but with a partially lower magnitude. Two variables (BOPS with Delivery and minimum shelf stock cover) also become significant. However, only in 4% of the stores BOPS and delivery are offered, and the minimum level supports the argumentation about the importance of inventory levels in general. Moreover, we implement an 80/20 train-test split of the PLR, as opposed to the previously used 70/30 split to evaluate whether the model maintains its accuracy with a larger portion of the dataset allocated for training. We get directionally similar results compared to the main contribution (see Table 2.7).

**Table 2.6:** Parameter estimates of store attributes on food waste using a linear model

| **Variables** | **Est.** | **Std.Err.** |
|---|---|---|
| *Intercept* | -0.066 | 0.002*** |
| $\text{MerchantOwned}_s$ | -0.003 | 0.000*** |
| $\text{BOPS}_s$ | 0.0002 | 0.000 |
| $\text{BOPSDelivery}_s$ | 0.002 | 0.001*** |
| $\text{MinShelfStockCover}_{p,s}$ | -0.001 | 0.000*** |
| $\text{MaxShelfStockCover}_{p,s}$ | 0.001 | 2.99E-05*** |
| $\text{BackroomDelivery}_{p,s}$ | 0.008 | 0.003** |
| $\text{BackroomInventory}_{p,s}$ | 1.22E-05 | 4.90E-06* |
| $\text{Kitchen}_s$ | 0.002 | 0.000*** |
| Controls | Yes | |
| $R^2$ | 0.404 | |
| *Adj.* $R^2$ | 0.404 | |
| $F - statistics$ | 575.500 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.;

**Table 2.7:** Parameter estimates of store attributes on food waste rate using DML based on 80/20 train-test-split of the data

| **Variables** | **Est.** | **Std.Err.** |
|---|---|---|
| $\text{MerchantOwned}_s$ | -0.014 | 0.003*** |
| $\text{BOPS}_s$ | 0.005 | 0.003* |
| $\text{BOPSDelivery}_s$ | 0.036 | 0.014 |
| $\text{MaxShelfStockCover}_{p,s}$ | 0.001 | 0.0002*** |
| $\text{MinShelfStockCover}_{p,s}$ | 0.001 | 0.0004 |
| $\text{BackroomDelivery}_{p,s}$ | 0.018 | 0.005*** |
| $\text{BackroomInventory}_{p,s}$ | 0.00002 | 0.00001* |
| $\text{Kitchen}_s$ | 0.041 | 0.014** |
| Controls | Yes | |
| $MSE$ | 0.014 | |
| $MAE$ | 0.007 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$;

### (ii) Alternative model specifications using varying control variables

We use a large set of control variables. The selection of the controls impacts the robustness and magnitude of the effect, particularly when we need to deal with a large set of treatment variables. We will, therefore, specify and analyze the following various specifications for the controls to show that our results are robust. Even though we can logically justify all the controls used in Section 2.3.3, some variations may change the results. However, we are able to confirm our main results in terms of direction and significance by estimating the effects with alternative control variables. Our results are detailed in the Appendix. We will highlight our findings along the structure of our controls: (1) different store size measures, (2) upstream operations, (3) demand-related factors, and (4) product-related factors.

(1) We apply different controls for the store size. Exchanging, removing, and adding different controls for the store size directionally yielded the same significant and substantial estimation results. In the first analysis, we replaced $\text{SalesArea}_s$ with $\text{AverageBasketSize}_s$ (see Table A1). The average basket size of a store can also serve as an indicator of purchase volume and store size. Larger stores usually have larger basket sizes and vice versa, e.g., because customers may do substantial weekly shopping in larger stores (e.g., by car) and small volume on-demand shopping in smaller stores (e.g., on the way between office and home). Secondly, we added $\text{Sales}_p, s$ as a control variable. This variable represents the total sales; however, it is also part of the target variable and may potentially lead to endogeneity. Directionally, we obtained the same results with this additional control (see Table A2). Subsequently, we estimate the treatment effect sizes by excluding $\text{SalesArea}_s$ from the set of variables (see Table A3) and finally also confirm our findings when including both $\text{SalesArea}_s$ and $\text{AverageBasketSize}_s$ (see Table A4).

(2) The store depends on the upstream supply chain settings determined by central, warehouse, and transportation functions. We model here, in particular, the $\text{DeliveryDays}_{p,s}$ and $\text{DeliveryType}_s$ as the control variable as these are set exogenously to the store. Nevertheless, determining the number of delivery days and the delivery type (morning vs. afternoon arrival of orders) requires some consultation with the central functions regarding the capacities and preferences in the store. Therefore, we exclude both in a further test. Table A5 shows that our results, when excluding those upstream operations-related variables, remain robust regarding direction and significance.

(3) Each store is subject to varying demand. We control for this effect by the variable $\text{DemandVariability}_{p,s}$. However, we could also use another approximation for the seasonality by using $\text{WeekendShare}_{p,s}$. This variable indicates the weekend's sales share compared to the entire week's total sales. Stores with a higher weekend share (i.e., on Friday and Saturday) may also exhibit higher demand variability. Our results show that the results remain directionally similar when accounting for an alternative type of demand variability across the week for each store (see Table A6).

(4) Lastly, we also confirm our findings when excluding product group-related binary variables $\text{ProductCategory}_{p,s}$ by finding directionally and qualitatively similar results compared to our main model (see Table A7).

**(iii) Alternative model specifications using varying treatment variables** In a further variation, we analyze the impact of the store location and its related economic potential and competitive situation. Our main analysis uses the binary variable urban, differentiating between urban and rural locations. Urban areas are characterized by a high population density, day population density, retail store density, and buying power per capita. To investigate the robustness (and to potentially obtain further insights), we include additional sociodemographic data based on a 10-minute car driving range around each store provided by WIGeoGIS. This data includes the *buying power per capita*, which refers to the monetary value based on the income average, the *day poplulation*, and the *number of residents* in this area. Furthermore, we use the data of *direct competitors* nearby provided by the retailer. We introduce $\text{BuyingPower}_s$, $\text{DayPopulation}_s$, $\text{NumberOfResidents}_s$ and $\text{NumberCompetitors}_s$ around the store as additional treatment variables. As the urban variable is correlated with these, we will not use urban as a control in these tests.

Tables 2.8 to 2.10 summarize the findings when store environment- or sociodemographic-related variables are included as treatments. We found no evidence that store types affect the food waste rate. Store environment data, such as the competitive situation and buying power, do not significantly impact waste levels. This is an interesting finding as a high competition level may force to ensure high availability that may turn into waste later (see Belavina, 2021). Ultimately, the limited influence of the store environment indicates that waste management is less affected by external factors beyond the retailer's control. In other words, waste primarily arises from the retailer's processes and operations.

**Table 2.8:** Parameter estimates of store attributes on food waste rate using DML **including** $\text{NumberCompetitors}_s$**) as additional treatment variable**

| **Variables** | **Est.** | **Std.Err.** |
|---|---|---|
| $\text{MerchantOwned}_s$ | -0.009 | 0.002*** |
| $\text{BOPS}_s$ | 0.003 | 0.002 |
| $\text{BOPSDelivery}_s$ | 0.013 | 0.011 |
| $\text{MaxShelfStockCover}_{p,s}$ | 0.001 | 0.0002*** |
| $\text{MinShelfStockCover}_{p,s}$ | 0.0005 | 0.0003 |
| $\text{BackroomDelivery}_{p,s}$ | 0.019 | 0.006*** |
| $\text{BackroomInventory}_{p,s}$ | 0.0002 | 0.00001* |
| $\text{Kitchen}_s$ | 0.050 | 0.015*** |
| $\text{NumberCompetitors}_s$ | 0.0004 | 0.0004 |
| Controls | Yes | |
| $MSE$ | 0.014 | |
| $MAE$ | 0.007 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$;

**Table 2.9:** Parameter estimates of store attributes on food waste rate using DML **including** $\text{BuyingPower}_s$ **as additional treatment variable**

| **Variables** | **Est.** | **Std.Err.** |
|---|---|---|
| $\text{MerchantOwned}_s$ | -0.015 | 0.003*** |
| $\text{BOPS}_s$ | 0.002 | 0.004 |
| $\text{BOPSDelivery}_s$ | 0.003 | 0.018 |
| $\text{MaxShelfStockCover}_{p,s}$ | 0.001 | 0.0002*** |
| $\text{MinShelfStockCover}_{p,s}$ | 0.0005 | 0.0004 |
| $\text{BackroomDelivery}_{p,s}$ | 0.020 | 0.005*** |
| $\text{BackroomInventory}_{p,s}$ | 0.00002 | 0.00001* |
| $\text{Kitchen}_s$ | 0.089 | 0.029** |
| $\text{BuyingPower}_s$ | 0.000001 | 0.000002 |
| Controls | Yes | |
| $MSE$ | 0.014 | |
| $MAE$ | 0.007 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$;

**Table 2.10:** Parameter estimates of store attributes on food waste rate using DML **including** $\text{DayPopulation}_s$ **and** $\text{NumberOfResidents}_s$ **as additional sociodemographic treatment variables**

| **Variables** | **Est.** | **Std.Err.** |
|---|---|---|
| $\text{MerchantOwned}_s$ | -0.012 | 0.002*** |
| $\text{BOPS}_s$ | -0.001 | 0.004 |
| $\text{BOPSDelivery}_s$ | 0.051 | 0.022 |
| $\text{MaxShelfStockCover}_{p,s}$ | 0.001 | 0.0002*** |
| $\text{MinShelfStockCover}_{p,s}$ | 0.0004 | 0.0004 |
| $\text{BackroomDelivery}_{p,s}$ | 0.020 | 0.005*** |
| $\text{BackroomInventory}_{p,s}$ | 0.00002 | 0.00001** |
| $\text{Kitchen}_s$ | 0.046 | 0.022* |
| $\text{DayPopulation}_s$ | 2.124E-8 | 2.297E-7 |
| $\text{NumberOfResidents}_s$ | -3.844E-7 | 2.769E-7 |
| Controls | Yes | |
| $MSE$ | 0.014 | |
| $MAE$ | 0.007 | |

Notes: $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$;

## 2.5 Discussion

This section discusses the results and applies counterfactual analysis to investigate the magnitude of the identified effects on food waste and to develop managerial insights. We further discuss the contribution to the literature.

### 2.5.1 Magnitude of the effect analysis and managerial insights

Our findings suggest several significant variables for mitigating food waste in grocery retail stores. Using counterfactual analysis, we estimate the potential impact of adjusting the treatment variable by one standard deviation. Specifically, assuming all other factors remain stable, we calculated the change in the food waste ratio resulting from altering the mean of each treatment variable by one standard deviation. This calculation, grounded in the linear relationship assumption of our model, indicates the potential reduction in food waste relative to the total food waste per store. Table 2.11 summarizes the potential impact of this approach. It can be treated as the minimum savings potential by smaller improvements.

**Table 2.11:** Magnitude of the effect analysis

| Variable | Coef.est. | Std.Dev. | Mean | Waste impact[1] |
|---|---|---|---|---|
| MerchantOwned | -0.014 | 0.485 | 0.379 | 0.8% |
| MaxShelfStockCover | 0.001 | 7.192 | 8.320 | 0.7% |
| BackroomDelivery | 0.018 | 0.073 | 0.066 | 0.1% |
| BackroomInventory | 0.00002 | 49.171 | 55.164 | 0.1% |
| Kitchen | 0.041 | 0.300 | 0.900 | 1.2% |

[1] Minimum impact: Based on one standard deviation change

By leveraging a scenario, denoted as "target", where the variables kitchen and backroom are fully adjusted to their non-occurrence, rather than merely shifting by one standard deviation, the reduction in food waste could increase by 1.5 times to 5.2%. This resembles a realistic possibility and the target for RetailCo. The most significant contribution to this additional reduction comes from the absence of kitchens, which alone leads to a 3.6% decrease in food waste. This represents a change equivalent to three standard deviations (0.9). All other variables in this scenario are still adjusted by only one standard deviation, as, for example, the MaxShelfStockCover cannot be reduced to zero.

Reducing the waste by 3.0 (minimum) to 5.2% (target) would mean for RetailCo to save per store between 184 and 320 consumer units per year in the chilled categories. Assuming that grocery retailers typically have only a profit margin of 2% or less and have some extra processing costs for food waste (e.g., removing from the shelf, waste management), the costs of a wasted product can be set equal to its sales price. The wasted unit translates then into 465 to 806 EUR of profit increase per store. Table 2.12 transforms the unit and monetary savings on a total regional level (with 323 stores) and total retailer level (with 3,500 stores). It shows that the savings potential is huge. The retailer can save up to 1.1mn consumer units and 2.8mn EUR per year in the chilled assortment. Assuming that the insights and best practices identified in chilled assortments can also be applied to other fresh categories, typically representing 30% to 40% of the store's share, the potential savings could be ten to twelve times higher. The retailer could save up to almost 14mn consumer units and up to 35mn EUR per year. Achieving these savings of 35mn EUR would also mean that the retailer can substantially increase the overall profitability by up to 14%.

**Table 2.12:** Waste reduction potential at RetailCo based on the magnitude of the effect analysis

| | in consumer units | | | in EUR | | |
|---|---|---|---|---|---|---|
| **Potential chilled assortment** | Current | Minimum[1] | Target[2] | Current | Minimum[1] | Target[2] |
| • per store | 6,147 | 184 | 320 | 15,495 | 465 | 806 |
| • total region[3] (323 stores) | 1,985,481 | 59,564 | 103,245 | 55,005,040 | 150,151 | 260,262 |
| • total retailer[3] (3,500 stores) | 21,514,500 | 645,435 | 1,118,754 | 54,234,180 | 1,627,025 | 2,820,177 |
| **Potential total fresh assortments in all stores** | | | | | | |
| • Lower bound[4] (30%) | 201,698,438 | 6,050,953 | 10,488,319 | 508,445,438 | 15,253,363 | 26,439,163 |
| • Upper bound[4] (40%) | 268.931.250 | 8.067.938 | 13.984.425 | 677,927,250 | 20,337,818 | 35,252,217 |

[1,2] Minimum: minimum expected improvement obtained with 3.0% savings; Target: Realistic possibility obtained with 5.2% savings
[3] Multiplication of the potential per store to regional and national level
[4] Assuming that savings can be generated in 30% (lower bound) to 40% (upper bound) of the total assortment

Minimizing food waste has not only economic benefits for the retailer but also for the environment. Saving this volume of food waste between 6 and 14mn consumer units can lead to an average decrease of about 1,000 tons of food waste and about 3,300 tons of CO2 emissions (CO2 emission estimates following Scholz et al. (2015)). To achieve this huge potential, we will elaborate on the potential opportunities along levers in (i) store organization and (ii) store operations.

**(i) Store organization and type** About 40% of the stores in our data set are run as merchant-owned stores that have a significantly lower food waste level. Altering the individual store ownership variable by one standard deviation presents a 0.8% potential reduction in food waste per store. While changing ownership may not be practical, adopting best practices remains sustainable. Merchant-owned stores apply a more streamlined approach to assortment selection and better inventory optimization. Smaller assortments allow for more precise inventory management as complex slow-movers (e.g., in terms of forecasting) are not included, reducing the risk of overstocking and expiration. Furthermore, the merchants allow a faster shelf depletion where some products are sold out at the end of the sales day. These practices help to minimize food waste by offering customers more consistent products with the same ED that also minimizes the undesired picking for fresh products (e.g., when multiple products are in stores). Regardless of the ownership structures, these approaches can be transferred to the managers-run stores.

**(ii) Store operations** The empirical findings confirm that inventory and operations policies impact food waste. This is indicated by the variables $\text{MaxShelfStockCover}_{p,s}$, $\text{BackroomDelivery}_{p,s}$ and $\text{BackroomInventory}_{p,s}$. These variables, though statistically significant, exhibit moderate effects, collectively contributing to approximately a 1% reduction in food waste, primarily driven by $\text{MaxShelfStockCover}_{p,s}$ (0.7%). The retailer can improve their waste levels by a better alignment of the maximum shelf inventory level with the demand (by $\text{MaxShelfStockCover}_{p,s}$) and the order sizes to avoid overstocks that need intermediate storage in the backroom (by $\text{BackroomDelivery}_{p,s}$ and $\text{BackroomInventory}_{p,s}$). RetailCo allows each store to manually determine the maximum stock on the shelves without any algorithmic support. The stores can set the maximum shelf stock independently, often "simply" done by filling up the available shelf space. This "fill-up the hole"-practice, also often found at other retailers, is likely to lead to overstocks that eventually result in food waste, particularly because the automated forecasting and replenishment tool relies solely on this store-determined order-up-to level and takes it as a parameter. The tool does not optimize for the order-up-to level.

Heavy reliance on backrooms as a buffer for storing excess inventory often indicates that the grocery store's inventory planning is not aligned with actual demand. The need for backrooms often indicates that inventory levels were overestimated. This suggests a lack of precise demand forecasting and a low fit of the minimum order sizes (e.g., case pack sizes) with the store demand. Proper inventory optimization should focus on keeping the right amount of stock on the sales floor, minimizing the need for backroom storage. When items are stored in the backroom, they are not immediately accessible to customers, which can lead at the same time to lost sales opportunities, higher inventory age, and spoilage. Using backrooms requires additional handling to move them from storage to the sales floor, increasing labor costs and the likelihood of errors. These issues highlight the need for better alignment of shelf space, order sizes, and replenishment frequency to streamline processes and reduce food waste, ensuring backrooms are used only in exceptional cases.

In a similar vein can the kitchen be seen. Kitchens have a separate stock like the backroom. Nine out of ten stores at RetailCo operate a kitchen, wherefore improving the inventory management for this double product placement represents a major food waste reduction lever. A one standard deviation change in the kitchen implies a 1.2% potential reduction in food waste for retailers. This significant impact can be achieved through various actionable steps, such as utilizing close-to-expiry products for fresh goods preparation and using inventory pooling. Food waste can be avoided in the kitchen and on the shelves by using close-to-expiration items for fresh meal preparation. As these foods are sold anyhow immediately, the close ED does not harm the product quality in this case. Inventory pooling can lead to significant benefits in terms of cost savings, improved service levels, and operational efficiency. The retailer can reduce the amount of safety stock by pooling inventory for the kitchen and store. This is because the variability of demand is often lower when aggregated across multiple occasions, leading to lower overall stock requirements. On the same side, this also leads to higher availability. Centralized inventory also allows for quicker response to changes in demand across different locations and better demand forecasting by aggregating data from multiple sources. This typically results in more accurate predictions. Although this might entail increased labor, it will lead to a substantial decrease in food waste.

**Summary of managerial insights** The research findings translate directly into actionable insights for practitioners. Implementing these strategies can enhance both operational efficiency and sustainability, offering a competitive advantage in an increasingly eco-conscious retail environment. To summarize and highlight, food waste can be saved by:

- **Adoption of merchant-owned store practices in retail-owned stores:** Practices of merchant-owned stores', such as incentive structures that include waste as criteria, maintaining smaller assortments, or more shelf depletion, are beneficial for retail-owned stores.
- **Optimization of MaxShelfStockCover:** The stores have the degree of freedom to set the order-up-to-level by their own. This manual process aims to obtain full shelves by leveraging the total shelf space. Optimizing instead for $\text{MaxShelfStockCover}_{p,s}$ by aligning it more closely with the daily demand can minimize overstock situations.
- **Improvement in backroom inventory management:** Backroom should be only the last resort when demand and supply are not aligned. Using backrooms comes with additional process costs and problems with product expirations. Minimizing spoilage through backroom usage requires optimizing forecasts, replenishment frequencies, and operational processes.
- **Avoiding double stocking in the store:** Leveraging the stocks from the shelves for the preparation in the kitchen leads to substantial reductions in food waste. By pooling the inventories, retailers can optimize the flow of products, ensuring that items approaching their ED are utilized in meal preparation rather than discarded.

### 2.5.2 Contribution to literature

The findings also contribute to the current literature by adding empirical insights to store performance research, highlighting the need for inventory optimization and the missing impact of macro- and socioeconomic settings on food waste in stores.

**(1) We identify novel store-related variables that are relevant for overall store performance** The current literature on store attributes predominately looked at store-related variables like types of shop, basket sizes, physical store characteristics, or employees (see e.g., Reinartz and Kumar, 1999; Kumar and Karande, 2000; Fisher et al., 2006; Perdikaki et al., 2012). The main target of these studies is to develop options to enhance customer satisfaction, increase revenues, or other profit-related metrics. Food waste is out of the scope of the current literature. Only Gruber et al. (2016) point out using qualitative interviews that show that store ownership impacts managers' perceptions of food waste.

Our findings extend this by empirically proving that merchant-owned stores exhibit significantly lower food waste rates. Furthermore, we are identifying internal variables related to organizational matters and operations practices that drive store performance. We are the first to identify and quantify store-related attributes related to food waste. This answers a call for research articulated in many current research papers (see, e.g., Akkaş et al., 2019; Akkaş and Gaur, 2022).

**(2) We highlight the need for advanced inventory and optimization models** Multiple studies investigated the effectiveness and efficiency of store operations on food waste (see e.g., Akkaş et al., 2019; Akkaş and Honhon, 2022; Riesenegger et al., 2023). Amorim et al. (2024) demonstrating that BOPS can mitigate waste through inventory pooling. Further conceptual research emphasizes the impact of operational factors such as demand forecasting and inventory management on food waste (Akkaş et al., 2019; Huang et al., 2021; Hübner et al., 2024). However, it remained very general or was based on a purely conceptual model. Only Belavina (2021) shows theoretically that high-performing stores often exhibit better inventory practices, leading to reduced overstocking.

We prove this empirically and show that high-performing stores (in our case, merchant-owned stores) perform better. We can specify operational practices such as maximum shelf stock levels, backroom storage, and double stocking substantially affect food waste rates.

**(3) Retailers have control over food waste management practices**

A further literature stream has extensively examined external factors on store performance like competitors, customer buying power, and population density (Gauri et al., 2009; Talukdar et al., 2010; Trivedi et al., 2017), however, again only on the general store performance. Only Belavina (2021) demonstrated that greater grocery store density increases food waste at both the store and household levels. In such cases, the store performance depends mainly on these socio- and macro-economic attributes. Despite some first theoretical insights in Belavina (2021), the relationship between specific store attributes and food waste remains underexplored as the study focuses on a macroeconomic view.

In contrast, our findings did not identify any significant external and macroeconomic factor outside the retailer's control significantly affects food waste. Instead, food waste is primarily driven by internal and retailer-controllable factors, particularly those related to store type and operational practices. RetailCo's experience underscores this finding that internal factors, rather than environmental factors, provide more accurate insights into the impact of food waste. Nevertheless, customer behavior, which can be influenced but not controlled, may further impact food waste as an external factor and lies beyond the scope of our study.

## 2.6 Conclusion

Food waste is a significant global issue with substantial ecological, social, and economic consequences. This study aims to contribute to understanding how grocery retailers can proactively reduce fresh food waste by identifying key store attributes as food waste drivers. Therefore, our study sheds light on the different effects of store organization and type and store operations on food waste levels in retail. The organizational structure influences waste levels. Merchant-owned stores demonstrate lower food waste rates than retailer-owned stores, suggesting that incentives and operations practices are better designed at merchant-owned stores. We discover that operational areas within the retailer's control, such as setting optimal replenishment parameters, play a crucial role in minimizing food waste. Specifically, parameters like maximum shelf stock and the management of backroom storage are key factors. The presence of a double inventory for fresh-food preparation within the store, while potentially enhancing product offerings, also contributes to higher waste rates. We estimate the potential for reducing food waste through counterfactual analysis up to 5.2%, mostly driven by the food waste driver in-store kitchen and through the efficient operations of merchant-owned stores. Robustness checks affirmed the validity of our results, ensuring that our findings are reliable and consistent across different modeling approaches. Ultimately, this research strives to support the development of responsible retail practices and encourage food waste reduction.

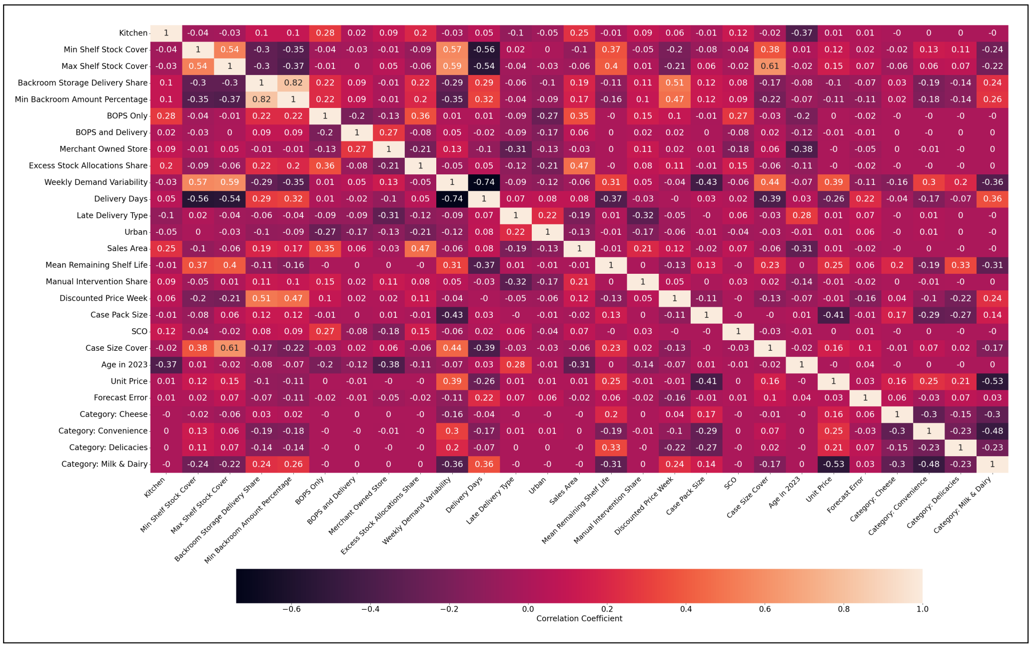
**Limitations and Future Research** Our research is limited in the following ways. First, we only received data for one region, comprising a sub-sample of grocery retail stores in one country of one retailer. Expanding the data by the rest of the retail stores in the respective country would facilitate better monitoring of regional disparities, such as store organization and type and store operations. Second, the omnichannel variables BOPS, BOPSDelivery, and the variable Kitchen were provided as binary variables.

The channel-related transactional data would have been beneficial in putting the findings into perspective. Furthermore, we are generally limited to brick-and-mortar stores and did not investigate online stores. Third, the scope of the study is restricted to the self-serviced chilled assortment, specifically five product categories (Milk/Dairy products, Convenience, Delicacies, Cheese, and Butter). While this focus was selected to exclude confounding factors, e.g., the appearance of fruit and vegetables or meat due to different ordering mechanisms, studying additional perishable goods may validate our findings. Our research paves the pathway for future research opportunities. First, exploring the impact of more detailed channel-related transactional data on our findings would be interesting. Second, while RetailCo serves as a representative retailer, and we do not anticipate significantly different results, extending the study to encompass multiple retail formats, such as discounters and hypermarkets, as well as different retailers, would provide a more comprehensive understanding of the market dynamics and validate the generalizability of our conclusions. Third, investigating the impact of external influences on food waste, such as weather, would be valuable. Unlike store organization, type, and operations, these factors are beyond the retailer's control but still significantly affect food waste. Weather conditions, for example, may force retailers to adapt their behavior steadily at an operational level, impacting both consumer purchasing patterns and the perishability of chilled products. Exploring these external factors could offer deeper insights into how retailers can effectively manage food waste.

# A1: Store attributes correlation

In Figure A1, the correlation matrix based on the correlation between the treatment variables and the covariates is shown.

**Figure A1:** Correlation matrix




# A2: Robustness checks

We highlight the rationale and results of the robustness checks in Section 2.4.3. This section now details the estimates obtained and further discusses the findings.

# Alternative model specifications

We highlight our findings here along the structure of our control variables: (1) different store size measures, (2) upstream operations, (3) demand-related factors and (4) product-related factors.

## (1) Robustness of using different variables for store size

Our first set of variables defines, amongst others, the size of a store. Here we use $\text{SalesArea}_s$ and $\text{DeliveryQuantity}_{p,s}$ as indicators of purchase volume and store size. We tested the impact when replacing different indicators for the store size and replaced it with the sales area. Please note that at least one size indicator is needed to find ways to neutralize the different volumes of the stores. In our first robustness test, we replace the $\text{SalesArea}_s$ with the average basket size as control. The average basket size ($\text{AverageBasketSize}_s$) of a store can also serve as an indicator of purchase volume and store size. Table A1 shows that our results are robust when using another control for store size. The same set of treatment variables is significant, and only additionally $\text{BOPS}_s$ also becomes significant at the level of $p < 0.05$ and has a positive effect on reducing waste. The estimators are on a similar level.

In the second size-related robustness check, we use directly $\text{Sales}_{p,s}$ as an additional control. This variable indicates the unit sales of a product and store. Table A2 shows directionally the same results as our main results in Table 2.4. However, we need to note that $\text{Sales}_{p,s}$ is also in the denominator of our target variable (see Equation (3.1)), indicating potential endogeneity and will therefore refrain from using it as a control variable going forward. It only can be used as a confirmation check that the direction of the results does not change.

**Table A1:** Parameter estimates of store attributes on food waste rate using DML **replacing** $\text{SalesArea}_s$ **by** $\text{AverageBasketSize}_s$ **size as control variable**

| **Variables** | **Est.** | **Std.Err.** |
|---|---|---|
| $\text{MerchantOwned}_s$ | -0.011 | 0.002*** |
| $\text{BOPS}_s$ | -0.006 | 0.003* |
| $\text{BOPSDelivery}_s$ | 0.012 | 0.014 |
| $\text{MinShelfStockCover}_{p,s}$ | 0.0004 | 0.0004 |
| $\text{MaxShelfStockCover}_{p,s}$ | 0.001 | 0.0002*** |
| $\text{BackroomDelivery}_{p,s}$ | 0.018 | 0.005*** |
| $\text{BackroomInventory}_{p,s}$ | 0.00002 | 0.00001* |
| $\text{Kitchen}_s$ | 0.028 | 0.002** |
| Controls | Yes | |
| $MSE$ | 0.014 | |
| $MAE$ | 0.007 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$;

**Table A2:** Parameter estimates of store attributes on food waste rate using DML **including total sales** ($\text{Sales}_{p,s}$) **as additional control variable**

| **Variables** | **Est.** | **Std.Err.** |
|---|---|---|
| $\text{MerchantOwned}_s$ | -0.006 | 0.001*** |
| $\text{BOPS}_s$ | 0.002 | 0.001 |
| $\text{BOPSDelivery}_s$ | 0.014 | 0.009 |
| $\text{MinShelfStockCover}_{p,s}$ | 0.001 | 0.0003 |
| $\text{MaxShelfStockCover}_{p,s}$ | 0.001 | 0.0001*** |
| $\text{BackroomDelivery}_{p,s}$ | 0.020 | 0.005*** |
| $\text{BackroomInventory}_{p,s}$ | 0.00002 | 0.00001** |
| $\text{Kitchen}_s$ | 0.017 | 0.005*** |
| Controls | Yes | |
| $MSE$ | 0.014 | |
| $MAE$ | 0.007 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$;

In the final robustness checks related to the size, we first drop the $\text{SalesArea}_s$ while keeping only $\text{DeliveryQuantity}_{p,s}$ as size indicator (see results in Table A3). Second, we add $\text{SalesArea}_s$ back to the set of controls and additionally consider $\text{AverageBasketSize}_s$ to investigate the influence of even more available size-related variables (see results in Table A4). Both results show that our findings remain robust in terms of direction and significance even when we reduce or expand the set of store size-related control variables.

**Table A3:** Parameter estimates of store attributes on food waste rate using DML **excluding** $\text{SalesArea}_s$ **as control variable**

| **Variables** | **Est.** | **Std.Err.** |
|---|---|---|
| $\text{MerchantOwned}_s$ | -0.006 | 0.001** |
| $\text{BOPS}_s$ | 0.002 | 0.001 |
| $\text{BOPSDelivery}_s$ | 0.014 | 0.006* |
| $\text{MinShelfStockCover}_{p,s}$ | 0.0004 | 0.0003 |
| $\text{MaxShelfStockCover}_{p,s}$ | 0.001 | 0.0001*** |
| $\text{BackroomDelivery}_{p,s}$ | 0.019 | 0.005*** |
| $\text{BackroomInventory}_{p,s}$ | 0.00002 | 0.00002* |
| $\text{Kitchen}_s$ | 0.011 | 0.004** |
| Controls | Yes | |
| $MSE$ | 0.014 | |
| $MAE$ | 0.007 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$;

**Table A4:** Parameter estimates of store attributes on food waste rate using DML **including** $\text{AverageBasketSize}_s$ **in addition to** $\text{SalesArea}_s$ **as control variables**

| **Variables** | **Est.** | **Std.Err.** |
|---|---|---|
| $\text{MerchantOwned}_s$ | -0.064 | 0.016*** |
| $\text{BOPS}_s$ | -0.002 | 0.013 |
| $\text{BOPSDelivery}_s$ | 0.043 | 0.037 |
| $\text{MinShelfStockCover}_{p,s}$ | 0.0002 | 0.0004 |
| $\text{MaxShelfStockCover}_{p,s}$ | 0.001 | 0.0001*** |
| $\text{BackroomDelivery}_{p,s}$ | 0.020 | 0.013** |
| $\text{BackroomInventory}_{p,s}$ | 0.043 | 0.037* |
| $\text{Kitchen}_s$ | 0.028 | 0.102*** |
| Controls | Yes | |
| $MSE$ | 0.014 | |
| $MAE$ | 0.007 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$;

## (2) Robustness of upstream operations as controls

The store depends on the upstream supply chain settings determined by central, warehouse, and transportation functions. We model here, in particular, the $\text{DeliveryDays}_{p,s}$ and $\text{DeliveryType}_s$ as the control variable as these are set exogenously to the store. Table A5 shows that our results, when excluding those upstream operations-related variables, remain robust in terms of direction and significance.

**Table A5:** Parameter estimates of store attributes on food waste rate using DML **excluding** $\text{DeliveryDays}_{p,s}$ **and** $\text{DeliveryType}_s$ **as control variables**

| **Variables** | **Est.** | **Std.Err.** |
|---|---|---|
| $\text{MerchantOwned}_s$ | -0.012 | 0.002*** |
| $\text{BOPS}_s$ | 0.003 | 0.002 |
| $\text{BOPSDelivery}_s$ | 0.018 | 0.013 |
| $\text{MinShelfStockCover}_{p,s}$ | 0.0004 | 0.0003 |
| $\text{MaxShelfStockCover}_{p,s}$ | 0.001 | 0.0001*** |
| $\text{BackroomDelivery}_{p,s}$ | 0.022 | 0.005*** |
| $\text{BackroomInventory}_{p,s}$ | 0.00002 | 0.00001* |
| $\text{Kitchen}_s$ | 0.017 | 0.005** |
| Controls | Yes | |
| $MSE$ | 0.014 | |
| $MAE$ | 0.007 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$;

### (3) Robustness of varying demand-related variables

Instead of the variable $\text{DemandVariability}_{p,s}$, we use the variable $\text{WeekendShare}_{p,s}$ to neutralize the demand variation and seasonality effects. Our results show that the results remain directionally similar when accounting for an alternative type of demand variability across the week for each store (see Table A6).

### (4) Robustness of product-related influences as controls

Finally, we check the estimation results when we exclude the product-related dummy control variables $\text{ProductCategory}_{p,s}$ and find directionally and qualitatively similar results compared to our main model (see Table A7).

**Table A6:** Parameter estimates of store attributes on food waste rate using DML **including** $\text{WeekendShare}_s$ **as alternative control variable**

| Variables | Est. | Std.Err. |
|---|---|---|
| $\text{MerchantOwned}_s$ | -0.041 | 0.020* |
| $\text{BOPS}_s$ | 0.012 | 0.011 |
| $\text{BOPSDelivery}_s$ | 0.049 | 0.025* |
| $\text{MinShelfStockCover}_{p,s}$ | 0.00003 | 0.0004 |
| $\text{MaxShelfStockCover}_{p,s}$ | 0.001 | 0.0002*** |
| $\text{BackroomDelivery}_{p,s}$ | 0.020 | 0.005*** |
| $\text{BackroomInventory}_{p,s}$ | 0.00003 | 0.9E-5** |
| $\text{Kitchen}_s$ | 0.209 | 0.082* |
| Controls | Yes | |
| $MSE$ | 0.015 | |
| $MAE$ | 0.007 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$;

**Table A7:** Parameter estimates of store attributes on food waste rate using DML **excluding** $\text{ProductCategory}_{p,s}$

| Variables | Est. | Std.Err. |
|---|---|---|
| $\text{MerchantOwned}_s$ | -0.016 | 0.003*** |
| $\text{BOPS}_s$ | 0.004 | 0.003 |
| $\text{BOPSDelivery}_s$ | 0.022 | 0.014 |
| $\text{MinShelfStockCover}_{p,s}$ | 0.001 | 0.0003 |
| $\text{MaxShelfStockCover}_{p,s}$ | 0.001 | 0.0002*** |
| $\text{BackroomDelivery}_{p,s}$ | 0.020 | 0.005*** |
| $\text{BackroomInventory}_{p,s}$ | 0.00002 | 0.9E-5* |
| $\text{Kitchen}_s$ | 0.037 | 0.014** |
| Controls | Yes | |
| $MSE$ | 0.015 | |
| $MAE$ | 0.007 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$;

# 3 From deals to dumps: The effect of promotions on food waste in retail

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In the submission process as of August 20, 2024

**Abstract** This paper combines promotion analysis with food waste impact. Promotions are an essential tool to uplift sales and increase store traffic. Food waste is an increasingly important issue in grocery retailing as the magnitude of food waste is similar to the industry's profit margin. This study is the first to analyze causal relationships between promotions and increased food waste. Using panel data for 414 products, 173 stores and more than 65,000 promotion events (24,443 store-SKU-level observations) from a large European retail chain, in conjunction with promotion and shelf life data, we reveal the extent to which promotions increase food waste. We show that promotions double the food waste rate, with an average increase from around 2% to 4%. The magnitude of the effect varies across product groups, with short-life products experiencing up to a fivefold increase in waste. In addition, cannibalization further drives waste in half of the product groups tested. A counterfactual analysis shows that the retailer at the focus of our study can reduce food waste by up to 9% by optimizing promotion planning (e.g., terminating promotions with no sales lift, reducing promotion frequency), focusing promotions on products with a longer shelf life and reducing promotions with high cannibalization effects. This research unveils a direct link between promotions and food waste, revealing how retailers tend to overstock during promotional events, resulting in unnecessary waste. Additionally, it delves into the time-lagged impacts of promotions and cannibalization, highlighting the importance of adopting a holistic approach to promotions and operations management..

## 3.1 Introduction

A large share of fast-moving consumer goods is sold during promotion weeks. For example, more than 50% of UK sales are promoted products (IRI, 2015). Promotions create a sense of urgency, encouraging existing and new customers to visit stores to take advantage of time-limited offers. They constitute a widely established retailer's tool to lift sales, increase store traffic, and strengthen the customer relationship (see, e.g. Wu and Honhon, 2023; Çetin et al., 2020; Gijsbrechts et al., 2003). Optimizing promotions is crucial as it directly influences retailers' profitability, especially in an industry where profit margins are notably slim. However, promotions are increasingly seen as contradictory to sustainability efforts. For instance, Black Friday, a day with substantial retail promotions, is criticized for its negative environmental and social impact. Promotions are seen to foster a culture of overconsumption and overproduction, contributing to environmental degradation and short-term profit orientation at the expense of sustainable practices.

In grocery retail, this means mastering the dilemma of increasing a store's attractiveness through frequent promotions and high product availability on the one hand and avoiding excessive overstocks on the other hand. Successfully planning promotion is a complex matter for multiple reasons. First of all, grocery retailers offer thousands of different products, and it is common to have hundreds of promotions simultaneously. In contrast to regular sales, no long-time series can usually be applied to estimate expected sales. Since promotions aim to attract customers and increase store traffic, the unavailability of the promoted product can disappoint customers. Retailers may tend to overstock stores with promoted products to prevent such situations. However, this poses a high risk that overstocks become food waste. For example, the Guardian reported that "Buy-one-get-one-free offers should be scrapped to cut food waste" (Guardian, 2014). Reducing food waste is crucial considering that approximately one-third of all food produced goes uneaten (FAO, 2022). This has a substantial negative environmental, social, and economic impact: it is estimated that 8-10% of global greenhouse gas emissions are associated with food waste (Forbes, 2021). The consumer sector, encompassing retail, food services, and households, contributes almost two-thirds of total food waste (Gustavsson et al., 2011), so retail plays a pivotal role in food waste prevention. Furthermore, product expiration has significant economic implications for retailers. The costs amount to about 2-4% of gross sales, being equivalent to retailers' margins (see, e.g., Akkaş and Gaur, 2022; Klingler et al., 2016). Gaining insights into the interplay of promotions and food waste is therefore indispensable. However, the time delay between promotional events and the occurrence of food waste necessitates the coupling of multiple periods, thus transforming it into a challenging problem.

Investigating food waste in retail constitutes a nascent field in research and practice (see, e.g., Riesenegger et al., 2023; Akkaş and Gaur, 2022; Belavina, 2021). Huang et al. (2021) identify from screening retailer reports, that current food waste strategies are mainly targeted at reducing existing overstocks and redistributing food surplus (e.g., short-term price discounts, donations, or disposal). Akkaş and Honhon (2022) identify a gap in the current literature in understanding how retail operations may contribute to minimizing food waste. They highlight the need to investigate the role of pricing, forecasting, and ordering related to promotions on food waste. We address this gap by empirically investigating the effect of planned promotions on retail-level food waste. The impact of promotions on food waste is so far undetermined. One might expect promotions to drive sales and empty shelves, leading to less food waste. However, promotions could also lead to supply and demand disruptions that complicate inventory management, leading to more food waste.

Retailers engage in two primary types of promotional activities: *short-term reactive price discounts* and *long-term planned promotions*. Short-term price discounts on a local store-level target the clearance of overstock. These reactive price reductions are driven by the current inventory and are set individually by each store to salvage close-to-expiry or unlisted products. In contrast, long-term planned promotions result from annual negotiations between retailers and manufacturers. The retailers negotiate special conditions with manufacturers to enable the promotions. These promotions are defined months in advance following a centralized approach and are advertised across multiple stores through various channels (e.g., in leaflets or apps). These encompass percentage discounts on specific products, discounts on bulk purchases like "Buy One, Get One Free" (BOGOF), loyalty program incentives, or providing free samples or gifts with purchases. Our research focuses on such centrally planned promotions across all stores that are part of an annual negotiation process. This allows us to treat these promotions as exogenous to the individual store, and we can measure their causal effect on food waste.

We leverage panel data from a European retail chain to contribute the first empirical study on the impact of promotions on food waste in retailing. The final data comprises almost 200 stores and more than 400 products. It covers weekly observations for one year and includes over 65,000 promotion events. Using the store-product-day level data, we find a significant increase in food waste from promotions, especially for highly perishable items. Further, we highlight the cannibalization effect, where customers shift from unpromoted to promoted products. Our research provides insights into reducing food waste in retail by adjusting promotion planning. We extend findings from Akkaş et al. (2019) towards fresh perishable products.

The remainder is structured as follows. We analyze related literature on food waste and promotions and develop the research setting and hypothesis in Section 3.2. Section 3.3 summarizes the research environment and empirical setting. Section 3.4 outlines the regression results. The main results and managerial implications are discussed in Section 4.5 before Section 3.6 concludes our paper.

## 3.2 Related literature and development of the hypotheses

This section analyzes related literature (Section 3.2.1) and derives the hypotheses (Section 3.2.2).

### 3.2.1 Related literature

We will review the literature with regard to the (i) impact of promotions and (ii) measures to prevent food waste in retail and then derive the research gap.

**(i) Literature on the impact of promotions** Promotions are a key driver to increase store visits by attracting customers with appealing temporary offers. These promotions aim to cater to diverse customer price sensitivities and create a sense of urgency. Simultaneously, they foster retail loyalty, ultimately increasing sales and enhancing the retailer's competitiveness. Current studies investigate but are not limited to the effects of promotions on sales (see, e.g., van Heerde et al., 2004; Gupta, 1988)including sales bumps during and dips before and after the promotion week (see, e.g. Trivedi et al., 2017; Van Heerde et al., 2000), brand choice (see, e.g. DelVecchio et al., 2006), effects like cross-selling (see, e.g., Leeflang et al., 2008; Kumar and Leone, 1988) and increased store traffic (see, e.g., Gijsbrechts et al., 2003), and changes due to the digitalization such as personalized promotions and personalized communication with customers (see, e.g. Villanova et al., 2021). Further optimization models for promotions for single or multiple items are developed by, e.g., Cohen et al. (2017) and Cohen et al. (2021).

**(ii) Literature on food waste in retail** The initial research focus in retail food waste literature has been on its quantification (see, e.g., Parfitt et al., 2010; Lebersorger and Schneider, 2014), and on causes of waste occurrence (see, e.g., Mena et al., 2014; Teller et al., 2018; Akkaş et al., 2019), while a key focus is now on food waste management in stores (see, e.g., Buisman et al., 2019) and retail supply chains (see, e.g., Akkaş and Gaur, 2022; Hübner et al., 2024). Regarding the causes of food waste, in a seminal paper, Akkaş et al. (2019) use cross-sectional data to identify multiple drivers for food waste in retail for ambient products with a relatively long shelf life: minimum order rule, case size covers, supply chain aging, and sales incentives. Teller et al. (2018) mainly use interviews to investigate potential causes of food waste and indicate promotions and retail operations as food waste drivers. Belavina (2021) use a modeling approach to show that store density and competition impact food waste at retail and household levels. Competition, sales incentives, and promotions are therefore considered drivers of food waste. First approaches to proactively address the food waste problem in retail stores are emerging. For example, Akkaş and Sahoo (2020) find that penalizing sales representatives for product expiry at the retailer can help to reduce waste and increase profits at the manufacturer. Broekmeulen and van Donselaar (2019) develop advanced inventory policies to reduce food waste while increasing sales and the freshness of the products. Wu and Honhon (2023) numerically show that BOGOF discounts are potential remedies for excess inventory of perishables or end-of-season products to reduce waste and increase retailers' profits while limiting a shift of waste to the household level. This paper's scope of price discounts differs from ours as the authors apply short-term price discounts to salvage overstock. We deal with regularly planned promotions. Finally, Lim et al. (2023) analyze costs for compensating stockouts of online retailers' fruit and vegetable assortments by selling items with substandard aesthetics.

**Research gap** While existing promotion literature extensively explores the positive side of promotions (namely sales uplift and traffic increase) and promotion effectiveness (e.g., which mechanism works best), the dark side of potential overstocking of promotions and its impact on food waste remains conspicuously unaddressed. Promotion-related literature predominantly focuses on identifying the beneficial effects of promotions and examines, if at all, only the decrease in sales after promotion and its cannibalization effects. Promotion-related literature has not yet explored the amount and consequences of overstock and food waste during promotions. Although the food waste literature provides some first indications (e.g., based on qualitative studies and analytical models) that competition and promotions may impact food waste, empirical quantification of this effect is lacking. The gap may be attributed to the intricate time lag between promotion and food waste, coupled with the associated complexity. There is a general gap in the current literature on how better planning can contribute to minimizing food waste (see also Akkaş and Honhon, 2022)

In conclusion, the research gap requires investigation into whether long-term planned promotions contribute to food waste in retail, and to what extent better inventory planning and operations management of promotions can reduce this sustainability issue. In the following subsection, we will discuss the expected impact of promotions on food waste. Our analysis is based on existing literature and discussions with industry practitioners.

### 3.2.2 Expected impact of promotions on food waste

Planned promotions are a critical, widely established retailer's tool to lift sales and store traffic. As the offers are only temporary, the customers are expected to visit the stores more frequently or to be nudged into impulse buying. Promotions are intended to drive sales of the promoted products and store sales in general. Therefore, promotions play a pivotal role in grocery retailing. Limited product availability of the products promoted jeopardizes retailers' targets to increase foot traffic and sales as frustrated customers who came for particular promotion offers but faced a stockout may, in the long term, not return to the store. Consequently, retailers may overstock for the promotion period to avoid customer aggravation without fully considering the hazards of increased waste.

Furthermore, promotion planning is accompanied by multiple difficulties in forecasting demand. First, whereas the retailer can refer non-promoted products to a long time series of sales, this is not available for promotions. For example, customers' price sensitivity (e.g., for different discount levels) may be difficult to estimate, particularly for fresh products where discounts may be associated with lower product quality. Despite promotions being executed multiple times throughout the year, they may be differently executed (e.g., as BOGOF, additional gifts), may be impacted by competitive actions (e.g., promotion of the same product at another retailer in the same period), influenced by public holidays (e.g., promotions before Christmas or Easter) placement in the store (e.g., the gondola end), types of advertising (e.g., leaflet, app) and other product-store-specific factors. This makes the demand forecast complicated.

A further complexity in promotion forecasting is that promotions impact customer choice regarding brand switching or complementary purchases (Van Heerde et al., 2003; Leeflang and Parreño-Selva, 2012) that need to be incorporated into demand updates. The problem is exacerbated by the longer order cycles of promotions. The planned promotions are part of annual negotiations with the manufacturers, and hence, the total promotion volume and order sizes are defined almost one year ahead. Retailers may also intentionally apply forward buying by ordering a higher volume for the promotion at lower prices and selling it at regular prices after the promotion. Manufacturers may also use promotions to stock up at retailers' stores and warehouses so that space for competitive products is further limited. As a result, multiple demand factors and strategic considerations make predicting sales for the stock-keeping unit (SKU) being promoted more difficult.

Featured promotion sales bumps may be followed by a sales dip due to cross-period effects, i.e., lower sales in the post-promotion week of the product promoted (Cohen et al., 2017; van Heerde et al., 2004). One reason behind post-promotion sales dips is stockpiling through customers (Cohen et al., 2021; Macé and Neslin, 2004; Van Heerde et al., 2000). Customers may opportunistically purchase large amounts of promoted products for future consumption (Cohen et al., 2017). That means promotions may lead to overstocking at retailers and increased sales with pantry loading at customers. This stockpiling limits the demand for future periods. Consequently, demand typically drops after the promotion period as the customers are still supplied with the product that has been promoted. Selling the overstocked products in the store takes longer and results in a lower inventory turnover. The decrease in demand causes overstocked items to be sold off slowly after the promotion period. Overall, these effects make inventory planning more complex. Difficulties in demand estimates intended overstocking for the promotion, and lower demand after the promotion may all lead to an intentional or unintentional oversupply of promoted products. In the case of perishable products, these quantities expire over time and may not be sold before their best-before date. It is, therefore, plausible that food waste will show a time-lagged spike after the promotional week. This results in our first hypothesis.

*Hypothesis 1 (H1): The amount of food waste in retail increases with planned promotions.*

We expect to find differences in the effect size of food waste between different product categories. A major difference between products is their shelf life length, which may drive the impact. Furthermore, customers' purchasing choices are heavily influenced by the freshness level of the products (Akkaş et al., 2019; Broekmeulen and Donselaar, 2016) and their availability (see, e.g., Honhon et al., 2010). The above-mentioned lower inventory turnover after promotions causes further issues as the age of the inventory increases. Customers pay attention to the expiration date (ED) (see, e.g., Hansen et al., 2023; Tsiros and Heilman, 2005) and actively search for and select the freshest products stocked on the shelf (Hübner et al., 2024). These effects may reinforce the problem of selling close-to-expiration units from the deliveries of the promotion week. Based on the challenges of selling off overstocked items directly after a promotion period, we expect the effect of promotions on food waste to be a bigger issue the shorter the remaining shelf life (RSL). This is plausible given that the retailer has less time to sell off the more perishable products after the promotion week. On the contrary, the retailer is given more time to level out a potential post-promotion sales dip the longer the RSL of a product, leading to the second hypothesis.

*Hypothesis 2 (H2): The amount of food waste in retail caused by planned promotions increases with shorter shelf lives.*

Planning retail promotions is a challenging process as cross-item effects on demand may be significant and need to be taken into account (Cohen et al., 2021). When an item is on promotion, it can also affect the demand for several other items. Promotions may, therefore, further increase food waste due to cannibalization effects. We expect to find evidence for cannibalization effects based on brand/item switching when the promoted product generates a promotional sales lift while net losses are recorded for unpromoted products during the promotion period (see also, e.g., Leeflang et al., 2008; van Heerde et al., 2004). Net loss in this context refers to lower sales during the promotion week compared to baseline sales during a period without promotional events. Reasons for product switching, besides price discounts, are, e.g., featuring or in-store displays (Kumar and Leone, 1988). Consequently, we expect the substitution effects identified to lead to increased food waste due to the dip in sales of the unpromoted cannibalized product. This is based on the expectation that the inventory level of the focal unpromoted item is too high for the lower demand due to net losses compared to non-promotional weeks. This leads to our third hypothesis:

*Hypothesis 3 (H3): The amount of food waste due to the cannibalization of unpromoted products increases with planned promotions.*

## 3.3 Research setting

We will investigate the hypotheses with store-product-week panel data. The proprietary data set comes from the cooperating retail chain, which we refer to as RetailCo for confidentiality reasons. In this section, we outline the study background (Section 3.3.1), describe the data set (Section 3.3.2), and define the variables used in the regression models (Section 3.3.3).

### 3.3.1 Study background

Our study is based on cooperation with a major European grocery retailer. The industry partner is a multi-billion Euro retailer headquartered in Germany and operates >3,500 stores in Europe. The assortment comprises over 50,000 SKUs across several categories, such as ambient, fruits & vegetables, and chilled and frozen products. We conducted field visits to stores and discussions with the sales department and the corporate headquarters to investigate the retailers' existing operations and promotion policies. During the visits we observed promotion practices, delivery policies, and replenishment processes, interviewed store employees, and met with senior analysts as well as sales and operations management executives. The retailer's management team was actively involved throughout the study design, data collection, review of our results for reasonableness, and provision of useful insights. The central motivation for the retailer's engagement is the management team's assessment of promotion as a significant driver of food waste. The retailer is organized in regions. Consistent organizational setup, operations and processes are essential for the analysis. We selected one region in Southeast Germany that reflects an internal homogeneity of stores concerning product categories and logistics processes. One regional warehouse supplies the stores daily. Orders are placed via an automated forecasting and replenishment system. The retailer aims to ensure maximum product availability. Store employees replenish the shelves, ensure the appropriate product arrangement, remove expired products from the shelves during the replenishment process, and book the spoilage. They also ensure that promotions are executed according to the guidelines defined by the headquarters. In addition, store and regional managers monitor compliance with promotion execution, shelf standards and planograms, refill practices, waste booking, and regularly visit the outlets for quality assurance and employee training.

In general, retailers and manufacturers agree on long-term planned promotional activities throughout the year as part of the annual negotiations. Retailers negotiate special conditions with manufacturers to enable the promotions and share the costs with the manufacturer. Retailers develop the annual promotion plan jointly with manufacturers by selecting the products promoted, defining the promotion frequency (e.g., six times per year) and exact promotion weeks (e.g., week 4, 12, ...), the promotion mechanism (e.g., BOGOF, price discount), the participating regions and stores, and ultimately also the total promotion volume for all stores.

At RetailCo, the headquarters plan promotions centrally within the scope of the manufacturer agreements for all stores in a region. The promotions run for one week in each store of a region (i.e., all stores need to execute the promotions) and are advertised in leaflets and apps. That also means we observe an exogenous effect of promotions on the individual stores.[1] The delivery planning process for the promotion week is as follows. After the annual negotiations and the agreed total promotion volume with the manufacturers, the retailer allocates the target quantities to regions and stores based on historical sales volumes of promotions. The store managers review this allocation recommendation six weeks before the promotion week. Based on the centrally recommended quantities and feedback of the stores, a regional planner defines the final order quantities for the entire region, places the order with the manufacturer three weeks prior to the promotion, and ultimately determines centrally for all stores the allocation quantity

[1] To avoid endogeneity issues, we ignore locally executed short-term price discounts to clear overstocks. The retailer generally wants to avoid such short-term price discounts as it may cause reputation issues. Hence, RetailCo does also not systematically apply such a salvaging policy.

to each store. That means the quantities are exogenously defined for each store. The first delivery of the products promoted to the stores typically arrives at the store on the Friday before the promotion week. A promotion event always lasts for one week from Monday to Saturday. In general, all stores in the sample are closed on Sundays. Usually, two additional deliveries arrive during the promotion week, and store managers can only – in exceptional situations – manually reorder extra deliveries during the promotion week.[2] Additionally, stores may receive additional stock , for example, in the event of overstock at the warehouse.

### 3.3.2 Data description and preparation

**Overview** RetailCo's proprietary store-product-week level data originates from one region (Southeast Germany) and only includes stores operating throughout the entire period and supplied by one regional warehouse with an identical supply planning and ordering mechanism. This ensures identical promotion and replenishment processes, e.g., minimum order rules, and eliminates the endogeneity issue at the store level caused by, for example, suboptimal inventories at the warehouse level (e.g., due to forecasting errors) or different levels of RSL (e.g., due to different delivery batches from the supplier to the warehouses). We focus on products with a fixed shelf life where the EDs are indicated by "best before" (e.g., "best before August-01") or "use by", etc. This is important as the freshness level is less prone to a subjective quality assessment than categories that do not carry ED labels (e.g., fruits & vegetables). Products that exceed their ED must be discarded by the retailer according to legal regulations. While most expired products end up as waste, a share of expired products may be donated to food banks or used for animal feed, composting, energy usage, or landfill. We concentrate on the self-serviced chilled assortment within the spectrum of perishable products for multiple reasons. First, chilled products are continuously promoted at RetailCo. Each week, there are multiple products

[2] For our main analyses, we drop promotions with instances of manual reorders by store managers, which affect less than 1% of the promotion events investigated.

of this assortment on promotion. The average share of promotion weeks compared to the total number of store-product-week observations of our study data set is about 6%. Furthermore, chilled products are standardized and carry printed ED labels. Chilled products mostly have a short shelf life upon store delivery (usually less than 2-3 weeks). Chilled products have a higher risk of spoilage and are, therefore, potentially more strongly affected by promotions. Other categories, such as ambient (e.g., canned food, rice, drinks) or deep frozen (e.g., frozen pizza), have a considerably longer shelf life (e.g., more than 12 months), and we expect that they are less susceptible to the impact of promotions on waste due to the time lag between promotions and spoilage. Finally, we use self-service product categories where no further influence by the sales personnel is possible (e.g., by sales conversations at a service counter). Together with the retailer's management team we therefore selected the chilled assortment and focused on the product categories Cheese, Convenience, Delicacies, and Milk/Dairy. The four categories were further organized into 83 product groups (e.g., Organic Milk, Fresh Milk, Low Fat Fresh Milk). We ultimately obtained the following data:

(i) **Panel data on a daily store-product-level**, including inventory, sales, forecasts, spoilage, and daily unit price of each product (SKU)
(ii) **Promotion plans**, incl. promotion week and promoted products
(iii) **Expiry data** and remaining shelf life information of products upon store delivery from a pilot study (as sales and inventory data do not contain the ED)
(iv) **Master data** about products, e.g., case-pack size, and about stores, e.g., store format and size

The **panel data** initially comprises 204 stores and 4,895 products (SKUs) and covers daily observations from 52 weeks (January to December 2019). This only includes products with sales in 2019 and excludes all discontinued products (e.g., removed from the assortment). These daily data include sales volume, shipment volume to the stores, end-of-day inventory at the store, forecasts, and spoilage separated into expiry, breakage, and theft, and the unit price of each product. This data set only includes centrally assigned order quantities (i.e., generated with an automated forecasting system; no instances with manual orders by the store managers.) The data on **promotion plans** included all information about the promotion, including the promotion week, promoted products, participating stores, and the demand forecast, as well as sales realized. The **expiry data** are obtained from an additional data collection. In general, grocery retailers track their inventories with barcodes. Products are scanned when entering the store and at the cash desk. Yet RetailCo (like all retailers) lacks systematic ED information on the inventory in the store as the currently applied barcodes do not include EDs. That means inventory and sales data (and hence also our panel data) do not contain any ED information. However, ED information and store receipts are indispensable in our study. Otherwise, the food waste cannot be traced back to the promotion event. To overcome this issue, we developed an approximation approach of the ED for each store-product combination to be able to match a promotion week to a lagged food waste record. This could only be done as we also collected data within the scope of an additional study. RetailCo started systematically recording the actual EDs for selected products from May to December 2021 (see 3.7 for details of this specific data collection effort and process). The ED was tracked on receipt at the store of deliveries from the warehouse. These novel and first time collected data allowed us to calculate the mean time until expiry upon arrival of each product at each store. These unique ED data supplement our panel data, and we only include store-product combinations for which the approximation of the ED data is available. Finally, we focus on fresh products with an average RSL of 21 days or less in order to be able to trace the food waste back to a recent promotion event. This is in line with definitions for fresh products in retail (see, e.g. van Donselaar et al., 2006).

The final sample contains 24,443 store-product combinations based on 173 stores, 50 product groups, and 414 products. The final inclusion of stores and products is based on three major steps. First, we remove all product groups for which no promotion events have taken place. Second, not all stores and products were part of the pilot study to gather the ED. Finally, we filter the data set by fresh products based on a RSL of 21 days or less, which account for roughly 10% of the full data set. The total sales of all products and stores in the final sample amounted to approx. EUR 25.8mn for the year 2019. The food waste for this sample was about EUR 380k in the same period. Table 4.2 summarizes our data.

**Table 3.1:** Summary statistics per product category, across all products and stores in data sample

| Data | Milk/Dairy | Delicacies | Cheese | Convenience |
|---|---|---|---|---|
| Number of observations (#) | 645,622 | 229,749 | 114,807 | 167,762 |
| Number of promotion weeks (#) | 42,330 | 9,237 | 5,874 | 5,348 |
| Number of product groups (#) | 24 | 4 | 6 | 16 |
| Number of products (#) | 202 | 69 | 51 | 92 |
| Sales (EUR) | 16,643,050 | 4,970,174 | 2,801,881 | 1,466,534 |
| Food waste (EUR) | 163,386 | 128,937 | 32,840 | 55,095 |
| Food waste (units) | 175,198 | 55,140 | 23,489 | 31,741 |
| Mean waste rate (%) | 2.1 | 3.6 | 1.8 | 3.4 |
| Mean RSL (days) | 18.3 | 16.3 | 18.4 | 17.9 |
| Median sales price (EUR) | 1.0 | 2.5 | 1.5 | 2.0 |
| Average number of promotion weeks per product (#) | 3.6 | 2 | 2.8 | 1.6 |
| Mean price discount per promotion (%) | 18.6 | 14.5 | 17.4 | 17.6 |
| Max price discount (%) | 57.6 | 46.5 | 56.3 | 54.4 |

**Subsample approach** It is necessary to introduce different aggregation levels of the data sets to investigate each hypothesis, as data that are too aggregated or too granular may blur effects and create biases. Depending on the scope and hypotheses to be tested, we slice our data set in four ways: by *(a) promotion event*, *(b) RSL*, *(c) product level*, and *(d) promotion effectiveness*. Applying a sample with (a) a promotion event means that we only include products that were promoted in a store and a specific week or all products (including additional products without a promotion). (b) The second filter separates the data set into perishable products with a maximum RSL of 21 days or longer. (c) makes use of different product aggregation levels, namely on a total, category or product group level. (d) Finally, we separate the data into a data set with successful promotions that achieved a sales lift and unsuccessful promotions without a sales lift. Each of the data sets applied and their rationale for the sampling approach are specified in the analysis and the respective results section. We provide an overview and detailed definition of the subsamples in 3.8.

### 3.3.3 Variables

The unit of analysis is store-product-week level with $s$ as a retail store, $p$ as a product (SKU), and $t$ as a week (between calendar weeks 1-52 in 2019). We denote the set of stores $S, s \in S$, set of products $P, p \in P$, and set of weeks $T, t \in T$. We introduce $\tau$, with $\tau \in T, \tau \leq t$, denoting the promotion week of a product $p$ that expired in period $t$. Table 3.2 provides an overview of all the variables considered, while Table 3.3 presents the summary statistics of the variables applied.

**Table 3.2:** Overview of variables

| | |
|---|---|
| **Dependent variable** | |
| $\text{WasteRate}_{p,s,t}$ | Share of waste caused by product expiry of product $p$ in store $s$ in period $t$ |
| **Promotional variables of interest** | |
| $\text{Promotion}_{p,s,\tau}$ | Binary variable indicating whether product $p$ in store $s$ was promoted in the week $\tau$ |
| $\text{RSL}_{p,s}$ ($\text{RSL}^2_{p,s}$) | Average number of days until product $p$ expires upon delivery to store $s$ (squared, for testing nonlinear effects) |
| $\text{Substitution}_{p,s,\tau}$ | Binary variable; indicating whether product $p$ in store $s$ in promotion period $\tau$ is a substitute for a promoted product |
| **Control variables** | |
| $\text{EoDStock}_{p,s,t}$ | Average number of consumer units of product $p$ available at the end of each day in store $s$ in period $t$ |
| $\text{SalesPrice}_{p,s,t}$ | Sales price of product $p$ in store $s$ in period $t$ |
| $\text{OverForecastError}_{p,s,\tau}$ | Percentage of consumer units of product $p$ at store $s$ in period $\tau$ being over forecasted, derived from forecast minus sales |

**Table 3.3:** Summary statistics

| Variable | Mean | Std. dev. |
|---|---|---|
| $\text{WasteRate}_{p,s,t}$ | 2.53 | 11.69 |
| $\text{Promotion}_{p,s,\tau}$ | 0.05 | 0.23 |
| $\text{RSL}_{p,s}$ | 17.86 | 3.49 |
| $\text{Substitution}_{p,s,\tau}$ | 0.11 | 0.31 |
| $\text{EoDStock}_{p,s,t}$ | 10.26 | 12.90 |
| $\text{SalesPrice}_{p,s,t}$ | 1.57 | 0.86 |
| $\text{OverForecastError}_{p,s,\tau}$ | 0.28 | 0.74 |

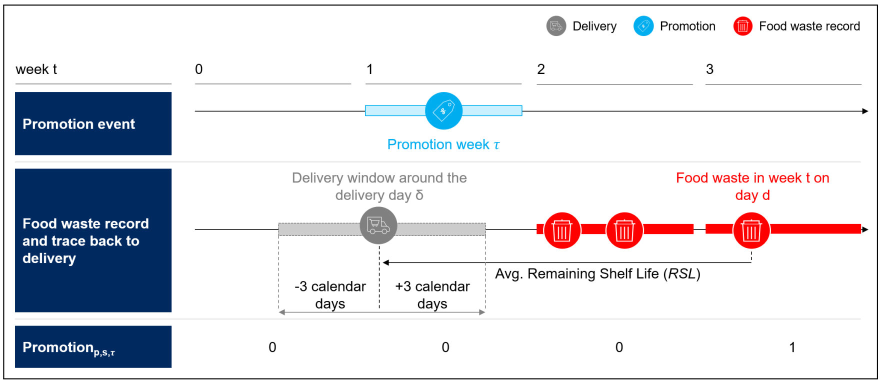
**Dependent variables** The target variable $\text{WasteRate}_{p,s,t}$ denotes the fraction of wasted units of a product $p$, in store $s$, and week $t$. It is calculated as the amount of food waste per week (denoted $\text{FoodWaste}_{p,s,t}$) divided by the sum of sales (denoted $\text{Sales}_{p,s,t}$) and food waste per week:

$$\text{WasteRate}_{p,s,t} = \frac{\text{FoodWaste}_{p,s,t}}{\text{Sales}_{p,s,t} + \text{FoodWaste}_{p,s,t}} \tag{3.1}$$

**Promotional variables of interest** We apply three variables related to promotions. The first one defines the promotion week. We apply a time-lag logic to account for the fact that the spoilage of products delivered for a promotion week occurs weeks (or days) after the actual promotion. Figure 3.1 illustrates how the hypothesized binary variable $\text{Promotion}_{p,s,\tau}$ is derived. The determination of the promotion week $\tau$ relies on the estimated delivery day $\delta$ of product $p$ to store $s$. This is calculated using the spoilage record's day $d$ in the panel data, adjusting for the mean RSL. To establish the promotion identification window, i.e., the days when products arrived at the store, we employ a range of $\pm 3$ calendar days around $\delta$. This window allows us to link product delivery to store promotion, defining the resulting promotion week with a time lag as $\tau$, i.e. if the delivery window ($\delta \pm 3$) overlaps with the promotion week in period $\tau$, then the promotion week variable $\text{Promotion}_{p,s,\tau}$ is set to 1. The necessity of a $\pm 3$ days delivery-identification window arises for three reasons. First, spoilage records of product $p$ at store $s$ on day $d$ might have expired one or two days earlier, as some records are booked into the system with this delay. Second, the first planned delivery for a promotion week arrives on the Friday or Saturday before the promotion week. Our time-lag logic covers deliveries from Friday to the following Monday (Friday plus three days), capturing initial and subsequent deliveries planned during the promotion week. Third, given that we received mean RSL data on a store-product level, the actual EDs may vary slightly by a few days. We can only capture this food waste record with such a time window.

We further introduce the variable $\text{RSL}_{p,s}$ and its squared version $\text{RSL}^2{}_{p,s}$ representing the different levels of the perishability of a product. These variables are needed to investigate the hypothesized amplified effect of

**Figure 3.1:** Illustration of established connection between promotion week $\tau$ and waste record booking in week $t$



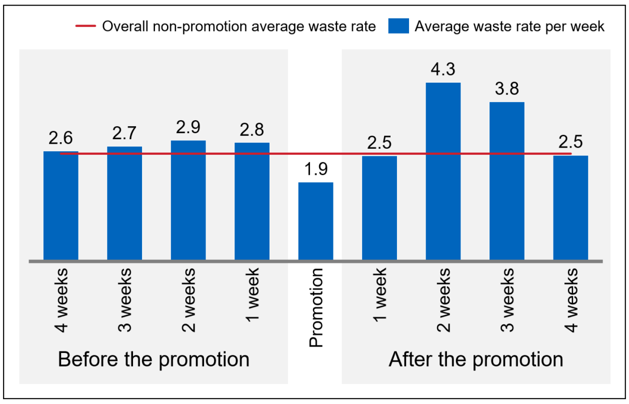

promotions on products with greater perishability. Including the squared version helps to identify non-linearity in shelflife: for example, whether effects become negligible, the less perishable products are. Finally, there is the variable for investigating cannibalization effects within a product group on the lowest product aggregation level. The variable Substitution$_{p,s,\tau}$ is a binary variable that indicates whether product $p$ at store $s$ is not promoted in week $\tau$ and at the same time faces lower sales during week $\tau$ compared to the baseline, calculated as the mean of the non-promotion sales of the month (boundary condition), while a similar product, i.e., an SKU from the same product group, is promoted. Substitution$_{p,s,\tau}$ equals 1 if all three conditions are fulfilled.

**Control variables** We additionally include multiple control variables. The continuous variable EoDStock$_{p,s,t}$ represents the average stock in units at the end of each day of product $p$ in store $s$ in week $t$, and hence controls for varying inventory levels. SalesPrice$_{p,s,t}$ refers to the sales price in currency units of a product $p$ in store $s$ in period $t$. The continuous variable OverForecastError$_{p,s,\tau}$ represents the MAPE (mean absolute percentage error) of product $p$ in store $s$ of the promotion week $\tau$, which denotes the difference between the overestimate of demand and sales realized in period $\tau$ compared to the actual sales for this promotion week. Underestimates are not included. Finally, we use dummy variables for stores, products, weeks, months, and quarters depending on the empirical setting of the linear regression. Including time effects and the over forecast error are reasons against endogeneity concerns due to selection of products and promotion timing.

## 3.4 Empirical results

Promotions impact food waste. Figure 3.2 gives a first insight into the impact of promotions on food waste by providing unconditional means of food waste rates before, during, and after promotion weeks. The waste rate sample mean of weeks without promotion (2.6%) is presented as a red line. There is a strong increase in waste of the promoted product in the subsequent weeks after a promotion event.

**Figure 3.2:** Averaged food waste rates of promoted products before, during and after the promotion week




In the following, we will further investigate the effect of promotions on food waste in general (*H1*; Section 3.4.1), whether promotions and short shelf life reinforce the increase of food waste (*H2*; Section 3.4.2), and whether cannibalization resulting from promotions increases food waste (*H3*;

Section 3.4.3). Section 4.4.4 concludes the empirical findings with multiple robustness checks based on various model specifications and estimation methods.

### 3.4.1 Impact of promotions on food waste

To test hypothesis *H1* and the impact of promotions on food waste, we estimate the effect of the time-lagged independent $\text{Promotion}_{p,s,\tau}$ on the dependent variable $\text{WasteRate}_{p,s,t}$ while monitoring for additional potential influences. Our results are based on pooled OLS models. Here we apply a similar approach as Perdikaki et al. (2012) and Fisher et al. (2021), who study sales in related retail settings with panel data and linear regression models that include several dummy variables as controls. The related Model 1 is defined by Equation (3.2). Besides monitoring for the average stock at the end of the day, the sales price, and over forecast error, we include dummy variables for the store, the quarter, the month, the week, and the product as AdditionalControls. Standard errors are clustered at the store level.

$$
\begin{aligned}
\text{WasteRate}_{p,s,t} = &\beta_0 + \beta_1 \cdot \text{Promotion}_{p,s,\tau} \\
&+ \beta_2 \cdot \text{EoDStock}_{p,s,t} + \beta_3 \cdot \text{SalesPrice}_{p,s,t} \\
&+ \beta_4 \cdot \text{OverForecastError}_{p,s,\tau} \\
&+ \text{AdditionalControls} + \epsilon_{p,s,t}
\end{aligned}
\tag{3.2}
$$

We investigate the effects on total level and by product category. To do this, we apply Model 1 (Equation 3.2) on different aggregation levels for all categories (denoted C-NS subsample, see definition of samples in 3.8), separately for each category (C-PCS subsample) and each product group (C-PGS subsample). The rationale behind studying the effects of subgroups is to identify potential heterogeneity of the promotion effects between these subgroups. Such findings add greater depth to our main area of investigation and help retailers focus their food waste reduction efforts on the items most prone to food waste.

**Results on a product category level** Table 3.4 shows the estimates obtained from Model 1 across all categories and for each category separately. It shows that food waste is caused by promotion events. Food waste increases by about 2.1 percentage points (pp) across all categories (see "All Categories"). Considering the unconditional average food waste levels, our estimates imply that promotions effectively double food waste in the following weeks. Using our estimates from Table 3.4 and the unconditional mean waste rates from Table 4.2 implies that promotions increase food waste in the following weeks between 79% and 126% As our main results, we can confirm *H1* and identify a significant effect of promotions on food waste for all product categories – when analyzing all categories jointly and within each category when analyzing each separately. All of these effects are statistically significant at $p < 0.001$, which strongly supports *H1*. The strongest effects are for the categories Delicacies and Convenience, with estimated coefficients of 3.3 and 4.3 for Promotion$_{p,s,\tau}$. This means that every promotion week leads, on average, to an increased waste rate of 3.3 and 4.3 pp in the subsequent weeks. Finally, Cheese and Milk/Dairy products are estimated to perform similarly with coefficients of 1.7.

**Table 3.4:** H1 parameter estimates on a category and total level

| | Milk/Dairy | | Delicacies | | Cheese | | Convenience | | All categories | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variables** | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** |
| *Intercept* | -2.085 | 0.317*** | -9.787 | 1.067*** | -0.468 | 0.647 | -4.450 | 2.250* | -5.000 | 0.319*** |
| *Promotion* | 1.658 | 0.088*** | 3.329 | 0.230*** | 1.723 | 0.240*** | 4.317 | 0.372*** | 2.130 | 0.091*** |
| *EoDStock* | -0.007 | 0.002** | -0.007 | 0.009 | -0.001 | 0.004 | -0.058 | 0.016*** | -0.006 | 0.002** |
| *SalesPrice* | 2.891 | 0.184*** | 2.460 | 0.201*** | 1.085 | 0.237*** | 3.590 | 0.701*** | 2.725 | 0.161*** |
| *OverForecastError* | 1.279 | 0.049*** | 1.839 | 0.082*** | 0.980 | 0.084*** | 1.383 | 0.075*** | 1.368 | 0.042*** |
| *DummyStore* | Yes | | Yes | | Yes | | Yes | | Yes | |
| *DummyProduct* | Yes | | Yes | | Yes | | Yes | | Yes | |
| *DummyTime* | Yes | | Yes | | Yes | | Yes | | Yes | |
| *Observations* | 645,622 | | 229,749 | | 114,807 | | 167,762 | | 1,157,940 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; The sample data sets are based on store-product-week observations from product category-specific (C-PCS) and all categories (C-NS).

Furthermore, different promotion mechanisms are applied. Mechanisms other than pure price reductions were applied for roughly 25% of the promotions. Our results for *H1* remain highly statistically significant, with similar results in size and direction even when focusing only on pure price promotions (see Table A10 in the Appendix). This means, in turn, that promotions drive general food waste and are not related to a specific mechanism. Further, we show the estimation results based on an additional model specification, where the variable $\text{Promotion}_{p,s,\tau}$ is replaced by $\text{PriceDiscountDepth}_{p,s,\tau}$ as the independent variable of interest to investigate the effects of the size of the discount on food waste in the Appendix in Table A16.

Furthermore, stores may reduce unit prices of products that have recently been promoted to salvage overstock even after the promotion week is over. These local reductions by stores are not centrally steered and not labeled as promotion events in our data set. We find that such a short-term store-specific discounting practice is only identified for 3.3% of the products promoted either in the first, second, or both weeks after the promotion week. Based on this finding, the discounting impact of these close-to-expiry products is minor. Even if the effect was considerable, we can conclude that our approach only underestimates the actual effect size of promotions on waste.

**Results on a product group level** To deepen our understanding of the effect investigated on a more granular level, we additionally test *H1* on the product group level (C-PGS subsamples). The significant coefficients vary widely overall with up to 9.2, hence showing more varied effects than on the more aggregated category level in general and more pronounced individual effects for selected product groups.[3] The detailed regression results on the product group level are outlined in Table A11 in the Appendix.

**Results for sales lift/no lift promotions** Promotions aim to uplift sales. This objective may not always be fulfilled. As a result, the increasing food waste may be explained by unsuccessful promotions without any sales

[3]Only product group Sour Cream with significant negative value; all others positive.

uplift. In such failures, the retailer may have ordered more, but the uplift was not achieved, so more units remain in the stock of the store. To better understand the causes of food waste, we differentiate the promotions accordingly into ones with a sales uplift (SL) and no sales uplift (NSL). We define a promotion as a SL promotion if it achieved sales during the promotion week above the yearly mean non-promotion baseline sales. The NSL promotion remained below the baseline. Table 3.5 shows remarkable differences between SL and NSL promotions. When statistically significant with $p < 0.001$, then the NSL promotions have a higher waste coefficient than SL promotions. This confirms the expectations that the effectiveness of promotions (i.e., with or without SL) will significantly contribute to food waste. It could be expected that food waste increases in the weeks after the promotion that did not generate a sales increase. At the same time, higher quantities were ordered to meet the higher demand that was expected, but not realized.

**Table 3.5:** H1 parameter estimates, sales uplift and no sales uplift comparison

| | Milk/Dairy | | Delicacies | | Cheese | | Convenience | | All Categ. | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** |
| **Sales Lift** | 1.577 | 0.092*** | 3.401 | 0.238*** | 1.019 | 0.270*** | 3.197 | 0.401*** | 1.988 | 0.091*** |
| **No Sales Lift** | 2.120 | 0.225*** | 0.716 | 0.929 | 2.613 | 0.347*** | 5.958 | 0.702*** | 2.934 | 0.202*** |
| **Combined** | 1.658 | 0.088*** | 3.329 | 0.230*** | 1.723 | 0.240*** | 4.317 | 0.372*** | 2.130 | 0.091*** |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; The sample data sets are based on store-product-week observations from product category-specific (C-PCS) and all categories (C-NS) and divided into Sales Lift and No Sales Lift promotions and combined.

Notably, the picture looks slightly different on a product group level (using the product group subsamples C-PCS). Table A11 indicates that some promotions with an SL have a higher coefficient than those with NSL. For product groups with $p < 0.05$ for SL and NSL, this holds true for two product groups. For example, Fresh Milk has a coefficient of 2.875 for SL and of 2.480 for NSL. This partially contradicts the finding from above. However, as a cross-check with RetailCo revealed, these product groups and promotions are the "important blockbuster promotions" that have a high impact on the retailer's image, for which the central promotion planners want to avoid out-of-stock situations "by any means". Additionally, the blockbuster products at RetailCo are typically also important products at direct competitors; larger promotions or slightly earlier promotions at the competitor may, therefore, may strongly affect sales at RetailCo during the promotion week. Finally, we learned that the higher the price discount, the more planners struggle to forecast sales, which may lead to a SL promotion but higher food waste if the expected demand of so-called "hammer prices" does not fully materialize. This is not true for the less important promotions in the NSL set.

### 3.4.2 Impact of product perishability and promotions on food waste

The analysis above revealed differences between product groups. To test *H2* and further investigate the impact of a product's perishability on food waste, we study the effect size of the $\text{RSL}_{p,s}$. We add the squared version ($\text{RSL}^2_{p,s}$) to study the turning point at which the hypothesized effect diminishes by including a non-linear component in Model 2 (see Equation (3.3)). We use the same control variables compared to Model 1 (Equation (3.2)). Standard errors are clustered at store level.

$$\begin{aligned}\text{WasteRate}_{p,s,t} =& \beta_0 + \beta_1 \cdot \text{RSL}_{p,s} + \beta_2 \cdot \text{RSL}^2_{p,s} \\ &+ \beta_3 \cdot \text{EoDStock}_{p,s,t} + \beta_4 \cdot \text{SalesPrice}_{p,s,t} \\ &+ \beta_5 \cdot \text{OverForecastError}_{p,s,\tau} \\ &+ \text{AdditionalControls} + \epsilon_{p,s,t}\end{aligned} \tag{3.3}$$

To understand how the RSL and promotions interact concerning food waste, we applied an expanded data set (sample NC-NS-PO) that also includes products with an RSL longer than 21 days. Furthermore, we only investigate weeks $t$, products $p$ and stores $s$, for which previously a promotion happened in week $t$ minus $\text{RSL}_{p,s}$. That means we only include weeks with lagged food waste at the end of the product's shelf life for products supplied to the store for a promotion week. This differs from the data used for Model 1 and Model 3, for which additional promotion and non-promotion weeks are included.

The main results are that the amplifying effect of promotions on food waste is greater for products with a shorter RSL. This confirms *H2* on a high statistical significance level of $p < 0.001$. Table 3.6 summarizes the regression results. Using the linear and quadratic relationships of the treatment variables $RSL_{p,s}$ and $RSL^2_{p,s}$, we get 156 as the threshold RSL value[4], where the negative trend identified of $\text{RSL}_{p,s}$ on $\text{WasteRate}_{p,s,t}$ turns around and becomes positive. The U-shaped relationship between $\text{RSL}_{p,s}$ and $\text{WasteRate}_{p,s,t}$ results from an estimated coefficient of -0.156 and a minimal but positive coefficient for $RSL^2_{p,s}$. Thus, the larger the RSL, the less a promoted product is prone to turn into waste. The potential impact on food waste is therefore more critical for those products with shorter shelf life. Additionally, we calculate the average effect of a product with an RSL of, e.g., 40 days to be -4.6 based on both treatment variables calculated against the intercept. In summary, products with a shorter RSL are more prone to cause food waste after promotions.

**Table 3.6:** H2 estimation results

| **Variables** | **Est.** | **Std. Err.** |
|---|---|---|
| $Intercept$ | 22.932 | 15.648 |
| $RSL$ | -0.156 | 0.005 *** |
| $RSL^2$ | 0.001 | 2.53e-05 *** |
| $EoDStock$ | -0.034 | 0.003 *** |
| $SalesPrice$ | 0.059 | 0.051 |
| $OverForecastError$ | 1.319 | 0.061 *** |
| $DummyStore$ | Yes | |
| $DummyTime$ | Yes | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; Sample data set is based on store-product-week observations from promotion-only (NC-NS-PO), incl. all expiry dates.

[4]Solving for x: $-0.156x + 0.001x^2 = 0$.

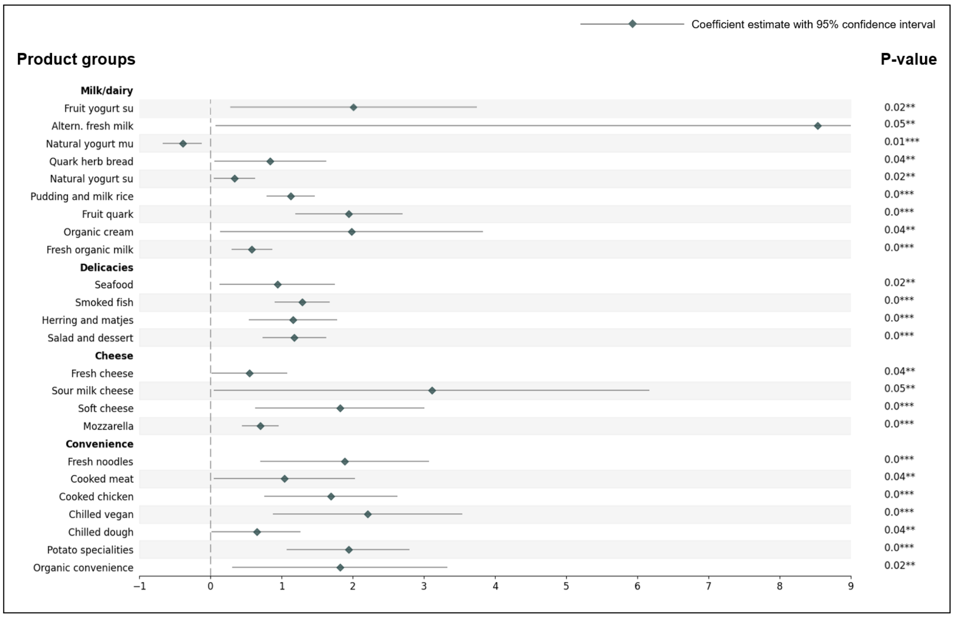
### 3.4.3 Promotional impact on cannibalization and food waste

To test *H3* and investigate the substitution effects of promoted products on the food waste of unpromoted products in the actual promotion week $\tau$, we use $\text{Substitution}_{p,s,\tau}$ as the regressor for the dependent variable $\text{WasteRate}_{p,s,\tau}$. Note, here we look directly at the food waste impact in the promoted week and do not apply the time-lag. This is because we expect the direct impact of declining sales of cannibalized, non-promoted products in the promotion week. Therefore, let $\tau$ represent both the promotion and the waste record week for *H3*. The Model 3 for testing *H3* is specified by Equation (3.4), and the associated additional controls are taken from Model 1 (Equation (3.2)). Only the variable $\text{OverForecastError}_{p,s,t'}$ refers here to a different forecasting period as the forecast for the replenishment in the period $\tau' = \tau - \text{RSL}_{p,s}$ is decisive in this instance. Again, standard errors are clustered at the store level.

$$\begin{aligned}
\text{WasteRate}_{p,s,\tau} =& \beta_0 + \beta_1 \cdot \text{Substitution}_{p,s,\tau} \\
&+ \beta_2 \cdot \text{EoDStock}_{p,s,\tau} + \beta_3 \cdot \text{SalesPrice}_{p,s,\tau} \\
&+ \beta_4 \cdot \text{OverForecastError}_{p,s,\tau'} \\
&+ \text{AdditionalControls} + \epsilon_{p,s,\tau}
\end{aligned} \tag{3.4}$$

Our results provide empirical evidence for cannibalization being a food waste driver in general, on both a category level and a product group level. Cannibalization generally takes place within a product group, e.g., one would not expect a promoted Organic Cream product to cannibalize any kind of Fresh Milk products. As such, we investigate the cannibalization effects on the product group level, i.e., an Organic Cream SKU cannibalized by a promoted Organic Cream SKU, for which the product group subsamples (C-PGS) are used. Each product group contains, on average, 8 products.

**Figure 3.3:** H3 coefficient plot of Substitution$_{p,s,\tau}$ on WasteRate$_{p,s,\tau}$ (statistically significant results)




**Results on a product group level** We find cannibalization effects of promotions on food waste (*H3*) for about half of the tested product groups (23 out of 50). Customers' demand shift from unpromoted to promoted products increases food waste in these product groups. The estimated effect sizes are highly heterogeneous with a coefficient of up to 8.5. Natural Yogurt MU is the only product group where cannibalization surprisingly results in a significant reduction of food waste with a coefficient of -0.4. The statistically significant coefficient estimates are presented in Figure 3.3. It becomes apparent that the small effect sizes, i.e., estimated coefficients <2.0, are relatively precise compared to the high effect size product groups with a coefficient above 2.0. The three most extensive cannibalization effects are also the most uncertain ones, with large 95% significance intervals: Alternative Fresh Milk, Sour Milk Cheese, Organic cream and Fruit Yogurt. The regression results for all 50 product groups in the C-PGS sample are in Table 3.7.

**Results for sales lift/no lift promotions** The cannibalization effect on food waste is also apparent when looking only at the successful promotions with a positive sales uplift (SL-C-PGS subsample). Promoted products that show a sales uplift cannibalize sales of unpromoted products. The coefficients are equal to or slightly higher than the complete data set across product groups. Again, Natural Yogurt MU is the only product group with a significant reduction in food waste. All significant coefficient estimates are presented in Table 3.7.

**Table 3.7:** Parameter estimates for H3 hypothesized variable for sales uplift and no sales uplift comparison

### 3.4.4 Robustness checks

We apply multiple robustness checks to validate the reliability and consistency of our findings. The first set of checks is to validate the impact of the different model specifications. The second set tests whether the results still hold true if we use different estimation methods. We highlight the main findings of these additional tests in the main section below and detail the estimation results in 3.10. We can confirm that we have obtained qualitatively the same results with each robustness check.

**Different model specifications** Changing boundary conditions, studying interaction effects between the variable of interest with product categories, and adjusting the set of controls yielded similar results to those of the models from the main contribution regarding the impact and for the majority of the model specifications, as well as in terms of the size of the effects identified. Consequently, all of the following robustness checks confirm the results obtained. We apply different robustness checks for Model 1 with regard to (i) manual order interventions, (ii) out-of-stock exclusion, (iii) interaction effects between categories, (iv) including further promotion-relevant variables, (v) without control variables, and (vi) test the logarithmic version of our dependent variable. We also apply robustness checks for concerning (vii) RSL effects without the nonlinear RSL and (viii) cannibalization on a higher product aggregation level.

(i) We first look at the impact of manual order interventions when store managers adjust the centrally given order quantities and rerun our analyses with data that includes the managers' interventions. Table A12 in the Appendix shows that the effects remain the same.

(ii) A further assumption is that the out-of-stock situation between the promotion week and the time-lagged food waste booking cannot lead to food waste caused by the promotion week. Hence, we estimate the Model 1 specification with an adjusted treatment variable Promotion$_{p,s,\tau}$ considering out-of-stock occurrences between a promotion event and a lagged food waste record. The results (see Table A13) match the findings from above.

(iii) Instead of estimating the effects of each product category separately, we estimate the interaction effects between categories and the treatment variable Promotion$_{p,s,\tau}$ in one model. Table A14 indicates similar and heterogeneous effects between the product categories.

(iv) We include the Substitution$_{p,s,\tau}$ in Model 1 to test for additional promotion effects. Furthermore, we include promotion frequency as a control variable in Model 1 to check whether the total number of promotions throughout the year influences the findings. The estimated results for the hypothesized variable Promotion$_{\mathrm{p,s},\tau}$ are directionally similar to our reported findings, while the control variable PromotionFrequency is not significant (see Table A15). for all product categories.

(v) Furthermore, we estimate the effect of the Model 1 treatment variable Promotion$_{p,s,\tau}$ on WasteRate$_{p,s,t}$ by excluding all control variables, which avoids any potential multicollinearity issues of the controls with the regressor (see Table A17).

(vi) To further examine the impact of promotions on food waste beyond the fractional increase, we replace the dependent variable $\text{WasteRate}_{p,s,t}$ by the logarithmic version of the absolute number of waste units, $\text{LogWasteUnits}_{p,s,t}$. This transformation allows us to represent changes in waste units in a manner that captures proportional changes and better handles variations across different scales. By analyzing $\text{LogWasteUnits}_{p,s,t}$, we gain insight into the overall change in waste, which is particularly relevant for retailers and policymakers concerned with the total volume of waste generated (see Table A18).

(vii) We exclude the non-linear term $\text{RSL}^2_{p,s}$ from Model 2 to understand the pure effect of the treatment variable $\text{RSL}_{p,s}$ on the dependent variable $\text{WasteRate}_{p,s,t}$. Table A19 shows again that we obtain directionally similar results.

(viii) We extend our main findings by showing that we also find cannibalization effects on a higher aggregation level by using the product category (C-PCS) subsamples. This confirms our main findings from the Model 3 estimates (see Table A20). We thus conclude that the product category level is representative of the individual product groups, so our findings can be generalized and applied to other settings.

**Estimation methods** As a second set of robustness checks, we applied two further estimation methods. (i) First, we run panel OLS estimations with store- and product-fixed effects and time effects. These estimation results are presented in Tables A21 and A22. (ii) Additionally, given that 92% of our store-product-week combinations show zero food waste values, we also check the robustness of our results by using a Zero-Inflated Negative Binomial (ZINB) Model (see Table A23) following Akkaş et al. (2019), who used such a count model because of approximately 80% zero values in their cross-sectional data set. Aggregating our data to cross-sectional would lead to 21% zeros, which is reasonable based on the higher perishability of the products in our study compared to Akkaş et al. (2019)'s products.

Given that we are keeping the panel structure due to the nature of our research question of investigating time-lagged effects of specific weeks, we use pooled OLS for our main contribution and only use a ZINB model as a robustness check. These tests also confirm our results. We see that using alternative estimators like Fixed Effects models and the ZINB count model results in estimation results that are directionally similar to the pooled OLS models.

## 3.5 Discussion and managerial implications

This section highlights the main results, managerial insights, and impact of the findings.

### 3.5.1 Summary of main results and interpretation

We find evidence that promotions increase food waste through direct and cannibalization effects. The findings are robust across different data settings, methods and aggregation levels. *H1* confirms the increase in food waste by promotions. Food waste increases by about 2 pp on average across all categories due to promotion events. Based on the unconditional means presented in Table 4.2 and the estimated parameters as presented in Table 3.4, we derived that food waste rates increase by 79% to 126% due to the promotion. Similarly, the waste of cannibalized products increases by 19% to 47% depending on the product category based on the parameter estimates shown in Table A20. The food waste increase with promotions holds true across all types of promotion mechanisms (e.g., BOGOF, loyalty points). The effects are heterogeneous across product categories and product groups, with an increase of almost 10 pp based on the highest parameter estimates. Here, promotions increase waste by a factor of 4 to 5. Products with a shorter RSL are more prone to cause food waste after promotions.

This confirms *H2*. The less effective a promotion is, the higher the effect of the perishability of a product on its risk of causing food waste. With regard to *H3*, promotions also increase food waste due to cannibalization during promotion weeks. We again find different effects across product groups. Almost half of the product groups reveal that promotions significantly affect substitutions that then turn into waste of the unpromoted products.

Promoted items exert a food waste impact up to nine times greater than their cannibalization effect on non-promoted items. The food waste increase can only be partially explained by the missing sales lift during the promotion week. Interestingly, even promotions resulting in higher sales than during non-promotional weeks contribute to increased food waste. This dilemma underscores the challenge retailers face: the products driving sales increases are also the culprits behind food waste. This phenomenon is exacerbated by the complexity of predicting promotion volumes and the deliberate overstocking of promoted items. Retailers who target capitalizing from sales bumps may sacrifice inventory efficiency. While retailers may justify this practice based on the potential financial gains from increased sales, they must weigh these gains against the economic and environmental costs associated with wasted inventory.

### 3.5.2 Managerial implications and insights

Our estimation results suggest several pathways to overcome the trap from deals to dumps. Understanding the impact of promotions on food waste will be useful for promotion planners, supply chain managers, and category managers who need to align the promotion plans with stores, logistics, and suppliers. In the following, we assess the food waste reduction potential based on our models and with counterfactual analyses along *H1* to *H3* to draw insights on future promotion planning. The options identified are ordered along the respective hypotheses and include *(1) reducing overstocks and promotion frequency (H1)*, *(2) shifting towards promotions with less* *perishable products (H2)* and *(3) mitigating cannibalization effects (H3)*. By applying the estimated coefficients, we derive the absolute and relative food waste reduction potential. Please recall that our data set for the full year included 65,811 promotion weeks for fresh products with EUR 380k in food waste and sales of EUR 25.8m. We will highlight the relative savings potential for each lever and then summarize the overall impact in financial terms at RetailCo as well as the environmental and social footprint. In the following, we will first introduce the mitigation strategy, indicate the potential impact, and then discuss its limitations. The strategies are as follows:

**1a. Avoiding overstocks from NSL promotions** The optimal approach, financially, socially and ecologically, involves completely eliminating unsuccessful promotions or, at the very least, minimizing overstocks resulting from such events. Retailers need to use our models to identify NSL promotions at an early stage. If the complete elimination of these promotions is not feasible, perhaps due to specific targets (e.g., brand image) or contractual obligations with suppliers, retailers can mitigate the early onset of overstock associated with these promotions. Retailers may reduce the initial allocation volume (especially for promotions known to typically result in NSL), implement smaller but more frequent replenishment during the promotion period, significantly decrease order volumes in the weeks following the promotions, or even allow these products to run out of stock towards the end of the promotion period. At RetailCo, an 8-9% reduction potential of food waste is feasible for NSL promotions if these promotions are canceled or promotion-related overstocking can be avoided. This is not only conceivable but is also likely the best financial solution for the retailer. Since about one-fifth of the promotion-related food waste results from NSL promotions, approx. 3% of the total food waste in our data sample can be minimized. These results ultimately suggest that retailers should accept lower inventory levels toward the end of such promotional events.

**1b. Reducing overstocks of SL promotions** Promotion forecasting is a complex matter. Certain products are expected to experience a 10-15 times sales lift compared to non-promotional weeks. Overestimating the demand only slightly naturally results in considerable overstocking. Further optimization potential, therefore, lies within the SL promotions. The retailer can apply, as for NSL promotions, a more conservative upfront volume allocation, later more frequent replenishments with lower quantities during the promotion week, and significantly lower replenishment volumes after the promotion to cope with the after-sales dip. The latter requires adjustments of the automated forecasting that need to anticipate the after-promotion dip in the demand calculation. Fully eliminating the overstocks resulting from the SL promotions has the potential to reduce the total food waste in our sample by 6%. However, these promotions generate an SL and enforce the retailer's dilemma of weighing waste against sales. Retailers want to ensure availability "at all costs", which ends in extensive overstocking. Non-financial benefits of promotions, such as increased store traffic and enhanced customer relationships, and financially quantifiable effects, such as cross-selling, should be weighed carefully against the increased food waste risk.

**1c. Reducing promotion frequency** Retailers may also wish to reduce promotion frequency. With fewer promotions, retailers are less likely to overstock their shelves with excess inventory in anticipation of increased demand during promotional periods. Lower promotion frequency further eases retailers' inventory planning. Forecasts and replenishment practices are then based on historical, non-promoted data rather than artificially inflating sales and stock levels for promotional events. The same holds true for cannibalization effects. Reducing promotion frequency can encourage customers to engage in more consistent purchasing behavior. Frequent promotions may encourage consumers to wait for discounted prices before making purchases, leading to erratic buying patterns and increased waste as consumers may buy more than they need during promotional periods and discard the excess later. Less frequent promotions allow retailers to emphasize the quality of perishable products rather than relying solely on price markdowns to attract customers. This shift can lead to more sustainable consumption patterns. Reducing the number of promotion events of the SL promotions by 10-50% yields a reduction potential of 1-3% on total food waste. Suppose this logic is applied to all promotions (incl. NSL), again with 10-50% fewer promotions and on the assumption that all other coefficients remain the same. In that case, the potential is 1-4%. Reducing the number of promotions inherits the additional impact potential of avoiding food waste from cannibalization, which is separately estimated below in 3a/b.

**2a. Shift promotions from ultra-fresh products towards products with a higher shelf life** The promoted products with a shorter RSL are more prone to turn into food waste. Promotions for ultra-fresh products may be less significant for several reasons. First of all, consumers often prioritize freshness, and discounts may not significantly influence their purchasing decisions within the short time frame (Hansen et al., 2023; Tsiros and Heilman, 2005). Consumers usually buy these products based on their immediate needs and preferences rather than waiting for promotions. Even worse, as consumers usually prioritize the quality and freshness of ultra-fresh products, discounts or promotions may raise concerns about the product's quality or freshness (see, e.g., Yang et al., 2021). Finally, the availability of ultra-fresh products can be highly influenced by seasonal factors, weather conditions, and agricultural cycles (Parfitt et al., 2010). Further promoting these products may, therefore, counteract the seasonal revenue cycles (e.g., promoting seasonal products in off-seasons with lower availability). Promotions may not be as effective or feasible for these products due to their inherent variability in supply and demand. Increasing the average RSL of promoted products by one standard deviation (3.5 days, see Table 3.3) will lead to a decrease in food waste of 2% caused by promotions. Retailers can follow two directions to achieve this. First, shift promotions towards products with a longer shelf life. Second, try to shorten the lead time in the supply chain to obtain a higher RSL upon store arrival. Whereas the first shift is a change in promotion planning, the second imposes potentially higher costs in the supply chain via higher delivery frequency and different delivery modes.

**2b. Agile adaption of order volumes for promoted short-life products** Agile adaptation of order volumes for product groups with a low RSL is a meaningful way to reduce waste. Retailers can achieve a better demand response to the actual demand by aligning reorder quantities to observed demand faster during the promotion week. This minimizes the likelihood of unsold inventory and increases inventory turnover. The latter is again particularly relevant to fresh products. Again, reducing overstocks of the short-life products (with an RSL of less than 14 days), will lead to a decrease in food waste to less than 1% caused by promotions. This is mainly because those products represent less than 1% of all products. Despite decreasing order volumes enabling retailers to adapt more effectively to dynamic demand, smaller order sizes, and more frequent replenishments increase operational costs, may result in higher emissions from transportation, and may contradict the operational efficiency of the entire distribution system. Furthermore, lower inventory levels may be difficult as customers may leave disappointed in the store when not receiving the promoted products. Therefore, an increase in reorder cycles and smaller order quantities needs to be carefully evaluated. However, appropriately communicating the negative environmental consequences of overstocking highly perishable products may counteract future customer reactions to this problematic situation.

**3a. Reduce promotions with a high cannibalization effect** Reducing promotions with high cannibalization rates can be advantageous for retailers. Promotions cannibalize sales from non-promoted products. This erodes margins and complicates inventory management by the demand fluctuations of regular-priced items. Our analysis reveals that promotions lead to cannibalization within half of the product groups. As this affects sales and results in the waste of products other than the promoted ones, the retailer may try to reduce these problematic promotions. By reducing the promotions within this product group by 10 to 20%, the food waste could be reduced by ∼1%.

**3b. Reduce inventory of unpromoted substitution products** A further option to reduce the waste caused by substituting unpromoted to promoted products. Our analysis reveals product groups that are cannibalized during promotions. Hence, the unpromoted products should be restocked with lower quantities than usual. Leveraging our insights on cannibalization and its integration into automated forecasting systems will lead to an adaption of the reorder volumes of the cannibalized products during promotion weeks. Reducing overstocks of unpromoted products by 75-100% would reduce food waste by 1-2%. The automated forecasting systems should thus reflect the cannibalization effect during promotions.

### 3.5.3 Impact analysis

The available options for reducing promotion-related food waste have a significant economic, environmental, and social impact. As the counterfactual analysis can be conducted only on the level of individual options, we base the translation into financial and environmental terms on all options for reducing overstock. This includes eliminating all NSL promotions, reducing overstocks for 50% of the SL promotions, increasing the mean RSL of promoted products by one standard deviation, and reducing all overstocks of cannibalized products.

**Economic impact at RetailCo** Reducing promotion-related overstocks has significant cost reduction potential for RetailCo. In our sample data set, the retailer's annual sales of the chilled assortment of products with a maximum RSL of 21 days is approx. EUR 26m. The food waste amounts to approx. EUR 380k over the same period. Here, promotion events account for sales of EUR 1.9m and lagged food waste after promotions for EUR 57k. Hence, in the case of the chilled assortment, promotional sales represent 7% of the total sales volume and 15% of the total food waste volume, again highlighting the massive impact of promotions on waste. Leveraging all options from above and improving the efficiency of promotions results in savings of up to 9% of total food waste. This is equivalent to EUR 34k and about 0.13% of the total sales. The share of 0.13% is equivalent to about 7% of the retailer's profit margin, as European grocery retailers typically achieve a profit margin of merely 2% (Klingler et al., 2016). This means mitigating food waste stemming from promotions could theoretically augment the profit margin by as much as 7%. Extrapolating this savings potential to the entire chilled assortment and all of the retailer's stores would reduce more than EUR 4m per annum[5]. This demonstrates the significant impact that reducing food waste can have on the profitability of a grocery retailer.

**Environmental and social impact at RetailCo** We add an ecological perspective by assessing the CO2-equivalent impact of the total reduction potential. We use the multipliers presented by Scholz et al. (2015) to assess the CO2 equivalent of the food waste in our data set. The estimate for the wasted food for our data set is 29 tons. This is equivalent to the yearly per-capita consumption of fresh dairy products in Germany in 2019 for 336 people (Statista, 2022). Further, a food waste reduction by 9% thanks to the measures identified would mean a minimization of CO2 emissions of approx. 800 tons for all of the retailer's stores in Germany.

The retailer has a market share in Germany of about 20%. Again, the straight and simple extrapolation would yield a savings potential of 1,600 tons of food waste in Germany, which is equivalent to 5,000 tons of CO2 emissions and the yearly per-capita dairy consumption of 120k people.[6] Despite the simplifications relating to the environmental impact assessment,

[5] National chilled assortment food waste in 2019: EUR 48m
[6] Extrapolated based on the revenue share of RetailCo retrieved from Statista (2024)

the analysis highlights that specific sustainability performance metrics should be introduced to incentivize promotion planners to reduce food waste in addition to hitting sales targets.

## 3.6 Conclusion

Driven by the need to tackle a significant global sustainability challenge related to reducing food waste, we conducted research to investigate the role of promotions as a driver of food waste in grocery retail. We found that food waste doubles during promotions. This study establishes a clear correlation between promotions and food waste, shedding light on retailers' inclination to overstock during promotional events, leading to wastage. It also uncovers insights regarding the time-lagged effects of promotions and cannibalization, highlighting the necessity for a more comprehensive approach to promotions and inventory management. While promotions are identified as a food waste driver, they still constitute an important sales and traffic tool for retailers. The vast majority of promotional products lead to a sales lift, often at the cost of food waste as the products intended for promotion are overstocked by the retailer. Retailers, therefore, need to consciously re-think additional ordering for promotions in view of the high demand uncertainty and its impact on sustainability and food waste. Our results can guide retailers to sharpen their promotion planning, which needs to extend beyond the product promoted and the promotion week alone. The findings can be directly translated into actionable initiatives for RetailCo and further retailers. The growing amount of data allows retailers to develop data-driven insights based on our models to simultaneously optimize promotions and food waste. We then discuss our findings in relation to the literature and limitations and delineate future research areas.

**Contribution to literature** Our findings extend the pertinent literature on food waste and promotions. We contribute to the call for research with data-driven identification of food waste drivers in grocery retail (see, e.g., Akkaş et al., 2019). The more competitive the market, the more retailers use promotions. The competitive intensity (indicated by the level of promotions, (see IRI, 2015)) is a driver of food waste as indicated in the simulation study of Belavina (2021). Food waste has been attributed to sales and incentives (Teller et al., 2018; Mena et al., 2014), where the empirical evidence is mainly based on expert interviews. Our study is the first data-driven and empirically based contribution to the relationship between promotions on food waste. As such, it also contributes to the general discussion on the relationship between large-scale promotions (like Black Friday) and sustainability. The current literature on promotions (see e.g., Cohen et al., 2021; van Heerde et al., 2004) and data-driven studies on food waste reductions are based on fast-moving consumer goods with a longer shelf life. For example, a seminal paper of Akkaş et al. (2019) empirically identifies food waste drivers in grocery retailing based on the effects of product, retailer, and other supply chain variables. However, their findings are based on products with an average shelf life of 195 days. We distinguish our work from their results by using data on fresh and ultra-fresh products, i.e., perishable goods with a shelf life of a few weeks or less. Moreover, testing *H2* intensifies the direct effect by adding perishability as a product characteristic and thus adds an additional level of interest.

One might also expect promotions to clear inventories, hence reducing food waste. However, the opposite is the case. We establish a novel connection and highlight how planned promotions contribute to increased food waste due to intricate forecasting, intentional overstocking, and substitution practices. This differs from the outcomes observed with short-term discounting promotions aimed at salvaging overstocks. For example, Buisman et al. (2019) and Wu and Honhon (2023) analyze the performance of the such short-term-discounting practices for different target stock levels. They show that these different types of promotions, namely short-term promotions to clear overstocks, increase profitability while decreasing waste.

Finally, our findings contribute to the extensive body of literature examining the impacts of promotions in grocery retail, encompassing phenomena such as sales bumps and cross-period effects. Specifically, we enrich this literature by investigating sales lifts during promotions and the subsequent time-lagged levels of food waste (Trivedi et al., 2017; Macé and Neslin, 2004). A current gap in promotion studies, though, is that none measures food waste. By identifying cannibalization effects leading to increased food waste, we contribute to the literature stream about substitution through promotions such as brand switching (Cohen et al., 2021; van Heerde et al., 2004; Kumar and Leone, 1988) or cross-category effects (Leeflang and Parreño-Selva, 2012) by adding the dimension of food waste via a promotional effect of this kind.

**Limitations and future research** Our research is constrained by several limitations. Firstly, we only obtained data from a single region comprising a sub-sample of grocery retail stores within one country. Expanding our dataset to include all retail stores across the country would facilitate better monitoring of regional disparities, such as variations in assortments, inventory practices, and promotion processes. The study could also be extended to multiple retail formats (e.g., discounters, and hypermarkets) and different retailers. Furthermore, we work with average RSL data from the year 2021 to estimate the time lag in 2019 between an event and a food waste record. Third, our data set includes January and December, which could create spillover effects due to the time lag logic applied to our analyses. We lack information regarding the execution of the promotions and retail operations. Disparities such as dedicated areas with special promotional displays, usage of backroom storage, or less frequent replenishment could potentially influence food waste and warrant further investigation. Last but not least, some of the boundary conditions, e.g., the out-of-stock boundary condition, are based on data that is known to be less accurate than other data points (see, e.g., DeHoratius and Raman, 2008). Although this represents our most reliable information, we have meticulously assessed the influence of even minor inaccuracies using robustness checks.

There are several promising research directions stemming from our study. One avenue is to delve into supply chain dynamics. The bumps and dips of promotions and the lead time pressures for the finite duration of promotions cause issues not just at the store level but also at retail warehouses and upstream in the supply chain. Moreover, retailers may batch their orders to suppliers during promotional periods to take advantage of volume discounts. This forward buying can result in irregular order patterns and amplify demand variability upstream, e.g., when suppliers may need to adjust production schedules. The demand variability causes and exacerbates the bullwhip effect along the entire supply chain. Exploring the various interactions between promotions, demand variability and the bullwhip effect offers valuable insights for improving supply chain resilience, efficiency, and responsiveness. Future research could, therefore, focus on developing more robust forecasting models, optimizing end-to-end inventories, and enhancing coordination among supply chain partners to mitigate the negative effects of promotions on food waste. Investigating how our findings regarding promotions may have implications for other retail sectors and online platforms with significant promotional activities, such as consumer electronics and fashion. Promotions can, however, also increase food waste in households. During promotions, customers may be tempted to buy more than they need because of the perceived value of the promoted product. This triggers impulse purchases that later do not match needs, meal plans or counteract mindful consumption. As for retailers, this overstocking may lead to the expiry of the products before they have been sold.

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# Online Appendices

The appendices outlines the pilot study to obtain ED, provide an overview of the subsampling applied, further details of estimation results reported in the main body of the paper and details the robustness checks completed.

## 3.7 Collection of expiry data in pilot study of retailer

Prior to RetailCo's pilot study, systematically obtaining information about the RSL of each product in stores was not possible given that the stores did not receive any information about the EDs of each delivered product. This is due to the fact that EDs are generally printed on the product but are not incorporated, e.g., in the bar code. However, to be able to accurately create the correct time lag for each product to trace back the lagged food waste of products delivered for promotions, knowing the RSL is inevitable. RetailCo's pilot study started in January 2021 and recorded for a broad group of products in the majority of its stores the ED of each delivery from the warehouse to one of the stores. With this comprehensive data collection effort in the pilot study, the ED of each delivered product became available for the retailer. We use this RSL data to derive RSL average values for each store-SKU combination, which allows us to identify higher perishable goods and identify food waste records of promoted products weeks after the promotion. Summary statistics of the pilot study dataset are shown in Table A8, which underscores the selection choice of store-SKU combinations on the store-SKU level as, e.g., the standard deviation of half of the products is 1 day based on the store they are shipped to.

**Table A8:** Expiration date pilot study summary statistics

| **Quantile** | Count | Mean RSL | RSL SD |
|---|---|---|---|
| **0.1** | 54 | 18.332 | 0.513 |
| **0.25** | 90 | 22.607 | 0.688 |
| **0.5** | 137 | 28.268 | 1.052 |
| **0.75** | 163 | 43.379 | 1.810 |
| **0.9** | 170 | 74.039 | 3.134 |

## 3.8 Subsample approach

We apply different subsamples for studying each hypothesis based on the required scope. Table A9 summarizes the subsamples applied.

**Table A9:** Subsample overview

| **Name of data set** | **(a) Time-lagged** | **(b) RSL Cap** | **(c) Product aggregation** | **(d) Sales lift** |
|---|---|---|---|---|
| **NC-NS (Full sample)** | - | All | All | All |
| **NC-NS-PO** | ✓ | All | All | All |
| **C-NS** | - | 21 days | All | All |
| **C-PCS** | - | 21 days | Product category | All |
| **C-PGS** | - | 21 days | Product group | All |
| **SL-NC-NS-PO** | ✓ | All | All | Sales lift only |
| **SL-C-PCS** | - | 21 days | Product category | Sales lift only |
| **SL-C-PGS** | - | 21 days | Product group | Sales lift only |
| **NSL-NC-NS-PO** | ✓ | All | All | No sales lift only |
| **NSL-C-PCS** | - | 21 days | Product category | No sales lift only |
| **NSL-C-PGS** | - | 21 days | Product group | No sales lift only |

We denote the entire data set as NC-NS (Non-Capped and Non-Split). We slice this data set in four ways: (a) promotion event, (b) RSL, (c) product level, and (d) promotion effectiveness.

(a) To test *H2*, we limited the primary data set to time-lagged promotion week only to enable the testing of interaction effects on food waste between treatment variables and promotion weeks. This is denoted as Promotion-Only (PO).

(b) Secondly, we call the data set with the fresh products only with RSL $\leq 21$ days Cap21 subsets and denote it C. The counterpart also includes the non-fresh products with RSL $> 21$. This is denoted Non-Capped (NC).

(c) Thirdly, the data set may be split into four product category subsets (denoted PCS) to test differences between product categories. We use these subsamples to test *H1* together with the sample that includes all categories. Further, to test *H3*, i.e., cannibalization effects, on the lowest product aggregation level, the data set is divided into Product Group subsamples (PGS).

(d) Lastly, we extend our main findings by investigating the influence of sales uplift (SL) and the no sales uplift (NSL) products on the effects of promotions on food waste. We compare the SL of promotion weeks to the yearly mean baseline sales for product categories and groups. The result is SalesUplift-Capped-Split subsamples (SL-C-PCS and SL-C-PGS). We find SLs, thanks to promotion weeks, for approximately 79% of the SKUs promoted (716 out of 908) based on a two-sample t-test. The counterparts of the SL subsamples are the NSL subsets of data, namely NSL-C-PCS and NSL-C-PGS. Only product-specific sales are considered for calculating the SL.

## 3.9 Further analysis for main estimation results

This section presents a more detailed view of the estimation results shown in Section 3.4. These include the SL and NSL estimation results for Model 1 and 3, both on a product group level. Additionally, we present the Model 1 estimation results for the promotion weeks, in which significant price discounts were granted compared to the weeks after the promotion week.

**H1 Analysis of promotion mechanism** Given that 75% of the promotion weeks have actual price reductions compared to the sales price and 25% have a different promotion mechanism (e.g., loyalty points), we also check whether the effects identified still exist if we focus on the pure price promotions only (i.e., only where price reductions are granted). Table A10 presents the estimation results when only price promotions are included.

**Table A10:** H1 parameter estimates on a category and total level with price promotions alone

| | Milk/Dairy | | Delicacies | | Cheese | | Convenience | | All categories | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variables** | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** |
| *Intercept* | -2.08 | 0.317*** | -10.17 | 1.077*** | -0.150 | 0.651 | -4.518 | 2.250* | -4.986 | 0.319*** |
| *Promotion* | 1.728 | 0.092*** | 3.224 | 0.253*** | 1.926 | 0.287*** | 3.954 | 0.380*** | 2.163 | 0.098*** |
| *EoDStock* | -0.007 | 0.002** | -0.007 | 0.009 | -0.001 | 0.004 | -0.058 | 0.016*** | -0.006 | 0.002** |
| *SalesPrice* | 2.885 | 0.185*** | 2.548 | 0.204*** | 0.942 | 0.239*** | 3.611 | 0.701*** | 2.716 | 0.161*** |
| *OverForecastError* | 1.279 | 0.049*** | 1.842 | 0.082*** | 0.979 | 0.084*** | 1.385 | 0.075*** | 1.368 | 0.042*** |
| *DummyStore* | Yes | | Yes | | Yes | | Yes | | Yes | |
| *DummyProduct* | Yes | | Yes | | Yes | | Yes | | Yes | |
| *DummyTime* | Yes | | Yes | | Yes | | Yes | | Yes | |
| *Observations* | 645,622 | | 229,749 | | 114,807 | | 167,762 | | 1,157,940 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; The sample data sets are based on product category-specific (C-PCS) and combined (C-NS) store-product-week observations.

**H1 analysis on a product group level** Table A11 shows the Model 1 product group level estimation results for the treatment variable $\text{Promotion}_{p,s,\tau}$. These are reported for the combined data sets and separately for SL and NSL data sets.

**Table A11:** Parameter estimates for H1 hypothesized variable on a product group level for all data sets, split into sales uplift (SL) and no sales uplift (NSL)

| Category | Product Group | All | SL | NSL |
|---|---|---|---|---|
| **Milk/Dairy** | Fruit Yogurt SU | 3.288*** | 3.232*** | 3.057** |
| | Fresh Organic Milk | 0.632 | 0.247 | 1.594 |
| | Sweet Cream | -0.059 | 0.175 | 0.007 |
| | Organic Cream | -0.096 | 0.442 | -1.815 |
| | Organic Fruit Yogurt SU | 1.401 | -0.249 | 3.368 |
| | Fresh Milk SU | 2.827*** | 2.875*** | 2.480*** |
| | Sour Cream | -5.282*** | n/a | -11.344 |
| | Fruit Yogurt MU | 0.178 | 0.178 | n/a |
| | Organic Quark Cheese | 1.289 | n/a | 1.289 |
| | Pudding and Milk Rice | 0.382 | 0.269 | 6.022 |
| | Fruit Quark | 3.690*** | 4.037*** | -1.824 |
| | Natural Yogurt SU | 1.367*** | 1.684 | 2.717 |
| | Dessert Mouse Cream | 1.273 | 1.167 | n/a |
| | Altern. Fresh Dairy Drinks | -0.759 | n/a | -0.759 |
| | Buttermilk | 4.013*** | 4.013*** | n/a |
| | Cocoa Mixed Drinks | 1.599 | 1.669 | n/a |
| | Mixed Organic Drinks | 0.556 | 0.556 | n/a |
| | Quark Herb Bread | 3.171*** | 2.672*** | n/a |
| | Natural Yogurt MU | 0.314 | 0.314 | n/a |
| | Regular Sandwich Spread | 1.230*** | 0.275 | 2.018 |
| | Altern. Fresh Milk | -2.156 | -2.156 | n/a |
| | Creme Fraiche | 0.058 | 0.849 | n/a |
| | Cocoa Milk MU | 3.256*** | n/a | 0.764 |
| | Bars | 0.864 | 0.864 | n/a |
| **Delicacies** | Smoked Fish | 2.105*** | 2.038*** | 0.592 |
| | Salad and Dessert | 3.745*** | 3.686*** | 1.426 |
| | Seafood | 6.612*** | 9.050*** | -2.128 |
| | Herring and Matjes | 2.826*** | 2.151 | n/a |
| **Cheese** | Mozzarella | 1.586*** | 1.031 | 1.957*** |
| | Organic Cheese | -0.139 | 0.355 | -0.360 |
| | Sour Milk Cheese | 7.315 | n/a | 7.073 |
| | Cheese for Warm Use | -1.412 | -1.412 | n/a |
| | Fresh Cheese | 0.410 | 0.195 | 1.398 |
| | Soft Cheese | 4.354*** | 1.588 | 7.371 |
| **Convenience** | Chilled Dough | 1.850 | 1.042 | -7.742*** |
| | Potato Specialities | 4.585*** | 5.751*** | 1.516 |
| | Chilled Vegetarian Fine | 3.959 | 4.014 | n/a |
| | Cooked Meat | 6.857*** | 6.300 | -2.430 |
| | Pizza Baguette | -2.866 | -2.866 | n/a |
| | Antipasti | -0.412 | n/a | 1.039 |
| | Cooked Chicken | 1.110 | -0.210 | -1.029 |
| | Juice | 3.604 | 4.046 | n/a |
| | Chilled Vegetarian | 9.216*** | n/a | 4.214 |
| | Fine Bread Spread | 9.824 | 6.758 | -7.286 |
| | Instant Cold Snacks | -0.201 | 4.323 | -1.693 |
| | Fresh Noodles | 1.162 | 1.344 | n/a |
| | Soup and Hotpot | 4.412 | 4.412 | n/a |
| | Chilled Vegan | 1.215 | 1.215 | n/a |
| | Organic Convenience | -0.131 | -0.131 | n/a |
| | Chilled Snacks | -7.469 | -7.469 | n/a |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; n/a: not available.
The sample data sets are based on product group-specific (C-PGS) store-product-week observations.
SU and MU represent single-use and multi-use packaging, respectively.

## 3.10 Robustness checks

We highlight the rationale and results of the robustness checks in Section 3.4. This section now details the estimates obtained and further discusses the findings.

### 3.10.1 Model specifications and boundary conditions

**(i) Impact on food waste by manual order interventions** First, as outlined in Table 3.3 to test hypothesis *H1*, we take into account the quantities centrally allocated to the store during the promotion week. However, further quantities can be ordered via intervention by store managers. Whenever a store manager places an additional order during the promotion week, we excluded this week in the analysis above (i.e., from the C-PCS sample) to avoid any human bias. We add back the eliminated data points by integrating manual interventions as a boundary condition. The results in Table A12 indicate that the effects remain stable even when also considering manual order interventions.

**Table A12:** Parameter estimates including data with manual order interventions

| Variables | Milk/Dairy Est. Std. Err. | Delicacies Est. Std. Err. | Cheese Est. Std. Err. | Convenience Est. Std. Err. | All categories Est. Std. Err. |
|---|---|---|---|---|---|
| *Intercept* | -2.089 0.317*** | -9.778 1.067*** | -0.465 0.647 | -4.449 2.250* | -5.005 0.319*** |
| *Promotion* | 1.651 0.087*** | 3.317 0.229*** | 1.713 0.239*** | 4.299 0.371*** | 2.119 0.091*** |
| *EoDStock* | -0.007 0.002** | -0.007 0.009 | -0.001 0.004 | -0.058 0.016*** | -0.006 0.002** |
| *SalesPrice* | 2.898 0.185*** | 2.458 0.201*** | 1.085 0.237*** | 3.590 0.701*** | 2.728 0.161*** |
| *OverForecastError* | 1.279 0.049*** | 1.839 0.082*** | 0.980 0.084*** | 1.383 0.075*** | 1.368 0.042*** |
| *DummyStore* | Yes | Yes | Yes | Yes | Yes |
| *DummyProduct* | Yes | Yes | Yes | Yes | Yes |
| *DummyTime* | Yes | Yes | Yes | Yes | Yes |
| *Observations* | 645,622 | 229,749 | 114,807 | 167,762 | 1,157,940 |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; The sample data sets are based on product category-specific (C-PCS) and combined (C-NS) store-product-week observations.

**(ii) Out-of-stock boundary condition** In cases where an out-of-stock situation occurs between the promotion week and the time-lagged food waste record, the food waste cannot be caused by the promotion week. We include this additional boundary condition as a robustness check for the hypothesis *H1*. This is necessary for multiple reasons. First, the stock data provided may suffer from data inaccuracies compared to other data points (see e.g., DeHoratius et al., 2023; DeHoratius and Raman, 2008). Also, RetailCo confirmed that the stock data have the lowest accuracy of all other data. We may, therefore, falsely exclude promotion weeks from our sample even though an out-of-stock might not have occurred. Second, taking out out-of-stock might bias the estimation results given that we exclude those observations where promotions lead to lower food waste.

Due to computational limits when running tests for out-of-stock on each day between a promotion week and a food waste record on a store-product-day level, we tested *H1* with 44 stores, corresponding to 25% of the entire sample. The results of this robustness check on the C-PCS (*H1*) data sets directionally match the findings from our Model 1 to a high statistical significance level (see Table A13), while the effect size is even higher.

**Table A13:** Parameter estimates with the out-of-stock boundary condition

| | Milk/Dairy | | Delicacies | | Cheese | | Convenience | | All categories | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variables** | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** |
| *Intercept* | 3.284 | 2.757 | -3.845 | 1.352** | -4.86 | 1.190*** | -10.366 | 2.419*** | -4.421 | 0.770*** |
| *Promotions* | 1.992 | 0.830* | 2.168 | 0.610*** | 2.229 | 0.273*** | 5.610 | 1.249*** | 2.656 | 0.312*** |
| *EoDStock* | -0.005 | 0.036 | 0.010 | 0.009 | -0.009 | 0.004* | -0.125 | 0.058* | -0.007 | 0.005 |
| *SalesPrice* | 1.931 | 0.749* | 2.569 | 0.649*** | 2.376 | 0.857** | 4.488 | 1.090*** | 3.075 | 0.472*** |
| *OverForecastError* | 1.435 | 0.223*** | 0.767 | 0.206*** | 1.411 | 0.171*** | 1.647 | 0.230*** | 1.288 | 0.136*** |
| *DummyStore* | Yes | | Yes | | Yes | | Yes | | Yes | |
| *DummyProduct* | Yes | | Yes | | Yes | | Yes | | Yes | |
| *DummyTime* | Yes | | Yes | | Yes | | Yes | | Yes | |
| *Observation* | 165,232 | | 68,219 | | 29,752 | | 42,756 | | 305,959 | |

Notes: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$; The sample data sets are based on product category-specific (C-PCS) and combined (C-NS) store-product-week observations.

**(iii) Product category interaction effects** To avoid any bias due to the different sample sizes of the product category samples, we run the Model 1 regression with the combined data set and use interaction terms with the treatment variable Promotion$_{p,s,\tau}$ to test differences between product categories (Table A14). Similar to our main contribution (see Table 3.4), we find directionally similar and heterogeneous effects between the product categories.

**Table A14:** H1 Parameter estimates using interaction effects

| **Variables** | **Est.** | **Std. Err.** |
|---|---|---|
| *Intercept* | -2.300 | 0.335*** |
| *Cheese* **x** *Promotion* | 1.775 | 0.234*** |
| *Delicacies* **x** *Promotion* | 3.217 | 0.229*** |
| *Milk* **x** *Promotion* | 1.613 | 0.087*** |
| *Convenience* **x** *Promotion* | 4.531 | 0.373*** |
| *EoDStock* | -0.006 | 0.002** |
| *SalesPrice* | 2.703 | 0.160*** |
| *OverForecastError* | 1.368 | 0.042*** |
| *DummyStore* | Yes | |
| *DummyProduct* | Yes | |
| *DummyTime* | Yes | |
| *Observations* | 1,157,940 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; The sample data set is based on store-product-week observations of all categories (C-NS).

**(iv) Additional promotion-related variables** We further include the two promotion-related variables $\text{Substitution}_{p,s,\tau}$ and $PromotionFrequency_{p,s}$ as control variables in Model 1 to test for additional promotion effects. The latter accounts for the number of promotions per store-product combination. Table A15 shows estimation results that are still highly statistically significant for the treatment variable $\text{Promotion}_{p,s,\tau}$, similar in direction and effect size to the main findings.

**Table A15:** Parameter estimates for the H1 hypothesized variable with promotion-related variables

| **Variables** | **Milk/Dairy** Est. | Std. Err. | **Delicacies** Est. | Std. Err. | **Cheese** Est. | Std. Err. | **Convenience** Est. | Std. Err. | **All categories** Est. | Std. Err. |
|---|---|---|---|---|---|---|---|---|---|---|
| *Intercept* | -2.405 | 0.370*** | -9.429 | 1.064*** | -0.419 | 0.730 | -4.389 | 2.267 | -4.990 | 0.325*** |
| *Promotion* | 1.639 | 0.087*** | 3.329 | 0.229*** | 1.736 | 0.241*** | 4.312 | 0.370*** | 2.120 | 0.090*** |
| *Substitution* | 0.513 | 0.060*** | 0.925 | 0.117*** | 0.833 | 0.112*** | 0.821 | 0.175*** | 0.657 | 0.053*** |
| *EoDStock* | -0.007 | 0.002*** | -0.007 | 0.009 | -0.001 | 0.004 | -0.059 | 0.016*** | -0.006 | 0.002** |
| *SalesPrice* | 2.824 | 0.182*** | 2.333 | 0.198*** | 0.824 | 0.238** | 3.517 | 0.709*** | 2.635 | 0.159*** |
| *OverForecastError* | 1.252 | 0.048*** | 1.779 | 0.081*** | 0.939 | 0.083*** | 1.357 | 0.076*** | 1.335 | 0.041*** |
| *PromotionFrequency* | 0.040 | 0.021 | 0.032 | 0.072 | 0.043 | 0.044 | 0.004 | 0.081 | 0.015 | 0.019 |
| *Observations* | 645,622 | | 229,749 | | 114,807 | | 167,762 | | 1,157,940 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; The sample data sets are based on product category-specific (C-PCS) and all categories (C-NS) store-product-week observations.

Additionally, we replace $\text{Promotion}_{p,s,\tau}$ by $\text{PriceDiscountDepth}_{p,s,\tau}$ as the independent variable of interest to investigate the effects of the depth of the discount. We find that the higher the discount, the lower the waste rate increase. This indicates too low discounts drive food waste.

**Table A16:** Parameter estimates for the variable discount height

| **Variables** | **Est.** | **Std. Err.** |
|---|---|---|
| *Intercept* | -2.049 | 0.335*** |
| *PriceDiscountDepth* | -0.010 | 0.003** |
| *EoDStock* | -0.006 | 0.002** |
| *SalesPrice* | 2.539 | 0.234*** |
| *OverForecastError* | 1.373 | 0.042*** |
| *DummyStore* | Yes | |
| *DummyProduct* | Yes | |
| *DummyTime* | Yes | |
| *Observations* | 1,157,940 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; The sample data sets are based on all categories (C-NS) store-product-week observations.

**(v) Exclusion of control variables** We test the hypotheses without store or product-related controls to avoid multicollinearity issues by adding control variables that might be correlated with store or product dummy variables. Table A17 shows results that are highly statistically significant for the treatment variable $\text{Promotion}_{p,s,\tau}$, similar in direction and effect size to the main findings.

**Table A17:** Parameter estimates for the H1 hypothesized variable without controls

| | **Milk/Dairy** | | **Delicacies** | | **Cheese** | | **Convenience** | | **All categories** | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variables** | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** | **Est.** | **Std. Err.** |
| *Intercept* | 1.924 | 0.066*** | 3.435 | 0.110*** | 1.735 | 0.074*** | 3.221 | 0.108*** | 2.402 | 0.070*** |
| *Promotion* | 2.020 | 0.099*** | 3.515 | 0.238*** | 1.561 | 0.244*** | 5.400 | 0.392*** | 2.323 | 0.105*** |
| *Observations* | 645,622 | | 229,749 | | 114,807 | | 167,762 | | 1,157,940 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; The sample data sets are based on product category-specific (C-PCS) and all categories (C-NS) store-product-week observations.

**(vi) Logarithmic waste as the dependent variable** We present the estimation results of Model 1 on the dependent variable $\text{LogWasteUnits}_{p,s,t}$

in Table A18. The identified effect of promotions on the logarithm of food waste is consistent with the main findings.

**Table A18:** Parameter estimates for the H1 hypothesized variable without the boundary condition of at least one promotion per product group

| **Variables** | **Est.** | **Std. Err.** |
|---|---|---|
| *Intercept* | 0.008 | 0.019 |
| *Promotion* | 0.068 | 0.003*** |
| *EoDStock* | 0.001 | 9.94e-05*** |
| *SalesPrice* | 0.034 | 0.003 |
| *OverForecastError* | 0.018 | 0.001*** |
| *DummyStore* | Yes | |
| *DummyTime* | Yes | |
| *Observations* | 1,157,940 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; The dependent variable is $\text{LogWasteUnits}_{p,s,t}$. The sample data sets are based on product category-specific (C-PCS) and all categories (C-NS) store-product-week observations.

**(vii) Exclusion of the non-linear hypothesized variable** $\text{RSL}^2$ To check the robustness of our H2 results, we exclude ${\text{RSL}^2}_{p,s}$ from our model using the promotion-only uncapped data to study only the linear relationship between the RSL and food waste. We again achieve directionally similar results as by including the non-linear variable (see Table A19).

**(viii) Cannibalization on a product category level** Finally, we present the estimation results for Model 3 on the product category level in Table A20.

### 3.10.2 Estimation methods

**(i) Panel OLS with fixed effects** To avoid bias from the pooling effect of Pooled OLS, which we used in the main section, we also run Panel OLS

**Table A19:** H2 parameter estimates without $RSL^2$

| Variables | Est. | Std. Err. |
|---|---|---|
| *Intercept* | 21.477 | 15.720 |
| *RSL* | -0.047 | 0.002*** |
| *EoDStock* | -0.039 | 0.003*** |
| *SalesPrice* | 0.099 | 0.051 |
| *OverForecastError* | 1.322 | 0.062*** |
| *DummyStore* | Yes | |
| *DummyTime* | Yes | |
| *Observations* | 396,587 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.; The sample data set is based on promotion-only (NC-NS-PO) store-product-week observations, including all EDs.

**Table A20:** H3 parameter estimates on a product category level

| | Milk/Dairy | | Delicacies | | Cheese | | Convenience | | All categories | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variables | Est. | Std. Err. | Est. | Std. Err. | Est. | Std. Err. | Est. | Std. Err. | Est. | Std. Err. |
| *Intercept* | -2.014 | 0.316*** | -10.525 | 1.071*** | -0.26 | 0.654 | -5.047 | 2.267* | -5.209 | 0.323*** |
| *Substitution* | 0.531 | 0.060*** | 0.916 | 0.118*** | 0.812 | 0.111*** | 0.83 | 0.174*** | 0.667 | 0.053*** |
| *EoDStock* | -0.007 | 0.002*** | -0.008 | 0.009 | -0.001 | 0.004 | -0.061 | 0.016*** | -0.007 | 0.002** |
| *SalesPrice* | 2.943 | 0.185*** | 2.595 | 0.202*** | 0.968 | 0.239*** | 3.771 | 0.710*** | 2.779 | 0.162*** |
| *OverForecastError* | 1.257 | 0.048*** | 1.789 | 0.081*** | 0.942 | 0.083*** | 1.369 | 0.075*** | 1.34 | 0.041*** |
| *DummyStore* | Yes | | Yes | | Yes | | Yes | | Yes | |
| *DummyProduct* | Yes | | Yes | | Yes | | Yes | | Yes | |
| *DummyTime* | Yes | | Yes | | Yes | | Yes | | Yes | |
| *Observations* | 645,622 | | 229,749 | | 114,807 | | 167,762 | | 1,157,940 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; The sample data sets are based on product category-specific (C-PCS) and all categories (C-NS) store-product-week observations.

models. Here, we include fixed effects based on two Hausman tests (J. A. Hausman, 1978) for each study with the all-category data set. All Hausman tests were highly statistically significant (Model 1: $\chi^2 = 73.3$, $p < 0.001$; Model 3: $\chi^2 = 356.7$, $p < 0.001$). The estimation results are qualitatively and quantitatively in line with the reported findings of the pooled OLS (see Table 3.4. The Model 1 estimation results are presented in Table A21 and the Model 3 estimation results in Table A22.

**(ii) Zero Inflated Negative Binomial Model** Due to 92% of Zeros of our dependent variable $\text{WasteRate}_{p,s,t}$ on the store-product-week level, we

**Table A21:** H1 parameter estimates with the fixed effects model

| **Variables** | **Est.** | **Std. Err.** |
|---|---|---|
| *Intercept* | -3.400 | 0.481*** |
| *Promotion* | 2.114 | 0.091*** |
| *EoDStock* | -0.021 | 0.002*** |
| *SalesPrice* | 2.700 | 0.145*** |
| *OverForecastError* | 1.283 | 0.040*** |
| *StoreFixedEffects* | Yes | |
| *ProductFixedEffects* | Yes | |
| *ProductCategoryFixedEffects* | Yes | |
| *TimeEffects* | Yes | |
| *Cov.Est.* | Clustered | |
| *Observations* | 1,157,940 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; Standard errors are clustered on a store level. The sample data set is based on store-product-week observations of all categories (C-NS).

**Table A22:** H3 parameter estimates with the fixed effects model

| **Variables** | **Est.** | **Std. Err.** |
|---|---|---|
| *Intercept* | -3.500 | 0.480*** |
| *Substitution* | 0.660 | 0.053*** |
| *EoDStock* | -0.023 | 0.002*** |
| *SalesPrice* | 2.773 | 0.146*** |
| *OverForecastError* | 1.255 | 0.039*** |
| *StoreFixedEffects* | Yes | |
| *ProductFixedEffects* | Yes | |
| *ProductCategoryFixedEffects* | Yes | |
| *TimeEffects* | Yes | |
| *Cov.Est.* | Clustered | |
| *Observations* | 1,157,940 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.; Standard errors are clustered on a store level. The sample data set is based on store-product-week observations of all categories (C-NS).

estimated the effect of promotions on food waste using the Zero-Inflated Negative Binomial Model. Table A23 indicates directionally similar results compared to our main model.

**Table A23:** H1 parameter estimates using the Zero-Inflated Negative Binomial Model

| **Variables** | **Est.** | **Std. Err.** |
|---|---|---|
| *Inflation constant* | -6.073 | 0.002*** |
| *Intercept* | 0.876 | 0.005*** |
| *Promotion* | 0.716 | 0.015*** |
| *alpha* | 60.786 | 0.205*** |
| *DummyStore* | Yes | |
| *DummyProduct* | Yes | |
| *DummyProductCategory* | Yes | |
| *DummyTime* | Yes | |
| *Observations* | 1,157,940 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.; The sample data set is based on store-product-week observations of all categories (C-NS).

# 4 Stormy skies, spoiled supplies? The impact of weather on food waste in grocery retail

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In the submission process as of August 20, 2024

**Abstract** Food waste is a significant issue in the retail sector, contributing to both environmental and economic challenges. The weather and weather changes significantly impact customer traffic and buying behavior. This is the first study that examines the impact of weather conditions—specifically temperature, precipitation, and snow-on food waste in retail stores. We leverage related literature to develop hypotheses investigating the relationship between weather and food waste. Panel data from a cooperating European retailer for the period 2019 constitutes the main data source. Our sample includes 44 retail stores, resulting in 12,368 store-day observations. We combine the retail data with weather information from a national weather data provider. We accounted for individual heterogeneity using fixed effects models by incorporating store-fixed effects and several time effects. The results indicate that precipitation, temperature, and snow significantly affect food waste. Additionally, our findings reveal that these effects vary by season, day of the week, and store type. In particular, we find that precipitation, precipitation height, and the amount of snow increase food waste. This study contributes to the existing body of literature by providing insights into weather-related drivers of food waste in the retail sector, extending research on the effect of weather conditions on sales and other industries than grocery retail, e.g., apparel. Additionally, our study offers practical guidance for practitioners aiming to reduce food waste with short-term countermeasures due to specific weather events.

# 4.1 Introduction

Undoubtedly, the climate has changed, impacting many aspects of daily life. According to the German Federal Ministry for the Environment, climate change is leading to more frequent and severe weather events such as heatwaves, storms, and heavy rainfall, with significant impacts expected in the coming decades (UBA, 2019). While our focus is on investigating non-catastrophic weather conditions, the consequences of climate change, such as increased periods of rainfall, may alter "normal" weather patterns. Weather and changes in the weather significantly impact store sales for several reasons. Weather conditions can directly influence consumer behavior and shopping habits. For example, bad weather (like rain, snow, or heatwaves) can deter people from going out, reducing foot traffic in brick-and-mortar stores. Conversely, pleasant weather can encourage more people to go out and shop. The impact is particularly evident in brick-and-mortar stores, where physical presence is crucial for sales. Inclement weather can lead to declining customer visits, while favorable weather conditions can result in increased store traffic and, subsequently, higher sales (Badorf and Hoberg, 2020). The rise of online grocery shopping adds another layer of complexity for brick-and-mortar retailers, as customers can easily switch to quick commerce or other delivery options during adverse weather conditions (McKinsey, 2020). Weather conditions introduce a layer of complexity to demand forecasting, as they can cause sudden and unpredictable changes in consumer behavior. By integrating weather data into demand forecasting models, retailers can enhance their predictive accuracy and responsiveness, reducing the risk of both overstocking and stockouts. While the weather may already play an important role in demand forecasting of retail stores, the impact on sales and footfall has been investigated by empirical studies (see, e.g., Martínez de Albéniz and Belkaid, 2021; Gallino et al., 2019; Arunraj and Ahrens, 2016), yet the effect of weather on inventory management and food waste on the retail level remains an open research gap

Retailers typically adjust their inventory based on weather forecasts. For instance, grocery stores may stock more products consumed for BBQs or other outside activities when good weather is forecasted. By understanding these dynamics, retailers can better predict and respond to short-term changes in consumer behavior due to weather, optimizing their sales and inventory strategies accordingly. However, the variability of weather forecasts themselves poses a challenge. This variability necessitates that retailers remain vigilant about weather conditions, as they significantly impact customer shopping behaviors, particularly concerning the expiration of inventory in the store. As weather predictions become less reliable over longer time horizons, retailers must develop adaptive strategies that allow for flexibility and responsiveness in their inventory management practices (Steinker et al., 2017; Bertrand et al., 2015). Brick-and-mortar stores must continuously adapt to weather patterns to maximize their sales potential and minimize losses due to unsold inventory (Gallino et al., 2019).

This involves adjusting order quantities and considering logistical aspects such as storage capacity, transportation, and supply chain coordination. Effective inventory management of perishable products is paramount to ensure availability and freshness and reduce food waste.

Reduced footfall due to bad weather can lead to overstocking and increased holding costs, as unsold products occupy valuable shelf space and storage. Conversely, unexpected spikes in foot traffic during good weather can strain resources, leading to stockouts and missed sales opportunities, ultimately affecting customer satisfaction and store profitability. Finally, weather can affect the purchasing behavior of customers in brick-and-mortar stores. We, therefore, aim to identify if the weather on a specific day affects the food waste of those products that would expire on the same day.The economic implications of food waste are significant, with retailers incurring costs related to disposal, lost sales, and reduced profitability. Additionally, reducing food waste aligns with broader sustainability goals, addressing ethical concerns and regulatory pressures regarding environmental impact (Parfitt et al., 2010). To sum up, by exploring the interplay between weather conditions, inventory planning, and food waste in the chilled assortment of grocery retail, this research seeks to fill the identified research gap about the effect of weather on product expiration of perishables in grocery retail.

The research aim of this study, therefore, is to analyze how different weather conditions, specifically temperature, precipitation, and snow amount, affect the amount of food waste generated in retail stores. The scope of the research is geographically focused on Germany, utilizing a panel dataset from 2019 that includes store-SKU-level observations across various retail store types from a German retailer. We extend the proprietary dataset with daily weather observations from Deutscher Wetterdienst (DWD). By identifying weather conditions as drivers of food waste, our empirical approach enables us to develop actionable recommendations for retail store managers to reduce food waste. Our final dataset comprises 53 stores, which recorded a total food waste amounting to approximately EUR 850,000 over the one-year period of our study.

Our results reveal the effects of certain weather conditions on food waste in retail stores. Notably, temperature, precipitation, and snow are identified to substantially impact food waste. We also find that the impact of weather on food waste varies by season, the day of the week, and store type. This variation suggests that tailored strategies are necessary at different times of the year, on different days of the week and in different geographical settings. Our paper contributes to the existing body of literature in two ways. First, we contribute to the literature stream about the impact of the weather on retail store performance, including Roth Tran (2023); Bertrand et al. (2015); Rose and Dolega (2022). Second, we add to the growing literature about the empirical identification of food waste drivers, adding to research from Akkaş et al. (2019); Hübner et al. (2024). The implications of these findings are highly relevant for practitioners. Understanding that specific weather conditions can lead to increased food waste may help retailers adopt more dynamic inventory management strategies that consider weather forecasts to project the potential expiry of products. For instance, before days with high precipitation in the winter or a high temperature on the weekend during the summer, stores might try to reduce perishable stock beforehand to prevent spoilage and subsequent waste. In conclusion, our study identifies weather conditions as drivers for food waste in the retail sector. By adopting weather-dependent inventory management practices, retailers can significantly reduce food waste, enhancing their sustainability and profitability.

The remainder is structured as follows. We analyze related food waste and weather literature and develop the hypotheses in Section 4.2. Section 4.3 summarizes the research environment and empirical setting. Section 4.4 outlines the regression results and the robustness checks. The main results and their contribution to literature and management practice, as well as limitations and future avenues of research, are discussed in Section 4.5 before Section 4.6 concludes our paper.

## 4.2 Related literature and development of hypotheses

This section analyzes related literature (Section 4.2.1) and derives the hypotheses (Section 4.2.2).

### 4.2.1 Related literature

This literature review explores two streams of literature related to our study. First, we present existing literature about the effect of weather on retail store performance. Second, we identify prevalent research about identifying food waste drivers within retail environments.

**Weather and retail performance** The first stream of literature deals with the effect of weather on retail store performance. Studies have shown that weather variations significantly impact consumer behavior, store traffic, and sales outcomes. Steele (1951) categorized the effects of weather on retailing into four aspects: discomfort leading to reduced shopping activities, physical hindrances, psychological effects altering consumer behavior, and changes in product demand based on weather conditions. Agnew and Thornes (1995) found that extreme weather conditions, such as heavy rain or snow, can lead to store switching of consumers, affecting sales and increasing food waste due to decreased foot traffic. In a more recent study, Martínez de Albéniz and Belkaid (2021) found that temperature and rain affect sales of apparel retail stores. Badorf and Hoberg (2020) studied the influence of temperature, sunshine duration, and precipitation on sales and further identified that sales forecasting accuracy can be increased by incorporating weather forecasting in the short term. Arunraj and Ahrens (2016) investigated how temperature, precipitation, snow amount, sunshine duration, and humidity affect store sales and traffic in the food and fashion industries. Tian et al. (2021) examined the impact of sunshine, rain, air quality, temperature, and wind on the retailer's sales performance. Roth Tran (2023) recently found that extreme heat, extreme cold, precipitation, snowfall, and snow amount affect sales of an apparel and sporting goods retailer. Yet none of these studies has investigated the impact of weather on food waste.

**Food waste in retail** A small but growing body of studies investigates the reasons for food waste in retail stores. This second stream of literature focuses on identifying drivers of food waste in retail stores. Akkaş et al. (2019) found that, e.g., case pack size, supply chain aging, manufacturer sales incentives, replenishment workload, and minimum order rules can increase food expiration and waste. Mena et al. (2014) highlighted that factors such as demand transparency, quality management, process controls, shelf-life management, and packaging design significantly impact food waste. Inefficient stock management, including overstocking and poor inventory control, also increases food waste. Teller et al. (2018) focused on the root causes of food waste within the retail environment, emphasizing unwanted customer behavior and irregular demand patterns as key drivers. Wink et al. (2024a) find that food waste levels are affected by certain store characteristics, e.g., fresh-cut products, double placement and inventory, or the ownership of a store. Hübner et al. (2024) find that customers actively searching for products with longer expiration dates increase food waste at retail stores. Wink et al. (2024b) identify promotions as food waste drivers for promoted and cannibalized perishable products in grocery retail.

However, empirically studying the impact of weather on food waste in retail stores remains an open research gap. Our study, therefore, aims to fill this gap by empirically analyzing the relationship between, for example, temperature, precipitation, and snow on the ground and food waste levels in retail stores.

### 4.2.2 Expected impact of weather on food waste

This section develops hypotheses regarding the relationship between weather factors and food waste. Generally, the weather in Bavaria in Germany exhibits a varied climate based on four seasons. It is characterized by cold winters with average temperatures between -10 to 0°C, frequently accompanied by snowfall. The summer season typically features dry and hot conditions, with average temperatures ranging from 20°C to 30°C. Transitional seasons, such as fall and spring, bring cooler temperatures and vibrant foliage in autumn, while spring is marked by gradual warming and blooming flora. Due to the variability among the four seasons, the research focuses on weather conditions in relation to the adjacent days.

Warmer temperatures can significantly impact consumer behavior, mood, and purchasing decisions. Research indicates that positive moods, often induced by warmer weather, are associated with increased time spent outdoors (Keller et al., 2005). Steinker et al. (2017) found that temperature fluctuations significantly affect daily sales, particularly in the summer, influencing consumer demand and potential waste. While warmer temperatures can reduce foot traffic in retail stores, as extreme heat can deter shopping trips, this reduction in store visits might lead to unsold inventory and increased food waste. However, others, like Rose and Dolega (2022), argue that warmer weather can increase outdoor activities and shopping trips, leading to higher sales and potentially less waste. However, grocery shopping may not be considered a hedonistic buying driven by appeal to the senses and emotions. Grocery shopping is attributed to utilitarian buying, which refers to purchasing goods based on practical, functional, and rational considerations rather than emotional or sensory gratification. This buying behavior is driven by necessity, efficiency, and a product or service's utility. We will hypothesize that a high-temperature deviation leads to temporal shifts in consumer behavior, e.g., delaying grocery shopping to use the good weather for leisure activities, and hence to demand shifts that increase food waste:

*Hypothesis 1 (H1): The amount of food waste in retail increases on days with the highest temperature of the week.*

In a similar vein, precipitation, particularly heavy rainfall, can discourage consumers from visiting retail stores. This decrease in customer footfall reduces sales, resulting in a surplus of unsold products that may not be consumed within their shelf life, thus increasing food waste. Martínez de Albéniz and Belkaid (2021) has shown that rainfall negatively impacts the number of shoppers in streets, while the footfall in malls increased. Badorf and Hoberg (2020) found that rainfall can sometimes increase foot traffic to indoor shopping centers as consumers seek refuge from the weather. Additionally, Tian et al. (2021) argue that modern retail strategies, such as targeted promotions and adjusted stock levels, can mitigate the impact of rainfall on food waste. Given that the usual setting for retail stores are not located in a shopping mall, we hypothesize that the decrease in customer footfall due to precipitation reduces sales in grocery stores, which may result in a surplus of unsold products, thus increasing food waste.

*Hypothesis 2 (H2): The amount of food waste in retail increases on precipitation days.*

While single precipitation events can lead to increased food waste due to sudden drops in consumer footfall, consecutive days of precipitation may mitigate this effect. Consumers may adapt their shopping habits in response to persistent adverse weather conditions, potentially altering their purchasing patterns to accommodate longer periods without shopping trips. For example, consumers might stock up on non-perishable items during breaks between rainy days or during the initial days of rain, reducing the need for frequent trips. This adaptive behavior could lead to more balanced inventory management by retailers, who might also adjust their stock levels in anticipation of prolonged adverse weather. Therefore, we hypothesize that food waste decreases again on the day after a precipitation day, even if the second day in a row is a precipitation day.

*Hypothesis 3 (H3): The amount of food waste in retail decreases is lower on the second of two consecutive precipitation days.*

Moreover, we argue that the severity and duration of precipitation events will likely directly impact food waste levels. More severe or prolonged rainfall can significantly disrupt consumer behavior. Heavy precipitation can deter shopping trips to a greater extent, leading to higher levels of unsold perishable goods that contribute to food waste. Our hypothesis is that heavier or longer precipitation during the day affects customer purchasing behavior and consequently increases food waste. Additionally, we hypothesize that this effect is non-linear and diminishes at a certain threshold so that the precipitation height beyond a certain point does not affect food waste any further.

*Hypothesis 4 (H4): The amount of food waste in retail increases with the precipitation height.*

Snowfall can significantly disrupt consumer mobility. Severe snowfall, snowy or icey roads and sidewalks can lead to road closures and public transport delays, preventing consumers from reaching retail stores. Snow can deter consumers from making non-essential shopping trips, leading to decreased foot traffic and sales in retail stores (see e.g., Roth Tran, 2023). However, one might think that snow can sometimes increase spending on essential items to avoid frequent store visits during prolonged times of snow on the ground. This behavior could potentially reduce food waste if retailers manage their inventory effectively. However, we hypothesize that food waste increases during snow on the ground due to the restricted mobility of the customers.

*Hypothesis 5 (H5): The amount of food waste in retail increases with the amount of snow.*

## 4.3 Data description

We received our panel data from a major German retail chain referred to as AlphaCo. In this section, we describe the data used for our study, how we extended the panel data using weather data from DWD, and define the variables used in the regression models.

**Study background and retail setting** Our partnering retail chain is headquartered in Germany and operates a vast network of stores across Europe, totaling more than 3,500 grocery stores. Their product range encompasses over 50,000 items spanning various categories such as fruits, vegetables, chilled, frozen and non-food products. The original dataset includes daily observations from 209 stores from 1st January to 31st December 2019 from stores in the state of Bavaria in Germany. The dataset comprises two distinct types of retail stores: 97 urban stores and 112 non-urban stores. Urban stores are, e.g., characterized by a greater population density and enhanced public transportation infrastructure. In contrast, non-urban stores are positioned in less densely populated areas with comparatively limited commercial development. Consequently, these stores are typically located in more rural environments. The region provides an ideal setting for studying the effect of weather on retail performance due to large weather differences between the seasons. This, for example, allows us to study precipitation and snow amount in addition to temperature effects. The store opening hours are consistently 7 am to 8 pm from Monday to Saturday. Due to computational reasons based on store-product-day level data of the initial sample, we draw a random sample of 30 urban and 30 non-urban stores from our initial dataset and ensure via a z-score that the sample is a good enough representation of the full sample[1]. For each store-SKU-day observation, we obtained sales, food waste and forecasting data.

We focus our study on the standardized chilled assortment, which is not subject to the customers' perception of the visual appearance of, e.g., fruits and vegetables. We, therefore, exclude biases due to so-called "ugly produce". The initial dataset contains 2,700 chilled stock-keeping units (SKUs) distributed among six primary categories. Based on discussions with the partnering retail chain, we select the self-service product categories Delicacies, Convenience, Milk/Dairy, and Cheese, given that these product categories have an identical ordering process at the retailer and to avoid any biases on our estimations through differing ordering and replenishment mechanisms. This process is based on automated ordering, while other categories, e.g., fresh meat, are not based on the automated ordering process and are, therefore, subject to the replenishment performance of each individual store. Two additional replenishment mechanisms need to be considered. First, store managers can place manual orders for the selected product categories in addition to the automatically ordered amounts, usually based on specific customer orders. Note that store managers cannot reduce the automatically generated amounts but can only order more. Second,

[1]The z-values are based on the null hypothesis that the sample mean and the full data set's mean do not differ. We fail to reject the null hypothesis based on a z-score for sales of 52.10 on a 0.001 significance level

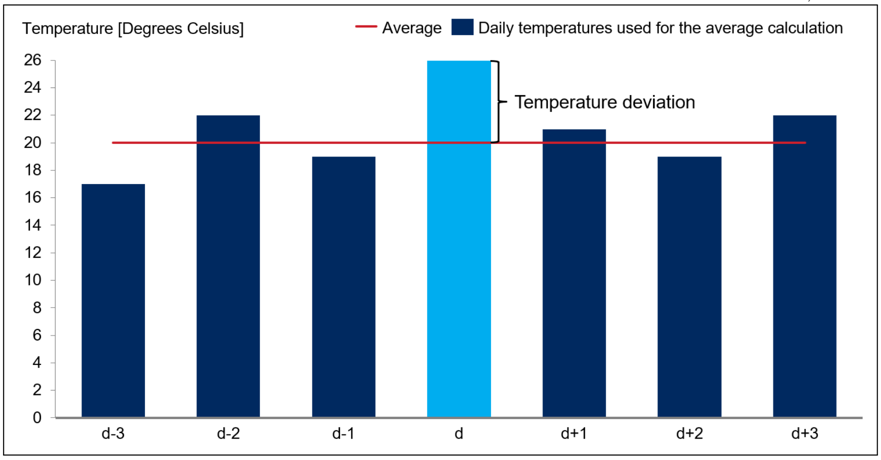
warehouse-level stock, e.g., close-to-expiry excess stock, can be allocated to stores without specific automated or manual orders, shifting product expiration from the warehouse to the retail level. After the arrival at the store, all products are replenished by store employees on the shelves and sold through customer self-service.

**Weather data** We extend our dataset by using non-catastrophic weather features depending on precipitation, snow amount, and temperature to investigate the impact of weather conditions on food waste within retail stores. Weather data in this research is sourced from the DWD, an official unit belonging to the German Federal Ministry for Digital and Transport, offering information on various weather metrics. Since food waste units in the retail dataset are logged daily, only daily weather information was gathered to analyze its causal effects with daily food waste records. Following pertinent literature (see, e.g., Martínez de Albéniz and Belkaid, 2021), we consciously did not include additional weather parameters due to high correlations between the features, e.g., relatively high temperature, a relatively long sun duration, or less cloud coverage. The weather data collection spans from January 2019 to December 2019. Considering the dispersion of retail stores across different cities in Southern Germany, weather data and their corresponding postal codes were retrieved from all weather stations. Subsequently, each store was linked to its nearest weather station (within a 20 km radius) based on the postal code. When matching the weather data with our drawn sample of 60 stores, we only achieved a balanced weather dataset for 53 stores, the number of stores included in the final sample.

All stores are open from Monday to Saturday. Food waste bookings for unsold goods on a Saturday happen the next day, so we accounted these values to Saturdays. Further, we removed all non-revenue days from the dataset, e.g., due to public holidays, to avoid any biases from daily events during which the store was not open. Additionally, we extended our panel data set by storing attribute data. We included all stores for which full information was available to avoid stores that opened or closed during the data collection period. Thus, the final sample contains 12,368 store-day combinations based on 44 stores and reduced by all Sundays and non-revenue days, e.g., public holidays, as explained above. The total food waste across all products and stores in the final sample is almost EUR 750k.

**Variables** The target variable $\text{FoodWasteUnits}_{s,d}$ denotes the total amount of wasted units in the store $s$ on day $d$. Note that our research aims to identify the effect of weather on product waste on the same day that the investigated weather condition happened. Therefore, we use the absolute value of food waste and assume that all other effects of customer behavior on food waste, e.g., picking for expiration dates, remain stable throughout the year. Given that products expire every day in the retail store and food waste is recorded every day, our approach is suited to identify the additional food waste on a daily basis based on the daily weather conditions. To investigate hypothesis $H1$, we develop the independent variable $\text{TemperatureDeviation}_{s,d}$, calculated as the absolute deviation in degrees Celsius compared to the adjacent previous and following three days. This means that a higher temperature deviation remarks days with more favorable weather within seven days (see Figure 4.1). To extend the investigation of $H1$ related to different average temperature levels across the year, we add the variable $\text{MeanTemperature}_{s,d}$, representing the average temperature in degrees Celsius over one week. Next, we convert the precipitation amount variable into a binary variable $\text{PrecipitationBinary}_{s,d}$ to further explore the impact of precipitation events on food waste alongside precipitation intensity, i.e., to test hypothesis $H2$. Further, we develop the lagged variable $\text{Precipitation2DaysInARow}_{s,d,\delta}$, which checks if the previous day *delta* of the day $d$ was a precipitation day for store $s$ and if day $d$ was a precipitation day as well ($H3$). To study hypothesis $H4$, $\text{PrecipitationHeight}_{s,d}$ refers to the volume of precipitation in millimeters (mm) on the day $d$ in the postal code of store $s$, which can be rain or snow. Additionally, we define the variable $\text{PrecipitationHeightSquared}_{s,d}$ to analyze potential non-linear effects of $\text{PrecipitationHeight}_{s,d}$. Finally, we use the DWD weather data point about the amount of snow to create the independent variable $\text{SnowAmount}_{s,d}$, how much snow in centimeter (cm) existed to study hypothesis $H5$. Table 4.1 summarizes the variables for our study.

**Figure 4.1:** Illustration of the calculation logic for $\text{TemperatureDeviation}_{s,d}$ on day $d$




We additionally include multiple control variables. $\text{Sales}_{s,d}$ refers to the summed-up sales of all SKUs in store $s$ on day $d$. $\text{Allocation}_{s,d}$ is the sum of all shipments from the regional warehouse to the store $s$ on the day $d$ that the regional warehouse delivered to the store. That means this was not ordered by the store but centrally allocated. This represents excess stock on the warehouse level that is at risk of expiring there. Further, stores can manually re-order products, e.g., based on individual end customer needs or if they want to receive more stock than automatically ordered. We account for those manual orders by also adding the control variable $\text{ManualOrders}_{s,d}$, which represents the number of consumer units of all products arriving at the store $s$ on day $d$ because of manual ordering. The continuous variable $\text{ForecastError}_{s,d}$ represents the average of the MAD (mean absolute deviation) of all products in the store $s$ on day $d$, which denotes the difference between forecasted and realized sales in units on one specific day. Additionally, we include multiple fixed effects in our models. First, we add store-fixed effects to account for any store-dependent effects on food waste, e.g., based on their store attributes. Second, we include weekday-fixed effects to account for weekly patterns, e.g., Saturday as a predominant day to make larger grocery purchases. We find short-term discounts of close-to-expiry products for a negligible amount of observations of approximately 3%, which we disregard for the identification of weather effects on food waste.

**Table 4.1:** Overview of variables

| | |
|---|---|
| **Dependent variable** | |
| $\text{FoodWasteUnits}_{s,d}$ | Amount of food waste caused by product expiry of store $s$ on day $d$ |
| **Weather variables of interest** | |
| $\text{Temp.Deviation}_{s,d}$ | Deviation in degrees Celsius of the temperature in the postal code of store $s$ on day $d$ compared to an average temperature of three previous and next days in store $s$ |
| $\text{PrecipitationBinary}_{s,d}$ | Binary variable indicating whether precipitation happened in the postal code of store $s$ on day $d$ |
| $\text{PrecipitationRow}_{s,d,\delta}$ | Binary variable indicating whether precipitation happened in the postal code of store $s$ on day $d$ and the day before $\delta$ |
| $\text{MeanTemp}_{s,d}$ | Average temperature in degrees Celsius in the postal code of store $s$ on day $d$ as an average over seven days |
| $\text{PrecipitationHeight}_{s,d}$ ($\text{PrecipitationHeight}^2_{s,d}$) | (Squared) Volume of precipitation in millimeter (mm) on the day $d$ in the postal code of store $s$ |
| $\text{SnowAmount}_{s,d}$ | Amount of snow in centimeter (cm) on the day $d$ in the postal code of store $s$ |
| **Control variables** | |
| $\text{Sales}_{s,d}$ | Sold number of consumer units in store $s$ on day $d$ |
| $\text{Allocation}_{s,d}$ | Volume of allocated consumer units from the warehouse to store $s$ on day $d$ |
| $\text{ManualOrders}_{s,d}$ | Volume of shipped consumer units based on manual orders to store $s$ on day $d$ |
| $\text{ForecastError}_{s,d}$ | Average of the MAD of all products in store $s$ on day $d$, which denotes the difference between forecasted and realized sales in units on one specific day |

**Descriptive statistics** Table 4.2 shows descriptive statistics of the introduced variables for our study.

## 4.4 Impact of weather on food waste

In this section, we develop the regression models to test our hypotheses and show the estimation results. We find empirical evidence that weather affects

**Table 4.2:** Summary statistics

| Variable | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|
| $\text{FoodWasteUnits}_{s,d}$ | 40.755 | 44.251 | 0 | 620 |
| $\text{Temp.Deviation}_{s,d}$ | -0.011 | 1.931 | -5.643 | 6.129 |
| $\text{PrecipitationBinary}_{s,d}$ | 0.434 | 0.496 | 0 | 1 |
| $\text{PrecipitationRow}_{s,d,\delta}$ | 0.262 | 0.440 | 0 | 1 |
| $\text{MeanTemp}_{s,d}$ | 10.577 | 7.386 | -9.100 | 28.100 |
| $\text{PrecipitationHeight}_{s,d}$ | 1.990 | 5.508 | 0.000 | 88.300 |
| $\text{PrecipitationHeight}^2_{s,d}$ | 34.292 | 271.409 | 0.000 | 7,796.890 |
| $\text{SnowBinary}_{s,d}$ | 0.075 | 0.264 | 0 | 1 |
| $\text{Sales}_{s,d}$ | 2,554 | 1,616 | 558 | 23,361 |
| $\text{Allocation}_{s,d}$ | 376.919 | 585.770 | 0 | 4,640 |
| $\text{ManualOrders}_{s,d}$ | 10.099 | 95.015 | 0 | 5,323 |
| $\text{ForecastError}_{s,d}$ | 22.043 | 18.662 | -45.658 | 374.477 |

food waste in multiple ways. In greater detail, we find that temperature, precipitation, and snow amount significantly affect food waste. Table 4.3 shows each independent variable's effect direction and size. We extend our main findings by presenting identified interaction effects of the weather variables of interest with the type of weekday, seasons, and the store format in Table 4.4. We conclude this section with multiple robustness checks in Section 4.4.4 based on different model specifications and estimation methods.

### 4.4.1 Model description

Our results are based on fixed effects (FE) models, which include store- and weekday fixed effects. As our dependent variable is $\text{FoodWasteUnits}_{s,d}$ and the unit of analysis is on store-day level, the results can be directly interpreted as unit changes in each store and generalized to other retail stores. The main model is presented in Equation (4.1). We extend the findings from our main model through interaction effects.

$$\begin{aligned}\text{FoodWasteUnits}_{s,d} =&\beta_0 + \beta_1 \cdot \text{Temp.Deviation}_{s,d}\\ &+\beta_2 \cdot \text{MeanTemp}_{s,d} + \beta_3 \cdot \text{PrecipitationBinary}_{s,d}\\ &+\beta_4 \cdot \text{PrecipitationRow}_{s,d,\delta} + \beta_5 \cdot \text{PrecipitationHeight}_{s,d}\\ &+\beta_6 \cdot \text{PrecipitationHeight}^2_{s,d} + \beta_7 \cdot \text{SnowAmount}_{s,d}\\ &+\text{Controls} + \epsilon_{p,s}\end{aligned} \tag{4.1}$$

### 4.4.2 Weather effects on food waste

**Temperature deviation effect** Our empirical results, summarized in Table 4.3, confirm the hypothesis *H1.* Temperature deviations have a significant influence on food waste. Recall that temperature deviation is calculated as the absolute deviation in degrees Celsius compared to the adjacent previous and following three days. That means a higher deviation remarks days with more favorable weather within seven days. We show that food waste increases by 0.574 units in Model 1 for each degree temperature deviation against the rolling adjacent days' temperature average. This means that warmer days compared to the current week significantly increase food waste volume.

**Percipitation effect** We find empirical evidence for the existence of multiple effects of precipitation on food waste. Firstly, we confirm hypothesis *H2* since precipitation as a binary variable increases food waste of 3.381 consumer units. This finding aligns with the result of Martínez de Albéniz and Belkaid (2021), who state that rain decreases footfall in retailing and, in our case, leads to lower sales that turn into increased expiration of products. Secondly, we find that food waste decreases on the day after the precipitation day with a coefficient estimate of -4.567. Hence, we confirm hypothesis *H3.* Considering that potential grocery purchases are held back on precipitation days to the next day without precipitation, if possible, this underscores our finding from hypothesis *H2* and, thus, demonstrates the impact of precipitation on customers' mobility. Thirdly, we confirm hypothesis *H4* since we find two effects related to the variable $PrecipitationHeight$. On days with higher precipitation volumes, the absolute number of waste units increases by 0.483 for a one mm increase in precipitation. This effect saturates due to the negative coefficient (-0.006), so that at a certain threshold, waste does not increase any further, even though the precipitation volume may increase further.

**Snow effect** Beyond the effect of precipitation on food waste, we also find evidence for the existence of the effects of snow on food waste with a parameter estimate of 4.255, hence confirming *H5*.

**Table 4.3:** Parameter estimates for weather variables

| **Variables** | **Est.** | **Std.Err.** |
|---|---|---|
| Intercept | 14.159 | 2.944*** |
| Temp.Deviation | 0.574 | 0.196** |
| MeanTemp | 0.140 | 0.073 |
| PrecipitationBinary | 3.381 | 1.019*** |
| PrecipitationRow | -4.567 | 1.498** |
| PrecipitationHeight | 0.483 | 0.136*** |
| PrecipitationHeight$^2$ | -0.006 | 0.002** |
| SnowAmount | 4.255 | 1.540** |
| Controls | Yes | |
| $\mathrm{R-squared}$ | 0.106 | |
| Num.Observations | 12,368 | |
| $\mathrm{F-statistic}$ | 91.263 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; The dependent variable is $\mathrm{FoodWasteUnits}_{s,d}$.

## 4.4.3 Interaction effects of weather on food waste

We extend our main findings by investigating the interaction effects of the weather on food waste as follows. We analyze how weather variables interact with three key factors. Firstly, we examine whether weather effects vary between weekdays and weekends to discern weekly patterns.

Secondly, we explore the influence of seasons and weather on food waste by creating interaction terms between each weather variable and the four seasons: Winter (December-February), Spring (March-May), Summer (June-August), and Fall (September-November). Lastly, we investigate how store attributes and weather jointly affect food waste by categorizing stores into urban and non-urban settings to estimate their respective impacts.

**Weekday interaction effects** Model 2 in Table 4.4 shows the results from the interaction of the weather variables of interest with the type of day. The results indicate that different weather effects on food waste are observed depending on the day of the week. Interestingly, the estimation results reveal that the effects of PrecipitationBinary$_{s,d}$ (3.428) and PrecipitationHeight$_{s,d}$ (0.969) significantly influence weekday food waste. Similar to the findings from Model 1, the effect of PrecipitationHeight$_{s,d}$ diminishes above a certain threshold, as indicated by the negative coefficient estimate for the squared term PrecipitationHeightSquared$_{s,d}$ (-0.012). SnowBinary$_{s,d}$ is also only statistically significant on weekdays (5.773). To conclude, the day of the week influences all variables related to precipitation and snow on food waste, while most of the effects are mostly relevant on weekdays.

**Season interaction effects** The estimation results for the interaction of weather variables with seasons are presented under Model 3 in Table 4.4. We find significant effects for selected seasons on different weather variables. First, the interaction effect of precipitation with the winter season is strongly significant, with a high positive coefficient (14.090). The coefficient for Precipitation2DaysInARow$_{s,d,\delta}$ is negative for winter (-12.245) with no other season for which we identify this effect, indicating that winter is the driving factor behind the influence on food waste. The analysis of interaction effects with MeanTemperature$_{s,d}$ is highly interesting due to two emerging clusters. On the one hand, a higher mean temperature during fall and winter indicates reduced food waste. On the other hand, a higher mean temperature during spring and summer indicates exactly the opposite, leading to increased waste. A closer look at the summer season shows that a higher temperature deviation increases food waste, while precipitation reduces food waste based on a coefficient estimate of -8.392.

**Store type interaction effects** Finally, Model 4 in Table 4.4) shows the estimation results for the interaction of weather variables with the store type. The store-fixed effects are removed from the model specification to estimate the parameters. While the precipitation event matters in non-urban stores due to a coefficient estimate of 4.073, the precipitation height is only significant for urban stores (0.632). The effect of snow on food waste is identified for non-urban stores (4.319). Finally, the effect of temperature deviation on food waste is identified for urban stores based on the coefficient estimate of 0.632.

### 4.4.4 Robustness checks

We apply multiple robustness checks to validate the reliability and consistency of our findings. First, we replace the dependent variable that measures food waste in absolute terms with a dependent variable that measures food waste relative to sales. Second, we show that the results still hold true when using the Pooled OLS models instead of FE models. We confirm that we obtain qualitatively the same results with each robustness check.

**Waste rate as dependent variable** We substitute the dependent variable from our main model with $\text{WasteRate}_{s,d}$[2], employing the relative food waste compared to sales. Table 4.5 displays the estimation results, which are directionally similar to our main findings.

[2] $\text{WasteRate}_{s,d} = \text{FoodWasteUnits}_{s,d}/(\text{FoodWasteUnits}_{s,d} + \text{Sales}_{s,d})$

**Pooled OLS model** We employ a pooled OLS model to assess the findings from the FE models by disregarding the panel structure of our dataset. To account for heterogeneity among stores and varying weekdays, we introduce dummy variables for both stores and weekdays. Our analysis reveals consistent results in terms of direction and effect size when compared with the FE models, both without interaction effects (refer to Table 4.6) and with interaction effects (refer to Table 4.7). However, the only deviation arises with the interaction effects of weekdays and mean temperature, which attain statistical significance only at the 0.05 level and should, therefore, be approached with caution in terms of significance.

## 4.5 Discussion

This section provides an interpretation of our main results. Overall, we find empirical evidence for the existence of the effects of temperature, precipitation and snow on food waste levels at the retail level. The effect sizes and directions are heterogeneous and dependent on the weekday and the season.

As discussed earlier, rain restricts customer mobility. Consequently, food waste increases on working days with precipitation when time is limited, e.g., for customers who work regularly from Monday to Friday. However, this effect diminishes beyond a certain threshold due to non-linear impacts. Interestingly, the negative coefficient for weekend precipitation height is counterintuitive at first glance. However, since customers have more flexible schedules on weekends, they may choose grocery shopping over other non-outdoor related activities. The stronger the precipitation, the more likely they are to grocery shop, as outdoor activities become less attractive. Further, snow increases food waste during the week but not on weekends. This could be caused by the fact that many workers tend to do grocery shopping in the evening after work, where snowy pavements could become icey and more slippery than during the day on the weekend.

Additionally, the temperature deviation matters most during winter, when customers may use the best weather days for outdoor activities, e.g., skiing in the Alps. The effect of temperature deviations on food waste during summer is lower but still positive. Summer days in Germany typically represent the best days during the year for many outdoor leisure and social activities, so postponing grocery shopping may be a logical consequence of higher temperatures. During these occasions, grocery shopping and cooking at home may be replaced with dining in restaurants or leisure locations. This is underscored by our finding that rainy days led to reduced waste during the summer months, which is when customers may consider grocery shopping as ideal for not having to do obligatory grocery shopping on better weather days. Further, our finding that precipitation during winter is strongly significant and large in terms of effect size makes sense, as rain or snow in the winter in Southern Germany could lead to slippery roads and sidewalks if the temperature is around 0 degrees Celsius. The danger of physically slipping and falling to the ground apparently inhibits a significant risk for customers, restricts their mobility tremendously, and leads to increased food waste. Snowfall may be problematic when the fallen snow starts to freeze, which causes the roads and sidewalks to get slippery. To avoid having to leave home to, e.g., have dinner in a restaurant and having trouble coming back during the night, one potential reason would be that people tend to stay in more often and therefore delay buying groceries.

## 4.6 Conclusion

**Summary** This study investigates the impact of weather on food waste in grocery retail. Based on existing literature about weather's effect on retail performance, we formulated hypotheses and used fixed effects models as our identification strategy. Our analysis utilizes a proprietary panel dataset from a major European retail chain. We identify temperature and precipitation as key factors influencing food waste. Additionally, we examined the interaction effects of weekdays, seasons, and store types with weather on food waste. In particular, we find that temperature deviations, precipitation events and height and snow amount influence food waste. The size and direction of these effects vary depending on the day of the week, season and the store type.

**Managerial Insights** Our insights from this study can be readily translated into actionable initiatives for our collaborating retail chain and industry practitioners. By harnessing weather data, retailers can refine their inventory management strategies. For instance, anticipating hot days, particularly on weekends during the summer, could prompt proactive measures to mitigate food waste, such as implementing targeted promotions or adjusting inventory levels to accommodate anticipated shifts in consumer demand. Strategic timing of promotions for close-to-expiry products can be aligned with periods of heightened food waste expected due to weather conditions, thus optimizing sales while minimizing waste. Another example is that precipitation during the summer implies an opportunity to reduce food waste, so overstocks from the central warehouse should be allocated to the stores before the precipitation day.

**Contribution to literature** Our study makes two main contributions to the literature. First, by providing empirical evidence on the impact of weather variables on food waste, we enhance the understanding of weather's effect on retail performance. We contribute to the empirical identification of weather effects on store performance, extending recent work in the operations management literature, including Roth Tran (2023), Martínez de Albéniz and Belkaid (2021) and Bertrand et al. (2015). Second, we contribute to the growing body of research on identifying food waste drivers in grocery retail. Our findings offer practical insights for managers to improve inventory management using weather forecasts, thereby addressing a critical global sustainability issue by outlining strategies to reduce food waste in grocery retail. We add to the growing literature about food waste in grocery retail incl. Akkaş et al. (2019), Wu and Honhon (2023), Riesenegger and Hübner (2022) by identifying additional opportunities for food waste reduction.

**Limitations and future research** Our research is limited in the following ways. Firstly, based on the daily precipitation values, precipitation could also have happened outside the opening hours as the opening hours only account for 13 (7 a.m.-8 p.m.) out of 24 hours. While this represents a limitation, even precipitation outside the opening hours may influence customers' mobility and, therefore, may affect the footfall and sales of the grocery store. Secondly, we only have stores from one state in Germany, wherefore a broader geographical area would be beneficial to increase the generalizability to other countries beyond Germany as well. Thirdly, our dataset is limited to a one-year period. Expanding the geographical area and the time period remains a great opportunity for future research. Additional avenues for future research follow. Fourth, we only consider same-day expiration of products, which represents a limited database, given that for each product, days exist without product expiration, and other drivers exist for food waste, e.g., customer picking for expiration dates. Investigating ultra-fresh products, such as fresh-cut products that expire the next day after preparation, would be a good setting for a consecutive study to validate our findings.

Based on our findings and empirical setting, we propose several research opportunities. Firstly, as noted by Steinker et al. (2017) and Martínez de Albéniz and Belkaid (2021), research should be extended to include the shift toward online sales by retailers. This shift could help reduce food waste through strategies like close-to-expire promotions. Additionally, understanding if inventory pooling can mitigate food waste, particularly during precipitation days in winter or hot summer days, would be valuable. Secondly, we encourage researchers to develop or adjust demand forecasting models to enhance the consideration of weather events and to link such forecasting to the projection of potential effects on food waste. Thirdly, given our limitations regarding precipitation data, we recommend studying the impact of precipitation hourly. This includes investigating precipitation height and its occurrence during specific hours, such as evening versus morning, and analyzing the share of precipitation hours within the total opening hours per day.

**Table 4.4:** Parameter estimates for weather interaction effects

| | Model 2 | | Model 3 | | Model 4 | |
|---|---|---|---|---|---|---|
| **Variables** | **Est.** | **Std.Err.** | **Est.** | **Std.Err.** | **Est.** | **Std.Err.** |
| Intercept | 18.338 | 2.511*** | 19.493 | 3.463*** | 14.167 | 2.943*** |
| Temp.DeviationxWeekday | 0.354 | 0.192 | | | | |
| Temp.DeviationxWeekend | 0.900 | 0.544 | | | | |
| PrecipitationBinaryxWeekday | 3.428 | 0.996*** | | | | |
| PrecipitationBinaryxWeekend | -0.479 | 3.790 | | | | |
| PrecipitationRowxWeekday | -5.007 | 1.497*** | | | | |
| PrecipitationRowxWeekend | 2.219 | 4.644 | | | | |
| MeanTempxWeekday | 0.162 | 0.074* | | | | |
| MeanTempxWeekend | 0.210 | 0.138 | | | | |
| PrecipitationHeightxWeekday | 0.969 | 0.130*** | | | | |
| PrecipitationHeightxWeekend | -1.023 | 0.368** | | | | |
| PrecipitationHeight$^2$xWeekday | -0.012 | 0.002*** | | | | |
| PrecipitationHeight$^2$xWeekend | 0.019 | 0.013 | | | | |
| SnowAmountxWeekday | 5.773 | 1.724*** | | | | |
| SnowAmountxWeekend | 3.862 | 4.278 | | | | |
| Temp.DeviationxWinterSeason | | | 1.944 | 0.542*** | | |
| Temp.DeviationxSpringSeason | | | -0.211 | 0.309 | | |
| Temp.DeviationxSummerSeason | | | 0.968 | 0.405* | | |
| Temp.DeviationxFallSeason | | | 0.432 | 0.317 | | |
| PrecipitationBinaryxWinterSeason | | | 14.090 | 2.415*** | | |
| PrecipitationBinaryxSpringSeason | | | -1.278 | 1.642 | | |
| PrecipitationBinaryxSummerSeason | | | -8.392 | 2.618** | | |
| PrecipitationBinaryxFallSeason | | | 3.848 | 1.822* | | |
| PrecipitationRowxWinterSeason | | | -12.245 | 2.448*** | | |
| PrecipitationRowxSpringSeason | | | -2.852 | 2.002 | | |
| PrecipitationRowxSummerSeason | | | 0.119 | 3.116 | | |
| PrecipitationRowxFallSeason | | | -0.684 | 2.059 | | |
| MeanTempxWinterSeason | | | -0.797 | 0.239*** | | |
| MeanTempxSpringSeason | | | 0.490 | 0.162** | | |
| MeanTempxSummerSeason | | | 0.300 | 0.081*** | | |
| MeanTempxFallSeason | | | -0.456 | 0.115*** | | |
| PrecipitationHeightxWinterSeason | | | 2.284 | 0.799** | | |
| PrecipitationHeightxSpringSeason | | | 0.272 | 0.166 | | |
| PrecipitationHeightxSummerSeason | | | 1.239 | 0.320*** | | |
| PrecipitationHeightxFallSeason | | | 1.658 | 0.905 | | |
| PrecipitationHeight$^2$xWinterSeason | | | -0.167 | 0.036*** | | |
| PrecipitationHeight$^2$xSpringSeason | | | -0.005 | 0.002* | | |
| PrecipitationHeight$^2$xSummerSeason | | | -0.010 | 0.009 | | |
| PrecipitationHeight$^2$xFallSeason | | | -0.131 | 0.063* | | |
| Temp.DeviationxUrbanStore | | | | | 0.632 | 0.222** |
| Temp.DeviationxNon − urbanStore | | | | | 0.484 | 0.314 |
| PrecipitationBinaryxUrbanStore | | | | | 2.576 | 1.505 |
| PrecipitationBinaryxNon − urbanStore | | | | | 4.073 | 1.306** |
| PrecipitationRowxUrbanStore | | | | | -5.606 | 2.114** |
| PrecipitationRowxNon − urbanStore | | | | | -3.470 | 1.949 |
| MeanTempxUrbanStore | | | | | 0.154 | 0.099 |
| MeanTempxNon − urbanStore | | | | | 0.126 | 0.110 |
| PrecipitationHeightxUrbanStore | | | | | 0.632 | 0.203** |
| PrecipitationHeightxNon − urbanStore | | | | | 0.360 | 0.196 |
| PrecipitationHeight$^2$xUrbanStore | | | | | -0.007 | 0.003* |
| PrecipitationHeight$^2$xNon − urbanStore | | | | | -0.007 | 0.004 |
| SnowAmountxUrbanStore | | | | | 4.149 | 2.473 |
| SnowAmountxNon − urbanStore | | | | | 4.319 | 2.065* |
| Controls | Yes | | Yes | | Yes | |
| R − squared | 0.098 | | 0.105 | | 0.106 | |
| Num.Observations | 12,368 | | 12,368 | | 12,368 | |
| F − statistic | 74.438 | | 44 | | 63.709 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; The dependent variable is $\text{FoodWasteUnits}_{s,d}$. Note that the estimation of Snow with Seasons is not possible due to perfect collinearity and is therefore excluded from this table.

**Table 4.5:** Parameter estimates for weather variables on the dependent variable $\text{WasteRate}_{s,d}$

| Variables | Est. | Std.Err. |
|---|---|---|
| Intercept | 0.019 | 0.001*** |
| TemperatureDeviation | 0.0004 | 7.87E-05*** |
| MeanTemp | 3.23E-05 | 3.20E-05 |
| Precipitation(Binary) | 0.0013 | 0.0004** |
| PrecipitationRow | -0.002 | 0.001*** |
| PrecipitationHeight | 0.0004 | 5.83E-05*** |
| $\text{PrecipitationHeight}^2$ | -5.45E-06 | 1.09E-06*** |
| SnowAmount | 0.002 | 0.001** |
| Controls | Yes | |
| R − squared | 0.052 | |
| Num.Observations | 12,368 | |
| F − statistic | 42.024 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

**Table 4.6:** Parameter estimates for weather variables using pooled OLS estimator

| Variables | Est. | Std.Err. |
|---|---|---|
| Intercept | 19.939 | 3.557*** |
| TemperatureDeviation | 0.593 | 0.199** |
| MeanTemp | 0.153 | 0.082 |
| Precipitation(Binary) | 3.356 | 1.026** |
| PrecipitationRow | -3.832 | 1.544* |
| PrecipitationHeight | 0.423 | 0.159** |
| $\text{PrecipitationHeight}^2$ | -0.006 | 0.002* |
| SnowAmount | 4.779 | 1.968* |
| Controls | Yes | |
| R − squared | 0.092 | |
| Num.Observations | 12,368 | |
| F − statistic | 78.106 | |

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

**Table 4.7:** Parameter estimates for weather interaction effects using pooled OLS estimator

| | Model 7 | | Model 8 | | Model 9 | |
|---|---|---|---|---|---|---|
| **Variables** | **Est.** | **Std.Err.** | **Est.** | **Std.Err.** | **Est.** | **Std.Err.** |
| Intercept | 23.740 | 3.247*** | 19.493 | 3.463*** | 20.244 | 3.625*** |
| Temp.DeviationxWeekday | 0.374 | 0.202 | | | | |
| Temp.DeviationxWeekend | 1.213 | 0.560* | | | | |
| PrecipitationBinaryxWeekday | 3.302 | 1.057** | | | | |
| PrecipitationBinaryxWeekend | -1.016 | 3.847 | | | | |
| PrecipitationRowxWeekday | -4.840 | 1.547** | | | | |
| PrecipitationRowxWeekend | 6.538 | 5.016 | | | | |
| MeanTempxWeekday | 0.145 | 0.090 | | | | |
| MeanTempxWeekend | 0.380 | 0.141** | | | | |
| PrecipitationHeightxWeekday | 0.886 | 0.155*** | | | | |
| PrecipitationHeightxWeekend | -1.057 | 0.376** | | | | |
| PrecipitationHeight$^2$xWeekday | -0.011 | 0.002*** | | | | |
| PrecipitationHeight$^2$xWeekend | 0.020 | 0.012 | | | | |
| SnowAmountxWeekday | 5.120 | 2.166* | | | | |
| SnowAmountxWeekend | 9.350 | 4.888 | | | | |
| Temp.DeviationxWinterSeason | | | 1.944 | 0.542*** | | |
| Temp.DeviationxSpringSeason | | | -0.211 | 0.309 | | |
| Temp.DeviationxSummerSeason | | | 0.968 | 0.405* | | |
| Temp.DeviationxFallSeason | | | 0.432 | 0.317 | | |
| PrecipitationBinaryxWinterSeason | | | 14.090 | 2.415*** | | |
| PrecipitationBinaryxSpringSeason | | | -1.278 | 1.642 | | |
| PrecipitationBinaryxSummerSeason | | | -8.392 | 2.618** | | |
| PrecipitationBinaryxFallSeason | | | 3.848 | 1.822* | | |
| PrecipitationRowxWinterSeason | | | -12.245 | 2.448*** | | |
| PrecipitationRowxSpringSeason | | | -2.852 | 2.002 | | |
| PrecipitationRowxSummerSeason | | | 0.119 | 3.116 | | |
| PrecipitationRowxFallSeason | | | -0.684 | 2.059 | | |
| MeanTempxWinterSeason | | | -0.797 | 0.239*** | | |
| MeanTempxSpringSeason | | | 0.490 | 0.162** | | |
| MeanTempxSummerSeason | | | 0.300 | 0.081*** | | |
| MeanTempxFallSeason | | | -0.456 | 0.115*** | | |
| PrecipitationHeightxWinterSeason | | | 2.284 | 0.799** | | |
| PrecipitationHeightxSpringSeason | | | 0.272 | 0.166 | | |
| PrecipitationHeightxSummerSeason | | | 1.239 | 0.320*** | | |
| PrecipitationHeightxFallSeason | | | 1.658 | 0.905 | | |
| PrecipitationHeight$^2$xWinterSeason | | | -0.167 | 0.036*** | | |
| PrecipitationHeight$^2$xSpringSeason | | | -0.005 | 0.002* | | |
| PrecipitationHeight$^2$xSummerSeason | | | -0.010 | 0.009 | | |
| PrecipitationHeight$^2$xFallSeason | | | -0.131 | 0.063* | | |
| Temp.DeviationxUrbanStore | | | | | 0.711 | 0.236** |
| Temp.DeviationxNon − urbanStore | | | | | 0.438 | 0.293 |
| PrecipitationBinaryxUrbanStore | | | | | 2.114 | 1.658 |
| PrecipitationBinaryxNon − urbanStore | | | | | 4.448 | 1.591** |
| PrecipitationRowxUrbanStore | | | | | -4.873 | 2.160* |
| PrecipitationRowxNon − urbanStore | | | | | -2.723 | 1.871 |
| MeanTempxUrbanStore | | | | | 0.115 | 0.154 |
| MeanTempxNon − urbanStore | | | | | 0.201 | 0.103 |
| PrecipitationHeightxUrbanStore | | | | | 0.588 | 0.211** |
| PrecipitationHeightxNon − urbanStore | | | | | 0.303 | 0.251 |
| PrecipitationHeight$^2$xUrbanStore | | | | | -0.007 | 0.003* |
| PrecipitationHeight$^2$xNon − urbanStore | | | | | -0.007 | 0.004 |
| SnowAmountxUrbanStore | | | | | 3.618 | 3.564 |
| SnowAmountxNon − urbanStore | | | | | 5.765 | 2.418* |
| Controls | Yes | | Yes | | Yes | |
| R − squared | 0.084 | | 0.105 | | 0.093 | |
| Num.Observations | 12,368 | | 12,368 | | 12,368 | |
| F − statistic | 63.205 | | 44 | | 54.967 | |

Notes: $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; The dependent variable is FoodWasteUnits$_{s,d}$. Note that the estimation of Snowfall with Seasons is not possible due to perfect collinearity and is therefore excluded from this table.

# 5 Conclusion and outlook

This doctoral thesis comprises three empirical studies about how different drivers affect food waste in grocery retail. Chapter 2 uses exploratory analysis to identify store attributes that lead to increased food waste levels. Adding to the findings about store operations, Chapter 3 focuses on the effects of promotions on food waste. Finally, Chapter 4 investigates how certain weather conditions affect food waste levels. In the following, the overarching contribution of this doctoral thesis to the body of literature and to managerial insights is given.

This doctoral thesis contributes to the empirical research in operations management, sustainability, and retail by addressing the pressing issue of food waste in grocery retail. While retail operations and sustainability research have already explored efficiency, resource management, and environmental impacts, the specific topic of food waste in grocery retail remains underexplored. This thesis fills this gap by providing empirical evidence on the complex interplay of factors at grocery retailers that lead to food waste. By situating food waste within the larger framework of sustainable retail operations, the thesis demonstrates how operational decisions and sustainability initiatives can mitigate or exacerbate food waste. It emphasizes the need for integrated approaches that align retail operations with sustainability goals, particularly in the context of food retailing, where waste reduction is both an environmental and economic imperative. The findings contribute to the academic literature and offer practical insights for retailers aiming to enhance sustainability while maintaining operational efficiency. This is especially relevant due to the generally low profitability margins in the retail industries, where even one-digit percentage cost reductions have major implications on a retailer's profitability. The contribution to literature and practitioners for each study is given below.

First, the thesis enhances the empirical operations management literature by identifying store-specific attributes and operational practices that exacerbate food waste. It underscores the importance of optimizing store planning and inventory management to mitigate waste. This contributes globally by providing actionable insights that can be applied across different retail environments, fostering more sustainable operational practices.

Second, exploring retail promotions as a significant driver of food waste offers a novel perspective on the trade-offs between sales growth and sustainability. This study advances the literature on the environmental impact of retail activities by highlighting the unintended consequences of promotions, which are a common practice worldwide. It challenges retailers to rethink their promotion strategies, integrating sustainability into the core of their operations, and contributes to the broader research on sustainable retail practices.

Third, the investigation into the effects of weather conditions on food waste extends the existing literature on the intersection of environmental factors and retail outcomes. By demonstrating how weather variability influences consumer behavior and food waste levels, the findings from this thesis contributes to the understanding of how external, uncontrollable factors can be managed to reduce waste. This research has broader implications for developing adaptive strategies that could be applied in various geographical and climatic contexts.

Overall, for researchers, this thesis advances the understanding of which factors contribute to food waste, offering a foundation for future studies to explore these relationships further, particularly in diverse geographical and climatic contexts. For practitioners, it challenges existing practices, particularly in inventory management and promotion strategies, urging retailers to integrate sustainability into their core operations. The societal relevance lies in the broader implications for reducing food waste, a critical global issue with significant economic, social, and environmental impact.

Going forward, I suggest the following avenues for future research. First, connecting the dots of research on multiple supply chain stages. Optimizing food waste levels on one supply chain stage might bear the risk of shifting food waste to the subsequent stage, e.g., from the wholesaler to the retailer or from the retailer to the end consumer. Research, incl. this doctoral thesis, about reducing food waste levels across multiple supply chain stages remains scarce.

Second, the grocery industry is developing fast, e.g., increasing penetration of online retailing, cashier-free mobile check-out stores, or personalized promotions based on customer accounts. The identified empirical food waste drivers must be validated in the new retailing world.

Third, the role of employee training and involvement in waste reduction needs further exploration. Studying the role of retail employees in food waste management, including the impact of training programs and employee engagement on reducing waste, could highlight best practices for involving frontline staff in sustainability initiatives.

Fourth, the influence of digital technologies and data analytics on food waste management offers another promising research avenue. With the increasing use of big data, artificial intelligence, and machine learning in retail, future studies could explore how these technologies can optimize inventory management, predict demand more accurately, e.g., for promotions, and ultimately reduce food waste.

Fifth, the impact of regulatory frameworks and policy interventions on food waste in grocery retail warrants further investigation. As governments worldwide introduce policies aimed at reducing food waste, research is needed to assess the effectiveness of these regulations and how they interact with retail operations and consumer behavior.

Sixth, cultural and regional differences in food waste generation across various retail environments present an important area for research. Understanding how cultural practices, regional food preferences, and local retail strategies influence food waste can lead to more tailored and effective waste reduction strategies.

Seventh, investigating the potential of circular economy practices, such as food waste valorization and redistribution, could offer significant insights into sustainable retail operations. Research could focus on how grocery retailers can integrate circular economy principles into their operations to minimize waste and create additional value from surplus food.

Eighth, given that the collaborating retail chain heavily benefitted from our study by getting transparency on food waste quantification and drivers, the impact of supply chain transparency on food waste needs further attention, i.e., examining how increased transparency and traceability in the food supply chain affect food waste levels. This research could explore the role of technology or other digital solutions in enhancing supply chain visibility.

Finally, exploring how partnerships between retailers, suppliers, and non-profit organizations can mitigate food waste represents another promising path for research for inter-organization food waste reduction opportunities. This research could include studies on, e.g., food donation programs or shared inventory systems to reduce waste across the supply chain.

To conclude, while the sustainability issue of food waste in grocery retail has garnered increasing attention from researchers and practitioners over the last decade, significant challenges remain. This dissertation addresses this urgent problem and highlights that the path toward achieving "zero waste" is complex. Retailers, especially large retail chains, possess an unparalleled opportunity and responsibility to mitigate food waste risks due to their scaling effects. Retailers should rethink their store operations and replenishment strategies based on specific store characteristics. They must carefully evaluate over-ordering for promotional activities and proactively reduce the close-to-expiry stock by considering weather forecasts that drive food waste. Further empirical research is needed to identify additional drivers of food waste, providing a foundation for effective countermeasures. Addressing these factors is essential to solving one of our time's most pressing global economic, social, and ecological problems.

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