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Measuring the resilience-efficiency trade-off: an empirical application for retail logistics

Katharina Berendes
University of Göttingen, Göttingen, Germany
Aliasghar Arabmaldar
Hertfordshire Business School, University of Hertfordshire, Hatfield, UK
Maik Hammerschmidt
University of Göttingen, Göttingen, Germany
Dominic Loske
TU Darmstadt, Darmstadt, Germany, and
Matthias Klumpp
Politecnico di Milano, Milan, Italy and University of Bremen, Bremen, Germany

Abstract

Purpose – Retail logistics is facing higher levels of disruptions, forcing retailers to enhance resilience. However, resilience initiatives such as higher safety stock levels often come at the expense of lower operational efficiency through higher cost levels and/or reduced outcomes.

Design/methodology/approach – This study offers a novel approach for addressing this critical resilience-efficiency trade-off based on robust data envelopment analysis (RDEA), combining DEA as a non-parametric tool for measuring efficiency and robust optimization as an established approach for dealing with disruptions. Based on RDEA, this study introduces a metric for quantifying the resilience-efficiency trade-off. Our study empirically validates this novel metric using a representative data set comprising distinct input and output values for stores of a German retail group.

Findings – By empirically proving this metric for a real-world retail logistics case, we show that most stores sacrifice significant portions of efficiency for an increased level of resilience. However, we identify stores that can align resilience and efficiency and are able to provide a refined understanding of how different stores navigate the challenges of a resilience-efficiency trade-off.

Originality/value – For practitioners, this study offers novel insights into assessing the costs of resilience, preventing managers from losing efficiency by prioritizing certain resilience initiatives over others (e.g. logistics activities over personnel resources). These insights enable a more balanced perspective in strategic resilience decision-making and logistics management.

Keywords Resilience, Efficiency, Data envelopment analysis, Robust optimization, Retail logistics

Paper type Research paper

1. Introduction

Firms in several industries struggle with an increasing number of disruptions occurring within demand, process capacity and supply sections of supply chains. For example, in retail, the COVID-19 pandemic has changed customers' channel preferences making demand more volatile (Dannenberg *et al.*, 2020) and amplifying labor shortages (e.g. truck drivers) that put

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process capacities and product availability under pressure (Ivanov and Dolgui, 2022; Sheffi, 2021). Altogether, such disruptions increasingly impose uncertainty on firms, which cannot be fully addressed by traditional approaches. Therefore, new approaches have been developed to make firms more resilient against disruptions. Resilience describes the adaptive ability of a system to be prepared for, respond to, and recover from sudden disruptions in a way that a system remains robust and functional despite such adverse events (Ponomarov and Holcomb, 2009; Rose, 2007; Tukamuhabwa *et al.*, 2015). For instance, in retail, resilience means maintaining a continuous level of product assortment availability (Bianchi-Aguiar *et al.*, 2021; Pan *et al.*, 2020), such as ensuring that a large part of the product assortment (e.g. at least 85%) is available to meet customer demand at all times.

However, increasing resilience often comes at the cost of sacrificing a system's performance, reflecting the extent to which an operational system achieves its financial or economic objectives (Lebas *et al.*, 2006; Neely *et al.*, 1995). Arguably, in order to respond flexibly to disruptions, different resilience initiatives like additional resources for redundant systems, surplus logistics capacity and buffers are needed, causing performance losses due to increased input levels (e.g. costs) (Alikhani *et al.*, 2021; Hohenstein *et al.*, 2015; Ivanov, 2022). For example, firms increase inventory levels of finished goods to buffer against sudden disruptions, increasing logistics costs (Kamalahmadi *et al.*, 2021). In an effort to be resilient, a firm might also impose restrictions on its outputs. For example, it may choose not to take on every customer order or may limit the range of products offered. This restriction can help to cope with disruptions but at the same time, may also limit the firm's ability to capitalize on market opportunities, leading to decreased outputs (e.g. sales). This potential trade-off between resilience and performance is a well-recognized challenge in the literature (Auf der Landwehr *et al.*, 2023; Ivanov *et al.*, 2014) and recently researchers have begun to develop approaches to quantify and manage it. However, most approaches employ input-related (e.g. personnel costs) or output-related (e.g. service level) metrics to measure the performance losses associated with resilience initiatives.

Extant studies neglect that firms typically deploy multiple resource inputs (e.g. personnel costs, logistics costs, selling space) to achieve multiple goals (e.g. sales, service level). Hence, so far there is no approach that enables the measurement of performance consequences of resilience initiatives comprehensively by simultaneously considering both performance dimensions (i.e. input and output) in terms of an efficiency metric capturing the transformation of multiple inputs into multiple outputs (see Table 1). Using isolated input or output metrics, as most extant studies do, may not offer a valid measurement of the resilience-performance trade-off. Moreover, as major studies have modeled this trade-off through simulations or based on fictive data (see Table 1), they cannot examine whether and to what extent this trade-off exists in real-world settings. Therefore, these studies do not consider the possibility that some firms can overcome a trade-off between resilience and performance (i.e. exhibit a zero trade-off) and thus are able to maintain high resilience without any performance losses. Hence, knowledge is missing on contingent firm characteristics that drive the extent of the trade-off.

To fill these research gaps, this study answers the following research questions:

RQ1. How can the resilience-efficiency trade-off be quantified?

RQ2. How do structural and process characteristics of firms drive the extent of the trade-off?

We answer these questions by introducing a new approach for analyzing the trade-off between resilience and performance based on robust data envelopment analysis (RDEA). While data envelopment analysis (DEA) is a common method for measuring a system's efficiency in transforming multiple inputs into multiple outputs as our focal performance metric, robust optimization is a highly appropriate technique for modeling the resilience of a system in terms of its robustness after output- and input-disruptions. Hence, RDEA measures the resilience-efficiency trade-off as the efficiency loss associated with achieving a certain level of resilience.

Table 1. Key studies addressing the relationship between resilience and performance

Publication	Focal performance metric	Methodology	Real-world data? No (synthetic data)	Yes, subjective (survey data)	Yes, objective (secondary data)	Revealed nature of the resilience-performance relationship: Alignment	Trade-off	Considering drivers of the resilience-performance relationship?
Chowdhury *et al.* (2019)	Output	Structural equation modeling	✗	✓	✗	✓	✗	✗
Hosseini *et al.* (2019b)	Input	Multi-stage stochastic programming with exogenous probabilistic modeling	✓	✗	✗	✗	✓	✗
Belhadi *et al.* (2021)	Output	Structural equation modeling	✗	✓	✗	✓	✗	✗
Taleizadeh *et al.* (2021)	Input	Multi-stage stochastic programming with exogenous probabilistic modeling	✓	✗	✗	✗	✓	✗
Kraude *et al.* (2022)	Input, output	Network data envelopment analysis	✗	✓	✗	✗	✓	✗
Qader *et al.* (2022)	Output	Structural equation modeling	✗	✓	✗	✓	✗	✗
Aldrighetti *et al.* (2023)	Input	Multi-stage stochastic programming with endogenous probabilistic modeling	✓	✗	✗	✗	✓	✗
Pahwa and Jaller (2023)	Output	Continuous approximation programming with gradient modeling	✓	✗	✗	✗	✓	✗
Zhao *et al.* (2023)	Output	Structural equation modeling	✗	✓	✗	✓	✗	✗
This study	Input, output	Robust data envelopment analysis	✗	✗	✓	✓	✓	✓

Source(s): Authors' own work

Our approach allows for exploring whether and to what extent a resilience-efficiency trade-off exists. The greater the trade-off is, the more resilience and efficiency conflict with each other, while a low trade-off value reflects that resilience and efficiency can be aligned. In the latter case, resilience initiatives are a value-creating component in business operations as they allow firms to safeguard a resilient system without efficiency losses (Belhadi *et al.*, 2021; Ivanov, 2022; Ruiz-Benítez *et al.*, 2018; Xue and Li, 2023).

To demonstrate the applicability of our novel approach, in a first step, we use this approach to quantify the extent of the trade-off for 20 stores of a large German grocery retailer. In a second analysis step, we identify characteristics of exemplary stores that allow them to allocate their inputs and outputs in a way that they are efficient and resilient at the same time (i.e. exhibit a zero trade-off).

Our study makes several important contributions. First, we contribute to the resilience management literature by providing an approach for quantifying the relationship between resilience and efficiency with efficiency representing a comprehensive performance measure that captures the ratio of multiple outputs to multiple inputs (instead of limiting the analysis to a single performance facet). In doing so, we extend the methodological toolbox in resilience research by introducing robust optimization models and suggesting RDEA for the first time in resilience literature. Second, as our empirical analysis demonstrates the general feasibility of our approach, we contribute to the discussion on the empirical nature of the relationship between resilience and efficiency (i.e. trade-off vs. alignment) by using objective real-world data. Our findings highlight that while some firms can align resilience and efficiency, others sacrifice large portions of efficiency for being resilient against disruptive events. Thus, we show that, in general, firms can achieve both. Third, our findings provide important managerial contributions, empowering firms to successfully navigate the resilience-efficiency trade-off. For instance, our study provides initial insights into the drivers of the trade-off that inform about managerial levers for configuring business operations in a way that a firm can be resilient and efficient.

The paper is structured as follows. Section 2 contains a literature review on the current state of focal metrics used for capturing the performance consequences of resilience initiatives and arguments regarding the nature of the relationship between resilience and performance. Section 3 presents our new RDEA-based approach for quantifying the relationship. Section 4 demonstrates the results of an empirical study in the retail logistics context identifying the extent of the trade-off across different stores and the reasons for differences in the extent of the trade-off. Section 5 discusses the results in the light of previous research, provides theoretical and managerial implications and points out the limitations and future research.

2. Literature review

There is a significant body of literature in resilience research that has investigated the conceptual nature of resilience as well as conditions and initiatives for increasing resilience (Ali and Gölgeci, 2019). For example, common resilience initiatives in the retail context include inventory management strategies (e.g. prepositioning of inventory levels), developing diversification strategies (e.g. using multiple suppliers), or leveraging flexibility strategies (e.g. outsourcing of logistics operations; back-up suppliers) (Alikhani *et al.*, 2021; Namdar *et al.*, 2018; Saghafian and Van Oyen, 2016; Song *et al.*, 2017). In contrast, as Table 1 shows, only recently studies have started to explore metrics and methods for quantifying the relationship between resilience and performance (Behzadi *et al.*, 2020; Hosseini *et al.*, 2019a) being the focus of this paper. As we discuss in more detail in Section 2.1, the performance metrics that most extant studies use are too narrow, mostly representing input- or output-related metrics to examine the relationship between resilience and performance, and most studies do not use real-world data for measuring their focal variables. In Section 2.2, we further discuss that extant studies often do not allow for the possibility that different firms can exhibit a different nature of the relationship between resilience and performance with some showing a highly conflicting relationship (i.e. a trade-off where high resilience comes at the cost of intense performance losses), while others have a low or even zero trade-off, allowing them to align both resilience and performance. Consequently, these studies are also limited in their ability to reveal drivers for the differences in the nature of the resilience-performance relationship.

2.1 Focal performance metrics and data used

Defining a meaningful and holistic performance metric is an essential prerequisite for analyzing the performance consequences of resilience initiatives. However, most extant studies are limited in this respect. As Table 1 indicates, most of the studies focus on one performance dimension (i.e. input or output), typically on cost-related or quality-related metrics (Behzadi *et al*., 2020). For instance, in the input-related stream, Hosseini *et al.* (2019b) introduce a metric for measuring different supplier selection costs, concentrating on resilience initiatives like supplier capacity expansion, back-up suppliers and supplier recovery, which allows for assessing the trade-off between specific cost components and resilience. Aldrighetti *et al*. (2023) extend the supplier perspective by proposing a metric that contrasts the different costs for resilience initiatives along a network of suppliers and facilities, including facility protection and capacity expansion. Building on this network-based perspective, Taleizadeh *et al*. (2021) focus on resilience initiatives in inventory management, evaluating these practices through a total cost metric that considers the interdependencies between ordering, holding, and shortage costs for backordering of products in a retail network. In the output-related stream, the study by Pahwa and Jaller (2023) focuses on quality-related metrics, examining the impact of different outsourcing operations as resilience initiatives on last-mile distribution performance captured by service level and punctuality losses. While insightful, these studies rely on an isolated performance metric (input or output), which may not offer a valid measurement of the resilience-performance trade-off, as firms typically invest different types of input resources for targeting different output goals. Hence, there is a clear need for performance metrics that acknowledge its *multi-dimensional* nature to paint a complete picture on the performance impact of resilience (Behzadi *et al*., 2020). Kraude *et al*. (2022) attempt to address this gap by employing a network DEA (NDEA) that determines the efficiency of different decision-making units (DMUs) with efficiency reflecting a ratio of multiple outputs to multiple inputs. This multi-dimensional approach offers a more nuanced view of the performance consequences of resilience. However, as we outline in more detail below, their approach encounters limitations regarding the data used for measuring inputs and outputs.

In addition to the limitations regarding the comprehensiveness in performance metrics, many studies employ methodological approaches that rely on synthetic data (e.g. randomly generated data) and use these data for simulating the performance implications of resilience activities. For example, Hosseini *et al.* (2019b) and Taleizadeh *et al*. (2021) employ multi-stage stochastic programming with exogenous probabilistic modeling to generate disruption scenario probabilities, while Aldrighetti *et al*. (2023) enhance this approach by integrating an endogenous probabilistic model, thereby extending decision-dependent scenario probabilities. All these studies rely on the integration of probability measures to model uncertainties, requiring assumptions about data distributions and relying on post-event outcome data (Olesen and Petersen, 2016), with the challenge being particularly acute when historical data for disruption probabilities are lacking (Aldrighetti *et al*., 2023). Hence, these studies examine the relationship between resilience and their focal performance metric in simulated (artificial) settings. As a result, the revealed relationship between resilience and performance may hold for the simulated setting but not in real-world environments, entailing the risk of potential misinterpretation due to the absence of empirical tests for the underlying simulation assumptions (Kinra *et al*., 2020; Sengupta, 1992).

While a few recent studies are empirical in nature by using real-world data, most studies rely on subjective data collected through surveys and analyze them predominantly through structural equation model approaches (Aldrighetti *et al.*, 2023; Belhadi *et al.*, 2021; Chowdhury *et al.*, 2019; Qader *et al.*, 2022; Zhao *et al.*, 2023) or, as a notable exception, through NDEA as outlined above (Kraude *et al.*, 2022). These studies use subjective manager ratings of different performance-related statements, which may be valuable for capturing qualitative insights, but may not provide the objective and quantifiable data necessary to fully capture the performance implications of resilience initiatives. Those subjective data might compromise the validity of the results. Hence, there is a clear need for empirical studies that employ *objective* real-world data to measure the impact of resilience on performance (Hosseini *et al.*, 2019b).

Given the identified limitations of extant studies in terms of too narrow performance metrics and limited data validity, recent studies like Behzadi *et al.* (2020) and Hosseini *et al.* (2019a) call for research that uses comprehensive, multi-faceted performance metrics capturing the input and output side of business operations while at the same time using optimization methods that leverage objective (i.e. secondary) real-world data for measuring performance. Our study addresses this call by employing an efficiency metric as a performance measure that captures the translation of multiple inputs into multiple outputs and using RDEA as a combination of robust optimization approaches and DEA models for assessing the impact of resilience on efficiency using real-world data.

Hence, our study is closely linked to Kraude *et al.* (2022) who also use a multiple input and output efficiency measure in a DEA framework. However, their approach encounters limitations due to the reliance on subjective data for both inputs and outputs, which limits the validity of their model (Kraude *et al.*, 2022). Moreover, Kraude *et al.* (2022) apply NDEA, which requires an exact understanding of how inputs and outputs are interrelated across sub-DMUs, resulting in a significant challenge, as this approach demands a comprehensive and often complex mapping of these dependencies. Additionally, this approach commonly assumes that changes in inputs or outputs are proportional and tends to overlook the presence of shared inputs among different sub-DMUs (Zhang *et al.*, 2019), potentially leading to a misrepresentation of efficiency, an issue not encountered with RDEA.

Unlike NDEA and DEA, which are deterministic approaches that do not incorporate uncertainty, RDEA is preferable, because at first, it provides a more realistic and adaptable assessment of efficiency under varied disruptions by taking uncertainty into account. Second, it deals with uncertainty effectively as it does not require probability distributions or historical data, which is also advantageous compared to stochastic programming approaches. Hence, RDEA provides solutions that are feasible and perform optimally across various uncertainty scenarios. This characteristic renders RDEA a particularly valuable tool in resilience management. Overall, by relying on RDEA, our study provides the first metric for quantifying the resilience-performance relationship that allows for capturing the multi-dimensional nature of performance – by using an efficiency metric – and is based on objective real-world data, in our case for the grocery retail industry.

2.2 The nature of the relationship between resilience and performance

We further discuss the differences in the nature of the relationship between resilience and performance revealed in the literature. The nature of this relationship is the subject of ambiguity and debate (see Table 1). While some studies highlight the highly conflicting relationship due to several reasons like additional resources, other studies stress the possibility of a low or even zero trade-off and emphasize that achieving an alignment between certain resilience strategies and performance is feasible.

2.2.1 Trade-off. On one side of the spectrum, there could be a perceptible trade-off, suggesting that as resilience increases, performance is compromised (Auf der Landwehr *et al.*, 2023; Ivanov *et al.*, 2014; Ruiz-Benítez *et al.*, 2018). Arguably, quickly responding to disruptions is associated with additional costs for structures and processes that build flexibility in assets such as capacity reservations (e.g. emergency suppliers) and decentralized warehouses (e.g. logistics hubs), all causing decreases in performance (Alikhani *et al.*, 2021; Ivanov and Dolgui, 2019). Additionally, increasing redundancies, such as prepositioned inventory to buffer stocks of raw materials and finished goods, is a common initiative for enhancing resilience in supply chains (Kamalahmadi *et al.*, 2021). This approach involves strategically placing inventories at various points along the supply chain, thereby mitigating the impact of potential disruptions. By maintaining higher levels of inventory, firms can absorb disruptions caused by delays or shortages, ensuring continuity of operations (Ergun *et al.*, 2023). However, this resilience initiative is not without challenges. Increased inventory levels can lead to higher holding costs and potential obsolescence, which negatively impact overall performance (Moosavi and Hosseini, 2021). Moreover, the fact that resilience requires building redundancies to maintain the flow of goods and information conflicts with business practices such as lean approaches (Belhadi *et al.*, 2022; Eckstein *et al.*, 2015). Lean approaches focus on continuous improvement and the elimination of all types of waste within a company, i.e. the elimination of non-value adding resources and initiatives (Vonderembse *et al.*, 2006). Therefore, most of the studies that link resilience to performance highlight a trade-off between both (Aldrighetti *et al.*, 2023; Hosseini *et al.*, 2019b; Pahwa and Jaller, 2023).

As noted in Section 2.1, we conceptualize performance as an efficiency ratio of multiple outputs to multiple inputs. In this sense, a trade-off denotes that resilience initiatives come at the expense of efficiency losses through higher amounts of inputs needed or less outputs generated. Higher inputs can be reflected through extra costs for personnel and logistics for flexible processes while less outputs could result when not every order from customers can be fulfilled due to supply chain shortages leading to sales drops. In addition, often decision makers are more conservative in disruptive situations surrounded by high uncertainty, making them less willing to take risks for exploiting market opportunities which might further reduce outputs and hence efficiency (Chopra *et al.*, 2021). In addition, being forced to respond to disruptions poses specific additional restrictions in managing resources (Auf der Landwehr *et al.*, 2023). For example, holding redundant resources is restrictive, e.g. a minimum stock level must be maintained, leading to fewer degrees of freedom in deploying inputs and outputs and hence efficiency losses. In sum, a trade-off perspective denotes that an increase in resilience is offset by a corresponding decrease in efficiency.

2.2.2 Alignment. Recent literature is stressing that some firms might overcome the trade-off and establish resilience and performance as aligned relatives (Belhadi *et al.*, 2021; Chowdhury *et al.*, 2019; Ivanov, 2022; Qader *et al.*, 2022; Ruiz-Benítez *et al.*, 2018; Zhao *et al.*, 2023). Those studies explore how firms can simultaneously achieve high resilience without any performance losses, highlighting the importance of integrating resilience as a proactive, value-creating component in transformation processes (Belhadi *et al.*, 2022; Ivanov, 2022; Ruiz-Benítez *et al.*, 2018; Xue and Li, 2023). By integrating resilience components in everyday business operations (Aldrighetti *et al.*, 2023; Ivanov, 2022) instead of using them only in the event of disruptions, firms can resolve the conflict between resilience and efficiency.

Diversification strategies such as tailored sourcing and omnichannel retailing exemplify this integration, providing the potential to optimize daily operations while ensuring resilience at no additional cost (Chopra *et al.*, 2021; Talluri *et al.*, 2013). Tailored sourcing combines two sourcing channels: one for uncertain demand with rapid response at higher costs, and another for predictable demand with lower costs and slower response. This ensures resilience while reducing overall logistics costs, as disruptions are unlikely to affect both channels simultaneously (Chopra *et al.*, 2021; Talluri *et al.*, 2013). Omnichannel retailing, on the other hand, could boost sales and resilience, allowing seamless transitions between different sales channels in response to disruptions, exemplified by the pivot from in-store to online sales during the COVID-19 pandemic (Akhtar *et al.*, 2022; Chopra *et al.*, 2021; Song *et al.*, 2022).

Furthermore, using commons at different levels (e.g. within a company, within an industry) enables firms to use pooled resources leading to resilient practices without performance losses (Chopra *et al.*, 2021). For example, third-party logistics providers can offer e-commerce delivery and storage resources that are shared across competing firms in normal and disruptive times. The integration of digital technologies also plays a pivotal role in building resilient and high-performing processes (Akhtar *et al.*, 2022; Belhadi *et al.*, 2022; Xue and Li, 2023). By leveraging technologies such as real-time inventory tracking and big data analytics, firms can optimize their resource allocation and minimize waste (i.e. decrease inputs) (Akhtar *et al.*, 2022). Additionally, advanced automation technologies like artificial intelligence and machine learning reduce reliance on manual labor (Berendes *et al.*, 2024), avoiding the adverse impact of operational disruptions on performance caused by labor shortages or human errors (Dubey *et al.*, 2022; Qader *et al.*, 2022; Zamani *et al.*, 2023).

Reflecting these advancements, Chowdhury *et al*. (2019) reveal that supply chain resilience and supply chain performance for manufacturing firms can coexist. Other studies by Belhadi *et al*. (2021), Qader *et al*. (2022), and Zhao *et al*. (2023) utilizing structural equation model approaches have supported this perspective of alignment by demonstrating how a high level of resilience can be achieved without sacrificing performance.

Given the observations discussed above, the relationship between resilience and efficiency does not necessarily manifest as a conflict. Our study therefore considers a sample of different firms (i.e. retail stores) and allows for the possibility that some stores exhibit a high trade-off while others are able to minimize or nullify this trade-off, with the latter reflecting a coexistence of resilience and efficiency. As Table 1 (last column) also shows, no extant study so far has examined firm characteristics that explain the differences in the extent of the trade-off. We do this in our study by considering structural and procedural store characteristics that allow for optimal input-output allocations and hence function as drivers of the extent of the trade-off. In the next section we present our methodology for quantifying the resilience-efficiency trade-off.

3. Methodology

This section introduces the methodology for analyzing the resilience-efficiency trade-off by first describing the RDEA and secondly introducing the metric for measuring the trade-off. Our methodology uses multifaceted elements to comprehensively address the impact of resilience initiatives that are taken as responses to disruptions. In Section 3.1, we consider the uncertainties stemming from potential disruptions through different levels of uncertainty that a system must withstand by introducing RDEA. This methodological approach allows for systematically accounting for disruptions in both inputs and outputs, thereby protecting the system against potential disruptions. In Section 3.2, we outline that the comparison of the efficiency scores of the robust DEA model with a deterministic DEA model, which considers no disruptions (i.e. no resilience initiatives), yields our novel trade-off metric. This metric indicates whether, and if yes, to what extent efficiency losses are associated with responding to disruptions.

3.1 Robust data envelopment analysis

DEA is a non-parametric method for measuring the relative efficiencies of decision-making units (DMUs), in our case retail stores, which transform multiple inputs into multiple outputs.

Unlike parametric methods, such as statistical regression, DEA does not require a predetermined functional form for the relationship between inputs and outputs. Instead, DEA constructs a best-practice frontier, representing the most efficient transformation of inputs into outputs. The efficiency of all other stores is then assessed by comparing them to this frontier, rather than to an average performance benchmark. This approach allows for the evaluation of each store's efficiency relative to the most efficient stores operating under similar conditions and scales.

Two basic DEA models commonly used in the literature are the CCR (Charnes, Cooper, and Rhodes) model and the BCC (Banker, Charnes, and Cooper) model.

The CCR model, introduced by Charnes *et al*. (1978), operates under the assumption of constant returns to scale, meaning that any proportional change in inputs leads to a proportional change in outputs. In contrast, the BCC model, developed by Banker and Thrall (1992), assumes variable returns to scale, allowing for more flexibility in how input changes affect outputs. Over the years, DEA has become a widely accepted method in operations research and management science for efficiency analysis across various sectors, including retail (Keh and Chu, 2003).

DEA models can be either input-oriented or output-oriented (Dyson *et al*., 2001), depending on the objectives of the decision maker. The input-oriented DEA model focuses on minimizing input usage while maintaining the same level of output, aiming to identify the extent to which input quantities can be proportionally reduced without compromising output levels. In this model, a store is efficient (i.e. receives an efficiency score of 1 or 100%) if it cannot reduce any input while holding the same level of outputs. Otherwise, a store is not efficient and receives an efficiency score smaller than 1. Conversely, the output-oriented DEA model emphasizes maximizing output production from a given set of inputs, seeking to determine the potential increase in outputs without requiring additional inputs. Both orientations address the same underlying efficiency problem but from different perspectives, thus providing complementary insights into the performance of DMUs (Cooper *et al*., 2007).

In our study, we have opted for an input-oriented DEA model, which is particularly well-suited to the grocery retail industry. In this context, minimizing operational costs and optimizing resource efficiency are crucial due to the highly competitive nature of the market and the narrow profit margins typical in the grocery sector. This model is therefore effective in identifying opportunities for cost savings and improved operational practices without compromising sales.

Consider n stores indexed as store$_j (j = 1, \ldots, n)$ where each unit consumes m semi-positive inputs $\boldsymbol{x}_j = (\ldots, x_{ij}, \ldots)$; $i \in I = \{1, \ldots, m\}$ to produce s semi-positive outputs $\boldsymbol{y}_j = (\ldots, y_{rj}, \ldots)$; $r \in R = \{1, \ldots, s\}$. If the input and output data are subject to potential disruptions (and hence to uncertainty) to which a store responds through resilience initiatives, then employing deterministic DEA models (i.e. DEA without accounting for disruptions) for measuring the efficiency is inappropriate. In such cases, decision-makers need to apply a so-called robust DEA approach, which extends the traditional DEA framework by incorporating fluctuations in inputs and outputs. Consequently, RDEA allows for modeling a system's resilience in terms of its robustness after input-and-output disruptions.

Specifically, in the retail context, robust parameters within RDEA account for disruptions in key environmental factors such as customer demand or labor strikes. These parameters quantify the extent to which these factors can deviate from expected values while maintaining resilience. By incorporating these deviations, RDEA allows retail managers to assess store or operational efficiency under the response to disruptions while acknowledging that maintaining resilience might come at the cost of sacrificing efficiency.

Consequently, our study uses RDEA as a state-of-the-art approach for considering disruptions in the inputs and outputs of stores and measuring reliable efficiency values that account for these disruptions (Arabmaldar *et al*., 2024; Klumpp *et al*., 2023; Toloo *et al*., 2022). By considering different levels of possible disruptions as a common approach for modeling disruption effects (e.g. Aldrighetti *et al*., 2023), RDEA shows the efficiency losses associated with keeping the system robust despite these disruptions (i.e. the efficiency losses incurred for being resilient). Formally, the RDEA model can be written as follows (Toloo *et al*., 2022):

$$
\begin{aligned}
&\theta_R^*\left(\Gamma_j^x, \Gamma_j^y\right) = \max \sum_{r=1}^{s} u_r y_{ro} - p_o^y \Gamma_o^y - \sum_{r=1}^{s} q_{ro} \\
&s.t. \\
&\sum_{i=1}^{m} v_i x_{io} - p_o^x \Gamma_o^x - \sum_{i=1}^{m} w_{io} \le 1 \\
&\sum_{r=1}^{s} u_r y_{ro} - \sum_{i=1}^{m} v_i x_{io} - p_o^x \Gamma_o^x - p_o^y \Gamma_o^y - \sum_{r=1}^{s} q_{ro} - \sum_{i=1}^{m} w_{io} \le 0 \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + p_j^x \Gamma_j^x + p_j^y \Gamma_j^y + \sum_{r=1}^{s} q_{rj} + \sum_{i=1}^{m} w_{ij} \le 0 \quad \forall j \ne o \\
&u_r \widehat{y}_{rj} - p_j^y - q_{rj} \le 0 \qquad \forall j, \forall r \\
&v_i \widehat{x}_{ij} - p_j^x - w_{ij} \le 0 \qquad \forall j, \forall i \\
&q_{rj}, w_{ij}, p_j^y, p_j^x, v_i, u_r \ge 0 \qquad \forall i, \forall r, \forall j
\end{aligned}
\tag{1}
$$

where θ_R^* is the efficiency score which informs about the portion of inputs that can be saved while holding the same level of outputs; v_i and u_r are the weights of the i^{th} input and r^{th} output, respectively. In Model (1) $\widehat{x}_{ij} = ex_{ij}$ and $\widehat{y}_{rj} = ey_{rj}$ are the deviations of inputs and outputs, respectively, in which e represents the percentage of deviations of the uncertain data from their nominal values due to disruptions. Hence e represents the disruption level of a store. Model (1) measures the robust efficiency of a focal store (store$_o$) and specifies the level of disruptions with the robust parameters Γ_j^x and Γ_j^y associated with input and output data. The model includes variables that protect the objective function and constraints against disruptions, thereby measuring the robust efficiency of the DMUs. For example, the variables (p_j^x, p_j^y) and (q_{rj}, w_{ij}) quantify the sensitivity of the inputs and outputs data when the level of disruptions changes. Besides, the quantities $p_j^x \Gamma_j^x + \sum_{i=1}^{m} w_{ij}, j = 1, .., n$ and $p_j^y \Gamma_j^y + \sum_{r=1}^{s} q_{rj}$ leverage the worst-case deviations of the inputs and outputs from their nominal values. Furthermore, the pre-defined robust parameters $\Gamma_j^x (\Gamma_j^y)$ reflect the maximal number of uncertain inputs (outputs) that are subject to disruptions (i.e. can fluctuate due to disruptions). In addition, to protect the system against input and output disruptions, the objective function value of the robust model is penalized by a loss of efficiency compared to the deterministic model. This comparison informs the managers about the resilience-efficiency trade-off which is defined in the following section.

3.2 The metric for measuring the trade-off

The resilience-efficiency trade-off represents the difference between the deterministic efficiency (i.e. efficiency without disruptions) and the robust efficiency (i.e. efficiency after responding to disruptions) and can be calculated as follows:

$$
\text{Trade} - \text{off metric} = \frac{\theta_R^*(0,0) - \theta_R^*\left(\Gamma_j^x, \Gamma_j^y\right)}{\theta_R^*(0,0)}, \forall \Gamma_j^x, \Gamma_j^y > 0 \tag{2}
$$

where $\theta_R^*(0,0)$ is the deterministic efficiency measure of a store, and $\theta_R^*(\Gamma_j^x, \Gamma_j^y)$ is the robust efficiency measure of a store for varying levels of Γ_j^x, Γ_j^y. The trade-off metric provides a clear-cut image of the resilience impact on efficiency. For example, let us assume the level of disruption is 5% meaning that inputs and outputs deviate from their nominal values by 5%. If the resulting resilience-efficiency trade-off is 10%, this means that if a store responds to this deviation to keep the system robust, the resulting efficiency loss will be 10%.

4. Empirical analysis

As research has not yet empirically examined the existence and extent of a resilience-efficiency trade-off in real-world settings, our trade-off metric is applied using a dataset from the grocery retail sector where inputs and outputs are measured objectively through secondary data (compared to randomly generated data used in many extant studies). For this reason, we first explain the context of grocery retailing and our dataset before describing the results of the empirical analysis.

4.1 Study context and data

Given that approximately 80% of the food retail sector in Germany was significantly affected by several disruptions in recent years (ifo Institut, 2023), the grocery retail context is particularly appropriate for the empirical application of our trade-off metric. Global challenges like the COVID-19 pandemic and climate change-induced events, such as California's droughts, have stressed grocery retail logistics through disrupted supply chains and agricultural output instability (Ivanov, 2020; Lesk *et al.*, 2016). Specifically, in the grocery retail sector, the consequences of those events are further aggravated by rapid shifts in consumer behavior toward convenient and swift shopping, both in-store and online (Verhoef *et al.*, 2015), and by the volatility in traditional retail due to labor shortages and frequently changing product trends, resulting in shorter product life cycles and greater price sensitivity (Kumar and Reinartz, 2016). These developments lead to frequent disruptions affecting both inputs and outputs of retail stores.

We cooperate with a large high-quality brick-and-mortar grocery retailer in Germany. Our focal units of analysis are individual grocery stores that operate as relatively independent business units with a large share of resources being allocated at the store level, which would be different for low-price discounter stores in grocery retail. The dataset contains input and output data for a random selection of 20 stores in the south of Germany for September 2022, a month without public holidays. Figure 1 illustrates the five inputs (I) on the left side and two outputs (O) on the right side (Neves Bezerra de Melo *et al.*, 2018) that are considered in this study for calculating efficiency scores. These inputs and outputs are widely used in the literature for investigating retail store efficiency (e.g. Neves Bezerra de Melo *et al.*, 2018). To ensure an agnostic and unbiased approach in evaluating the resilience-efficiency trade-off, the DEA model for measuring the efficiency should not include variables that directly reflect specific resilience initiatives.

Personnel costs (I_1) is the salary paid to store employees in the focal month. *Logistics costs* (I_2) is the store-level costs for retail warehouse order picking and transportation in the focal month. Order picking costs depend on the number of products picked for the store multiplied by a firm-wide unified cost rate. Transport costs depend on the number of transport units delivered to the store multiplied by a uniform transfer price per transport unit. *Frontend space* (I_3) is the space in square meters of a store dedicated for customers to make purchases, excluding the backroom area, checkout area, and entrance/exit areas. *Backend space* (I_4) is the space for backroom operations in square meters. It is the space that is separated from the sales

Source(s): Authors' own work

Figure 1. Input and output data

area and used to buffer inventory for shelf replenishment. *Population* (I_5) depicts the potential customer base within the immediate store neighborhood and hence, this input is considered as a proxy for demand size. For measuring this variable, we combine archival company data on the postal code of each store with secondary data from German Federal Statistical Office [1] covering the number of inhabitants living in the catchment area which is defined by the focal retailer as a radius of approximately 10 kilometers around the store. *Sales* (O_1) is the store sales without further adjustments as the circumstances (e.g. taxes) are equal for all observed stores. *Assortment variety* (O_2) in the store reflects the variety of products offered to customers. It is classified as an output, reflecting the store's ability to deliver a diverse product range to customers, which directly enhances customer satisfaction and store competitiveness (Arabmaldar *et al.*, 2024; Broniarczyk *et al.*, 1998). Given that all products sold through cash desk counters are recorded by the retailers' merchandise management system, the number of different products sold is provided by counting unique article numbers passing the cash desk. Table 2 shows the descriptive statistics for input and output variables for the 20 stores, highlighting the differences in input-output-allocations between the stores.

4.2 Results for the resilience-efficiency trade-off

As outlined above, for determining the trade-off metric, we first calculate the efficiency scores of the stores for the deterministic DEA model and the RDEA model. To represent disruptions in the inputs and outputs of the selected stores in the RDEA model, we set the disruption level in the robust model to 1%, 5%, and 10%. Consequently, we assume that the values of the uncertain inputs and outputs are realized within the respective intervals. For example, at $e = 0.05$, $\bar{x}_{ij} \in [x_{ij} - 0.05 \times x_{ij}, x_{ij} + 0.05 \times x_{ij}]$ and $\bar{y}_{rj} \in [y_{rj} - 0.05 \times y_{rj}, y_{rj} + 0.05 \times y_{rj}]$. Additionally, we set the number of uncertain parameters $\Gamma_j^x = 5, \Gamma_j^y = 2$, implying that all five input variables and two output variables are subject to disruptions (and hence to uncertainty). Specifically, grocery retailers are commonly impacted by environmental disruptions occurring in the process, demand, or supply components (Shekarian *et al.*, 2021). For instance, process disruptions can occur when in-store refrigeration fails, leading to spoilage of perishable goods, while demand disruptions may result from unexpected peaks in customer demand during crises, such as the spike in toilet paper sales during the COVID-19 pandemic. Supply disruptions might arise if a key supplier misses a delivery due to transportation failures, like truck breakdowns or extreme weather conditions, such as floods (Lesk *et al.*, 2016). For instance, floods can lead to partial or complete store closures, as seen in regions like Dresden and Ahrtal in Germany, where increased flood frequency has forced supermarkets to reduce the use of both frontend and backend spaces. However, even less catastrophic but still severe weather conditions, such as extremely hot summers or harsh

Table 2. Descriptive statistics for input and output measures

Variable	Min	Max	Average	Standard deviation
Inputs				
Personnel costs	37778.81	91938.63	49815.48	14417.05
Logistics costs	18458.71	90632.62	51267.72	16262.16
Frontend space	1091.00	2388.00	1543.30	316.04
Backend space	34.39	78.43	52.21	12.19
Population	6556.00	36653.00	16052.95	8517.90
Outputs				
Sales	108456.40	269840.90	162770.50	32472.87
Assortment variety	3240.00	4087.00	3635.20	214.43

Source(s): Authors' own work

winters, can disrupt operations. These conditions may limit the usability of outdoor areas, such as entryways (e.g. reduced frontend space) and loading docks (e.g. reduced backend space), complicate logistics and ultimately reduce customer access.

We first calculate the efficiency of the stores from the deterministic DEA model (i.e. $\Gamma_j^x = \Gamma_j^y = 0$) where disruptions in inputs and output data are ignored (see efficiency scores in Table 3, column 2) and find that 14 stores (see Table 3, last row) are efficient representing 70% of the stores. Then we calculate robust efficiency scores (see *model (1)*) for the three different disruption levels (see the 1%, 5%, and 10% columns in Table 3). In the last row of Table 3, we see that the number of efficient stores (No. Eff. Stores) decreases from 12 stores for a disruption level of 1% to two stores for disruption levels of 5% and 10%, respectively.

As also shown in Table 3, for Store 5 and Store 20 an efficiency score of 1 is measured for the deterministic model as well as across all disruption levels of the robust model. The second-best performance can be attributed to Store 2 and Store 9, as the efficiency scores for the disruption levels 5% and 10% are 0.9973 and 0.8156 (Store 2) and 0.9862 and 0.8065 (Store 9). The worst efficiency score of 0.6065 is measured for Store 17 for a disruption level of 10%.

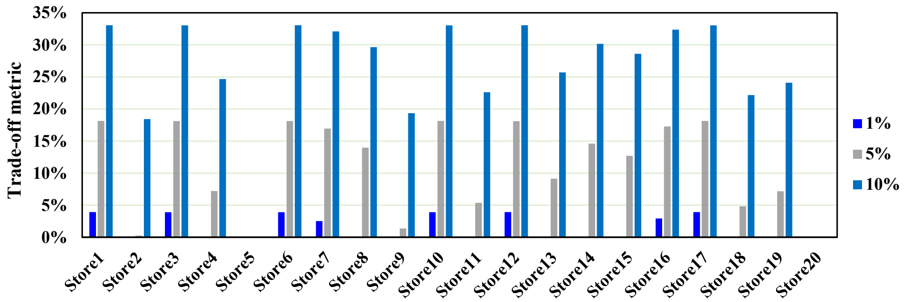
In addressing the first research question, Figure 2 shows across the three disruption levels the values of the trade-off metric (calculated by using *model (2)*) for all stores measured as the deviations between the deterministic and robust efficiency scores. As shown in Figure 2, our trade-off metric provides insights about the nature of the relationship between resilience and efficiency.

The lower the trade-off metric, the more desirable for the manager as a lower portion of efficiency is sacrificed for being resilient against disruptions. We find that most stores can withstand disruptions up to a disruption level of 1%. Additionally, we identify some stores that sacrifice one-third of their efficiency for being resilient against disruptions. For example, we measure the highest trade-off metric of 33.1% for Store 1, Store 12 and Store 17 for the disruption level of 10%. In contrast, we measure a trade-off metric of zero across all disruption

Table 3. Efficiency scores under different disruption levels

Store	Deterministic	1%	5%	10%
Store 1	0.9425	0.9055	0.7715	0.6309
Store 2	1	1	0.9973	0.8156
Store 3	0.9692	0.9312	0.7934	0.6488
Store 4	1	1	0.9278	0.7533
Store 5	1	1	1	1
Store 6	0.9918	0.9529	0.8119	0.6639
Store 7	1	0.9747	0.8305	0.6791
Store 8	1	1	0.8603	0.7036
Store 9	1	1	0.9862	0.8065
Store 10	0.9597	0.9221	0.7856	0.6425
Store 11	1	1	0.9463	0.7739
Store 12	0.9990	0.9598	0.8183	0.6687
Store 13	1	1	0.9086	0.7430
Store 14	1	1	0.8539	0.6983
Store 15	1	1	0.8729	0.7139
Store 16	1	0.9707	0.8271	0.6764
Store 17	0.9060	0.8704	0.7416	0.6065
Store 18	1	1	0.9516	0.7782
Store 19	1	1	0.9282	0.7590
Store 20	1	1	1	1
No. Eff. Stores	14	12	2	2

Source(s): Authors' own work



Source(s): Authors' own work

Figure 2. The trade-off metric under different disruption levels

levels for two stores (Store 5 and Store 20). This shows that these stores are able to be resilient in terms of absorbing high disruption levels while keeping high relative efficiency. In other words, for these two stores we observe no trade-off but an alignment, as these two stores achieve high levels of resilience without any efficiency losses. Overall, all these findings call for deeper insights into the allocation of inputs and outputs and specific store characteristics, in order to identify the key drivers of the differences in the trade-off metric.

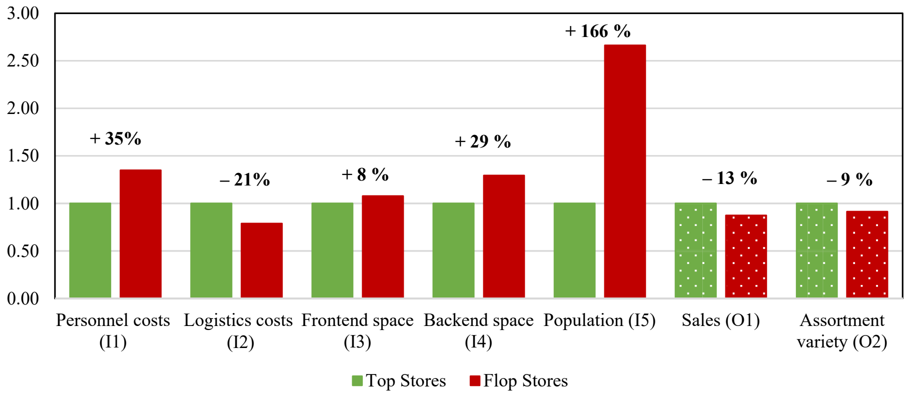
4.3 Results for the drivers of the trade-off

To answer the second research question regarding the main drivers for the differences in the trade-off metric across stores, we perform a contrast analysis. The essence of this analysis is to compare the absolute average inputs and outputs for selected stores, as the differentials in the trade-off metric can be explained by the allocation of inputs and outputs, from which the drivers can be derived.

First, we ranked the 20 stores based on their trade-off metrics for the highest disruption level of 10%. The stores are sorted from those with the lowest trade-off metric values (top stores) to those with the highest (flop stores). From this ranking, we selected two top stores (Store 5 and Store 20) and two flop stores (Store 1 and Store 17), each representing 10% of the sample at the extreme ends of the trade-off spectrum.

Afterward, we calculated the absolute average values of the five inputs and two outputs for these selected stores in the first step. By normalizing these values in the second step, we aim to uncover how the specific allocation and utilization of resources in top stores differ from those in flop stores, thereby explaining the observed differences in their trade-off metrics. Therefore, we set the absolute average values of inputs and outputs for the top stores to 1, and the corresponding values for the flop stores are expressed relative to these normalized values. This normalization ensures that the differences between inputs and outputs are presented on a comparable scale, allowing for direct visual comparison in Figure 3.

The results are shown in Figure 3, highlighting that in general, top stores are able to generate more outputs from lower inputs, particularly in terms of personnel costs and population compared to flop stores. Additionally, Figure 3 shows that top stores are characterized by smaller frontend space and backend space and produce higher logistics costs than the flop stores. To clarify the differences between top and flop stores further, we calculated and annotated the relative differences in percentage terms above the bars in Figure 3. These percentages highlight, for example, that flop stores consume 35% more personnel costs, 8% more frontend space and 29% more backend space while generating 13% less sales and offering 9% less assortment variety compared to top stores. Furthermore, the significant difference in population shows that the flop stores operate in areas with 166% higher population density, while the top shops are particularly successful in less densely



Source(s): Authors' own work

Figure 3. Normalized input and output differences between top and flop stores

populated areas. This approach underscores the importance of resource allocation and utilization in explaining the observed differences in the trade-off metric.

To further confirm the validity of our research, we follow the principle of triangulation according to Creswell (2003) and extend our input and output data set through additional proprietary databases available from the retailer for explainable store characteristics. By considering these additional databases, our research uncovers specific store characteristics, detailed in Table 4, that define the top store group.

Table 4 highlights relevant store characteristics, showing that top stores often managed by self-employed merchants, and exhibit a greater prevalence of diverse channel approaches, such as the use of both offline and online channels, as well as multiple sourcing approaches, such as the combination of centralized procurement and local suppliers. In contrast, flop stores belong to the retail group and typically do not employ different channel and sourcing approaches, such as relying on single sourcing by focusing on centralized procurement. These results provide a clear view of the store characteristics that differentiate top stores from flop stores, setting the stage for deriving the key drivers.

Thus, the drivers are derived by linking the observed differences in the allocation of inputs and outputs (as depicted in Figure 3) with the store characteristics (outlined in Table 4). These drivers represent the strategic and operational decisions observed in top and flop stores, which manifest in good and bad practices that influence the trade-off metric, as shown in Table 5.

Table 5 provides a detailed illustration of the four key drivers identified in this study, derived by linking the allocation of inputs and outputs with store characteristics. These drivers are manifested in good and bad practices that influence a store's ability to align resilience and

Table 4. Comparison of the store characteristics of top and flop stores

	Type of ownership		Type of channel approach		Type of sourcing approach	
	Retail group	Self-employed merchant	Offline channel	Online channel	Centralized procurement	Local suppliers
Top stores	✗	✓	✓	✓	✓	✓
Flop stores	✓	✗	✓	✗	✓	✗

Source(s): Authors' own work

Table 5. Drivers and related good and bad practices

Driver	Good practice	Bad practice
Strategic resource management		
Personnel strategy	Flexible and adaptive scheduling	Rigid scheduling
Logistics strategy	Frequent and smaller deliveries	Infrequent bulk deliveries
Customer relationship management	Intensive, personal customer collaboration, leveraging localized knowledge	Standardized, impersonal customer relationships
Organizational structure	High autonomy for store managers in decision-making	Limited autonomy for store managers in decision-making, rigid corporate rules
Diversification strategies		
Omnichannel strategy	Seamless integration of offline and online channels, including Buy-Online-Pick-Up-In-Store systems	Reliance solely on traditional in-store sales
Sourcing strategy	Multi-sourcing strategy, centralized procurement and local suppliers	Single-sourcing strategy, centralized procurement

Source(s): Authors' own work

efficiency. The first driver reflects the strategic resource management of the stores, including personnel and logistics strategies, as highlighted in Table 3 by the variations in personnel and logistics costs. Good practices for this driver result in flexible scheduling, frequent and smaller deliveries, enabling resilience and efficiency. In contrast, flop stores often rely on bad practices, including rigid personnel scheduling and infrequent bulk deliveries, which reduce their adaptability.

Due to the lower population and personnel costs (Table 3), it stands to the reason that customer relationship management is practiced differently in these stores, which we identify as a second key driver. Operating in less populated areas with reduced employee levels, these stores are able to establish a more localized and personalized relationship with their customers, adapting more effectively to changes in demand. This intensive, personalized customer collaboration enables top stores to adapt efficiently to disruptions.

Furthermore, additional drivers could be derived through the store characteristics in Table 4. Therefore, Table 5 highlights the importance of an organizational structure as a third driver that fosters high autonomy for store managers, empowering them to implement context-specific strategies. It also underscores the critical role of diversification strategies, such as omnichannel integration and multi-sourcing, in achieving efficient resilience. Stores with good practices in these areas successfully align resilience and efficiency, while those with centralized decision-making and limited diversification fail to do so.

5. Discussion

Resilience is defined as the ability of a system to respond to disruptions without losing the robustness of the system, which often comes at additional cost, thus creating a trade-off. Although this trade-off is widely discussed in the resilience literature, appropriate metrics to quantify this trade-off are rarely proposed and only a few studies have examined whether this trade-off exists in real-world settings. Thus, the nature of the relationship between resilience and efficiency (i.e. trade-off vs. alignment) and structural and process characteristics that drive this nature remain unclear. The research in this paper narrows these important research gaps by first proposing a novel multiple output-input-oriented metric to quantify this trade-off and second empirically proving this trade-off and identifying drivers for the trade-off, specifically in retail logistics operations within the context of a German grocery retailer. In this final section, we discuss our results in the light of previous research and derive theoretical and managerial implications. Furthermore, we point out the limitations of our research, which provide avenues for future research.

5.1 Theoretical implications

Our research has several theoretical implications. First, we are the first to provide a trade-off metric that considers the ratio of multiple outputs to multiple inputs as a comprehensive metric for quantifying the performance consequences of resilience. In doing so, we contribute to the methodological portfolio in resilience research, by responding to the call of Hosseini *et al.* (2019a) for applying robust optimization techniques, and by introducing RDEA to resilience literature. We empirically demonstrate the general feasibility of our approach by applying our metric using a dataset from a large German retailer and determining the metric for 20 stores. This study thus opens up new possibilities for applying robust optimization models in resilience management by demonstrating their practical feasibility.

Second, our empirical analysis highlights that while some stores are able to align resilience and efficiency, others sacrifice significant portions of efficiency to maintain resilience. This finding contributes to the ongoing debate on the relationship between resilience and efficiency (i.e. whether they are in trade-off or alignment). Specifically, our study contributes to the literature, by shedding light on specific key drivers that enable the achievement of efficient resilience. We identified four key drivers that merit further investigation, as they have been examined for the first time in relation to both resilience and efficiency, though traditionally studied in separate research streams.

The first driver highlights the strategic resource management of logistics and personnel resources, revealing that top stores achieve efficient resilience by maintaining lower personnel costs. Reduced personnel costs indicate that these stores employ fewer store employees, which simplifies the complexity in personnel (re)scheduling and overall management. This streamlined approach contributes to an operationally agile environment capable of swift adaptation to disruptions, as empirically shown by the slightly increased logistics costs observed in the top store group. This finding aligns with existing research on the importance of lean operations in enhancing a store's ability to respond quickly to disruptions (Ruiz-Benítez *et al.*, 2018), while also helping dissipate inconsistent findings regarding the effects of complexity (Birkie *et al.*, 2017; Gunasekaran *et al.*, 2015).

The observed increase in logistics costs among the top stores suggests that these stores use logistics activities as an efficiency buffer while maintaining lower personnel costs. Hence, this substitution of personnel resources through logistics resources is the key lever for keeping the efficiency losses of resilience activities low. For example, through an increased number of deliveries (i.e. higher logistics costs), a lower level of personnel cost can be achieved by limiting the number of employees. This enables to "smooth out" the transport volumes across different days during the week, avoiding demand peaks which would result in personnel demand peaks. These findings reinforce the pivotal role of logistics strategy in gaining competitive advantages (e.g. Umar and Wilson, 2024).

Moreover, our results contribute to the ongoing discussion about flexibility (in our case in terms of logistics resources) versus redundancy (in our case in terms of personnel resources). Our findings suggest that stores should prioritize logistics flexibility over personnel redundancy to achieve efficient resilience, challenging some literature that advocates for a mixed strategy (Kamalahmadi *et al.*, 2021). By focusing on flexibility in logistics activities, stores can better manage disruptions and reduce the need for excess personnel, thereby enhancing both resilience and efficiency. Therefore, our study contributes to the strategic decision-making processes in grocery retail contexts.

Additionally, our study identifies customer relationship management, specifically focusing on localized knowledge and collaboration with customers, as a second key driver. Top stores are often located in less populated areas, where fewer employees are needed due to lower customer traffic. With a smaller customer base, these stores can more flexibly adapt products and services to changes in demand, as retailers in such areas often have deeper, more personal knowledge of their customers (Gupta and Ramachandran, 2021). This better predictable demand allows for more adaptable supply chain arrangements, such as minimized inventory as a reflection of the smaller backend spaces observed in top stores. Previous research supports this finding, showing that localized knowledge and smaller, more predictable markets contribute to efficient operations (Chuang *et al*., 2019; Panigrahi *et al*., 2024). Our study is the first to emphasize that collaboration with customers is not only a driver of efficiency but also a critical factor for resilience. While existing research predominantly focuses on supplier-buyer relationship in terms of information-sharing and communication (e.g. Scholten and Schilder, 2015), our findings reveal that engaging directly with customers (i.e. customer collaboration) plays an equally crucial role in achieving both resilience and efficiency.

Our third identified driver is organizational structure, particularly the difference in store ownership types. Stores directly owned by the retailing group tend to adhere to stricter corporate regulations, in contrast to those managed by self-employed merchants, who enjoy greater autonomy and flexibility, particularly in reallocating and managing resources. This flexibility is reflected in the lower personnel costs of stores and in the higher logistics costs, as self-employed merchants have more freedom in strategy decision-making. This is why they are able to implement the “favorable” strategy of prioritizing logistics activities as logistics costs are generally lower than personnel costs in retailing (Toloo *et al*., 2022). Incidentally, when these stores realize that this strategy of increased logistics activities is not successful in unexpected situations, for example, in the event of severe disruptions, they are able to allocate personnel resources more quickly (e.g. ordering overtime workers), as they are not dependent on a head office and works councils for their decisions. These findings underscore the significant impact of organizational structure on operational flexibility and hence resilience. They also contribute to the broader discussion on the role of organizational culture in enhancing supply chain resilience and performance (Altay *et al*., 2018), suggesting that both types of stores might benefit from rethinking strict corporate regulations to foster greater adaptability and responsiveness in times of crisis. These findings also suggest that leadership plays a significant role in supply chain resilience. Although initial studies have begun to explore these softer factors in supply chain resilience management (e.g. Nikookar and Yanadori, 2022), they remain underrepresented in the literature.

Finally, the fourth key driver focuses on diversification strategies. Based on the additional in-depth insights we obtained from the retailer’s sales and process database, we note a strategic differentiation regarding sourcing and marketing approaches: top stores embrace diversification through multiple sourcing and omnichannel retailing strategies. These stores have transcended traditional sales models by integrating a Buy-Online-Pick-Up-In-Store system, thereby effectively merging offline and online customer demands, leading to more efficient personnel allocation and the potential for continued sales even during periods of demand-side disruptions, such as those experienced during the COVID-19 pandemic (Akhtar *et al*., 2022; Chopra *et al*., 2021; Song *et al*., 2022). Conversely, stores with a less diversified supplier base, often relying on centralized procurement, are more vulnerable to disruptions. Top stores benefit from adaptable supply chain arrangements and multiple sourcing strategies, working with local farmers to quickly mitigate stock shortages and ensure stable sales during disruptions. Recent studies (e.g. Birge *et al*., 2023; Lou *et al*., 2024) support our results, by stating that relying on a single supplier is advantageous for a firm only when the risk of supplier failure is minimal; otherwise, employing a multi-sourcing strategy proves to be more efficient.

Overall, our research not only provides valuable insights for measuring and managing the resilience-efficiency trade-off, but it also bridges the gap between two traditionally separate research streams. By simultaneously considering both resilience and efficiency, our work contributes to a more integrated understanding of how this trade-off can be solved, offering a comprehensive framework for future studies.

5.2 Managerial implications

Our findings also have important managerial implications for navigating the resilience-efficiency trade-off. First, our insights can strongly support RDEA acceptance in operational resilience management and decision-making; this is because managers are enabled (1) to weigh resilience quantitatively against efficiency and (2) to identify systems that are simultaneously resilient and efficient. Store managers and retail groups should therefore consider integrating the trade-off metric into their key performance indicator dashboards to optimize both resilience and efficiency in their operations.

Second, our study provides initial managerial insights into the drivers of successfully overcoming the trade-off, particularly in achieving resilience without extra inputs or output losses. Our first driver highlights that store managers should consider carefully the importance of the strategy for logistics activities. By increasing the number of deliveries and smoothing transport volumes throughout the week, store managers can avoid demand peaks, minimizing the need for additional personnel and reducing the complexity of personnel management. These findings suggest that store managers should prioritize management approaches that provide high flexibility, enabling them to respond quickly to disruptions while maintaining high operational efficiency.

The second driver emphasizes the importance of the grocery retail store's customer relationship, particularly the role of localized knowledge and customer collaboration. Store managers should prioritize building strong relationships with customers to enhance their ability to respond to demand fluctuations. By leveraging insights from close customer relationships and localized knowledge, managers can implement more customer-centric supply chain practices, further improving resilience and efficiency. Frontend space plays a key role in this by facilitating customer engagement through strategic layouts, clear signage, and adaptive displays. Managers with smaller frontend spaces can maximize their impact by focusing on flexible arrangements, such as implementing dynamic product presentations or dedicating promotional zones that align with seasonal or demand patterns. Larger frontend spaces must also be carefully managed to avoid cluttered layouts or underutilized areas that impair customer experience. Additionally, managers should prioritize clear navigation paths and logically grouped product arrangements to enhance the shopping experience. For store managers in densely populated areas, applying these practices is particularly challenging yet crucial; they should focus on creating localized strategies that cater to diverse customer needs while managing the complexities of higher traffic and more volatile demand patterns.

Additionally, our results underscore the critical role of organizational structure, emphasizing the need for autonomy and flexibility in managerial decision-making. We recommend that firms establish independent and adaptable decision-making processes. This is especially relevant for stores within a retail group, where managers must navigate stricter regulations, such as those imposed by works councils, while still fostering mechanisms that enable flexibility and swift responses to changing circumstances.

Lastly, we show the benefits of diversification strategies, such as omnichannel retailing and multiple sourcing, in safeguarding both high resilience and high efficiency. Store managers should focus on diversifying their supplier base to enhance efficient resilience and integrating omnichannel strategies to ensure continued sales across multiple channels.

In sum, to improve resilience and efficiency simultaneously, stores should recognize the importance of strategies in logistics activities, collaboration with the customer, autonomy in decision-making, diversified sourcing, and omnichannel retailing strategies. As the grocery retail environment continues to get more volatile, understanding and implementing these strategies will be paramount for achieving efficient resilience in case of disruptions.

5.3 Limitations and future research

While our study provides valuable insights into the resilience-efficiency trade-off, there are limitations that should be noted. First, our analysis is based on a dataset from 20 retail stores of a single German grocery retail group, which may limit the generalizability of our findings. Future research could extend this analysis to other retail contexts and geographical regions, especially rural areas, to validate and expand upon our findings. Second, our study relies on secondary data, which may not capture all relevant aspects of the resilience-efficiency trade-off. Incorporating primary data through qualitative interviews with store managers and employees could provide a more comprehensive understanding of the tension between being resilient and being efficient and how to balance both. Third, our study does not delve into the role of digital technologies (e.g. artificial intelligence) and softer human factors (e.g. human capital) in influencing the trade-off, which represents an important avenue for future research. For example, it remains unclear how the use of algorithm-driven delivery decisions affects the trade-off in store operations, although initial studies highlight the pivotal role of the interaction between store employees and artificial intelligence (e.g. Berendes *et al*., 2024). For a more comprehensive analysis and further research, qualitative interviews with store managers and employees are needed.

Additionally, although complexity has been explored in the resilience literature (e.g. ifo Institut, 2023; Ivanov, 2020), there has been little to no focus on the impact of complexity in planning and managing personnel resources on resilience. This gap represents a critical area for future research and should be a key consideration for both firms and managers. Understanding how complexity in human resource management affects resilience could lead to better strategies for achieving resilience and efficiency.

Moreover, our results demonstrate that grocery stores in less densely populated areas can successfully align resilience and efficiency. This finding suggests a need for intensified research on grocery retail stores in these areas. Specifically, future studies should aim to distinguish between urbanized and rural areas to uncover unique challenges and strategies relevant to each setting. This distinction could provide a more nuanced understanding of how geographic context influences the trade-off leading to more tailored management practices.

Lastly, we see two promising future research directions in terms of our model. In this study, we employed the robust counterpart of the classical deterministic DEA model, while considering the dynamic and network structure of retailing and developing a robust dynamic network DEA model for identifying the sources of high efficiency losses in times of disruptions could be the first promising future research direction. A second direction could be to improve the measurement of the nature of the relationship. Notably, our model is designed to identify the presence and quantify the extent of trade-offs or to reveal the absence of a trade-off, referred to as alignment, but it does not directly capture the underlying dynamics of alignment. Alignment can indicate a balance or potential synergies between resilience and efficiency, where these two factors not only coexist but also reinforce each other positively. Enhancing the model could provide researchers with a more nuanced understanding of the nature of the relationship between resilience and efficiency.

Notes

1. https://www.destatis.de/DE/Themen/Laender-Regionen/Regionales/_inhalt.html

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Corresponding author
Matthias Klumpp can be contacted at: matthias.klumpp@polimi.it