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Two pawns in their game

Inventory and customer efficiency

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Acknowledgements

The title of this thesis is inspired by the song "Only a Pawn in Their Game" by the singer, songwriter, and Nobel laureate Bob Dylan.

Writing a doctoral dissertation is challenging, and major setbacks can occur along the way. On the other hand, the process can result in enormous satisfaction comparable to a runner's high. During this project, I have experienced both, and I want to thank several people for their help and support.

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Abstract

This thesis is motivated by the need to develop further knowledge on key concepts of efficiency in the setting of logistics and customer behaviour in the retail industry. Retailers invest significant resources in operations management to enhance firm performance and to better cater to customer needs. Because of the introduction and advancement of online retailing, the brick-and-mortar retail industry has experienced prominent changes during the last decade to in efforts to contribute to and reinforce the quest for improvements that enable superior performance. The transition to developing sustainable physical retail outlets requires that several tenets of retailing best practices be revised to compete with online retailing.

The overall research question of this thesis is therefore as follows:

Under which conditions and to what extent do retailers manage to facilitate logistical and customer efficiency?

To address this research question, the thesis reviews the literature and examines efficiency in two different directions. In the first setting, the link between inventory efficiency and performance is examined in relation to firm characteristics and exogenous explanatory variables. More specifically, in addition to general firm-specific characteristics, the effects of chain affiliation and time trends within retail chains are examined. The effects of business environment factors on inventory turnover are examined on the basis of geographic location and market conditions. In the customer efficiency setting, efficiency is studied by observing customers' in-store behaviours to identify how specific customer characteristics in general, and the use of in-store carrying equipment in particular, are associated with shopper efficiency. These two avenues for detecting important retail efficiency metrics are examined in three individual research papers, all published in international peer-reviewed journals.

The first paper argues that inventory performance varies between and is correlated with retail chain affiliations. It concludes that the examined retail firms, and retail chains in general, experienced a negative time trend during the 1998–2013 period, even when firm-specific key financial ratios are controlled.

The second paper examines logistic performance and efficiency, utilizes the information in the inventory turnover metric and measures the association with geographic location and market conditions. It claims that different elements in the business environment are associated with differences in inventory efficiency. In addition, it identifies regional geographic differences and suggests that lead time plays a significant role in store performance, depending on the degree of rurality of the geographic location.

The third paper examines customer in-store behaviour by observing purchases, customer characteristics, and the use of carrying equipment (cart, basket, or no equipment) while at the same time measuring different in-store behavioural metrics closely related to effort and efficiency (convenience). It finds that most shoppers resist using a carrying device and shows that the type of in-store carrying equipment consistently explains differences in key in-store shopper metrics. In terms of customer efficiency, it finds that customers who do not use a shopping device when visiting a retail store have lower efficiency in terms of walking distance per purchased item than those using a basket or shopping cart. This has important implications for retailers, as shopping trips involving relatively few items have increased over the past year and now represent a significant portion of all shopping trips in physical retailing.

The papers empirically demonstrate two different perspectives on efficiency that are important for retailers to be aware of. From this customer and retailer perspective, several dilemmas exist that have been only partly covered in the three papers. This dissertation aims to discuss some of these dilemmas and to demonstrate some of the dualities that exist in the intricate interconnection between the customer and the retailer in the pursuit of efficiency.

Overall, the thesis offers new insights, makes significant contributions to the literature and to retail practice in terms of the complex topic of retailer logistical performance and customer efficiency and develops a better understanding of some tenets of eminent and sustainable brick and mortar retailing. As such, strategies for retailer efficiency and consumer convenience should not be focused merely on logistical efficiency or consumer efficiency but should instead be viewed in a balanced way – as a duality. This is particularly important in situations where consumers make a trade-off between price/assortment and time/effort (convenience). Both price/assortment and time/effort are factors that can be significantly affected by retailers' quest for efficiency. Retailers should therefore be careful to increase their efficiency at the cost of consumer efficiency, particularly for segments with high willingness to abandon low cost and better selection in favour of a more efficient shopping trip.

Table of Contents

List of Tables

List of appended papers

The following papers are included in the PhD dissertation:

I: Breivik, J. (2019). Retail chain affiliation and time trend effects on inventory turnover in Norwegian SMEs. *Cogent Business and Management*, 6(1), 1–17. https://doi.org/10.1080/23311975.2019.1604932

II: Breivik, J., Larsen, N. M., Thyholdt, S. B., & Myrland, Ø. (2021). Measuring inventory turnover efficiency using stochastic frontier analysis: building materials and hardware retail chains in Norway. *International Journal of Systems Science: Operations and Logistics.* https://doi.org/10.1080/23302674.2021.1964635

III: Larsen, N. M., Sigurdsson, V., Breivik, J., & Orquin, J. L. (2020). The heterogeneity of shoppers' supermarket behaviors based on the use of carrying equipment. *Journal of Business Research*, 108 (February 2019), 390–400. https://doi.org/10.1016/j.jbusres.2019.12.024

Contributions:

Table 1 represents the contributions of supervisors and co-authors to the appended papers. For more detailed information about contributions on each paper, see the signed co-author statements given in Appendix 1.

Table 1: Contributions form supervisors and co-authors

Phase	Paper I	Paper II	Paper III
Concept and idea	JB	JB	NML/VS/JB
Study design and methods	JB	JB/ØM	NML/VS/JB
Data collection	JB	JB	NML/JB
Data analysis	JB	JB	JB
Interpretation of results	JB	JB	NML/VS/JB
Manuscript editing	JB	JB/NML/SBT/ØM	NML/VS/JB/JLO

Critical revision of the intellectual content	JB	JB/NML/SBT/ ØM	BML/VS/JB/ JLO

Authors	Supervisors and authors
JB – Jørgen Breivik	ØM – Øystein Myrland
VS – Valdimar Sigurdsson	NML – Nils Magne Larsen
JLO – Jacob Lund Orquin	SBT – Sverre Braathen Thyholdt

PART I

If economists did not concern themselves with economic efficiency, nobody would.

-Dennis Holme Robertsen

1. Introduction

Increasingly, the retail industry is becoming an important institution in the intricate machinery needed to maintain and develop modern society. The spread of the COVID-19 pandemic once again reminded us of how essential it is for this industry to be continuously able to serve the needs of individuals, companies and the public. Due to the devastating pandemic event, numerous industries have suffered severe supply chain disruptions (Wahba, 2021; Nikolopoulos et al. 2021), leading to problems with sourcing and shelf availability. Instability and unpredictability negatively affect financial performance (Kovach et al., 2015), and such variations increase the complexity of maintaining efficient operations while catering to customer needs. Additionally, the ongoing duration of the pandemic has created persistent challenges for businesses, as time is essential to sustain and improve operational performance (Ghalayini & Noble, 1996). Additionally, time and effort (convenience) play a vital role for customers (Reimers, 2014). This is elegantly summarized by Sorensen, who claimed that "Efficiency and convenience is the glue that binds the United States together" (Sorensen, 2017, p. 32). From a broader viewpoint, beyond the perspective of customer convenience and the retailer's continuous quest for increased efficiency, productivity growth is the main tool that enables improvements in the standard of living and welfare (Parmeter & Sickles, 2020).

This thesis is positioned within the broad literature of economic efficiency and combines two different but interdependent research themes: logistics management and customer convenience. The field of inventory management has attracted increased attention in recent decades. One reason for this emerging interest is that recent studies have empirically identified links between inventory turnover, inventory leanness and inventory agility and financial and stock performance (Capkun et al., 2009; Shockley & Turner, 2015; Isaksson & Seifert, 2014; Eroglu & Hofer, 2011; Alan et al., 2014). In addition, in the field of customer convenience, attention has increased due to research indicating that shopper efficiency has a positive relationship with sales (Sorensen, 2017) and that attributes of convenience are linked to a rise in profitability (Kumar & Karande, 2000).

From the overall perspective, this thesis addresses the term "efficiency" in the context of retail firms and their customers. Efficiency is, in short, defined as "the performance of the processes transforming a set of inputs into a set of outputs" (Førsund & Hjalmarsson, 1974, p. 141).

Inventory efficiency is most often measured by use of the terms "inventory turnover," "inventory days," and "inventory leanness." Previous research has found that inventory turnover, for most industries, has a significant association with gross margin, capital intensity and changes in sales (Gaur et al., 2005). Studies have also indicated that inventory efficiency varies across different industrial sectors and must be accounted for in empirical analyses (Eroglu & Hofer, 2011; Isaksson & Seifert, 2014). Economies of scope and scale have also been suggested, as increasing firm size is associated with improved inventory efficiency (Kesavan et al., 2016). At present, the effects of other firm-specific characteristics on inventory turnover have been less widely examined empirically in the operations management literature. Although retail chains play an increasingly significant role in the markets of developed countries (Kosová & Lafontaine, 2012; Perrigot, 2006), the effects of retail chains on store-level inventory turnover have not been empirically examined.

The most commonly used inventory control models rely on assumptions about lead time for optimizing when and in what quantity purchases should be made. Environmental factors such as demand density, urbanization and centrality have been found to be important in several firm-level efficiency metrics (Aiello & Bonanno, 2016; Ko et al, 2017; Hernant et al., 2007); thus, it is reasonable to assume that a store's geographic location may impact its inventory turnover efficiency. However, researchers have not empirically examined the effects of environmental factors on inventory turnover.

Shopper efficiency is a key dimension of customers' in-store shopping experience (Davis & Hodges, 2012). In the literature, customers' in-store efficiency has been measured using different units of measurement: deviance between the actual versus the most efficient in-store path (Hui et al., 2009), shopping duration in seconds (Sorensen et al., 2017; Bogomolova et al., 2016), in-store travel distance (Larsen et al., 2020), actual spending per time unit (minute or second) or the inverse (Davies & Bell, 1991; Sorensen, 2017), per-item shopping time (Bogomolova et al., 2016), and dollars spent per item (Davies & Bell, 1991; Sorensen, 2017; Bogomolova et al., 2016). One of the attributes defined as offering customer convenience is the availability of carts and baskets (Reimers, 2014). However, a literature review by Larsen & Sigurdsson (2019) shows that only a few studies had examined the relationship between carrying equipment and shopper behaviour (e.g., Gil et al., 2009; Seiler & Pinna, 2017; Van den Bergh et al., 2011). In addition to the scantiness of this body of knowledge, these studies have all disregarded the behaviour of shoppers without equipment. Since customers tend to make more frequent visits to retail stores and buy fewer items, the number of shoppers without equipment is growing, and these shoppers are thus becoming more attractive to retailers. What is efficient for the retailer and other customer groups is not necessarily efficient for shoppers without equipment. To better cater to this segment, retailers need more insights into how this customer group spends time in the store between shopping (buying what they need) and in-store travel (getting around). Such insights are essential to develop more efficient solutions that respect the valuable time and effort of these shoppers during their time in the store.

Acknowledging the difficulties that firms encounter in remaining competitive by maintaining and boosting operational performance reveals the need to extend the current body of knowledge and fill some of the gaps identified in the literature on inventory and customer efficiency. This forms the basis for the research question (RQ) that this dissertation seeks to clarify.

The RQ to be answered in this thesis is therefore as follows:

> *Under which conditions and to what extent do retailers manage to facilitate logistical and customer efficiency?*

To further describe the scope of the dissertation, the RQ is divided into three sub-RQs (Q) that align with three independent empirical papers.

> Q1 – Paper I: What role does retail chain affiliation play in inventory turnover performance?
>
> Q2 – Paper II: How do environmental factors impact inventory performance and efficiency?
>
> Q3 – Paper III: How does shopper efficiency vary depending on customers' choice of shopping equipment?

In more detail, paper I aims to empirically examine the role of firm characteristics (key financial figures), and particularly the role that retail chain affiliation plays in firm-level inventory turnover and inventory turnover time trends. Paper II builds on the results of Paper I and elaborates on these findings to empirically examine the effects of the business environment on inventory turnover. Finally, paper III aims to examine shopper efficiency (basket size/travel distance) and the role of customer characteristics (age and gender), with a particular emphasis on the use of carrying equipment (no equipment, basket, cart) with control variables for shopping period and shopping time.

This thesis condenses the main themes in the attached papers, explores the dualism in shopper and inventory efficiency and argues that from an overall perspective, a duality exists between customer convenience and retailer logistical efficiency. It further discusses in more detail some of the intricate dilemmas that retailers must be aware of when strategies are developed and executed.

The rest of this thesis is organized in two parts. Part I, section 2 outlines a review of the theoretical background on inventory efficiency and customer in-store efficiency, and section 3 describes the research design and applied methods. Section 4 presents the papers in this thesis. In the fifth section, the main results of each of the three papers are discussed in the context of duality, followed by a final part that describes the contributions and implications of this research and suggests directions for further research. Part II presents each individual paper in its full-length version.

2. Theoretical background

This section provides a condensed overview of the theoretical background of the concept of efficiency and the empirical literature relevant to inventory turnover performance and customer efficiency.

2.1. The nature of efficiency

The British politician and author Benjamin Disraeli once wrote, “There can be economy only when there is efficiency.”

This statement supports many basic topics in economic theory and can be understood in a number of contexts. Even though the term “efficiency" is frequently used in research, management and daily language, no clear and common agreed-upon definitions exist (Neely et al., 2005; Tangen, 2005). To further complicate the understanding of the term, it is frequently used interchangeably with “productivity.” In this section, an attempt is made to clarify the meanings of the concepts of productivity, performance and efficiency.

The term “productivity” has several interpretations; it has been described from both verbal and mathematical perspectives and hence is a multidimensional term with varying meanings that depend on the context (Tangen, 2005). Productivity is commonly referred to as the relationship between input and output (Heady, 1952; Tangen, 2005). To identify productivity, the effects of production processes must be analysed, and in some fields of research, this process is labelled technology, as it depicts the underlying production process. The methodology of analysing productivity can be used for any economic system, from the firm level to the country level (Heady, 1952; Sickles & Zelenyuk, 2019). To assess productivity, a comparison must be made on the basis of either a standard (Førsund & Hjalmarsson, 1974), as a change over time, or a comparison with other firms at a certain point in time (Tangen, 2005). According to researchers (National Academy of Sciences, 1979), the main areas of application for productivity measurements are identifying the need for cost reductions and production planning and identifying productivity development over specific periods.

Efficiency within economics research has been explained as a relative concept that concerns “the performance of the processes transforming a set of inputs into a set of outputs” (Førsund & Hjalmarsson, 1974, p. 141). More specifically, Neely et al. (2005) argue that efficiency is about how well a firm can utilize its resources, or a utilization rate (Tangen, 2005). Within the field of efficiency and productivity analysis, economic efficiency is divided into technical and allocative efficiency (Parmeter & Sickles, 2020). Technical efficiency refers to the maximum possible outputs from given inputs or minimizing the inputs for given outputs (Kumbhakar & Lovell, 2000), and allocative efficiency is the optimal allocation of inputs to maximize outputs. Metrics of the degree of efficiency are commonly extracted by specific types of analysis, such as stochastic frontier and data envelopment analysis. Moreover, efficiency is intricately connected with the term “effectiveness.” Effectiveness is more difficult to quantify (Tangen, 2005), although in the retailer/customer setting, it refers to the extent to which a customer requirement is met (Neely et al., 2005). Both effectiveness and efficiency are fundamental parts of performance (Neely et al., 2005). Tangen (2005) refers to performance as a wide and overlying construct in relation to productivity (and profitability) that partly surrounds the terms “efficiency” and “effectiveness,” while performance contains the terms and concepts of “quality,” “delivery,” “speed,” and “flexibility.”

There are a number of commonly used performance measures. Such metrics have been categorized as follows: financial measures, measures based on activity-based costing, partial and total productivity measures, time-based productivity measures and non-cost performance measures (Tangen, 2003). While financial performance measures have existed and been used by firms for decades, Eccles (1991) highlights the importance of using nonfinancial information, such as quality, market share, customer satisfaction, and customer retention, as metrics for firm performance.

A subtle yet important dimension of efficiency, productivity and performance is the nature of time, as accelerated time performance in businesses is assumed to reduce cost and improve profitability (Kumar & Motwani, 1995). It has further been argued that time cannot be borrowed, traded, sold, or stored but only consumed, and at a constant rate; it is assumed to be scarce and connected to opportunity costs and interest and is therefore fundamental in economics (Klein, 2007). Researchers have further implied that time flows in one direction and is irreversible (Klein, 2007). In addition, time is important to understanding how phenomena and variables develop over given intervals of time, their consistency over time, their functional form and the speed or rate of change in them (Stritch, 2017). Within economics, finance and operations management, time is frequently used in statistical models to capture time trends and to follow individuals and entities in longitudinal studies. Time is also used as an entity of a larger construct, e.g., in variables such as key financial figures. Finally, time is measured per se and serves as an independent efficiency measure (Tangen, 2005).

Other research has focused on distinct avenues for research on time; the first is the mathematical approach, as to some degree described in the previous paragraph, while a second category is the human ability to experience and communicate the flow of time (Rickles & Kon, 2014). While the mutual understanding regarding the nature of time for most practical matters is undisputed, the perception of time at the individual level is another matter. As Núñez & Cooperrider (2013, p. 220) remark, "Time is not a monolith, but rather a mosaic of construals with distinct properties and origins". In addition, other research has identified a linear relationship between the judgement of temporal intervals and actual time intervals (Allan, 1979) and found that the mean internal time for most humans in general is reasonably correct but comes with large variances (Grondin, 2010). Some of this deviation in time judgement is linked with the workload or effort needed to perform a task (Brown & Boltz, 2002). In addition, time scales are a cognitively challenging task, and we improve performance when we think about time in terms of events (Resnick et al., 2012). Within departments and organizations, people have wildly different visions of time (Saunders & Kim, 2007). For instance, Hornik (1984) finds that customers perceive the waiting time in cashier lines to be longer than the actual waiting time and that shopping enjoyment is the only independent variable that explains this discrepancy.

Finally, it should be mentioned that even though most firms and chains have room for improvements in efficiency (reductions in inefficiency) (Gauri, 2013), when performance is assessed at the microeconomic level (firm level), a firm may be fully efficient based on its own objectives but not according to the objectives set in the analysis (Førsund & Hjalmarsson, 1974).

2.1.1. Inventory performance

Inventories continue to play a significant role in present-day manufacturing and retail industries, as US business logistics costs account for 7.5% of US GDP (Monahan et al., 2017). In addition, the COVID-19 pandemic has clearly demonstrated the dependence of modern society on reliable supply chains. The pandemic has created major supply chain disruptions, as supply has halted due to suspended production (Butt, 2021); a surge in demand for medical, food and essential products caused by health care needs; and hoarding and panic buying (Singh et al. 2021).

In this context and at the retail store level, inventory is supposed to act as a countermeasure for demand volatility (Baker, 2007; Chopra & Sodhi, 2004) and to cater to instant customer needs (Corsten & Gruen, 2003). On the other hand, the costs of holding inventory are linked with the costs of capital, storage and handling, obsolescence, damage and deterioration, pilferage/shrinkage, insurance, and management costs (Christopher, 2016). To manage an optimal level of inventory, inventory control models are used that date back as far as 1913 (Harris, 1990). Many such models have since been developed that can be divided into main two categories. The first category is (Q, r) models that estimate the optimal quantity (Q) to reorder at a given reorder point (r). The second type of model is the periodic review (S, T) model, which aims to set an order that adjusts the stock level to a specific predetermined level (S) at a regular time interval (T). Both groups of models are applied at the stock-keeping unit (SKU) level and represent the most detailed disaggregated description of the product. Inventory management research continues to identify prerequisites and factors to include in inventory control models; see, e.g., Williams & Tokar (2008).

Financial accounting inventory is reported in levels, and to convert inventory levels to a performance measure, two approaches are commonly used. The first calculates inventory turnover as average inventory divided by the cost of goods sold. An increasing inventory turnover metric then serves as an indicator of improved inventory performance and inventory leanness. The second performance measure is inventory days, calculated as 365 days (or another period length) divided by the inventory turnover ratio. While the retail industry uses inventory performance measures only for finished goods inventories, manufacturing firms are also required to assess such metrics for raw material and work-in-progress inventories.

Even though early inventory control models date back over one hundred years, researchers have empirically assessed the effects of such models on overall inventory performance at the firm level and across industries only for the last few decades. Coinciding in time, other research has empirically examined the relationship between inventory management and financial performance and profitability. Initially, these studies identified no significant association (Cannon, 2008); however, a pattern of relationships has recently emerged that is positive but beyond a certain point may cause performance to deteriorate (Rumyantsev & Netessine, 2007b; Shockley & Turner, 2015; Eroglu & Hofer 2011; Isaksson & Seifert, 2014). Moreover, for US retail, inventory turnover has been found to predict future stock returns (Alan et al., 2014).

Several important contributions have recently been made to the literature on key financial characteristics associated with differences in inventory turnover performance. First, the key financial ratio of gross margin has been found to be negatively connected with inventory turnover (Gaur et al., 2005; Rumyantsev & Netessine, 2007a; Kolias et al., 2011). It has further been suggested that this association is connected to and serves as a proxy for retailers' differences in product price, product variety, service level and product life cycle (Gaur et al., 2005). These are important underlying variables that are too modest and difficult to access across multiple firms and over time. The product price has theoretically been closely linked to gross margins and has been depicted as representing policies set by each retailer for markups on individual SKUs or product categories. Theory has also indicated that increased product variety leads to larger inventories and allows retailers to achieve improved profit margins. Furthermore, increased product variety has in general been found to reduce inventory turnover and has been assumed to be caused by losses from risk pooling (Wan et al., 2020). In addition, it should be safe to presume that facilitating customers with increased service levels should be accompanied by higher costs that necessitate higher prices. Capital intensity and sales growth have also been found to be positively correlated with inventory turnover (Gaur et al., 2005; Kolias et al., 2011). Capital intensity is arguably caused by differences in the use of and investments in information technology (Cachon & Fisher, 2000; Shah & Shin, 2007), warehouses and logistics management systems and other fixed assets (Gaur et al., 2005), while unexpected sales growth is assumed to cause inventory levels to fall for the examined period, which also affects the inventory turnover ratio (Gaur et al., 2005). The literature has also suggested that retailers with high versus low inventory turnover respond differently to demand shocks (Kesavan et al., 2016). Contributing to the literature on inventory turnover and the association with factors that help explain differences in inventory performance, Eroglu & Hofer (2011) suggest a lean inventory indicator that controls for a nonlinear relationship with firm size and industry characteristics.

Economies of scale have been widely accepted in many areas of economic research. However, beyond theoretical inventory control models and simulations that provide valid arguments for such properties to also exist in inventory management, less empirical research on this important topic has been published. A few notable exceptions have suggested economies of scale in inventory management (Rumyantsev & Netessine, 2007a; Gaur & Kesavan, 2009, Eroglu & Hofer, 2011). Economies of scale are also portrayed in relation to chain affiliation in terms of purchasing and sales, as retail chains use more advanced inventory control systems and offer more standardized products at lower prices (Dinlersoz, 2004). In developed countries and in the retail sector, chain stores are an important part of the economy (Kosová & Lafontaine, 2012; Perrigot, 2006), as they contribute to productivity gains (Doms et al., 2004; Foster et al., 2006).

The literature also aims to measure time trends in inventory for retail firms. Firm-level data from both wholesale and retail firms for the 1981–2000 period indicate that the median number of inventory days decreased from 73 to 49 and that the inventory levels for the retail segment started to decline in the mid-1990s (Chen et al., 2007). In contrast to these findings, Gaur et al. (2005) find for the 1987–2000 period that inventory turnover declined by 0.45% annually, which implies an increase in relative inventory levels. Similar to the above findings, Kolias et al. (2011) find a 3.4% annual decline in inventory turnover for Greek retail for the 2005–2008 period.

Lead time is of considerable significance in inventory control models, as increased lead time raises inventory levels (see, e.g., Das, 1975; Ben-Daya & Raouf, 1994) and thus reduces inventory turnover.

Rumyantsev & Netessine (2007a) examine, among other lead times in manufacturing and retailing firms for the 1992–2002 period, using days accounts payable as a proxy for lead time and find that lead time accounts for approximately 2% of the variance in inventory levels in the pooled sample. However, the usefulness of days accounts payable as a proxy for lead time is questioned.

2.1.2. Customer efficiency

In the previous section, and based on the current literature, the concept of inventory performance was described, and its significance for the retailer was justified. For retailing to be successful, inventory performance also must facilitate efficient customer shopping since customer efficiency is as important for some customers as efficiency is for the retailer (Heckman, 2017; Sorescu et al., 2011; Larsen et al., 2020).

It is generally agreed that time and money are the most important resources that the customer brings to the store (Bogomolova et al., 2016; Sorensen, 2017). Others point to shopping speed and ease (Seiders et al., 2000) and customers' intention to conserve time and effort (Berry et al., 2002) or simply customer transaction costs (Larsen et al., 2020). It has also been suggested that customers in most cases consider shopping a necessity and not a recreational activity (Seiders et al., 2000). The term "convenience" has long been debated and undefined by academics (see, e.g., Reimers. 2014; Brown & McEnally, 1993), beyond the minimization of time and effort (Burke & Morgan, 2017). The literature has made noble attempts to categorize convenience. In the context of customers' time and effort, Berry et al. (2002) conceptualize a model that suggests dividing convenience into five different categories: decision convenience, access convenience, transaction convenience, benefit convenience, and finally postbenefit convenience. These classifications reflect the stages of activities in which the customer participates through his or her purchases. According to Berry et al. (2002), the five different stages include the following descriptions and activities related to the perceived use of time and effort: 1) decision convenience concerns the decision on whether to buy the product and from which supplier; 2) access convenience is the process of acquiring the desired product or service, such as store location, parking, opening hours; 3) transaction convenience embodies activities such as ease and fast checkout; 4) benefit convenience is the perceived time and effort needed to experience the service; and 5) postbenefit convenience refers to the need for maintenance, repair, or exchange or simply experiencing service failure. Recently, attempts have been made to empirically examine different attributes of convenience. Seiders et al. (2007) find that shopping enjoyment significantly relates to the service convenience categories suggested by Berry et al. (2002) (decision, access, transaction, benefit, and postbenefit). In a retail-specific setting, Reimers (2014) studies customer perceptions of store convenience and lists 25 different attributes that relate department store convenience to shopper efficiency (time and effort). His findings further suggest that payment options, checkout, product clusters, trading hours, and one-stop shopping are the five most important store convenience attributes. In addition, Reimers (2014) identifies the category that comprises attributes such as clearly labelled prices, quick and easy checkout and signs that assist the customer to easily locate products as the most important, explaining as much as 28% of the variance in search and transaction convenience.

Understanding service convenience and its antecedents and consequences is important for businesses that wish to minimize customers' time and effort (Berry et al., 2002; Seiders et al., 2007). The connection between convenience and shopper efficiency is pronounced, and a convenience attribute can be converted into an input/output ratio by use of the key input of concern with time as the denominator (Holbrook, 1999). The empirical literature on in-store behaviour and key shopper metrics is growing, and several notable contributions have been made. Sorensen et al. (2017) find in a large study across several continents and multiple retail formats that most shopping trips in supermarkets have a mean length of approximately 25 (median of 17) minutes and include a mean of 15 (median of 4) purchased items. Sorensen (2017) further argues that there is a need to balance the need for efficient customer shopping based on easy access to the most wanted and best-selling products and fast checkout with arranging and organizing the store to attract shoppers who want to explore a wider assortment. Other research has focused on actual individual in-store behaviour and tracked customer walking paths by the use of radio frequency identification (RFID) tracking tags attached to the cart that enable software to locate the shopper/cart within the store. In this research, Hui et al. (2009) assess the deviations from the optimal walking path and demonstrate that consumers take longer-than-optimal routes in the store (based on what they buy and where products are located). They find that a large number of shoppers deviate from their optimal path due to travel deviations, while the order deviation (between product categories) is small. Bogomolova et al. (2016) study in-store behaviour in supermarkets and examine several aspects of time from a shopper efficiency perspective. They collect data by customer interviews prior to entering the store and after finishing the shopping trip and record the shopping time and number of purchased items. They find that older shoppers are less efficient (minutes per number of purchased items) than younger shoppers and that on a per-item basis, females are more efficient than their male counterparts. In addition, their data show no significant differences in shopper efficiency during peak versus off-peak hours. Researchers have also studied differences in shopper efficiency for quick trips versus regular trips (Larsen et al., 2020). The findings indicate that shoppers on quick trips on average purchase approximately 2.4 items, while shoppers on regular trips on average buy nearly 10 items. The paper further finds that several shopper efficiency metrics are influenced only by the distinction between types of shopping trip (quick or regular), and some metrics by age. Larsen et al. (2020) argue that the design principles of stores are the hurdle to clear, as quick shopping trips are less efficient than regular trips.

In many cases, at least in practice, there is conflict between the retailer and the consumer regarding the quest for efficiency in retail. Such conflicting interests may be caused by retailers with merchandise located unfavourably in terms of the preferred travel path and queues at checkout counters, particularly during peak hours, as well as the location of frequently bought products at the back of a store to improve sales and save on staffing and other costs (Seiders et al., 2000). It is important for retailers to improve their understanding of the relationships between forms of convenience to enhance customer efficiency, particularly shopping speed, which saves customer time and energy (Seiders et al., 2000). In addition, Seiders et al. (2000) argue that convenience is not a static measure but develops as the industry improves convenience and that retailers constantly seek to increase their targets to offer competitive shopper efficiency. In addition, providing convenience to customers has been found to serve as an effective tool to reduce exit intention (Sabine et al., 2009). Despite recent findings on convenience and in-store behaviour, the empirical literature on customer time and effort, such as in-store travel distance, is limited, including knowledge of how attributes of convenience (in-store carrying equipment) affect shopper efficiency.

3. Research design

This section describes how each of the papers is connected to the overall RQ, the data collection process, and the strengths and weaknesses of the different types of data. Finally, it ends with a paragraph on ethical considerations.

To answer the overall RQ and the three Qs, as stated in the introduction, the scope of the three individual papers is described in Table 2. The table also specifies how each of the three papers is linked to each of the Qs and RQ and provides a brief description of the types of data used in the individual papers.

Table 2: Overview of papers and their role in answering the overall RQ.

Appended papers	Scope	Relation to RQ	Type of data
Paper I	Examines the relationship between retail chain affiliation, firm size, and time trends in inventory turnover performance.	How is retail chain affiliation connected with inventory turnover performance?	Financial accounting panel data containing retail chain affiliation.
Paper II	Examines the relationship between external factors (regional store location, municipal population, rurality) and inventory turnover performance and efficiency.	How are business environmental factors connected with inventory performance and efficiency?	Financial accounting and demographic panel data.

Appended papers	Scope	Relation to RQ	Type of data
Paper III	Examines the relationship between customer characteristics (age and gender), shopping time, the use of in-store carrying equipment and shopper efficiency (in-store behaviour metrics).	What role does shopping equipment play in shopper efficiency?	Two independent studies: Study I: Large field observational study on the choice of in-store carrying equipment across retail formats. Study II: Large field study of entire shopping trips utilizing observations in combination with a path-tracking software.

Each paper individually contributes to and portrays different research topics within business research. This thesis condenses the main themes in the papers and exclusively emphasizes the construct of efficiency, with particular attention to the retail industry.

The three papers rely on different sources of data that are collected in multiple ways. In principle, the papers utilize two types of data: first, financial accounting and spatial and population data derived from public sources and second, observational and path-tracking data. In addition, the papers utilize various methodological approaches, each individually selected to be suitable for the phenomena examined and data needed to answer the RQ.

The inventory performance data comprise a panel representing 16 years of financial accounting and market environment data. The data were from 186 building materials and hardware stores within three retail chains. The data collected for use in paper I were from public sources (forvalt.no) and encompassed yearly financial accounting data at the firm level. These data also included the number of employees and/or full-time equivalents. In addition, for each firm, the chain affiliation was collected from public information available online, and these records were later confirmed by each retail chain administration. Additionally, the postal code and NACE/Standard Industrial Classification were collected from the online services provided by the Brønnøysund register centre as of the end of 2013. Therefore, the variables chain affiliation, postal code, and NACE code are nonvarying. Paper II used the same data as paper I, with the difference that it also entailed information on store location (by postal code) in one of six different national regions. In addition, the study connected each store (by postal code) with a municipality. Each municipality was classified to a specific degree of geographic centrality as defined by Statistics Norway (1999). In addition, the paper used the yearly municipal population (Statistics Norway, 2018). The paper assumed that these variables in sum served as a proxy for the effects that stem from the business environment. These two papers were analysed using two methods: Prais-Winsten panel regressions for paper I and stochastic frontier analysis for paper II.

Cross-sectional panels or longitudinal data constitute observations on units (e.g., firms, stores) that are recorded for several periods of time. Longitudinal data have three main advantages compared to cross-sectional data (recorded for only one period): first, they provide a more accurate inference of the parameters of the estimated model; second, they have a better ability to capture complex behaviour; and third, they can simplify estimation and statistical interpretation (Hsiao, 2007). In summary, longitudinal data have the advantage of capturing behaviour in detail, assessing time trends and serving as a basis for better predicting and forecasting estimates.

While panel data have several advantages, as described above, they are also associated with issues that should be taken into consideration in the modelling process. In empirical economic panel data, missing observations are more predominant than in cross-sectional data due to entities or firms entering or leaving the market at different points in time and being unable to respond (Baltagi & Song, 2006). The datasets used in papers I and II contain missing observations. The papers used different techniques to counter such randomly missing data. In paper I, gaps in the data (within firm nonconsecutive runs) were identified, and the run containing the fewest observations was deleted, as the applied model was unable to efficiently manage such gaps. In paper II, the model supported such gaps, and no further action was taken. It is also worth mentioning that the datasets were unbalanced, meaning that the starting year of observations (by firm) varied. As all firms included in the study were affiliated as of the end of 2013, the analysis did not capture firms leaving the market in the study period due to shutting down, bankruptcy or taking part in a merger. This implies that these data are prone to survivorship bias, as is common for such data. Ideally, such firms should have been included; however, it is difficult, if not impossible, to obtain such data. In addition, as mentioned in the previous section, chain affiliation, firm location (postal code), and NACE code are time-invariant variables that were collected only at the end of the study period. This implies that changes in these variables, such as firm relocation to another municipality, were not taken into consideration. It should also be noted that a few of the firms represented in the data operated more than one store. This implies that some subentities (stores) could potentially have been located in other municipalities or could have previously had another chain affiliation.

The observational data used in paper III were collected in two separate studies and grouped into two datasets. Study I observed customer behaviour across 15 stores within different store formats and gathered information on customer age, gender, and the choice of in-store carrying equipment (no equipment, basket, or cart) from the time the customers entered the store until they made the choice of what type of carrying equipment to use. Study II, a large-scale observational study, observed 635 complete shopping trips in a discount grocery convenience store by using in-store cameras that covered the entire store combined with state-of-the-art path-tracking software that provided detailed information on shopper metrics, such as walking speed, walking distance, store area covered, and number of items purchased. Multivariate linear regression was used to extract estimates of the relationship among the efficiency variables representing customer in-store behaviour.

Cross-sectional data are observations across units for a particular period and are the most frequently used type of data. The main advantages of such data are generally that collecting them is quick, easy, and cheap. The data generation process in study I (paper III) reflected these advantages. However, in study II, several hurdles had to be overcome prior to data collection[1]. The customer behaviour data in paper III are quite unique because the study was one of the first to truly observe an entire shopping trip and measure important in-store behaviour metrics such as in-store speed, travelling distance, number of items purchased, gender, age and choice of in-store carrying equipment. This approach was in contrast to studies that used methods such as RFID or Bluetooth (see, e.g., Hui et al., 2013; Phua et al., 2015) and that targeted only certain groups, thus excluding entire segments of customers and their shopping behaviour. The use of video/software technology in paper III countered this potential bias, as most segments were included. The technology also benefited from the advantage of being discreet

[1] Regarding study II in paper III, the thesis authors' contribution to the data collection process started at the same time as the observations began; hence knowledge of the initial application and funding process, agreements related to which store to collect data from, sourcing of cameras and software was limited.

relative to other methods of observation. Compared to RFID studies, where the chip is located within the cart, the methods used in paper III tracked the actual behaviour of each individual shopper and did not use the shopping cart as the point of interest. However, the technology used in paper III still had some limitations identified with families and groups entering the store and the problem of categorizing the main individual to track during the shopping trip, his or her age and gender in relation to other individuals in the same family/party, and his or her behaviour and involvement in picking items and placing them in the basket or cart. Observing and tracking multiple individuals simultaneously is generally challenging and necessitates appropriate resources for such observations and/or software adapted for such use. Nevertheless, these issues are also present in RFID/Bluetooth studies. As no common approach to recording such instances was identified during the data collection period, such observations were disregarded in the analysis, and the study was therefore limited to individual shoppers. Moreover, convenience stores frequently offer their customers a choice of two different types of basket: a small basket that is usually carried in one hand and a larger basket with four wheels that can be pulled behind or pushed in front of the customer or may sometimes be carried by hand. The store subject to the observations in study II of paper III offered both types of basket. In the data presented in paper III, these types of baskets were merged for practical reasons. It is likely that significant differences in the volume, design and practicality of these baskets could affect shopper key metrics and thus the estimates. This was not tested in the analysis, and a future study could provide further insights into the differences between types of baskets.

Researchers are increasingly required to reflect on and exercise ethical considerations in their research. In Norway, the National Committee for Research Ethics in the Social Sciences and the Humanities issues guidelines on research ethics in the social sciences, humanities, law and theology. The guidelines are essential for promoting good scientific practices and are based on recognized norms for research ethics, regulating research in different areas and in different relationships. In the following section, a discussion of ethical considerations is based on NESH recommendations (NESH 2021).

The research for the papers and the development of the dissertation were performed in the expectation that they would be relevant to the research community and larger society; thus, the results of this project were made available to the public. To promote the research, all three papers were published in peer-reviewed academic journals with open access outlets. In an early stage, paper II was also presented at an academic conference to reach a broader academic audience. In addition, a public presentation on the broad term “efficiency” was held during the project.

Regarding the use of empirical data, several ethical assessments had to be made, in particular concerning social sciences and the humanities, as such data are an integral part of the research process. This applies in particular to paper III, as observations of actual customers' in-store behaviour presented specific challenges, such as obtaining and evaluating the variables that were observed and later processed empirically. In addition, papers I and II both contained substantial samples of retail firms' financial data as well as, more importantly, a lengthy sample that posed different challenges regarding the use of methods and the process of omitting data from the sample. In this process, I have, to the best of my abilities, tried to be honest, provide detailed documentation, and be transparent about uncertainties in the data collection process, the use of methods and the inferences drawn from the data.

4. Presentation of papers

All three papers emphasize efficiency. The first two papers address efficiency within the operation of brick-and-mortar retailers and specifically examine inventory turnover. Inventory turnover is the leading key metric of inventory performance visible to competitors, investors, and analysts and is easily accessible in public financial statements. In addition, this metric is commonly regarded as a key within-business performance indicator and is closely monitored by management at the retail chain and store levels. The final paper explores customer efficiency related to customer in-store behaviour. More specifically, it examines differences in behavioural metrics such as walking speed, shopping duration and number of purchased products dependent on customer choice of in-store carrying equipment.

4.1. Paper I

Breivik, J. (2019). Retail chain affiliation and time trend effects on inventory turnover in Norwegian SMEs. *Cogent Business and Management*, *6*(1), 1–17.

Extending the current literature, this paper aims to gain more knowledge of firm characteristics as drivers of inventory turnover in retail businesses. More specifically, the paper addresses the effects of retail chain affiliation and the associated time trends and examines the effects of economies of scale. The analysis is based on an unbalanced panel dataset containing 16 years of financial accounting data from three specific Norwegian hardware and lumber retail chains. A Prais-Winston estimator (a special case of the feasible generalized least squares) is employed, enabling the paper to control for a panel-specific first-order autocorrelation. The main novelty and findings of this study indicate that inventory turnover varies significantly among retail chains and over time. Moreover, inventory turnover generally deteriorates at 5.2% annually when firm financial characteristics are controlled for and 2.3% annually without such controls. In addition, the study suggests that it is important to control for the specific industry code when inventory turnover is used as a benchmark across neighbouring sectors and even within a limited number of retail chains.

4.2. Paper II

Breivik, Jørgen; Larsen, Nils Magne; Thyholdt, Sverre Braathen; Myrland, Øystein. (2021) Measuring inventory turnover efficiency using stochastic frontier analysis: building materials and hardware retail chains in Norway. *International Journal of Systems Science: Operations & Logistics*, DOI: 10.1080/23302674.2021.1964635

Extending paper I, this paper aims to increase the understanding of business environmental characteristics as drivers of inventory turnover in retail businesses. In detail, the paper focuses on the effects of the exogenous business environment, more specifically in terms of market size and dynamics, rurality and spatial dependence. The analysis is based on the same unbalanced panel data as those described in paper I. However, information on municipal rurality, municipal population and store location divided among six geographic regions is appended. This paper relies on stochastic frontier analysis that utilizes information modelled by a response (production) function that represents the frontier of the best-performing firms and simultaneously estimates the score of (in)efficiency with the Battese & Coelli (1995) specification. The main findings of this study are that the market conditions in the area surrounding the store impact inventory turnover efficiency and that an increased municipal population increases inventory efficiency. The findings also indicate that inventory turnover varies depending on location in the six geographic regions and suggest that this variation is associated with increased lead time.

4.3. Paper III

Larsen, N. M., Sigurdsson, V., Breivik, J., & Orquin, J. L. (2020). The heterogeneity of shoppers' supermarket behaviors based on the use of carrying equipment. *Journal of Business Research*, *108* (February 2019), 390–400. https://doi.org/10.1016/j.jbusres.2019.12.024

The aim of this paper is to acquire extended knowledge of the determinants of shopper efficiency. In greater detail, the paper examines the effect of customer characteristics and the use of in-store carrying equipment on customers' in-store behaviour. More specifically, the paper measures in-store behaviour metrics such as walking distance, walking speed, number of purchased items and choice of in-store carrying equipment (no equipment, basket or cart). The data used in this paper are based on two observational studies. The first observed 3520 shopping trips in a broad range of food retailing formats, recording customers' use of in-store carrying equipment and their age and gender. The second combined observations and tracking software to capture details of the entire shopping trips of 635 customers, including their path, age, gender, average pace, and number of purchased items. It recorded key behavioural metrics as well as the use of in-store carrying equipment. This cross-section of observational data is analysed by multivariate linear regression. The main findings in this paper emphasize heterogeneity in shopper in-store behaviour and the association of the use of in-store carrying equipment with significant differences in shopper efficiency. Most importantly, the paper demonstrates that shoppers without equipment have the least efficient shopping trips, although this segment of customers represents the majority of shoppers.

5. Discussion, contributions, and implications

5.1. Discussion

The objective of the thesis is to develop new knowledge by examining the extent to which retailers manage to facilitate logistical and customer efficiency and influencing factors. To answer the overall RQ, the thesis builds on the data and empirical analysis described in papers I–III. To achieve the objective and to cover the different perspectives, the papers (relative to paper I) use supplementary or altogether new data. Furthermore, each paper uses different methods to analyse the key variables of interest.

This section integrates and synthesizes the findings of papers I–III in relation to a broader perspective rooted in the complex issues of customer convenience and retailer efficiency. These interconnected themes are discussed in the general perspective of duality as described by Giddens (1984).

Inspired by Giddens and as addressed in the duality of social structure (Giddens, 1984), I find it useful to conceive of the customer and the retailer as both mutually enabling and constraining in the context of efficiency. The RQ and the empirical findings in paper I–III will therefore be discussed in the context of the duality of efficiency in the retail setting and the interdependence between the retailer and the customer.

The mutual interdependence between the retailer and the customer is an interesting and important topic for retail managers and analysts to consider and understand. From a general and broader viewpoint, the aim of both the retailer and the consumer is to maintain and increase efficiency. One of the most salient dualities in the customer/retailer efficiency perspective is their simultaneous roles as enabler and constrainer, as both can facilitate and promote change while also restraining development and improvements. Obviously, the retailer is equipped with the most tools to address price and customer convenience, as it controls the entire sphere of the store and is likely to optimize the retail outlet according to its beliefs and knowledge regarding the sweet spot in terms of increasing the store's efficiency while simultaneously catering to customer needs. The customer, on the other hand, given the price and convenience provided by the retailer, is in a more advantageous position, as he or she can fully or partly accept this transaction cost; alternatively, the customer can switch to a competitor (given competition) that can better fulfil his or her wants and needs (Sabine et al., 2009). These wants and needs can be viewed as a trade-off between sacrifices and benefits (Payne & Holt, 2001) or between input and output (Ingene, 1984) and have been described as consumer efficiency (Atkins & Kim, 2012; Larsen et al., 2020).

Furthermore, it is reasonable to assume that a mutual understanding concerning efficiency exists, at least to some degree, between the retailer and the customer. The retailer and the customer can be regarded as independent entities that are nonetheless simultaneously dependent upon each other. One of the evident dualities in the retailer/customer relationship is the intersection between convenience and price, as returns (per minute) from a search are associated with a $2.10 price reward (Seiler & Pinna, 2017). This duality is evident (paper III), as shoppers without equipment face less efficiency (measured in terms of basket size divided by travel distance) and hence higher transaction costs than shoppers using any type of in-store carrying equipment. There is often a trade-off between price and convenience in the sense that some inconvenience is involved in achieving a better price (e.g., more searching, longer in-store paths). Alternatively, the customer may visit a more convenient retail format (e.g., a gas station or corner store), but the convenience then comes at the cost of higher prices and a narrower assortment. Another dilemma is the complexity of facilitating efficiency for all customer segments since increased efficiency for one segment may result in a reduction in convenience for other important groups of shoppers.

Shopper in-store behaviour metrics such as shopping duration, travel distance and thus shopper efficiency (basket size/travel distance), as examined in paper III, could be divided into the behaviours of navigation (travelling) and searching (at the shelf) (Larsen & Sigurdsson, 2019). In general, consumers in retail stores are trying to maximize the ratio of search gains (value – prices, products that satisfy needs) relative to search costs (time) (Seiler & Pinna, 2017; Sabine et al., 2009). This implies that customers are trying to maximize their search efficiency by the optimal use of their scarce time. When a consumer enters a store, he or she searches for a limited number of products (Inman et al., 2009), and he or she stops searching and starts to shop when the gain from shopping is outweighed by the search costs (Hauser, 2014) because it is not worth spending more time on further searching. This implies that the time spent on searching ultimately affects shopper efficiency, and the literature suggests several tenets of best practices to decrease search time, such as adding additional shelf facings, signalling the most popular (most frequently sold) products and keeping shelfs tidy (Burke & Leykin, 2014; Chandon et al., 2009). Navigation, on the other hand, which comprises a major part of the time used for customers' in-store travel (as depicted in paper III), is closely linked with the customer walking from the entrance to the desired category, moving between categories, and continuing to the checkout area. In-store navigation (in metres) comprises not only the actual metres walked but also knowledge of (or search for) where to find the desired category. As store size, store design and category location and labelling highly impact travel distance and thus shopper efficiency, this also constitutes a duality between customer convenience and retailer efficiency.

The use of carrying equipment, as emphasized in paper III, is itself a duality, as it contributes to the increased heterogeneity of shopper efficiency. This variance in customer efficiency (basket size/travel distance and speed) is by and large supported and amplified by the specific types of carrying equipment facilitated by the retailer. Introduced in the 1930s, shopping carts have been regarded as retailers' "greatest salesman" due to their capacity to assist consumers in carrying their chosen items to the cashier desk (Grandclément, 2009; Cochoy, 2009). However, this choice has consequences for how the consumer can act thereafter; for instance, selecting a cart automatically decelerates customers and thus hinders those who wish to complete their shopping as quickly as possible (paper III). Although retailers prefer that customers choose carts due to the likelihood of increased sales volume, many consumers are on shopping trips for which a cart is not needed and would instead prefer to use a basket or no equipment. The choice of specific types of in-store carrying equipment is, however, mostly customer-driven (when the wanted options are available), and this choice is related to age and gender (paper III) and possibly to individual preferences and shopping goals. This poses a dilemma for the retailer. When alternatives to the cart are offered, many customers may choose to shop without a carrying device. When the retailer offers alternatives, such as a basket, some shoppers without equipment may select a carrying device (which can lead to increased sales), but some who might otherwise use a cart may switch to a basket with lower capacity (and sales potential). Furthermore, it may prove difficult to provide the desired efficiency across all customer segments. Therefore, some kind of prioritization seems to be necessary. As paper III demonstrates, shoppers without equipment represent a large and important segment in all store formats (42–66%), and, according to A.C. Nielsen store formats facilitating quick trips are growing in volume (Convenience store news, 2018). This suggests that retailers should redesign stores to better accommodate improved efficiency for this major customer segment (Larsen et al. 2020). This can be considered a major shift in retail orientation, as most stores have traditionally been designed to facilitate stocking-up trips.

The previous paragraphs focus on customer convenience and efficiency (as the focus in paper III is on the customer) and portray some dualities in retailer efficiency. The next sections discuss possible dualities in the intersection between inventory management and customer convenience (as the focus in papers I and II is on the retailer).

From the retailer perspective, the quest to enhance efficiency (in a broad range of areas) is significant, as it is linked with profitability (Gauri, 2013; Foster et al., 2008; Shah & Shin, 2007; Hernant et al., 2007). This includes the more specific areas of inventory management and inventory performance (Shockley & Turner, 2015; Rumyantsev & Netessine, 2007b).

Prior to the discussion of the duality of logistical efficiency, a clarification of some of the dynamics of the inventory turnover metric is necessary. First, papers I–II use inventory turnover metrics at an aggregate level. However, it is also common to use the inventory turnover measure at the SKU level. It is important to be aware that the aggregated level of inventory turnover entails a price-weighted average of all units in storage, while the SKU-based metric provides a specific performance measure for a certain item. This suggests that the aggregate inventory turnover metric is prone to hide the complexities in holding inventory. For instance, compared to a high-cost SKU, a low-cost SKU will affect the aggregate inventory turnover metric to a lesser extent, ceteris paribus. The aggregate metric (more than the single unit measure) also hides variability in SKU-level inventory turnover and may include a considerable number of SKUs with problems. Such problems may stem from items being out of stock or slow moving and may cause deteriorating service levels that are currently not visible in the aggregate inventory turnover ratio. Second, the inventory turnover ratio for most businesses is calculated on a yearly basis in relation to financial statements to avoid issues related to seasonality. However, in day-to-day business operations, this causes the metric to be stale or to some degree obsolete, as it describes the course of action too far back in time to be a good indicator of present performance. This could be countered by a more frequent calculation (e.g., monthly) of the metric based on the last running 12-month period, with more attention paid to the change ratio of inventory turnover. Third, the inventory turnover ratio is not a measure that fits all types of inventories and may lack relevance for some types of merchandise, such as luxury products, e.g., Rolex watches, due to the trifling cost effects of inventory relative to profit and demand. Fourth and last, the inventory turnover metric does not signal the problem of loss of opportunity; that is, it measures actual sales and does not provide information on the loss of opportunity in the case of the product not being available on the shelf when there is a demand for it (Burke & Morgan, 2017).

All parts of the inventory management process, including the purchase of products, order confirmation, receipt and inspection of products, storage, refilling of shelves, and inventory control with its many independent tasks, have the potential to impact retailers (papers I and II) and their customers in diverse ways. First, shelf availability is one of the main links that directly connect inventory management and customer convenience. The consumer ideally always wants to find the desired items available on the shelf, particularly in full spacing, as this reduces search time (Burke & Leykin, 2014; Chandon et al., 2009). The retailer, on the other hand, is faced with the intricate problem of adjusting inventory levels to align with its product availability strategy. Too little inventory results in stock-outs and the problem of lost sales opportunities, as customers may substitute other items, delay purchase, or leave the store (Zinn & Liu, 2001), while overstocking leads to increased costs. The out-of-stock problem is quite common in retail, ranging from 5% for the best retailers to as high as 12% for the most troubled ones, and constitutes on average approximately a 4% sales loss (Corsten & Gruen, 2003). While not as easy in practice as in theory, the remedy for this delicate yet important retailer problem is to maximize service levels while simultaneously minimizing inventory (Salam et al., 2016). While the out-of-stock situation only affects the inventory turnover ratio to a limited extent, except when customers choose a substitute product, overstocking fully impacts this efficiency metric. This not only necessitates caution regarding how to interpret the inventory turnover ratio but also provides a reason to better understand the duality that exists in this context of efficiency.

Another area of particular interest for both the customer and the retailer is product variety (assortment size). In many cases, product assortment strategies are part of defining the retailer's image. Product assortment and assortment size are important for the consumer, as it has been suggested that they are related to perceived convenience and search time (Sabine et al., 2009). The retailer must carry a minimum assortment size to attract customers, while having too many SKUs may cause customer choice paralysis (Chernev & Hamilton, 2009). While product variety increases sales (Wan et al., 2020), the literature has found that it also increases inventory levels (Rajagopalan, 2013; Wan et al., 2020) and hence increases costs. Adding to this dilemma of assortment sizing, it has been suggested that demand variability is linked with declining sales and increasing inventory (Wan et al., 2020). This expresses yet another interdependence in the customer-retailer relationship. Furthermore, increased assortment size often results in larger stores being measured in square metres of selling, which increases navigation time/distance and thus negatively affects the efficiency of customers buying relatively few items.

Several retailer characteristics (papers I and II) are associated with increasing inventory performance (capital intensity, growth in sales, sales), reduction in inventory turnover (gross margin), and industry code to move bilaterally. Firm size and economies of scale have long been key topics of economics research. The findings in papers I and II support previous studies regarding scale effects in inventory turnover in relation to both sales and number of employees (Gaur & Kesavan, 2009) and may be connected with reduction in safety stock and centralization of inventory (Eppen, 1979). For the customer, economies of scale seem to be important as retail chains grow faster than and capture markets from single-unit retailers (Jarmin et al., 2009). Paper II further demonstrates the existence of differences in efficiency within different chains and finds that economies of scale are also present for inventory turnover (paper II – Figure 5). This implies that the customer and the retailer, particularly larger retailers, are increasingly interlinked in the seller/buyer relationship, as these retailers are more likely to deliver convenience and price.

Regional conditions may also have an impact on both customer and retailer. As paper II demonstrates, there are regional differences in inventory turnover, and regions located farther from the main logistical hub in southeastern Norway suffer from decreased inventory turnover. Paper II suggests that this reduced inventory turnover is linked with increased lead time (Ballou, 2005; Rumyantsev & Netessine, 2007a) and hence the need to keep more safety stock, resulting in lower inventory turnover. Moreover, environmental factors have been found to impact retail efficiency (Gauri, 2013), and paper II identifies population size and municipal rurality as influences on retailer behaviour and inventory efficiency. More specifically, paper II recognizes that inventory efficiency varies with the degree of municipal rurality and that the most and least rural locations are the most efficient. Once again, this could be associated with metropolitan areas in general having larger stores (but a smaller number of firms per capita), while rural areas have smaller stores (and a larger number of firms) (Jarmin et al., 2009) owing to economies of scale. In addition, small retailers suffer a lower continuance rate than large retailers (Jarmin et al., 2009), and this demand improves efficiency in maintaining operations. Another exogenous factor suggested to explain inventory efficiency (paper II) is municipal population. Figure 3 (paper II) clearly demonstrates the significant impact of an increase in population on enhanced inventory efficiency. Based on the close connection with economies of scale and rurality as well as population size, it should be safe to assume that such stores, to counter deteriorating inventory performance, keep a smaller product assortment and, as discussed above, impact customer convenience accordingly.

There are also visible differences in industry practices related to how specific functions are organized in the interface between marketing and operations. The role of procurement/purchasing, in particular, may cause dilemmas related to issues of product variety versus inventory turnover because increased product variety generally reduces inventory turnover (Wan et al., 2020). This provides incentives for retail businesses to clarify the mandate of the unit responsible for procurement/purchasing and the need to develop an integrated strategy between marketing and supply chain management on these relevant topics (Golgeci & Gligor, 2017).

The essence of the above discussion is that strategies and tactics associated with retailer efficiency and consumer convenience should not be siloed and concentrated towards the goal of either logistical efficiency or consumer efficiency. Instead, retailer and consumer efficiency should go together as a balanced duality, especially in situations where consumers make a trade-off between price/assortment and time/effort (convenience). Both price/assortment and time/effort can be significantly affected by retailers' quest for efficiency. Retailers should therefore be cautious of increasing their efficiency at the expense of consumer efficiency for segments with high willingness to opt out of low cost and better selection in favour of a more efficient shopping trip.

5.2. Contributions

It is important for retailers to identify the sweet spot in retailing, that is, to acknowledge and manage the interconnected interests of the customer and the retailer regarding efficiency.

In summary, the three individual papers (I–III) included as part of this dissertation contribute to the body of knowledge in several ways and across scientific disciplines. The main contributions of the papers are as follows. While paper I unveils the important role of retail chains in facilitating store-level inventory turnover performance and development over time, paper II empirically demonstrates that regional location and the store operational environment, in relation to rurality and municipal population, affect inventory turnover performance, and paper III introduces and empirically examines three new customer in-store behavioural metrics (travel distance, walking speed, and shopper efficiency) and demonstrates how in-store efficiency for shoppers without equipment deviates substantially from that of customers using physical carrying equipment.

Research on inventory management has grown substantially in volume for decades, with several important contributions (see, e.g., Williams & Tokar, 2008). There has also been a growing body of empirical research in recent decades on how company-specific factors affect companies' inventories, but mainly in manufacturing. In the retail sector, empirical research on inventory performance and its development over time has been conducted at both the firm and industry levels (Gaur et al., 2005; Chen et al., 2007), with the main interest in examining the effects of inventory on financial performance (Eroglu & Hofer, 2011; Isaksson & Seifert, 2014; Shockley & Turner, 2015). In this literature, it has been found to be important to control for industry-level characteristics (Eroglu & Hofer, 2011). Although retail chains are important institutions in developed economies (Perrigot, 2006; Kosová & Lafontaine, 2012), the literature on how retail chain affiliation affects inventory levels and inventory turnover is scarce. Paper I addresses this gap in the literature, as it empirically examines inventory turnover at the store level and identifies significant differences between stores affiliated with different chains and over time. In contrast to other research on retail inventory time trends (Chen et al., 2007), paper I supports prior research in finding deteriorating inventory turnover, both unadjusted and adjusted for capital intensity, gross margin, sales, and sales growth, over the 1999–2013 period (Gaur et al., 2005; Kolias et al., 2011).

Similarly, the literature in the field of inventory and operations management concerning environmental factors and their impact on inventory levels and turnover is limited. Paper II contributes to the literature by bridging this empirical gap, as it finds that both population and degree of rurality are connected with inventory efficiency. Moreover, this paper suggests a close relationship between regional store location and inventory turnover, as differences in geographic location likely impact the average lead time and thus the need to carry more safety stock, resulting in decreasing inventory turnover. While other papers have used the same methods to examine the mediating role of inventory leanness in firm operational efficiency (Chuang et al. 2019), to my knowledge, paper II is the first to employ stochastic frontier analysis in determining store-level differences in inventory turnover efficiency, with inventory turnover being the dependent variable.

Regarding customer in-store behaviour, paper III enhances the empirically based theory of in-store shopper behaviour in the brick-and-mortar retail environment, as it introduces new behavioural metrics to the literature and examines these metrics through a large observational study involving tracking software. While recent studies focusing on shopper efficiency have used the metrics of store coverage, basket size, shopping trip length (Sorensen et al., 2017), and per-item use of time (Bogomolova et al., 2016), paper III demonstrates the usefulness of measuring customer effort as travel distance per items purchased. The study further argues the importance of controlling for the use of shopping equipment, as it significantly affects shopper efficiency. A prior study (Bogomolova et al., 2016) claims that women are more efficient shoppers than men (basket size/shopping duration), and even though paper III does not exclusively examine the same metric, it examines efficiency (basket size/travel distance) and finds no statistically significant gender specific differences except that male customers on average walk faster than females. This implies that the estimates of Bogomolova et al. (2016) could have been affected by not controlling for the role that carrying equipment plays in customers' in-store efficiency.

The thesis emphasizes the importance of efficiency for both the retailer and the customer and suggests that neither of them exists in isolation. It provides examples of important interconnections that exist in relation to inventory and shopper efficiency. Additionally, it points to some of the dilemmas that retailers face in providing customers with a competitive level of shopper efficiency and illustrates the duality that exists in creating efficiency in the customer-retailer affinity.

Overall, this thesis focuses on efficiency from different perspectives, contributes to the literature and identifies areas for improvements in efficiency. This is important because from a broader perspective, removing inefficiencies (increasing efficiency) by better utilization of scarce and costly resources should contribute to productivity growth in society and enable improvements in welfare and living standards (Parmeter & Sickles, 2020).

5.3. Implications for practice

The findings in papers I–III have several implications for retail practice and the analysis of customer and retailer efficiency. First, papers I–II unveil new factors that assist in explaining firms' inventory performance, such as the heterogeneous role of retail chains, regional location, and environmental factors, and highlights some of the key variables that help improve logistical and inventory management. In addition, retailers' search for ways to improve their own financial performance by seeking to advance inventory efficiency need to be balanced with the needs of customers who have increased the value that they ascribe to shopping efficiency. These findings also imply the need to assess whether established service levels and logistical and inventory policies are designed to cope with heterogeneity in expected customer convenience, different regional locations and variations in market conditions. In addition, the findings should be considered when new stores are planned, when stores are designed or redesigned, and when the service level is determined in benchmarking activities and store performance assessments.

At present, most retailers are only partially capable of identifying and making the necessary operational changes to minimize the conflicting interests related to the main two shareholders of efficiency in the retail store setting: the retailer and its customers. The perspective of duality may provide a tool to better understand the interconnections of managing and improving the key drivers of convenience and retailer efficiency. One such driver of convenience is reported in paper III: the use of in-store carrying equipment and the duality of efficiency interests related to the retailer facilitating efficiency for shopper in general and the shopper type that most likely seeks efficiency the most – the shopper without equipment.

With respect to customer convenience, retailers should also be aware of customers' growing attention to sustainability. This manifests at the product level, where consumers increasingly claim to be aware of and demand healthier and more environmentally sustainable products (Nielsen, 2018). To preserve convenience, retailers need to battle the increase in product variety when meeting these demands and avoid the issue of unnecessary clutter in the retail space (Sabine et al., 2009).

It should also be noted that the duality of efficiency from the customer/retailer perspective may be visible in the way retail organizations are organized, that is, the degree of interconnectedness between the marketing department and logistics department. An improved mutual strategy between these departments could counter the negative effects on inventory turnover that stem from increased product assortment, as previous studies have suggested (Wan et al., 2020; Golgeci & Gligor, 2017).

In summary, instead of choosing one efficiency perspective (retailer/customer) at the expense of the other, managers should view both efficiency perspectives simultaneously, as they complement each other, and seek dynamic solutions to counteract any conflicting interests. These implications are particularly important to retail chain and store managers, inventory managers, planners, marketers and analysts.

5.4. Directions for future research

Even though each of papers I–III contributes to important topics of retail efficiency and the overall scope of this dissertation provides a fresh perspective on the duality of interests within the retailer/shopper connection, several avenues exist for developing new and compelling knowledge within these specific research fields and for the retail industry.

One avenue for future research regarding the topic of in-store behaviour is using a mixed-methods research design. This research design combines quantitative and qualitative research, such as interviews or questionnaires and observations. Related to the specific design used in paper III (study 2), a survey prior to entering the store that examines the motivation for and purpose of the shopping trip could possibly help understand how shopper intention and motivation are connected to actual customer in-store behaviour. More specifically, in a seminal paper on improving the analysis of customer in-store behaviour, Granbois (1968) emphasizes the importance of collecting data based on a combination of interviews and observations to capture planned versus actual behaviour. Such data are valuable for the industry and researchers, as they provide information on customer intentions and motivation and the relationship with actual behaviour. In addition, observing each shopper multiple times, dependent on different modus operandi (motivation and purpose), could indicate how stable efficiency within each customer segment is and whether new store formats should be developed to justify adjustments in product variety, product or product category location, store layout, etc.

In relation to inventory turnover, paper II identifies some spatial dependencies present in the data. However, further knowledge of how inventory turnover is connected with exogenous factors is needed. The utilization of more detailed data in combination with improved methods to extract spatial dependence from inventory performance is a more appropriate route to better understand how such factors actually and empirically impact business operations.

This research further demonstrates the need for more interdisciplinary work that specifically addresses the dilemmas, paradoxes and dualities in the connection between the customer and the retailer in the quest for improved convenience and efficiency.

6. References

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PART II

APPENDED PAPERS

6.1. Paper I

Breivik, J. (2019). Retail chain affiliation and time trend effects on inventory turnover in Norwegian SMEs. *Cogent Business and Management*, *6*(1), 1–17.

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MANAGEMENT | RESEARCH ARTICLE

Retail chain affiliation and time trend effects on inventory turnover in Norwegian SMEs

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Abstract: Inventory is a significant and important asset for retailers and represents what a store has to offer its customers for instant purchase; at the same time, considerable costs are associated with holding inventory. In this study, we use inventory turnover as a measure of inventory performance. We build upon previous research and use firm-specific measures to untangle the link between inventory performance and chain affiliation as well as time trends for SMEs. We employ panel regressions on data for the 1998–2013 period for Norwegian stores affiliated with three different retail chains that operate within the industry of retail sale of hardware, paints and glass. We estimate inventory turnover both with and without controlling for explanatory variables, and we find that inventory performance over the sampling period varies but decreases over time for the examined retail chains controlling for factors known to affect relative inventory levels. We further find that retail chain affiliation affects inventory turnover at the store level when controlled for gross margin, capital intensity, growth in sales, and that inventory increases with firm size. These findings have important implications for practice.

Subjects: Operational Research / Management Science; Operations Management; Supply Chain Management; Strategic Management

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PUBLIC INTEREST STATEMENT

Inventory is important for physical stores because it gives their customers instant access to products when they need them. On the other hand, there are considerable costs involved in holding inventory, which makes it immensely important for retailers to manage inventory levels. In this study of Norwegian firms, we examine inventory performance in small and medium-sized independent retail stores belonging to three chains selling home improvement products and tools to end users. We find that inventory performance varies between stores, retails chains, and over time. Although some of the retail stores perform better than others, they exhibit on average a deteriorating inventory performance over the period 1998–2013. This negative time trend is alarming and may contribute to partly explain the ongoing retail crisis. The findings also suggest that firm size affects inventory performance positively. This implies that smaller stores should be more attentive to inventory management to withstand competition.

Keywords: inventory turnover; inventory leanness; inventory management; inventory performance

1. Introduction

The ongoing crisis within traditional brick-and-mortar retail stores has received growing media attention in recent years. "High street delivers worst performance in 12 years as retail crisis deepens" (Clarke, 2018) is an example of a headline from such media coverage. Several factors contribute to this crisis, such as costs rising at a faster pace than revenue, high debt, and competition with online shopping (Thomas, 2018). Economic data for the period 2012–2017 simultaneously show that for US retail, the inventory to sales ratio has grown (US Bureau of the Census, 2018). This indicates that inventory performance for some retailers deteriorates, leading to additional costs that impair store earnings and thus, contribute to the crisis.

Inventory management is considered an important management practice in any retail business because of its impact on retail profits (see, e.g., Cronin, 1985). The most frequently used measure of inventory management performance is inventory turnover. This measure is closely monitored by senior executives in practice at both retail chain and store levels, and is the only performance measure on inventory management available to other stakeholders through publicly available financial statements. Business analysts and shareholders are showing an increased interest in this business performance measure. An example of a recent occurrence of such interest is the report of Hennes & Mauritz following its capital market day in which the analysts of Credit Suisse commented, "We remain unclear as to how H&M is going to trade out the inventory mountain without doing further damage to full price sales..." (Irwin & Pratti, 2018).

The early discovery of the EOQ (Economic Order Quantity) model enabled computation of the optimal number of items to order as to minimize total inventory holding costs and ordering costs (Harris, 1913), and has been significant to the inventory management literature. From the advent of this model, research has been growing significantly over a lengthy span of time, originally in the single entity model setting and more recently in the collaborative and across business framework (Williams & Tokar, 2008). Recent empirical findings indicate inventory performance to be positively related to financial performance measures, such as return on assets, return on sales, earnings before interest and taxes (Alan, Gao, & Gaur, 2014; Capkun, Hameri, & Weiss, 2009; Chen, Frank, & Wu, 2005, 2007; Eroglu & Hofer, 2011a; Isaksson & Seifert, 2014; Kesavan & Mani, 2013; Rumyantsev & Netessine, 2007a; Shockley & Turner, 2014), and stock value and return (Alan et al., 2014; Chen et al., 2005, 2007). This makes inventory turnover a popular indicator for evaluating the profitability of a firm. Moreover, time trends in inventory turnover were initially found to be improving; for manufacturing firms in particular (Chen et al., 2005; Rajagopalan & Malhotra, 2001). For wholesale and retail, there have been contradictory findings for some time, but recent research on time trends for retail firms suggests that inventor turnover deteriorates (Gaur, Fisher, & Raman, 2005; Kolias, Dimelis, & Filios, 2011).

Our study contributes to the literature on time trends in inventory turnover and is to the best of our knowledge the first study on the effect of voluntary chain affiliation on inventory turnover of independent retail stores. Research on inventory turnover has mostly been conducted using data from large American-listed retail corporations (e.g. Gaur et al., 2005), and the findings may thus not be valid across other geographical regions, firm sizes, or for privately owned firms. We therefore further contribute to the literature by providing findings from privately owned small and medium-sized corporations. We examine inventory turnover based on public financial data for the period 1998–2013 on businesses operating stores affiliated to either one of three voluntary cooperative retail chains belonging to the same segment of stores selling home improvement products. This period reflects rapidly increasing knowledge on efficient business management, historically unprecedented growth in computational force, increases in consumer affluence, and not least a steady rise of e-commerce in size and reach. Earlier studies on time trends in inventory turnover cover periods with quite different economic and societal conditions. There is as such a need to revisit this issue again.

Our paper reports three main findings. First, we estimate inventory turnover, both with and without controlling for explanatory variables, and we find that inventory turnover on average has deteriorated annually with a much higher percentage than comparable figures reported in the study by Gaur et al. (2005). Second, we find that retail chain affiliation affects inventory turnover at the store level when controlled for gross margin, capital intensity, growth in sales, and firm size. This finding has implications for practice as it demonstrates that some retail chains outperform others on inventory management. Third, we find the firm size to affect inventory turnover. This implies that the small business owner should give inventory management more attention to withstand competition, for instance by more closely monitoring inventory levels.

The remainder of this article is organized as follows. Section two reviews the relevant literature, while section three describes the data and methods. The fourth section contains results and is followed by a conclusion section that discusses the main findings, limitations, and implications for practice.

2. Literature review

Research on inventory management has been conducted predominantly on the operations level, analysing firm-specific business data or simulations of inventory systems, models and practices. However, over the past two decades, interest in identifying issues related to inventory performance across firms and industry segments has increased. This research has been conducted in the retail, wholesale and manufacturing industries. One difference in these examinations is that retail stores and wholesale firms as a rule hold only FGI, while manufacturing firms in addition hold the discrete components of inventory as RMI and WIPI.

Rajagopalan and Malhotra (2001) were among the first to examine how inventory levels evolve over time. They find that inventory levels decreased for most segments in the 1964–1984 period and further abated in approximately half of the manufacturing firms in the decade after 1984. These findings were later supported by Chen et al. (2005), who use data for the 1981–2000 period to show that the inventory holding period was reduced from 96 to 81 days. This 2% annual average reduction occurred mainly through WIPI, while the FGI holding period remained unchanged. Furthermore, Chen et al. (2007) find that the median wholesale inventory declined from 73 to 49 days between 1981 and 2004, while retail inventories started to decline from 1995 onwards. The results regarding retail inventories were, however, contradicted by Gaur et al. (2005), who show that inventory turnover decreased (e.g. relative inventories increased) by 0.45% annually for the 1987–2000 period for listed US retail firms, whereas Kolias et al. (2011) find that inventory turnover in Greek retail slowed by 3.4% annually during 2000–2005.

The presence of economies of scale with respect to inventory levels and firm size is demonstrated in several papers (Gaur & Kesavan, 2009; Rumyantsev & Netessine, 2007b). Rumyantsev and Netessine (2007b) use total assets as a proxy for firm size, while Gaur and Kesavan (2009) extend this model with a quadratic term to allow for non-linear impacts of firm size. The results support economies of scales, but at a decreasing rate as firm size increases.

Another approach to measuring inventory performance is the performance metric empirical leanness indicator (ELI) developed by Eroglu and Hofer (2011b). The ELI measures, by industry segment, the level of inventory relative to sale and control for economies of scale. This performance indicator provides a single-value benchmark measure of firms within defined segments or industries. In measuring ELI, Eroglu and Hofer (2011b) find a concave relationship for a large number of industry segments. A similar measure that can be used as an industry yardstick is the adjusted inventory turnover (AIT) metric proposed by Gaur et al. (2005). This measure controls for gross margin, capital intensity and sales surprise; however, it does not include a proxy for firm size.

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Levels of inventory relative to other financial metrics are important for stakeholders over the longer term. However, the ability of a firm to rapidly adapt inventory in line with demand plays a key role in inventory management. Rumyantsev and Netessine (2007a) propose several different measures of such adjustment capability and responsiveness and find an association between financial performance and these measures. Responsiveness is divided into two categories. The over-responsive measure expresses that a change in sales is accompanied by a greater increase/decrease in inventory, while the under-responsive measure indicates a smaller change in inventory relative to a change in sales. More specifically, they find that over-responsiveness at the firm level is associated with lower return on assets (ROA). Shockley and Turner (2014) find similar results at the firm level and for some industry segments. Recent findings by Kesavan, Kushwaha, and Gaur (2016) suggest that high inventory turnover (HIT) retailers respond to shocks by adjusting their purchases, while low inventory turnover (LIT) retailers respond to shocks by adjusting prices. Their analysis implies that financial performance drops more among LIT than among HIT retailers when demand shocks occur.

A large part of the more recent literature on inventory performance metrics focuses on establishing a link between efficient inventory management and financial performance. So far, this strand of research suggests that such a link exists (Alan et al., 2014; Capkun et al., 2009; Chen et al., 2005, 2007; Eroglu & Hofer, 2011b; Isaksson & Seifert, 2014; Kesavan et al., 2016; Kesavan & Mani, 2013; Rumyantsev & Netessine, 2007a; Shockley & Turner, 2014). Of the discrete components of inventory, which are of particular interest to the manufacturer, RMI appear to have the strongest relationship with financial performance. For the retailer and wholesaler, the level of FGI is positively linked to measures of financial adeptness (Capkun et al., 2009; Eroglu & Hofer, 2011a, 2011b; Isaksson & Seifert, 2014; Kesavan et al., 2016; Kesavan & Mani, 2013; Shockley & Turner, 2014). Some authors have also been able to establish a relation between relative levels of inventory and the long-run value of firms. (Alan et al., 2014; Chen et al., 2005, 2007). Finally, several articles indicate that when firms respond to changing demand by adjusting inventories rather than prices (e.g. responsiveness), financial performance is positively impacted (Kesavan et al., 2016; Rumyantsev & Netessine, 2007a; Shockley & Turner, 2014).

As we have seen, research on inventory performance can be divided into two main categories. The first category treats inventory performance as a self-contained performance metric and analyses inventory performance indicators such as inventory in levels, inventory turnover, and inventory in days. This approach can be augmented by correcting the raw metric for certain macroeconomic factors, such as the interest rate, gross domestic product, or a purchase manager index (Chen et al., 2005, 2007). One can also adjust by some determinants of inventory, such as gross margin, capital intensity and sales growth (Eroglu & Hofer, 2011a; Gaur et al., 2005; Gaur & Kesavan, 2009; Kolias et al., 2011; Rumyantsev & Netessine, 2007b).

The second category is concerned with how inventory performance affects financial performance measures such as ROA, return on sales (ROS), earnings before interest and taxes (EBIT) and stock value (Alan et al., 2014; Capkun et al., 2009; Chen et al., 2005, 2007; Eroglu & Hofer, 2011a; Isaksson & Seifert, 2014; Kesavan & Mani, 2013; Rumyantsev & Netessine, 2007a; Shockley & Turner, 2014).

Several inventory management approaches are employed by businesses to control inventory. In the single business entity context, two main directions exist within inventory control models, namely fixed quantity systems and fixed period systems. First, fixed quantity systems, frequently denoted (Q,R) models, with Q representing the lot size or quantity to replenish and R the level where the order is placed. Within this category of models, EOQ, reorder point and base stock policy being the most frequently published (Williams and Tokar 2008). The second approach to control inventory is the fixed period systems, often defined (S, T) models, with S denoting the amount to order, where T is the time period between review of inventory levels. Even though popular in the industry, only a few scientific papers are published on such models (Williams and Tokar 2008).

The amount of choices in inventory control models available for implementation in businesses are significant. All such models have in common the desire to match supply and demand, and maximize inventory performance. In measuring inventory performance, we employ inventory turnover and build on previous research to control for effects known to be correlated with relative levels of inventory.

3. Data

3.1. Data sample

In this article, we analyse financial accounting statements for Norwegian firms that are equivalent to a corporation (Inc. or Corp.) in the US or a private limited company (Ltd.) in the UK. The dataset consists of yearly financial statements for all firms affiliated with one of three retail chains, namely, XL-Bygg, Byggmakker and Byggtorget. These chains operate within the industry of retail sale of hardware, paints and glass, and have similarities of the larger and more well-known retailers Bauhaus in Europe and The Home Depot in North America. We record chain affiliation as of the end of 2013, and changes in chain affiliation during the sample period are disregarded. The sample period is 1998–2013 and contains 184 firms with 2107 observations. These retail chains represent approximately 30% of the total domestic industry revenue and are all represented in the top 10 largest home improvement retail chains of Norway. Broad metrics for the remaining dominating retail chains suggest only marginal differences in measures constituting the base of this analysis. The Norwegian economy has during the same period grown steadily; consumer prices and GDP for instance increasing by 31% and 24.4%, respectively (Statistics Norway, 2019, 2018).

These stores carry a wide product assortment with product line width and merchandise depth depending on the store size, location and strategy. Although there is some variability between stores, in general, these product groups are present: lumber, roofing, masonry, stones, brick, doors and windows, hardware and tools, paint, floor covering, and cabinets. In addition, some of these stores carry products such as light fixtures, electrical fittings and plumbing. Although a product might be on display, it is not necessarily in stock and hence may need to be ordered based on the specifications of the customer. For larger construction projects, a substantial part of the materials needed is delivered directly to the building site without passing through the store. These stores are generally specialized to serve both professionals, such as carpenters, builders, and general contractors, and homeowners in both product guidance and supplies for home improvement, remodelling, new home builds, or the construction of offices and industrial facilities. The mix of customers by type of professional and homeowner varies for each store.

The selected retail store chains are in principle voluntary cooperative organizations, with each store owned and managed independent of the retail chain. The main task of the retail chain is to attend to common marketing, develop and negotiate purchase agreements and offer store management computer support technology such as accounting, sales and inventory. The fundamental differences between the retail chains are primarily that Byggtorget has the most stores but also the smallest ones, located in the most rural and least populated areas. In comparison, XL-Bygg and Byggmakker outlets are located in municipalities with larger populations and increased centrality; however, XL-Bygg stores are smaller than Byggmakker stores.

Table 1 shows the frequency of the number of observations on financial statements and the number of firms in total and for each of the retail store chains. With regard to the number of firms and years, Byggtorget is the largest of the retail chains measured in a number of stores with 84, compared to 47 and 53 for Byggmakker and XL-Bygg, respectively. The table also indicates that approximately 65% of the observations represents the full-time dimension of 15 years.

There may be several reasons why some firms have fewer than 15 years of accounting statements available. Some businesses might have started up during the sampling period or been affected by

Table 1. Frequency table showing number of years of financial statements in data (1998–2013)

Years of financial statements	Full sample		Byggmakker		XL-Bygg		Byggtorget	
	No. of firms	No. of obs.	No. of firms	No. of obs.	No. of firms	No. of obs.	No. of firms	No. of obs.
≤3	13	31	0	0	2	4	11	27
4–6	21	106	4	19	6	29	11	58
7–9	27	216	9	73	3	23	15	120
10–12	18	196	4	43	8	88	6	65
13–14	14	193	5	70	2	28	7	95
15	91	1365	25	375	32	480	34	510
Total sample	*184*	*2,107*	*47*	*580*	*53*	*652*	*84*	*875*

mergers and acquisitions. Furthermore, missing observations due to a lack of reported financial statements or calculation of variables may also influence frequency. The next section contains an enhanced description of handling missing observations.

The use of full-year financial accounting data safeguards the registration quality because all Norwegian firms are obligated to perform a yearly audit. A shorter time increment, and hence lack of an audit, might weaken the quality of the data. We note that beginning in May 2011, Norwegian legislation deregulated the mandatory yearly audit for the smallest firms, but this change affects a marginal number of the firms in our sample. Because very few firms would satisfy the criterion of the new regulation by choosing not to perform a yearly audit, we take no action in our analysis to account for this change.

3.2. Methods

We design the following variables, as shown in Table 2, to support this analysis.

Inventory turnover, *IT*, is calculated as the ratio of the cost of goods sold (*COGS*) relative to the mean inventory level (*INV*). *GM* denotes gross margin and is defined as the difference between sales (*S*) and *COGS* divided by sales. *CI* denotes capital intensity and is the ratio of gross fixed assets (*GFA*) to *GFA* and *INV*. The variable *G* represents sales growth. Sales (*S*) is the current year total revenue, and S^2 is its quadratic coincide. Finally, the subscript i identifies the firm, while t embodies the period of time, i.e. the financial accounting year. In addition, the indicator variable *IndC* is used to group firms by industry code at the 2-digit level and based on the standard of industrial classification (Statistics Norway, 2008). This sample of firms is confirmed to be affiliated with one of three retail chains: Byggmakker, XL-Bygg or Byggtorget. The status of the retail chain affiliation is registered at the end of 2013, while *IndC* is registered at the beginning of 2015 and is by this time-invariant.

Table 3 shows that the mean inventory turnover is 5.61 for the entire sample, while Byggtorget on average has 6.34, in contrast to 4.88 and 5.27 for Byggmakker and XL-Bygg, respectively. Furthermore, the table reports gross margin measures to be 30% for the full sample with little deviation for the different retail chains. The relative measure of mean capital intensity is estimated to be 27%, varying in range for the included retailers from 22% to 31%. Growth in sales averages 1.19 but varies from 1.16 to 1.23 among the three retailers. Finally, sales on average vary from 14.5 million NOK for Byggtorget to 84.4 million NOK for the retailer with the largest stores, Byggmakker, averaging 43.6 million NOK in total.

In Table 4, correlations between the constructed variables for the N = 2107 observations are reported.

For this analysis, we specify two models. The first model is similar to that of (Gaur et al., 2005) but is enhanced to unveil the effects of firm size on inventory performance, with the modification that our model uses the growth in sales variable rather than sales surprise.

Table 2. Definition of variables

Measure	Calculation
Inventory turnover	$IT_{it} = \frac{COGS_{it}}{\frac{INV_{it}+INV_{i,t-1}}{2}}$
Gross margin	$GM_{it} = \frac{S_{it}-COGS_{it}}{S_{it}}$
Capital intensity	$CI_{it} = \frac{GFA_{it}}{GFA_{it}+INV_{it}}$
Growth in sales	$G_{it} = \frac{S_{it}}{S_{i,t-1}}$
Sales	$S_{it} = Annual\ sales$

Table 3. Descriptive statistics

	Full sample				Byggmakker	XL-Bygg	Byggtorget
	Mean	S.D.	Min.	Max.	Mean	Mean	Mean
IT	5.61	4.45	0.73	61.47	4.88	5.27	6.34
GM	0.30	0.07	0.06	0.71	0.29	0.30	0.31
CI	0.27	0.22	0.00	1.00	0.22	0.26	0.31
G	1.19	2.41	0.44	87.78	1.18	1.23	1.16
S^a	43,620	84,380	298	1,215,708	87,047	44,084	14,488

N = 2,107, ^{a} 1,000 NOK.

Table 4. Correlation matrix

	IT(log)		GM(log)		CI(log)		G(log)	S(log)
IT(log)	1							
GM(log)	−0.261	***	1					
CI(log)	0.260	***	0.197	***	1			
G(log)	0.178	***	−0.064	***	0.052	**	1	
S(log)	0.206	***	−0.075	***	−0.064	***	0.029	1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Model 1 is stated as follows:

$$logIT_{it} = \beta_1 logGM_{it} + \beta_2 logCI_{it} + \beta_3 logG_{it} + \beta_4 logS_{it} + \beta_5 logS^2{}_{it} + \sum_{a=1}^{8} \beta_{6a} IndC_i + \beta_7 time_i + \varepsilon_{it} \quad (1)$$

Inventory turnover (*IT*) represents the dependent variable, and the model includes the independent variables gross margin (*GM*), capital intensity (*CI*) and growth in sales (*G*), followed by the variable sales (*S*) and its squared version (S^2) to address potential non-linear effects regarding economies of scale. Furthermore, the model inherits industry segment (*IndC*) and a time trend variable (*time*). In addition to the previously defined variables, common to all models, the explanatory β coefficient represents the parameter to be estimated, while ε_{it} represents the remaining error term.

Based on previous research and the argument for choosing the independent variables included in the design of both models, gross margin (*GM*) is negatively correlated with inventory turnover in several studies (Gaur et al., 2005; Kolias et al., 2011; Shockley & Turner, 2014). This empirical research similarly reveals a positive relationship between capital intensity (*CI*) and inventory turnover (*IT*). Further growth in sales (*G*) is shown to be positively associated with inventory turnover (*IT*) by Kolias et al., 2011. Finally, sales (*S*), as previously stated, acts as a proxy for size and is assumed to address economies of scale.

We design the second model to uncover the effects of chain affiliation and its time component. In examining differences in inventory performance between the three retail chains, model 1 is extended with variables to capture such effects. Model 2 examines retail chains fixed and time trend effects:

$$logIT_{it} = \beta_1 logGM_{it} + \beta_2 logCI_{it} + \beta_3 logG_{it} + \beta_4 logS_{it} + \beta_5 logS^2_{it} + \sum_{a=1}^{8} \beta_{6a} IndC_i + \sum_{b=1}^{3} \beta_{7b} Chn_i + \sum_{c=1}^{3} \beta_{8c} Chn_i * time_i + \varepsilon_{it} \quad (2)$$

The dummy variable *Chn* represents firms affiliated with the retail store chains of Byggmakker, XL-Bygg and Byggtorget, respectively. To capture differences in time trends for each retail chain, an interaction variable is constructed between *Chn* and *time*.

As previously indicated, all variables except *IndC*, *Chn* and *time* are transformed by the natural logarithm. This implies that the β coefficient represents the elasticity of inventory turnover with respect to the associated dependent variable, while for the variable representing *IndC*, *Chn* and the interaction between *Chn* and *time* are log-linear coefficients.

Several model specifications have been applied and tested; however, the constructed models and estimations techniques reported in the following sections this paper are the most consistent.

We test for serial correlation using the Wooldridge test (Drukker, 2003) and find evidence of an AR(1) structure in the data.

We employ a Prais-Winsten estimator (a special case of the feasible generalized least squares, FGLS), controlling for a panel-specific first-order autocorrelation because we have a relatively long time dimension in our data and thus assume varying serial correlations within firms. We further assume that the disturbance is heteroscedastic and contemporaneously correlated across panels. Because our data are unbalanced with no common time periods for all panels, calculation of the covariance is based on the pairwise estimation of observations present in the panels. In addition, the applied estimator return panel corrected standard errors (Stata: xtpcse) found to be less optimistic than that of the traditional FGLS estimator (Beck & Katz, 1995; Katz, 2016).

The initial dataset consists of 192 firms with 2448 observations. We delete observations for only three reasons. First, by computing the variables, the first year of data is lost in the transformation process due to the calculation of variables by use of prior year values, such as for inventory turnover. All observations that are missing due to these calculations are deleted, as well as observations missing for other reasons. Furthermore, observations equal to zero drop out due to log transformation, as the natural logarithm is defined only for positive values. Second, because this is an unbalanced dataset, the number of time periods T is not the same across all individuals i. This difference indicates that the data are unequally spaced and that different firms may have observations in different periods. In addition, these observations might include firms with non-consecutive runs; data belonging to one given firm might be missing and constitute a gap in the time dimension, implying that one year might be missing in the middle section, resulting in two consecutive runs. For firms with non-consecutive runs, only the sections within each firm containing the most observations are retained. Third, we delete observations with values exceeding 75 for inventory turnover and 100 for growth in sales because a few observations contain values that severely influence the analysis. In addition, firms with only one remaining observation, owing to the fact that they do not contribute to adding information to the construct, are dropped. No further deletion of observations is performed, as we trust the model specifications to handle such deviations. These deletions result in a final dataset that consists of 184 firms with 2107 years of financial statements.

Retailers use several different methods for valuation of inventory, namely, first in, first out (FIFO), weighted average and last in, first out (LIFO). The first two mentioned are the most common, although other approaches may be practised. Since 2003, Norwegian accounting standards have not approved of the LIFO method. The choice of and change in the valuation method in this sample may affect inventory valuation but is not inherent in this dataset. Furthermore, as for most accounting data collected, this panel might suffer survival bias because only firms affiliated with a retail store chain at a given time constitute a part of the data; hence, firms filing for and going bankrupt during the sample period are not present in this sample. Finally, even though this analysis tests several different model specifications, more complex models that are not considered may potentially fit our data even better.

4. Results and discussion

We find when estimating the models previously defined, as reported in Table 5, that gross margin, capital intensity and sales growth contribute to explain variance in inventory turnover as reported, for model 1 as well as for model 2. The results imply that gross margin is negatively associated with inventory turnover, while capital intensity and growth in sales are positively related to it. These estimates are significant ($p < 0.01$) and return the anticipated signs that are similar to those found by previous research (Gaur et al., 2005; Kolias et al., 2011).

Estimates of firm size (S) reported for both models return a positive and significant ($p < 0.01$) coefficient of 0.11 for model 1, shifting to 0.93 for model 2. This finding must be evaluated in light of changing signs for S^2 between models 1 and 2 (significant at $p < 0.05$ and $p < .01$, respectively). This finding suggests that inventory turnover increases with firm size but that there is diminishing return to scale with an increase in firm size. These results are in line with the notion of economies of scale and are similar to those found previously (Ballou, 2005; Gaur & Kesavan, 2009).

Furthermore, both models 1 and 2 control for the official registered industry code. Estimates indicate that inventory levels vary significantly depending on what segment the business operates within, from −0.75 to 0.52 and −0.62 to 0.63 for models 1 and 2, respectively. This variance in data may stem from the fact that even though firms operate a store outlet within the store format and marketing concept of the affiliated retail chain, they may simultaneously have operations in other areas, such as being a builder or running a sawmill, which may naturally influence the results.

The time trend variable included in model 1 returns significant estimates at the $p < 0.01$ level, with a coefficient of −0.026. This finding implies that on average over the 15 years analysed, inventory turnover annually decreases by 2.6%. Table 5 further shows (model 2) that the time trend differs among the three retail chains, with XL-Bygg having the least decline in inventory performance, measuring −1.7% annually, followed by Byggmakker with −2.3% and finally Byggtorget with −5.9%; all estimates are significant at $p < 0.01$. A Wald test confirms that the chain-specific time trend of Byggtorget is significantly different from that of Byggmakker and XL-Bygg ($p < 0.01$), but no significant statistic difference exists between the latter two. These results indicate large differences between the analysed retail chains; however, over time, some of them perform better than the others do. This negative time trend is generally a matter of concern, particularly in the case of stores affiliated with Byggtorget, because an increase in relative inventory levels constitutes an increase in cost. To maintain an unchanged level of earnings, this finding indicates that cost reductions must be obtained from other parts of firm operations. An alternative to reducing costs could be to increase gross profit margins to uphold earnings or a combination of these two managerial efforts.

Finally, Table 5 shows that intercepts for each retail chain vary and return significant coefficients ($p < 0.01$). Whereas estimates for Byggmakker and XL-Bygg differ only slightly (−4.97 vs. −4.93), the intercept for Byggtorget is lower at −4.19. Tests of equality (Wald) imply at the $p < 0.01$ significance level that the estimate for Byggtorget is significantly different from those for Byggmakker and XL-Bygg, but there is no significant difference between the latter two estimates. As previously described, the time trend for Byggtorget is significantly more negative than that for the other chains. However, the chain intercept estimate implies that Byggtorget had a head start on its competitors and to some extent improved the overall competitive setting for these stores.

Although estimations return signs in accordance with recent research controlled for gross margin, capital intensity and growth in sales and firm size, these indicate a downward-sloping inventory turnover during the past one and a half decades. The reasons for this reduction in inventory efficiency are not provided by our models; however, research suggests that an increase in product variety is one of several reasons, making forecasting sales more challenging and therefore increasing inventory levels (Rajagopalan, 2013; Randall & Ulrich, 2012). Effects of a continued long-run negative trend will ultimately cause an additional rise in cost, eventually making positive profits impossible.

While estimates in Table 5 give adjusted measures of inventory turnover, similarly unadjusted changes in the inventory turnover and other key variables are of interest. We implement a linear growth model using OLS and fixed firm effects estimations. These estimations return the results reported in Table 6. The log specification of the dependent variable implies an exponential growth model. The full sample shows that inventory turnover is negative by 2.3% annually. Furthermore, that gross profit margin has increased by 0.7% annually, while capital intensity and growth have decreased annually by approximately 2.1% and 0.8%, respectively; all estimates are at significant levels. For each chain of retailers, similar estimations are executed, revealing differences in estimates, however not significant. The exception is the time trend in inventory turnover for Byggtorget, which is notably more negative than the other two.

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Table 5. Regression estimates

DV = IT(log)	Model 1		Model 2	
	Coefficient		Coefficient	
GM(log)	−0.480	***	−0.443	***
CI(log)	0.068	***	0.060	***
G(log)	0.220	***	0.180	***
S(log)	0.117	***	0.928	***
S^2(log)	0.004	**	−0.030	***
IndC 16	base		base	
IndC 41	0.006		−0.062	
IndC 43	−0.362	**	−0.602	***
IndC 46	−0.288	***	−0.273	***
IndC 47	−0.335	***	−0.310	***
IndC 52	−0.196	***	−0.174	**
IndC 68	−0.754	***	−0.618	***
IndC 71	0.521	*	0.631	**
Time trend	−0.052	***		
Byggmakker * time			−0.023	***
XL-Bygg * time			−0.017	***
Byggtorget * time			−0.059	***
Byggmakker			−4.971	***
XL-Bygg			−4.926	***
Byggtorget			−4.191	***
Rho	0.627		0.596	
R^2	0.884		0.873	
Wald Chi2/ Prob>chi2	26,983	***	25,617	***
N/groups	2,107	184	2,107	184

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, Prais-Winsten regression with panel-specific AR(1) disturbances and panel corrected std. err.

Figure 1 shows a scatterplot of predicted inventory turnover values using model 2 relative to firm size. The figure clearly indicates economies of scale, however, in a non-linear fashion, by the median spline based on a polynomial function.

Based on the regression estimates in Table 5 (model 2), we calculate and find that the stores connected to the retail chain of Byggmakker return a 23.4% lower inventory turnover than those of Byggtorget. Furthermore, XL-Bygg stores, on average, have 15.3% less inventory turns than Byggtorget stores. As Figure 2 shows, predicted average inventory turns (based on model 2) for all three retail chains in our analysis indicate a decrease over the sampling period. Although stores of Byggtorget on average perform better than their competitors, this decrease in inventory turns is predominantly more significant for this retail chain relative to both XL-Bygg and Byggmakker. At the same time, and as previously stated, the stores of Byggtorget have the greatest improvement in gross profit margin, which to some extent may compensate for an increase in costs in holding higher levels of inventory.

5. Conclusions

In the current research, we examine time trend effects on inventory turnover for the period of 1998–2013 in Norwegian retail. We find a yearly decline in inventory performance in the range of 1.9% to 5.9%, depending on chain affiliation. Controlled for gross margin, capital intensity and growth

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Table 6. Time trends in IT, GM, CI and S

Dependent variable	Full sample		Byggmakker		XL-Bygg		Byggtorget	
IT(log)	−0.023	***	−0.017	***	−0.008		−0.041	***
GM(log)	0.007	***	0.005	**	0.006	*	0.009	***
CI(log)	−0.021	***	−0.013		−0.020		−0.029	**
G(log)	−0.008	***	−0.008	***	−0.006	**	−0.010	***
S(log)	0.058	***	0.057	***	0.053	***	0.062	***
N/groups	2,107	184	580	47	652	53	875	84

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, fixed effects OLS with robust errors.

Figure 1. Firm size effects on inventory turnover.

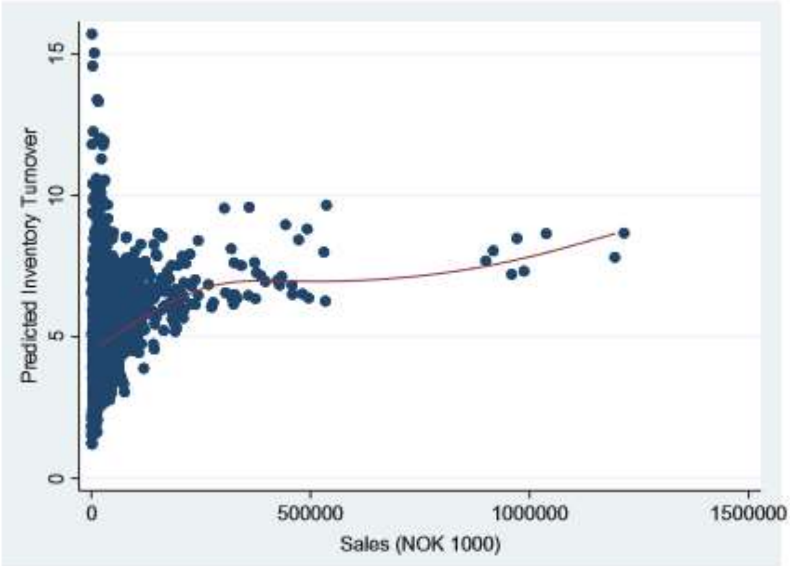
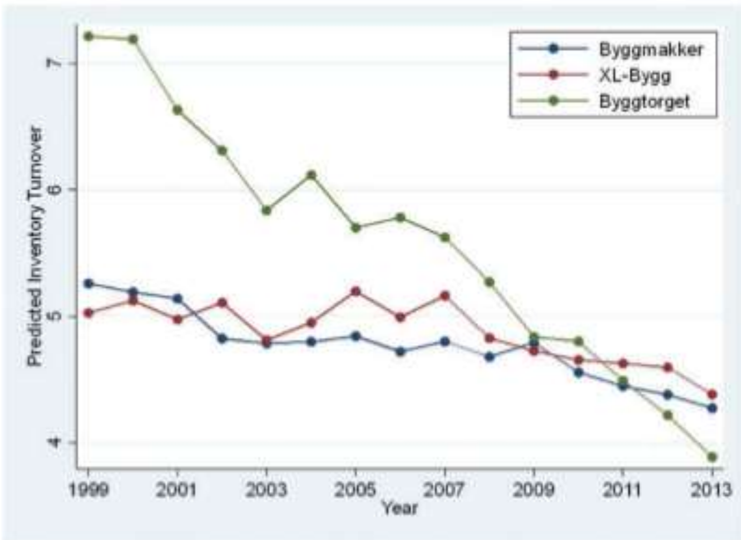


Figure 2. Development in inventory performance: 1999–2013.



in sales, we find inventory turnover to deteriorate annually with −2.6% on average. These findings add further insights on the development in inventory performance over time, not only for the individual retail chain at hand, but also in general. The results in this study stand in contrast to comparable findings by Gaur et al. (2005), who report for an annual deterioration of 0.45% in inventory turnover for US retail (the period 1987–2000). Our study point to a much higher decline in inventory performance, which may reflect differences in economic and societal conditions between the two studies. Recent findings from Greek retail, although measured for a shorter time duration than in our study (Kolias et al., 2011), find inventory turnover to drop at an annual rate of 3.4%. Thus, there seems to be a downward curve in inventory performance occurring despite continuous developments in technology, management and operations. Some retailers may perform better than others perform, but as our study demonstrates, even the retail chain with the strongest time trend has experienced a negative curve in inventory performance. This may suggest that there is a general negative trend in inventory performance among traditional bricks-and-mortar retailers, and in light of previous literature, even from an international perspective.

Possible explanations of this negative time trend may be increased competition in general, particularly with online sales, different pricing strategies, extent of service, as well as increases in assortment, product variety, and safety stocks; all to better meet customer wants and needs.

Moreover, similar to previous research in this area we find economies of scale to exist for inventory turnover (see for instance Gaur & Kesavan, 2009). As firm size increases, so does inventory performance, although at a diminishing rate. Economies of scale related to relative inventory levels may be linked to several circumstances, such as better inventory management, including inventory operations, expertise and software to support it.

Our findings further support earlier studies that have revealed a strong negative association between inventory turnover and gross margin (Gaur et al., 2005; Kolias et al., 2011), and those reporting a positive correlation between capital intensity, sales growth and sales (Gaur et al., 2005; Rumyantsev & Netessine, 2007b; Gaur & Kesavan, 2009; Kolias et al., 2011; Eroglu & Hofer, 2011b). Furthermore, we find inventory turnover to be dependent on and vary between industry segments and support previous research (Gaur et al., 2005).

This study contributes to the literature on time trends in inventory turnover (Gaur et al., 2005; Kolias et al., 2011), and is to the best of our knowledge the first study on the effect of voluntary chain affiliation on inventory turnover of independent retail stores. Since this stream of literature is based on findings from large American listed retail corporations, we further contribute to the literature by providing findings from privately owned small and medium-sized corporations.

5.1. Limitations and future research

Although this study contributes to examining chain affiliation and time trend effects on inventory turnover performance, it has some limitations. As our data do not offer measures on specific types of inventories, while at the same time include firms in industry segments likely to hold both RMI and WIPI, generalizations may not prove consistent in the time dimension. Even though we argue that inventory turnover performance depends on chain affiliation and diminish over time for all retail chains involved in our study, it may have been influenced by the actions and performance of the remaining businesses representing about 70% of the industry revenue.

Access to time-variant information on firm chain affiliation, industry code, data on firms closing, bankruptcy, change of industry segment, and switching retail chain affiliation, would also bring more dynamics into the data and potentially provide further insights into this topic.

In addition to the limitations described above, there is overwhelming potential for further research on this issue. Access to business data, such as the ratio of sales to professionals versus regular customers, or the degree of wholesale versus retail distribution, may contribute to explain inventory turnover beyond what can be determined through metrics used in this study. In addition, it is known that lead time significantly affects inventory turnover, and a study that includes store location can potentially be of help in understanding this important metric from the microeconomic perspective. Furthermore, different approaches are available to access information on efficiency or productivity, such as stochastic frontiers or data envelopment analysis. This approach aims to define the frontier of the most efficient firms, thereby identifying those firms that are not efficient, and may potentially provide insight into inventory productivity.

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5.2. Managerial implications

Because firm size affects inventory turnover, owners of small businesses should give inventory management more attention to withstand competition. We recommend in particular that small firms monitor inventory levels more closely. Moreover, we advise small firms to train their key personnel to manage and develop further important inventory tasks within the business, as inventory is key to what the firm has to offer its customers. At the same time, holding inventory carry considerable costs and thus, has to be managed well. If not, the firm risk contributing to the rising negative trend in inventory performance that may contribute to partly explain the ongoing retail crisis.

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6.2. Paper II

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Measuring inventory turnover efficiency using stochastic frontier analysis: building materials and hardware retail chains in Norway

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ABSTRACT
Operational efficiency in the retail business is vital in order to be profitable in a competitive environment. This paper investigates how environmental factors, firm size and time trends are linked to inventory performance. We use location data, demographic data and 16 years of financial accounting data from small and medium-sized home improvement retailers to explain inventory performance at a chain and a regional level. Traditionally a regression model could be used to assess the impact of the explanatory variables on inventory performance. We choose to use a stochastic frontier model since inventory turnover is linked to efficiency and productivity. Furthermore, we allow the model to control for key financial figures such as gross margin, capital intensity and sales growth. We find that efficiency in inventory performance varies depending on local market conditions and store location. Moreover, increased firm size tends to increase inventory efficiency, while time trend in inventory efficiency varies by retail chain affiliation. This paper provides new insights into the literature on operations- and inventory management, and suggests that retail managers should consider including environmental factors as part of their analysis when using inventory turnover as an efficiency benchmark.

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Inventory turnover; logistics management; efficiency; market conditions; retail

Introduction

Inventory is a critical asset in the retail sector and associated with considerable costs (Azzi et al., 2014). In 2016, inventory costs were estimated at $409.8 billion for US businesses alone, representing nearly 30% of the total logistics costs and accounting for as much as 2.2% of US GDP (Monahan et al., 2017). Inventory is further considered the asset that is most difficult to manage (Kolias et al., 2011). Inventory represents what the business can offer its customers and determines the firm's service level. There are costs related to both over- and understocking inventories. While excessive inventories lead to higher storage costs, increased capital tie up, and risks of spoilage and obsolescence, a shortage of inventory may lead to unsatisfied customers and reduced sales. Inventory levels must therefore be balanced with the associated costs of holding inventory (Salam et al., 2016).

The most frequently used measure to evaluate inventory efficiency is the inventory turnover ratio (Gaur et al., 2005). The inventory turnover ratio is calculated as the cost of goods sold divided by the average inventory level, and can be used as a comparative measure across firms. Since research shows that inventory efficiency is linked positively to financial performance (Eroglu & Hofer, 2014; Isaksson & Seifert, 2014; Shockley & Turner, 2015), most firms will gain financial benefits by increasing their efforts to enhance inventory efficiency.

Surprisingly little research has been done on the effect of environmental factors on inventory efficiency in retail businesses. We find this interesting because geographical store location due to topography and transportation distance can result in differences in replenishment lead times between stores located in different regions and consequently affect the need for more or less safety stock (Ballou, 2005). Furthermore, geographical presence, market concentration, demand density, density of economic activity, competitive environment, urbanisation and centrality have all been shown to be associated with firm-level efficiency in the more general literature on productivity (e.g. Aiello & Bonanno, 2016; Assaf et al., 2011; Bos & Kool, 2006; Carlino & Voith, 1992; Ciccone & Hall, 1996; Ko et al., 2017). Thus, it is likely that environmental factors affect inventory efficiency in retail businesses.

To address these shortcomings, we estimate the effects of geographic store location, degree of rurality, and

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market conditions on inventory turnover efficiency. We further decompose retail inventory efficiency at the chain and store levels using firm size and time trends. While the main novelty of this paper is related to the effects of environmental factors on inventory turnover efficiency, we are also the first to estimate inventory efficiency by empirically applying stochastic frontier analysis (SFA). The benefit of SFA is that it computes a relative measure of performance. Specifically, a frontier is estimated which allows comparison of each firm to the best-practice companies. This deviation gives an efficiency score and, consequently, this efficiency score measure how close a firm's inventory turnover is to what a firm's optimal turnover would be (Weill, 2008).

The results show that market conditions in the area surrounding the location of the store affect inventory efficiency. The most rural locations and the most central locations are the most efficient. However, relative to municipal population size, inventory efficiency at the store level increases as the population size rises. These findings contribute to theory by bridging an important theoretical gap in the literature on operations- and inventory management concerning environmental factors affecting inventory efficiency. Since the results suggest that retail managers should consider including environmental factors as part of their analysis when using inventory turnover as an efficiency benchmark, the findings also have important managerial implications. We also find firm size to be positively associated with inventory efficiency. The estimates indicate that increasing firm size from five to 25 employees improves inventory efficiency by approximately 12 percentage points. Moreover, no firms with more than 40 employees display inventory efficiency scores below 80% of the best performing firms. Further, although inventory efficiency varies widely both at the store and retail chain levels, we find that stores affiliated with one of the retail chains have increased their inventory efficiency over time while the stores affiliated with the other two chains have become less efficient. The stores affiliated with the outperforming retail chain advanced their efficiency on inventory by 10.5 percentage points in the 1998–2013 period relative to the lesser performing chain.

The rest of the paper is organised as follows. In the next section, we discuss relevant literature and present our analytical framework. This is followed by a description of the data, the variables, and the foundation of the applied method and models. We then present and discuss the results. Finally, as part of the conclusion section, we present and discuss possible implications, suggest further research and discuss the limitations of the current study.

Literature review

From a theoretical point of view, it is evident that inventory management is of significant importance to minimise costs in holding inventory. The early findings of these relations date back to Harris (1913/1990) through the construction of the economic order quantity model, which states that there is an optimum number of items to replenish. Even though the assumptions for this model are rather restrictive, the contribution from these insights and subsequent inventory control models have had a prominent impact on operations management in industries carrying inventory. Thus, the early focus of research on inventory management was on inventory systems and practices (Williams & Tokar, 2008).

However, research during the past two decades shows a shift in research focus on inventory management. For instance, the interest towards factors related to inventory performance across firms and industry segments has increased. In this section, we first look into the literature on inventory and financial performance. Although this topic is not directly related to the scope of this article, these research projects provide useful insights into what has been done in the broad field of inventory research. Then, we look at firm characteristics relevant for the current research, followed by research on environmental factors that can affect inventory levels. This section concludes with a figure presenting our analytical framework.

Inventory and financial performance

Most studies have examined manufacturing firms and similar industries with discrete inventory components as raw materials inventory (RMI), work-in-progress inventory (WIPI) and finished-goods inventory (FGI). The attention paid to retail and wholesale businesses has been scarcer. To some extent and depending on context, there are similarities between inventories of retail companies and FGI of manufacturing companies. However, there are also visible differences. Transportation, direct labour, and inventory holdings represent 11-20% of the total costs for process industries, while similar numbers for retail are 5% (Moser et al., 2017).

A large part of the literature on inventory performance focuses on the effect efficient inventory management has on financial performance. The association between inventory and financial performance was for some time inconclusive and examined initially only for manufacturing firms. Rumyantsev and Netessine (2007b) examined listed manufacturing businesses across eight different OECD countries and found a negative relationship between days of FGI and profitability in half of the sample. Further, Rumyantsev and Netessine (2007c) and Cannon (2008) found no relationship between inventory and financial performance. However, Capkun et al. (2009) found a negative relationship between levels of RMI, WIPI, and FGI scaled on sales, and concluded, contrary to Rumyantsev and Netessine (2007b), that FGI was the most important inventory. Still, as pointed out by Eroglu and Hofer (2011a), these findings may be subject to poor modelling and data issues. First, scaling the dependent and explanatory variables with the same variable, i.e. sales as done by Capkun et al. (2009), would introduce a significant bias in estimates. Second, the use of large samples and broad segments would also lead to incorrect benchmarking results. Correcting for these issues, they find that RMI have the greatest effect of financial performance.

There has also been a discussion about the shape of the relationship between inventory levels and financial performance, and some of the aforementioned research in the previous paragraph support a linear association. However, there seem to exist a non-linear relation between inventory and profitability. Thus, there is an optimum level of inventory and beyond this level profitability suffers, and most companies will gain financial benefits by increasing inventory efficiency (Eroglu & Hofer, 2011a; Isaksson & Seifert, 2014).

In the retail sector, there is a positive relationship between inventory turnover, return on sales and assets (Shockley & Turner, 2015). Retail firms with high inventory turnover respond better to demand changes than do firms with low inventory turnover (Kesavan et al., 2016). Furthermore, inventory performance predicts future stock returns for U.S. retailers (Alan et al., 2014), and inventory level is negatively associated with cost efficiency for medium-sized companies operating in seven European countries (Weill, 2008).

From an overall corporate perspective, inventories have been analysed in several different research directions, such as their association with financial performance, scale effects, and other firm-specific drivers that are associated with inventory performance. These factors are, to some degree, possible for the management to adjust. However, exploring the relationship between inventory performance and environmental factors that are harder to control by management, has not caught the same attention in research of inventory performance. Still, some studies have investigated how inventory levels evolve over time. Others have highlighted the importance of varying lead-time to explain differences in inventory performance due to various distances between retailers and central warehouses. This and other environmental factors, such as local market conditions, could also affect inventory performances for firms. In the following section, we discuss the relationship between firm characteristics and environmental factors on inventory performance in more detail.

Firm characteristics

When analysing inventory performance metrics such as inventory turnover or inventory in days, these should be controlled for financial metrics such as gross margin, capital intensity, and sales surprise (Gaur et al., 2005). There seem to be a negative relationship between gross margin and inventory turnover, and a positive relationship between capital intensity and sales growth (Gaur et al., 2005; Kolias et al., 2011). This implies that firms with better margins on their sales have higher relative inventory levels, while firms with high investment in assets relative to inventory return better inventory performance.

As several authors have identified, and Eroglu and Hofer (2011a, 2011b, 2014) and Isaksson and Seifert (2014) in particular, there are considerable differences between firms in broadly defined industrial sectors, and failure to adjust for that may lead to incorrect benchmarking results. Thus, it is important to control for different industry segments when modelling inventory performance. Table 1 presents an overview of selected studies in the context of firm characteristics, which are relevant for the current research.

The interest in how firm size affects firm specific measures is evident throughout the management and operations literature. Within the productivity literature, Diaz and Sanchez (2008) found in their analysis of Spanish manufacturing firms in the 1995–2001 period that firm size negatively affects value added. However, related to inventories, the number of studies is limited. Kesavan et al. (2016) and Breivik (2019) found that firm size measured in term of sales is positively correlated with inventory turnover.

In addition to firm size, chain affiliation is also recognised for possessing scope-and-scale economies in sales and purchasing. Retail chains utilise more sophisticated distribution and inventory control systems and tend to offer lower prices and more standardised products (Dinlersoz, 2004). Chain stores are an important part of the economy in developed economies, and this is especially the case for the retail sector (Kosová & Lafontaine, 2012; Perrigot, 2006). Studies show that national chains in the U.S. have contributed to productivity gains in the retail sector (Doms et al., 2004; Foster et al., 2006) and that national chains have experienced faster growth (Jarmin et al., 2009).

Table 1. Selected studies on firm characteristics.

Scope of study	Dataset/sample	Dependent var. (output)	Independent var. (input)	Key findings	Authors
Examines the structure of retail markets by type of organisation: stand-alone stores and chain stores.	1995-1998. U.S.	Fraction of total establishments.	Store type, population, income, non-white, age, wage, rent, metropolitan statistical area.	Chain stores are larger than stand-alone stores. Chain store expand their scales when market size increases, while stand-alone stores increase in numbers.	Dinlersoz (2004)
Examines the relationship between investments in information technology and firm performance.	U.S. retail. 1992-1997. (N = 6,036)	Sales per worker.	Employment, industry segment, investment in information technology, total capital investment.	Positive relationship between investments in information technology and sales.	Doms et al. (2004)
Develop a model to evaluate inventory turnover while controlling for key financial figures.	U.S. retailers. 1985-2000. (N = 3,407)	Inventory turnover.	Gross margin, capital intensity, sales surprise, sales, industry segment, time trend.	Inventory turnover negatively correlated with gross margin and positively associated with capital intensity and sales surprise. Negative time trends in inventory turnover.	Gaur et al. (2005)
Explores the relationship between retail restructuring and labour productivity.	U.S retail. 1987, 1992, and 1997.	Labour productivity at industry level.	Labour productivity at establishment level,	The entry of establishments of national chains on displacement of single-unit establishments contribute to overall productivity growth.	Foster et al. (2006)
Review differences between franchise chains; retail and service.	228 services chains, 302 retail chains. France. 2005.		Chain and store specific measures on age, fees, investment, sales and others.	Identify differences between retail and services, such as: age, fees, royalties and length of contract.	Perrigot (2006)
Examines determinants of technical efficiency.	1,898 Spanish manufacturing, 20 industry segments. 1995-2001.	Value added.	Capital stock, employment, time, industry segment, share of temporary workers, foreign shareholders, gross investment/capital, public limited company, size – number of employees.	SMEs more efficient than larger firms. Firms with a lower ratio of temporary workers are more efficient.	Diaz and Sanchez (2008)
Study the effects of inventory leanness on financial performance.	U.S. manufacturing. 2003-2008. 1,600 firms. (N = 7,804)	Inventory scaled by industry segment, return on assets, return on sales.	Sale, assets, growth in sales, time effects, inventory scaled by industry segment.	Inventory leanness effects financial performance. Argue in general that results point towards a positive relationship.	Eroglu and Hofer (2011a)
Examines effects of the three discrete components of inventory on financial performance.	U.S. manufacturing. 2003-2008. (N = 4.121)	Return on sales.	Assets, total inventories, raw material inventories, work in progress inventories, finished goods inventories, industry segment, time.	Discrete components of inventory have different effects on firm financial performance.	Eroglu and Hofer (2011b)
Study determinants of inventory turnover.	566 Greek retail firms, 2000-2005. (N = 3,336)	Inventory, inventory turnover.	Gross margin, capital intensity, sales growth, sales surprise, time trend.	Inventory turnover heterogeneity caused by industry segment effects. That changes in sales is affected by sales decline in the location region.	Kolias et al. (2011)
Examines effects of demand shocks on retailers with high/low inventory turnover.	460 U.S. public retailers. 1985-2009.(N = 11,905)	Return on assets.	Cost of goods sold (COGS), delta COGS, abnormal inventory growth, gross margin, delta gross margin, return on assets lagged.	Low (LIT) and high (HIT) inventory turnover retailers respond differently to demand shocks. HIT retailers adjust shortages and excesses by adjusting quantity, LIT retailers rely on price changes.	Kesavan et al. (2016)
Study inventory turnover performance and its association with retail chain affiliation and time trends.	184 Norwegian retail firms. 1998-2013. (N = 2,107)	Inventory turnover.	Gross margin, capital intensity, sales, growth in sales, industry segment, retail chain affiliation, time trend.	Retail chain affiliation explain some of the variance in inventory turnover. Inventory turnover decline with 2.3 % annually, and by 5.2 % when controlling for key financial ratios.	Breivik (2019)

Various measures of capital turnover is frequently used to identify a firms' ability to operate efficiently by being able to utilise invested capital in an optimal way. Delen et al. (2013) classify the asset turnover rate as asset utilisation and that this ratio indicate a firms' ability to generate sales, hence operating efficiently. Shockley and Turner (2015) find in analysing financial performance that firm level deviations from segment levels on asset ratios affected firm financial performance in a positive manner.

Environmental factors

The variation in inventory performance is affected by factors over which the managers have little control, due to circumstances present in the firm's environment. Empirical studies have shown that environmental factors have moderating effects from organizational- and ownership structure to strategic decisions (Eroglu & Hofer, 2014). In the productivity literature, geographical presence, market concentration, demand density, density of economic activity, competitive environment, urbanisation and centrality have all been shown to be associated with firm-level efficiency (e.g. Aiello & Bonanno, 2016; Assaf et al., 2011; Bos & Kool, 2006; Carlino & Voith, 1992; Ciccone & Hall, 1996; Ko et al., 2017). Hence, environmental factors could help explain why some firms are more efficient in their inventory management compared to other firms. Table 2 gives an overview of relevant studies.

When assessing relative inventory levels in multiple firms, it is essential to control for geographic store location. This is because the distance between retail stores and the warehouses of producers, importers and wholesalers, as well as the centralised retail chain inventory, vary and affect lead times. Ballou (2005) showed by simulations for various inventory models that aggregated inventory levels increased when lead-time increases. This is due to an added need for safety stock to countermeasure the demand uncertainty associated with an increase in lead-time (Baker, 2007). Research on how regional factors affect retailers is limited, but earlier examinations have shown that total factor productivity across U.S. states increased with urbanisation (Carlino & Voith, 1992).

Several studies show that local market conditions affect company performance. Eroglu and Hofer (2014) show that reduction in inventory levels may lead to negative financial performance in markets with lower degrees of competition. In the retail sector, Ko et al. (2017) examined sales revenue and number of customers and found a positive association between efficiency and competitive environment, measured as similar stores within a radius of 500 metres. In the bank sector, however, there has been contrary results. Aiello and Bonanno (2016) found that cost- and profit efficiency dropped when the competitive environment increases, measured as an increase in number of local bank branches.

Further, Bos and Kool (2006) found environmental factors to be less important than managerial performance using urban versus rural location and population size as proxies for market conditions. However, using other measures of local market conditions could lead to other results. Ciccone and Hall (1996) are using density, measured as intensity of humans, labour, and physical capital relative to physical space, and state that density is a better measure than size (of the municipality) in the regard of explaining productivity. Otsuka (2017) found that population agglomeration, investments in infrastructure, and density of firm clusters increased regional productivity.

Several studies aim to measure time trends in inventory, and time trends are in general used to capture time effects not otherwise captured in a model (Hill et al., 2011). Rajagopalan and Malhotra (2001) investigated manufacturing firms using industry-level data and concluded that finished-goods inventories vary among industries in both directions, but they identified no significant time trend for half of the industries. Chen et al. (2007) found that the median number of inventory days decreased from 73 to 49 using firm-level data from both retail and wholesale firms, but that the inventory for the retail segment only started to decline in the mid-1990s. Contradictory to these, Gaur et al. (2005) found for the 1987–2000 period that unadjusted inventory turnover declined by 0.45% annually, which demonstrates an increase in relative inventory levels. For Norwegian home improvement stores for the 1998–2013 period, Breivik (2019) found inventory turnover to decline by 2.3% annually. Although research at the present time does not clearly indicate the direction of the time trends for inventory in retail firms, several findings point towards some firm specifics that are closely associated with relative levels of inventory (Gaur et al., 2005; Kolias et al., 2011).

Figure 1 illustrates the proposed model for analysing the effects of firm characteristics and environmental factors on inventory performance. The first component analyses the factors explaining inventory turnover, while the second component analyses the factors explaining the differences in inventory efficiency.

Methodology

Data

The data used in this study are annual financial statements for firms affiliated with three different Norwegian

Table 2. Overview of studies on environmental effects.

Scope of study	Dataset/sample	Dependent var. (output)	Independent var. (input)	Key findings	Authors
Examines determinants of aggregate productivity at state level.	48 U.S. states. 1967-1986. (N = 960)	Aggregate annual real wage/no. employees.	Education level, union membership, total highway system, time, energy shocks, population in metropolitan area, real gross state product, the real output share per industry segment, aggregate employment, state dummy.	Productivity is affected by the state's industrial mix, infrastructure, education level and metropolitan structure.	Carlino and Voith (1992)
Study labour productivity across U.S states.	Gross state output on. 1998. (N = 50)	Output on state level.	Data on labour input on county level, area data on county level, education level.	Employment density increases labour productivity.	Ciccone and Hall (1996)
Estimate time trends in inventory ratios.	U.S. manufacturing. 1961-1994. 20 industry segments.	Inventory ratio.	Time trend parameters.	No statistical time trend for finished goods inventories.	Rajagopalan and Malhotra (2001)
Evaluate aggregate inventory level effects of different inventory control policies.	Monte Carlo simulation.	Inventory/Inventory turnover.	Item characteristics, inventory policy.	Aggregate inventory levels can be estimated based on product characteristics and inventory policy.	Ballou (2005)
Examines the role of environmental factors in bank efficiency.	Micro- and macroeconomic data. 401 Dutch banks. 1998-1999.	Profit before tax, total costs.	Bank specific factors, market factors, macro factors	Environmental factors to some degree to affect efficiency.	Bos and Kool (2006)
Examines inventory holding periods for retail and wholesale.	1,254 U.S. retail & wholesale firms. 1981-2004. (N = 10,000+)	Inventory days, inventory to sales, inventory to assets.	Industry segment, macro-economic control variables.	Wholesale reduced median holding period from 73 to 49 days. Retail inventories to decline from about 1995.	Chen et al. (2007)
Exploratory study on inventory levels and inventory control models.	722 public U.S. companies. 1992-2002.	Inventory.	Cost of goods sold, fixed assets, gross margin, sales, positive sales surprise, time trend.	Firms operating with increased lead time and demand uncertainty have elevated inventories.	Rumyantsev and Netessine (2007a)
Examines quantitative measures of lead time and perceptions of supply chain risk.	Case studies of 13 supply chains within six firms.	Lead time.	Lead time.	Supplier lead time exceed customer lead time. Inventory mitigates risks associated with variability in demand and transportation.	Baker (2007)
Study factors to impact cost efficiency in supermarkets.	77 Spanish supermarket retail chains. 2001-2007.	Total cost/price of capital.	Price on labour, price on capital, vertical integration, low price retailer, age of firm, geographic expansion.	Efficiency is associated with age of firm, geographic presence and if chain is low price retailer.	Assaf et al. (2011)
Examines effects of environmental factors in the relationship between inventory leanness and firm financial performance.	123 U.S. manufacturing firms. 1997, 2002 and 2007. 108 industries segments (N = 5,749)	Return on sales	Size, growth, inventory leanness, innovative intensity, demand uncertainty, competitive intensity.	Innovative and competitive intensity affect the effects lean inventories have on firm financial performance.	Eroglu and Hofer (2014)
Examines effects from local market conditions on cost and profit efficiency.	Italian banks. 2006-2011. (N = 3,766).	Total costs, total profits.	No. of employees, gross banking product, debt, labour costs, cost of capital, cost of deposits, bank density, market concentration.	Bank efficiency increase with increased market concentration and demand density. Negative time trend.	Aiello and Bonanno (2016)
Study efficiency in Korean individual retail chain stores.	Korean retailer. 32 outlets.	Sales revenue, number of customers.	Store size, number of items, number of employees, rental cost, trade area index, no. of competitive stores, trade area index.	Competitive environment and number of items per employer affect store efficiency.	Ko et al. (2017)

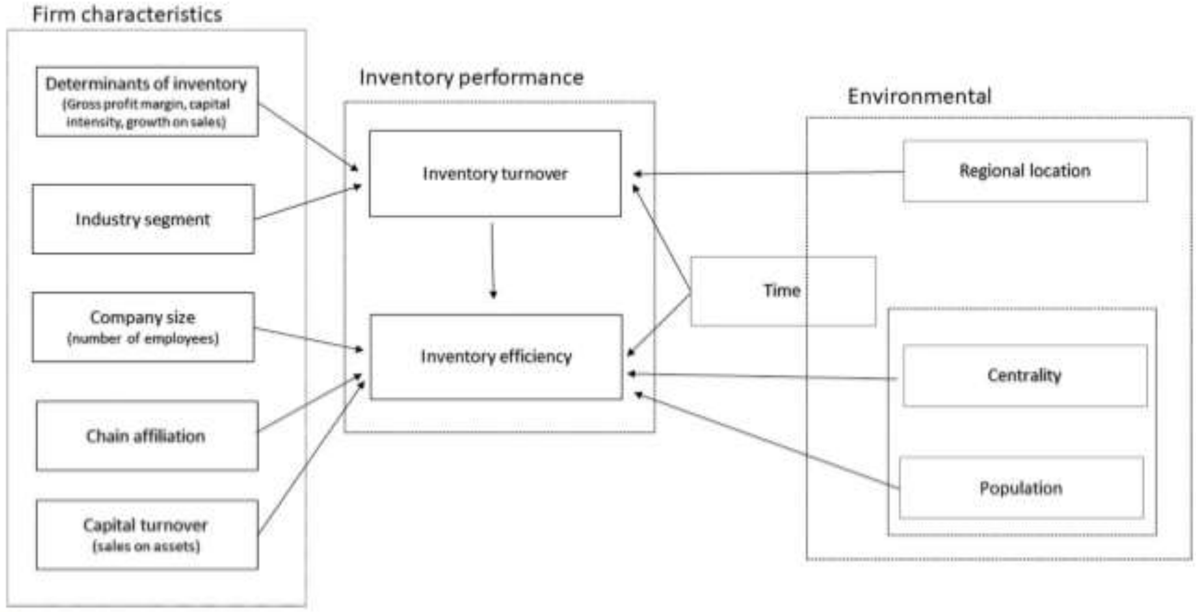


Figure 1. Analytical framework.

retail chains. The firms are operating as home improvement retailers selling construction products and tools to end users in Norway. The original dataset consists of all the firms affiliated with the chains, but some firms were excluded in the final dataset due to the following criteria: (1) The data are limited to include only private limited companies, thus leaving out firms organised as sole proprietorships since those firms are not legally bound to report accounting records according to the Norwegian Accounting Act. (2) Missing observations on inventory turnover or growth in sales are removed. (3) Observations with an inventory turnover > 80 and growth in sales > 10 are removed since these values are considered extreme values and are mainly related to enterprises in a start-up phase. (4) Firms with turnover of more than 50 million Euro (approximately 500 million NOK[1]) are removed since such firms are not considered small- and medium sized enterprises based on EU recommendation 2003/361.

Approximately 10.6% of the observations were removed from the original dataset due to these criteria, and the final dataset comprises of 2,189 observations from 187 firms for the period of 1998-2013. Not all firms are represented every year in our study period, making our panel unbalanced. Moreover, there may exist gaps in the observations of the firm. All the firms present in our dataset report financial statements according to Norwegian General Accepted Accounting Principles (N-GAAP). According to N-GAAP, transactions enter in the accounts when risk and control of the good is transferred from seller to buyer, meaning that goods in transit would not be present in the accounts either as sales and COGS (for the seller) or as inventory (for the buyer). The study period of 1998–2013 was chosen since there have been substantial structural changes in the marketplace post 2013, with several mergers and acquisitions taking place.

The three retail chains present in our study represented approximately 30% of the industry revenue in 2014. These chains were chosen since the local stores are registered as limited companies with independent accounts. Other players in the market are either part of conglomerates that operate in several different sectors of the economy, e.g. groceries and real estate, and do not present stand-alone accounting data for their activity in the sector for building materials and hardware, or where the local stores are not registered as a limited company. Thus, these actors only provide accounting data for their total activity in Norway as a whole. The retail chains present in our study consists of Byggtorget, XI-bygg, and Byggmakker. The latter is owned by a foreign building and construction material company, while the other two are owned by their members. According to statistics from Virke (Byggeindustrien, 2018), total turnover for the building materials and hardware retail industry in Norway was in 2017 approximately 4.58 billion Euro (45.8 billion NOK[2]).

In addition to store level accounting data, we include in the analysis records on annual municipal population reported by Statistics Norway (2018) and a classification

Table 3. Description of variables (the panel data indicative of firm i at time t).

Variable	Description	Measure
IT_{it}	Inventory turnover	Measured as: $\frac{COGS_{it}}{\overline{Inventory_{it}}}$, whereas $\overline{Inventory_{it}} = \frac{Inventory_{it} - Inventory_{it-1}}{2}$
GM_{it}	Gross profit margin	Measured as: $1 - \frac{COGS_{it}}{Sales_{it}}$
CI_{it}	Capital intensity	Measured as: $\frac{\text{Fixed assets}_{it}}{\text{Fixed assets}_{it} - Inventory_{it}}$
G_{it}	Growth in sales	Measured as: $\frac{Sales_{it}}{Sales_{it-1}}$
$IndC_i$	Sector code based on SIC 2007	Dichotomous variable: 1 if firm operates in a specific industrial sector; 0 if not. Based on the firm's sector code in 2013. Included sector codes (2-digit): 16, 41, 43, 46, 47, 52, 68 and 71.
REG_i	Geographical region where the firm is located	See map for details. Based on the firm's post code in 2013.
SOA_{it}	Sales on assets	Measured as: $\frac{Sales_{it}}{\text{Total assets}_{it} - Inventory_{it}}$
MC_i	Measure of municipal centrality as defined by Statistics Norway (1999)	Factor variable: 3 if it is a central municipality, 2 if it is a fairly central municipality, 1 if it is a fairly remote municipality, and 0 if it is a remote municipality
POP_{it}	Population of municipality	Population of municipality of which the store is located
CHN_{it}	Retail chain affiliation of the firm	Based on the chain affiliation the firm has in 2013. The retail chain affiliations are Byggmakker. XI-Bygg and Byggtorget.
NoE_{it}	Company size	Number of employees in firm
$Time_{it}$	Time trend	Discrete variable: 1 for the first year of observation for the firm

Note: The EU NACE rev.2 and UN ISIC standards are basis for the Norwegian Standard Industrial Classification - SIC 2007 (Statistics Norway, 2008).

Table 4. Summary statistics.

	Mean	Std.Err.	Min.	Max.
Inventory turnover (IT)	5.81	4.36	1.60	37.55
Gross profit margin (GM)	0.30	0.07	0.16	0.62
Capital intensity (CI)	0.25	0.19	0.00	0.85
Growth in sales (G)	1.11	0.22	0.84	3.61
Employees (NoE)	15.81	23.49	1.20	196.67
Sales over fixed assets (SOA)	5.01	2.42	0.92	18.47
Population (POP)	18.351	48.757	618	549.807

on centrality on municipal level as defined by Statistics Norway (1999).

Variables

A full description of the variables used in this study is presented in Table 3, and summary statistics is given in Table 4.

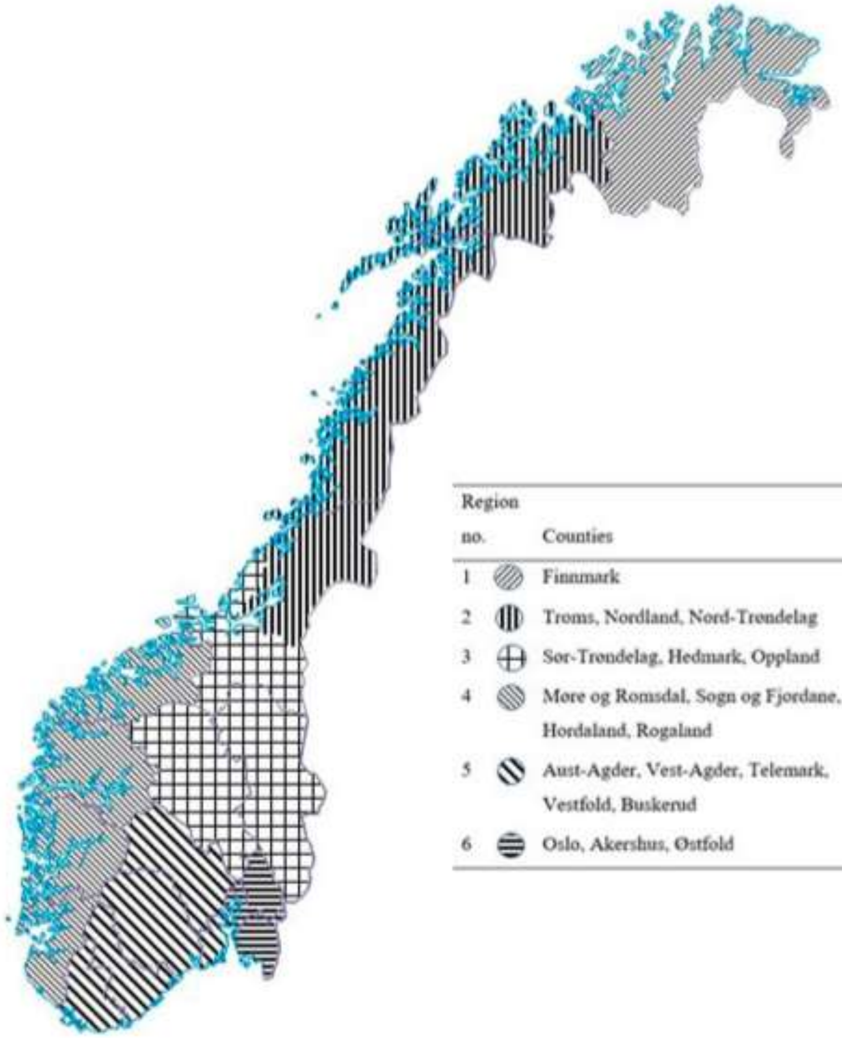
Some of the variables in Table 3 need a more thorough description. The dependent variable is inventory turnover, represented by IT_{it}, and this variable is commonly used as measuring efficiency in the retail sector (Gaur et al., 2005). Since the inventory turnover is calculated using both the opening and closing balance of the accounting year, the analysis starts from the year 1999.

Norway is a long and narrow country which consists of 323,752 km^2 (CIA, 2020), and the driving distance from the southernmost point (Lindesnes) to the northernmost point (Nordkapp) is about 2,350 km. In addition, approximately 3/10 of the area is situated above the Arctic Circle, and these factors are causing logistical challenges that may not be present in other countries. In Norway, as in most countries, there are present regional differences in terms of population and population density. Thus, geographical locations may influence replenishment lead times and consequently affect the need to increase or decrease safety stock (Ballou, 2005). To capture the spatial dependence and regional differences in our data, we include a regions variable, represented as REG_i, using the structure of nomenclature territorial units, NUTS, defined by Statistics Norway (1999). Figure 2 presents the six different regions including population and population density of those regions.

Further, we are using the population of the municipality, represented by POP_{it}, as a proxy of the size of the local market. But, since there is a difference of being situated in a small municipality in terms of population nearby Oslo, the capital of Norway, than being situated in a similarly small municipality in a more sparsely populated part of the country, we include a measure of municipal centrality, represented by MC_i, to control for a more competitive environment in nearby areas.

Measuring efficiency

To determine the inventory efficiency, the stochastic function analysis (SFA) of Aigner et al. (1977) and Meeusen and van Den Broeck (1977) is used as a methodological starting point. The frontier methodology is based on a frontier function that gives limit (i.e. minimal or maximal) output values for any given level of inputs (Baltas, 2005). This approach presents the advantage of disentangling the efficiency and statistical noise taking exogenous events into the distance from the efficiency frontier. Hence, the error term consists of two components, one to account for purely random statistical noise, and another error-term to account for the deviation from



Region no.	Counties	Area (km²)	Population	Population density
1	Finnmark	48,618	76,149	1.56
2	Troms, Nordland, Nord-Trøndelag	86,745	545,731	6.29
3	Sør-Trøndelag, Hedmark, Oppland	71,437	703,032	9.84
4	Møre og Romsdal, Sogn og Fjordane, Hordaland, Rogaland	58,532	1,368,527	23.38
5	Aust-Agder, Vest-Agder, Telemark, Vestfold, Buskerud	48,867	1,000,858	20.48
6	Oslo, Akershus, Østfold	9,553	1,564,020	163.72

Figure 2. Geographic regions, population and population density in Norway.

the frontier. Thus, the frontier is specified as:

$$y_{it} = \beta' x_{it} + \epsilon_{it} \tag{1}$$

$$\epsilon_{it} = v_{it} \pm u_{it} \tag{2}$$

in which y_{it} is the dependent variable, inventory turnover in our case, x_{it} is a vector of explanatory variables. The error term, ϵ_{it}, is asymmetric and consists of two components. The first term,v_{it}, of the composite error term is the white-noise stochastic term as in a standard regression disturbance which is normally distributed with zero mean and constant variance, i.e. $v_{it} \sim N(0, \sigma^2)$. The second term, u_{it}, is the firm inefficiency as a non-negative measure with assumption on distributional properties as $N(u_{it}, \sigma_u^2)$. Further, the inefficiency term, u_{it}, could incorporate exogenous variables, Z_{it}, that explain inefficiency characterising the environment in which the firm operate, such as competitive conditions, network characteristics, and so on (Kumbhakar & Lovell, 2000). The two terms, v_{it} and u_{it}, are distributed independently. Hence, in addition u_{it} have the following specifications:

$$u_{it} = \delta Z_{it} + \mu_{it} \tag{3}$$

The advantages of using a SFA approach is that it computes a relative measure of performance which allows comparison of each firm to the best-practice companies in the frontier. Further, this deviation gives an efficiency score that measures how close a firm's inventory turnover is to what the optimal inventory would be for that specific firm (Weill, 2008).

Traditionally, SFA was estimated by a two-stage procedure, where the frontier, Equation (1), was estimated in the first-stage, and the obtained efficiency, Equation (3), was regressed on a set of explanatory variables in the second-stage (Weill, 2008). However, as pointed out by Kumbhakar and Lovell (2000), this leads to some econometric issues. The explanatory variables, in Equation (3), must be assumed as uncorrelated to the frontier, in Equation (1), or else the maximum likelihood estimates of the frontier would be biased due to omission of explanatory variables. Further, it assumes that the efficiency terms are identically distributed in the first step, while this assumption is contradicted in the second step since the regression on explanatory variables assumes that the efficiency term is not identically distributed (Weill, 2008).

For that reason, we are using the one-stage procedure proposed by Battese and Coelli (1995). Based on their proposition, we are using panel data in which the non-negative inefficiency term, u_{it}, has the truncated distribution as $N(u_{it}, \sigma_u^2)$ with different means for each firm. As a result, the distributions of the inefficiency terms are then independently but not identically distributed, since it is expressed as a function of explanatory variables.

The analysis of inventory turnover consists of two components. The first component, Equation (4), is to estimate the stochastic frontier that serves as a benchmark of differences in efficiency between the firms. The second component, Equation (5), concerns the incorporation of exogenous variables that exert an influence on the performance of the firms.

The model is then specified as followed:

$$\log(IT_{it}) = \alpha_0 + \sum^{j} \beta_j \log \mathbf{X}_{jit} + \frac{1}{2} \sum^{j} \sum^{k} \beta_{jk} \log \mathbf{X}_{jit} \log \mathbf{X}_{kit} + \sum_{j=1}^{7} \zeta_j IndC_i + \sum_{j=1}^{5} \eta_j REG_i + \iota Time_{it} + v_{it} - u_{it} \tag{4}$$

where the dependent variable is the inventory turnover for firm i at time t. The X-vector is represented by the variables GM_{it}, CI_{it}, and G_{it}. $IndC_i$ are industry sectors, REG_i are regions, and $Time_{it}$ is a time trend. α, β, ζ, η and ι are the estimated parameters, v_{it} is the random noise component, and u_{it} is the inefficiency term.

$$u_{it} = \kappa_0 + \sum_{j=1}^{4} \nu_j MC_i + \sum_{j=1}^{4} \pi_j MC_i {*} \log(POP_{it}) + \sum_{j=1}^{3} \tau_j CHN_i {*} \log(NoE_{it}) + \sum_{j=1}^{3} \upsilon_j CHN_i {*} Time_{it} + \sum_{j=1}^{3} \psi_j CHN_i {*} \log(SOA_{it}) + \mathrm{e}_{it} \tag{5}$$

Table 5. Estimates of the translog response function.

Variable	Estimate	Std. Err.	z value	Pr(> |z|)	
(Intercept)	2.309	0.207	11.158	0.000	***
log(GM)	−0.041	0.262	−0.156	0.876	
log(CI)	0.641	0.058	11.147	0.000	***
log(G)	0.670	0.223	3.010	0.003	**
I(0.5 * log(GM)^2)	0.208	0.200	1.039	0.299	
I(0.5 * log(CI)^2)	0.067	0.012	5.415	0.000	***
I(0.5 * log(G)^2)	0.148	0.169	0.874	0.382	
I(log(GM) * log(CI))	0.280	0.043	6.594	0.000	***
I(log(GM) * log(G))	0.317	0.178	1.778	0.075	.
I(log(CI) * log(G))	−0.013	0.049	−0.264	0.791	
IndC41	0.004	0.055	0.068	0.946	
IndC43	−0.054	0.098	−0.553	0.580	
IndC46	−0.031	0.050	−0.613	0.540	
IndC47	−0.094	0.045	−2.093	0.036	*
IndC52	0.252	0.232	1.087	0.277	
IndC68	−0.584	0.101	−5.793	0.000	***
IndC71	0.743	0.143	5.201	0.000	***
REG1	−0.409	0.063	−6.461	0.000	***
REG2	−0.352	0.058	−6.107	0.000	***
REG3	−0.249	0.064	−3.867	0.000	***
REG4	−0.253	0.058	−4.362	0.000	***
REG5	−0.259	0.058	−4.482	0.000	***
Time	−0.006	0.004	−1.733	0.083	.

Notes: * * *, **, *, ., – significant at the 0.1%, 1%, 5%, 10% levels, respectively (two-sided).

in which MC_i is the centrality of the municipality, POP_{it} is the population in the municipality, CHN_i is the affiliated retail chain, NoE_{it} is the number of employees, SOA_{it} is the ratio of sales to fixed assets, and $Time_{it}$ is a time trend. κ, ν, π, τ, υ and ψ are estimated parameters and e_{it} is a truncated zero-mean residual.

Results and discussion

Estimation of the translog response function

Through the estimation of the translog response function, we obtained estimates of the frontier defined by observations of the best firms. Inefficiency relative to the frontier is then estimated simultaneously for each store. Estimates are provided by use of maximum likelihood on the translog response function defined in Equation (3) and the specification of inefficiency effects as defined in Equation (4). For this analysis, we use R (R core team, 2020) and the Frontier package (Coelli & Henningsen, 2017) with the specifications formulated by Battese and Coelli (1995). The estimates of the translog response function are presented in Table 5.

We find estimates of the response function for logCI (0.641) and log$G$ (0.670) to be significantly different from zero at the $p < 0.001$ and $p < 0.01$ levels, respectively. These estimates imply that both investment in fixed assets and growth in sales are associated with an increase in

Table 6. Elasticities from the translog response function.

	Mean	Std.Err.	Min	Max
Gross profit margin (GM)	−0.78	0.34	−2.43	0.10
Capital intensity (CI)	0.18	0.11	−0.27	0.70
Growth in sales (G)	0.32	0.08	−0.13	0.66

inventory turnover. The squared coefficient estimates are significant for the $\log CI^2$ variable ($0.067, p < 0.001$) and represent the nonlinear elasticity to scale. Furthermore, the estimates of the interaction variables return significant values for $\log(GM) * \log(CI)$ ($.280, p < 0.001$) and for $\log(GM) * \log(G)$ ($.317, p < 0.1$). In addition, Table 5 reports three estimates of the industry segment that return significant values at the $p < 0.05$ level or higher. This indicates that inventory turnover varies between different industries and verifies the necessity to control for such firm characteristics.

To simplify the interpretation of the translog response function, we calculate the composite elasticities. These estimates of $\log(GM)$, $\log(CI)$ and $\log(G)$ are presented in Table 6 and based on Equation (3). The estimates of these coefficients represent elasticities, which are evaluated at the mean level. We find that a one percent increase in the gross profit margin is associated with a 0.78% lower inventory turnover ratio. Furthermore, this table reports that a one percent increase in capital intensity is associated with a rise in inventory turnover by 0.18%. Finally, we identify that a one percent expansion in sales growth is associated with a 0.32% increase in inventory turnover.

The effects of regional variables on inventory performance and time trend

When we estimated the translog response function in Table 5, we controlled for regional differences. The argument for this approach rests on topography and logistic challenges that cause large differences in the transportation distance between stores located in different regions and hence are likely to influence the lead time at the store level. As Table 5 shows, all of the estimates of the regional variables (*REG*) are significant at the $p < 0.001$ level, which implies that geographic location affects inventory turnover. This is in line with research on retail store productivity, which measures regional effects on sales per square foot of the selling area (Kumar & Karande, 2000). As the estimates in Table 5 show, the lowest inventory turnover ratios reported are for those stores located in the most northern regions (REG1 and REG2). One possible explanation is the varying but generally increasing lead times for those regions located to the north and further away from the capital of Oslo, as the latter in many cases serves as a logistic centre in Norway. The relationship between lead time and inventory levels is recognised in the literature (Ballou, 2005; Ben-daya & Raouf, 1994; Rumyantsev & Netessine, 2007a).

Table 7. Estimates of inventory turnover inefficiency determinants.

Variable	Estimate	Std. Err.	z value	Pr(> |z|)	
Z_(Intercept)	5.641	2.045	2.758	0.006	**
Z_MC0	−5.461	2.081	−2.624	0.009	**
Z_MC1	14.734	7.412	1.988	0.047	*
Z_MC2	0.365	1.981	0.184	0.854	
Z_MC3	−3.998	2.021	−1.978	0.048	*
Z_I(MC0 * log(POP))	0.038	0.031	1.198	0.231	
Z_I(MC1 * log(POP))	−2.393	1.128	−2.121	0.034	*
Z_I(MC2 * log(POP))	−0.632	0.187	−3.390	0.001	***
Z_I(MC3 * log(POP))	−0.155	0.057	−2.724	0.006	**
Z_I(CHN_BM * log(NoE))	−0.015	0.052	−0.298	0.765	
Z_I(CHN_XL * log(NoE))	−0.291	0.054	−5.407	0.000	***
Z_I(CHN_BT * log(NoE))	−0.368	0.056	−6.576	0.000	***
Z_I(CHN_BM * Time)	0.019	0.013	1.457	0.145	
Z_I(CHN_XL * Time)	−0.002	0.009	−0.160	0.873	
Z_I(CHN_BT * Time)	0.029	0.008	3.723	0.000	***
Z_I(CHN_BM * log(SOA))	−0.290	0.112	−2.601	0.009	**
Z_I(CHN_XL * log(SOA))	0.160	0.070	2.281	0.023	*
Z_I(CHN_BT * log(SOA))	0.046	0.045	1.017	0.309	
sigmaSq	0.205	0.014	15.121	0.000	***
Gamma	0.219	0.066	3.318	0.001	***

Notes: * * *, **, *, ., – significant at 0.1%, 1%, 5%, and 10%, respectively (two-sided).

The estimates reported in Table 5 also indicate that a linear time trend is present in the frontier of inventory performance ($p < 0.1$). The estimate of the time coefficient indicates that the frontier of inventory performance represented by the best performing firms is decreasing annually by 0.6%. This is in line with previous findings in the literature (Gaur et al., 2005; Kolias et al., 2011) and may stem from general industry characteristics where product assortment and variety have increased to meet customer demands, which leads to increased levels of inventory and lower turnover.

Inventory efficiency and environmental factors

Table 7 presents the estimates of the inventory inefficiency determinants. The model explains 21.8% of the detected inefficiency and 20.5% of the variation within the observed data.

Related to the main emphasis in this paper, Table 7 shows that the environment in which the store is located (*MC*) has an effect on inventory turnover. MC is a categorical variable representing how close or remote the municipal, in which the store is located, is to another larger urban area. Based on the more general literature on efficiency, which for instance suggests improved bank efficiency when demand density and market concentration increase (Aiello & Bonanno, 2016), we expected that inventory turnover efficiency generally improves when stores are located in more urban areas. However, the estimate for *MC*0 is significant ($p < 0.01$) and points to reduced inefficiency for the most rural areas. In contrast, locations in more central areas *MC*1 indicate lower levels of efficiency. For the *MC*3 variable, which represents the most central municipalities, the estimate again indicates better efficiency ($p < 0.05$). Hence, the most remote municipalities deviate from the general trend. There may be several reasons for this deviancy. First, all of the municipalities embedded in this group represent small communities, and retailers in some of these locations operate as monopolists with the accompanied consequence of reduced service level and product variety (Hernant et al., 2007), thereby improving inventory turnover. Second, several of the municipalities embedded in this group have suffered depopulation over recent decades and simply need to operate effectively to be able to run a sustainable business, avoid bankruptcy and survive, particularly with regard to inventory management, as it is important to keep costs down and achieve financial results (Isaksson & Seifert, 2014; Weill, 2008).

The estimates reported in Table 7 further indicate that an increase in population (*POP*) in the *MC*1 through *MC*3 variables reduces inefficiency at significant levels,

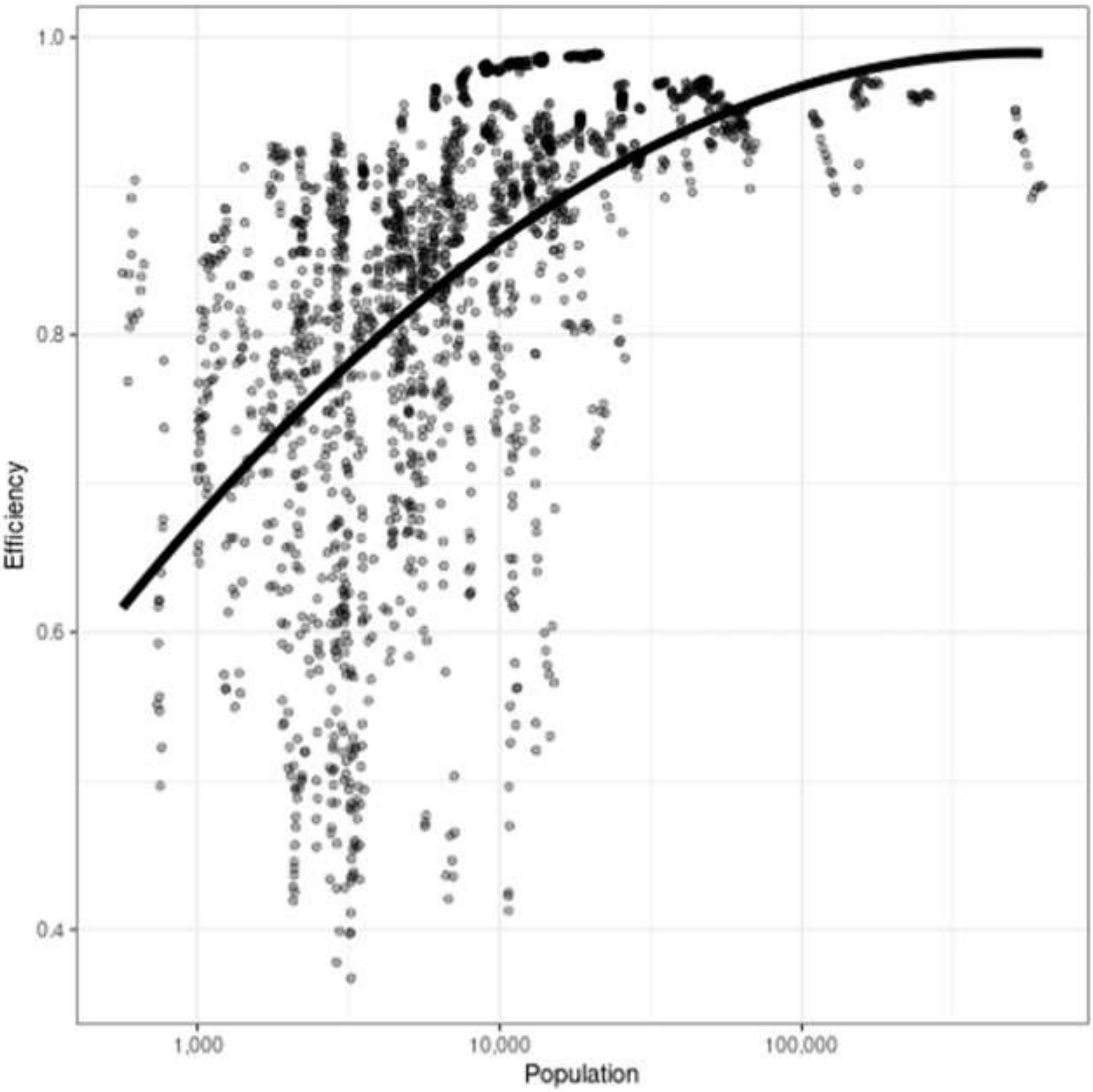


Figure 3. Inventory turnover efficiency by population.

but at a diminishing rate. This is in accordance with the existing literature, which has identified that store productivity increases with growth in population density (Kumar & Karande, 2000).

As illustrated in Figure 3, we find that inventory efficiency in general increases with an increase in the municipal population. The figure also reveals a high variation in the data at the point of approximately 3.000 inhabitants.

In Figure 4, we plot inventory turnover efficiency by geographical region (*REG*). As portrayed, inventory efficiency differs significantly among the six regions. Region 6 represents the most efficient firms, while region 3 contains the stores that are the least efficient. The most northern region of Norway (region 1), which is the most sparsely populated, demonstrates an inventory efficiency that is below average. In contrast, the firms located in region 6, which consists of the area surrounding the capital of Norway and the area that is the most densely populated, are the most efficient. Figure 1 further implies that the stores located in less population dense areas are less efficient. Regions 1 through 3 have less than 10 inhabitants per square km and the stores in these regions have all suffered the greatest decline in inventory inefficiency.

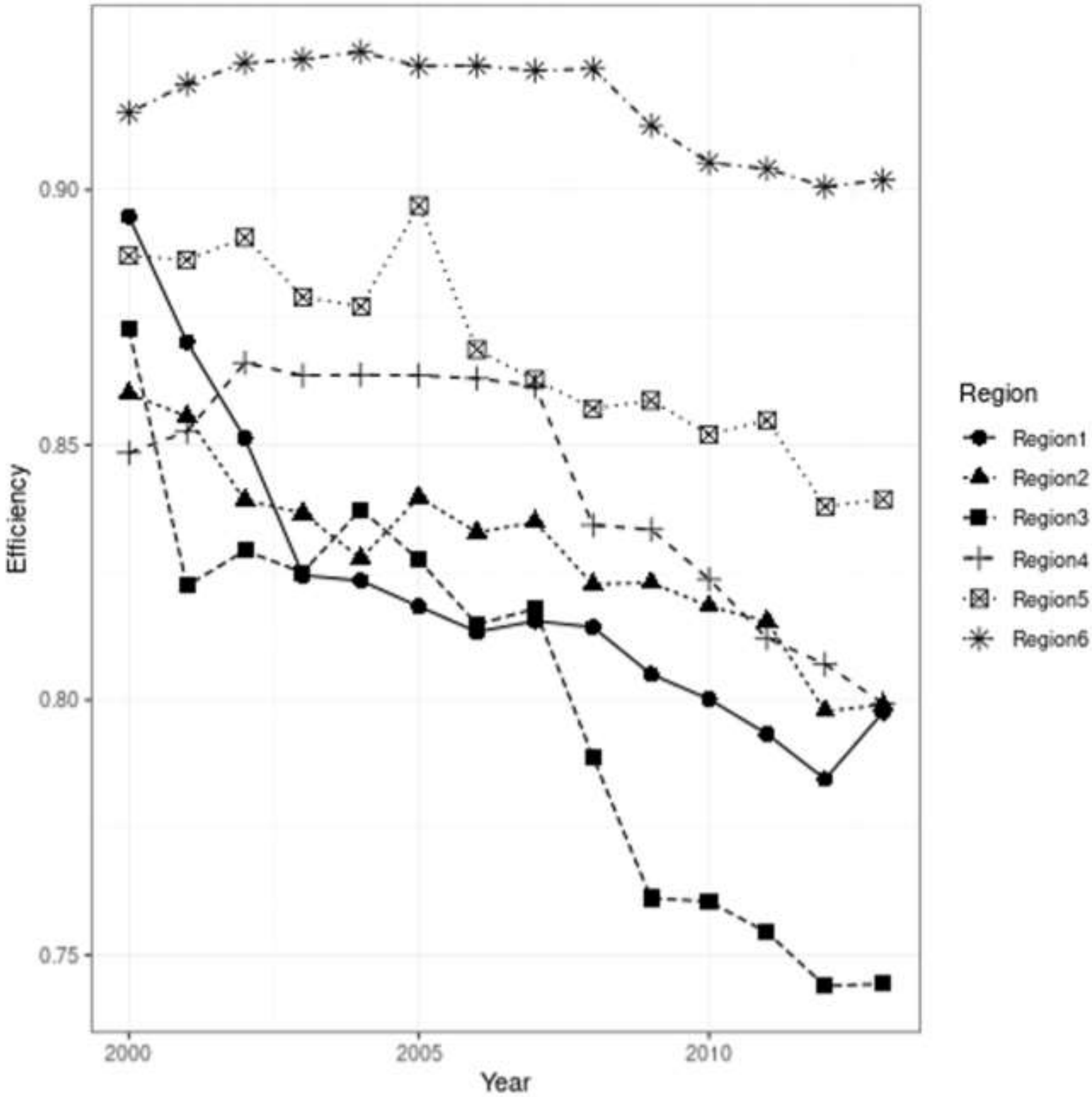


Figure 4. Inventory turnover efficiency by region.

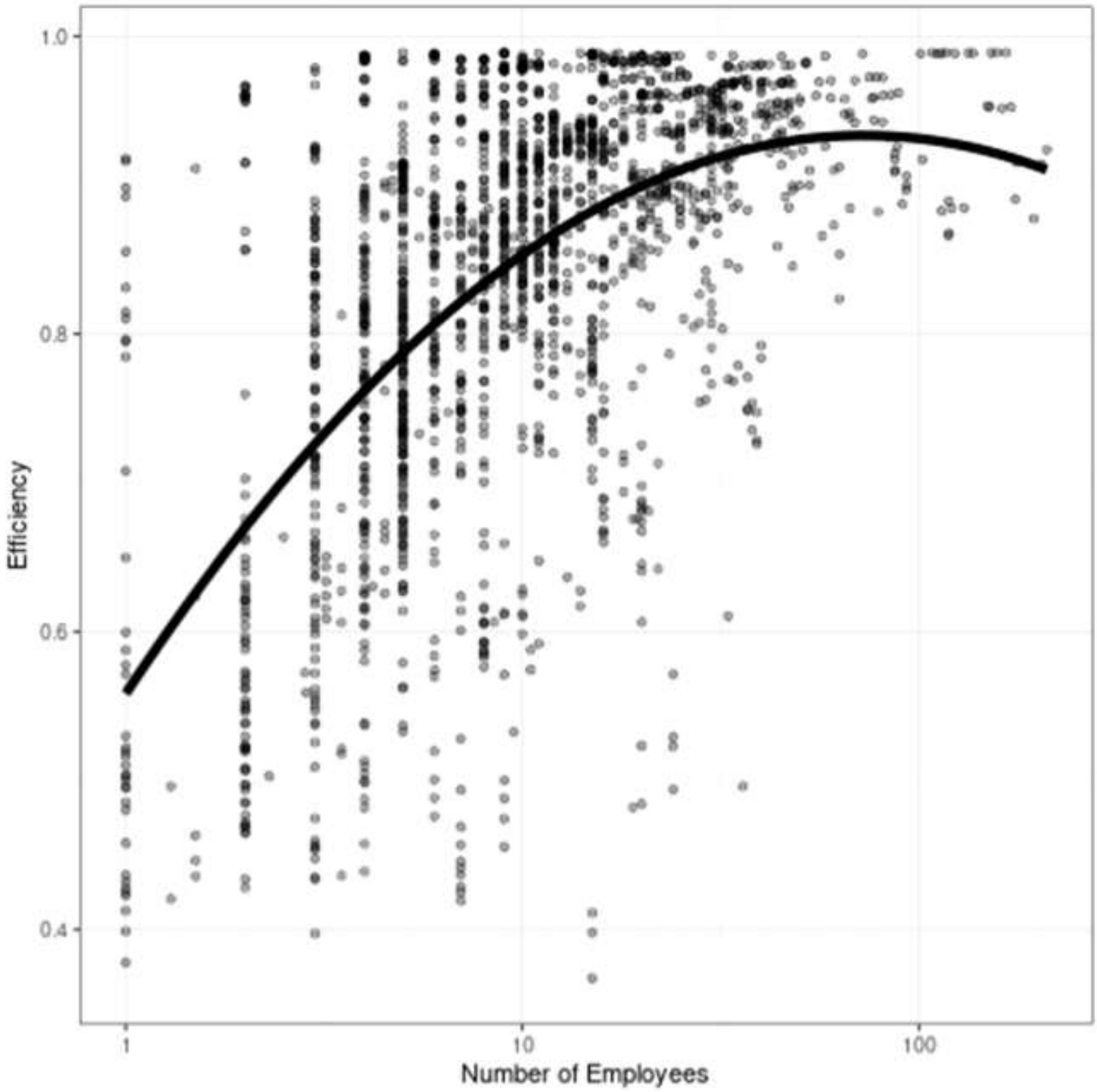


Figure 5. Inventory turnover efficiency by firm size.

The estimates reported in Table 7 further show that retail chain affiliation plays an important role in explaining firm inefficiency. First, the effects of firm size (*NoE*) on inventory turnover are significant at the $p < 0.001$ level for both XL-bygg and Byggtorget. Both estimates indicate that an increase in firm size reduces inefficiency. These findings extend and elaborate on previous findings in the literature (Gaur & Kesavan, 2009; Rumyantsev & Netessine, 2007a) and suggest that scale effects apply for efficiencies and vary among chains of retailers. Effective inventory management depends on updated transaction information (Yao & Carlson, 1999), such as the number of units sold and in stock, at the SKU level, and it requires high operating standards. In addition, inventory record inaccuracy is a substantial problem in retail operations that can be prevented by good auditing practices (DeHoratius & Raman, 2008). On average, high operating standards are more likely to be present in larger firms with staff trained and dedicated to monitor, follow-up and fine-tune inventory decisions.

Figure 5 displays the effects of firm size on efficiency, regardless of chain affiliation. The figure suggests that efficiency rises as firm size increases but at a diminishing rate. The figure further illustrates a great variance for

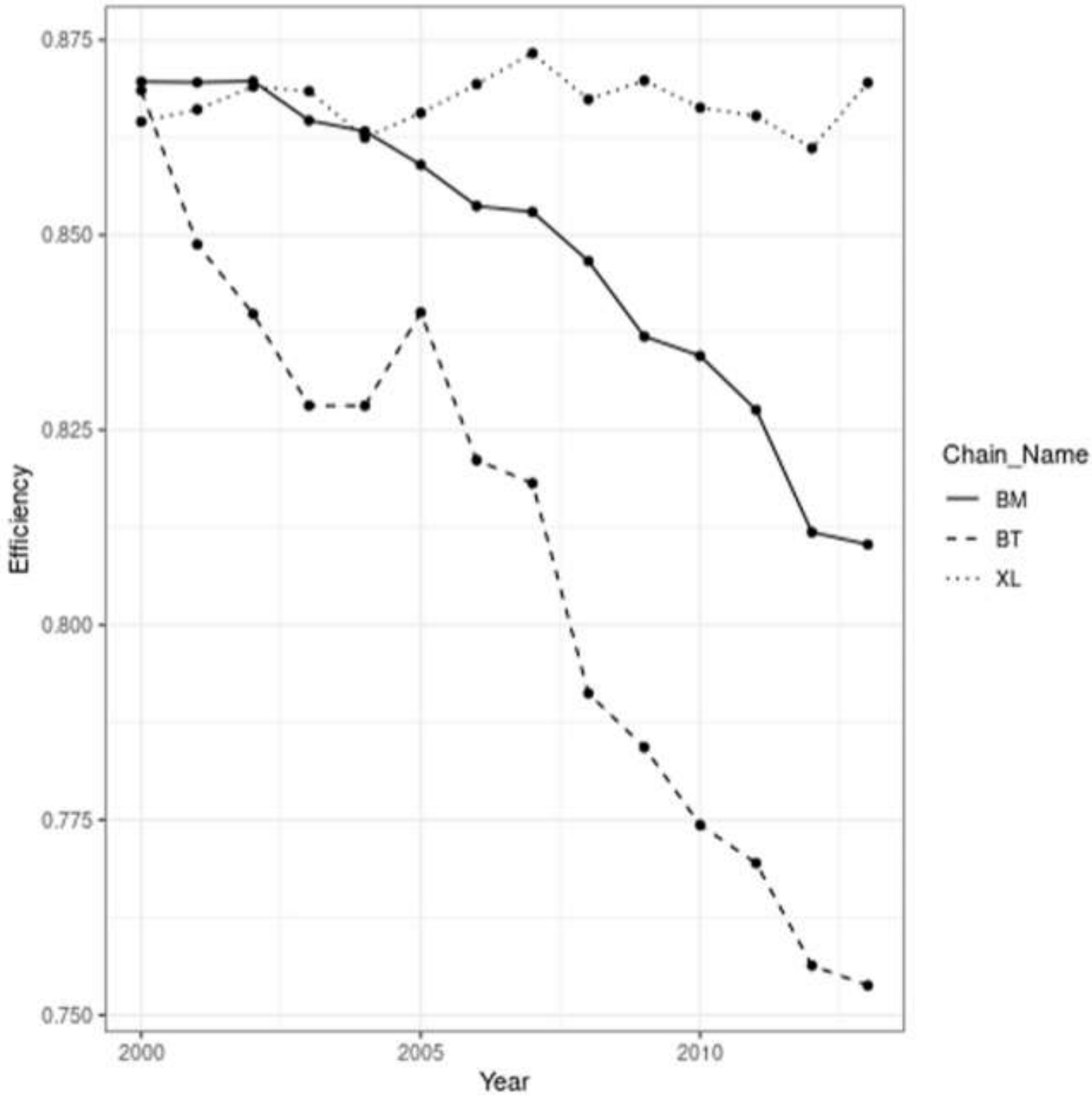


Figure 6. Inventory turnover efficiency by retail chain.

firms with fewer than approximately 20 employees and that beyond this point, all firms have efficiency scores better than and above 80% of the best performing firms. In assessing efficiency for firms that employ five workers, we find it on average to be 78.7% of the best performing firms, whereas for those employing 25 employees, it is estimated to be approximately 90.8% of the best performing firms.

Second, the coefficient estimate reported in Table 7 for time trends (*Time*) is significant ($p < 0.001$) for Byggtorget and indicates that these stores, over time, become less efficient.

Figure 6 visualises the mean retail store chain efficiencies by year. As the figure depicts, inventory turnover efficiency evolves differently over time for the retail chains examined. The efficiency frontier for Xl-bygg is principally steady over the time period, with only minor changes year by year. Stores affiliated with Byggtorget do, however, evolve in a bearish manner and indicate a significant drop in efficiency. A decline is noted for Byggmakker as well, but it is not as substantial as that for the latter stores. Extracting the mean inventory efficiency score by each retail chain on the two last years of observations reveals that Byggtorget underperforms Xl-bygg by 10.5 percentage points. A similar estimation for Byggmakker relative to Xl-bygg returns a 4.9 percentage point inferior efficiency score.

Differences in technology and strategy are likely explanations for inventory turnover efficiency varying among retail chains over time. Such factors may affect efficiency at the chain level as well as at the store level. The implementation and use of technology, such as software for resource planning, is important in running a successful retail store. To keep track of core business operations or processes, such software aims to monitor, among others, customer services, sales, accounting and, most importantly, inventory management. The latter focuses on forecasting demand, inventory replenishment and monitoring status in stock-keeping units. In recent decades, decisions on software have been made by the store owner and local management. As the increase in purchase orders and invoices started to run through the retail chain enterprise, recommendations on what software to use at the store level were generally made by chain management or even as a single supported option. There are many advantages to running the same software throughout all chain stores; this is especially true when centralised systems are used. The advantages that stem from such solutions may be faster and less costly transactions on orders and invoices, improved forecasting of demand and the possibility of adjusting prices from chain headquarters as part of common advertising and sales campaigns or the maintenance of product data on stock keeping units (SKU). Furthermore, in terms of strategic decisions, several conditions may explain chain differences over time. One such may be that as a main rule, terms and conditions for the purchase and choice of vendors are negotiated at the chain level. The added difference in purchase volume over time substantiates the notion that larger chains have advantages in regard to actual product price, fast delivery, and terms and conditions for purchasing, for instance, more store-friendly requirements regarding relinquishment, which underpin inventory performance.

Finally, the *SOA* estimates reported in Table 7 are significant at the $p < 0.01$ level for Byggmakker and at the $p < 0.05$ level for XL-bygg. However, these estimates have different signs. An increase in *SOA* for Byggmakker reduces inefficiency, whereas it has the opposite effect for XL-bygg. This is in line with the study of Shockley and Turner (2015), who report a positive relationship between firm performance and SOA, but also one that vary considerably between different retail industry segments. Moreover, as total assets, in addition to inventory, also include cash, accounts receivable, property, plant and equipment, this metric encompasses several dimensions that can signal a firm's efficient operation. For instance, the literature report a positive association is previously made between accounts receivable and firm profitability (Rumyantsev & Netessine, 2007b). Some likely explanations for the differences in the SOA estimates may be connected to decisions that stem from strategy, such as whether the plant or store is leased or owned and whether it is listed in the balance sheet of the retail store. Similarly, SOA may be influenced by other assets being owned, leased or rented, such as software, shop fittings or assets for internal materials handling, such as forklifts. Similarly, cases where the delivery of goods from the store to the customer is an in-house service, which necessitates the need for one or several trucks or vans, would increase assets and lower the SOA measure. If, however, hired transporters provide this service, it might slightly increase sales and thus increase the SOA measure. Decisions such as these may originate from more or less deliberate actions taken in regard to the moulding of strategy or due to operational convenience. On the other hand, a low measure of sales on assets, at least in the short-term, may result from investments in property and plants to support future growth ambitions.

Conclusions

In this paper, we are concerned with determining how inventory turnover is associated with key financial figures, store- and chain-specific measures, and environmental factors, with a particular emphasis on how the environment surrounding the individual firm affects efficiency.

Main findings

First, to estimate efficiency scores of inventory management, we examine two external environmental factors. However, to be able to produce unbiased efficiency estimates, it is necessary to control for regional differences. The results indicate that regional location (*REG*) plays a significant role in inventory turnover ratios and that noteworthy regional differences exist. The results show lowest inventory turnover ratios for those stores located in the most northern regions (*REG*1 and *REG*2). We explain this result by pointing towards generally increasing lead times for regions located further away from the capital of Oslo, especially since the surrounding area of Oslo often serves as a logistic hub in Norway.

The second environmental variable and the first to contribute to explain efficiency is the categorical variable that represents municipal centrality. This variable represents how close or remote the store is located (at the municipal level) to another larger urban area. The results indicate that inventory turnover efficiency differs depending on store location and generally improves when stores are located in more urban areas. However, we find the most remote municipalities to deviate from this general trend, as the results indicate that the stores belonging to this group are the most efficient.

The third environmental variable is population, which is modelled as an interaction variable with location centrality. As shown from the results, inventory turnover efficiency rises as population increases across the three statistically significant cohorts but at a diminishing rate. The results further indicate that inventory turnover efficiency varies in magnitude, depending on location and municipal centrality. An increase in market concentration and demand density supports such progress.

Economies of scale are important within most business research topics and this is no less true for inventory management. We find inventory efficiency to increase as the number of employees rises, but also that these effects differ between the retail chains examined in this paper. We conclude that scale effects apply for efficiencies and vary among chains of retailers, and that effective inventory management requires high operating standards, which are more likely to be present in larger firms.

We find the time trend in the inventory turnover efficiency to vary among the retail chains. While the mean efficiency for one of the retail chains is principally steady over the time period examined, with only minor changes year by year, stores affiliated with the least efficient retail chain show a significant drop in inventory efficiency over time. This might be a result of differences in technology and strategy.

Sales over total assets less inventory (SOA) is an indicator that expresses how efficiently the firm is able to make assets generate revenue. The results also show that the retail chains examined in this paper vary greatly on this efficiency metric. The results further suggest that SOA has contradictory effects on inventory turnover efficiency among the examined retail chains. Such differences may also be attributed to decisions that stem from strategy, such as different approaches to investing in property and equipment.

Managerial implications

While firm-specific measures play an important role in assessing relative inventory levels, environmental factors cannot be neglected as a significant influence, both in the regional setting and even from the perspective of local market conditions.

When using inventory turnover as a benchmark for performance, analysts, chain and store management should consider including environmental factors such as the population and centrality of the municipality of store location, as well as regional belonging, in the analysis. Similarly, these or equivalent variables should be part of strategic planning when making decisions about product variety and merchandise depth. In addition, such environmental factors are found to impact decisions about the design of central warehousing versus direct store delivery from suppliers and vendors and solutions for transportation to bring SKUs to the retail store. They are key to reducing the lead time and its associated variation, thereby causing uncertainty in product availability at the store level. Moreover, environmental factors should be embedded in contract terms with suppliers and vendors to guarantee a given service level and maximum lead time and variability for all chain stores. In addition, chain management is recommended to support store management and staff on inventory management and training, software programmes to improve inventory control and the monitoring of inventory levels at the SKU level, replenishment procedures and inventory record inaccuracy.

Stores located in sparsely populated areas with a small customer base are likely to have less product variety and merchandise depth. This makes them vulnerable for online competition. Such stores should have an inventory policy that is agile and that makes the store able to respond to customers' demand in terms of ordering products outside the determined assortment and returning items to the supplier when necessary.

As traditional brick and mortar retail stores face increased competition with online retailers, attention to cost and operating performance is even more important. Only managerial comprehension of this problem and effective actions may avoid further impairment of inventory turnover and thus financial performance.

Limitations and further research

As this sample of retailers represents approximately 30% of the Norwegian home improvement and building materials industry, the claim of generalisation would be inappropriate. In addition, while the geographic location of this market, with stores located in the Arctic Circle, makes it expedient to clarify the regional and environmental effects on inventory performance, such outcomes are likely to be different from those in more densely populated areas such as central Europe and the US, where the effects for environmental variables may be less conclusive. Even though the data include three complete retail chains, the geographic store locations may not be representative of the domestic market, and the results must be interpreted accordingly.

There are several areas where research on inventory performance in the future can be of importance. First, effects that stem from local market conditions such as the number of competitors, the level of competition and the market growth rate are to some extent covered by centrality and changes in population size. However, better instruments for these measures could bring about further insights regarding such effects. As this research points out, there are large differences between geographic regions, and further research is needed to unveil more specific details about what causes these differences in inventory performance, such as effects from long-term demand changes, lead times and other closely related logistical topics.

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Notes

1. According to the exchange rate NOK/EUR at 27.04.2021. NOK = Norwegian Krone.
2. According to the exchange rate NOK/EUR at 27.04.2021.

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6.3. Paper III

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The heterogeneity of shoppers' supermarket behaviors based on the use of carrying equipment☆

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ABSTRACT

Research on in-store behavior has largely focused on shoppers with carts. In a study involving 15 stores and a total of 3540 shoppers, we document that only 20 percent of shoppers actually use shopping carts, while 28 percent use baskets and 51 percent use no carrying equipment. To better understand the role of carrying equipment, we collected data in a second study from 635 complete shopping trips using behavioral tracking technology and systematic sampling. We show that there is important heterogeneity in in-store behavior related to equipment and that carrying equipment is a suitable variable for segmenting shoppers. It is an objective and observable measure that consistently explains the variance in travel distance, shopping duration, store area coverage, walking speed, basket size, and shopper efficiency. We also find non-equipment trips to be least efficient, despite their popularity. The findings have implications for both research and retail practices.

1. Introduction

Academic research on what shoppers actually do in supermarkets is valuable but the handful of studies on shopper paths and in-store behavior is mostly restricted to shoppers using shopping carts with RFID tags on them. Supermarkets and small store formats have become increasingly attractive for shoppers – such as Walmart Neighborhood Markets, Target Express, and Tesco Express (Peterson, 2015; Statista, 2018), leading in general to less need for shopping carts or other in-store carrying equipment. Retail specialists report that shoppers worldwide generally tend to travel more frequently to grocery stores and also that they prefer to shop at small grocery stores to a greater extent than before (Nielsen, 2015; Scamell-Katz, 2004; Steiner, 2018).

To test this trend further, and to get more concrete figures, we systematically observed 3540 shopping trips to 15 different stores in five municipalities. Non-equipment trips represented the largest category of shopping trips overall and was shown to be widespread across all retailers and retail formats as 66.67 percent of the convenience store shopping trips involved no carrying equipment, 55.23 percent for discount stores, 46.25 percent for supermarkets, and 35.83 percent for hypermarkets. This points toward a problem as academic research on shopper paths and grocery buying behavior is mostly based on data from shoppers using shopping carts, meaning that short shopping trips are likely to be under-represented and non-cart behaviors ignored. Since shoppers entering the store without any carrying device have been disregarded in earlier research, we know nothing about the behaviors associated with trips where the shopper chooses not to use any equipment. There is also limited knowledge on how trips involving a shopping cart deviate from those involving a basket.

Our approach is to look at the shopping trip as the unit of analysis, as the contribution includes a more holistic approach from around the beginning (choosing carrying equipment) to the end of a typical in-store experience (number of items purchased at checkout). Empirical research on key metrics of continuous streams of in-store behavior, such as store area coverage, shopping duration, and basket size, has laid the foundation for an empirically grounded shopper behavior theory (Sorensen et al., 2017), and has provided benchmarks for retailers as well as other stakeholders to apprehend in-store marketing performance. In the current paper, we introduce three new behavioral metrics: travel distance, walking speed and shopper efficiency, in the research literature. We argue that these three metrics contribute unique and important insight needed to document how shoppers on non-equipment trips behave compared to those using either a basket or a cart. While travel distance accounts for the shopper's effort along the entire shopping trip, average walking speed over the course of the shopping trip provides useful insight for determining shoppers'

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attentiveness to in-store stimuli. Shopper efficiency, which in this paper is measured as purchases per meter travelled, complements the other fundamental behavioral metrics through its ability to acquire insight into how well the retailer serves various customer segments in terms of offering them an efficient trip. We show how such insight challenges widely used retail practices. In particular, we challenge the general assumption in the shopper marketing literature that an increase in shopper time or travel distance results in more opportunities to sell. As we argue, this depends on the shopper's walking speed. The higher the walking speed, the less attentive the shopper would be to in-store stimuli, thus leaving the retailer fewer opportunities to sell (unseen is unsold). Our data suggest that compared to other shoppers, those on non-equipment trips are less likely to be attentive to stimuli on their way to their in-store destinations.

Our data further show that the type of carrying equipment involved in shopping trips should not be ignored, neither in practice nor in research. There is important heterogeneity related to carrying equipment as the key shopper metrics (shopping duration, travel distance, store area coverage, walking speed, basket size, and shopper efficiency) differ across shoppers selecting different carrying equipment (no equipment, basket, cart). Carrying equipment is a suitable variable for segmenting shoppers. Type of equipment involved in a shopping trip is an objective and observable measure explaining a larger proportion of the variance in the behavioral metrics than, for instance, age and gender. In fact, it is the only variable in our empirical analysis that consistently explains the variance in key behavioral metrics. It is predictive in terms of occurring before the in-store behavior. It is therefore surprising that the choice of carrying equipment so far has not been used for behavioral segmentation (see Larsen & Sigurdsson, 2019).

We find non-equipment trips to be the least efficient, despite their popularity. This is an important input in the current discussion on retail disruption because shoppers deciding not to use any shopping equipment might be most vulnerable to new disrupting retail formats, such as grab-and-go stores and digital solutions, as their time and effort are not well spent. We provide evidence that knowing the proportions of shoppers selecting different types of carrying equipment (no equipment, basket, cart) can provide retailers with an important prediction of fundamental shopping patterns, transactional value, and vulnerability. The paper is organized as follows. In the next section, we give an overview of the relevant literature, followed by a description of our approach to data collection, measurements, and sampling. We then present the results of our study. The last section is concerned with discussion, conclusions, suggestions for further research, and managerial implications.

2. Carrying equipment and fundamental in-store behavioral patterns

Procedures for tracking in-store shopper behavior appeared in the marketing literature during the 1960s. An often cited example is Granbois (1968), who suggested a behavioral metric consisting of number of items purchased and the number of spots that the shopper passes in the retail store. At first, tracking was conducted mostly by means of researcher observation/shadowing, but since then, behavior tracking tools have changed immensely, with RFID tags attached to shopping carts in combination with antennas (receptors) being the most popular approach for tracking in-store behavior. However, other techniques have been used, such as RFID belts (e.g., Hui, Inman, Huang, & Suher, 2013), Bluetooth tracking from shoppers' mobile phones (e.g., Phua, Page, & Bogomolova, 2015), and as in this paper, video observation in combination with a tracking software, building on discrete in-store observations of shoppers.

Larson, Bradlow, and Fader (2005) were among the first to examine paths using the then new and exciting RFID technology on shopping carts. The procedures and findings were important for the establishment of an empirical science of shopping patterns as it could dispel a number of old assumptions and folklore. Their data showed the importance of the perimeter and that shoppers rarely weaved up and down all aisles. Shoppers tended to make short excursions into aisles rather than traversing the entire length, pointing to the importance of "colder" (such as middle aisles) and "warmer" areas (e.g., end-cap displays). This underpinned the need for more academic research into in-store marketing. Previously, in-store travel behavior had only been publicized from a basic foundation with applied methods in Underhill (1999) book "Why We Buy". Larson et al. (2005), on the other hand, scrutinized complete paths and found, based on multivariate clustering algorithm, that length of visit was important, leading to three clusters for short, medium, and long trips. The limitations found in their study were, however, that it included only studying shoppers using carts and not being able to predict shopper clusters with an objective variable. In this paper, we introduce an analysis of all types of shopping trips based on the objective choice of carrying equipment (including the choice of not using any equipment).

Our study contributes to the literature on the fundamental patterns of in-store shopper behavior (e.g., Hui, Bradlow, and Fader, 2009b; Hui, Fader, & Bradlow, 2009a; Hui et al., 2013; Sorensen et al., 2017) by examining and confirming fundamental heterogeneity of in-store behavior throughout the in-store shopping journey. To the best of our knowledge, studies reporting in-store behavioral data by using RFID, a tracking software or in-person observation either examine the shopping trip involving a regular shopping cart (e.g., Hui et al., 2009a, 2009b; Larson et al., 2005; Wagner, Ebster, Eske, & Weitzl, 2014) or do not report on the type of carrying equipment used (e.g., Hui et al., 2013; Sorensen et al., 2017). No studies examine the behavior of non-equipment users in particular and, therefore, we believe the empirical results from this study yield relevant insight for retailers as well as other stakeholders. We agree with Sorensen et al. (2017) that to advance the science of shopping (Underhill, 1999, 2009), it is important to use several key metrics each providing its own piece to the overall puzzle. We chose to go beyond store area coverage, shopping duration, and basket size (as introduced in paper by Sorensen et al.) to include walking speed, in-store travel distance, and shopper efficiency. We consider these to be suitable metrics for an empirical science of shopping and complementing those introduced by Sorensen et al. (2017).

In the following, we review relevant literature on in-store carrying equipment and the key behavioral metrics involved in the current study. Since there is little knowledge on carrying equipment and in-store shopper behaviors in general, we cannot derive explicit hypotheses from prior theory about the direction of effects for the different metrics.

2.1. In-store carrying equipment

The data presented in this paper show that different types of carrying equipment represent significantly different behaviors. We define in-store carrying equipment as any device offered by the retailer helping the shopper to convey items while shopping. Most store managers believe in the power of shopping baskets and carts to increase sales. The literature also recognizes this power (e.g., Cochoy, 2008; Grandclément, 2009). The most obvious result of shoppers' choice of carrying equipment is a physical constraint on the volume they can buy (Cochoy, 2008) and their freedom of movement in the store (Bogomolova, Vorobyev, Page, & Bogomolov, 2016; Larsen, Sigurdsson, & Breivik, 2017; Van den Bergh, Heuvinck, Schellekens, & Vermeir, 2016). Shoppers with no carrying equipment can move freely but can only buy what they can carry themselves. In line with this, the data from the current paper show that the choice shoppers make at the store entrance is associated with different average walking speed as well as number of purchases.

To the best of our knowledge, only three studies report behavioral data for more than one type of carrying equipment (Gil, Tobari, Lemlij, Rose, & Penn, 2009; Seiler & Pinna, 2017; Van den Bergh, Schmitt, &

Warlop, 2011). Gil et al. (2009) provide profiling data on patterns of shopper movement and behavior in a supermarket. They found many shoppers making short and medium trips and moving at a medium or fast pace. A short trip movement pattern was displayed by shoppers who tended to use baskets and not deep shopping carts; none of them were on a main shopping mission, and they spent limited time shopping. Prolonged shopping trips were mostly performed using a shopping cart. Using data collected from RFID tracking involving both shopping carts and baskets, Seiler and Pinna (2017) examined shoppers' search behavior in a physical retail store. Their findings show that carrying a basket rather than pushing a shopping cart significantly decreased search time. Van den Bergh et al. (2011) tracked shoppers in a hypermarket, from entry to exit, to examine behavioral differences between shoppers pushing a shopping cart versus those carrying a basket. They found that type of carrying equipment predicts whether a shopper will purchase vice products at checkout or not. They also found store visit duration to be significantly lower for basket users compared to cart users. Despite the limited number of studies, their results indicate that in-store behavior differs contingent on the type of carrying equipment shoppers use to assist them while shopping. We recognize that this stream of literature seems to neglect the behavior of non-equipment users.

2.2. Store area coverage

Store area coverage refers to the share of the total store area that shoppers traverse in their overall trip. The area that shoppers cover while shopping in a store plays an integral part in how in-store marketing stimuli will be received. Understanding how shoppers shop in a store and how they move around has been a focus for many researchers (Granbois, 1968; Scamell-Katz, 2012; Sorensen, 2016; Sorensen et al., 2017). Traditionally, it was believed that shoppers followed a methodical route up and down the store aisles covering the entire store (Hui et al., 2013; Larson et al., 2005). This is far from reality. Scamell-Katz (2012) found that while 25 percent of shoppers claimed they had been through the entire store during their shopping trip, less than two percent of that group covered more than half of the store. Sorensen et al. (2017) found shopping trips in large stores to cover a smaller proportion of the store (14% for hypermarkets) while trips in small stores covered a larger proportion of the store (i.e., 21% for small format stores and 30% for supermarkets). The challenges of understanding where shoppers go in a store has decreased with technologies such as RFID tags (Larson et al., 2005; Sorensen, 2016), but still there are challenges. Limitations to fixing RFID tags on carts and baskets are that it leaves out shoppers who choose not to use any carrying equipment, which could be an essential proportion of the shoppers visiting the store. Another limitation is that when shoppers leave their cart or basket to search for something, their behavior is unobservable (Sorensen et al., 2017). The shopper must hold on to the equipment at all times for us to have the data needed. While technological advancements have assisted researchers in understanding how people shop, the methodology still does not account for different shoppers and shopping styles, possibly leading to different results. As can be seen, for instance in Sorensen et al. (2017), the same store type, size, and country can still show a large difference in store coverage.

Sorensen (2016) describes three types of trips: quick, fill-in, and stock up. In his book, he describes a study where 75,000 shoppers from three stores were identified and categorized into these trip types. The study found that, on average, shoppers on quick trips visited 11.2 percent of the store, whereas fill-in shoppers and stock-up shoppers visited 21.1 percent and 41 percent of the store, respectively. Based on proprietary studies, Underhill (1999) found that the type of trip shoppers take determines their choice of carrying equipment. When shoppers enter a store, their choice of carrying equipment, or lack thereof, could be a descriptor of their trip type, but this is an academically underdeveloped area.

2.3. Shopping duration

Shopping duration refers to the total time spent in the store to complete an individual shopping trip. Shopping duration can be used to evaluate the level of shopper involvement (Sorensen, 2016), but best practice is to combine various metrics as shopping duration can also be related to inefficiency and shopper frustration. The time spent in the store is, for instance, related to store area coverage (and shopping trip type) as shown by Sorensen (2016); the more of the store visited, the higher the average shopping duration. Fill-in trips typically satisfy more urgent needs than stock-up trips and would thus generally involve less effort and time commitment (Kollat and Willet, 1967). Hui, Fader, and Bradlow (2009b) further note that grocery shoppers being goal directed (e.g. shopping with a list) probably exhibit different search behaviors than those without a clear set of purchase goals. Time pressure may also play a role in trip duration (Larsen & Sigurdsson, 2019), forcing the shopper to shop more productively, buying more items in less time (Bogomolova et al., 2016). Therefore, shopping trips involving the same proportion of the total store area can be quite different in terms of shopping duration. Combining store area coverage and shopping duration can as such give more detailed insights into shopping behavior – classifying shoppers as either "walkers" or more active shoppers based on the time they spend in various store areas (see a discussion of active shopping in Sorensen, 2016).

Like store area coverage, the introduction of technology such as RFID has made studying this metric all the easier. As mentioned earlier, applying such technology enabled Larson et al. (2005) to link trip duration to paths traveled in the store, finding that shoppers on shorter trips travel along the perimeter of the store and in the quick-convenience areas. Store layout, specifically the dominant path, can affect trip duration. Stores like Costco with their large dominant paths are capable of retaining shoppers in the stores for a long period of time as compared to stores that have many pathway options (Sorensen, 2016).

2.4. Travel distance

Travel distance can be defined as the length of the shopper's actual path in the store measured in terms of feet or meters. This is a metric that Hui et al. (2013) recently have used to study the effects of in-store path length on unplanned spending. Hui et al. (2009a) also use data on in-store travel to measure shoppers' travel deviations from the most optimal path (based on items the shopper actually purchase). Beyond this, few studies measure in-store travel distance, the main reason being, according to Hui et al. (2013), the difficulty of measuring path length. Researchers have concentrated on behavior that is easier to measure and correlate with path length. For instance, Granbois (1968) used number of aisles passed, while Sorensen et al. (2017) focus on store coverage as a proxy for path length. Although travel distance shares some similarity with area coverage, it does not replace it as a metric. Rather it complements it. While area coverage gives a perspective on how large a share of the total store area that a shopper visits, travel length demonstrates the extent of walking during the shopping trip. Disclosing only area coverage is not enough to account for a shopper's entire movements during the trip. Shoppers may visit the same area several times, or walk up and down some aisles in search of an item. Thus, travel distance reveals patterns that might be hidden in the rougher measure of area coverage. Although both metrics have been used to measure product exposure during a specific shopping trip, Hui et al. (2013) suggest that travel distance is a better measure of product exposure.

2.5. Walking speed

Walking speed is the distance covered during a certain period divided by the time taken to cover that particular distance. The three behavioral metrics discussed so far (store area coverage, shopping duration, and travel distance) are all proxies for the extent to which shoppers are exposed to in-store stimuli along their shopping trip (e.g., product displays and in-store communication). However, visiting a store area is not the same as being influenced by stimuli in that area. A visit is an important prerequisite for influence; but for stimuli to trigger unrecognized needs and desires, or to trigger recollection of forgotten needs, requires the shopper's attention (Inman, Winer, & Ferraro, 2009). It is well known that shoppers spend a large proportion of their shopping time on intra-store travelling, visiting various store sections, where the perimeter serves as the main thoroughfare (Larson et al., 2005). We know only little about how much of this is "transit travel" where the shopper is just crossing to other store areas, walking faster (Larson et al., 2005), and is less likely to spend time shopping (Hui, Bradlow, & Fader, 2009c). Further, shoppers that perceive time pressure show less search activity in the store (Beatty & Smith, 1987); search time (in front of shelves) has also been found to be negatively correlated with average walking speed over the course of the shopping trip (Seiler & Pinna, 2017). Time pressured shoppers focus on getting to the store areas that carry categories that they plan to buy (Hui et al., 2009c), walking faster than normally (Helbing, Molnár, Farkas, & Bolay, 2001). As Seiler and Pinna (2017) argue, speed closely reflects a shopper in a hurry. Researchers and retailers have taken for granted that store area coverage and travel distance pay off in terms of unplanned purchases (Sorensen, 2016). This might prove to be correct for some types of shoppers using carts (the typical subject in shopper research), who might be on a stock-up mission (see Hui et al., 2009c; Kollat & Willett, 1967). The literature shows that walking speed is related to the choice of carrying equipment (Seiler & Pinna, 2017; Gil et al., 2009). Shoppers can "visit" many areas without actually perceiving much. Higher pace reduces the number of products that can be fixated in a given aisle, which affects the likelihood of making unplanned purchases. Average walking pace must be taken into account along with the other key metrics to better understand shoppers' search activity and attentiveness to stimuli along the entire in-store path. The metrics therefore make more sense when combined rather than considered in isolation.

2.6. Basket size

Basket size is the total number of items that the shopper purchases on a given shopping trip. Basket size is a key indicator for success when it comes to retail marketing performance. Shoppers' goals affect in-store behavior (Bell, Corsten, & Knox, 2011; Kollat and Willet, 1967) and trip type and basket size tend to go hand in hand. Therefore, the increasing practice of quick trips has entailed decreased basket sizes. Most shopping trips end in fewer items purchased than ever before (Sorensen et al., 2017). This trend has made more shoppers refrain from using any kind of carrying equipment enabling quick entry and exit (Larsen et al., 2017). Cultural differences also come into play when it comes to basket size. Some countries have a daily-shopping, quick-trip culture, while others may be more inclined towards stock-up trips – each with very different basket sizes and therefore carrying equipment needs (Scamell-Katz, 2012). There is a need for a clear and objective classification of shoppers – possibly based on the objective measure of choice of carrying equipment.

2.7. Shopper efficiency

The term efficiency is generally associated with the ability to accomplish something with the least waste of time and effort (Atkins & Kim, 2012). Time and effort are non-monetary sacrifices consumers must make in the exchange with the retailer and that affect shoppers' perceived value (Inman & Nikolova, 2017). From this perspective, shopper efficiency refers to consumers' actual performance compared with what they can achieve with the same consumption of non-monetary resources. Shoppers would as such be more efficient if they solved a given shopping task using less input in terms of shopper seconds (Sorensen, 2009, 2016; Bogomolova et al., 2016) or in-store travel (Larsen, Sigurdsson, Breivik, Fagerstrøm, & Foxall, 2019). The importance of efficiency has increased in shopping situations (Davis & Hodges, 2012), resulting in consumers demanding more convenience and effort-saving solutions from retailers (Nielsen, , 2014). From a retailer perspective, research indicates that shopper efficiency has a positive association with total store sales (Sorensen, 2009).

Prior literature examines efficiency either from a per dollar/item perspective (Bogomolova et al., 2016; Sorensen, 2009; Davis and Bell, 1991) or from a path perspective (Hui et al., 2009a). To date the per-dollar/item perspective draws exclusively on shopping duration as the non-monetary sacrifice. Sorensen (2009) uses observations of more than 100,000 shopping trips in the United States to examine the relationship between seconds per dollar (how fast shoppers spend) and store sales. Davies and Bell (1991) examine average expenditure per minute and the average number of items purchased per minute over the entire shopping trip. Bogomolova et al. (2016) propose an approach in measuring shopper efficiency that includes a "per-item shopping time" measure focused specifically on the purchasing tasks in the store (the time spent purchasing one item, including approaching the shelf, considering available options and making the purchasing decision). On the other hand, the path perspective involves a greater focus on "excessive walking", such as deviances from the most optimal in-store path, leading to more walking (more effort) than necessary to acquire the items wanted. For instance, Hui et al. (2009a) compare consumers' actual in-store path with the most efficient path based on items of the purchase.

Better access to in-store behavioral data, such as travel distance, has opened up new opportunities in measuring shopper efficiency. Since travel distance reflects the number of feet/meters the shopper travels in the store to acquire items, it accounts for the shopper's effort along the entire shopping trip compared to shopping duration in a better way. Travel distance is also less sensitive to in-store behaviors not related to acquiring items, such as when shoppers stop to spend time chatting with other shoppers or on the phone (see Larsen et al. [2017] for a categorization of basic behaviors occurring in a retail store). Finally, certain types of carrying equipment, shopping carts in particular, decelerate shoppers delaying those who want to shop as fast as possible (Larsen et al., 2017; Larsen & Sigurdsson, 2019). Type of carrying equipment involved in a shopping trip may therefore influence time-based efficiency measures directly, while having no direct effect on measures based on travel distance. Travel distance is therefore a more valid replacement for shopping duration in the efficiency equation. Although the present knowledge on how travel distance-based shopper efficiency should be measured is limited, it is logical to connect in-store travel distance with basket size (e.g. purchases per feet/meter travelled or distance travelled per item purchased). This would indicate how efficient each feet/meter travelled is for the shopper.

3. Method

3.1. Study 1

In order to determine the prevalence of non-equipment trips in grocery retailing, the objective of Study 1 was to examine, across different grocery stores, store formats, and grocery segments, the proportion of shoppers selecting either a shopping cart or a basket when entering the store. This study was conducted in three cities and two communities in Norway and included 15 grocery stores belonging to different retailers, retail formats and retail chains. 240 observations were made at the entrance of each store, and the observations were distributed equally between three time slots (08:00–10:00; 10:30–12:30; 15:00–17:00) and equally between Monday, Wednesday, Friday and Saturday.

The total sample consisted of 3540 observations. Using a systematic sampling process, we chose a random starting point and then picked every fifth shopper entering the store for our sample (Malhotra & Birks, 2007:416). For each grocery store, we checked the availability of different types of carrying equipment (carts and baskets) and whether or not the store had cart locks. We used a structured observation guide.

3.2. Study 2

Research objective. The objective of Study 2 was to examine entire shopping trips in a typical grocery store to determine how non-equipment trips differ from trips involving either a basket or a shopping cart on key behavioral metrics.

Data and data collection method. We collected data from one major retail chain soft discount store during the period of March to October 2016. The store was located in a suburban area of a Norwegian city. The store had a sales area of approximately 1200 m^2, it carried an assortment of 5500 stock-kept units (SKU) and its layout resembled that of most other supermarkets of this size. We used a system of Wi-Fi cameras and tracking software to collect in-store behavioral data from individual shopping trips. The cameras covered the entire sales area and were used to observe shoppers' movements in the store and where and when shoppers picked an item from a shelf or a display. Shoppers' arm and hand motions reveal much information about their interaction with items and the purchase of items (Liu, Gu, & Kamijo, 2017). In our study, an item purchase is an item observed, picked by the shopper from a display or a shelf and not returned to the display/shelf. We applied the same tracking software and procedures as Larsen et al. (2017). The interface of the tracking software represented the store layout but was down-scaled to fit a computer screen. The pattern of movement and item pick-ups were fed into the tracking software in real time. We refer to Larsen et al. (2017) for details on the functionality and interface of this software, which type of data it registers automatically, and the procedures for feeding real-time observational data into the software. The advantage of camera-based observations in combination with tracking software is that shoppers' natural shopping experience is uninterrupted since there are no interventions during the shopping trip.

Targeted shoppers' entire shopping trips were observed, one-by-one, from their point of entry and all the way to the checkout. Entry time was marked by the shopper picking up an in-store carrying equipment (or choosing not to use one) and crossing a predefined spot at the beginning of the shopping trip. We used two predefined entry points, one at the main entrance that most shoppers cross to approach the first zone displaying items, and a second at the checkout for those shoppers taking a shortcut through the space between the cash registers. Our exit time measure was the exact moment when a shopper would place the first item on the checkout belt (if there is no queue), or the moment when the shopper joined the queue. This excludes time spent queuing (which depends on whether there is a queue or not), and time at the checkout involving barcode scanning, which is dependent on basket size (see Bogomolova et al., 2016). While a system consisting of RFID tags (on baskets and/or shopping carts) and antennas is unable to perfectly identify the start and end of every shopping trip (Hui et al., 2009c) and captures data only from equipment users, our approach overcomes these shortcomings.

We fed demographic data (gender and age) and the shopper's choice of carrying equipment into the tracking software immediately after the completion of the shopping trip. Two researchers were involved in tracking each of the shopping trips. As shopper interventions were precluded, we estimated age and gender based on visual inspection of the real-time images provided by the Wi-Fi cameras; we particularly scrutinized the shoppers' face, hair and body shape.

Dependent variables. The entire store was divided into 85 store areas based on product categories. We operationalized travel duration as the time it takes to complete the shopping trip, from the point of entry to the exit point (measured in minutes). Travel distance was operationalized as the number of meters travelled from the point of entry to the exit point. Store area coverage was operationalized as the number of store areas visited divided by total number of store areas. Walking speed (meter per second) was operationalized as travel distance divided by shopping duration (converted into seconds), and basket size was operationalized as number of purchased items from the point of entry to the exit point. Finally, shopper efficiency was operationalized as basket size divided by travel distance.

Independent/control variables. Age, carrying equipment, type of shopper, shopping period and shopping time are dummy variables. We categorized age into seven age groups, and carrying equipment into three types (no equipment, a basket or a shopping cart). The basket type include shoppers using either a small hand-held basket or a larger basket with wheels. Four types of shoppers are predefined in the tracking software: male, female, family or group. Thus, gender only applies to individual shoppers in the dataset. Shopping period refers to weekday or weekend, where weekend reflects the period from Friday at 12:00 and throughout Saturday (store is closed on Sunday). Finally, we split shopping time into peak and off peak shopping time, where peak shopping time represents the period from 12:00 until 18:00, whereas the remaining opening hours represents off-peak shopping time.

Sampling approach. We split the opening hours as well as weekdays and weekends into strata, and we used the store's entire traffic pattern for February of 2016 (derived from a traffic counter we placed at the entrance) to determine the total number of shopping trips to target in each strata (proportionate stratified sampling). We designed a plan for the data collection, including which strata to target when. The selection of shoppers for tracking (within a selected strata) was based on the rule of choosing every fifth shopper entering the store. We tracked a total of 635 shopping trips, 522 of which were individual shoppers (272 male and 250 female). We used a sign at the entrance of the store to inform shoppers about observational activities involving the use of Wi-Fi cameras, and we notified the appropriate authorities prior to the study.

4. Data analysis

This section reports on the results from the two studies separately. We start by presenting shoppers' carrying equipment choice frequencies based on data from Study 1. Then, we present the results of Study 2. By means of several sets of linear regressions, we offer further insight into fundamental behaviors connected to type of carrying equipment.

4.1. Results – Study 1

Study 1 was conducted to detect how widespread non-equipment trips are in grocery retailing. The results from in-person observations at 15 stores of different retail formats are shown in Table 1. We have also added comparable statistics from our Study 2 to this table. Note that

Table 1
Shoppers' choice of carrying equipment across retailers and store formats.

		Carrying equipment		
Retail format	No equipment	Basket	Cart	Total
Convenience store	320	90	70	480
	66.67%	18.75%	14.58%	100%
Discount store	1296	790	494	2580
	50.23%	30.62%	19.15%	100%
Supermarket	111	84	45	240
	46.25%	35.00%	18.75%	100%
Hypermarket	86	41	113	240
Total	35.83% 1813	17.08%	47.08% 722	100%
	51.21%	1005	20.40%	3540
		28.39%		100%
Study 2 (A discount store)	270	252	113	635
	42.52%	39.69%	17.80%	100%

two of the stores in Study 1, one discount store and the hypermarket, had cart locks. These two stores represent 13.5 percent of all observations in Study 1.

As shown in Table 1, shoppers' most frequent choice in three out of four retail formats is no equipment. Although the most frequent choice in hypermarkets is a shopping cart, the data demonstrate that non-equipment and basket use also is rather common.

4.2. Results study 2

4.2.1. Carrying equipment and in-store behavior

Frequency statistics reported in Appendix 1 show sample characteristics by choice of carrying equipment. Of the 635 shopping trips studied, 42.5 percent involve no carrying equipment, while 39.7 percent and 17.8 percent of the trips involve a basket or a shopping cart, respectively. For the 522 shopping trips carried out by individual shoppers only, 43.9 percent of the trips involve no equipment, while 40.8 percent involve a basket and 15.3 percent involve a shopping cart.

Table 2 reports average statistics on the six key behavioral metrics (See Appendix 2 for a correlation matrix). The data in Table 2 indicate that the key behaviors vary widely by choice of carrying equipment. As an example, average walking speed doubles for non-equipment users relative to those using a cart. Further, the data indicate that shopping duration is more than four times longer for cart users relative to non-equipment users. Moreover, store area coverage for cart users is about double that of non-equipment users.

To examine the heterogeneity of key in-store behaviors, we performed linear regressions using OLS. The independent variables were gender, age, type of carrying equipment (including no equipment), basket size (but not included where it is modeled as the dependent variable), shopping period (weekday or weekend) and shopping time (peak/off peak). Model development and decision on the model employed were based on best overall fit assessed by Akaike information criterion (AIC) and Schwartz Criterion (BIC) on the behavioral metrics. Due to heterogeneity in the estimated models, we report robust standard errors based on the Huber/White estimate of variance. In this analysis, families and groups are disregarded as classifying them through observation is inflicted with potential for bias; therefore only cases involving individual shoppers are included. In addition, one observation is removed based on measures of leverage assessed by DFBETA and Cook's D. Thus, the final sample consists of 82 percent of the total sample, or 521 complete shopping trips. Table 3 reports unstandardized regression estimates for the five dependent variables representing the key behavioral metrics. We have tested for multi-collinearity by calculating the variance inflation factor (VIF) and find the levels to be below the frequently used threshold of 5.

To ease interpretation of the estimated coefficients, the constant term of the linear regressions reported in Table 3 has been suppressed into the coefficients representing no equipment. Thus, the coefficients for no carrying equipment represent values with reference to the baseline for the control variables: age, gender, shopping period, shopping time, and zero purchases (regression 1 through 4 in Table 3).

The OLS results indicate that cart users, basket users and non-equipment users exhibit different in-store behaviors. Our estimates demonstrate that shopping duration, walking speed, travel distance, store area coverage, and basket size (number of items purchased), all return significant coefficients for all categories of carrying equipment. In addition, tests of joint equality in carrying equipment coefficients indicate these to be different from each other for all specified models (at $p < 0.01$, while $p < 0.05$ for shopping duration). The importance of carrying equipment in explaining the variance in the in-store behaviors is further substantiated by tests implying that removing carrying equipment would reduce R-square and increase AIC/BIC. This implies that carrying equipment enhances model fit beyond what may be inferred from demographics, shopping period and shopping time alone.

Further inspection of Table 3 implies differential effects of age and gender on the behavioral metrics. For instance, age and gender are not significantly related to travel distance, and only gender ($p < 0.001$) and the oldest age category ($p < 0.01$) are associated with shopping duration. Walking speed refers to number of meters covered per second, representing the shopper's average walking speed throughout the shopping trip. Our estimates demonstrate that walking speed decreases when choosing a basket; a further decrease happens when using a shopping cart, both relative to no equipment. Further, the estimates imply that increased age is associated with lower walking speed and that the walking speed of females is slower than that of men.

Our estimates further suggest that weekend shopping is linked to area coverage ($p < 0.05$), indicating that in this period shoppers visit a smaller percentage of the total number of store areas. Moreover, weekend shopping trips seem to include more items as basket size increases by 0.97 units on average. Further, peak-hour shopping impacts area coverage ($p < 0.01$) by an average of 1.26 percent increase in store areas visited.

The estimated models vary in explaining the variance in the observed data, ranging from 73.8 percent to 94.0 percent. Choice of carrying equipment together with basket size are the only explanatory variables among those tested that consistently contribute to explaining the variance of the five behavioral metrics. This research does not study causality but shows instead that carrying equipment, age, gender, weekend shopping, and peak hour control for and can be used to capture the heterogeneity in the key behavioral metrics, suitable for behavioral segmentation and new managerial insights.

We also conducted OLS estimations with robust errors to extract coefficient estimates on in-store shopper efficiency. We measured in-store shopper efficiency as basket size divided by travel distance, which expresses how efficient the shopper is in terms of purchases per meter travelled. Table 4 reports the regression estimates. Similar to Table 3, the constant term in Table 4 has been suppressed into the coefficient representing no equipment.

The unstandardized regression estimates reported in Table 4 indicate that shopping trips involving a cart, a basket or no equipment, on average, exhibit a significant association ($p < 0.001$) with in-store shopper efficiency. The coefficient estimates imply that non-equipment trips are the least efficient, while shopping trips involving a cart are most efficient. Table 4 further indicates that efficiency decreases with the increase of shoppers' age, while neither weekend, peak shopping hours, nor gender are related to better or poorer shopper efficiency.

5. Discussion, conclusions and managerial implications

In this section, we first discuss the key findings related to carrying equipment for each behavioral metric. This is followed by a short discussion of the control variables. We then present the main conclusions before discussing managerial implications and limitations.

5.1. Discussion

5.1.1. Store area coverage

Store area coverage was 19.62 percent on average. This is similar to the findings on store coverage presented in Sorensen et al. (2017), where they found that shoppers covered 21 percent of the small store formats.[1] Sorensen et al. (2017) have shown that most shoppers tend to cover a small proportion of the store, and that they shop quickly and only purchase a few items. The current research can be classified in a

[1] Their smaller store formats consist of 200–300 m^2, while our store is a soft discount store, located in Norway and around 1200 m^2. Sorensen et al. (2017) have shown that findings tend to generalize between countries (USA, UK, China, and Australia), most store formats (supermarkets, hypermarkets, convenience, and specialty stores), and store sizes (from 200 m^2 to 19.000 m^2). We here add to that generalization.

Table 2
Descriptive statistics of in-store behavior by choice of carrying equipment.

Variable	No equipment		Basket		Cart		Overall	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Average walking speed (m/s)	0.60	0.27	0.45	0.17	0.30	0.11	0.49	0.24
Travel distance (m)	94.95	43.05	159.38	63.29	214.38	103.07	141.77	79.03
Shopping duration (min)	3.30	2.26	7.05	4.19	13.43	8.45	6.59	5.90
Basket size	2.21	1.41	6.58	3.61	14.06	8.91	6.06	6.15
Store area coverage (%)	14.23	5.72	22.04	6.18	27.12	7.72	19.62	8.02
Shopper efficiency	0.026	0.015	0.042	0.019	0.065	0.027	0.039	0.024
N	270		252		113		635	

Table 3
In-store behavior estimates.

Dependent variable	Shopping duration (min)			Walking speed (m/s)			Travel distance (m)			Area coverage (%)			Basket size		
Carrying equipment															
No equipment	1.452	(2.91)	**	0.768	(12.66)	***	76.62	(8.20)	***	11.57	(9.99)	***	1.139	(2.95)	**
Basket	2.255	(3.75)	***	0.675	(10.56)	***	98.39	(8.68)	***	15.66	(11.99)	***	5.562	(11.05)	***
Cart	2.673	(3.30)	**	0.651	(9.55)	***	75.20	(5.48)	***	13.51	(8.66)	***	12.72	(12.04)	***
Age															
0–20[1]															
21–30	−0.578	(−1.02)		−0.066	(−1.06)		−8.119	(−0.74)		0.189	(0.15)		1.128	(2.59)	**
31–40	−0.441	(−0.78)		−0.109	(−1.74)		−11.13	(−1.02)		−0.315	(−0.24)		0.602	(1.39)	
41–50	−0.171	(−0.28)		−0.110	(−1.80)		−1.410	(−0.13)		1.004	(0.77)		0.924	(1.66)	
51–60	−0.018	(−0.03)		−0.132	(−2.11)	*	−4.424	(−0.37)		0.406	(0.30)		−0.603	(−1.15)	
61–70	1.094	(1.82)		−0.168	(−2.69)	**	−5.842	(−0.53)		0.291	(0.23)		−0.676	(−1.24)	
71+	2.704	(3.01)	**	−0.240	(−3.53)	***	21.15	(1.43)		3.918	(2.61)	**	−1.950	(−1.95)	
Gender															
Male[1]															
Female	0.990	(3.78)	***	−0.0917	(−4.97)	***	−0.425	(−0.09)		0.0963	(0.20)		0.225	(0.62)	
Basket size	0.632	(14.98)	***	−0.0108	(−5.51)	***	9.661	(14.16)	***	0.876	(14.30)	***			
Shopping period															
Weekday[1]															
Weekend	−0.379	(−1.38)		0.0369	(1.82)		−6.475	(−1.45)		−1.078	(−2.29)	*	0.968	(2.26)	*
Shopping time															
Off peak[1]															
Peak	0.187	(0.72)		0.0043	(0.24)		8.581	(2.01)	*	1.259	(2.70)	**	0.517	(1.39)	
R^2/adj.R^2/Prob > F	0.865	0.861	***	0.869	0.866	***	0.905	0.903	***	0.940	0.938	***	0.738	0.732	***
AIC/BIC	2608.2	2663.6		−149.5	−94.1		5538.9	5594.3		3204.7	3260.1		2973.5	3024.6	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, [1] = base, t statistics in parenthesis, N = 521, OLS with robust errors

similar vein, working on the empirical generalization of in-store shopping behavior contrary to armchair theorizing. Our results are in the same direction for short trips, and we operationalize them as "non-equipment" shopping to avoid any possible tautology or forced outcomes ("small trips leading to small shopping"). While Sorensen et al. (2017) focused on store area coverage between different store formats and store sizes, the current study demonstrates that there are also important differences between shopping trips within a store, where choice of carrying equipment can be used as a behavioral segmentation. Our results showed that the largest consumer group, non-equipment shoppers representing 42.52 percent of the total number of shoppers, only visited on average 14.23 percent of the store, meaning that the largest consumer group did not visit over 85 percent of the total store area. The other types of shopping trips cover more of the store but still ignore most of the areas. Those using a basket covered on average 22.04 percent, and the smallest segment, cart users covered on average 27.12 percent of the store, implying that most of the store is currently irrelevant to the shopper, with no opportunity to sell. This adds to the literature and managerial discussion on the recent changes happening in shopping trips and paths and has clear implications for the literature on shopper behavior and the possible contribution of in-store marketing. Larson et al. (2005) introduced the expediency of equipping shopping carts with RFID tags for shopper research. They profiled shopping paths based on zones visited and showed, contrary to conventional wisdom, that shoppers did not tend to weave up and down the aisles. The current research adds data on non-equipment use and shows that the use of carrying equipment can also be used to profile different shopping trips as the findings generalize across the in-store behavioral metrics, including store area coverage. Data on shopping trips not involving any carrying equipment are valuable as they have been seriously underrepresented in previous studies.

5.1.2. *Shopping duration*

The average shopping duration was 6.59 min, a finding that is in line with many retail specialists reporting decreased store-shopping willingness and increased emphasis on "grab and go" shopping (Nielsen, 2015; Scamell-Katz, 2004; Steiner, 2018). This average shopping duration is similar to the mean value Sorensen et al. (2017) reported for small format stores (5 min) and the main conclusions are the same. Although the main contributions are on a different level, our results also show that most shopping trips are short. Sorensen et al. (2017) show an inter-store heterogeneity of key behavioral measures, while the current research reveals intra-store heterogeneity based on shoppers use of carrying equipment during the consumer journey. This is an important addition to the literature as the limited research on how shoppers actually act in stores in terms of shopper paths and in-store

Table 4
Shopper efficiency estimates.

Dependent variable	Shopper efficiency (Basket size/Travel distance)		
Carrying equipment			
No equipment	0.0203	(8.25)	***
Basket	0.0364	(12.35)	***
Cart	0.0610	(14.02)	***
Age			
0–20[1]			
21–30	0.00924	(3.25)	**
31–40	0.00676	(2.30)	*
41–50	0.00482	(1.66)	
51–60	0.000335	(0.10)	
61–70	−0.00125	(−0.40)	
71+	−0.0106	(−2.29)	*
Gender			
Male[1]			
Female	0.000348	(0.21)	
Shopping period			
Weekday[1]			
Weekend	0.00265	(1.52)	
Shopping time			
Off peak[1]			
Peak	0.00106	(0.63)	
R^2/adj. R^2/Prob > F	0.828	0.824	***
AIC/BIC	−2653.4	−2602.4	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, [1] = base, t statistics in parenthesis, N = 521, OLS with robust errors

behaviors has mostly been restricted to shoppers using shopping carts fitted with RFID tags. This can lead to a significant overestimation of shopping time, under-representation of short shopping trips and unawareness of instances during the shopping trip when the carrying equipment is not actively used, or when it is not used at all. Larsen, Bradlow and Fader (2005), for instance, noted that the data included a number of long shopping paths (up to 6 h) that most likely did not consist of actual shopping behavior. As a consequence, they excluded all paths lasting more than two hours. The current findings reveal substantial differences in shopping duration based on the shoppers' choice of carrying equipment. Shopping trips involving no carrying equipment lasted on average 3.30 min, while those involving either a basket or a cart took on average 7.05 min and 13.43 min to complete, respectively. These results support previous research findings pointing towards shorter duration for trips involving baskets rather than carts (Van den Bergh et al., 2011; Gil et al., 2009). Larsen and Sigurdsson (2019) put forward a conceptual framework on research on in-store carrying equipment in terms of antecedents and consequences. Their literature review reveals that consumers have a "shopping time budget", where available time and the opportunity cost of time could be linked to the choice of carrying equipment, taking retailers from psychographics over to a more manageable segmentation through a simple behavioral choice. Furthermore, the current research adds to the literature in terms of data on the most frequent and quickest shopping trips: those performed without any carrying equipment.

5.1.3. *Travel distance*

The average travel distance for all shopping trips was 141.77 m. The findings demonstrate that carrying equipment is associated with how many meters shoppers cover. While non-equipment users travelled on average a distance of 94.95 m, basket users and cart users travelled on average 159.38 m and 214.38 m, respectively. This suggests that non-equipment users take shorter trips within the store compared to both basket and cart users, which limits their exposure (opportunity to see) to in-store stimuli. Although there is some evidence in the literature suggesting that shoppers on shorter trips use more baskets while those on longer trips mostly use a shopping cart (e.g., Gil et al., 2009), the current study is the first to systematically examine how shoppers' actual travel distance is linked with type of carrying equipment. Besides providing meaningful information on shoppers' exposure to products, travel distance also provides valuable input to the shopper efficiency equation.

5.1.4. *Walking speed*

Walking speed is a relevant behavioral metric because increased pace can have a negative effect on shoppers' attention to stimuli along their in-store paths. The average walking speed for all 635 observations was 0.49 m per second (m/s), and the analysis shows that carrying equipment is associated with average walking speed over the course of the entire shopping trip. Non-equipment users walked on average twice as fast as shoppers pushing a shopping cart (0.60 m/s versus 0.30 m/s), and basket users had a pace in between (0.45 m/s). One explanation for non-equipment users walking fastest could be that their passage through the store is less impeded (Larsen et al., 2017; Wagner et al., 2014), and that they are less likely to spend time searching. For instance, due to the size of a shopping cart, cart users tend to be decelerated when maneuvering it in the store, such as when turning corners, due to the worry of bumping into other carts or shoppers. Cart users can also easily get stuck behind other cart-users and thus, experience a slower pace in parts of their shopping trip (Larsen et al., 2017). Seiler and Pina (2017) show that basket users are less likely to search than cart users and that they as such exhibit a higher average walking speed. Following those lines, non-equipment users are even less likely to be on the lookout for products. They know exactly which few items they want, in which areas these are placed, and they have no carrying equipment slowing them down on their beeline to these few items. Our findings are in line with the few studies displaying data on how shoppers with baskets and carts deviate in terms of walking speed (Seiler & Pinna, 2017; Gil et al., 2009), and we contribute to this scarce literature by adding insights on non-equipment users in this respect.

5.1.5. *Basket size*

The average basket size across the 635 shopping trips was 6.06 items, which reflects the presence of many shopping trips where shoppers purchase a relatively small number of items. This is in line with Sorensen et al. (2017) who found a consistent pattern across formats and countries involving fewer than ten purchased items on most shopping trips. Our findings also point to considerable differences in average basket size when shopping trips are segmented on the basis of carrying equipment. The largest group, non-equipment shoppers, purchased on average 2.21 items, meaning that most shoppers only bought a few items. On the other hand, shoppers carrying a basket or pushing a cart purchased on average 6.58 items and 14.06 items, respectively. The large group of non-equipment shoppers with limited basket sizes challenges existing retail principles, including store layout and in-store tactics to increase unplanned purchases.

5.1.6. *Shopper efficiency*

Our data show that non-equipment shoppers have the lowest efficiency among all shoppers in terms of purchases per meter (p/m) travelled (0.026 p/m for non-equipment trips, 0.042 p/m for basket users and 0.065 p/m for cart users, on average). We attribute this mainly to store layout, which follows design principles that most grocery stores have drawn on for decades (see Granbois, 1968). The characteristics are a grid layout with a main thoroughfare on the outside edge of the aisles and popular product categories located around the store to encourage consumers to walk longer distances and thereby to pass many other products on their way. Such a store layout forces non-equipment shoppers to walk through the entire store despite their few needs, spending more time and effort than necessary. The larger the store, the more inefficiency for non-equipment shoppers in particular.

Because Hui et al. (2009a) merely treat store layout as a fixed parameter in their analyses, their approach to measure efficiency would not identify the type of inefficiency we detect in our study. As such, Hui et al. (2009a) do not discuss the extent to which the most optimal path in itself is inefficient for some group of customers. Their finding that longer shopping trips with a larger basket size and a longer shopping durations are least efficient (most deviation from the optimal path), is therefore not necessarily contradictory to our findings.

5.1.7. Control variables

In the current study, carrying equipment is the only independent variable that consistently contributes in explaining the variance in all of the six behavioral metrics. Gender, shopping time and shopping period, each contributes in explaining the variance in only two of the six metrics. Gender is only associated with shopping duration and walking speed. Shopping period is only associated with basket size and store area coverage, and shopping time is associated with only travel distance and store area coverage. Furthermore, the results imply differential effects of age on the six behavioral metrics. For instance, age is not associated with travel distance, and only the oldest age category is associated with shopping duration and area coverage. Type of carrying equipment (or the absence of one) involved in the shopping trip should therefore not be overlooked in research examining shoppers' in-store behaviors.

5.2. Conclusions

An emerging empirical literature built on technological innovations to study consumers' actual behavior in retail stores has shown generalizable patterns related to key behavioral metrics, describing the heterogeneity of shopping trips across retail outlets, formats, and countries. We repeat similar analyses and broaden the exploration of fundamental in-store patterns by adding three additional metrics: travel distance, walking speed, and shopper efficiency. These new measures complement those proposed by Sorensen et al. (2017) as they lead to better documentation and understanding of how shoppers differ in their behaviors. Our findings draw attention to the important role of the choice of carrying equipment in understanding in-store behavioral patterns. Our data show heterogeneity in shopping trips connected to type of carrying equipment, and based on the results, we find carrying equipment to be a suitable variable for segmenting shoppers. It is an objective and observable measure and also predictive in terms of occurring before the in-store behavior. Although carts and baskets have been around for many decades (Grandclément, 2009) and still today provide valuable customer service for shoppers, surprisingly few studies investigate their association with behavioral patterns in the store.

We find non-equipment use to be widespread across stores and retail formats and to represent a considerable proportion of shoppers. We contribute unique and important insight on how this segment of shoppers behave compared to those using either a basket or a cart. The findings indicate that non-equipment users on average walk at a faster pace, visit a smaller share of the store area, walk shorter distances, spend less time in the store, buy fewer items, and exhibit lower shopper efficiency than cart users (while basket users show behaviors that lie in between). Although we cannot conclude anything about causality, we show that carrying equipment can be used to capture the heterogeneity in these key behavioral metrics. Thus, by not distinguishing between different in-store carrying equipment, researchers examining shopping trips and in-store behaviors unintentionally neglect an important discriminator for differences in key behavioral metrics.

5.3. Limitations and suggestions for further studies

While conducting this study, we faced methodological issues related to shopping trips involving multiple shoppers (e.g. families, couples and groups) that led us to focus only on single-person shopping trips in the analysis of our data. A shopping trip with multiple shoppers introduces sources of potential bias that must be overcome. For instance, who should be tracked? What if the group splits up one or more times during the trip and more than one member purchases items?

Another dilemma is how to profile the shopping trips using relevant shopper characteristics such as gender and age. In cases where shoppers shop together as a group, most likely more than one age group and gender are involved. Shopper characteristics can be rather ambiguous if used for trips involving multiple shoppers. We used visual inspection to determine age and gender. Therefore, please note that the data on these variables may be subject to some measurement error.

When the shopping trip is the unit of analysis, then the entry and the exit measures become important not only for between-study comparisons but also for the validity of the fundamental behavioral metrics: those based on time in particular. Shoppers may spend a lot of time both at the start and at the end of the shopping trip on tasks not associated with purchases (e.g., picking a basket/cart, queuing at the checkout, and item scanning). Measures for when to start and stop tracking should be established, and all studies examining in-store behavioral patterns should apply these. Our procedure was to stop tracking when the shopper started queuing, or in the absence of a queue, when the shopper placed the first item on the conveyor belt. One concern is that subsequent purchases (e.g., items displayed at the checkout) are not added to the number of purchases since they occur after the defined shopping trip.

In this paper, we introduce average walking speed, but measuring walking speed within each area would be an improvement as it could add further insight regarding shopping patterns. We also recognize that the behavioral metrics do not provide any insight as to shoppers' actual attention to stimuli along their in-store path. Store area coverage, travel distance and shopping duration are only indicative of opportunities to notice in-store stimuli, and average walking speed is only indicative of the shopper's search activity, visual field, and attentiveness to stimuli. It seems that there is a need for a more fine-tuned measure of attentional patterns based on, for instance, eye-tracking that can complement the other key behavioral metrics. Further research should therefore explore this opportunity.

5.4. Implications for retailers

Our data point to a high extent of non-equipment trips in grocery retailing and that in many stores, the shopping cart has passed to a more marginal role overall in terms of use on shopping trips. Since carrying equipment expands consumers' shopping capacity and is related to increased buying, physical retailers need to monitor, nurture and reward carrying equipment use. Observing consumers' choice of carrying equipment at the entrance should be an important retail metric, which can act as a benchmark for measures intended to increase the likelihood of shoppers selecting a piece of carrying equipment and for benchmarking against competitors. By deciding on which types of equipment to offer shoppers, in terms of the stock size for each alternative and their pick-up location in the store, retailers set the scene for their customers' choice of carrying equipment (including no equipment). Miscalculating the size of the need for a given type (resulting in periods of unavailability), or failure to offer shoppers the right types of equipment (small/large; plastic/metal) at the appropriate place (at the entrance/close to the entrance/inside the store), can presumably result in more non-equipment use. Optimizing the number of shoppers selecting a shopping cart should be the aim of most retail grocery stores. Retailers should focus on making it easy and appealing to select a cart and avoid any barriers to cart use, such as cart locks. This includes drawing attention to the benefits of or increasing the consumer value from using a cart. For instance, technology mounted on shopping carts (so called "smart carts") can offer consumers other types of benefits than the regular shopping cart (e.g., assistance in finding relevant products). Retailers could also attach discounts or reward points to cart use to motivate shoppers to select a cart for their shopping.

A high extent of non-equipment use also points to the need to offer shoppers suitable carrying equipment at secondary locations in the store. Shoppers occasionally misjudge their need of carrying capacity at the start of their shopping trip. This is evident, for example, from situations where shoppers are trying to stretch the capacity of what their arms are capable of handling. Thus, placing equipment inside the store can lead shoppers to easily upgrade their choice of carrying equipment (without having to make the effort to retrace their steps to the entrance). This is customer service that may contribute to a more pleasant experience and improve sales.

We have shown that non-equipment trips are the least efficient among all shopping trips as measured in terms of purchases per meter travelled. For most retailers, the shopping trend is now moving dramatically in the direction of smaller, more frequent trips (Sorensen, 2016), many of which involve no carrying equipment. The paradox here is that non-equipment shoppers presumably are those who mostly seek a quick and efficient trip, but who in practice experience the least efficient trip among all shoppers. Our data suggest that non-equipment shoppers walk rather fast to the few products that initiated their visit. Nevertheless, they spend the longest time per item bought, and compared to other shoppers, their pace makes them less likely to be attentive to stimuli on their way to their in-store destination. To cater to a growing segment of non-equipment shoppers in a better way, retailers should consider using special shelves in close vicinity to the entry and checkout for products bought frequently by non-equipment shoppers. Alternatively, retailers can attempt to establish a convenience store within their main store (store-in-store concept) stocking those items and categories that are most relevant for non-equipment users. Such store-in-store concepts have already started to appear in practice. Further, retailers can focus on initiatives that make the checkout more time efficient for non-equipment shoppers buying few items, such as self-checkout stations, express lanes, or no-checkout stores (such as Amazon Go). In addition, retailers can facilitate shortcuts in the store aimed particularly at reducing intra-store travel for non-equipment shoppers who know exactly what they want.

Our results suggest that carrying equipment is the best directly observable variable for segmenting shoppers as it explains a larger proportion of the variance in the in-store behavioral metrics than age and gender do. Segmenting on carrying equipment is objective and actionable in terms of product, place and promotion strategy. Further research could study this in terms of pricing and willingness to pay as well as in terms of in-store marketing communication. The problem with traditional retailing is that retailers show everything to everyone. By using, for instance, movement sensors and RFID tags in baskets and carts, targeted ads on in-store screens could be displayed (if movement, but no RFID is detected, then display ads targeted to non-equipment shoppers. If cart RFID is detected, then show ads to cart shoppers etc.). Thus, behavioral segmentation based on carrying equipment selection offers retailers the opportunity to segment customers.

Appendix 1. . Frequencies by choice of carrying equipment

Variable	No equipment	Basket	Cart	Total
Customer type				
Female	93	101	56	250
Male	136	112	24	272
Group/family	41	39	33	113
Total	270	252	113	635
Age[1]				
0–20	28	2	–	30
21–30	54	42	1	97
31–40	53	54	6	113
41–50	37	36	26	99
51–60	24	41	15	80
61–70	29	32	24	85
71 +	4	6	8	18
Total	229	213	80	522
Shopping period				
Weekday	185	172	78	435
Weekend	85	80	35	200
Total	270	252	113	635
Shopping time				
Off Peak	240	230	106	576
Peak	30	22	7	59
Total	270	252	113	635

[1] Age frequencies for female and male customers only.

Appendix 2. . Correlation matrix for the six key behavioral metrics (dependent variables)

	Shopping duration (min)	Walking speed (m/s)	Travel distance (m)	Area coverage (%)	Basket size	Shopper efficiency
Shopping duration (min)	1.0000					
Walking speed (m/s)	−0.6256	1.0000				
Travel distance (m)	0.8181	−0.3515	1.0000			
Area coverage (%)	0.7861	−0.3728	0.9423	1.0000		
Basket size	0.7895	−0.4230	0.7529	0.7276	1.0000	
Shopper efficiency	0.4596	−0.4203	0.2668	0.3163	0.7612	1.0000

The table shows that several behavioral metrics are highly correlated. This should be expected given the definition of the metrics. For instance, the longer distance a shopper travels in the store, the more time he or she spends in the store and thus on average, the longer the shopping duration. Despite being correlated, all behavioral metrics capture and explain different aspects of shopper behavior (see Sections 2.2–2.7). For instance, the high correlation between travel distance in meters and area coverage in percentage demonstrates that shoppers only to a small extent go back to previously visited store areas.

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Appendix: Co-author statements

6.4. Paper II

Author declaration

Name of candidate: Jørgen Breivik

Paper title: Measuring inventory turnover efficiency using stochastic frontier analysis: building materials and hardware retail chains in Norway .
Authors: Breivik, J., Larsen, N. M., Thyholdt, S. B., & Myrland, Ø.
Published: 2021. International Journal of Systems Science: Operations and Logistics. doi: https://doi.org/10.1080/23302674.2021.1964635

Contributions

Phase	Jørgen Breivik	Nils Magne Larsen	Sverre Braathen Thyholdt	Øystein Myrland
Concept and idea	X			
Study design and methods	X			X
Data collection	X			
Data analysis	X			
Interpretation of results	X			
Manuscript editing	X	X	X	X
Critical revision of the intellectual content	X	X	X	X

With my signature I consent that the article where I am a co-author can be a part of the PhD thesis of the PhD candidate.

Nils Magne Larsen — Sverre Braathen Thyholdt — Øystein Myrland

6.5. Paper III

Author declaration

Name of candidate: Jørgen Breivik

Paper title: The heterogeneity of shoppers' supermarket behaviors based on the use of carrying equipment.
Authors: Larsen, N. M., Sigurdsson, V., Breivik, J., & Orquin, J. L.
Published: 2020, Journal of Business Research, 108, 390–400. doi: https://doi.org/10.1016/j.jbusres.2019.12.024

Contributions

Phase	Nils Magne Larsen	Valdimar Sigurdsson	Jørgen Breivik	Jacob Lund Orquin
Concept and idea	X	X	X	
Study design and methods	X	X	X	
Data collection	X		X	
Data analysis			X	
Interpretation of results	X	X	X	
Manuscript editing	X	X	X	X
Critical revision of the intellectual content	X	X	X	X

With my signature I consent that the article where I am a co-author/supervisor can be a part of the PhD thesis of the PhD candidate.

Nils Magne Larsen   Valdimar Sigurdsson   Jacob Lund Orquin