THAI YOUNG KIM

Data-driven Warehouse Management in Global Supply Chains

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Acknowledgments

In this section, I would like to express my deep gratitude for help in completing this thesis. When was a child, I enjoyed hearing tales from my grandfather who studied abroad in his twenties but could not finish due to The Pacific War. At that time, my research motivation may have already started. 30 years later at a graduation ceremony for my Master’s, I had courage to express my plan for Ph.D. study to my current Promoter, Prof. Rommert Dekker. His openness toward research topics initiated my long journey with him. I remain grateful to Rommert Dekker for offering me this precious opportunity. My experience in real-life supply chains made my topic initially attractive, but much effort was required to merge with extant theory or literature. Whenever I got lost in this process, Rommert Dekker kindly stayed with me until my research topics finally gained academic attention. Though hesitant to express my gratitude at that time, I later realized that he always accompanied me with perseverance. I really enjoyed our research discussions and his willingness to share my interest and passion in topics, some times not necessarily familiar to him. I especially thank him for inviting me as an expert forum presenter. Through those opportunities, I improved my presentation and speech skills in front of many audience types. Last but not least, he gave an important lesson in perseverance at academia. “Sometimes (or may be always) science is hard work, but continuing it works in the end”.

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extending into late evening and weekends. I sincerely appreciate that he taught me what practitioners really lack in academia. His extensive expertise in statistics offered rigor to my research. I was always able to consult him regarding the validity of my data analytics. He also taught me that writing of research results can be a state-of-the-art process. I admit to not putting enough passion into drafting a readable paper before he enlightened me on the importance of writing in academia. Beyond merely correct grammar, writing means managing the flow of thought over the entire research process. Writing often forces researchers to realize flaws in an idea. Just as a fine manuscript cares for readers well, Christiaan also gave lessons on how to respect and care for partners in the research process. During seminars at RSM and ESE, I felt confidence just finding Christiaan sitting in the audience. I also learned much about preparing presentations for different types of audiences. I could not have delivered understandable presentation without his advice on how the audience absorbs information from the presentation process.

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Chapter 1

Introduction

1.1 Warehouse role in global supply chain management

Global supply chain management is of primary importance in manufacturing industry. To address cost pressures in competitive markets, manufacturers have shifted manufacturing activities to lower-cost countries and have located warehouses in countries with high demand. Today's transnational supply chain thus has a significant impact on manufacturer profit. In principle, global supply chain management (global SCM) aims to minimize distribution costs while retaining the benefit of low-cost production. However, global SCM must also offer customer value via logistics performance. Manufacturers in global supply chains need to provide superior international logistics service quality (Mentzer et al. 2004) to compete with domestic suppliers. Otherwise, revenues may drop due to poor customer satisfaction in supply chain performance (Closs and Mollenkopf 2004). Much of the supply chain management literature focuses on "lean" manufacturing to minimize inventory levels over globally extended supply chains. An added principle emerges from agile production known as "leagility", a term linking the paradigms of leanness and service agility (Naylor et al. 1999, Naim and Gosling 2011). Yet, little research has investigated how to run efficient logistics services at warehouses in global supply chains.

In supply chains, warehouses form a pivotal link between three main stakeholders: vendors for supply, haulers for transport, and customers at points-of-sale (Van den Berg, 2007). Warehouses receive goods from suppliers to maintain efficient inventory, fulfil customer orders, and manage efficient trips with haulers. In concert with these three stakeholders, warehouses perform wide-ranging activities (e.g. receive, put-away, pick, pack, and ship) using their resources (e.g. labor, handling equipment, facilities). To attain efficient logistics, warehouses must manage conflicting aims among diverse stakeholders when planning and executing tasks. Suppliers want to reduce inventory, customers want fast delivery of a wide selection of products, and haulers seek maximum truck volume per trip. Warehouse managers must allocate resources efficiently to meet these various demands in logistics services from geographically diverse stakeholders.

Previously, the allocation of resources has relied mainly on the individual experience of warehouse managers. However, trusting individual expertise is risky because of the far-reaching consequences of wrong perceptions in these global operations. Instead, best practices for global supply chains use well-connected data analytic systems to manage warehouse resources. Decision-making based on insights from data analytics can reduce inefficient allocation of resources in global supply chains. This thesis advocates data-driven warehouse management as a key determinant toward efficient global supply chains.

1.2 Challenges for warehouses in global SCM

This thesis aims to answer the following research question: How can warehouses manage the challenges of the global supply chain with the support of data-driven warehouse management? This thesis first defines the three main challenges for warehouses in global SCM: uncertainty, responsiveness, and complexity.

Challenge one is uncertainty. Uncertainty in handling volume has always been a challenge in warehouse operations. Warehouse managers must allocate resources based on expected demand volume. For instance, they must assign storage space for goods before delivery to customers. This requires forecasting on-hand inventory. First, they must estimate the demand volume within the distribution scope of the warehouse. Second, they must estimate the demand size for the warehouse for certain time frames (i.e. daily or weekly), and third, they must plan the inbound-outbound volume for the warehouse considering the supply chain network from origin to end user. Here, uncertainty in demand size and time frames can trigger unexpected issues regarding warehouse space – an important warehouse resource. In global supply chains, this uncertainty often originates from volatility in demand and disruption of distribution. Moreover, the impact of inaccurate estimates is difficult to counter in cross-border networks involving diverse parties. When manufacturers ship goods from overseas factories based on forecast ranges in demand, it is time consuming to mitigate the impact of inaccurate forecasts as in-transit goods take a long time to arrive at warehouse destinations. As a result, warehouses then hold an aging inventory of unneeded goods. Uncertainty leads to waste of warehouse resources such as handling labor and storage space.

Challenge two is responsiveness. Responsiveness is regarded as one of the most important supply-chain performance indicators, even emphasized as a long-lasting value advantage over competitors. It has been difficult and expensive to develop responsiveness in global SCM with long distances separating suppliers and customers. However, growing cross-border electronic commerce (e-commerce) has made responsiveness more affordable in the global supply chain. More manufacturers now consider cross-border, overseas markets as their extended business scope through e-commerce. At first, they competed only with price schemes. Now, easy price searching on the Internet has narrowed price gaps among competitors. In contrast, non-price value distinctions in logistics services still endure since it takes time and capital for rivals to fully develop similar advantages. For instance, faster delivery service or flexibility for order cut-off times can lead to a competitive advantage. Although responsiveness in the global supply chain has become easier in many ways (e.g. international express parcel service), it remains a challenge for manufacturers with global supply chains to efficiently surpass the responsiveness of local manufacturers. Warehouses must offer innovative, responsive order fulfilment to achieve a sustainable competitive business advantage.

Challenge three is complexity. Complexity of order fulfilment in warehouses increases when global manufacturers pursue manufacturing postponement strategies. For instance, a manufacturer serving both the Netherlands and the United Kingdom markets tends to postpone product customization (e.g. different power code cable and language panel) until receiving each customer's actual purchase order. This helps to maintain lower inventory levels, but it also creates an extra warehouse process of customizing. Complexity of order fulfilment can cause inefficient use of labor, another key warehouse resource. Customizing products in warehouses interrupts smooth operations, triggering bottlenecks in the workflow. Therefore, warehouses should cope with complexity of orders in two ways: by determining the efficient size of the labor force and by including a buffer in case of erratic occurrences in complex demand, and by designing efficient job sequences.

1.3 Positioning and methods of research

This thesis investigates how data-driven warehouse management can help to solve the three main challenges in the global supply chain. In real-world situations, warehouse managers, fully occupied with their daily routines, are often reluctant to adopt data-driven warehouse management, as they are not sure which methods are most suitable for their particular case. This thesis bridges this gap between academics and practitioners with tangible examples of global SCM.

This thesis examines original equipment manufacturing (OEM) warehouses of a consumer electronics manufacturer. The warehouses in this thesis receive goods from overseas suppliers and ship them to wholesaler's warehouses in multiple countries. These warehouses are categorized as central warehouses that share inventory and facilities for a large region (e.g. Europe). Such warehouses naturally run large-scale operations serving customers in many nations. The basic task unit at these warehouses is much bigger than for local warehouses that provide goods to smaller, local customers. For instance, picking at central warehouses mostly involve handling a single full pallet from one location instead of picking a few pieces or boxes from multiple locations. Outbound pallets must be custom-packed according to customer warehouse specifications (e.g. pallet type, pallet height). In this thesis, picking is less labor intensive due to automated pallet-handling equipment. Packing, though, still requires manual box handling (e.g. disassembling, re-palletizing into other types). This thesis investigates how to improve efficiency for the packing process beyond the well-studied research about picking optimizations (Petersen 2000, De Koster et al. 2007). Warehouses in this thesis are run by third-party logistics service providers (TPL) whose core business is operating warehouses. Management levels of third-party warehouses tend to surpass those of private warehouses operated by the owners of the goods (De Leeuw and Wiers 2015). A benchmark result of leading third-party logistics service providers (Min and Jong Joo 2006) shows that top-tier TPLs in operational efficiency make intense use of information technology, even recommending their own proprietary software solutions for TPL resource utilization. This thesis studies the importance of using rigorous data for operations within the scope of data-driven warehouse management.

Since this thesis focuses on the benefits of data-driven warehouse management, it includes mostly mathematical modelling and simulation based on empirical observations. We use an installed-base model (Yamashina 1989) to predict spare part demand of consumer goods. The number of products in use, called the installed base (IB), is of primary interest as a generator of spare part demand. Whereas estimates of the installed base for capital goods have been accurate due to detailed maintenance contracts, estimates of the installed base for consumer goods is still challenging due to limited availability of data. We propose hypotheses for predicting the IB size in consumer goods by examining various user behavior according to product categories. We further test whether such IB estimates can improve demand forecasting accuracy consistently across various datasets.

The warehouse order fulfilment process in the case study is modeled as a tandem queue model (Burke 1956), mostly studied within the production management area. This thesis extends the concept and examines how priority rules known from the literature can be applied to improve the responsiveness of warehouse order fulfilment. Hypotheses are verified via simulation with real-life parameters extracted from historical warehouse data (e.g. occurrence of orders per day, throughput of warehouse processes). The warehouses in this thesis employ real-time job scanning communications linking the Warehouse Management System (WMS) with floor operators. This rich pool of warehouse activity data allows us to accurately measure warehouse productivities and performance.

To enhance forecast accuracy, this thesis involves the well-known debate (Sanders and Mandrodt 2003) about judgmental and quantitative forecasting. We compare installed-base forecasting (judgmental) with black-box forecasting from historical data (quantitative) in estimating spare part demand. We employ empirical data to validate diverse forecasting models. We develop research hypotheses for both explanatory power and predictive power separately.

To investigate our research hypotheses, we also use data from external sources (e.g. Eurostat Database). For instance, we combine internal sales data from e-shops (e.g. order size, order frequency, and re-purchase ratio) with published data (e.g. GDP per capita of buyer's origin, distance from seller etc.). This approach offers practical prospects for cross-border, e-retail market expansion within the EU through customized express-delivery application.

To complement the quantitative approach, we also use a qualitative approach. The results of the quantitative approach show unexpectedly higher labor productivity in the over-allocated staffing cases. We validate these results result using a qualitative approach. A survey with warehouse managers identifies why the quantitative analysis shows contradictory results; It shows that collaborative behavior throughout multiple sequential steps requires additional labor to cope with possible disruptions.

1.4 Thesis outline

This thesis studies warehouse management solutions for distribution challenges in the global supply chain. Global SCM faces large volume uncertainty, high responsiveness requirements, and complex order fulfilment. Data analytics is an effective method to address these challenges. Actual application examples in real-world situations demonstrate the importance of such data-driven warehouse management.

The thesis is structured as follows. Chapter 2 shows long-term opportunities (years ahead) in data-driven warehouse management by predicting determinants of expanding cross-border e-commerce in the European Union. This application helps warehouses to plan long-term investment for developing new transportation platforms or rescaling warehouse space. This chapter examines time and cost dimensions of distance in cross-border e-commerce. It studies these dimensions within the general setting of gravity models for international trade. Such models are suitable for studying cross-border e-commerce trade flows since they incorporate important demand factors, including income and objective-versus-subjective distance dimensions as perceived by e-customers. The empirical study concerns B2C supply from a centralized distribution center of an electronics company linking cross-border on-line shops to clients in 721 regions of five countries in the European Union. The main research questions of interest are the following:

- To what extent does distance affect cross-border on-line demand, and how much does express delivery help in reducing this effect?
- What factors influence the willingness of clients abroad to pay for such express services?
- To what extent is the adoption of express services by clients related to loyalty in terms of repurchase rates?

The answers to these questions offer insight into the behavior of on-line clients abroad. These can help e-commerce managers devise strategies that reduce distance to potential cross-border clients and to improve the satisfaction experienced from buying via their on-line shops. Warehouses face increased demand for responsiveness that requires express delivery and thus need to prepare for fast and efficient order fulfilment using data analytics.

Chapter 3 examines data-driven forecasts to secure mid-term opportunities (several months ahead) to reduce uncertainty of demand for spare parts during the end-of-life phase. The main research question of interest is the following:

- How should firms choose the lot size in the final production run to cover spare part demand by forecasting expected replacement?

The answer to this question can helps warehouses to plan efficient man power and storage space to handle expected spare parts demand. Although it is beneficial for companies to apply installed-base (IB) spare part forecasting, companies tend to rely only on past spare parts sales data. A case study involving seven industrial companies (Wagner and Lindemann 2008) shows that most companies have a 'cloudy view' of their current installed bases. In the consumer business area, users and manufacturers usually have little contact, and manufacturers thus have limited information on their installed bases. They are likely to know the number of sales per region, but generally lack data on how many products are still in use and when they will be phased out, which is crucial information for predicting future demand of spare parts. Chapter 3 therefore introduces detailed classifications of installed-base concepts that can be used to forecast consumer demand of spare parts in various ramifications. The proposed installed base concepts are lifetime IB, warranty IB, economic IB, and mixed IB. These IB concepts are discussed and empirically validated by comparing them to standard forecasting for a sample of real cases drawn from a major consumer products manufacturer.

Chapter 4 employs detailed productivity data to manage short-term (weekly or daily) uncertainty in order flows. Warehouses can use data analytics for identifying the interplay between forecast error and productivity to redesign their management strategies for demand forecasting and labor planning. It is often difficult to determine the exact workforce as the workload tends to vary. Even with flexible pools, labor planning may be inefficient, leading to negative effects on labor productivity. Forecasting workload and the required labor resources is thus an essential step in warehouse manpower planning. Quantitative forecasting methods using historical data can be combined with expert judgment, although this may introduce bias, i.e. systematic differences between forecasts and actual order sizes. The main research questions of interest are the following:

- What is the quantitative nature of errors in demand forecasting?
- How does forecast bias affect labour efficiency?
- What is the optimal level of forecast bias for labour efficiency?

This chapter also presents an empirical methodology to detect forecast bias defined as the ratio of forecast error over actual order size. It shows how a controlled level of bias can be implemented to optimize labor efficiency in warehousing.

Chapter 5 considers real-time (hourly or shorter) data-driven warehouse management applications for job priority allocation to tackle the challenge of responsive order fulfilment. Operational responsiveness of warehouses is measured as flexibility in dispatching products ordered by retailers. To improve responsiveness, warehouses try to postpone the cut-off time while handling the same order volume with less slack. Since orders typically have different fulfilment deadlines, priority-based job scheduling offers the key for efficient solutions. Just as job scheduling has notably reduced waste from over-production and waiting times for “just-in-time” manufacturing, it can also improve responsiveness in warehouse order fulfilment. The main research question of interest is the following:

- How can job priority scheduling help OEM warehouses improve their responsiveness to meet current trends of postponed daily order cut-off times for next-day delivery?

This chapter presents a general framework for cost-effective job scheduling using flow-shop priority methods to aid warehouses that postpone order cut-off times. This framework integrates the multiple objectives of low earliness, low tardiness, low labor idleness, and low stock through processing lanes into a single cost criterion, with weights derived from the cost structure and performance goals of the warehouse. A simulation study shows which scheduling methods perform best under which circumstances. The methods and results presented here advance extant literature by applying traditional flow-shop theories from manufacturing research to real-world warehouse distribution tasks. Warehouse practitioners can incorporate this task-scheduling framework in their warehouse management system to schedule and execute order fulfilment jobs in real time.

Finally, chapter 6 summarizes the main findings and conclusions from the thesis.

1.5 Contributions

The chapters of this thesis can be read individually. As a result, there is some overlap in the introduction and problem descriptions of the individual chapters. This thesis is composed of chapters based on co-authored academic papers either published or submitted to scientific journals. These papers are the result of a cooperation among authors. The references and contributions of the chapters are shown below.

Chapter 2 This chapter was primarily drafted by the first author under the supervision of prof.dr.ir. R. Dekker and dr. C. Heij. It is based on:

Thai Young Kim, Rommert Dekker, and Christiaan Heij. 2017. Cross-border electronic commerce: Distance effects and express delivery in European Union markets. *International Journal of Electronic Commerce* 21 (2), 184-218. doi.org/ 10.1080/10864415.2016.1234283.

Chapter 3 This chapter was primarily drafted by the first author under the supervision of prof.dr.ir. R. Dekker and dr. C. Heij. It is based on:

Thai Young Kim, Rommert Dekker, and Christiaan Heij. 2017. Spare part demand forecasting for consumer goods using installed base information. *Computers & Industrial Engineering* 103, 201-215. doi.org/10.1016/j.cie.2016.11.014

Chapter 4 This chapter was primarily drafted by the first author under the supervision of prof.dr.ir. R. Dekker and dr. C. Heij. It is based on:

Thai Young Kim, Rommert Dekker, and Christiaan Heij. 2018. Improving warehouse labour efficiency by intentional forecast bias. *International Journal of Physical Distribution and Logistics Management* 48 (1), 93-110. doi.org/10.1108/IJPDLM-10-2017-0313

Chapter 5 The research for this chapter was conducted by single author in close cooperation with prof.dr.ir. R. Dekker and dr. C. Heij. It is based on:

Thai Young Kim. 2018. Improving warehouse responsiveness by job priority management.Tech. rep., Econometric Institute, Erasmus School of Economics. URL https://repub.eur.nl/pub/104262. Report number: EI 2018-02.

Summary in Dutch This chapter was composed by Thai Young Kim and translated by dr. C. Heij.

Chapter 2

Cross-border electronic commerce: Distance effects and express delivery in European Union markets

2.1 Introduction

International trade has traditionally been studied for off-line trade flows from supplying countries to satisfy demand in other countries. A popular model to study such international trade flows is the gravity model (Head and Mayer 2014, Techatassanasoontom 2006) that explains the volume of trade between two countries in terms of their gross domestic product and the distance between them. The general finding is that the volume of trade flows between two countries grows with increasing income and declining distance. Initially distance was defined simply in terms of geographical distance, but later extensions of the gravity model also incorporated subjective and institutional distance dimensions such as whether or not the two countries share a common language, history, legal system, or trade agreement. Firms active in international trade invest in long-term relations with their partners abroad to reduce distance by creating mutual trust and reducing psychological barriers.

Nowadays, customers can purchase goods in borderless on-line markets. Cross-border electronic commerce offers attractive opportunities to customers because of competitive prices and wide product assortments. The rapidly expanding international e-commerce market (Zwass 1996) for on-line business-to-customer (B2C) supply shares the importance of income and distance factors with traditional off-line business-to-business (B2B) international trade flows. The main distinction with traditional international trade lies in the distance dimensions that separate on-line buyers from e-business suppliers across borders. Internet has made the world flatter (Friedman 2007) and some have claimed the 'death of distance' (Cairncross1997), whereas others (Lendle at al. 2016) still find cross-border distance effects for on-line trade but to a lesser extent than for off-line trade.

E-business suppliers have various options to reduce the distance to their on-line clients abroad. For example, they can reduce psychological barriers for cross-border clients by offering websites in their own language, by personalizing websites based on client-specific purchase history and personal information (Gupta et al. 2004, Massad et al. 2006), and by simplifying the search and comparison of products and suppliers through websites for international product comparisons and supplier ratings (Park et al. 2010, Zeithaml 2002). Suppliers can also improve the objective cost and time dimensions of distance to their clients. They can overcome cost barriers by flattening their transport tariffs and basing them on the willingness of clients to pay for the delivered service (Frischmann st al. 2012), and they can reduce time barriers by offering fast transport modes like express delivery, which result in shorter lead times between product order and delivery to the client.

The aim of this paper is to improve understanding of the time and cost dimensions of distance in cross-border electronic commerce. We study these dimensions within the general setting of gravity models for international trade. Such models are attractive to study cross-border e-commerce trade flows as they incorporate important demand factors, including income and objective and subjective distance dimensions as perceived by e-customers. This empirical study concerns B2C supply from a centralized distribution center of an electronics company via cross-border on-line shops to clients in 721 regions of five countries in the European Union. The main research questions of interest are the following.

To what extent does distance affect cross-border on-line demand, and in how far does express delivery help in reducing this effect? What are the factors that influence the willingness of clients abroad to pay for such express services? And to what extent is the adoption of express usage by clients related to loyalty in terms of repurchase rates? The answers to these questions provide insight in the behavior of on-line clients abroad, which can help e-commerce managers in developing strategies to reduce their distance to potential cross-border clients and to improve the satisfaction experienced from buying via their on-line shops.

2.2 Literature review

Gravity model and distance dimensions in international trade

The gravity model for bilateral trade flows was originally proposed by Tinbergen (1962) and Pöyhönen (1963). The name 'gravity' refers to the assumption that the attraction between two countries depends in a multiplicative way on their distance and on their economic 'masses' measured by their gross domestic products (GDP's), similar to Newton's law of gravity in classical mechanics. Nowadays, the gravity model is well-grounded in the economic theory of international trade (Head and Mayer 2014). The distance factor does not only refer to the geographical distance between the two countries, but also to institutional and psychological factors such as home bias and (not) sharing a trade union, legal system, currency, language, or history (Lendle at al. 2016). The persistence of distance effects is not only due to transport costs but also to unfamiliarity (Huang 2007) and even exists on the intra-national level (Wolf 2000). Distance can be used as proxy for transport cost and border taxes as proxy for economic distance (Anderson 1979). Contrary to popular beliefs that the world has become 'flat' (Friedman 2007) and that distance is 'dead' (Cairncross1997), empirical economic research on traditional, off-line international trade demonstrates the opposite (Head and Mayer 2014). National borders remain an important barrier to trade (Anderson and Wincoop 2003, McCallum 1995), and distance is not dead (Leamer 2007). A meta-analysis of a large number of international trade studies spanning more than a century shows persistent distance effects that do not decrease over time (Disdier and Head 2008).

The above literature is concerned with distance effects for traditional, off-line product flows between countries or in international B2B trade. We next review some findings related to the distance dimensions for cross-border B2C trade. An important difference between B2B and B2C trade is the establishment of trust, as it is much easier for firms to build mutual trust with their major business partners than with their numerous individual customers abroad. As trust is an important driver of cross-country on-line shopping (Gupta et al. 2004, Mahmood et al. 2004), e-commerce managers should exploit the specific opportunities that on-line technology offers to reduce the distance perceived by their customers. This distance can be reduced along three main dimensions: information, cost, and time. First, e-commerce managers can reduce information frictions by simplifying the search and comparison of products via manufacturer websites and price and reputation comparison websites. Consumers with higher price-search intentions are more likely to switch to on-line channels (Gupta et al. 2004), but poor seller reputation discourages consumers from transactions with distant agents (Hortaçsu et al. 2009). The service quality of e-suppliers can be compared via customer ratings (Park et al. 2010). An example is eBay's seller-rating technology that reduces distance effects on eBay (Lendle at al. 2016). Second, e-commerce managers can influence the perceived cost dimension of distance by adapting their transport pricing strategies. E-commerce demand can be influenced by partitioned shipping prices and free-shipping (Frischmann st al. 2012, Lewis 2006, and Gumus et al. 2013) provides an empirical comparison of these two pricing strategies. The effects of distribution services and shipping fees on the profit of internet retailers are investigated empirically in studies (Rabinovich et al. 2008) and by means of numerical studies (Jiang et al. 2013), and some cross-border e-commerce studies find no significant distance impacts on parcel delivery cost (Gomez-Herrera et al. 2014, Lendle at al. 2016). Third, e-commerce managers can reduce the time dimension of distance by offering reliable express delivery options to their customers. Opportunities for express delivery services do not yet seem to have received much attention in the literature so far.

The empirical findings on the three distance dimensions in cross-border e-commerce are currently still somewhat mixed. Because of cultural differences, negative distance effects persist for digital products even in absence of transport costs, search costs, and other trade barriers (Blum and Goldfarb 2006). Compared to off-line purchasing in ‘brick-and-mortar’ stores, customers in on-line e-commerce profit from better information and lower search costs (Hortaçsu et al. 2009, Lendle at al. 2016), but they are worse off when crossing linguistic borders (Gomez-Herrera et al. 2014). Geographic distance affects on-line trade to a lesser degree than off-line trade (Lendle at al. 2016), but home bias persists due to the perceived risks of contract breach (Hortaçsu et al. 2009). The cost dimension of distance is sometimes found to be relevant (Frischmann st al. 2012) and sometimes not, for example, for eBay (Lendle at al. 2016).

Trends and barriers in European cross-border e-commerce

Globalization of e-commerce is a common trend in contemporary e-retail business (Ben-Shabat et al. 2013, Mahmood et al. 2004). Both consumers and manufacturers can profit from cross-border e-commerce, because centralized e-shops with large product assortments can serve multiple countries and are less costly (Quelch and Klein 1996). E-commerce continues to gain traction also in the European retail industry, where off-line retail has recently stagnated or dropped. On-line retail sales in Europe reached approximately 185 billion euro in 2015, an increase of 18 percent compared to 2014, while off-line retail sales were expected to decline by 1 percent in the same period (Ecommercenews 2014). In the European Union (EU), 15 percent of the inhabitants purchased goods on-line from sellers outside their country of residence in 2014, compared to 8 percent in 2009 (Nagelvoort et al. 2015). The on-line share of total retail trade varies across the EU, ranging in 2014 from 2 percent in Italy to 13 percent in the UK (Nagelvoort et al. 2015), reflecting varying degrees of e-commerce maturity. The main drivers of e-commerce growth in EU countries are internet penetration ratio, intensity of telecom investment, availability of venture capital, availability of credit cards, education level, and spill-over effects from neighboring countries’ e-commerce (Ho et al. 2007). There is much potential for growth in cross-border sales, both in mature e-retail markets and in markets with lower on-line shares due to regional contagion effects (Techatassanasoontom 2006). From this perspective, cross-border e-commerce is the key to accelerating the growth of on-line retail in Europe (Gomez-Herrera et al. 2014) and globally (Ben-Shabat et al. 2013).

Several barriers to still constrain further growth in cross-border e-commerce, including unreliable and lengthy transit times, complex and ambiguous return processes, customs bottlenecks, limited transparency on delivery, price opacity, limited ability to alter delivery times, and limited mutual trust (Van Heel et al. 2014). Except for customs bottlenecks, e-commerce managers can reduce most of these barriers by providing clear delivery and return policies to their customers. Transit times for cross-border e-commerce in the EU are currently still considerably longer than those for interstate e-commerce in the US. Although the land area of the EU is only 45 percent of the US (United Nations Year Book, 2011), it has similar or even longer transportation times due to border effects (Helble 2007). As predicted by the gravity model (Head and Mayer 2014), such lengthier transit times make e-retail customers more reluctant to purchase goods outside their home country. This may explain the lower propensity for e-commerce in the EU compared to the US. On-line retail sales in the US reached 224 billion euro in 2014, which is 43 percent higher than in the EU (Ecommercenews 2014), despite the fact that GDP in the EU is 6 percent higher (World Bank, 2014).

US e-commerce data suggest that the EU can expand its e-commerce market by shortening transit times of cross-border trade, for example, by adopting express delivery. Consumers using cross-border e-shops will perceive less geographical distance if express delivery is well-implemented in terms of low prices and short lead times. Current express solutions can offer reliable next-day delivery through the airfreight network in Europe. A survey of EU national regulatory authorities (ERGP 2014) shows that standard and express offers are substitutes for parcel delivery at the cross-border level. Some retail programs like Amazon Prime and Google Express have recently introduced prime express delivery services and have even implemented their own transport networks. Thus, express delivery has gained acceptance as a means for providing substantial value for cross-border e-commerce (Rabinovich et al. 2008), and European Courier, Express, and Parcel services provide opportunities to increase cross-border e-commerce in Europe (Ducret 2014). Still, rational consumers regard express delivery charges as additional transaction costs (Coase 1937), even if retailers include these costs as part of the product price (Gumus et al. 2013). Several studies have suggested cost-effective delivery strategies by means of simulation studies (Becerril-Arreola et al. 2013, Jiang et al. 2013) and empirical studies (Gumus et al. 2013, Lewis 2006), but these studies do not examine e-commerce offering express delivery services.

Customer satisfaction in cross-border e-commerce

In neoclassical micro-economics, consumers base their individual choices on marginal utility in terms of costs and benefits (Edgeworth 1967, Jevons 1888, Marshall 1890). In line with this general idea, the theory of buyer behavior (Howard and Sheth 1969) suggests that consumer satisfaction results from an evaluation of the rewards and sacrifices associated with the purchase. The experienced utility or satisfaction of consumption depends on the price, quality and value of products (Zeithaml 1988) or services (Cronin et al. 2000, Rust and Oliver 1994), also for on-line customers (Lopes and Galletta 2006). Consistency of price with performance is an important moderator for customer satisfaction in the process of pre-purchase expectation, actual performance, and post-purchase assessment (Voss et al. 1998). E-service quality in terms of efficiency, reliability, fulfilment, and privacy are key factors to encourage repeat purchase and to build customer loyalty (Zeithaml 2002). On-line shoppers experience costs in terms of product price, charged prices for transportation and delivery, and waiting time between order and delivery, and they experience benefits in terms of quality of delivered products and value of offered services. Because on-line customers miss face-to-face contact with retailers, e-commerce managers need to pay attention to all the aspects of the buying experience and the satisfaction of their customers (Massad et al. 2006, Saeed et al. 2005). Better experiences lead to higher customer e-loyalty, defined as the "customer's favourable attitude toward the e-retailer that results in repeat buying behaviour" (Srinivasan et al. 2002). Loyalty is very important for business profitability, as it costs five to eight times more to attract a new customer than to retain an existing one (Reichheld and Schefter 2000). E-commerce is characterized by a relatively high level of customer loyalty, depending on market share, positioning strategy, concentration of customer spending, and number of operating categories (Huang 2012).

The service quality experienced by on-line customers can be enhanced by offering personalized webpages in the own language of the customer (Gomez-Herrera et al. 2014) and the perceived costs can be reduced by adjusting transport pricing policies and by offering fast delivery options (Jiang et al. 2013). A case study of an on-line grocery shop shows that shipping fees are more important for customer retention than for customer acquisition (Lewis 2006). Simulation models indicate that free ground shipping policies attract 26 percent more customers, but has a negative effect of 82 percent on profit compared to the optimized delivery strategy (Jiang et al. 2013). On-line retailers can try shipping-fee partitioning tactics to generate more customer demand without destroying their margins by subsidizing light, small, and premium priced products, since consumers hesitate about paying shipping charges for these categories (Gumus et al. 2013). They can compete in on-line markets with full product and price information by improving their physical distribution service performance, in particular delivery speed (Rabinovich et al. 2008). The value of freight transport time saving, or equivalently, the willingness to pay for reduced in-transit freight transportation time, has been studied from the B2B viewpoint, showing that express delivery becomes more attractive for regions with higher congestion, for higher-valued goods, and for consumers with higher disposable incomes (Massiani 2014, Zamparini and Reggiani 2007). The choice for express delivery in e-commerce can be seen as the adoption of a new technology, just as e-commerce itself has been studied within the framework of the technology acceptance model (Celik and Yilmaz 2011, Molla and Licker 2005).

E-shoppers in the EU considering a vendor outside their own country used to encounter two problems compared to domestic e-shops: longer lead-times and higher delivery charges. These problems have largely been solved due to express delivery services and increasing economies of scale in cross-border e-commerce traffic (Ducret 2014). A recent survey (ERGP 2014) reveals that express delivery of cross-border e-commerce can substitute standard delivery options. Shorter delivery times provide greater customer satisfaction. From this B2C perspective, rational consumers may base their decisions on the marginal utility of money (Ajzen and Madden 1986, Mahmood et al. 2004) by comparing the extra charges for express delivery with the associated benefits. The express delivery cost depends on the distance of the delivery address from the distribution center and on the weight and volume of the delivered products. The main benefit for the customer is a shorter lead-time. The e-business supplier may also benefit from offering express services, as demonstration of high logistic competence increases customer satisfaction with associated benefits of higher repurchase intention. As stated before, B2C e-commerce equipped with express delivery options for on-line customers has not yet received much attention in the literature so far.

2.3 Research hypotheses

Distance in cross-border e-commerce

The gravity model of international trade postulates that cross-border trade is affected positively by income and negatively by distance. A recent issue of much interest and debate is whether distance effects are declining in modern globalized economies. Whereas some have claimed the death of distance (Cairncross1997) in a flat world (Friedman 2007), others find that distance effects are increasing for off-line international trade (Head and Mayer 2014), and some argue that the world will never be culturally or economically flat (Leamer 2007). Results for cross-border on-line B2C trade are mixed. Distance effects are found to be 65 percent smaller for eBay compared to traditional transactions (Lendle at al. 2016), whereas costs related to payment systems and language barriers eliminate these differences so that the home-bias of European on-line trade is of similar magnitude as that of off-line trade (Gomez-Herrera et al. 2014). Such barriers between countries, as well as other institutional and psychological dimensions like legal frameworks, trade agreements, and culture and history, can be accounted for by allowing for country-specific effects in gravity models (Feenstra 2004, Head and Mayer 2014). These findings lead to the first hypothesis:

Hypothesis 1 (Distance in cross-border e-commerce): E-commerce does not kill distance, because demand for cross-border B2C e-commerce is negatively affected by distance measured in terms of delivery cost and time (after correcting for income and country-specific effects).

E-commerce offers various options to influence the distance perceived by on-line customers (Lendle at al. 2016). On-line shops can employ partitioned delivery pricing strategies that differ from actual shipping charges, which depend mainly on product weight and volume (Gumus et al. 2013). For example, on-line retailers sometimes offer free shipping for expensive products. Express delivery is of particular interest, as it provides e-commerce managers the option to offer their on-line customers a trade-off between the two distance dimensions of delivery time and delivery cost. By including average shipping costs in the product price, e-suppliers can present a flat price when products are delivered by standard ground services. As express services by air are costly and depend on the weight and volume of products, such flat rates are less feasible for express deliveries. The charges for express delivery from transport agents increase with transportation distance, so that cross-border on-line shops may choose to charge higher express delivery costs to customers located farther away from their distribution centers (Massiani 2014). On-line buyers can choose between cheap and slow standard delivery or fast and more expensive express delivery on the basis of perceived values (Zeithaml 1988). Within the EU, express delivery via air freight networks is reliable and guarantees next-day delivery for almost all destinations. The lead-time benefit, that is, the reduction in time between order and delivery, and the extra cost of express charges both depend on the geographical distance between the customer and the (nearest) supplier's distribution center. Express delivery reduces the time dimension and increases the cost dimension of distance experienced by on-line customers. E-customers who choose for the service (Zeithaml 1988, Zeithaml 2002) of express delivery trade their money for time savings and hence show stronger time preference and less price resistance than e-customers who choose for standard delivery. This leads to the following hypothesis:

Hypothesis 2 (Express delivery in cross-border e-commerce): Demand for express delivery in cross-border B2C e-commerce is positively related to reduction of delivery time and negatively related to express delivery charges, and e-demand delivered by express services is more time sensitive and less price sensitive than e-demand delivered by standard ground delivery.

Demand for express delivery in cross-border e-commerce

According to the theory of buyer behavior (Howard and Sheth 1969, Rust and Oliver 1994), consumer satisfaction from purchase decisions depends on the evaluation of the sacrifices made and the rewards obtained. The above discussion shows that express delivery options present on-line customers with a trade-off between the sacrifice of higher charges and the reward of shorter lead times. It is usually assumed that the effect of extra stimuli is proportional to the base level (Weber 1975) and hence diminishes at higher levels (Gossen 1983). The utility derived from, for example, one extra unit of money is higher for smaller income, just like the eye is more sensitive to light when coming from the dark. Customers will tend to compare the utility derived from express delivery with that of standard ground delivery in terms of the associated relative – as opposed to absolute – gains and losses. The lead-time benefit is therefore defined as the difference between the delivery times of standard and express transport, relative to the standard delivery time. The express cost mark-up ratio is defined in a similar way in terms of the total price the customer has to pay for the product and its delivery, that is, as the difference between the total price charged for express and standard delivery relative to the total price charged for standard delivery. Furthermore, as negative stimuli of express charges are felt less intensely for higher income levels, the willingness to pay for express services is expected to increase with income (Zamparini and Reggiani 2007). These considerations lead to the following hypothesis:

Hypothesis 3 (Adoption of express delivery in cross-border e-commerce): The willingness to adopt express delivery services in cross-border B2C e-commerce is positively related to income and lead-time benefits and negatively related to the express cost mark-up ratio.

Customer loyalty and express delivery adoption

Like any other business, cross-border e-commerce has to be a financially viable enterprise. Indicators of financial performance of e-shops are the repurchase rate, i.e., the fraction of all purchasing transactions made by returning customers; the average order size per transaction; and the order incidence, that is, the average number of orders per unit of time and population. E-commerce managers have various ways to influence the financial performance of their business. They can increase the repurchase rate by providing satisfactory levels of service quality to improve loyalty (Cronin et al. 2000, Rabinovich et al. 2008, Rust and Oliver 1994), and the order size by exploiting threshold effects (Becerril-Arreola et al. 2013) and by offering discounted or free shipping (Gumus et al. 2013). The quality of provided services is important to attract and retain e-customers (Massad et al. 2006, Saeed et al. 2005). The usefulness of e-commerce to customers depends on how far it simplifies and improves the effectiveness of their shopping. Reliability and speed of delivery are dominant factors, and express delivery provides an important service to cross-border on-line buyers to reduce distance effects. This leads to:

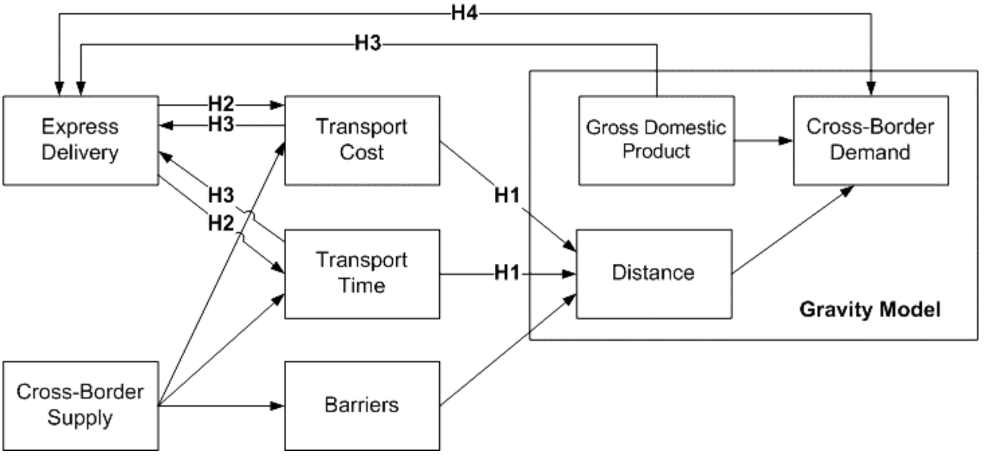


Figure 2.1: Gravity factors in cross-border e-commerce with four hypotheses.

Hypothesis 4 (Customer loyalty and adoption of express delivery in cross-border e-commerce): The adoption rate of express delivery in cross-border B2C e-commerce is positively associated with customer loyalty in terms of repurchase rates.

Figure 2.1 summarizes the main variables, relations, and hypotheses related to cross-border e-commerce within the framework of gravity models for cross-border B2C e-commerce.

2.4 Data and methodology

Case study setting

Cross-border e-shopping is especially attractive for customers looking for products that are not easily available from domestic e-shops or local off-line shops. This holds true, for example, for products with low and uncertain demand and low profit, such as accessories, recently launched products, and spare parts. Cross-border e-commerce is therefore an attractive business model for product categories like consumer electronics that have high stock keeping costs due to short life spans and widely differentiated assortments. Manufacturers of such products often prefer to run a centralized distribution system because cross-border virtual presence is more feasible and less expensive than local supply of these products (Quelch and Klein 1996). They can bypass retailers through on-line distribution channels (Van Heel et al. 2014) using a central distribution center (CDC) to efficiently manage stock and uncertain demand. Some consumer electronics manufacturers are already selling directly, enabling shoppers in many countries to buy products on-line and have them shipped from the company’s factory or CDC. Such centralized on-line shops offer an interesting case to examine the relationship between express delivery and on-line behavior, in particular if customers have no alternative purchasing channels for the products they need.

This paper provides an empirical analysis of express delivery services in cross-border e-commerce by means of a case study with transaction data of a large and worldwide operating consumer electronics manufacturer. The CDC is located in the Netherlands and provides cross-border e-commerce services to 721 regions in five EU countries: Germany, Italy, Spain, Sweden, and the United Kingdom. These countries are EU members that share a largely common legal system and free trade agreements. The on-line product assortment consists of consumer electronics products such as brown goods and white goods, and the e-shop is divided into five main departments: mobile telephony, TV and audio, home appliances, IT products, and accessories. The total number of offered products, including options, varies over time and lies between 1,500 and 2,000. The e-commerce platform is presented to on-line shoppers in their own language (based on their IP address). It provides the same information and services, so that all customers can choose from the same range of products with identical conditions, on-line payment systems, and service options. The manufacturer is currently developing systems for personalized websites for its cross-border on-line customers, but such personalization had not yet been implemented during the case study period that ran from September 2013 through October 2015. Out of a total of 67,899 cross-border on-line purchase transactions during this period, 56,170 of these were delivered by standard ground transport and 11,729 were delivered by express (17 percent).

The e-manufacturer employs a partitioned pricing policy for transport costs. For standard transport, the actual costs that the e-manufacturer has to pay for logistic delivery services are not revealed to the customer and are included in the product price. As these costs differ per destination country, product prices show some variation across countries, but customers within the same country pay the same price for the same product irrespective of where they live. The actual costs that the e-manufacturer has to pay for express delivery depend on the distance between the CDC and the customer as well as on the weight and volume of the product. Express delivery networks in the EU are concentrated in urban areas with suitable freight volumes and low road transportation costs due to high competition between transport companies. Tight links between airfreight networks and well-built road infrastructure allow for fast and reliable express delivery in such areas, whereas in non-urbanized regions the costs of transportation and express services are higher. On the e-shop's website, customers can choose between standard and express delivery. Standard delivery is the default option, and customers have to pay a cost mark-up for express delivery with a flat tariff per country independent of the product, except that for some countries no express costs are charged for orders above a threshold value.

Gravity-based models: trade flows, income, and distance

The classical gravity model (Anderson and Wincoop 2003, Lendle at al. 2016) postulates a multiplicative relation of the form

$$Q_{ij} = \frac{Y_i Y_j}{Y_W} \left(\frac{T_{ij}}{R_i R_j} \right)^{\delta} , \qquad (1)$$

where the symbols have the following meaning: Qij is the trade flow from exporting country j to importing country i; Yi and Yj denote the total income of these two countries, and YW is total world income; Tij are the trade costs from country j to country i; Ri and Rj denote resistance effects against import to country i and export from country j, respectively; and δ is the trade cost elasticity. In the gravity literature, the trade costs Tij are usually expressed in terms of the distance Dij between countries i and j, so that $T_{ij} = D_{ij}{}^{\rho}$. By taking the natural logarithm ('ln') of both sides of the trade equation (1), this equation becomes

$$\ln(Q_{ij}) = \ln(Y_i) + \ln(Y_j) - \ln(Y_W) + \delta\rho \ln(D_{ij}) - \delta \ln(R_i) - \delta \ln(R_j) . \qquad (2)$$

This macro-economic model for bilateral trade flows between countries can be adapted to the type of data considered in this paper. These data are at the micro-level of a single manufacturer, and the products flow unilaterally from this manufacturer to customers in various countries. As the manufacturer delivers the products from a single CDC, the exporting country (j) is fixed, so that the term $\alpha_0 = \ln(Y_j) - \ln(Y_W) - \delta\ln(R_j)$ in equation (2) is also fixed. Furthermore, the import delivered by this manufacturer will only be a (small) part of the total imports to each country, so that the income effect ln(Yi) is replaced by βln(Yi). Finally, the term αi = α0 – δln(Ri) in equation (2) acts as a country-specific effect for each importing country (Feenstra 2004, Head and Mayer 2014). By substituting these results into equation (2) and defining γ = δρ, we get

$$\ln(Q_i) = \alpha_i + \beta \ln(Y_i) + \gamma \ln(D_i) , \tag{3}$$

where Qi is the cross-border e-commerce trade flow from the CDC to on-line customers in country i with income Yi and at distance Di from the CDC. As the income and distance effects are constant across countries, the five country-specific models (3) can be combined in the joint model

$$\ln(Q_i) = \sum_{h=1}^{5} \alpha_h \Delta_{hi} + \beta \ln(Y_i) + \gamma \ln(D_i) , \tag{4}$$

where Δhi denote country dummies with value Δhi = 1 for h = i and Δhi = 0 for h ≠ i. Finally, as each destination country (i) is divided into various delivery regions (r) with region-specific cross-border on-line demand Qir, regional income Yir, and distance Dir from this region to the CDC, the gravity-based model for the case study data becomes

$$\ln(Q_{ir}) = \sum_{h=1}^{5} \alpha_h \Delta_{hi} + \beta \ln(Y_{ir}) + \gamma \ln(D_{ir}) + \varepsilon_{ir} , \tag{5}$$

where εir represents all effects on cross-border e-commerce flows that are not captured by the gravity factors. This model allows us to estimate distance effects in cross-border e-commerce after controlling for income and country-specific effects including institutional and psychological barriers for trade across borders. Although the distance Dir is taken as the geographical distance in classical gravity models for off-line trade, alternative specifications in terms of delivery time and delivery cost are of interest for e-commerce applications.

The slope parameters (β and γ) in equation (5) have the economic interpretation of elasticities, i.e., e-commerce demand from a region is expected to be β percent higher for each percent higher income and γ percent higher for each percent extra distance from the

CDC. Note that these parameters in equation (5) measure partial effects, i.e., after controlling for the country in which the region lies. Stated otherwise, the gross differences in e-commerce demand between countries with regard to income and distance from the CDC will be captured in the country-specific effects (αh). Evidently, differences in income and especially in distance will be more pronounced between countries than between regions within the same country. For this reason, the country-specific effects may obscure the actual distance effects on e-commerce demand. It is therefore of interest to estimate the above model also after omitting the country-specific effects, so that

$$\ln(Q_{ir}) = \alpha + \beta \ln(Y_{ir}) + \gamma \ln(D_{ir}) + \varepsilon_{ir} \ . \qquad (6)$$

As noted before, the country-specific effects have been introduced in gravity models to account for trade barriers between countries. If these barriers are small, the country-specific effects can be omitted, as no resistance means $Ri = 1$ in equation (1) so that $\alpha i = \alpha 0 – \delta \ln(Ri) = \alpha 0$ is fixed for all countries. It seems not unrealistic to assume that these barriers are relatively small for our case data, because the destination regions lie in five EU countries with close economic and social ties, the e-shop is user-friendly in terms of provided website languages and paying system options, and the manufacturer is world-renowned and based outside the EU so that consumer sentiments with respect to this manufacturer will not differ much among the five countries.

The studied regions differ considerably in terms of population size and income, which affects the value of trade flows and also the amount of uncertainty in the error terms εir in the gravity equations (5) and (6). Stated in statistical terms, the variance of these error terms may differ across regions, in which case the ordinary least squares standard errors are incorrect. It is therefore imperative to test for the presence of heteroskedasticity, for which we use the well-known Breusch-Pagan test (Breusch and Pagan 1979). As we find substantial heteroskedasticity in all our gravity models, we employ White standard errors (White 1980) that are robust to any form of heteroskedasticity.

Gravity statistics per country

We obtained data on population size, geographical distance, and gross domestic product (GDP) from the Eurostat database (Eurostats 2016). These data were collected at the NUTS-

3 level (Nomenclature of Units for Territorial Statistics) with in total 741 regions for the five countries of the case study. The principles for this regional division are that population sizes should be roughly comparable and that administrative divisions and geographic units are favored. The case study is restricted to 721 of these regions, as no demand data are available for twenty regions. The excluded regions, seven of which are for the islands of the Canarias, are relatively small (1.8 percent of total population) and lie relatively far away with an average transportation distance of more than four times that of the other 721 regions.

Table 2.1 provides an overview of some key statistics per country. Population size per region varies considerably, with largest average size in Spain and smallest in Germany. Sweden has the highest income per capita and Spain has the lowest, with a difference of about 80 percent. The other statistics in Table 2.1 are provided by the e-manufacturer. The observation period runs from September 2013 (week 36) to October 2015 (week 44) with operating periods that differ per country because web-shops opened at different moments. The cross-border e-transactions included in the analysis run from July 2014 to October 2015 (71 weeks) for Germany and Spain; from July 2014 to September 2015 (68 weeks) for Italy; from October 2014 to October 2015 (56 weeks) for Sweden; and from September 2013 to October 2014 (60 weeks) for the UK. Among these five countries, the UK is a forerunner in e-commerce and relatively has the most competitive e-market. This manufacturer started its first e-commerce business in the UK, has offered only the express option to the UK since November 2014, and established a new CDC solely for deliveries in the UK in December 2015. For these reasons, we included observations for the UK only until October 2014. Measured per year and per capita, Sweden has the highest number of e-commerce transactions, followed by Germany and the UK. These numbers are relatively the smallest for Italy and Spain. The considerable differences across countries can partly be explained by geographical conditions. Sweden, for example, is sparsely populated and many of its inhabitants live far from off-line shops, making e-commerce an attractive alternative.

	GER	ITA	SPA	SWE	UK	Total
(1) Regions	409	109	48	21	134	721
(2) Population (total, thousands)	81,656	60,550	43,635	9,447	60,739	256,027
(3) Population per region (average, thousands)	200	556	909	450	453	355
(4) Gross domestic product (total, billion euro)	2,606	1,574	997	385	1,694	7,255
(5) Gross domestic product per capita (euro)	31,914	25,988	22,846	40,790	27,884	28,339
(6) Distance from CDC (average, kilometer)	522	1,534	1,796	1,627	806	845
(7) Operating weeks	71	68	71	56	60	65
(8) E-commerce demand (average total per year, euro)	3,103,700	662,826	818,268	977,395	1,588,286	7,150,474
(9) E-commerce demand per thousand capita (average total per year, euro)	38	11	19	103	26	28
(10) Transactions (total)	26,717	11,870	6,599	5,600	17,113	67,899
(11) Transactions (average total per year per million capita)	240	150	111	550	244	209

Table notes

* Regional data for (1-6) are obtained from Eurostat, from the February 2016 releases of 'nama_10r_3popgdp' for population, of 'nama_10r_3popgdp' for gross domestic product, and of the so-called 'tercet flatfiles' for distance.
* Country codes are Germany (GER), Italy (ITA), Spain (SPA), Sweden (SWE), and United Kingdom (UK); 20 of the 741 Eurostat NUTS-3 regions are excluded, with total population size 4,793 thousand (1.8 percent of total), and all statistics (2-11) apply for the 721 included regions.
* The statistics in (3) and (6) are averages per region per country, those in (8), (9), and (11) are yearly averages per country, and those in (10) are totals over the full operating period per country.
* Total is sum total over the five countries in (1), (2), (4), (8), and (10), total average in (5) and (9), average per region in (3) and (6), simple average in (7), and weighted average in (11) with population weights (2) for the five countries.
* Euro values for Sweden and the UK are obtained from the average exchange rate over the operating period per country (1 SEK = 0.108 €, 1 GBP = 1.250 €).

Table 2.1: Gravity statistics per country

E-commerce statistics per region

Table 2.2 shows summary statistics per region of several variables related to the e-commerce transactions of the case study. The total number of transactions per region ranges from 1 to 1,792, with an average of 94. As operating periods differ per country and population sizes differ per region, the available weekly e-sales data per region are evaluated in terms of the yearly average order value per thousand inhabitants, with an average of €16 for standard delivery and €11 for express delivery. The express usage ratio is defined as the percentage of all e-shop transactions delivered by express services. Although this ratio is only 13.4 percent on average, the average regional value of products delivered by express services is 48.6 percent of all deliveries (4,823 out of 9,917), so that express orders are on average much more valuable than standard orders. In other words, customers who order expensive products tend to choose for express delivery more often. The average repurchase rate of all transactions is 10.8 percent, with 10.1 percent for standard deliveries and 13.3 percent for express deliveries.

The lead-times and delivery costs for the e-shop are based on service level agreements from carriers that provide delivery services for cross-border e-commerce shops. Average standard lead-times range from 2.0 days in Germany to 4.4 days in Sweden. Express lead-times are much shorter and flatter across regions and on average range from 1.0 day in Germany and the UK to 1.5 days in Italy. Express deliveries therefore contribute substantially to making the world flatter when measured along the time dimension of distance. The lead-time benefit is defined as the difference in lead-times between standard and express delivery, as a percentage of the standard lead-time. The lead-time of standard deliveries is on average more than twice as long compared to that of express deliveries, and the lead-time benefit of express deliveries is on average 55 percent.

As mentioned before, the e-manufacturer follows a partitioned pricing policy that incorporates the actual overall transport costs in product prices (for standard deliveries) and cost mark-ups (for express deliveries). Details of the pricing policy are confidential and not available for analysis, but transport costs are carried in one way or another by the customers and as such affect total e-commerce demand. The actual delivery costs, relative to the order size per region, are therefore postulated as one of the factors driving the value of cross-border e-commerce demand. These relative delivery costs range from 6.3 to 33.7 percent per region, with an average of 17.0 percent. Furthermore, the express cost mark-up shown to customers will be one of the driving factors for their choice between standard and express delivery, by comparing this cost mark-up to the price they have to pay for their order. The express cost mark-up ratio, defined per region as the express cost mark-up relative to the average order value, is therefore one of the factors that attract customers to express delivery. This ratio ranges from 9.4 to 57.8 percent per region, with an average of 24.4 percent. The e-commerce manager follows country-specific pricing policies, resulting in average express cost ratios that are considerably higher for Spain, Sweden, and the UK (34.6 percent) than for Germany and Italy (20.4 percent). The model for the choice between standard and express deliveries will therefore contain a country-group indicator to account for this difference in cost gap between the two modes of delivery that customers experience in the two country groups.

Variable	Acronym	Mean	Median	Max	Min	St. Dev.
E-commerce demand (total average value per year, euro)	-	9,917.4	4,535.6	369,815.3	55.3	24,703.3
Standard		5,094.7	2,878.6	127,104.7	55.3	9,690.3
Express		4,822.7	1,613.1	279,892.1	0.0	17,825.2
E-commerce demand per thousand capita (total average per year, euro)	Q	27.5	22.2	199.8	0.1	21.6
Standard		16.3	13.5	67.1	0.1	12.1
Express		11.1	7.6	134.6	0.0	13.8
Gross domestic product per capita (thousand euro)	GDPC	27.8	25.4	164.1	11.4	11.9
Distance (average distance from CDC, kilometer)	DIST-KM	844.7	680.3	2,607.1	96.1	531.4
Lead-time (average transport time from CDC, days)	DIST-DAY	2.3	1.9	6.0	1.5	0.8
Standard		2.5	2.0	6.0	2.0	1.0
Express		1.1	1.0	5.0	1.0	0.4
Lead-time benefit (of express, as % of standard lead-time)	LTB	54.5	50.0	83.3	16.7	9.8
Actual delivery cost (average per order, standard and express, euro)	-	6.7	6.3	11.6	6.2	0.8
Relative delivery cost (actual cost as % of value of delivered products)	COST	17.0	16.1	33.7	6.3	3.9
Express cost mark-up charged to customer (euro)	-	8.7	8.4	14.5	5.6	1.1
Express cost mark-up ratio (% of value of delivered products)	ECR	24.4	21.6	57.8	9.4	7.4
Germany and Italy		20.4	20.3	30.6	9.4	2.8
Spain, Sweden, and UK		34.6	34.3	57.8	18.8	5.2
Order size (average per order, standard and express, euro)	-	125.2	126.8	343.2	19.0	59.0
Repurchase rate (% of transactions from existing customers)	RP	10.8	10.8	50.0	0.0	7.3
Express usage ratio (% of transactions delivered by express)	EX	13.4	12.5	45.2	0.0	7.4
Transactions (total, regular and express, full operating period)	N	94.2	55.0	1,792.0	1.0	159.1

Table notes

* The statistics are for 721 regions in five countries: Germany, Italy, Spain, Sweden, and the UK.
* All euro values for Sweden and the UK are obtained by using the average exchange rate over the operating period per country.

Table 2.2: E-commerce statistics per region

2.5 Results on express delivery, distance, and customer loyalty

We first consider simple bivariate relations before presenting empirical results obtained from multivariate models for the empirical investigation of each of the four research hypotheses.

Preliminary results based on bivariate correlations

The classical gravity variables of interest are the value of transport flows, income, and geographical distance. For the value of transport flows (Q), we take the regional order size, i.e., the average value of e-commerce demand per year per thousand inhabitants of the region. Income is measured by annual gross domestic product per capita (GDPC), and distance by the average distance (KM) from the CDC. In e-commerce, customers experience distance along the dimensions of transport time and transport cost. We define transport time as the average number of days between ordering and receiving products (DAY), and transport cost (COST) as the average actual delivery costs relative to the value of delivered products per region. Figure 2.2 shows scatter diagrams of the transport flows for the 721 regions against income and against the three distance variables, for standard deliveries (top row) and for express deliveries (bottom row). Each scatter diagram also shows the simple regression line obtained by regressing the transport flow data on the variable shown on the horizontal axis, where all variables are taken in natural logarithms as is usual in gravity models. Cross-border B2C e-commerce demand is positively related to income and negatively related to distance for each of the three distance dimensions: geographical, time, and cost. These results support Hypothesis 1.

As it is not easy to assess the magnitude of the effects from the diagrams in Figure 2.2, parts (a) and (b) of Table 2.3 show bivariate correlations between the gravity variables (in logarithms). Table 2.3(a) shows the correlations for the combined standard and express delivery flows, and these two flows are split up in Table 2.3(b). Compared to e-demand with standard delivery, e-demand with express delivery shows smaller correlations with income (0.39 vs. 0.47), with geographical distance (-0.34 vs. -0.43), and with delivery cost (-0.46 vs. -0.63), although the correlations with delivery time are similar (-0.34 vs. -0.32). We therefore find support for Hypothesis 2 that all three distance dimensions have negative effects on cross-border B2C e-commerce with express delivery and that the cost and geographical dimensions of distance matter less for express delivery than for standard delivery. However, the time dimension of distance seems to be of similar importance for the two delivery modes.

The scatter diagrams in Figure 2.3 and the correlations in Table 2.3(c) are related to Hypotheses 3 and 4 on the express usage ratio (EX), the percentage of all transactions delivered by express services. As mentioned before, the e-manager uses different pricing policies for delivery costs for Germany and Italy compared to Spain, Sweden, and the UK. We therefore study the bivariate relations of interest separately for these two country groups. The variables involved are the express cost mark-up ratio (ECR) defined by the express cost mark-up as a percentage of the value of delivered products, the lead-time benefit (LTB) of express delivery as percentage of standard lead-time, and the repurchase rate (RP) defined as the percentage of transactions made by previous customers. The first three columns of Figure 2.3 show scatter diagrams of EX against GDPC (in logarithms), LTB, and ECR, for

Germany and Italy in the top row and for Spain, Sweden, and the UK in the bottom row. These diagrams indicate that express usage is negatively related to express costs and weakly positively related to lead-time benefit. Furthermore, it is positively related to income in Spain, Sweden and the UK, but nearly unrelated to income in Germany and Italy. These findings are supported by the correlations in Table 2.3(c), showing the largest cost effects for Spain, Sweden and the UK. As a rule-of-thumb, correlations are significant at the 5 (or 10 or 1) percent level if they are larger in absolute value than $2/\sqrt{n}$ (or $1.65/\sqrt{n}$ or $2.58/\sqrt{n}$), where n is the sample size. In our case n = 721, so that correlations are significant at the 5 (or 10 or 1) percent level if they are larger than 0.075 (or 0.061 or 0.096) in absolute value. The correlation of EX with GDPC is 0.07 and is therefore significant only at the 10 percent level, whereas the positive correlation with LTB (0.24) and the negative correlations with ECR (-0.40 and -0.57) are significant at the 1 percent level. We therefore find support for Hypothesis 3 that willingness to adopt express delivery services in cross-border B2C e-commerce is positively related to lead-time benefits, and negatively related to express charges. However, we find only weak support for the classical gravity variable of income. Finally, the right-most scatter diagram in Figure 2.3 and the correlation of 0.11 between EX and RP (significant at the one percent level) in Table 2.3(c) are in line with Hypothesis 4 that adoption of express delivery and customer loyalty in terms of repurchase rates are positively associated.

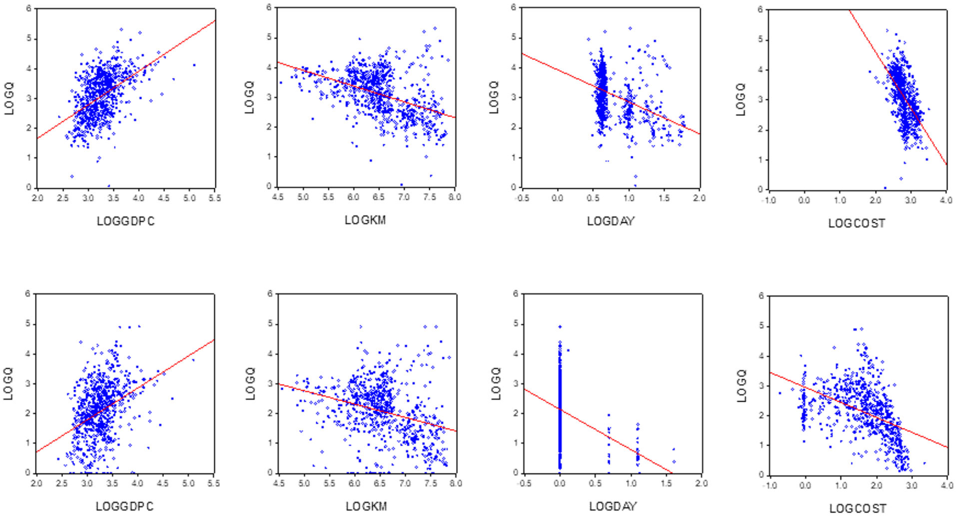


Figure 2.2: Gravity factors in cross-border e-commerce for transactions with standard delivery (top) and with express delivery (bottom)

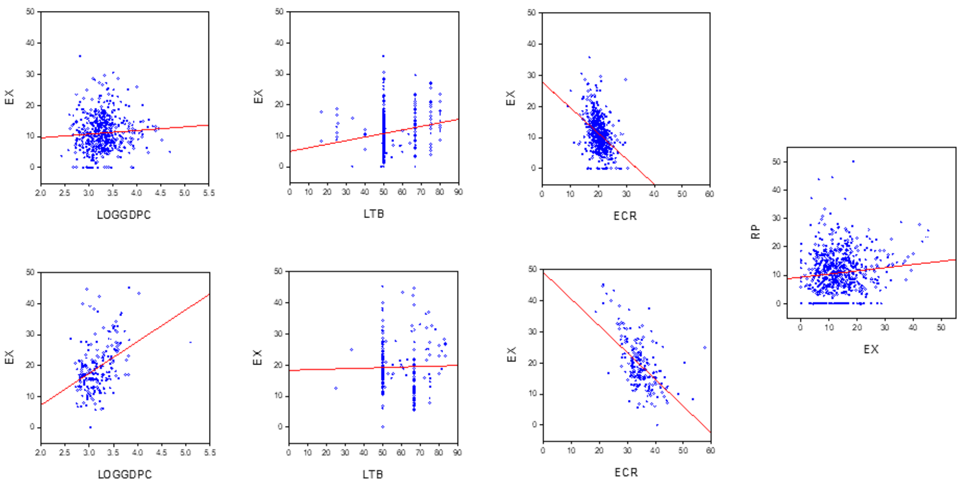


Figure 2.3: Three factors for express delivery adoption (EX) in cross-border e-commerce in Germany and Italy (top) and in Spain, Sweden

(a) Total	Q	GDPC	DIST-KM	DIST-DAY	COST
Q	1				
GDPC	0.50	1			
DIST-KM	-0.45	-0.27	1		
DIST-DAY	-0.41	-0.24	0.64	1	
COST	-0.56	-0.34	0.35	0.22	1
(b) Standard / Express					
Q	X	0.39	-0.34	-0.34	-0.46
GDPC	0.47	X	-0.27	-0.27	-0.14
DIST-KM	-0.43	-0.27	X	0.37	0.37
DIST-DAY	-0.32	-0.21	0.67	X	0.26
COST	-0.63	-0.29	0.34	0.21	X

(c) Total	EX	GDPC	LTB	ECR-GI	ECR-SSU	RP
EX	1					
GDPC	0.07	1				
LTB	0.24	-0.03	1			
ECR-GI	-0.40	-0.14	-0.10	1		
ECR-SSU	-0.57	-0.28	0.14	X	1	
RP	0.11	0.11	-0.01	-0.18	-0.39	1

Table notes

* Variable acronyms are explained in Table 2; ECR-GI and ECR-SSU are the average express cost mark-up ratio (ECR) respectively for Germany and Italy and for Spain, Sweden and the UK.
* All variables in Tables (a) and (b) are in logarithms, and in Table (c) income (GDPC) is in logarithms whereas the other (ratio) variables EX, LTB, ECR, and RP are all in levels.
* Tables (a) and (c) are for the regional observations of joint regular and express flows, whereas Table (b) shows correlations for the regular flows at the south-west corner and those for express flows at the north-east corner (the express flows are 0 for 21 regions and COST is undefined for those 21 cases).
* In Table (c), the correlations for ECR-GI are based on 518 regions and those for ECR-SSU on 203 regions.

Table 2.3: Correlations between (logarithmic) gravity variables and between e-commerce variables

Empirical results for distance in cross-border e-commerce (Hypothesis 1)

The case study data provide cross-border e-commerce flows from the manufacturer's CDC to e-customers in 721 regions in five EU countries. We start by relating these flows to the classical gravity variables income and distance by means of the simple gravity model (6). Because the regions vary in operating period and population size, the value of demand flow per region is standardized to the average e-commerce demand (with standard and express deliveries combined) per year per thousand inhabitants of the region (Q as defined in Table 2.2). In line with this standardization, the income variable (Y) is defined as the regional gross domestic product per capita (GDPC in Table 2.2). Distance (D) is the average transport distance per region between the CDC and the delivery addresses in that region (DIST-KM in Table 2.2). The least-squares residuals of equation (6) show a considerable amount of heteroskedasticity (the Breusch-Pagan test (Breusch and Pagan 1979) has p-value < 0.0005), so that White standard errors (White 1980) are employed. Similar results hold true for all other gravity regressions in Tables 2.4 and 2.5, so that we will always present White standard errors for the coefficients of all these models. The outcomes of the gravity model (6) are shown in Model (a) in Table 2.4. The income effect is positive and the estimated income elasticity of e-demand of 0.923 does not differ significantly from 1 (p-value 0.335 for the null hypothesis of unit elasticity). This means that two regions that are equally far from the CDC and differ by one percent in income show on average also about one percent difference in e-commerce demand. The distance effect is negative, and one percent extra distance from the CDC leads, under the assumption of fixed income, to about 0.4 percent less demand on average, with 95 percent confidence interval from 0.3 to 0.5 percent. This negative distance effect is in line with classical gravity theory and indicates that (geographical) distance is not 'dead' in e-commerce. The obtained e-demand elasticity of -0.4 confirms elasticities estimated for eBay transactions in a study (Lendle at al. 2016) that range from -0.3 to -0.5. These outcomes support Hypothesis 1.

Model (a) in Table 2.4 neglects possible differences in trade barriers across countries. Model (b) in Table 2.4 corrects for such country-specific effects by including e-demand level effects per country, where Germany is taken as reference country as it has the majority of destination regions (409 out of 721). This model is the classical gravity model with trade resistance factors shown in equation (5). The results show that, compared to

Germany and for given income and distance, e-commerce demand is smaller in Italy, the UK, and Spain, and larger in Sweden. The income elasticity is now estimated at about 0.67 (with 95 confidence interval 0.54 to 0.79), which is somewhat smaller than in Model (a). The reason is that the income effect in Model (b) is the effect within each country, thereby eliminating effects that are due to income differences between countries. For the same reason, the distance effect in Model (b) is also smaller than before, with an elasticity of about -0.14 (with 95 percent confidence interval -0.23 to -0.06). Evidently, distances from the CDC differ much less within a country than between countries. Still, distance has a significantly negative effect on e-demand for fixed income and within each of the destination countries. The outcomes of Model (b) therefore also support Hypothesis 1.

Whereas distance is measured in terms of geographical distance in Models (a) and (b), the distance dimensions of time and cost that are relevant for e-commerce are added as additional demand drivers in Models (c) and (d) in Table 2.4. The outcomes of the simple model (6) are qualitatively similar to those of model (5) that includes country-specific effects, so we discuss only the results of the latter Model (d) in Table 2.4 (in terms of 95 percent confidence intervals for the estimated e-demand elasticities). The income elasticity is positive (0.35 to 0.59) and the distance elasticity is negative along all three considered dimensions, i.e., geographical (-0.26 to -0.10), delivery time (-0.49 to -0.17), and delivery cost (-2.02 to -1.16). Note that these distance effects are partial effects so that, for example, if delivery time decreases by 10 percent, demand increases by about 1.7-4.9 percent for fixed geographical distance and fixed delivery cost. Table 2.3(a) shows the evident fact that the three distance variables are positively correlated (with correlations 0.22, 0.35, and 0.64), so that the partial effects in Model (d) in Table 2.4 can be seen as a split-up along three dimensions of the total distance effect. Model (e) in Table 2.4 shows the estimated e-demand elasticities if geographical distance is removed from the model to get uncorrected time and cost effects as experienced by e-customers. The estimated e-demand elasticity is -0.41 for delivery time and -1.52 for delivery cost. As all estimated distance effects in the gravity Models (c)-(e) are significant (even at the one percent level), these outcomes support Hypothesis 1. Distance remains a negative factor in e-commerce, as demand for cross-border B2C supply is significantly negatively affected by distance measured in terms of delivery cost and delivery time, after correcting for income and country-specific effects.

Model	(a)	(b)	(c)	(d)	(e)
Dependent variable	ln(Q)	ln(Q)	ln(Q)	ln(Q)	ln(Q)
Constant	2.688***	2.102***	5.762***	7.413***	6.089***
	(0.447)	(0.348)	(0.452)	(0.745)	(0.627)
Italy	x	-0.936***	x	-0.534***	-0.692***
		(0.071)		(0.092)	(0.074)
Spain	x	-0.364***	x	0.467***	0.244**
		(0.093)		(0.131)	(0.109)
Sweden	x	0.940***	x	1.357***	1.183***
		(0.110)		(0.108)	(0.093)
United Kingdom	x	-0.582***	x	0.067	-0.033
		(0.063)		(0.111)	(0.103)
Gross domestic product per capita (GDPC, log)	0.923***	0.665***	0.668***	0.470***	0.502***
	(0.080)	(0.061)	(0.073)	(0.058)	(0.059)
Distance in kilometer (DIST-KM, log)	-0.399***	-0.143***	-0.140***	-0.175***	x
	(0.040)	(0.043)	(0.043)	(0.040)	
Distance in delivery time (DIST-DAY, log)	x	x	-0.467***	-0.325***	-0.407***
			(0.101)	(0.079)	(0.076)
Distance in delivery cost (COST, log)	x	x	-1.269***	-1.589***	-1.517***
			(0.118)	(0.215)	(0.212)
Sample	Total	Total	Total	Total	Total
Observations	721	721	721	721	721
R-squared	0.354	0.584	0.487	0.674	0.667

Table notes

* Dependent variable ln(Q) is the yearly average value of e-commerce demand per thousand inhabitants (Q, in logarithms) per region.
* Sample "Total" means that the values per region of Q, DIST-KM, DIST-DAY, and COST are based on the combined e-commerce demand flows of standard and express deliveries.
* Germany acts as baseline, and indicators for the other countries allow for country-specific effects; for example, ITALY is an indicator variable that takes value 1 for all regions in Italy and value 0 for all regions outside Italy.
* The table shows ordinary least squares coefficients with White standard errors that are robust against heteroskedasticity; *, ** and *** denote statiscal significance at respectively the 10%, 5%, and 1% level.

Table 2.4: Gravity models for cross-border e-commerce

Empirical results on express delivery in cross-border e-commerce (Hypothesis 2)

In the previous analysis of cross-border e-commerce demand, the trade flows delivered by standard transport and those delivered by express services were combined. We now separate these two flows for each region and estimate gravity models for each e-demand flow separately. The results are shown in Table 2.5, which is comparable in structure to Table 2.4 as Models (a), (c), (d) and (e) in Table 2.4 for the joint flows are split respectively in the model pairs (a,b), (c,d), (e,f), and (g,h) in Table 2.5 for standard and express flows separately. The sample size for express flows is 700 in Models (d,f,h), as 21 of the 721 regions have no demand for express deliveries so that the average delivery cost (COST) is undefined in those cases.

Models (a-d) in Table 2.5 provide e-demand elasticities corresponding to gravity equation (6) under the assumption that trade barriers do not differ between the five EU destination countries. The income elasticity of e-demand is slightly larger for express deliveries (0.91 and 0.76) than for standard deliveries (0.86 and 0.62). The geographic distance effect is weaker for express deliveries (-0.32 and -0.10) than for standard deliveries (-0.39 and -0.18), and the effect for express deliveries in Model (d) is significant only at the 10 percent level (p-value 0.071). The time effect of distance is significantly negative for express deliveries (e-demand elasticity -0.55), but not significant for standard deliveries (p-value 0.159). The cost effect is significant for both types of delivery, with much larger e-demand elasticity for standard deliveries (-1.54) than for express deliveries (-0.39). Summarizing the main findings, e- demand delivered by standard service is negatively affected by the geographic and cost dimensions but not by the time dimension of distance, whereas e-demand delivered by express service is negatively affected by the time and cost dimensions but hardly affected by the geographic dimension of distance. This provides support for Hypothesis 2. First, Model (d) shows that the speed and price of delivery affect cross-border e-commerce demand for products delivered by express service. Second, a comparison of Models (c) and (d) shows that e-commerce demand delivered by express service is more time sensitive and less price sensitive than e-demand delivered by standard ground services.

Models (e) and (f) in Table 2.5 correct for country-specific trade-barrier effects and correspond to the classical gravity model with trade resistance factors in equation (5). Compared to Germany, base levels of e-demand are roughly similar in Spain, lower in Italy, and higher in Sweden. The UK has a lower base level for standard deliveries and a higher level for express deliveries. The income elasticity of e-demand is again somewhat larger for express (0.64) than for standard deliveries (0.46). The time effect is a bit stronger for express (-0.13, significant at 10 percent) than for standard delivery (-0.11, not significant at 10 percent). The price effect is again stronger for standard (-1.42) than for express services (-0.38), and the effect of geographic distance is roughly comparable for both delivery modes (-0.15 and -0.19). Note that these are all partial effects so that, for example, the time elasticity of e-demand of -0.13 for express deliveries means that a 10 percent reduction in express delivery time leads on average to about 1.3 percent extra e-commerce demand delivered by express under the assumption of fixed income, fixed geographical distance, and fixed actual delivery cost.

In Models (e) and (f) of Table 2.5, the e-commerce distance dimensions of time and cost are correlated with geographical distance, and Models (g) and (h) in Table 2.5 show the estimated elasticities after omitting geographical distance. The e-demand elasticities of income, delivery time and delivery cost are roughly comparable to those in Models (e) and (f), except for stronger and more significant effects of time. For fixed income and fixed delivery costs, the e-demand elasticity with respect to delivery time is -0.21 for express and -0.17 for standard services. The outcomes of Models (a-h) in Table 2.5 provide support for Hypothesis 2. Reduced lead-time of express delivery has positive effects on cross-border B2C e-commerce demand according to all three Models (d,f,h). This time effect is indeed considerably larger than for standard delivery in Model (c), but the difference becomes much smaller in Models (e) and (g) after correcting for country-specific effects. The major cause of these reduced differences is that delivery times of standard ground services are strongly related to the destination country, so that much of the delivery time effects are absorbed by the country-specific effects in Models (e-h). The cost dimension of distance has significant negative effects on cross-border B2C e-commerce demand with much stronger effects for standard than for express delivery in all six models (c-h). All these results support Hypothesis 2.

Model	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Dependent variable	ln(Q)	ln(Q)	ln(Q)	ln(Q)	ln(Q)	ln(Q)	ln(Q)	ln(Q)
Constant	2.326*** (0.406)	1.206* (0.636)	6.363*** (0.434)	0.987* (0.577)	6.383*** (0.838)	1.185*** (0.545)	5.235*** (0.720)	0.564** (0.285)
Italy	x	x	x	x	-0.585*** (0.095)	-0.403*** (0.121)	-0.717*** (0.077)	-0.604*** (0.092)
Spain	x	x	x	x	0.356* (0.154)	-0.012 (0.122)	0.163 (0.132)	-0.255*** (0.087)
Sweden	x	x	x	x	0.823*** (0.145)	1.843*** (0.134)	0.673*** (0.129)	1.607*** (0.097)
United Kingdom	x	x	x	x	-0.436*** (0.127)	0.407*** (0.100)	-0.524*** (0.119)	0.316*** (0.093)
Gross domestic product per capita (GDPC, log)	0.857*** (0.080)	0.908*** (0.111)	0.620*** (0.067)	0.756*** (0.098)	0.460*** (0.056)	0.641*** (0.085)	0.490*** (0.055)	0.668*** (0.085)
Distance in kilometer (DIST-KM, log)	-0.386*** (0.033)	-0.320*** (0.056)	-0.184*** (0.040)	-0.101* (0.056)	-0.148*** (0.041)	-0.186*** (0.064)	x	x
Distance in delivery time (DIST-DAY, log)	x	x	-0.125 (0.088)	-0.548*** (0.083)	-0.109 (0.079)	-0.134* (0.078)	-0.171** (0.071)	-0.210*** (0.077)
Distance in delivery cost (COST, log)	x	x	-1.544*** (0.111)	-0.390*** (0.036)	-1.416*** (0.242)	-0.382*** (0.048)	-1.349*** (0.237)	-0.369*** (0.048)
Sample	Standard	Express	Standard	Express	Standard	Express	Standard	Express
Observations	721	721	721	700	721	700	721	700
R-squared	0.321	0.187	0.523	0.351	0.693	0.537	0.687	0.531

Table notes

* This table has the same structure as Table 4.
* Sample “Standard” ("Express') means that the values per region of Q, DIST-KM, DIST-DAY, and COST are based on the e-commerce demand flows with standard (express) deliveries.
* The sample size in Models (d,f,h) is 700, as 21 regions have no express deliveries at all so that the delivery cost (COST) is undefined for express deliveries in these regions.

Table 2.5: Gravity models for cross-border e-commerce with regular and express delivery

Empirical results on express delivery adoption (Hypothesis 3)

The above gravity models analyze cross-border e-commerce demand flows from a macro-economic perspective in terms of income and distance effects. We now turn to the micro-economic perspective of individual e-shoppers and analyze their decisions whether or not to choose express delivery and whether or not to repeat purchasing at the same e-shop. We first consider the express usage ratio, defined as the percentage of e-commerce transactions delivered by express services. Hypothesis 3 states that the willingness to adopt express delivery in cross-border B2C e-commerce is positively related to income and lead-time benefits, and negatively related to express charges. To investigate this hypothesis, we relate the express usage ratio (EX) per region to per capita income (GDPC), lead-time benefit (LTB), and the express cost mark-up ratio (ECR) as defined in Table 2.2. Here the variables EX, LTB and ECR are defined as ratios, so that the coefficients measure the effect of relative changes. For this reason, income is included in the model in logarithmic form so that its coefficient also measures the effect of relative changes in income. As the e-manufacturer applies different delivery pricing policies per country, we incorporate country-specific effects in the model to account for these differences. A disadvantage of including these country-specific effects in the model is that the lead-time benefit of express compared to standard deliveries is strongly related to the destination country, as standard delivery times are longer for distant countries (the multiple correlation between LTB and the five country indicators is 0.58). To reduce this kind of absorption of lead-time benefits, we take into account that the e-managers charge relatively low express prices to Germany and Italy and relatively high ones to Spain, Sweden and the UK (see Table 2.2). We therefore employ a country group indicator with value 1 for high-cost countries (Spain, Sweden and the UK) and value 0 for low-cost countries (Germany and Italy; the correlation between LTB and this country group indicator is 0.28).

Table 2.6 shows the outcomes of two weighted least squares (WLS) estimates for the effects of explanatory factors on the express adoption ratio per region, Model (a) with country-specific effects and Model (b) with country group indicator. We apply WLS because the number of e-commerce transactions varies per region. Let the number of these transactions for a given region be N, then the express usage ratio (EX) for that region is based on N individual choices of e-shoppers, and the sample standard deviation of EX for that region is proportional to $1/\sqrt{N}$. To obtain homoskedastic error terms, that is, with equal standard deviation, the e-commerce data for this region are multiplied by $\sqrt{N}$, and we apply WLS with these regression weights. More precisely, in order to allow estimation by ordinary least squares, we model the express usage ratio by the following equation where Nir is the number of transactions in region r of country i:

$$\sqrt{N_{ir}}\times \mathrm{EX}_{ir} = \alpha_i \sqrt{N_{ir}} + \beta \sqrt{N_{ir}}\times \ln(\mathrm{GDPC}_{ir}) + \gamma \sqrt{N_{ir}}\times \mathrm{LTB}_{ir} + \delta \sqrt{N_{ir}}\times \mathrm{ECR}_{ir} + \varepsilon_{ir} \, . \quad (7)$$

Here the intercept αi differs for all five countries in Model (a) and takes only two different values in Model (b), with one value for Germany and Italy and the other for Spain, Sweden, and the UK. Stated in intuitive terms, data of regions with more e-commerce transactions get a larger weight in estimation with weight proportional to the square root of the number of transactions. The outcomes of Model (a) show significant cost effects, but no significant effect is found for lead-time benefit whereas the income effect is weak and significant only at the ten percent level. Model (b) provides significant coefficients for all variables, with positive effects of income and lead-time benefit and a negative effect of express cost mark-up ratio. A simple interpretation of Model (b) is in terms of changes generating one extra percent point usage of express delivery. This can be achieved by increasing the lead-time benefit by seven percent (1/0.150) compared to the standard delivery lead-time, or by decreasing the cost mark-up of express delivery by 0.7 percent (1/1.477) compared to the price of the delivered product, or if income rises by 0.6 percent (1/1.557).

These outcomes support Hypothesis 3 that the share of express deliveries in cross-border e-commerce demand is significantly positively related to lead-time benefits and income, and significantly negatively related to the express cost mark-up ratio.

Model	(a)	(b)
Dependent variable	EX	EX
Constant	32.803*** (2.313)	28.254*** (2.414)
Italy	3.529*** (0.540)	X
Spain	25.277*** (0.986)	X
Sweden	35.807** (0.887)	x
United Kingdom	27.367*** (0.668)	X
Indicator for Spain, Sweden and the UK	X	29.370*** (0.727)
Gross domestic product per capita (GDPC, log)	0.756* (0.451)	1.557*** (0.489)
Lead-time benefit (LTB)	0.027 (0.021)	0.150*** (0.018)
Express cost mark-up ratio (ECR)	-1.286*** (0.049)	-1.477*** (0.051)
Sample	Total	Total
Observations	721	721
R-squared (weighted / unweighted)	0.806 / 0.407	0.750 / 0.323

Table notes

* Dependent variable is the express usage ratio (EX) per region, that is, the percentage of e-commerce transactions of the region delivered by express services.
* Country indicators and baseline in Model (a) are the same as explained in Table 4.
* The indicator for Spain, Sweden and the UK in Model (b) takes value 1 for these three countries and value 0 for Germany and Italy.
* The table shows weighted least squares coefficients with their associated (WLS) standard errors; the applied weight of each region is equal to the square root of the total number of transactions (N) of that region, that is, $\sqrt{N}$.
* The weighted R-squared applies for the regression with weighted regions, and the unweighted R-squared measures the model fit for unweighted data.

Table 2.6: Models for adoption of express delivery

Empirical results on the adoption of express delivery and customer loyalty (Hypothesis 4)

We finally consider the association between the adoption of express delivery and customer loyalty measured by the repurchase rate. A first indication of positive association is the positive correlation of 0.11 in Table 2.3, which is significant at the one percent significance level (as $0.11 > 2.58/\sqrt{721} = 0.10$). We can also perform the paired t-test to compare the repurchase percentage for express delivery transactions (13.28) with that for standard delivery transactions (10.07). The observations for both delivery modes are paired by means of the regions. The paired t-test (with White standard error) for the repurchase rate difference of 3.21 percent has t-value 4.92 (p-value < 0.0005). This result shows that the repurchase rate is significantly larger for express deliveries than for standard deliveries, which confirms Hypothesis 4 that these two variables are positively associated.

The positive association between the adoption of express delivery and the repurchase rate can be due to various reasons, for example, because the speed of express deliveries increases e-shopper satisfaction and hence repurchase intentions, or reversely, because repurchasing e-shoppers want to increase their satisfaction by adopting express delivery. One way to disentangle these two mutual effects is by analyzing the time lag structure of the relations between the two variables, express usage ratio (EX) and repurchase rate (RP), by means of the Granger causality test (Granger 1969, Sims 1972). As a crude check, we estimate models as in a study (Sims 1972) with single time lags for weekly data on express usage and repurchase rate aggregated over all 721 regions, resulting in time series for EX and RP with 114 weekly observations. The estimated models are $EX = \alpha1 + \beta1\ EX(-1) + \gamma1RP(-1) + \varepsilon1$ and $RP = \alpha2 + \beta2RP(-1) + \gamma2EX(-1) + \varepsilon2$, where (-1) denotes the value in the previous week. Then RP is said to be Granger-causal for EX if $\gamma1$ is non-zero, and EX is said to be Granger-causal for RP if $\gamma2$ is non-zero. Both coefficients are found to be significantly different from zero (p-value 0.008 for $\gamma1$ and 0.006 for $\gamma2$). When evaluated this way, we find that both variables affect each other mutually.

2.6 Discussion and conclusion

Main findings

The objective of our study was to gain insight in the main drivers of cross-border e-commerce demand, and in particular to investigate the effect of various distance dimensions for on-line shopping across borders. These distance dimensions can be reduced in international e-commerce by innovations both at the demand side, where the internet allows for instantaneous and global search for products, and at the supply side by offering fast delivery options. We formulated four hypotheses on cross-border e-commerce and express delivery and tested these by means of data from a case study for consumer electronics products with deliveries from a centralized distribution center to 721 regions in five EU countries. The results can be summarized as follows.

Distance effects in e-commerce and express deliveries were studied in terms of the well-known gravity model for international trade. Distance is still found to be of importance in e-commerce, as e-demand declines with growing distance between supplier and e-customer. The overall e-demand elasticity with respect to geographical distance is -0.4 (Table 2.4(a)), which is in line with the elasticities found for eBay transactions in a study (Lendle at al. 2016) that range from -0.3 to -0.5. The distance effect on e-commerce demand can be split along four dimensions: geographical distance, delivery time, delivery cost, and trade barriers. The overall partial e-demand elasticity with respect to delivery time is about -0.5 for express delivery (Table 2.5(d)) and insignificant for standard delivery (Table 2.5(c)), showing that e-shoppers choosing express delivery are more time sensitive than those choosing standard delivery. Geographical distance has a negative impact on e-commerce demand even after correcting for the effects of delivery time, delivery cost, and country-specific barriers, with partial e-demand elasticities ranging from -0.1 to -0.2 (Tables 2.4 and 2.5). Actual delivery costs are incorporated in product prices and affect e-commerce demand negatively with a partial elasticity of about -1.4 for standard delivery (Table 2.5(ceg)) and -0.4 for express delivery (Table 2.5(dfh)). The above results support Hypothesis 1 that that demand for cross border B2C e-commerce is negatively affected by the delivery cost and delivery time dimensions of distance. The results also support Hypothesis 2 that demand for express delivery in cross-border B2C e-commerce is positively related to shorter delivery times and negatively related to express delivery charges, and that e-demand delivered by express service is more time sensitive and less price sensitive than e-demand delivered by standard service. In the case study, the e-shop uses a partitioned and country-specific pricing policy where the actual costs of standard delivery are included in the product price. As actual delivery costs and hence product prices increase with distance, these costs imply negative distance effects on e-demand indirectly via product prices.

Hypotheses 1 and 2 are related to the macro-level of regional e-commerce flows with standard and express deliveries, whereas Hypotheses 3 and 4 are related to the micro-level of individual e-shopper decisions whether to choose for standard or express delivery, and whether to make repurchases. The willingness to pay for express delivery in cross-border

B2C e-commerce is positively related to income and lead-time benefits, and negatively related to express charges. One extra percentage point express delivery usage can be generated by increasing the lead-time benefit of express delivery by seven percent compared to standard delivery, by decreasing the cost mark-up of express delivery by 0.7 percent compared to the price of the delivered products, or if income rises by 0.6 percent. The repurchase rate lies three percentage points higher for express than for standard deliveries, which is a statistically significant difference. A tentative analysis indicates that express usage and repurchase rates affect each other mutually: past express usage increases current repurchase intentions and repurchasing e-shoppers are more inclined to choose express delivery. These results support Hypotheses 3 and 4 on the willingness to pay for express services and on the positive association between repurchase loyalty and adoption of express delivery in cross-border e-commerce demand.

Practical implications

The results provide insight in the behavior of on-line clients abroad, which can help e-commerce managers in developing strategies to reduce their distance to cross-border clients and to improve their satisfaction when buying via their on-line shops. Customers of e-shops still experience various consequences of the distance from their e-commerce suppliers. The price of ordered products and their delivery, and the lead-time between placing the order and receiving the products have negative impacts on demand volumes. Apart from these objective economic considerations, demand for cross-border B2C e-commerce is also affected by institutional and subjective trade barriers. The case study indicated substantial country-specific effects for e-commerce demand even after correction for differences in income, distance, delivery charges, and delivery times. For fixed income, distance, costs, and delivery times, the value of trade flows per capita is the smallest in Italy, comparable in Germany and in the UK, larger in Spain, and the largest in Sweden (Table 2.4(de)). From a more global perspective, reducing institutional barriers to international trade such as customs costs and border delays will, of course, be beneficial for cross-border e-commerce, but e-commerce managers can also take several measures to reduce distance as perceived by their customers. Examples include offering lower prices and improving delivery speed through improved contracts with transportation companies that provide international e-commerce logistics services. E-managers can rebalance the costs and benefits of their portfolio by applying the type of gravity analysis presented here to their own e-commerce data. Our study indicates that a well-developed international express parcel service integrated with an airfreight network to guarantee fast delivery is important for the development of an EU single digital market. Express delivery can alleviate distance effects along the time dimension at the expense of added distance along the cost dimension. Manufacturers who wish to offer free express delivery to promote market expansion across borders need to gain insight into the relationship between the adoption of express services and factors such as lead-time benefits and delivery costs in their target markets. Another opportunity to increase e-commerce demand is to reduce subjective barriers by means of effective communication and service policies. E-shop websites can be offered in the language of the e-customer and can be personalized based on the preferences and purchase histories of each customer. Simple payment systems and conditions as well as clear delivery and return policies are also essential. Even though our case study is restricted to five EU countries that largely share a common legal system and free trade agreements, the country-specific effects for e-commerce demand are still considerable. To illustrate the magnitude of these effects we consider the results of Table 2.4(e), where the country-specific effects on cross-border e-commerce demand are estimated after correction for differences in income, delivery time, and delivery cost. As the dependent variable in this model is the logarithm of the value of e-commerce demand, the country coefficients show multiplicative effects compared to the baseline country, Germany. For given income, delivery time, and delivery cost, the annual per capita value of e-commerce demand in the UK is about the same as in Germany, whereas in Italy it is about 50 percent lower (exp(-0.692) = 0.50), in Spain it is about 30 percent higher (exp(0.244) = 1.28), and in Sweden it is even more than 300 percent higher (exp(1.183) = 3.26). These country-specific effects are a catch-all for all kinds of differences between countries, including institutional and subjective barriers to international trade, geographic and demographic factors, differences in internet penetration ratio, and the availability of off-line shops in the near vicinity of customers.

The projections in a study (Nagelvoort et al. 2015) indicate great potential for further growth of e-commerce markets in the EU, which some expect to soon turn into a single market (ERGP 2014, Gomez-Herrera et al. 2014). Such projections provide useful knowledge in launching new cross-border e-commerce shops (Ben-Shabat et al. 2013). For the five countries of the case study, the projected e-commerce share as percentage of all retail sales in 2015 is the largest in the UK (15.5), followed by Germany(9.0), Sweden (6.4), Spain (3.0), and Italy (1.1). The projected cross-border e-commerce share as percentage of all e-commerce transactions is the highest in Sweden (23), followed by the UK (14), Germany (11), Spain (11), and Italy (7). These projections suggest ample space for increasing e-commerce activities in the EU and especially for enlarging the share of cross-border e-commerce, for instance, by means of fast and cheap systems for express delivery.

Limitations and future research

The methodology presented here provides an integrated framework for the study of cross-border e-commerce by identifying the driving factors of e-commerce demand and express delivery usage. It can be applied to any cross-border e-commerce market, although specific effect magnitudes may differ per application. Cross-border e-commerce operators can apply the methodology to their own operational data to expand their activities. This type of analysis requires an integrated database containing the following management information per destination region: consumer-related characteristics like (average) income, geographic distance, type of ordered products, and express delivery usage; commercial performance information such as number of transactions, value of ordered products, and repurchase rate; and logistics performance information such as transportation cost, lead-time, and express delivery surcharge. The magnitude of the effects reported here might be specific for the case study, but managers can apply the presented methodology to their own management data to evaluate their own performance and to prepare their own policies in cross-border e-commerce.

The analysis presented here has various limitations. The available data are limited to five EU countries that are relatively similar when judged from a global perspective. A valuable extension would be to include more countries that lie further apart and that differ more in terms of income, transportation costs, and delivery times. Another limitation lies on the supply side, as only a single supplier is included in the analysis. The applied gravity framework could therefore analyze only demand factors from importing countries, and not supply factors from exporting countries. Although on-line shoppers on personalized websites offered in their own language may be unaware of the physical location of the supplier and its distribution centers, more variation on the supply side would be helpful for a more detailed study of the effects of product prices and delivery lead-times and costs on cross-border e-commerce demand. Still another limitation relates to specific characteristics of the case study company. The involved product categories cover only a limited part of all cross-border e-commerce transactions. Furthermore, the e-managers of this company apply partitioned and country-specific pricing policies to cover actual transportation costs. One of the consequences of these policies is that e-shoppers make their purchase and delivery decisions based on distorted cost information. Inclusion of more manufacturers with differing pricing policies can help in improving the empirical analysis of the effects of delivery charges on cross-border e-commerce demand.

Conclusion

International e-commerce managers can expand their reach to clients across borders by offering services that reduce perceived distance. This study from an international on-line shop in consumer electronics shows positive effects of express delivery services, where international clients balance the benefits of faster delivery against express surcharges. The choice for express delivery is more probable for repurchasing clients with higher incomes and when express delivery provides greater lead-time benefits with low surcharges compared to standard delivery. The study is restricted to relatively wealthy EU countries, where the e-commerce market is still in its early stages as compared to US. Cross-border e-commerce is even less developed, and e-managers across the globe have great opportunities to extend their business across borders if they succeed in developing a closer relationship with their clients in terms of trust and services, including delivery time and price.

Chapter 3

Spare part demand forecasting for consumer goods using installed base information

3.1 Introduction

For owners and users, it is frustrating if a product or system can no longer be used because a small component failed and spare parts are not available. The timely availability of spare parts is therefore an important issue for users, especially for ageing products. Providing spare parts, however, is a challenge for Original Equipment Manufacturers (OEMs), as users can be spread over the world and demand is typically intermittent (Boylan and Syntetos 2009). In many cases, demand is high for some parts and very small for other parts, resulting in surplus stocks. Forecasting the location and size of demand per spare part is therefore an important aspect in spare parts management. It plays a major role in determining the final production run that should guarantee parts availability for the remaining service life (see e.g.

Van der Heijden and Iskandar 2013). It is also important to determine where and how much parts should be in stock, especially if the demand is decreasing.

Much research has been devoted to forecasting spare parts demand. Boylan and Syntetos (2009) give a recent overview of methods available so far. They propose a three phase approach, with pre-processing, processing and post-processing. In the pre-processing phase, one classifies the spare parts and selects the forecasting method, which is then applied per class in the second phase. Finally, the obtained forecasts are adjusted in the post-processing phase. The forecasting methods considered by Boylan and Syntetos (2009) are all based on demand data only, without taking any other information into account, similar to forecasting sales of new products. However, forecasting spare parts demand differs from forecasting demand for new products because spare parts are only needed to repair products which are still in use. Hence the location and number of products in use, also called the Installed Base (IB), is of primary interest as generator of spare parts demand. Several authors, including Jalil et al. (2011) and Dekker et al. (2013), have therefore proposed to use IB as the causal variable in forecasting spare parts demand. This kind of approach requires that companies keep track of their IB. That is possible in B2B cases, such as planes (Fokker Services), high-end computers (IBM), or advanced chip making machines (ASML), as users of these expensive systems have service contracts with manufacturers to guarantee timely parts supply. IB forecasting then consists of establishing the demand per product and forecasting the future development of IB. This two-step forecasting procedure does require some work in practice because products may have been adapted for customers and demand may also be influenced by local conditions (Jalil et al. 2011).

Although the aforementioned companies all apply IB forecasting, less advanced companies tend to rely only on parts demand data. In an empirical review of seven industrial companies, Wagner and Lindemann (2008) state: “However, most of the case study companies, regardless of their size, have only a ‘cloudy view’ of their current installed base.” In the consumer business area, the contacts between users and manufacturers are even less established and manufacturers usually have little information on their installed base. They are likely to know the number of sales per region, but they generally do not have data on how many products are still in use and when they will be phased out, which is the crucial information for predicting future demand of spare parts. In this paper, we therefore introduce new part classifications and related installed base concepts that can be used in the pre-processing phase of forecasting consumer demand for spare parts and that require a relatively limited amount of management information. The proposed installed base concepts are lifetime IB, warranty IB, economic IB, and mixed IB. Use of lifetime IB assumes that all products stay in the market according to their expected lifetime, which holds mostly for expensive products. Warranty IB assumes that spare parts demand is limited to products for which a warranty still applies. Economic IB assumes that products are discarded when repairs are no longer economic, which is relevant especially for products that evolve quickly, for example, due to technological innovations. Finally, mixed IB is a refinement of economic IB that applies when consumers show heterogeneity in their evaluation of the costs and benefits of repair. These IB concepts will be elaborated and they will be empirically validated through a comparison with standard forecasting for a sample of real cases drawn from a major consumer products manufacturer.

The remainder of this paper is structured as follows. Section 3.2 discusses some background literature, presents the employed concepts of installed base, and formulates the main research hypotheses. The methodology is described in Section 3.3, and it is illustrated in detail for a specific spare part in Section 3.4. Section 3.5 presents the results for a set of eighteen spare parts related to six products. Section 3.6 concludes and summarizes operational implications.

3.2 Installed base

3.2.1 Background literature

The main topic of this paper is spare part demand forecasting for consumer products over their end-of-life phase, using the concept of installed base (IB). We review some background literature on IB forecasting and on the end-of-life production decision, where it should be noted that the term ‘installed base’ has not always been used in the past for describing this concept.

One of the first authors considering life-cycles of products and their related spare parts demand is Yamashina (1989). Assuming given product failure rates and given development of the installed base, he gives formulas for the demand for spare parts. Cohen et al. (1990) mention IB as a possible way of updating forecasts, without going into detail. Brockhoff and Rao (1993) use the IB concept to forecast new product adoption, and Auramo and Ala-Risku (2005) focus on how to obtain IB information in service logistics. Wagner and Lindemann (2008) perform an empirical study on spare parts management within seven engineering companies. They consider the IB concept as part of advanced forecasting and observe that companies have problems in keeping track of their IB and hence have to resort to forecasting based on parts demand only. Hong et al. (2008) consider forecasting of discontinued products and base their forecasts on the number of product sales (without mentioning the term IB.), the discard rate of the product, the failure rate of the service part, and the replacement probability of the failed part. They illustrate their approach with data from an automobile factory. Jin and Liao (2009) use IB within a simulation context for inventory control to satisfy maintenance demand for spare parts and assume that the IB is known. Thereafter, Jalil et al. (2010) describe further experience with IBM and highlight the value of the IB concept. Dekker et al. (2013) review the use of this concept and its application at several companies. Minner (2011) combines reliability models with inventory control to arrive at better forecasts than those obtained by time series analysis, and he evaluates his approach by simulation data. Jin and Tian (2012) use the IB concept in optimizing inventory control policies in case of increasing demand. They illustrate their method by simulations and they do not consider forecasting. Bacchetti and Saccani (2012) provide an extensive overview of spare parts demand forecasting. They investigate the currently still existing gap between research and practice in spare parts management, and they also identify issues in obtaining the IB, using information from Wagner and Lindemann (2008). Finally, Chou et al. (2015) use the concept of IB to forecast final orders of automobile parts. Their first finding is that production costs are higher during EOL than during the mature phase because of loss of economies of scale and of economies of scope. Second, they find that the optimal warranty period during EOL depends on product failure rates.

All the aforementioned contributions to the IB literature assume that the IB information is readily available, or they mention that obtaining this information is an open issue. In practice, this assumption is reasonable only for advanced companies in a business-to-business environment. Further, most papers focus on modeling and determining optimal inventory control policies instead of doing empirical analysis with real data. Our contribution lies in proposing IB concepts that can be applied in practice for B2C supply management of spare parts by means of IB-based empirical demand forecasts during the end-of-life phase of consumer products. We therefore mention some contributions on the question of the final production run or final order size, which is also called the end-of-life decision, and we compare them to our research setting. Teunter and Fortuin (1998) optimize the final order size by minimizing costs for machines with known finite lifetime. They do not evaluate actual forecast accuracy, and their method requires information on production costs, holding costs, and penalty costs that are unavailable in our case. Tibben-Lemke and Amato (2001) predict demand for replacement parts from known failure ratios. Our products have unknown failure ratios, and demand also depends on heterogeneous consumer preferences. Kim and Park (2008) stress the importance of demand forecasting for the EOL phase to decide on final order sizes. Teunter et al. (2011) base their forecasts of sporadic demand on probabilities and potential benefits are illustrated by simulation, not with real data. Islam and Meade (2000) analyze factors inducing replacement rather than repair, including socio-economic factors and improved technology. Pourakbar et al. (2012, 2014) consider final order production decisions for consumer electronic products combined with the option for the manufacturer to replace instead of repair failing products during the warranty period, because prices of these products tend to erode fast while repair costs stay steady over time. We will consider a similar choice between repair and replacement for consumers after the warranty period has expired, and we will model this economic decision by means of the concept of economic installed base. Van der Heijden and Iskandar (2013) study last time buy decisions for products sold under warranty. Their focus on demand forecasting at the start of the EOL phase is similar to ours, but they consider only simulated data and no real-world spare part demand data.

3.2.2 Installed base concepts

Traditionally, demand forecasting is based on simple extrapolation of historical data. Such so-called black-box methods are popular because of their simplicity, as the required information is limited to historical demand data. For time series of (weekly, monthly, quarterly, or yearly) data, these methods have become widespread in business since the work of Box and Jenkins (1976).

For spare parts demand, the past sales of products that contain the part are evidently also relevant. The installed base of the product is the number of sold products that is in use and can therefore lead to demand of its spare parts. More precisely, we define the lifetime installed base as follows. For each time period (week, month, quarter, or year), the lifetime installed base increases with the quantity that leaves the warehouse and it declines with the number of returned products and with the number of products exceeding the expected lifetime. This definition is similar to what Wagner and Lindemann (2008) propose for spare parts business of engineering companies. Consumer (electronic) products are typically sold through independent retailers who do not share sales information with manufacturers. For the electronics company in our case study, it generally takes between two and three weeks after leaving the warehouse before the products are sold and enter the customer base. The sales and demand data are typically available on a weekly basis. Let S(t) be the product sales to customers in week t, let R(t) be the returns from customers of that week, and let L denote the average lifetime of the product, including second-hand usage. Then lifetime installed base (IBL) at the end of week t is defined as follows

$$\mathrm{IBL}(t) = \sum_{i=t-L+1}^{t} (S(i) - R(i))$$

(where sales start in period 1 and S(i) and R(i) are defined as 0 for times i < 1). Inderfurth and Mukherjee (2008) discuss the typical shape of IBL, as shown in Figure 3.1. This shape is characterized by three phases in the product life cycle. First is the initial phase with growing sales per time unit, followed by a mature phase where sales gradually fall back. The IBL curve in Figure 3.1 therefore has an inflection point where the initial phase passes into the mature phase. Finally comes the end-of-life phase, where the product is no longer produced. Demand for spare parts may be expected to be relatively low in the initial phase, as most products are relatively young and will generally function well. This demand is expected to rise during the mature phase and possibly also during early parts of the EOL phase, whereas later on, demand will gradually diminish as more products reach their lifetime.

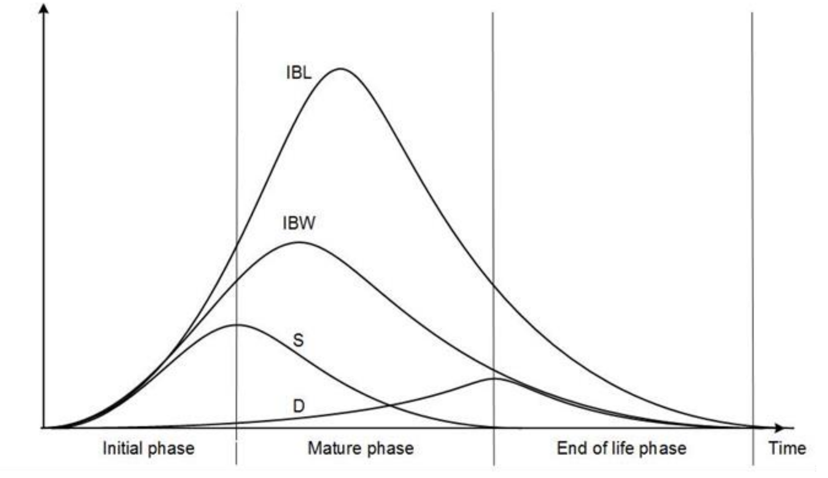


Figure 3.1: Sketch of product sales (S), installed base (IBL and IBW), and spare part demand (D), all measured on the vertical axis, against time on the horizontal axis

Black box methods forecast the demand of spare parts for the EOL phase by extrapolating demand that has been observed during the initial and mature phases. Such methods will tend to over-estimate actual demand, because the increasing demand trends during the mature phase will eventually break down somewhere during the EOL phase, because customers discard the products. Pince and Dekker (2011) report similar problems for forecasts based on exponential smoothing.

Figure 3.1 shows also the typical shape of what we call the *warranty installed base*. Consumers may determine their demand decision for repair based on product warranty regulations. The warranty period is the maximum duration for which the company supports sustainability of the product at its own expense. After this period, customers have to carry costs of repair and logistics by themselves, which may lead them to purchase a new product instead of asking repair of the old one. For a warranty period of W periods, the warranty installed base (IBW) is

$$\mathrm{IBW}(t) = \sum_{i=t-W+1}^{t} (S(i) - R(i)).$$

(again with $S(i) = R(i) = 0$ for $i < 1$). As the warranty period is smaller than the average lifetime of most consumer products, IBW is identical to IBL during the first W sales periods and IBW becomes smaller than IBL afterwards.

After expiration of the warranty period, consumers may still generate demand for spare parts. Such behavior is rational if the remaining economic value of the product after repair exceeds the repair costs. This leads us to the concept of *economic installed base* (IBE), of which the defining ingredients are shown in Figure 3.2. We use the following notation. For period t, let $c(t)$ be the repair costs, let $v_i(t)$ be the remaining economic value of the product bought in week i, and let the economic decision for repair be denoted by $E_i(t) = 1$ if $v_i(t) > c(t)$ and $E_i(t) = 0$ if $v_i(t) \leq c(t)$. Then the economic installed base is defined as that part of the lifetime installed base for which repair is economical, that is,

$$\mathrm{IBE}(t) = \sum_{i=t-L+1}^{t} E_i(t) \times (S(i) - R(i)).$$

(with $S(i) = R(i) = 0$ for $i < 1$). To make this base operational, values of repair costs and remaining value are needed. In our case study, we will take the price of the spare part as the repair cost. We do not incorporate handling and labor costs, as these cost figures are not available and vary per customer location and per type of failure. This choice implies under-estimation of actual costs, and hence over-estimation of the actual economic installed base. In other applications, more accurate values of IBE can be obtained if more accurate cost information is available. The remaining value $v_i(t)$ is determined by assuming exponential value decay and final unity value at the end of average lifetime. Let p_i (>1) be the price of the product sold in period i, then the decay rate a_i for products sold in that period is obtained from the condition that $1 = p_i \times \exp(a_i \times L)$, so that $a_i = -\ln(p_i)/L$. The remaining value in period t is equal to $v_i(t) = p_i \times \exp(a_i \times (t-i))$.

Usually, the remaining economic value of the product exceeds repair costs through all of the warranty period, in which case IBE will take values that lie between IBW and IBL. After the warranty period has ended, it is still economical for some time to demand spare parts for repair. This interim period is longer for longer lifetimes and lower repair costs, as it is more valuable to replace cheap spare parts for prolonged product use than expensive spare parts for short use. Figure 3.2 sketches the remaining value $v(t)$ of a product bought at time $t = 0$ for price p, where it remains economically attractive to pay the repair cost $c(t)$ until time E. Our concept of economic installed base is based on a trade-off between value

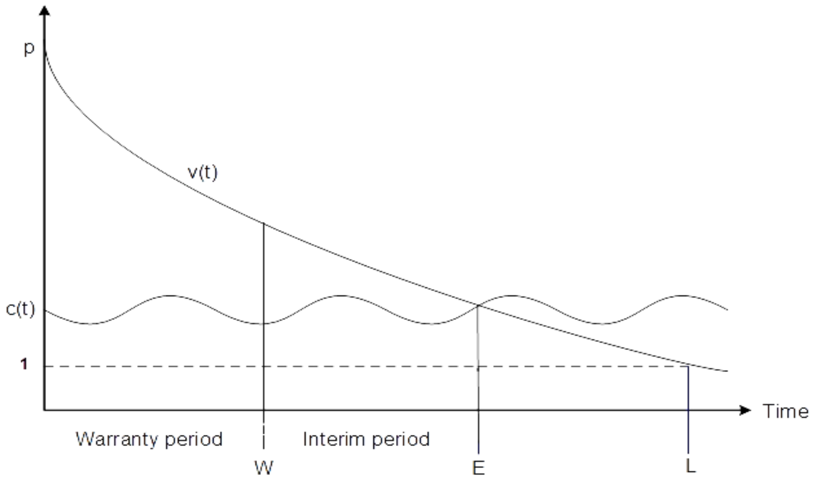


Figure 3.2: Relation between product price (p), remaining economic value (v), spare part cost (c), and lifetime (L); costs and values are measured on the vertical axis, and time on the horizontal axis

and costs made by consumers after expiration of the warranty period and somewhat resembles the trade-off between repair and replacement costs made by manufacturers during the warranty period as studied by Pourakbar et al. (2012).

In the construction of IBE, it is assumed that all consumers apply the same decay rate for remaining value of the product. Consumers may differ in their subjective evaluation of remaining value, for example, if they vary in their sensitivity for social trends and technological innovations. The decision on whether or not it is economical to repair the product will then depend on heterogeneous tastes. For this situation of mixed economic decisions, we define the mixed economic installed base (IBM) similar to IBE, but with varying perceived lifetimes so that value decay rates are heterogeneous across users. In our IBM applications, we follow Rogers (2003) and divide consumers in five adopter segments. Early adopters replace the product relatively fast, corresponding to a relatively short lifecycle. In line with Rogers (2003), the consumers are distributed as follows over the segments (in parenthesis is the lifecycle within each segment, as fraction of the overall average): 2.5% innovators (0.6), 13.5% early adopters (0.7), 34% early majority (1.0), 34% late majority (1.05), and 16% laggards (1.3).

3.2.3 Research hypotheses

As discussed in the literature review, the distinguishing feature of our research on installed base is that we consider its use in forecasting real-world demand for spare parts of consumer products during the end-of-life phase. Previous studies concerned either demand for end products instead of spare parts, or demand for spare parts arising from maintenance contracts with large clients and with operational information on the number of products in use, or simulation studies instead of real demand data. The main question in forecasting consumer spare part demand with installed base is which type of base gives the best information. The answer to this question is likely to depend on characteristics of the spare part and of the product. We formulate a set of research hypotheses, which are tested empirically in Sections 3.4 and 3.5.

The *first hypothesis* is that forecasts from installed base improve upon simple black box methods that only use historical demand data. This hypothesis is in line with the findings of Jin et al. (2006) and Pince and Dekker (2011) that the extrapolation of historical demand data may misrepresent actual spare part demand. The *second hypothesis* is that lifetime installed base provides the best forecasts for essential and expensive spare parts of non-trendy products with long lifetime, whereas warranty installed base is better for products with short life cycle. This hypothesis is motivated by the assumption that consumers make a rational decision when a product fails after its warranty has expired, by trading off the marginal benefits of repair against the repair costs. Obviously, the benefits are larger for longer life times. The *third hypothesis* is that economic installed base works best for non-essential spare parts of products with long lifetime. This situation corresponds to a relatively long interim period in Figure 3.2, where users can decide to repair non-essential parts if the remaining lifetime is long enough to compensate repair costs. If repair of the spare part is relatively expensive but not mandatory, then the product can simply still be used without repair. Finally, the *fourth hypothesis* is that mixed economic installed base works best if consumers differ much in their acceptance of new products. If, for example, many consumers switch to a new product before the old one has lost its function, then spare part demand for the old product falls below what is expected from a purely economic point of view. This kind of behavior can be observed in particular for innovative products if consumers derive higher utility from switching to a new product than from prolonged use of the old product.

Pourakbar et al (2012) mention the example of cathode ray tubes (CRT) for TV's and monitors, where CRT failures often lead users to switch to liquid crystal display (LCD), plasma, or organic light emitting diode (OLED) screens even if CRT repair would still be economically profitable when measured by expected gained lifetime.

3.3 Forecast methodology

3.3.1 Installed base and spare part demand

As we wish to use installed base to predict real-life spare part demand for consumer products, we need a model that relates installed base to this demand in terms of the available empirical information. In order to set up our model, we first make a set of simplifying assumptions that will later be relaxed. We first assume that the product is sold only in period 0 and that the spare part is so cheap that it will be replaced when it breaks down. As time goes by, ageing of the product affects spare part demand in two ways, that is, wear-out and end-of-use. For a given customer, let T_1 be the (continuously measured) time of failure of the product requiring a spare part for repair, and let T_2 be the (continuously measured) time where this customer ends use of the product. Both times can be seen as random variables, with survival distributions $S_i(t) = P_i(T_i > t)$, $i = 1,2$. This customer will not demand the spare part if $T_1 \geq T_2$. The demand probability $p_d(t)$ in period t, that runs in continuous time from t-1 to t, is equal to the joint probability $P(t\text{-}1 < T_1 < t,\ T_2 > t)$. Assume that the probability of break-down does not depend on the decision of continued product use, that is, $P(t\text{-}1 < T_1 < t \mid T_2 > t) = P(t\text{-}1 < T_1 < t)$, then the demand probability is

$$p_d(t) = P(t\text{-}1 < T_1 < t,\ T_2 > t) = P(t\text{-}1 < T_1 < t) \times P(T_2 > t) = (S_1(t\text{-}1) - S_1(t)) \times S_2(t). \quad (1)$$

If the hazard rates for product failure and product disuse are both assumed to be constant over time, so that the product and spare part do not age in that sense, then the survival functions are exponential, that is, $S_i(t) = \exp(-a_i t)$ with $a_i > 0$. Then (1) becomes

$$p_d(t) = (\exp(-a_1(t\text{-}1)) - \exp(-a_1 t)) \times \exp(-a_2 t) = (\exp(a_1) - 1) \times \exp(-(a_1 + a_2)t). \quad (2)$$

This is the probability per customer of demand in period t. The expected total demand $D(t)$ in period t, with remaining installed base IB(t), is equal to $p_d(t)\times\mathrm{IB}(t)$. Let $b_0 = \ln(\exp(a_1) - 1)$ and $b_2 = -(a_1 + a_2)$, then (2) gives

$$\ln(D(t)) = b_0 + \ln(\mathrm{IB}(t)) + b_2\times t. \qquad (3)$$

This relation has been obtained under various simplifying assumptions. The variable t in (3) denotes the age of the product, which depends on the moment it was bought. If we neglect product disuse, as this information is usually not available to the manufacturer, then installed base in period t is $\mathrm{IB}(t) = \sum_{s=1}^{t} X(t-s)$, where $X(t - s)$ are the sales in the period s time units before the current one. Then expected demand in period t is $D(t) = \sum_{s=1}^{t} p_d(s)X(t-s) = e^{b_0}\sum_{s=1}^{t} e^{b_2 s}X(t-s)$. The past sales information captured by installed base is not rich enough to retrieve this expected demand, as it only stores the sum-total of past sales and not the specific distribution of sales over the various periods. An approximation of expected demand is obtained by replacing the age-specific weights ($e^{b_2 s}$) by a single weighting factor evaluated at the weighted age of the products, that is, $e^{b_2\,\mathrm{AGE}(t)}$ where AGE(t) is the mean age of the installed base in period t. This approximation gives $D(t) = e^{b_0}e^{b_2\,\mathrm{AGE}(t)}\sum_{s=1}^{t} X(t-s) = e^{b_0}e^{b_2\,\mathrm{AGE}(t)}\,\mathrm{IB}(t)$, or

$$\ln(D(t)) = b_0 + \ln(\mathrm{IB}(t)) + b_2\times \mathrm{AGE}(t). \qquad (4)$$

The coefficient 1 of logarithmic installed base follows from the assumptions that no products are disused and that every break-down of the product results in demand for repair. We replace this coefficient by an arbitrary one to account for the fact that some products will be disused and only a portion of all break-downs will be repaired, as the owner can also decide to buy a new product. The resulting relation is

$$\ln(D(t)) = b_0 + b_1\times\ln(\mathrm{IB}(t)) + b_2\times\mathrm{AGE}(t). \qquad (5)$$

This model is, of course, still a simplification. For example, wear-out of spare parts and end-of-use of products may not have constant hazard rates, which results in more complicated relations. Demand models involving more flexible functions of installed base and product age can be used, provided that sufficient data are available. We mention one example. In our case study, we do not know the original purchase date of products that lead to spare part demand, that is, we do not know the individual ages. If this information were available, model (5) could be replaced by the disaggregated model (3), with t the age of the product and IB(t) the installed base remaining from the sales t weeks before the current date.

3.3.2 Estimation and model selection

Our modelling approach is rather pragmatic. The amount of relevant available demand data is generally limited, so we do not assume to know all details of the data generating process. For example, we do not know the purchase dates of products that lead to spare part demand. Our ambition is therefore limited to produce reasonably accurate forecasts and we choose for rather simple models that are evaluated in terms of their out-of-sample forecast performance. For our case study, we present forecast results that are all based on model (5). We also considered richer specifications, for example, including squared age, but the data available for estimation were in general not rich enough to improve forecasting power. Model (5) corresponds to a regression model if we add an unobserved error $\varepsilon(t)$ term to account for the (unknown) approximation errors of actual demand behavior. Further, to allow for zero values of demand and installed base, the estimated model is specified as follows.

$$\ln(1+D(t)) = b_0 + b_1\times\ln(1+\mathrm{IB}(t)) + b_2\times\mathrm{AGE}(t) + \varepsilon(t). \qquad (6)$$

For simplicity, the error term is assumed to follow an autoregressive (AR) process, because the unknown coefficients b_0, b_1, and b_2 in (6) can then be estimated simply by ordinary least squares. We could allow for more general error correlation structures like ARMA, but this would complicate the estimation and forecasting tasks and could easily cause over-fitting because of the relatively short time interval that is available for estimation in most practical applications. As the actual weekly demand data of the case study spare parts are quite erratic, these demand data are smoothed by taking an exponentially weighted moving average

(EWMA), and we have chosen for smoothing factor 0.06. We did not try to optimize the EWMA smoothing factor in order to prevent over-fitting and we simply used the value of 0.06 that has become popular since RiskMetrics of J. P. Morgan (1996). This means that the demand of the current week gets weight 0.06, whereas the combined weight of previous weeks is 0.94. We compared the results for this choice of left-hand variable in (6) with two other options: without weighting, that is, using actual weekly demand, or with eight-week averaging, as the company needs an average lead time of eight weeks to cover unanticipated demand. We found that models estimated from EWMA smoothed demand, denoted by $D_s(t)$, work best in forecasting, not only to forecast EWMA demand, but also to forecast actual demand and its eight-week average.

Black box forecasts are obtained from pure AR models, that is, with $b_1 = b_2 = 0$ in (6), and with b_0 estimated from the demand data of the initial and mature product phases. The error term is modeled as $\varepsilon(t) = c_1 \times \varepsilon(t\text{-}1) + \ldots + c_p \times \varepsilon(t\text{-}p) + \omega(t)$, where $\omega(t)$ is a white noise process and where the AR order p is determined by forward selection, that is, by increasing this order until the extra lag term becomes insignificant (at 5% level). These orders range from one to three for the spare parts of the case study, and the corresponding AR models provide in general a very good in-sample fit for demand during the initial and mature phases (R-squared values are typically larger than 0.99). We tried out some extensions of this simple black box model by allowing for linear or quadratic time trends and by smoothing, but as these extensions did not improve the forecasts we will only consider pure AR models.

The AR order of the black box model is also used in all installed base models. The corresponding model (6) is estimated for the initial and mature phase of the product for each of the four considered installed base types, that is, IBL, IBW, IBE, and IBM. The mean age is defined in terms of the corresponding installed base type, for example, using only products under warranty in the model with IBW. The installed base term ln(1+IB(t)) is removed from the model if it has a negative coefficient ($b_1 < 0$), as it is a natural requirement that demand is positively related to installed base (for given mean age). Although the above analysis for fixed hazard rates suggests that the coefficient of the mean age term AGE(t) should be negative ($b_2 < 0$), we do not impose this condition. The reason is that other hazard rates provide other age effects, and it is not illogical that spare part demand could increase for higher mean age of the installed base. Insignificant terms are not removed from the model, because insignificance may be due to a short estimation period for the model.

We summarize the steps needed to estimate the candidate models for spare part demand during the initial and mature product phases. First, determine the following characteristics of the product: average lifetime, sales for each period during the initial and mature phases. From the sales data, determine the numerical values of installed base types IBL, IBW, IBE, and IBM, for each period over the full life cycle (initial, mature, and EOL phases). This requires information on warranty period (for IBW), cost of the spare part (for IBE), and consumer segmentation (for IBM). For each installed base, compute the associated values of mean age for each period of the full life cycle. Next, determine the spare part demand data for each period during the initial and mature phases, and compute smoothed values by EWMA. For these smoothed demand data, estimate an AR model and select the AR order p. Estimate four types of installed base models, each with the same AR order, and keep the installed base variable only if it has a positive coefficient.

3.3.3 Forecast evaluation

The procedure described in the previous section provides a set of five models (AR, IBL, IBW, IBE, and IBM) that can be used to forecast spare part demand over the EOL phase. These forecasts use only information that is available at the end of the mature phase, as no EOL information is of course available at the start of EOL. Note, however, that the values of installed base and mean age are completely determined by product sales before EOL, so that these variables can be extrapolated perfectly for the full EOL phase. The forecasts are determined iteratively, as the AR structure implies that forecasts of previous periods affect the forecast for the current period. These forecasts for earlier periods during EOL are not replaced by realized demands, because this information is not available at the start of EOL. The forecasts concern the variable $\ln(1+D_s(t))$, which are easily translated into forecasts of $D_s(t)$. For periods where the installed base is zero, the forecasted demand is manually set equal to zero. This is a logical condition, provided that the installed base type is correct, because no spare parts can be demanded if the installed base has disappeared. The resulting forecasts are for smoothed demand, but in practice one is interested in actual demand. To prevent erratic behavior, the model forecasts are not "unsmoothed', and the forecasts of $D_s(t)$ are directly compared with actual demand $D(t)$.

The forecast performance of the various models can be compared graphically with actual demand by means of a joint time plot for the EOL phase. The forecasts are also numerically compared by means of the following three criteria. The summed error is the difference between the summed forecasts and the summed demand over the EOL phase. Suppose that actual demand data $D(t)$ are available for periods $t_1 \leq t \leq t_2$ of the EOL phase, and let $F(t)$ be the forecasts for these periods; then

$$\text{SUM} = \sum_{t=t_1}^{t_2} (F(t) - D(t)) \,/\, \sum_{t=t_1}^{t_2} D(t). \qquad (7)$$

Positive values correspond to over-estimation of the total need for spare parts during EOL, and negative values correspond to under-estimation. This is our main criterion to compare forecast methods, as it is measures the global quality of forecasting the spare part need during EOL. We also consider two other criteria that measure the local, week-by-week forecast quality, that is, the mean absolute prediction error (MAPE) and the root mean squared prediction error (RMSPE).

$$\text{MAPE} = \frac{\sum_{t=t_1}^{t_2} |F(t) - D(t)|}{\sum_{t=t_1}^{t_2} D(t)}\ , \ \text{RMSPE} = \frac{\sqrt{\frac{1}{t_2 - t_1 + 1}\sum_{t=t_1}^{t_2}(F(t) - D(t))^2}}{\frac{1}{t_2 - t_1 + 1}\sum_{t=t_1}^{t_2} D(t)} = \frac{\sqrt{\sum_{t=t_1}^{t_2}(F(t) - D(t))^2}}{\sum_{t=t_1}^{t_2} D(t) / \sqrt{t_2 - t_1 + 1}}\ . \qquad (8)$$

3.4 Illustrative case: compressor of refrigerator

3.4.1 Product and demand characteristics

The spare parts in our case study are provided by the Western European warehouse of Samsung Electronics. Refrigerators are one of their products with a relatively stable sales pattern. In this section, we analyze the demand for the compressor of a specific type of refrigerator, which we call type 1 to distinguish it from another refrigerator type 2 that is studied in the next section. The compressor is indispensable, as the refrigerator does not function if the compressor is out of order. Compressors are very reliable, and malfunctioning is mainly caused by extreme operating conditions. The compressor is somewhat expensive, as it costs about 100 euro, which is about 18.3 percent of the price of around 550 euro of the refrigerator. The warranty period is 2 years, and the average lifetime of refrigerators is 13 years according to the National Association of Home Builders (2007), which is relatively long for consumer electronics products.

In Section 3.2.3, we formulated a set of research hypotheses for the four installed base types. Consumers see refrigerators as a necessary product without much distinguishing characteristics, apart from size, price, and reliability. We therefore do not expect that consumers differ much in their subjective evaluation of remaining value of the refrigerator, so that a mixed economic installed base does not seem useful. The interim period for economic installed base is obtained from the formula in Section 3.2.2 for the (yearly) decay rate, $a = -\ln(p)/L = -\ln(550)/13 = -0.485$. The remaining value is 18.3 percent when $0.183 = \exp(-0.485 \times y)$, that is, after $y = 3.5$ years. The interim period of Figure 3.2, starting after the warranty period of 2 years, is therefore only 1.5 years. This is rather short for products with an average replacement cycle of 13 years, so that we do not expect large differences between economic and warranty installed base during initial periods. As refrigerators are such stable products, we expect that many consumers are willing to replace the compressor at their own cost for the benefit of considerable extra lifetime of the refrigerator. Our hypothesis is therefore that IBL will provide the best forecasts, better than black box (AR) and alternative installed base types (IBW, IBE, and IBM).

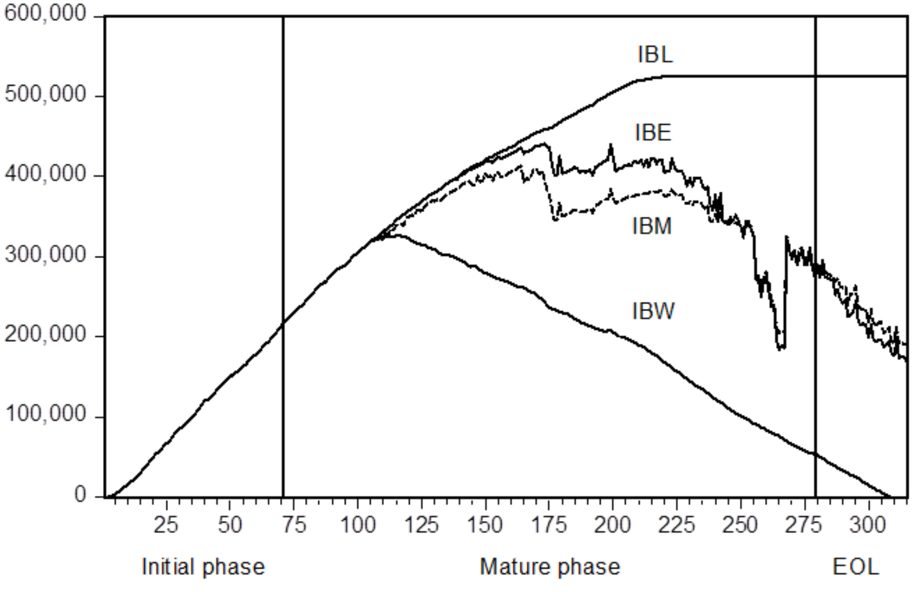


Figure 3.3: Installed base for refrigerator type 1, measured in units on the vertical axis, against time in weeks on the horizontal axis

Time plots of the various installed base types are shown in Figure 3.3. All installed base types are very similar in the initial phase, but start to get differentiated in the mature phase. The sales data run from week 12 in 2008, when sales of this refrigerator started, to week 29 of 2013, when sales ended. Weekly replacement data for the compressor are available from week 12 in 2008 to week 13 of 2014. Total sales of the refrigerator are more than half a million, and the total replacement demand for compressors is 5,678, of which 247 occur in the observed EOL phase. The six years of observations, with 279 weekly sales and 315 weekly demand data, cover less than half of the lifecycle of the product, and the observed EOL phase is only 36 weeks. The forecasting task is to predict demand for these 36 weeks, and there is a relatively long estimation period of 279 weeks for the initial and mature periods. As the case study has been conducted in April 2014, we are not able to evaluate forecasts beyond week 13 of 2014.

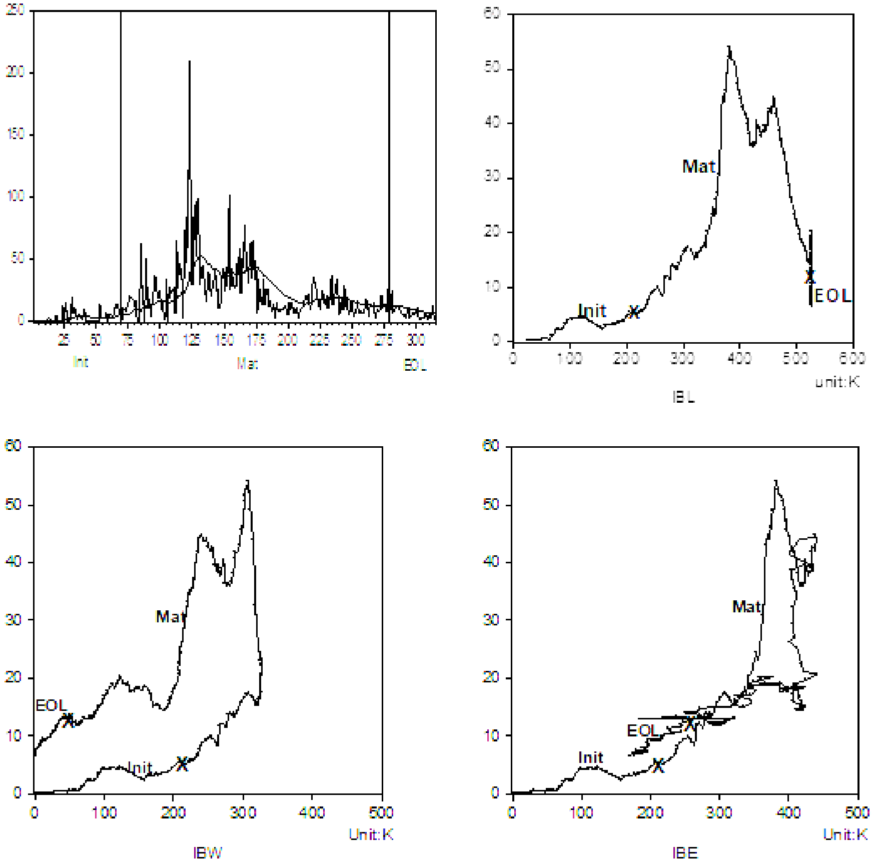


Figure 3.4: Demand for compressor of refrigerator type 1: time series of actual and EWMA smoothed demand against time in weeks (top left), and three scatter diagrams of smoothed demand in units on vertical axis against installed base in 1,000 units on horizontal axis, for lifetime installed base (top right), warranty installed base (bottom left), and economic installed base (bottom right)

The top left diagram in Figure 3.4 shows a time plot of weekly demand during 315 weeks, as well as its EWMA smoothed version. The other diagrams show scatter plots, with EWMA smoothed demand on the vertical axis and installed base (IBL, IBW, and IBE) on the horizontal axis. The task is to determine a relation between installed base and demand from data for the initial and mature phases, and to use this relation to forecast demand during EOL. The scatter diagrams indicate that this is not an easy task, as this relation changes among the various phases of the product. If, for example, one would fit a straight line in the

IBW scatter diagram for the initial and mature phases, then this would systematically overestimate actual demand during the EOL phase. It seems very difficult to make a choice among alternative installed base types solely from the statistical data information in the initial and mature phases. In the foregoing, we used economic arguments on consumer behavior to motivate the choice for IBL.

3.4.2 Forecast results

The obtained black box model is the following AR(2) model: $\ln(1+D_s(t)) = 3.30 + \varepsilon(t)$, with $\varepsilon(t) = 1.13\times\varepsilon(t\text{-}1) - 0.14\times\varepsilon(t\text{-}2) + \omega(t)$. This model provides a very good fit for the smoothed demand data, with $R^2 = 0.997$. Each of the four installed base models has a negative coefficient for installed base, so that this variable is removed. The reduced models contain mean age and AR(2) error terms. The mean age variable has an insignificant negative coefficient in all cases, with the following (one-sided) p-values: 0.09 for IBL, 0.44 for IBW, 0.47 for IBE, and 0.40 for IBM. Even though the effects are weak, we try to exploit this installed base information in forecasting.

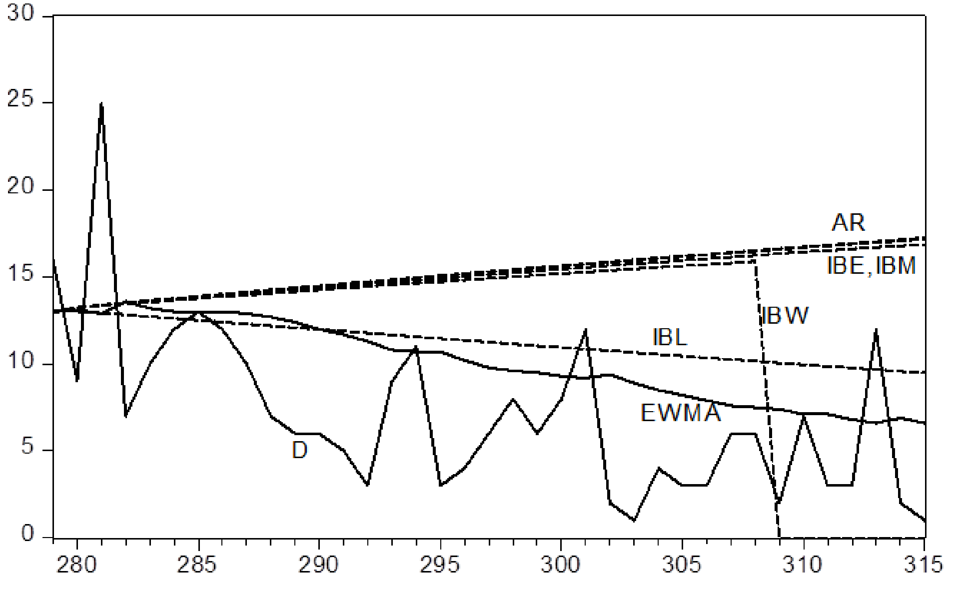


Figure 3.5: Actual demand (D) and smoothed demand (EWMA) for compressor of refrigerator type 1 during end-of-life phase and black box forecasts (AR) and four installed base forecasts (IBL, IBW, IBE, IBM), all measured in units on vertical axis against week number on horizontal axis

Figure 3.5 shows time plots for the observed EOL phase of actual demand and its EWMA smoothed version (solid lines), and the five alternative forecasts (dotted lines). IBL is clearly doing best and is rather successful in tracking the EWMA series that was used to estimate the model. The real interest lies in forecasting actual demand over the EOL phase, and IBL is also the best method in this respect. The models for IBW, IBE, and IBM provide forecasts that are nearly identical to that of the black box model, which is explained by the lack of significance of mean age in these models. The actual total demand over the observed EOL phase is 247, and the predicted totals are as follows: 551 (AR), 404 (IBL), 424 (IBW), 552 (IBE), and 545 (IBM). The relative total error, defined by SUM in (6), is 0.64 (IBL), 0.72 (IBW), 1.21 (IBM), 1.23 (IBE), and 1.23 (AR). IBL provides the best forecasts also in this respect, with IBW as second-best. This ranking is confirmed by the criteria MAPE (0.77 for IBL, 1.05 for IBW, 1.21 for IBE, 1.30 for IBM, 1.33 for AR) and RMSPE (0.87 for IBL, 1.21 for IBW, 1.44 for IBM, 1.46 for IBE, and 1.46 for AR).

Our conclusion is that lifetime installed base provides helpful information to forecast spare part demand for the relatively expensive and essential compressors for this type of refrigerator, which is a non-trendy product with long lifecycle. As compared to black box forecasting, the error in total EOL demand is reduced by a factor of about two (from 304 to 157). These results confirm our first and second research hypotheses formulated in Section 3.2.3.

3.5 Results for three types of consumer products

3.5.1 Overview of eighteen spare parts

We apply the methodology of Section 3.3 to a set of eighteen spare parts related to six products, and we test the relevant research hypotheses of Section 3.2.3 for each case. The products fall in three categories, that is, refrigerators, flat panel televisions, and smartphones. Consumer sentiments and behavior differ among these three products. Sales data are available for two types of each product, and for three spare parts for each product. These spare parts differ in functionality and price. The products differ substantially in terms of both the available estimation data, that is, length of initial and mature phases, and the forecast challenge as measured by the length of the observed EOL phase. Figure 3.6 shows installed base of various types for the two types of each product, refrigerators (top row), televisions (middle row), and smartphones (bottom row). IBE and IBM depend on the (cost of the) spare part, and Figure 3.6 shows these two types of installed base for the most expensive spare part per product. The top left graph is identical to Figure 3.3.

Some characteristics of the products and spare parts are summarized in Table 3.1. The price of spare parts does not incorporate handling and labor costs. These additional costs are rather marginal for televisions and smartphones, because customers can easily bring these products to repair shops. The labor costs are more substantial for refrigerators, because their repair requires that a skilled technician visits the owner at home. Table 3.1 also shows our hypothesis on which installed base is expected to be most useful in forecasting EOL demand. The motivation for each of these hypotheses is described below in Sections 3.5.2-3.5.4, together with the main forecast results for the eighteen spare parts. Further details on models and forecasts are available from the authors upon request.

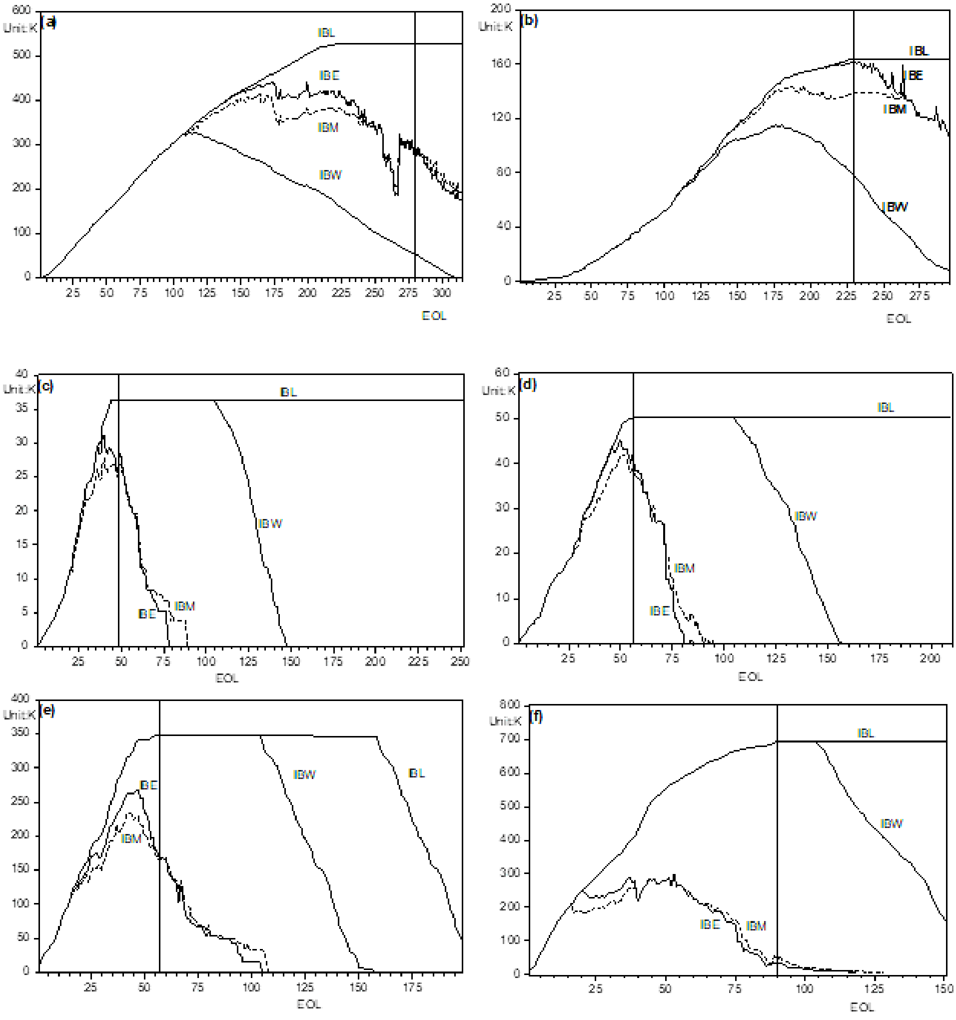


Figure 3.6: Time series of installed base in 1,000 units on vertical axis against time in weeks on horizontal axis for six products: refrigerators (top row), televisions (middle row), and smartphones (bottom row), for type 1 (left column) and type 2 (right column); in each diagram, the vertical line indicates the start of the end-of-life phase

Product	Consumer sentiments		Sales	Period	Estim.	Forec.	Lifecycle
	Life cycle	Tech trendy					
Refrigerator 1	Long	Low	538,386	08.12 - 13.29	279	36	676
Refrigerator 2	Long	Low	166,782	08.32 - 12.51	229	66	676
Television 1	Short	Low	36,766	09.23 - 10.17	100	152	360
Television 2	Short	Low	50,986	10.12 - 11.15	108	102	360
Smartphone 1	Short	High	348,153	10.24 - 11.28	109	89	160
Smartphone 2	Short	High	694,816	11.19 - 13.04	90	61	160

Spare part	Essential	Expensive	Demand		EOL %		Price %		Hypothesis
			1	2	1	2	1	2	
For refrigerator									
Compressor	Yes	Yes	5,678	6,090	4.4	13.6	46.7	39.8	L
Circuit board	No	Yes	9,596	3,518	17.7	36.5	7.6	5.6	E
Door gasket	No	No	4,581	698	17.7	10.0	3.5	3.4	W
For television									
LCD panel	Yes	Yes	868	889	24.9	20.6	47.0	39.4	W
Circuit board	No	Yes	562	774	37.7	39.1	9.6	8.2	W
Cover	No	No	152	230	9.2	16.1	3.2	4.5	W
For smartphone									
Touch screen	Yes	Yes	21,499	58,413	16.5	23.8	19.8	25.8	1W, 2M
Circuit board	No	Yes	6,325	14,492	14.2	37.6	28.6	40.0	1W, 2M
Back cover	No	No	5,259	11,033	42.4	45.8	1.6	1.2	L

Table notes

* Consumer sentiments describe aspects that affect consumer attidudes towards products and spare parts.

* Sales is total product sales during sales period, indicated in format year.week (e.g., 08.12 is week 12 of 2008).

* Estim. and Forec. show number of weeks of data available respectively for estimation and for forecast analysis.

* Lifecycle is average lifetime in weeks, obtained for refrigerators from National Association of Home Builders (2007), for televisions from NPD DisplaySearch (2012), and for smartphones from Entner (2011).

* "Essential" describes whether spare part is essential for product, and "Expensive" indicates relative price of spare part compared to product price (excluding spare part repair costs if service engineer is needed).

* Demand is total spare part demand until analysis date, i.e., week 13 of 2014, for products of type 1 and type 2.

* EOL % shows demand during EOL phase as percentage of demand in initial and mature phases.

* Price % is price of spart part as percentage of product price, for type 1 & for type 2.

* Hypothesis shows installed base hypothesis for the spare part (L for IBL, W for IBW, E for IBE, M for IBM).

Table 3.1: Overview of six products and eighteen spare parts

3.5.2 Refrigerator spare parts demand

Refrigerators have a long lifecycle, and Table 3.1 shows that the forecast evaluation period covers only a small part of the full EOL phase. The product warranty lasts for two years.

An essential and expensive spare part is the compressor (price 14-18% of that of the refrigerator). As was explained in Section 3.4.1, we expect IBL to perform best for this spare part, because repairing the compressor provides large gains in expected lifetime and refrigerators do not quickly get out of fashion. An expensive and non-essential part is the circuit board (relative price 6-8%). The refrigerator works well even if some functions of the circuit board have broken down. As the product has a much longer lifetime than the warranty period and keeps high utility until end of life, our third hypothesis in Section 3.2.3 suggests that consumers make economic decisions and replace this non-essential part if the remaining value of the refrigerator, which has a long lifecycle, is higher than the replacement costs. That is, we expect that IBE will provide the best forecasts. A cheap and non-essential spare part is the door gasket (relative price about 3.5%). Even though this spare part is relatively cheap, replacement by the manufacturer is costly as a specialized repairer should visit the owner at home. We therefore expect consumers to demand this spare part only during the warranty period and to find other solutions after warranty has expired. That is, we expect IBW to provide the best forecasts.

We applied the forecast methodology of Section 3.3.3 for each of the six spare parts, in the same way as was illustrated in Section 3.4 for compressors of the first type of refrigerator. The results are shown in Table 3.2. The outcomes for compressors support our hypotheses, as IBL provides more accurate EOL demand forecasts than the other installed base types. It also performs much better than the black box AR method. The results for the circuit board are varied. Our hypothesis that IBE performs best is confirmed for the first type of refrigerator, but not for the second type where black box forecasts are much better. The cause of the bad forecast performance of IBE in the latter case is that the model has a significant positive coefficient for mean age, which increases steadily over EOL, whereas actual EOL demand is rather stable. Note that this bad forecast performance could not be foreseen at the start of the EOL phase, as the future trends in spare part demand have somehow to be extrapolated from the past. The results for the door gasket are varied, as our hypothesis that IBW is best is confirmed for the second type of refrigerator, but not for the first type where IBM performs better. Overall, the outcomes provide support for the first and second hypotheses of Section 3.2.3 on the value of installed base forecasting and the usefulness of lifetime and warranty installed base, and partial support for the third hypothesis on the usefulness of economic installed base.

Spare part		Installed base			
	AR	L	W	E	M
1, Compressor					
SUM	1.23	0.64	0.72	1.23	1.21
MAPE	1.33	0.77	1.05	1.21	1.30
RMSPE	1.46	0.87	1.21	1.46	1.44
2, Compressor					
SUM	0.81	0.05	0.32	0.17	0.12
MAPE	0.98	0.49	0.62	0.53	0.52
RMSPE	1.08	0.68	0.75	0.69	0.69
1, Circuit board					
SUM	-0.10	0.03	-0.13	-0.01	0.03
MAPE	0.27	0.25	0.39	0.25	0.25
RMSPE	0.32	0.32	0.54	0.31	0.32
2, Circuit board					
SUM	-0.09	3.04	-0.27	2.94	1.37
MAPE	0.27	3.09	0.37	2.99	1.43
RMSPE	0.36	4.07	0.48	3.93	1.68
1, Door gasket					
SUM	-0.08	0.09	-0.15	0.07	0.05
MAPE	0.38	0.47	0.43	0.45	0.44
RMSPE	0.59	0.62	0.61	0.61	0.61
2, Door gasket					
SUM	1.43	0.18	0.07	0.17	0.19
MAPE	1.60	0.94	0.85	0.94	0.94
RMSPE	1.79	1.13	1.13	1.13	1.13

Table notes

* The two types of refrigerator are denoted by 1 and 2.
* Installed base L denotes lifetime, W warranty, E economic, and M mixed economic.
* SUM is the summed forecast error over observed EOL as fraction of EOL demand; a positive (negative) value corresponds to over-forecasting (under-forecasting) actual demand.
* RMSPE and MAPE are respectively the root mean weekly squared prediction error and the mean weekly absolute prediction error over observed EOL, each as fraction of the mean weekly EOL demand.
* The result for the best forecast method (per spare part and criterion) is underlined.

Table 3.2: Forecast results for refrigerator spare parts

3.5.3 Television spare parts demand

High-tech products, like televisions, experience decreasing lifecycles because of fast innovations and quickly developing consumer trends (Pourakbar et al., 2012, 2014). Consumers tend to base their buying decisions for these products less on economic value and more on the wish to own new product features. Therefore, the value of these products as experienced by consumers often decays much faster than the economic lifecycle would suggest. Because of the shortened lifecycle due to innovations, we expect that warranty installed base for these products is in general more informative than lifetime and economic installed base. The warranty period is two years.

Both types of flat screen televisions have very short sales periods of approximately one year. The estimation period for all models is too short to provide reliable forecasts. All methods, including black box, are far off the mark. We conclude that full EOL forecasting after such a short estimation period is too challenging, and instead we consider the more modest task to forecast remaining EOL demand one year after the end of product sales. The estimation period then becomes about two years, and the forecast evaluation period is about three years for television type 1 and about two years for type 2, as type 2 was introduced about one year after type 1.

An expensive and indispensable spare part of the television is the LCD panel. LCD panels are very expensive, with a price of about half that of a new television. As utility of televisions declines rather rapidly over time due to fast product innovations, we expect that IBW provides the best forecasts. An expensive but non-essential part is the circuit board (relative price 8-10%). In many cases, the circuit board keeps its main functionalities even if some options are lost. We expect that customers demand this spare part during the warranty period, but not afterwards, as they may accept some function losses of relatively old televisions with short remaining lifecycle. Again, we expect IBW to perform best. A cheap and non-essential spare part is the cover of the television (relative price 3-5%), but repair is more expensive as it requires a service engineer. As this part is not essential, we expect that owners demand this part only during the warranty period, so that IBW is again expected to give the best forecasts.

Table 3.3 shows the forecast results for television spare parts. Most of the outcomes support our hypotheses, as IBW provides the best EOL demand forecasts in five out of six cases. The only exception is found for circuit boards for the first type of television, where IBE and IBL do slightly better. The differences between the four installed base types are small for this specific spare part, and each of these four methods is considerably better than the black box method. The outcomes therefore support our first and second hypotheses of Section 3.2.3 on the usefulness of warranty installed base for products with short lifecycle.

Spare part		Installed base			
	AR	L	W	E	M
1, LCD panel					
SUM	4.60	22.03	-0.22	-1.00	-1.00
MAPE	4.64	22.03	0.89	0.99	1.00
RMSPE	4.79	24.42	1.48	1.76	1.76
2, LCD panel					
SUM	3.45	0.48	0.46	-1.00	-1.00
MAPE	3.46	0.78	0.95	1.00	1.00
RMSPE	3.73	1.00	1.34	1.39	1.39
1, Circuit board					
SUM	2.31	-0.16	-0.26	-0.03	0.15
MAPE	2.52	0.65	0.68	0.72	0.74
RMSPE	2.75	0.92	0.98	0.98	0.95
2, Circuit board					
SUM	6.26	7.55	0.85	5.77	8.03
MAPE	6.26	7.54	1.48	5.82	8.05
RMSPE	7.37	9.06	1.95	7.68	9.56
1, Cover					
SUM	13.86	5.86	1.20	3.58	3.62
MAPE	14.11	6.51	2.17	4.34	6.51
RMSPE	14.11	7.60	4.34	5.43	7.60
2, Cover					
SUM	4.45	3.53	0.25	2.40	2.01
MAPE	4.69	3.86	1.38	2.76	2.48
RMSPE	5.24	4.14	2.76	3.31	3.31

Table notes

* This table is similar to Table 3.2.

* Spare part demand forecasts are not for the full EOL phase, but for the subperiod starting one year (52 weeks) after begin of EOL.

Table 3.3: Forecast results for television spare parts

3.5.4 Smartphone spare parts demand

The market for smartphones has expanded very rapidly in recent years. Consumers are fast in adopting new technologies, as product innovations expand the functionalities of new phones. Giachetti and Marchi (2010) find that this market is highly competitive, not only between brands but also between products of the same brand. The continuous launch of innovative technologies in the global mobile phone industry stimulates replacing old phones by new ones and reduces spare part demand. The two smartphones in our case study are of the same brand. The first type is an early version, which is followed up within a year of its introduction by a second type that has much better functionalities. Both phones have a warranty period of two years, and the second type is introduced before the warranty period of the first type has expired. The far majority of phones is sold by telecom companies in combination with mandatory financial and maintenance contracts that last for one or two years. Consumers with such contracts are forced to use the product during this mandatory period, irrespective of their subjective evaluation of the remaining product value. We therefore expect that owners of the first type of phone will demand spare parts only during the warranty period, as later on they will wish to switch to the much improved new version. The second type of phone is still up-to-date and fashionable after the warranty period, and late adopters can continue using this phone whereas early adopters will move to newer products. We therefore expect that consumer decisions for the second phone will be mixed. Summarizing, we expect in general that IBW will be the best method for the first phone, and IBM for the second one.

Phones of type 1 have a short sales period of slightly more than a year, which is too short for all forecast models, including black box, to provide reliable forecasts for the full EOL phase. For this phone, we make the same choice as for televisions in the previous section, that is, we forecast remaining EOL demand one year after the end of product sales. The sales period of phones of type 2 is nearly two years, which is sufficiently long to forecast the full observed EOL phase.

Expensive spare parts of smartphones are their circuit board (relative price 29-40%) and touch screen (20-26%). For the reasons stated above, we expect that IBW provides the best forecasts for phone 1 and IBM for phone 2. A very cheap spare part is the back cover (relative price 1-2%). As this part is so cheap and very easy to buy at shops or via internet, we expect that the demand for this spare part is best predicted by IBL.

Table 3.4 shows the forecast results for smartphone spare parts. Our hypotheses for the circuit board are confirmed, as IBW is clearly the best for phone 1 and IBM for phone 2. IBW is also best for touch screens, and this confirms our hypothesis for phone 1 but not for phone 2. The outcomes show that users of both phones replace the touch screen mostly during the warranty period. IBW is also best for back covers, contrary to our expectation that this cheap spare part would be replaced also after warranty has expired. Smartphone users seem not to wish repairing cosmetic parts after warranty has expired, even if the spare part is cheap. Overall, the outcomes provide support for the first hypothesis of Section 3.2.3, and partial support for the second and fourth hypothesis on the usefulness of the various considered installed base types.

Spare part		Installed base			
	AR	L	W	E	M
1, Circuit board					
SUM	6.03	4.04	<u>-0.05</u>	-1.00	-1.00
MAPE	6.05	4.08	<u>0.96</u>	1.00	1.00
RMSPE	6.34	4.66	<u>1.76</u>	2.05	2.05
2, Circuit board					
SUM	0.71	0.78	0.76	-0.24	<u>0.03</u>
MAPE	0.85	0.91	0.89	0.73	<u>0.69</u>
RMSPE	0.99	1.06	1.03	0.93	<u>0.86</u>
1, Touch screen					
SUM	5.03	3.01	<u>-0.31</u>	0.97	2.20
MAPE	5.18	3.16	<u>0.65</u>	1.37	2.44
RMSPE	5.36	3.62	<u>1.25</u>	2.08	2.96
2, Touch screen					
SUM	1.74	0.54	<u>0.36</u>	1.15	-0.45
MAPE	1.77	<u>0.65</u>	0.67	1.26	0.88
RMSPE	1.89	<u>0.80</u>	0.91	1.41	1.15
1, Back cover					
SUM	3.53	4.46	<u>0.83</u>	5.74	5.69
MAPE	3.84	4.76	<u>1.59</u>	6.03	5.99
RMSPE	4.14	5.18	<u>2.07</u>	6.88	6.98
2, Back cover					
SUM	0.42	1.88	<u>0.18</u>	0.70	1.13
MAPE	0.86	2.17	<u>0.67</u>	1.08	1.49
RMSPE	1.13	2.51	<u>0.99</u>	1.25	1.79

Table notes
* This table is similar to Table 3.2.
* Forecast evaluation period is full EOL phase for smartphone type 2, and subperiod starting one year (52 weeks) after begin of EOL for smartphone type 1.

Table 3.4: Forecast results for smart phone spare parts

3.5.5 Theoretical and practical contributions of the study

The main theoretical contribution of our study lies in proposing installed base concepts that are practically viable for B2C companies. The use of installed base in demand forecasting is currently limited to advanced companies in a B2B environment, whereas B2C companies still tend to simply extrapolate past demand patterns. The demand for products of B2B companies often originates from long-term delivery and maintenance contracts with large clients that provide them with reliable operational information on the number of products in use. Even though B2C managers usually lack such detailed information, our study shows that such managers can substantially improve their consumer demand forecasts by employing installed base concepts (lifetime, warranty, economic, and mixed) that can be constructed from the management information available to them. The main question of interest to B2C managers then is which type of installed base gives the best information. We present and test a set of hypotheses on which type of installed base works best for which type of consumer products. The proposed hypotheses are based on characteristics of the product (such as life cycle length and innovation speed) and of the spare part (such as ease of repair and price of spare part relative to price of new product) as well as on product-specific consumer attitudes (such as sensitivity to innovations).

The practical contribution of our study consists of real-life illustrations of the favorable use of installed base in demand forecasting by B2C companies. In particular, we present empirical demand forecasts obtained from installed base to support B2C supply management of eighteen spare parts during the end-of-life (EOL) phase of consumer electronics products. Table 3.5 provides a summary of our hypothesis for each spare part, together with the outcomes discussed in preceding sections. The table also shows the outcomes of two tests to compare the forecast performance of two candidate methods. The first test is a comparison-of-means *t*-test for the forecast errors over the EOL phase, that is, the SUM criterion. The second test is a forecast comparison test proposed by Diebold and Mariano (1995), which is a comparison-of-means *t*-test for the absolute forecast errors over the EOL phase. Their test provides automatic correction for the extensive serial correlation that is present in the weekly series of forecast errors. If our hypothesis is confirmed, then we test whether this method is significantly better than the second-best method as measured by the SUM and MAPE criteria. If our hypothesis is denied, then we test whether the best method is significantly better than the method of the hypothesis. Small p-values indicate that one method is significantly better than the other. The final column in Table 3.5 shows whether our hypothesis is significantly confirmed or denied by the two tests. Confirmation is found in twelve out of eighteen cases, whereas denial occurs in six cases. Possible causes of these denials were discussed in previous sections.

Spare part	Hypothesis	Outcome	Test			Conclusion
			Type	SUM	MAPE	
Refrigerator						
1, Compressor	L	L	L > W	0.000	0.000	Confirmed (2x)
2, Compressor	L	L	L > M	0.000	0.006	Confirmed (2x)
1, Circuit board	E	E	E > L	0.000	0.400	Confirmed (1x)
2, Circuit board	E	AR	AR > E	0.000	0.000	Denied (2x)
1, Door gasket	W	M	M > W	0.001	0.855	Denied (1x)
2, Door gasket	W	W	W > E	0.000	0.293	Confirmed (1x)
Television						
1, LCD panel	W	W	W > E	0.000	0.000	Confirmed (2x)
2, LCD panel	W	W	W > L	0.378	0.995	Weakly confirmed (1x)
1, Circuit board	W	E	E > W	0.000	0.802	Denied (1x)
2, Circuit board	W	W	W > E	0.000	0.000	Confirmed (2x)
1, Cover	W	W	W > E	0.000	0.000	Confirmed (2x)
2, Cover	W	W	W > M	0.000	0.000	Confirmed (2x)
Smartphone						
1, Circuit board	W	W	W > E	0.000	0.400	Confirmed (1x)
2, Circuit board	M	M	M > E	0.001	0.228	Confirmed (1x)
1, Touch screen	W	W	W > E	0.000	0.000	Confirmed (2x)
2, Touch screen	M	W	W > M	0.000	0.021	Denied (2x)
1, Back cover	L	W	W > L	0.000	0.000	Denied (2x)
2, Back cover	L	W	W > L	0.000	0.000	Denied (2x)

Table notes

* Hypothesis on installed base: lifetime L, warranty W, economic E, or mixed economic M.
* Outcome shows the installed base that provides the best forecasts (taken from Tables 2-4); if best method varies across criteria, then method with best SUM is taken as outcome.
* Test type A > B tests whether method A provides better forecasts than method B; if the outcome confirms the hypothesis, then A is the hypothesis and B is second-best method (with respect to SUM); if the outcome differs from the hypothesis, then A is the outcome and B is the hypothesis.
* Test SUM is t-test for mean error, and MAPE is Diebold-Mariano test for absolute errors; the table shows the p-value for the one-sided alternative that base A is better than base B.
* Conclusion "confirmed" denotes that the hypothesis base is significantly better (for 1 or 2 tests) than second-best; "weakly confirmed" means that hypothesis base is best, but not significantly better than the second-best base; "denied" means that the hypothesis base performs significantly worse than the best base; significance level is 5%.

Table 3.5: Evaluation of forecast strategies

We summarize our empirical findings in terms of the four hypotheses of Section 3.2.3. The first hypothesis, that installed base forecasts are better than the considered black box AR methods, is confirmed for seventeen out of the eighteen spare parts in Table 3.5, and Tables 3.2-3.4 show that the improvements are substantial. The second hypothesis concerns the relative performance of lifetime and warranty installed base. Table 3.5 shows that one of these two installed bases is expected to be best for fourteen spare parts, and the hypothesis is confirmed for ten of these spare parts. The most notable exception occurs for back covers of smartphones, where the outcome that IBW is better than IBL is reverse to what was expected. The third hypothesis is on economic installed base, which is our hypothesis for one spare part of refrigerators. This hypothesis is confirmed for one type of refrigerator but not for the other type. The fourth hypothesis is on mixed economic installed base, which is our hypothesis for two spare parts of smartphone type 2. This hypothesis is confirmed for one of these spare parts, but not for the other one.

A final note for practitioners is that EOL demand forecasting is only feasible provided that the learning period consisting of the initial and mature phases is long enough. This condition holds equally well for simple extrapolation methods and for installed base forecasts, as both methods require product-specific information on demand patterns.

3.6 Conclusions

When production of a product stops, the producer faces the important question as to how many spare parts will be needed to cover all future demand of the product during the end-of-life (EOL) phase. The producer then needs to know how many users will repair the product when it fails and which spare parts are needed for the repair. We consider these questions for consumer goods. Consumer decisions on repair will depend on the price of the required spare part and on the evaluation by the user of the remaining value of the product. We propose the concept of installed base to forecast EOL spare part demand for consumer products to support B2C companies in their decisions on final production size. The most suitable type of installed base depends on characteristics of the product, the spare part, and the consumer market. Warranty installed base is advised for spare parts with relatively short lifecycle, and lifetime installed base for essential spare parts for products with long average lifetimes. Economic installed base is useful for non-essential spare parts of products with long average lifetimes that are out of warranty. If consumers differ in their adoption attitudes for product innovations, a mixed economic installed base can be useful. Our case study shows that installed base forecasts improve much upon straightforward black box autoregressive extrapolation of past demand patterns.

Although the specific results will vary across products, the proposed methodology is technically viable to forecast EOL spare part demand for any product. The required information for each product and spare part is the following. First, and most important, time series of product sales and of spare part demand until start of EOL. Further, the average lifetime of the product (for lifetime installed base), the warranty period (for warranty installed base), the cost of the spare part (for economic installed base), and consumer segments (for mixed economic base). We propose to smooth the demand data after screening them for extreme values that may occur, for example, in case of extraordinary failure rates briefly after introduction of a new product. The quality of the forecasts depends on the richness of the available data, ideally with a long estimation period during the production phase and with a limited EOL phase. In practice, the production period is often relatively short as compared to the EOL phase, and this also applies for the products in our case study. We advise to use simple models in such cases, in order to prevent forecast deterioration due to over-fitting. We do not advise a fully automated forecast procedure, because consumer behavior differs widely across products. It can be helpful to cluster products and spare parts in groups, depending on their characteristics and on expected consumer demand behavior. Within each cluster, EOL spare part demand can be forecasted by using one common type of installed base that applies for all products of that cluster.

Chapter 4

Improving warehouse labour efficiency by intentional forecast bias

4.1 Introduction

Warehousing serves as the primary link between producers and customers in the supply chain. It provides buffering for manufacturing operations to manage varying customer demand (Bowersox *et al*. 2002). Labour constitutes about half of all (non-automated) warehouse operation costs (Bartholdi and Hackman 2016). For retail warehouses it is often difficult to determine the exact workforce, as the workload tends to be variable and activities, especially outbound work, have tight deadlines. Many warehouse managers therefore prefer flexible labour pools (De Leeuw and Wiers 2015). Even with flexible pools, labour planning may be inaccurate with negative effects on labour productivity. Forecasting the workload and hence the required capacity is therefore an essential step in warehouse manpower planning (Bond 2012). As managers usually have a good view of upcoming orders, quantitative forecasting methods using historical data can be combined with expert judgement, although this may introduce bias, i.e. systematic differences between forecasts and actual order sizes (Goodwin 1996, 2002). Important questions are how to detect such biases, how to control them, and how they affect labour efficiency, defined as the ratio of required labour over actually hired labour.

This paper presents an empirical methodology to detect forecast bias, defined as the ratio of forecast error over actual order size. It shows how to implement a controlled level of bias to optimise labour efficiency in warehousing, in particular for Original Equipment Manufacturer (OEM) warehouses serving retail distribution centres. The main three research questions are the following. What is the quantitative nature of errors in demand forecasting? How does forecast bias affect labour efficiency? What is the optimal level of forecast bias to optimise labour efficiency? Two statistical models are used to investigate these research questions. One relates historical demand patterns to expert forecasts and forecast errors, and the other relates historical labour efficiency measurements to forecast bias.

The business analytic methods are illustrated in a case study conducted at Samsung Electronics. The analysis provides an empirical test of the theoretical claim in Sanders and Graman (2009) that forecast bias can improve labour efficiency and extends recent work of Van Gils *et al*. (2017) on forecasting methods for personnel planning. The data for the first research question consist of weekly time series on management forecasts and on actual orders. The second and third question are analysed by means of daily labour productivity data and order forecast biases, where productivity is measured at the three consecutive stages of the outbound warehouse operations: picking, packing and loading. To supplement the case study results, information from a survey among thirty warehouses is used to further investigate the productivity effects of forecast bias.

Although the specific details of our empirical findings are case-dependent, the methodology and general conclusions are relevant for warehouse labour management and forecasting. By following this methodology, warehouse managers can determine the level of forecast bias that works best for their situation. Figure 4.1 depicts the methodology as a flow diagram incorporating data, models and activities in data-driven adaptive labour management. We were able to implement this methodology in our case study because the company under investigation continuously collects and stores the required analytics data, including a refined barcode-based labour management system that registers and stores the activities of each individual worker. The company has incorporated the results presented here in the evaluation and redesign of their interrelated management strategies for demand forecasting and labour planning.

This paper is structured as follows. We first provide a literature review and formulate our research hypotheses. Next, we describe the case study environment and summarise data and methods. Then we present our results, starting with the statistical analysis of forecast errors and the demand forecast model in Figure 4.1, followed by the empirical investigation of the relationship between labour efficiency and forecast bias using the labour efficiency model in Figure 4.1. We also discuss the results of a small-scale survey among thirty warehouses. Finally, we summarise operational implications of our analysis and discuss topics for future research.

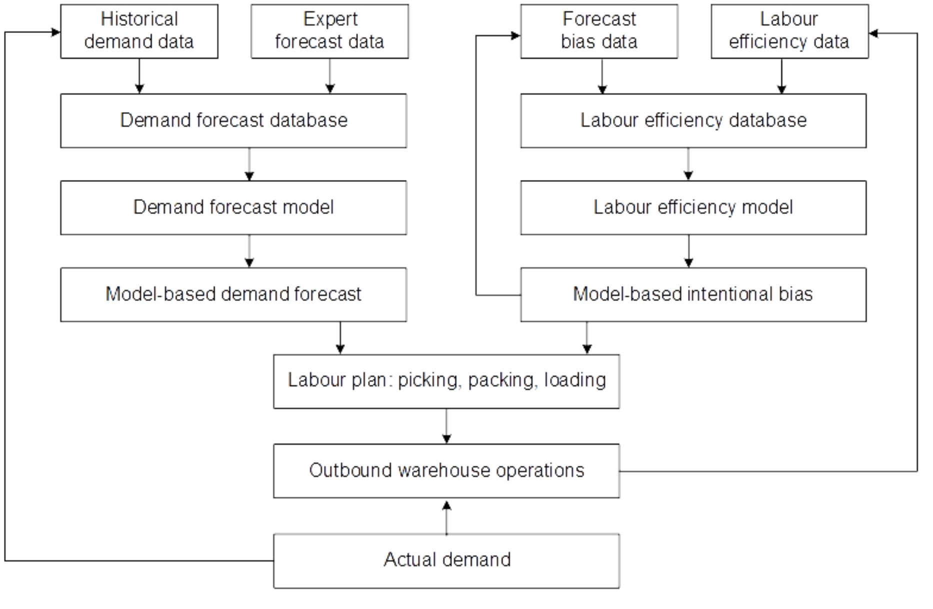


Figure 4.1: Flow diagram of warehouse data, models, activities, and management.

4.2 Literature review and research hypotheses

This literature review examines the three main aspects of our methodology: warehousing, labour management and demand forecasting.

Warehousing

Warehouses receive products in large quantities, reorganise and repackage them and send them out in smaller quantities. Warehouse operations thus consist of inbound processes (receiving and storing goods) and outbound processes (order-picking, packing and shipping). As warehouses can usually regulate the inflow of products well because of tight links with their suppliers, most research studies focus on stocking and outbound processes (Bartholdi and Hackman 2016). Several types of warehouses can be distinguished, e.g. warehouses for retail distribution, for spare parts and for e-commerce. This paper considers OEM warehouses serving retail distribution centres. Such warehouses often play a subordinate role between sales departments and buyer purchasing departments. Their outbound processes tend to be under time pressure as their customers usually operate in just-in-time modes and require deliveries at short notice. Their inbound processes are generally under less time pressure as incoming goods are typically stored as safety stock without small unit handling (Bartholdi and Hackman 2016), except for cross-docked goods. Such warehouses must adapt their workforce to fast demand fluctuations, which makes accurate short-term workload forecasting and efficient labour management essential for smooth operations (Van Gils *et al*. 2017). Although automation is steadily spreading, De Koster *et al*. (2007) report that 80% of all warehouses apply manual picking. Order picking still accounts for about 60% of total labour costs and 50% of overall operational costs (Bartholdi and Hackman 2016). Reviews of the warehousing literature (De Koster *et al.* 2007, Gu *et al*. 2010, Gong and De Koster 2011, Bartholdi and Hackman 2016) show that most research has focused on warehouse design and improved order picking, such as optimising picking routes and selecting good storage locations for fast picking.

Our paper examines interlinked outbound warehouse processes and focuses on labour efficiency and demand forecasting. It does not consider inbound processes and associated inventory strategies, or optimisation of used warehouse space.

Labour management

Customer demand of warehouses for retail distribution is usually characterised by short-term fluctuations. A recent survey by De Leeuw and Wiers (2015) indicates that many warehouses employ both permanent staff and temporary labour to accommodate workload fluctuations. Although temporary work agencies can provide workers at short notice, worker quality may be lower. Some warehouses deliberately operate with excess permanent staff capacity if they cannot rely on temporary staff being available at the right time (Van den Berg 2007). Some studies (Brusco and Johns 1995, Riley and Lockwood 1997) have investigated the balance between permanent and temporary labour under the restrictive assumption that fluctuations are known in advance. Managing the number of warehouse workers remains a key issue in tackling daily demand fluctuations (Ruben and Jacobs 1999, De Koster *et al*. 2007).

Our paper analyses the effect of an intentional level of forecast bias on labour efficiency and uses this relationship to determine the optimal level of bias to maximise this efficiency.

Demand forecasting

Demand and workload forecasting are crucial steps in manufacturing and warehouse management. Forecasts can be based on expert judgement or on quantitative methods. The first are easy to make and include information on future orders, but are often systematically biased (Goodwin 1996, 2002). Quantitative methods using historical data are more complex, but often provide more accurate forecasts (Sanders and Manrodt 2003). Even though unbiased forecasts are valuable for management purposes, some bias may be preferable if the costs of over-forecasting differ substantially from those of under-forecasting. Sanders and Graman (2009) provide simulation evidence that properly managed forecast biases reduce costs if the bias is related to labour and inventory costs. Under-forecasting is attractive if labour costs dominate, whereas over-forecasting is more appealing if the main costs are delay penalties for stock-outs.

Ritzman and King (1993) stress the relevance of forecast bias for inventories in multistage manufacturing, as buffers between stages like picking and packing are helpful in creating flexibility in labour and capacity utilisation. They warn for undesirable biases that originate from optimistic sales projections and misguided attempts at inventory reduction.

Demand forecasts can often be improved by combining expert judgements and historical sales statistics. Combination forecasts outperform individual forecasts especially when the latter employ diverse sources of information (Aiolfi *et al*. 2011). Managers incorporate qualitative information in their forecasts, but cannot extrapolate recent demand trends as accurately as statistical models. Wacker and Lummus (2002) emphasise the importance of the managerial side of sales forecasting. Managers need to understand the value and the limitations of forecasting strategies to be able to adopt them successfully. Van Gils *et al.* (2017) investigate several statistical forecasting methods for determining order picking work in a case study of a Belgian warehouse. A method combining exponential smoothing with (SARIMA) time series models outperforms current expert forecasts, but the authors do not consider bias or the integration of expert forecasts and statistical forecasts.

Our paper investigates how expert forecasts and historical sales information can be integrated to improve demand forecasts and how a certain level of intentional forecast bias can be implemented to optimise labour resource planning.

Research hypotheses and contributions

The brief review above and our focus on the relation between forecast bias and labour productivity leads us to formulate the following three research hypotheses:

Hypothesis 1

Expert forecasts of managers display systematic bias related to cost considerations.

Hypothesis 2

Integrating expert forecasts in statistical models supports intentional management of forecast bias.

Hypothesis 3

A controlled amount of intentional forecast bias derived from operational warehouse data improves labour efficiency.

Support for these three hypotheses in our study can provide the basis for the following three-step, business analytics strategy to optimise warehouse labour efficiency:

- Maintain a periodically (daily or weekly) updated database with (*ex ante*) management demand forecasts and (*ex post*) received order sizes.
- Implement a detailed labour productivity measurement system at the disaggregated level of individual activities and workers.
- Optimise labour capacity per activity by means of the relationship between demand forecast bias and productivity.

In terms of our case study, Hypothesis 1 provides an empirical test of the assertion in Goodwin (1996, 2002) that judgemental forecasts are often systematically biased because of asymmetric loss considerations (Zellner 1986, Christoffersen and Diebold 1996, 1997, Granger and Pesaran 2000, Amaldoss and Jain 2002, Elliott et al. 2005). We relate management forecast bias of the warehouse in our case study to its labour cost structure. To test Hypothesis 2, we implement and empirically validate the recommendations in Sanders and Ritzman (1991, 2004) and in Goodwin (2002), and use composite methodologies that integrate judgemental and statistical forecasts. The evaluation of the quantitative forecast gains of this integration in the warehouse of our case study supplements the cross-firm survey results of Sanders and Manrodt (2003) on the benefits of quantitative methods compared to judgemental methods. Finally, Hypothesis 3 is closely connected to bias management proposed in Ritzman and King (1993) and to forecast bias exploitation proposed in Sanders and Graman (2009). By using real-world data, our results provide an empirical validation of these two studies, which were based on artificially generated data to support their proposals.

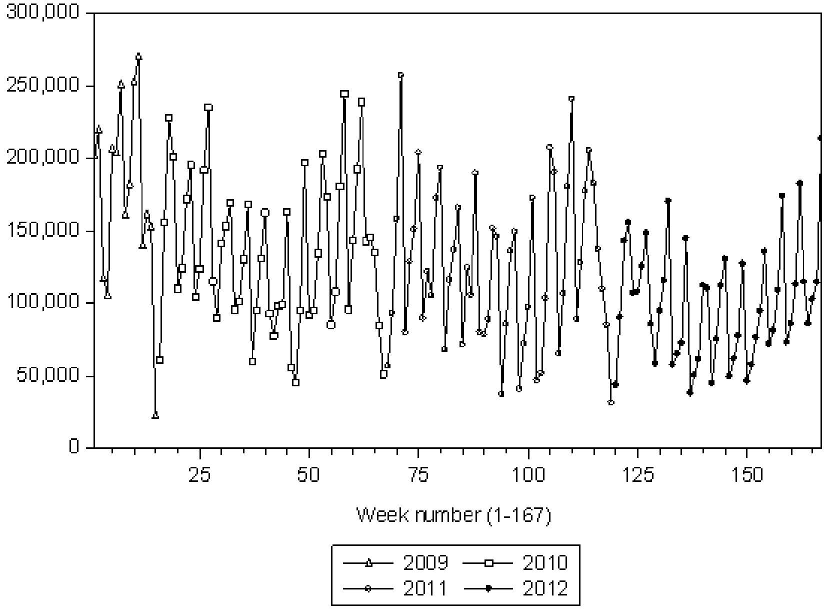
4.3 Case study environment

Warehouse characteristics

We illustrate our methodology in a case study for a Samsung Electronics warehouse in Western Europe. The warehouse has 250,000 pallet storage places, including racking and bulk storage, with a total space of 50,000 square meters. The products comprise finished goods in consumer electronics. These are fast-moving items with a total inventory volume of less than two weeks of demand. Distribution is a labour-intensive operation, and labour constitutes more than 40% of total warehouse costs. The outbound process of this warehouse has a multi-server queuing structure with consecutive stages of picking, packing and loading. As the warehouse delivers goods to customer warehouses instead of to end customers, delivery sizes are massive and on average comprise more than ten pallets. To satisfy delivery size constraints at destination, 80% of the pallets need re-palletising at the packing stage. On average this stage requires 85% of total labour, and overall outbound labour efficiency depends crucially on a smooth packing workflow. It is therefore essential that the pallets are retrieved from the picking stage and transported to the loading area as quickly as possible to prevent workflow disruption at the packing stage.

Demand characteristics

Warehouse operation volume is measured by the number of boxes handled. Figure 4.2 shows weekly order sizes from week 38 of 2009 to week 48 of 2012 (167 observations). The long-term average is rather stable, with considerable seasonal and short-term fluctuations. The annual cycle shows the same pattern for all four years. The September-November peak is typical for consumer electronics, and the end-of-the-month peak is related to the retailer behaviour, for example, to meet sales targets. Such historical sales patterns help sales managers with their weekly forecasts.



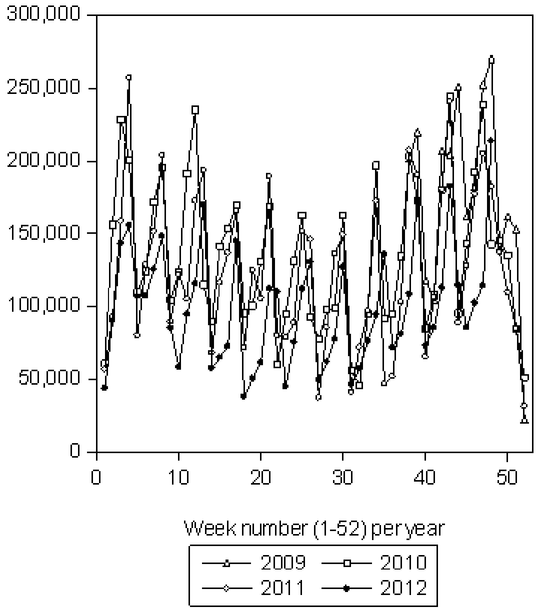


Figure 4.2: Time series of weekly order size, measured on the vertical axis as the number of boxes, from week 38 of 2009 to week 48 of 2012 (top) and after split-up per calendar year (bottom).

Labour characteristics

The warehouse translates the weekly order size forecasts into daily labour hiring decisions based on expected order sizes and past experiences. As order sizes fluctuate considerably, the warehouse employs flexible labour pools of about 60 full-time workers for each of two eight-hour shifts per day from a third-party logistics (3PL) provider of temporary labour. The provider permits the warehouse to furlough workers without payment if they have worked for more than three hours, and if the remaining workload does not justify hiring them for the remainder of the shift. This arrangement limits the costs of over-forecasting. On the other hand, if labour is insufficient, then impromptu demand for extra workers can often only be satisfied by hiring novices who are less productive, so that under-forecasting is costly.

As discussed in the literature review, forecast bias may reduce costs, but it depends on the labour situation which kind of bias is profitable (Sanders and Graman 2009). As over-forecasting is less expensive than under-forecasting for the warehouse of the case study, we specialize our Hypothesis 3 as follows:

Hypothesis 3*

In the case study warehouse, where over-forecasting is less expensive than under-forecasting, some amount of over-forecasting is beneficial for labour productivity.

Case study data and statistical methods

The warehouse has an active database management strategy with weekly recorded order sizes and management demand forecasts, daily recorded handled orders and labour hours, and continuously measured and daily recorded labour productivity data per stage of the warehouse process.

In our empirical analysis, we compare weekly management forecasts with weekly order sizes. A regression-type forecast model with lagged effects integrates these forecasts with historical sales data. We follow the Box-Jenkins methodology (Box et al. 1994), which consists of the stages of model identification, estimation and diagnostic checking. Because of its simplicity, this forecast methodology has found widespread application in business and in other fields. Because warehouse orders are unstable, we extend the forecast model by including seasonal effects and management forecast information. For the model identification stage, we use the "general-to-specific" procedure (Hendry 1995). This procedure has the advantage of working with correctly specified models as it starts with a general model where no factors have been omitted, followed by model simplification by removing insignificant factors. The models are estimated by (ordinary or recursive) least squares and simplified by standard tests. Standard diagnostics check for correct specification of the dynamic structure of the demand process (Breusch 1978, Godfrey 1978) and for normality of the model residuals (Jarque and Bera 1987). The significance of forecast gains is evaluated by forecast comparison tests, including standard paired t-tests and encompassing tests (Hendry 1995). An encompassing test for two forecast methods, A and B, is based on the following regression equation:

$$O(t) = \alpha + \beta \times F_A(t) + (1 - \beta) \times F_B(t) + \varepsilon(t) \qquad (1)$$

Here O is the variable of interest, order size in our case, F_A and F_B are the forecasts of methods A and B and ε is an error term. Method B is said to encompass method A if $\beta = 0$, that is, if the forecast of method A does not add to the forecast power of B. Similarly, method A encompasses B if $\beta = 1$, and the two complement each other if $0 < \beta < 1$.

In our further empirical analysis, we use daily data to study the relationship between forecast bias and labour efficiency. The weekly sales forecast is split into daily forecasts, based on historical spreads over the days and on operational information such as order cancellation notifications and postponed orders of previous days. Labour efficiency is measured continuously. Task durations are measured in seconds by time clock systems for picking, packing and loading activities. For each of these activities, the warehouse employs standard durations based on about 50 sub-tasks. The labour efficiency of each activity is automatically registered in the IT system daily, by comparing clock system data with standard durations. We compare efficiency on days with positive and negative bias, and we estimate the optimal amount of bias for each stage of the outbound warehouse process. In addition to the case study results on the relationship between forecast bias and labour efficiency, we also present the outcome of a small-scale survey among thirty warehouses and results of a simple simulation study.

4.4 Forecasting order size

Statistical model

To illustrate our forecast methodology, we analyse sales department forecasts and actual orders processed by the logistics department. The weekly data consist of 167 observations of management forecasts (denoted by F) and actual orders (denoted by O), both of which are measured in terms of number of boxes. For week t, the management forecast F(t) is confirmed on Monday morning of week t, and the actual delivery order O(t) is confirmed at the following Thursday's cut-off (as later orders are carried over to the next week). As the order size tends to be relatively large at the end of the month and at the end of the year (see Figure 4.2), we include end-of-the-month effects (for the last week of the month) and end-of-the-year effects (for weeks in September, October and November) as possible calendar effects. We also consider the forecast accuracy of previous weeks. For example, if management forecasts for the previous week underestimated the actual order size, a similar bias may apply for the current week. In other words, forecast error E(t) = F(t) – O(t) may have predictive power for future orders.

The statistical forecast model is obtained from the "general-to-specific" specification procedure. The starting point is a relatively rich model including information on order sizes and management forecasts of up to the last four weeks. We simplify this model by testing for various parameter restrictions and we apply diagnostic tests (on absence of serial correlation and on normality of model residuals) for the simplified models. We finally consider inclusion of calendar effects. The forecast model obtained by this procedure is

$$O(t) = 15{,}512 + 0.861 \times F(t) - 0.195 \times E(t-1) - 0.190 \times E(t-4) + r(t) \qquad (2)$$

Here r(t) denotes residuals of the model, which contain no significant serial correlation (p-value for lags 1-4 is 0.43) and which are reasonably normal (p-value 0.06). Additional calendar effects are insignificant (p-values 0.72 for end-of-the-year, 0.42 for end-of-the-month and 0.72 for both effects jointly), which can be explained by the fact that management forecasts, which is included as an explanatory factor, already includes these calendar effects.

Model interpretation

The model in equation (2) integrates judgemental forecasts and statistical sales data and can be interpreted in terms of bias correction (Goodwin 2002). The coefficient 0.861 of F(t) means that approximately 86% of the management forecast for the coming week is taken as the expected order, with corrections of about 20% of the management forecast error from the previous week and from four weeks earlier (which in most cases has the same position within the month as the upcoming week). If previous forecasts were too high (with error E = F – O > 0), the current forecast is corrected downward, and if they were too low, it is corrected upward.

As the model is obtained ex post and uses all available data, the forecasts from model (2) are not made in real time as they employ future data that were used to obtain numerical values of the coefficients. Real-time statistical forecasts are obtained if, for each week t, the model is estimated using only data that were available at the beginning of week t (i.e. management forecasts F for weeks up to and including t, and order sizes O for weeks up to and including t - 1). We construct such ex ante forecasts by re-estimating the above model with factors F(t), E(t - 1), and E(t - 4) by means of recursive least squares with different coefficients for every week t. The comparison of management forecasts and ex ante model forecasts is a fair one, as both methods use compatible information sets of past historical data at each forecast week. One might expect that ex post forecasts are qualitatively better than ex ante forecasts because the latter employ less information.

Forecast comparison

The empirical results are summarised in Table 4.1 for all weeks and for three busy periods: end-of-the-month (EM), end-of-the-year (EY, September through November), and end-of-the-month weeks in these three months (EMY). Management forecasts are consistently upward biased, and relative bias increases with order size. They are larger than actual order size in 56% of all weeks, 58% in EY weeks, and 72% in EM weeks. For the ex ante model, these percentages are 52%, 50% and 53%, respectively, showing a better balance between over-forecasting and under-forecasting. The ex ante forecasts have a much smaller bias and standard deviation, and perform only slightly worse than the ex post forecasts. The average management forecast bias is 3% and 6%-12% in busy periods (8.5% in EM, 6.4% in EY, and

11.9% in EMY). The ex ante forecast bias is less than 2% on average, also in busy periods (1.7% in EM, 1.0% in EY, and 0.7% in EMY). Measured by the root mean squared prediction error, which combines bias and variance, the error decreases from 16.4% to 13.5% on average (from 16% to 10% in EM, from 19% to 13% in EY and from 22% to 12% in EMY). The ex post forecasts are only slightly better. All these findings support Hypothesis 2 that integrating expert forecasts and historical sales data reduces forecast bias.

The lower part of Table 4.1 shows outcomes of various forecast comparison tests. The ex-ante forecasts have a significantly smaller bias (at 5% level) than management forecasts, and the ex-post bias is significantly smaller than the ex-ante bias only when evaluated over all forecasts (but not for the busy sub-periods). The ex-ante forecasts encompass management forecasts in all four cases (all weeks and the three busy sub-periods), but management forecasts never encompass the ex ante forecasts. This means that the ex-ante forecasts are more reliable than management forecasts, and that the ex ante forecasts cannot be further improved by taking a weighted combination average with management forecasts. The ex-post forecasts and the ex-ante forecasts are of equal quality, except if all weeks are considered, in which case the ex-post forecasts encompass the ex-ante forecasts.

It is also useful to compare forecasts in terms of absolute prediction errors, as an alternative to bias where large positive and negative errors cancel out. Ex ante statistical forecasts have smaller mean absolute prediction error than management forecasts: the error decreases from12% to 11% in all weeks, from 11% to 9% in EM, from 14% to 10% in EY and from 17% to 10% in EMY. This difference is significant for all weeks and for end-of-the-year weeks.

We further mention that management forecasts contain crucial information. If this information is excluded and order forecasts are based only on past orders and calendar effects, the general-to-specific procedure produces a model that contains order sizes of one and four weeks earlier as well as significant end-of-the-year and end-of-the-month effects. This model has about 80% higher root mean squared forecast error than model in equation (2), which provides further support of Hypothesis 2, and shows that the combination of judgement and statistical information provides better sales forecasts than can be obtained from either separately.

	Week			
	All	End month	End year	End month year
Sample size	159	37	42	10
Mean value				
Actual order size	122.03	176.97	142.98	213.32
Forecast management	126.08	192.09	152.15	238.80
Forecast ex ante models	124.36	179.91	144.38	214.86
Forecast ex post model	122.40	178.50	143.62	215.68
Prediction bias (forecast minus actual)				
Forecast management	4.05	15.12	9.17	25.48
Forecast ex ante models	2.33	2.94	1.41	1.54
Forecast ex post model	0.37	1.53	0.64	2.36
Mean absolute prediction error				
Forecast management	14.66	19.64	20.49	35.60
Forecast ex ante models	13.15	15.06	14.67	21.99
Forecast ex post model	12.74	14.07	15.46	23.60
Standard deviation				
Actual order size	53.49	43.75	61.39	33.80
Forecast error management	19.65	23.75	26.24	38.45
Forecast error ex ante models	16.35	18.14	18.50	26.07
Forecast error ex post model	16.17	17.16	19.37	27.06
Root mean squared prediction error				
Forecast management	20.06	28.15	27.80	46.12
Forecast ex ante models	16.52	18.38	18.55	26.12
Forecast ex post model	16.17	17.23	19.38	27.16
Prediction error comparison tests				
F-test variance EMAN vs EMOD_a	0.17	0.29	0.06	0.26
t-test EMAN vs EMOD_a	0.05	0.00	0.00	0.00
t-test EMOD_a vs EMOD_p	0.00	0.07	0.21	0.36
E-test MAN vs MOD_a	0.09 / 0.00	0.95 / 0.00	0.51 / 0.00	0.38 / 0.01
E-test MOD_a vs MOD_p	0.08 / 0.01	0.94 / 0.05	0.06 / 0.93	0.45 / 0.98
Absolute prediction error comparison tests				
F-test variance EMAN vs EMOD_a	0.06	0.01	0.11	0.09
t-test EMAN vs EMOD_a	0.05	0.06	0.02	0.09
t-test EMOD_a vs EMOD_p	0.16	0.15	0.15	0.24
W-test EMAN vs EMOD_a	0.26	0.15	0.04	0.14
W-test EMOD_a vs EMOD_p	0.10	0.09	0.31	0.36

Table notes

* We consider 159 weeks for which ex ante model forecasts are available (8 initial weeks are lost).

* The order size and all forecasts and forecast errors are expressed in terms of 1000 boxes per week.

* The forecast errors are denoted by EMAN for the manager, EMOD_a for the ex ante (real-time) models that vary per week, and EMOD_p for the ex post model that is estimated using data for all weeks.

* The tests show p-values (underlined if at most 0.05) for the following tests: Levene's F-test for equal variance (2-sided), paired samples t-test for mean (1-sided), Wilcoxon signed rank W-test (1-sided), and two encompassing E-tests (2-sided) for forecasts A vs B, with test equation O = c + dA + (1-d)B, with O actual order size; first test is for B encompasses A (d=0), second for A encompasses B (d=1).

Table 4.1: Comparison of manager forecasts with model based forecasts (2009 weeks 46~2012 weeks 48)

4.5 Labour efficiency and forecast bias

In this section, we first investigate Hypothesis 3* by comparing labour efficiency on days with positive and negative forecast bias. Next, we analyse the relationship between forecast bias and labour efficiency to determine the amount of bias that optimises this efficiency, and we perform a small simulation study that confirms the empirical case study findings. Finally, we present outcomes of a small-scale survey among thirty warehouses that confirm labour efficiency benefits of forecast bias.

Comparison of labour efficiency for days with positive and negative forecast bias

We investigate the relationship between forecast bias and labour efficiency for the warehouse in our case study. Labour efficiency is defined as the ratio of required labour over hired labour, so that an efficiency above (below) 1 corresponds to labour productivity being higher (lower) than standard. Forecast bias is defined as the ratio (F – O)/O where F and O are respectively the forecast and the actual order size, so that a positive (negative) forecast bias corresponds to management over-forecasting (under-forecasting).

Daily labour efficiency data are available for the first 40 weeks of 2012. The total number of observations is 195 (40 weeks of five working days, excluding five bank holidays). Daily information on actual order sizes are available for this period, as well as daily order forecasts derived from sales managers' weekly order forecasts. Table 4.2 shows the distribution of actual order sizes and management forecasts over the five working days of the week. The forecasts are considerably downward biased for Mondays and upward biased for the end of the week. One possible cause of these biases is a shifting demand pattern over the week compared to previous years. The table shows approximate daily distributions for 2008–2011 reported in interviews with warehouse managers, and the bias for Mondays may have been caused by these past expectations. Consequently, the forecast bias varies considerably and contains some aberrant values. In our analysis, we sometimes exclude aberrant observations by restricting the sample to days when the ratios of Forecast over Order (F/O) and of Order over Forecast (O/F) are both at most 1.5, so that the forecast bias (F-O)/O lies between -1/3 and +1/2, which eliminates 63 days (including 18 Mondays and 27 Fridays).

	Year	Sample	Day: Monday	Tuesday	Wednesday	Thursday	Friday
Orders	2008-2011	--	18.0	18.0	19.0	22.0	23.0
Orders	2012	195	25.4	20.8	19.0	23.7	11.0
Forecast	2012	195	18.5	20.2	20.4	27.2	13.7
Forecast error	2012	195	-27.2	-2.9	7.4	14.8	24.5
Bias > 1/2	2012	34	2	1	4	7	20
Bias < -1/3	2012	29	16	2	3	1	7

Table notes

* Daily distribution for 2008-2011 is obtained through interviews with warehouse managers.
* The 195 daily observations are for week 1 to 40 of 2012 (200 days, excluding 5 bank holidays).
* The first three rows of the table show daily shares (in percentages).
* The row "Forecast error" shows the percentage relative mean forecast error, that is, 100*(Forecast - Orders) / Orders.
* The rows "Bias > 1/2" and "Bias < -1/3" show the number of days with such large bias.

Table 4.2: Daily distribution of weekly orders and manager forecasts

Table 4.3 shows the effect of forecasting bias on labour efficiency. Average efficiency is the highest for loading, followed by picking, and the lowest for packing. The relatively high efficiency in picking and loading does not lead to appreciable efficiency gains in the overall outbound activities (efficiency of 1.034, close to 1). The mean daily efficiency of picking, loading and overall outbound procedures is significantly higher for days with a positive forecast bias than for days with a negative forecast bias. Compared to days with negative bias, the efficiency gain on days with positive bias is approximately 12% for loading, 3% for picking and overall outbound handling and 0% for packing. The results for the restricted data set, after eliminating aberrant observations, are very similar. The table also reports outcomes of rank comparison tests for all days with negative and positive bias. These tests are not sensitive to outliers in efficiency, and the results confirm those of conventional mean comparison t-tests described earlier. All these findings support Hypothesis 3*: for the given labour situation of this warehouse, over-forecasting is beneficial for labour productivity. More specifically, because packing comprises 85% of all outbound labour, efficiency is improved by introducing extra labour in the preceding picking stage and in the subsequent loading stage to guarantee a smooth workflow in the intermediate packing stage.

				Mean labour efficiency per activity			
Bias situation	Sample	Bias interval	Bias	Pick	Pack	Load	Out
Comparison of means							
All	195	All	0.190	1.123	0.954	1.220	1.034
Negative	95	Below 0	-0.254	1.103	0.957	1.147	1.016
Positive	100	Above 0	0.611	1.142	0.953	1.292	1.049
Difference (%)	95+100			3.5	-0.4	12.6	3.2
Equal means	95+100			0.023	0.946	0.000	0.050
Non-aberrant	132	-1/3 to +1/2	0.006	1.110	0.950	1.209	1.023
Negative	66	-1/3 to 0	-0.180	1.087	0.949	1.140	1.004
Positive	66	0 to 1/2	0.192	1.133	0.951	1.277	1.041
Difference (%)	66			4.2	0.2	12.0	3.7
Equal means	66+66			0.023	0.946	0.003	0.061
Comparison of ranks							
Negative	95	Below 0	-0.254	90.1	99.2	81.7	91.0
Positive	100	Above 0	0.611	105.5	96.8	113.5	104.7
Equal ranks	95+100			0.028	0.883	0.000	0.044

Table notes

* Forecast bias is defined as Bias = (Forecast - Order)/Order, where Forecast = manager forecast and Order = actual order size.

* To exclude aberrant forecasts, the data are limited to 132 days where the ratios Forecast / Order and Order / Forecast are both at most 1.5, that is, with Bias between -1/3 and +1/2; in this way, 63 of the 196 observations are lost (34 with Bias > 1/2, mean 1.43, and 29 with Bias < -1/3, mean -0.42).

* Labour efficiency is defined as the ratio of actually required labour over hired labour (all measured per day), so that the efficiency is positive (negative) if productivity is above (below) the value 1.

* The rows "Difference (%) " show the percentage difference: 100*(Positive - Negative)/Negative.

* The rows "Equal means" show the (one-sided) p-value for the t-test that the mean efficiency is larger in the Positive than in the Negative bias group (equal variances not assumed).

* The row "Equal ranks" shows the (one-sided) p-value of the Wilcoxon rank sum test.

* The column "Bias" shows the mean bias.

* The last four columns show the mean (rank) efficiency for four activities and (tests for) the difference in efficiency between the negative and positive bias groups.

Table 4.3: Effects of forecasting bias on labour efficiency (daily data from week1 to week40, 2012)

Estimation of optimal bias

Although some bias may improve efficiency, excessive bias can obstruct efficiency (Sanders and Graman 2009). Therefore, a relevant question for warehouse management is what level of bias leads to optimal efficiency. We analyse this by investigating the (non-linear) relationship between forecast bias and efficiency of each activity. We use 180 instead of 132 daily observations by allowing for a somewhat wider range of bias. We exclude only 15 observations with positive bias above 1, meaning that the forecast is more than twice the actual order size (the mean bias of these 15 observations is 2.3). Such forecast errors arise if big customers cancel orders or if the warehouse has an ICT system collapse. The efficiency of picking (denoted by EPick) is related as follows to the forecast bias (denoted by B), where the coefficients are obtained by regression and r denotes the residual:

$$\text{EPick} = 1.109 + 0.168 \times B + 0.182 \times B^2 - 0.564 \times B^3 + r \qquad (3)$$

The coefficient of the cubic term is significant (p-value 0.004), whereas higher-order terms are not (the p-value for jointly omitting B^4 and B^5 is 0.178). Within the bias range from -0.5 to +1.0, the above relationship has a local maximum for a bias of approximately 0.5. The associated gain in efficiency compared to unbiased forecasts is approximately 5% (maximum efficiency is 1.17 for bias 0.45 compared to 1.11 for bias 0). A rather wide bias range leads to similar efficiencies (the estimated efficiency is at least 1.16 for biases between 0.26 and 0.59). Since the data information is rather limited, the precise optimal value is uncertain, and an approximate 95% confidence interval for the optimal bias runs from 0.3 to 0.6.

We obtained comparable results for loading and total outbound activities with the same approach. The 95% confidence interval for optimal bias runs from 0.4 to 0.7 in both cases. The efficiency gain is approximately 10% for loading (maximum efficiency is 1.33 for bias 0.48 compared to 1.20 for bias 0) and 5% for total outbound activities (maximum 1.08 for bias 0.49 compared to 1.02 for bias 0). These outcomes confirm the previously obtained support for Hypothesis 3* in Table 4.3 that a certain level of over-forecasting is beneficial for labour efficiency of picking, loading and total outbound procedures. Bias has no significant direct (linear or non-linear) effect on packing efficiency. As was discussed before, packing is the most labour-intensive stage and is affected primarily by the preceding stage of picking and the subsequent stage of loading.

Simulation of optimal bias

We extend the above empirical analysis with a small-scale simulation study. The simulation model consists of three consecutive multi-server queuing blocks for the outbound process. The waiting space for each block is unlimited, and a server comprises a team of four workers for packing and of individual workers for picking and loading. Table 4.4 shows empirical warehouse data on daily order size, hourly peak order size and labour productivity. We assume fixed service rates at each queuing block, corresponding to stationary working speeds. The random part of the process consists of the arrival of pallets at the first queuing block for picking. These arrivals are assumed to follow exponential distributions with hourly varying mean based on historical data of the warehouse. After arrival at the picking stage, pallets go through the consecutive stages of picking, packing and loading. For each stage, throughput consists of the number of handled pallets and depends on the number of workers.

If arrivals were non-random and evenly spread over all hours, the results for this theoretical operation mode would show an overall outbound labour efficiency of 98.0% (see Table 4.4). In practice, arrivals are random, and the warehouse data show an hourly peak order of 13% on average per day at the packing stage (125.5 instead of 110.7 pallets). The standard labour plan in Table 4.4 accommodates for this hourly peak and allocates labour based on unbiased forecasts. Based on 1,000 simulation runs, overall labour efficiency is 77.7% on average. We use the same set of simulation runs to compute labour efficiency for a range of alternative labour plans. Table 4.4 shows the labour allocation that maximises average overall outbound labour efficiency. By allocating one extra worker both to the picking and to the loading stage, the resulting higher productivity (82.7% - 76.6% = 6.1 percentage points) of the intermediate (labour-intensive) packing stage compensates for lower productivity at the picking and loading stages, as the average overall outbound labour efficiency increases by 4.1 percentage points to 81.8%. This optimal plan corresponds to forecast biases of 11.1% for picking and 50.0% for loading. This simulation result is roughly in line with the previously discussed empirical study results indicating optimal biases of 30%-70%.

The simulation illustrates the beneficial effect of positive forecast bias on labour productivity as postulated in Hypothesis 3*. The quantitative results differ somewhat from those of the empirical study, which is due to several simplifying assumptions. In practice, arrival rates are not exponentially distributed and labour service rates are not constant over time. The simulation model ignores details of the (around fifty) sub-activities of the outbound process and the effects of furlough and overtime policies. Because of the limited number of available data, the simulation model is kept simple and is meant only as illustration.

		Unit	Formula	Pick	Pack	Load	Out
Theoretical operation (non-random arrivals, no peaks)							
(1)	Order size per day (15 labour hours)	Pallet	Empirical	1,661	1,661	1,661	1,661
(2)	Average order size per labour hour	Pallet	(1)/15	110.7	110.7	110.7	
(3)	Maximum pallets per hour per worker	Pallet	Empirical	13.0	2.0	60.5	
(4)	Required labour hours	Hour	(1)/(3)	128	829	27	985
(5)	Required workers per shift (7.5 hours)	Worker	(2)/(3)	9	56	2	67
(6)	Labour efficiency	%	100*(4)/(15*(5))	94.8	98.7	91.4	98.0
Standard operation (random arrivals, peaks, no bias)							
(7)	Peak order size per hour	Pallet	Empirical	110.7	125.5	110.7	
(8)	Allocated labour size per shift	Worker	(7)/(3)	9	64	2	75
(9)	Actual labour hours per day	Hour	15*(8)	135	960	30	1,125
(10)	Simulated average throughput per day	Pallet	Simulation	1,488	1,473	1,470	
(11)	Labour efficiency	%	100*((10)/(3))/(9)	85.0	76.6	80.9	77.7
Optimal operation (random arrivals, peaks, optimal bias)							
(12)	Peak order size per hour	Pallet	Empirical	110.7	125.5	110.7	
(13)	Allocated labour size per shift	Worker	Optimised	10	64	3	77
(14)	Actual labour hours per day	Hour	15*(13)	150	960	45	1,155
(15)	Simulated average throughput per day	Pallet	Simulation	1,613	1,590	1,588	
(16)	Labour efficiency	%	100*((15)/(3))/(14)	82.9	82.7	58.3	81.8
(17)	Labour bias	%	100*((13)-(8))/(8)	11.1	0.0	50.0	2.7

Table notes

* Labour days consist of two shifts, each with 7.5 working hours.
* Peak order size per hour in row (7) is derived from empirical data as the average hourly peak load per day.
* Labour efficiency in rows (11) and (16) is defined as the ratio of needed labour hours over actual labour hours.
* Labour efficiency of 'Out' is the weighted average of productivity of the three tasks, with labour shares as weights.
* Labour bias is defined as the extra allocated labour compared to standard operation without bias.
* Each packing lane requires four workers, so that planned labour size per shift for packing is a multiple of four.
* The column 'Formula' shows how rows are computed from previous ones; the (rounded) data in rows (1), (3), (7), and (12) are based on empirical data, and the averages in rows (10) and (15) are obtained from 1000 simulations.

Table 4.4: Simulation results for the effect of excess labour on efficiency

Survey outcomes on forecast bias and labour efficiency

We conduct a survey to supplement the case study results of a single warehouse. As we were primarily interested in sensitive information on forecast bias and labour productivity, we selected warehouses for which we knew how to find the right person in charge of manpower planning who has this exclusive information. Another selection criterion was that the warehouses should be comparable with respect to other relevant aspects, such as handled products, floor space and labour situation. We approached 34 warehouses, thirty of which participated in the survey. The thirty warehouses are located in ten European countries: France, Germany, Great Britain, Greece, Lithuania, the Netherlands, Poland, Portugal, Slovakia and Sweden. The warehouses deal with consumer electronics products of various manufacturers and deliver to retailers (22), to end users (3), or to retail or repair shops (5). We supported participation by providing Likert-scale answer options to overcome possible reluctance in providing sensitive information. The two main questions were related to the level of bias they usually applied in labour planning (11 options, ranging from 'below -40%' to 'above +40%') and to their average productivity measured as the ratio of required over actually available labour (six options, from 'less than 80%' to 'over 120%'). Other survey questions were related to warehouse conditions.

The warehouses are divided into three groups according to their bias strategy: 22 employ a positive bias strategy (use more workers than required), four have negative bias strategy (use fewer workers than required), and four do not employ bias. These three groups of warehouses are similar with respect to all considered warehouse conditions: handled products, floor space, labour contract flexibility, consignee type, planning flexibility, order fluctuation level, forecast frequency, shift size, shift cost, job complexity (number of stages), labour takt time and number of shippers. ANOVA tests for equal means in the three bias groups are all insignificant at the 5% level, except for shift size that is similar for warehouses with positive and negative bias, but is somewhat larger for the group without bias (p-value 0.04). Average labour productivity differs significantly among the three groups (p-value 0.02), with the highest productivity for warehouses with positive bias, followed by those without bias, and with the lowest productivity for warehouses with negative bias. The four warehouses of the latter type reported productivities of 80%-90% (2), 91%-100% (1), and 101%-110% (1), whereas the 22 warehouses with a positive bias strategy reported

Q-nr	Variable	Forecast bias strategy (Q2.3) All (30)	No (4)	Negative (4)	Postive (22)	ANOVA test F-value	p-value
Q1.3	Warehouse size	2.7	4.0	3.0	2.4	1.93	0.17
Q1.4	Number of shippers	1.9	1.3	3.8	1.7	3.25	0.05
Q1.5	Consignee	2.6	2.3	2.5	2.7	0.95	0.40
Q1.6	Hourly workload fluctuation	2.8	2.8	2.8	2.8	0.00	1.00
Q1.7	Daily workload fluctuation	2.6	3.0	2.5	2.6	0.20	0.82
Q1.8	Labour contract flexibility	3.0	3.0	2.8	3.0	0.23	0.80
Q1.9	Planning flexibility	2.9	3.3	3.0	2.9	0.24	0.79
Q1.10	Shift size	2.7	4.0	2.3	2.6	3.75	0.04
Q1.11	Planning cost (hourly rate)	2.5	2.8	3.0	2.4	0.67	0.52
Q1.12	Job complexity	4.0	4.3	3.0	4.1	2.70	0.09
Q2.2	Forecast error (absolute)	2.7	2.5	3.3	2.6	0.70	0.51
Q3.4	Job Takt time accuracy	2.1	2.5	2.0	2.0	0.62	0.55
Q4.5	Labour productivity	3.8	3.0	2.8	4.1	6.69	0.02

Table notes

* Forecast bias is defined as (Forecast - Order)/Order, where Order is the actual order size.
* Labour productivity is defined as the ratio of required labour over actually available labour.
* The ANOVA test is the F-test for equal means in the three bias groups (no, negative, and positive), with degrees of freedom (2, 27).
* The column "Q-nr" shows the question number of the survey questionnaire related to the variable.
* Answers are given on Likert-scales with numerical codings shown in the questionnaire, for example:
  Q1.5 1 = end user; 2 = retail shop / repair center; 3 distribution center / warehouse.
  Q2.2 1 = less than 5%; 2 = 6-10%; 3 = 11-20%; 4 = over 20%.
  Q4.5 1 = less than 80%; 2 = 80-90%; 3 = 91-100%; 4 = 101-110%; 5 = 111-120%; 6 = over 120%.

Table 4.5: Comparison of survey outcomes of three warehouse groups with different forecast bias strategies

productivities of 80%-90% (1), 91%-100% (4), 101%-110% (10), 111%-120% (5) and over 120% (2).

These survey outcomes support the case study results. As the survey warehouses are similar to the one of the case study, the predominance of positive bias in labour planning supports Hypothesis 1, and the beneficial effect for labour productivity supports Hypothesis 3*. The survey also indicates that many European warehouses already implement bias strategies to improve labour efficiency. However, as detailed information on sensitive aspects such as bias strategies and labour productivity at the disaggregated level of individual operations is unavailable from the survey, the case study provided a unique opportunity to study these mechanisms at actual floor level.

4.6 Implications

Forecast bias methodology for labour planning

The efficiency of warehouse operations largely depends on labour costs. Overall efficiency is high if sequential stages of the warehouse process are synchronised so that each stage receives a smooth stream of tasks from previous stages. This requires flexible and accurate labour planning. We investigated three research hypotheses related to forecast bias and labour productivity. First, management forecasts display systematic bias related to cost considerations. Second, integrating management forecasts in statistical models supports intentional management forecast bias. And third, intentional forecast bias derived from operational warehouse data improves labour efficiency.

We proposed a predictive analytic methodology to integrate management forecasts and statistical forecasts (Hypothesis 2) and to obtain the optimal level of forecast bias (Hypothesis 3). The required operational information consists of management forecasts, actual order sizes and labour productivity at various stages of the warehouse process. Our proposed strategy to optimise warehouse labour efficiency consists of three steps. First, maintain a database containing management demand forecasts and actual order sizes. Second, measure labour productivity at the level of individual warehouse activities and workers. Third, determine the predictive analytic relationship between demand forecast bias and productivity and optimise labour capacity planning accordingly for the sequential stages of the warehouse process. This methodology was illustrated with a case study, and we now summarise the main results. Management forecasts of order sizes are systematically upward biased, particularly in busy periods. As it is more expensive for our case study warehouse to solve labour shortages than to dismiss excess workers before the end of their shift, this systematic over-forecasting is in line with the asymmetric cost structure for this warehouse. This finding supports our first hypothesis. The real-time ex ante statistical forecasts that integrate expert forecasts provide significant improvements by reducing bias, improving forecast quality and reducing absolute prediction errors. This finding supports our second hypothesis. The bias can be managed by correcting for recently observed biases in management forecasts. Compared to these forecasts, the root mean squared prediction error is reduced by 18% on average and by 35% for busy periods. Real-time ex ante forecasts are only slightly inferior to ex post forecasts, which provide a benchmark that is unachievable in real-time. The combination of expert forecasts and statistical information provides better sales forecasts than can be obtained from either separately. Our findings further show that over-forecasting of required labour leads to higher labour efficiency of picking, loading and overall outbound procedures. Allocating more labour during the preliminary picking stage and during the final loading stage reduces waiting times and guarantees a smooth workflow for the labour-intensive intermediate packing stage. These findings support our third research hypothesis. Optimal efficiency of picking, loading and outbound labour is obtained by a positive forecast bias of roughly 30%-70%, including systemic bias from warehouse managers. Compared to unbiased forecasts, these biases lead to efficiency gains of approximately 10% for loading and 5% for picking and for the total outbound process. A small-scale survey among thirty warehouses confirms that over-forecasting generally improves labour efficiency, and this result is also confirmed in a simple simulation study.

The case study company has incorporated these results in their evaluation and redesign of their interrelated management strategies for demand forecasting and labour planning. It acknowledges the importance of investing more labour during picking and loading to support the packing stage. The company rewards its workers periodically by individual or team bonuses to sustain higher efficiency and flexibility among workers.

Implementation aspects

Implementing our methodology for warehouse labour planning involves two predictive analytic relations, that is, a demand forecast model and a labour productivity model, as summarised in Figure 4.1. The forecast model integrates expert judgement and historical demand data, and managers can decide what type of expert judgements are relevant for their situation and how to incorporate them. The respective weights of the various forecast sources can be determined empirically, for example, by means of forecast combination methods (Aiolfi *et al*. 2011). In the case study example, we apply such methods to determine the weights of management forecasts and historical demand. Various other strategies can be employed, e.g. using historical demand data to produce a benchmark forecast and adjusting the outcome by expert judgement. The productivity model relates labour efficiency to forecast bias based on historical labour productivity data for each stage of the warehouse process. This relationship depends on warehouse characteristics, including prevailing cost structures and labour hiring options. Managers can develop forecast bias strategies depending on their situation, and our advice is to analyse historical patterns of productivity and forecast bias.

The advantage of the above two predictive analytic steps is that their implementation is flexible and can be tuned directly to the warehouse situation. It should be noted, however, that the resulting demand forecast and labour planning strategies will be case dependent, as the relative weight of expert judgement and the amount of bias are determined empirically. Such an empirical approach provides only approximations of reality and may not represent the real nature of the process in its full extent, which is a common shortcoming of empirical research.

4.7 Future research and study limitations

Our main finding is that some controlled amount of bias improves overall efficiency of warehouse procedures. The specific results on optimal bias and associated efficiency gains obtained for our case will be different for other periods and other warehouses. By following similar methodologies as described in this paper, warehouse managers can determine the level of forecast bias that works best for their situation. The business analytic information required for this evidence-based labour management consists of available hiring strategies and cost structures as well as historical data on order sizes, forecasts and labour productivity. Such an implementation requires integrating information flows from various warehouse departments and provides an example of the potential benefits of the rapidly increasing interest for big data and business analytics (Waller and Fawcett 2013, Wang *et al*. 2016). The case study illustrates the methodology, and the results are confirmed in a small-scale survey among thirty warehouses and in a simple simulation study.

Because our methodology follows an empirical approach, the investigation of its benefits for other warehouse situations is an important topic for future research. More in general, supply chain management may benefit from further empirical case studies on the use of systematically collected warehouse data to support evidence-based management strategies.

Chapter 5

Improving warehouse responsiveness by job priority management: A European distribution centre field study [1]

5.1 Introduction

Intense competition for speedy order fulfilment characterizes current retail markets. Responsiveness (Barclay et al., 1996) includes the ability to react purposefully within an appropriate time to external environments for securing competitive advantage. Improving order fulfilment responsiveness is a major challenge for boosting customer satisfaction (Doerr and Gue, 2013) and many firms, such as Amazon Prime, invest hefty capital to propel responsiveness. Though responsiveness hones competitiveness, it often leads to resource misallocation (Vincent, 2011), and improved responsiveness leads for two-thirds of all firms to increased labour cost (Pearcy and Kerr, 2013). Web retailers show responsiveness by advertising 'Place an order before midnight for next-day delivery.' Customers are nowadays accustomed to fast demand satisfaction in online markets and expect comparable off-line service. Off-line retailers therefore attract customers with promises such as: 'Buy online now and pick up in store tomorrow', forcing off-line retail distributors to improve their responsiveness (Denman, 2017).

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[1] This chapter is based on a submitted single-authored working paper. The author thanks Rommert Dekker and Christiaan Heij for their assistance in this research project and for their substantial language support.

The overall speed of order fulfilment in off-line markets depends on processing and transportation speeds from manufacturers through warehouses and retail shops to end-users. This paper focuses on speedy order fulfilment in warehouses, in particular original equipment manufacturing (OEM) warehouses delivering to retailer warehouses. Their order fulfilment process includes the inbound processes of receiving products and putting them away and the outbound processes of picking, packing, staging and shipping. As OEM warehouses receive products from their manufacturer, the inbound process is easily controlled compared to the rather unpredictable consumer demand leading to fast fluctuations of retailer orders. Another characteristic of OEM warehouses is that retailers order relatively large quantities of relatively few products (Bartholdi and Hackman, 2011). This distinguishes such warehouses from those delivering directly to consumers, where order sizes are small and range over a much wider product assortment. Whereas picking is usually the crucial stage for the latter type, in OEM warehouses the packing stage is often the most demanding one. As the receiving retailer warehouses differ in capacity and layout and trucks should be loaded efficiently, re-palletising is a major task for OEM warehouses. Because of the large order volumes, the re-palletising activities of unpacking, repacking and stacking are relatively labour intensive.

Responsiveness of OEM warehouses is measured by their flexibility to dispatch products ordered by retailers as fast as possible. To mitigate the effect of demand spikes, most OEM warehouses limit their fulfilment liability by daily order cut-off time agreements with their clients to ensure sufficient slack for order fulfilment by the earliest dispatch day (Van den Berg, 2007). To improve responsiveness, these warehouses try to postpone the cut-off time and to handle the same order volume with less slack. Since orders typically have different fulfilment deadlines, priority-based job scheduling offers the key for efficient solutions. Just as job scheduling has notably reduced waste from over-production and waiting times in "just-in-time" manufacturing, it can also improve responsiveness in warehouse order fulfilment. Job scheduling allocates tasks to labour resources for chosen goals (Vincent and Billaut, 2006), and the question of central interest here is how OEM warehouses should schedule their orders to allow later cut-off times.

Warehouse operations are faced with various uncertainties, including dynamic arrival, service and departure times (Gong and De Koster, 2011). In particular, unexpected order arrivals can yield long delays. There is usually no priority rule that is universally optimal (Lee et al., 1997) because of these uncertainties. This paper presents a general framework for cost-effective job scheduling using flow-shop priority methods to aid warehouses facing postponed order cut-off times. This framework integrates the multiple objectives of low earliness, low tardiness, low labour idleness, and low stocks through processing lanes into a single cost criterion, with weights derived from the cost structure and performance priorities of the warehouse. A simulation study illustrates, which scheduling methods perform best under which circumstances. The methods and results presented here advance extant literature by applying traditional flow-shop theories from manufacturing research to real-world warehouse distribution tasks. Warehouse practitioners can incorporate this task-scheduling framework in their warehouse management system (WMS) to create and execute a string of order fulfilment jobs (Van den Berg, 1999; Ramaa et al., 2012).

The rest of this paper is structured as follows. Section 5.2 reviews literature related to responsiveness, warehousing and flow-shop methods. Section 5.3 describes the operational challenge of responsive order fulfilment for postponed cut-off times. Section 5.4 presents the priority rules and performance indicators. Section 5.5 shows simulation results for the case study, and Section 5.6 discusses some operational implications and conclusions.

5.2 Literature review

A brief review is given of literature related to the main aspects of the study, i.e., responsiveness, OEM warehouses, priority-based job scheduling, and performance criteria.

Shaw et al. (2002) defined a clear hierarchy among the concepts of agility, responsiveness and flexibility. Agility concerns talents for operating ‘profitably in a competitive environment of continually, and unpredictably, changing customer opportunities’. It involves both proactive initiatives and reactive responsiveness, and flexibility is one of the conditions enabling responsiveness. The study of Kritchanchai and MacCarthy (1999) identified four factors that determine responsiveness: stimuli, awareness, capabilities, and goals. In our OEM warehouse study, these factors consist respectively of hourly varying demand stimuli, awareness of demand fluctuations, job scheduling opportunities, and the goal of efficient order fulfilment.

Efficiency studies on warehouse processes focussed mainly on picking strategies (Jarvis and McDowell, 1991; Hall, 1993; Petersen, 1997; Roodbergen and De Koster, 2001; Petersen et al., 2004; De Koster et al., 2007; Chen et al., 2010; De Koster et al., 2012). Proposed strategies include interleaving put-away and picking (Graves et al., 1977), wave picking (Petersen, 2000), and joint order batching (Won and Olafsson, 2005; Van Nieuwenhuyse and De Koster, 2009). The focus on picking is natural for retailer warehouses delivering directly to consumers, as such warehouses typically process large amounts of small orders for a wide variety of products by customer totes via multiple processing lines. Conversely, OEM warehouses delivering to retail warehouses process very large orders for a comparatively narrow assortment by multiple pallets via few processing lines. The outbound operations constitute a tandem queue (Burke, 1956) with three stages: picking, packing and staging. Multiple orders from the same retailer are consolidated for single shipment, which requires customized re-palletising and packing to satisfy dimension restrictions of trucks and retailer warehouses. This makes packing by far the most labour intensive phase of the outbound process in OEM warehouses (Bartholdi and Hackman, 2011).

Consumers can nowadays easily use the Internet to compare quality and prices of products across different suppliers. The offered service level remains the major competitive quality, and warehouse clients perceive responsiveness mainly by the speed of delivery. Pagh and Cooper (1998) studied the effect of postponement strategies of producers on warehouse outbound processes, and this study evaluates the effect of postponing order cut-off times to obtain better responsiveness in terms of faster delivery speed. These cut-off rules induce order peaks just before the cut-off time, thus causing imbalanced workloads. Huang et al. (2006) showed that these imbalances could lead to the ‘self-contradiction of hands shortage and idleness’ within the day. Such imbalances can be smoothed in several ways, for example, by modelling from historical data to reduce uncertainty (Gong and De Koster, 2011) and by balancing the workload (De Leeuw and Wiers, 2015). The labour intensive packing lanes of OEM warehouses are akin to factory workstations or job shops in manufacturing where productivity has been scrutinized via job-shop theory (Johnson, 1954). This study pioneers the analysis of OEM warehouse outbound processes through job-scheduling methods using priority-dispatching rules to smoothen warehouse flows and to optimize responsiveness.

Without prioritising, jobs are commonly processed on a first-come first-served (FCFS) basis. Jackson's rule (Jackson, 1955) orders jobs according to non-decreasing due dates, and this sequencing method is usually called 'earliest due date' (EDD). The shortest processing time (SPT) rule of Smith (1956) orders jobs according to non-decreasing processing times. Berry and Rao (1975) proposed two other rules, SLACK defined in terms of job slack (its due date minus its processing time) and critical ratio (CR) that corrects job slack for queuing delays. Kanet and Hayya (1982) presented an early application in manufacturing and compared priority methods based on due dates. Kiran and Smith (1984) studied dynamic job-shop scheduling by computer simulation, Lee et al. (1997) incorporated machine learning techniques, and Freiheit and Wei (2016) conducted a case study to investigate imbalance effects on flow-shop performance. Kemppainen (2005) presented an extensive comparison of various priority scheduling rules and their use in integrated order management. The advance of IT (i.e.WMS) enables real-time job instruction to individual labourers. It deserves to investigate dynamic prioritising rules that incorporate dynamic factors into labour task instructions.

The benefits of priority-based job scheduling can be evaluated in terms of operational and financial performance criteria. The choice of which priority rule to employ involves a trade-off among multiple performance attributes of the outcomes, for example, handled volume, service level and operational cost (Chen et al., 2010). A popular method to assist this choice is data envelopment analysis (Hackman et al., 2001; De Koster and Balk, 2008). Treleven and Elvers (1985) assessed performance in terms of mean queuing times, mean earliness and percentage of late jobs. Ramasesh (1990) categorised performance in terms of idle machines, stalled promises, work-in-process inventories, and average value added in queue. Although contract terms often involve earliness and tardiness penalties (Baker and Scudder, 1990; Elsayed et al., 1993), Vincent (2011) noted that most production cost models neglected just-in-time principles. This study incorporates them 'en bloc' since warehouses face penalties both for tardiness because they have to meet carrier schedules and for earliness because pallets staged for loading occupy costly storage space. Warehouse performance is evaluated in terms of a common cost criterion that integrates the objectives of low earliness, low tardiness, low labour idleness, and low work-in-process stocks. The values of the cost parameters are case dependent, and a real-world case study for an OEM warehouse in consumer electronics specifies these parameters from operational data and investigates various cost scenarios depending on warehouse preferences across the performance dimensions. Other warehouses can incorporate this methodology in their own WMS for practical scheduling solutions derived from cost parameters and preferences that apply for their situation. In this way, this study supplements earlier studies like Cakici et al. (2012) that offered only theoretical solutions.

5.3 Simulation model and case study

The research question of central interest is how job priority scheduling can help OEM warehouses to improve their responsiveness to meet current trends of postponed daily order cut-off times for next-day delivery. As customers adapt their ordering policy by spiking demand briefly before the cut-off time, warehouses are confronted with order peaks that have to be processed faster when response times become shorter. OEM warehouses usually dispatch retailer orders by truck on agreed pick-up times on the next working day. These pick-up times are spread across the day so that incoming orders have different due times that help job prioritisation. As suggested by Van den Berg (2007), workload imbalances can be alleviated by distinguishing can-ship orders from must-ship orders and by shifting the former from busier to quieter hours. Therefore, instead of processing orders on a FCFS basis, the workflow can be balanced by postponing less pressing jobs that have relatively late due times. Balancing the workload has several operational advantages, including reduced overtime and absenteeism reported in the empirical study of De Leeuw and Wiers (2015). The balancing effect of job priority management is illustrated graphically in Figure 5.1 Through postponing part of the jobs, stemming from demand peaks, the hourly workload becomes smoother with less peaks and troughs compared to FCFS scheduling.

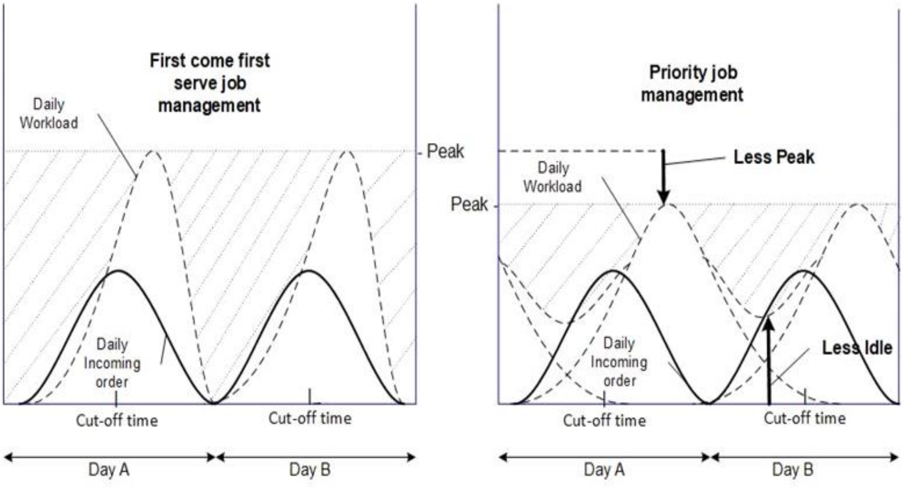

Figure 5.1: Daily incoming orders and two job management methods.

Ideally, the workload should be constant across the day as this greatly simplifies warehouse planning and operation. The incoming order arrival process is irregular so that this ideal situation cannot be achieved in reality. The performance of alternative scheduling strategies is investigated by a simulation study based on actual operational data of a case study warehouse. The methodology to improve order fulfilment responsiveness for postponed cut-off times consists of four steps:

(1) Building a simulation model of order fulfilment that includes the following operational aspects: arrival distributions, order peaks, due time distribution, service time distributions per operation, and a set of priority rules to schedule remaining jobs for each queue.

(2) Constructing a cost objective function that incorporates penalties for earliness, tardiness, idleness, and work-in-process stock.

(3) Simulating the model under various cut-off scenarios and determine the costs resulting from each priority rule.

(4) Evaluating the relative performance of these priority rules for the various scenarios and identify which rule performs best under which circumstances.

For the case study warehouse, the simulation model of step (1) above has the following characteristics. The order fulfilment process consists of a tandem queue (Burke,

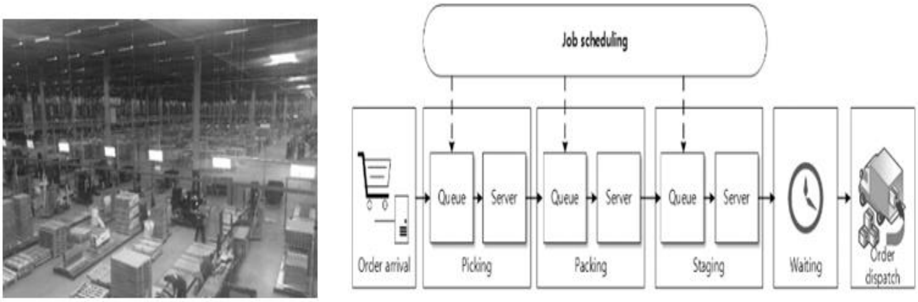

Figure 5.2: Actual warehouse process (left) and queuing model (right).

1956) with three service stages: picking, where a pallet or box is moved from storage to the packing lane; packing, where pallets are cubed according to customer requests; and staging, where pallets are moved from the packing lane to the staging zone. Figure 5.2 illustrates this tandem queuing process, where the three stages are linked without diversion and each stage consists of a set of servers with queues of unlimited capacity. The number of workers is fixed per service but varies between picking, packing and staging. Picking and staging is carried out by a single worker with automatized pallet handling equipment. Packing is the most labour intensive manual stage, with a group of workers per pallet. Packers perform re-palletizing and wrapping tasks to satisfy customer warehouse pallet size restrictions, they check that orders cubed as one pallet are complete, and theyregister it into WMS before staging.

As order arrival rates vary over the day, the arrival process at the picking stage is modelled as a non-homogeneous Poisson process with varying rates per hour of the day. Service times are modelled by simple exponential distributions with rates that differ for each of the three services of picking, packing and staging. The service rates for picking and packing depend on the customer order structure, with a distinction between relatively simple single-item pallets (SIP) with faster rates (pallet per hour) and complex multi-item pallets (MIP) with slower rates (pallet per hour). When the customer order is a single-line order, a pallet picker needs to visit only one location, and packers need simple cubing without complex stacking patterns. In contrast, if the customer order is a multi-line order, a pallet picker has to visit several locations for each item with a pick cage, and packers also should consider complex stacking patterns to optimize into a pallet. However, staging is the same for single-line and multi-line orders as it only involves moving a finished pallet from the packing area to the staging area. For given service and order type, the service rate is assumed to be constant per worker and per hour of the day. This assumption ignores ergonomic factors like fatigue, but the warehouse employs a refined measurement system for labour productivity per task per worker that indicates that this simplification is not unreasonable. All workers are directed independently via WMS instructions transmitted by hand-held terminals and they work per pallet without any knowledge of job priorities or shipment structures. The picking process is modelled as an M(t)/M/c queue with non-homogeneous Poisson arrivals, packing follows a G/M/c queuing model with arrivals determined by departures from upstream picking, and staging also follows a G/M/c queuing model with arrivals determined by upstream packing. The final phase of the order fulfilment process involves waiting, and the waiting time of pallets is defined as the length of time they stay at the staging zone after packing and before shipping.

Historical warehouse operational data are used to specify the simulation input parameters for hourly arrival rates (17, one for each hour of the working day from 6 am until 11 pm), service rates (6, one for SIP and one for MIP for picking, packing and staging), and the mix of SIP and MIP orders (with probability 0.77 for SIP and 0.23 for MIP). Due times are uniformly distributed over the 17 hours of the next working day, because the warehouse takes the lead in setting due times due to agreements with carriers to spread truck pick-up optimally during the day. Multiple orders from the same client are consolidated and have the same due time to reduce transport costs.

5.4 Priority rules and performance criteria

The literature review mentioned some well-known priority rules for job scheduling from flow-shop production theory, which will now be described in more detail. The simplest rule is first-come first-served (FCFS), where jobs that arrive earlier get higher priority. The so-called earliest due date (EDD) rule gives higher priority to jobs with earlier due time. Jackson (1955) proposed this priority rule and showed that it minimizes the maximum of job tardiness. In this thesis OEM warehouse case study, the operational due time of dispatch by the carrier is already assigned upon arrival of the order owing to pre-arrangements with the retailers placing the orders. Smith (1956) proposed an alternative priority rule where jobs with shortest processing time (SPT) get highest priority to get minimal mean flow time, that is, minimal work-in-process inventories. This result is related to Little's law (Little, 1961), which states that in steady state the mean number of units in the system (L) equals the product of the mean arrival rate (λ) and the mean time the unit spent in the system (W), so that $L = \lambda \times W$. An opposite rule gives highest priority to jobs with longest processing time (LPT). In our case study, processing times are defined in terms of the expected total service time of all remaining operations, i.e., picking plus packing plus staging for the picking queue; packing plus staging for the packing queue; and staging for the staging queue.

EDD and SPT focus on tardiness performance, but earliness and post-completion costs are also relevant. Berry and Rao (1975) studied the slack time (SLACK) and critical ratio (CR) rules to improve inventory performance. For given time (t), the slack time (S_t) of a job with due time (D) is defined as the difference between remaining time ($D_t = D - t$) and (expected) remaining processing time (P_t) with correction factor ($z > 1$) to account for expected queuing and other time losses in the process, so that $S_t = D_t - z \times P_t$. SLACK gives higher priority to jobs with less slack time and constitutes a trade-off between EDD and LPT, as it assigns higher priority to jobs with earlier due times that take longer to process. Berry and Rao (1975) showed that this rule averts both inventory surpluses from early replenishment and inventory shortages from late supplier deliveries. Similar to EDD and SPT, the SLACK priority of a job is static in the sense that all priority parameters (due times and expected remaining processing times) are known upon arrival. CR is a dynamic rule and replaces the correcting factor (z) by the expected queuing times that apply during dynamic operation. This rule assigns highest priority to the job with the smallest value of remaining time until due time ($D_t = D - t$) divided by the sum of expected remaining processing time (P_t) and currently expected remaining queuing time (Q_t), that is, $(D - t)/(P_t + Q_t)$. Here P_t depends on the stage of the job; for example, at the packing stage it involves the expected service times of packing and staging. Q_t depends not only on the stage of the job, but also on the queues it should still pass. These queues are dynamic and Q_t depends on the expected processing times of all unfinished jobs with higher priority. Putnam et al. (1971) reported that the CR rule reduces uncertainty by trimming tardiness variance. In general, CR is

Priority rule	Source	Performance objectives			
		Low tardiness	Short flow time	Just-in-time	Dynamic
First-come first-served (FCFS)	--	o	o	o	o
Earliest due date (EDD)	Jackson (1955)	+	o	o	o
Shortest processing time (SPT)	Smith (1956)	-	+	-	o
Minimum slack (SLACK)	Berry and Rao (1975)	+	-	+	o
Critial Ratio (CR)	Putnam et al. (1971)	-	+	-	+

Table notes
For each rule, + means advantage, - disadvantage, and o neutral performance for the objective.

Table 5.1: Performance of five priority rules for a set of four responsiveness goals.

expected to perform better than SLACK because it employs relevant extra dynamic information.

Table 5.1 provides a summary of the considered priority rules. EDD and SLACK reduce tardiness but may result in longer flow times than the alternatives. SPT and CR aim for short flow times, but often lead or lag due dates with resulting weaker just-in-time and tardiness performance. Both SLACK and CR leverage processing times to account for other factors. CR provides dynamic corrections by means of "live" waiting times and is therefore expected to give shorter flow times than SLACK.

Next the performance criteria to evaluate OEM warehouse operations, is considered. The warehouse outcomes are evaluated in terms of a common cost criterion that integrates the four objectives of low earliness, low tardiness, low labour idleness, and low work-in-process stocks. The weight of each objective is determined by the associated penalty for failing to reach it, and this cost structure will be case dependent. The cost criterion function for fulfilling a set of orders is given by

$$\text{Cost} = \sum_{i=1}^{n}(w_1 \times \alpha_i + w_2 \times \beta_i) + w_3 \times \gamma + w_4 \times \delta.$$

Here the symbols have the following meaning: 'i' denotes the order; 'n' is the total number of orders; 'α_i' is the earliness cost of job 'i' and involves space costs at the staging zone for awaiting pick-up; 'β_i' is the tardiness cost of the job and consists of demurrage costs for carriers from appointed pick-up time until actual dispatch time; 'γ' is the total idleness cost, the sum total of idle labour costs in the phases of picking, packing and staging; 'δ' is total work-in-process cost, the sum over all 'n' jobs of financial costs from work-in-process inventories during picking, packing, and staging; and 'w_i' (i=1,2,3,4) are selection weights that determine which objectives are incorporated (1 if yes and 0 if no), depending on the business environment.

The four objectives and expected performance of alternative priority rules are summarized in Table 5.2 Earliness penalties favour just-in-time strategies like SLACK by reducing staging buffer space, whereas CR and SPT exacerbate these penalties because of their shorter flow times. Tardiness penalties favour strategies like EDD that aims at early completion. Even though CR and SPT have shorter flow times, they tend to generate some very late jobs with large associated tardiness penalties. If favourable business relationships between warehouses and truckers allow rescheduling appointments without cost, then the tardiness penalty may be waived (w_2=0). Idleness and stock penalties, which are linked since curtailed stock-in-process requires less labour, are related to lean production principles (Krafcik, 1988). The law L = λ×W of Little (1961) implies that work-in-process inventories (L) and associated stock penalties are proportional to flow time (W), so that CR and SPT are expected to perform well in this respect. However, if handled products are relatively cheap so that inventory costs are negligible, then stock penalties could be discarded (w_4=0).

Penalty	Operations	Objective	Penalty Calculation			Priority rule	
			Cost Driver	Count	Unit cost	Advantage	Disadvantage
Earliness	Staging, appointment	Just-in-time	Staging stocks	Max	Storage cost (€ per pallet per week)	SLACK	CR / SPT
Tardiness	Appointment, dispatch	Early in time	Late hours	Sum	Demurrage cost (€ per pallet per hour)	EDD	CR / SPT
Idleness	Picking, packing, staging	Short flow time	Idle hours	Sum	Labour cost (€ per hour)	CR / SPT	SLACK
Stock	Picking, packing, staging	Short flow time	Work-in-process inventory	Average	Inventory value (€ per pallet per week)	CR / SPT	SLACK

Table notes
The sequence of operations consists of picking, packing, staging, appointment, and dispatch.

Table 5.2: Performance of various priority rules among four cost dimensions.

5.5 Simulation results

The cost performance of alternative job priority rules is investigated by a simulation study, with parameters derived from a case study OEM retail distribution centre of a multinational consumer electronics manufacturer. Figure 5.3 summarizes the interactions of this distribution centre with its manufacturer, sales department, retail warehouses and shops, carriers, and labour provider. The order arrival process is determined by the sales department, and due times for order fulfilment are agreed with carriers.

The main question of interest is how to improve responsiveness for postponed daily order cut-off times. Curve A in Figure 5.4 shows the historical hourly average order pattern for 2012-2014, with steep demand peak just before the order cut-off time that was fixed at 2 pm during that period. The simulation study considers postponed cut-off scenarios with cut-off time at 3 pm (B), 4 pm (C), or 5 pm (D) but keeps the same due times for all orders. The corresponding demand patterns are simply extrapolated by shifting the base scenario (A) forwards in time while keeping the size of demand peaks and daily totals fixed.

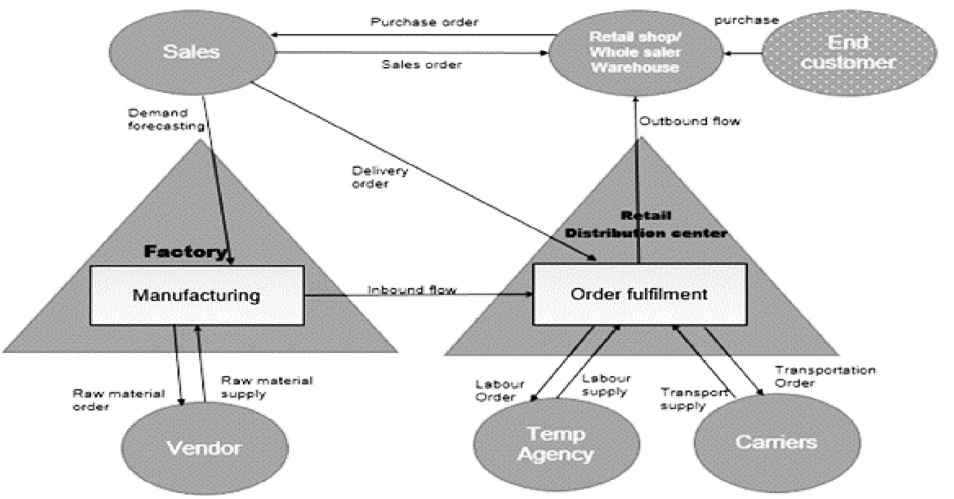

Figure 5.3: Retail distribution centre (OEM warehouse) and SCM partners.

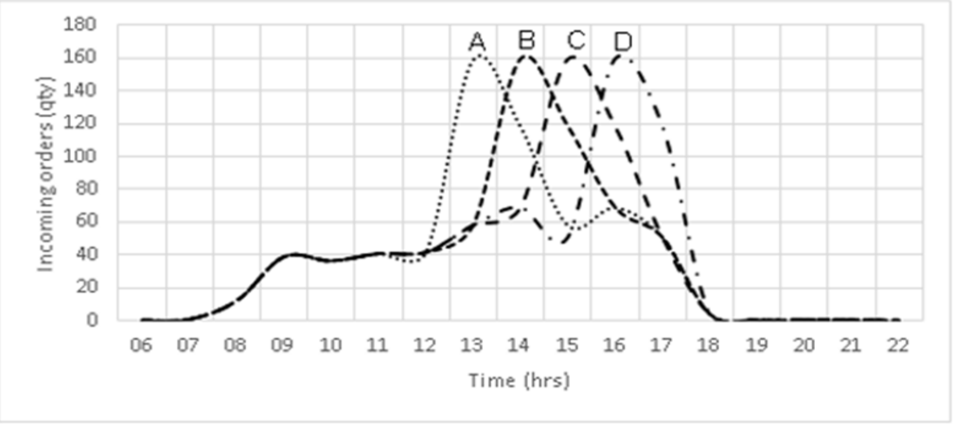

Figure 5.4: Average hourly incoming orders per for four cut-off scenarios (current is A).

Table 5.3 summarizes the input parameters for the simulations derived from historical operational data of the case study warehouse. The sales order desk is open from 8 am until 6 pm and orders rarely arrive outside these hours, resulting in relatively small means and large standard deviations of arrivals for out-of-office hours. Order arrivals have a 77% chance to be SIP and a 23% to be MIP, and service rates for SIP are higher than those for MIP by factors 2.83 for picking and 1.34 for packing. Weekly idleness costs are obtained by multiplying the average non-utilisation ratio by the weekly sum of total labour costs of €21.93 per hour. The stock-carrying cost of €10.14 per pallet per week for work-in-process stocks is derived from stock value and interest costs. The staging zone space cost of €6.96 per pallet per week is used as earliness penalty because this area can be used flexibly for extra bulk storage during peaks. Time criticality of order fulfilment for this warehouse is shown by high demurrage costs of €75.00 per pallet per hour. Finally, for the correction factor z in the definition of slack ($S_t = D_t - z \times P_t$) we choose the same value (20) as in the pilot study of FCFS by Kanet and Hayya (1982) to correct machine processing time for queuing times. The average total processing time is 0.197 hours (1/12.94 + 1/9.40 + 1/73.13) for SIP and 0.376 hours (1/4.57 + 1/6.99 + 1/73.12) for MIP. This corresponds (for z = 20) to average fulfilment durations of 20×0.197 = 3.9 hours for SIP and 20×0.376 = 7.5 hours for MIP, which reasonably fits experiences in the case study warehouse

Parameter		Unit	Specification	Value
Arrival rate		Pallets per hour	6-7 am	0.01 / 0.41
			7-8 am	0.85 / 20.86
			8-9 am	12.00 / 30.59
			9-10 am	38.82 / 54.65
			10-11 am	36.23 / 50.74
			11-12 am	40.70 / 57.53
			12-1 pm	41.46 / 58.94
			1-2 pm (cut-off)	158.84 / 116.53
			2-3 pm	118.00 / 142.31
			3-4 pm	57.88 / 71.95
			4-5 pm	68.68 / 86.70
			5-6 pm	50.64 / 84.02
			6-7 pm	3.94 / 21.62
			7-8 pm	0.34 / 5.17
			8-9 pm	0.53 / 7.94
			9-10 pm	0.43 / 6.90
			10-11 pm	0.01 / 0.33
Service rate	Picking	Pallets per hour per server	SIP	12.94
			MIP	4.57
	Packing	Pallets per hour per lane	SIP	9.40
			MIP	6.99
	Staging	Pallets per hour per server	SIP	73.13
			MIP	73.13
Penalty	Earliness	€ per pallet per week	storage cost	6.96
	Tardiness	€ per pallet per hour	demurrage cost	75.00
	Idleness	€ per hour	labour cost	21.93
	Stock	€ per pallet per week	work-in-process stock	10.14
	Queuing	Scalar value z	Slack = Dt - z×Pt	z = 20

Table notes
SIP and MIP denote respectively single-item pallets (77%) and multi-item pallets (23%).
Reported values are mean and standard deviation for arrival rates, mean for service rates, and financial penalty costs in terms of prime interest rates published by The Wall Street Journal for December 2016.

Table 5.3: Operational parameters for the case study warehouse (scenario A).

This study uses the Matlab Simulink (2018) tool to build the simulation model. Every single simulation run corresponds to one week of warehouse operations with hourly order arrivals, order types, and order service times. A week consists of five days of 17 hours each (85 hours in total) with expected total arrival orders of around 3,200 pallets (average 630 pallets x 5days). To process the order arrivals, the simulation model uses 4 pickers, 5 packing lanes (with 4 persons per lane), and 1 stager for each of the four cut-off scenarios.

One common set of 1,000 simulation runs is employed to study the outcomes of the five considered priority rules for each of the four cut-off scenarios (A-D). Each of these twenty scenarios is evaluated in terms of operational performance. To improve performance, this study applies the priority rules at each individual operation's queue separately, which is also called an operational due dates strategy (Kanet and Hayya, 1982). The flow time of a job is the total time it spends in the shop, that is, the time elapsing between arrival and completion. Earliness is defined as the difference between completion time and due time, so that negative values correspond to timely completion. For smooth operation it is preferred to have not only small mean but also small variation of flow times and earliness, and therefore both the mean and the standard deviation of these two characteristics are considered across the set of jobs within a given simulation run, that is, a given week of warehouse operations. Tardiness occurs if earliness is positive, that is, if jobs are completed after the due time limit. Maximum tardiness is defined as the maximum value of (positive) earliness across all jobs within a given simulation run.

The operational outcomes of 1,000 simulation runs (weeks of order fulfilment) are summarized in Table 5.4 and Figure 5.5. Table 5.4 shows that postponed cut-off times lead, as expected, to shorter flow times, less earliness and more tardiness. FCFS does not perform well across all performance dimensions and has the worst tardiness outcomes, especially for tight cut-off scenarios. Of the five priority rules, CR performs the best in terms of flow time, whereas EDD and SLACK have excellent tardiness results as none of their jobs have positive earliness. Figure 5.5 shows some outlying tardiness results for CR, both in the benchmark cut-off scenario (A, 2 pm) and in the most ambitious scenario (D, 5 pm). Table 5.4 shows SLACK and EDD perform roughly similar, but because SLACK amplifies the weight of processing times it has highest earliness mean value and highest flow times mean value of all priority rules. Compared to these two methods, SPT has shorter flow times but more tardiness. The outcomes in Table 5.4 are in line with those in Table 5.1, because CR and SPT have shortest flow times, EDD and SLACK have lowest tardiness, and SLACK comes closest to just-in-time planning as it has highest earliness.

		Flow time				Earliness				Tardiness			
		Mean		Standard dev.		Mean		Standard dev.		Maximum		Fraction (%)	
Cut-off	Priority	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
2 pm	FCFS	8.7	2.3	2.9	0.2	-16.6	2.3	7.2	0.2	2.6	2.5	1.1	1.5
	SPT	7.3	2.1	5.0	0.7	-18.0	2.1	6.9	0.2	2.3	2.4	0.6	0.8
	EDD	8.7	2.3	6.9	1.0	-16.6	2.3	3.2	1.0	0.0	0.0	0.0	0.0
	SLACK	9.3	2.4	7.2	0.9	-16.0	2.4	3.3	0.9	0.0	0.0	0.0	0.0
	CR	4.8	0.5	6.9	2.2	-19.9	0.6	6.8	1.5	33.7	24.4	1.0	0.8
3 pm	FCFS	8.5	2.2	2.9	0.2	-14.9	2.2	7.2	0.3	3.9	2.8	2.2	2.5
	SPT	7.1	2.0	5.2	0.7	-16.4	2.0	6.9	0.2	3.6	2.7	1.1	1.4
	EDD	8.5	2.2	7.0	0.9	-15.0	2.2	3.0	1.1	0.0	0.0	0.0	0.0
	SLACK	9.2	2.3	7.3	0.9	-14.3	2.3	3.2	0.9	0.0	0.0	0.0	0.0
	CR	4.5	0.6	6.9	2.3	-18.3	0.6	6.7	1.5	35.2	23.2	1.1	0.8
4 pm	FCFS	8.4	2.3	2.8	0.2	-13.0	2.3	7.3	0.2	5.8	2.9	4.5	4.0
	SPT	6.9	2.1	5.1	0.6	-14.5	2.2	6.9	0.2	5.5	2.9	2.4	2.4
	EDD	8.4	2.3	7.0	0.9	-13.1	2.3	2.8	1.1	0.0	0.0	0.0	0.0
	SLACK	9.0	2.4	7.2	0.8	-12.4	2.4	3.0	0.9	0.0	0.0	0.0	0.0
	CR	4.3	0.6	6.8	2.4	-16.4	0.7	6.6	1.6	36.0	25.5	1.1	0.9
												0.0	0.0
5 pm	FCFS	8.1	2.4	2.7	0.3	-11.7	2.4	7.2	0.2	7.0	3.1	6.8	5.2
	SPT	6.6	2.3	4.8	0.5	-13.2	2.3	6.9	0.2	6.7	3.1	3.9	3.3
	EDD	8.1	2.4	6.7	0.8	-11.7	2.4	2.7	1.1	0.0	0.0	0.0	0.0
	SLACK	8.8	2.5	7.0	0.7	-11.0	2.5	2.9	0.9	0.0	0.0	0.0	0.0
	CR	4.1	0.6	7.0	2.4	-15.0	0.7	6.5	1.6	37.7	25.2	1.2	0.8

Table notes

Underscored mean values are for the best performing priority rule per objective and per cut-off scenario.

Flow time, Earliness and tardiness are measured in hours, and fraction of tardiness is measured as percentage.

The standard deviation colummns (std) show the variation of outcomes across the 1,000 simulation runs.

Table 5.4: Simulated performance of five priority methods.

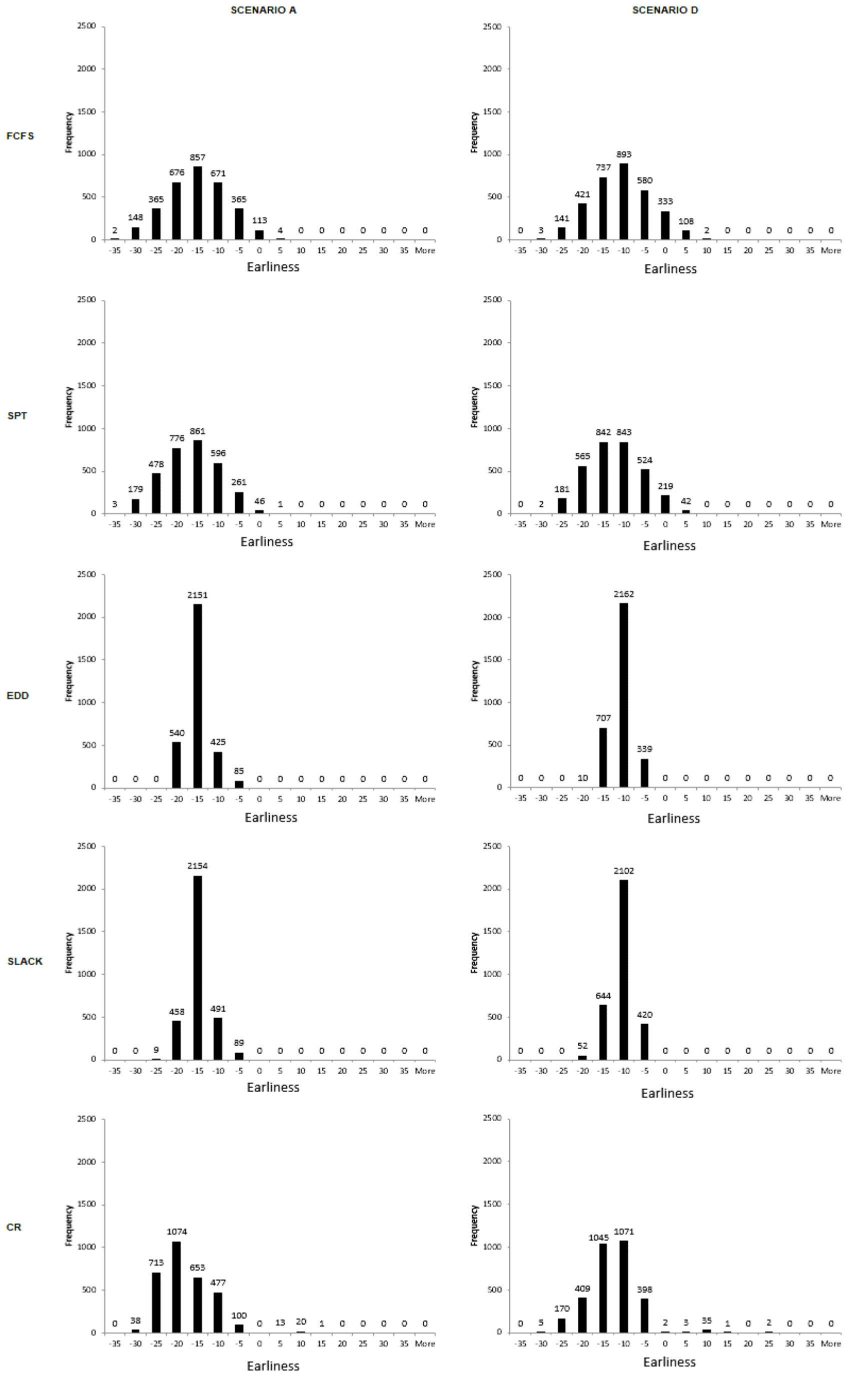

Figure 5.5: Histograms of simulated outcomes for Earliness (0 on horizontal axis means -4.99 to 0.00)

Objective		Earliness (α)		Tardiness (β)		Idleness (γ)				Stock (δ)	Cost specification €								
Measurement		Max. stage		Truck penalty		Pick	Pack	Stage	Total	Average	All four			No stock cost			No tardiness cost		
Unit		Pallet(Qty)		€		Utilization (%)				Pallet	(α + β + γ + δ)			(α + β + γ)			(α + γ + δ)		
Cut-off	Priority	mean	std	mean	std						mean	std	best (%)	mean	std	best (%)	mean	std	best (%)
	FCFS	687	80	4,708	8,242	97.2	81.2	48.2	82.4	327.4	22,056	11,546	0.1	18,657	10,882	9.4	16,323	890	0.1
	SPT	712	82	2,350	4,220	97.2	81.7	48.6	82.8	274.9	18,687	6,396	46.6	15,831	5,807	2.7	15,766	794	43.3
2 pm	EDD	687	81	0.00	0.00	97.2	81.2	48.2	82.4	327.0	16,324	893	46.5	12,927	557	39.7	16,324	893	0.0
	SLACK	668	86	0.00	0.00	97.2	80.9	48.0	82.2	351.5	16,571	916	0.0	12,922	570	48.1	16,571	916	0.0
	CR	782	31	47,841	57,230	97.2	80.6	47.8	82.0	179.4	61,648	52,689	6.8	59,826	52,499	0.1	15,678	633	56.6
	FCFS	629	79	11,070	18,080	97.3	81.1	48.2	82.4	322.4	27,330	18,948	0.0	24,054	18,266	3.1	15,791	860	0.0
	SPT	657	67	5,614	9,769	97.3	81.7	48.7	82.9	268.1	21,056	10,360	26.2	18,334	9,758	3.3	15,203	811	48.1
3 pm	EDD	629	80	0.00	0.00	97.3	81.1	48.2	82.4	321.6	15,780	857	69.4	12,515	581	40.4	15,780	857	0.0
	SLACK	607	87	0.00	0.00	97.3	80.7	47.9	82.1	346.2	16,024	875	0.0	12,508	596	53.2	16,024	875	0.0
	CR	726	29	50,023	62,785	97.3	80.5	47.8	81.9	170.9	62,125	55,679	4.4	60,394	55,495	0.0	15,121	600	51.9
	FCFS	561	82	26,973	33,274	97.2	81.2	48.3	82.4	316.6	45,424	35,018	0.0	42,088	34,249	0.4	15,366	925	0.0
	SPT	607	52	14,222	18,379	97.2	82.1	49.0	83.2	260.9	30,480	19,675	6.8	27,718	18,973	0.4	14,799	925	42.9
4 pm	EDD	561	83	0.00	0.00	97.2	81.2	48.3	82.5	315.9	15,347	928	87.3	12,018	601	35.0	15,347	928	0.0
	SLACK	535	89	0.01	0.25	97.2	80.8	48.0	82.1	340.9	15,583	949	0.1	11,994	610	64.2	15,583	949	0.0
	CR	657	31	53,694	70,056	97.2	80.7	47.9	82.1	163.9	64,066	66,456	5.8	62,415	66,254	0.0	14,610	644	57.1
	FCFS	509	85	45,756	48,295	97.2	81.2	48.3	82.4	307.0	63,757	48,231	0.0	60,559	47,444	0.0	14,865	926	0.0
	SPT	572	55	24,732	27,716	97.2	82.2	49.1	83.3	250.1	40,158	27,733	0.8	37,544	27,016	0.0	14,335	951	40.6
5 pm	EDD	508	87	0.00	0.00	97.2	81.2	48.3	82.4	305.5	14,848	912	93.7	11,661	563	32.9	14,848	912	0.0
	SLACK	480	89	0.06	1.27	97.2	80.8	47.9	82.1	330.8	15,164	1,709	0.1	11,715	1,393	66.6	15,080	941	0.0
	CR	604	33	60,877	68,854	97.2	80.8	47.9	82.1	155.8	75,991	65,710	5.4	74,406	65,517	0.5	14,116	644	59.4

Table notes

Idleness costs are for operation with 25 workers: 4 pickers, 5 packing lanes with in total 20 packers, and 1 stager.

Best (%) shows the percentage of all 1,000 simulation runs where this priority rule has lowest cost across the five considered rules.

The standard deviation colummns (std) show the variation of outcomes across the 1,000 simulation runs.

Table 5.5: Simulation outcomes of five priority rules for three customized performance criteria

Table 5.5 summarizes the financial outcomes of the simulation experiments. These outcomes consist of costs associated with earliness, tardiness, idleness, and stock costs. This study considers an integrated cost function that includes all four cost components as well as two restricted versions. One version excludes stock costs, which is relevant for warehouses at urban locations with just-in-time planning that have relatively low stock value compared to high storage rental costs. Another version excludes tardiness costs for warehouses that handle high-priced goods with high storage rental costs and that have flexible pick-up agreements with carriers to skip tardiness penalties. EDD performs best if all components are included, SLACK is best if there are no stock costs, and CR is best if there are no tardiness costs. These rankings of priority rules do not depend on the cut-off scenario and get more pronounced for tighter scenarios. In scenario A (2 pm), the percentage of simulation runs for which EDD, SLACK and CR are optimal are respectively 46.5, 48.1, and 56.6, and for scenario D these percentages are respectively 93.7, 66.6, and 59.4. The outcomes illustrate that there is no priority rule that is universally best for all business situations, but each warehouse may find a suitable rule by selecting the performance objectives that apply for its specific situation.

Evaluation	Objective	Unit	Mean Value EDD	SLACK	GAP	Significance t-statistic	p-value	Differ
Operational	Flow time	Hour	8.1	8.8	-0.7	-6.050	0.000	Yes
	Earliness	Hour	-11.7	-11.0	-0.7	-6.034	0.000	Yes
	Tardiness	%	0.0000	0.0002	-0.0002	-1.415	0.157	No
Financial	Max pallet staging (α)	Pallet	508	480	28	6.992	0.000	Yes
	Truck penalty (β)	€ / week	0.000	0.057	-0.057	1.416	0.157	No
	Server utilization (γ)	%	82.4	82.1	0.3	5.710	0.000	Yes
	Stock in progress (δ)	Pallet	306	331	-25	-6.050	0.000	Yes

Table notes
GAP is the difference between EDD and SLACK.
The p-value is based on the two-tailed t-distribution.
The column 'Differ' shows whether EDD and SLACK differ significantly (at 5% level).

Table 5.6: Welch t-test results for differences between EDD and SLACK priority rules (cut-off scenario 5 pm)

As EDD and SLACK perform roughly similar, a more detailed comparison of these two rules is provided by means of paired t-tests (Welch, 1947) for operational and financial performance for the tightest cut-off scenario (D, 5 pm). The sample size of 1,000 runs far exceeds the usual rule-of-thumb threshold (30), therefore the conventional standard normal distribution is employed to compute p-values. The results in Table 5.6 show significant differences between the two methods. In terms of operational performance, SLACK is more 'just in time' and EDD has shorter flow time. From a financial perspective, SLACK requires less staging space but EDD has higher server utilisation and less work-in-process stocks. The two rules do not show significant differences in tardiness and associated demurrage costs.

5.6 Some operational implications and conclusions

Enhanced competitiveness in retail markets asks for higher levels of responsiveness to satisfy consumer expectations. OEM warehouses, for example, can improve their order delivery speed by postponing order cut-off times for next-day delivery. To smoothen warehouse operations for efficient resource allocation, priority rules help in sequencing outstanding jobs at various stages of the warehouse process. The choice of which rule to apply, depends on the objectives and cost structure of the warehouse. The methodology proposed in this paper suggests careful examination of the business environment to identify relevant performance objectives and cost parameters. Historical operational warehouse data can be used to model the stochastic nature of the order arrival process and of the service and queuing times for the various stages of the outbound warehouse process.

In this analysis performance is distinguished along four dimensions by preventing earliness (staging costs), tardiness (demurrage costs), idleness (labour costs), and work-in-process inventories (stock costs). It depends on the business environment which of these dimensions is actually relevant. Preventing tardiness, for example, is imperative if delayed delivery spoils all product virtues, whereas it is less relevant if delays can be solved by penalty-free rescheduling of pick-up times. The latter situation often applies for OEM warehouses that deliver to retailer warehouses and shops. This study's simulation results show that the critical ratio (CR) priority rule performs well in such situations. It offers shortest flow time with least work-in-process stock, which is valuable for businesses that handle expensive products with high labour costs.

The case study warehouse currently uses the earliest due date (EDD) strategy for sequencing its order fulfilment jobs. The simulation results based on the warehouse-specific cost parameters indicate potential benefits of the CR rule. Compared to the other priority rules, CR has the unique property that it incorporates the dynamic queuing status of jobs in determining their priority. The simulation study employs a rough estimate of queuing times based on expected processing times of jobs with higher priority. Studying actual workflow patterns could refine these estimates by queuing data from the warehouse process and by forecasting queuing times using statistical and machine learning methods. The case study warehouse is interested in refining the job scheduling strategy in its WMS.

Summarizing the contributions of this paper, the current retail market leverages responsiveness of order fulfilment and forces higher levels of efficiency in distribution. From this perspective, job scheduling using flow-shop priority rules offers solutions for distribution centres facing cut-off time pressures. By prioritising each job, warehouses can efficiently maintain responsiveness without increasing labour to satisfy compressed order-fulfilment deadlines. This paper presents a simulation-based methodology for selecting priority rules by evaluating alternative rules in terms of composite cost objectives that can be tailored to warehouse-specific settings. Simulation results indicate good performance of the SLACK rule for just-in-time operations with high storage costs and of the CR rule for high-value product operations with flexible pick-up schedules.

Further research is needed to analyse the trade-off between potential revenue gains through better service with postponed cut-off times against increased costs due to tighter processing conditions. It is also of interest to study historical workflow patterns in more detail to refine CR-type priority rules by improving forecasts of remaining processing and queuing times.

Chapter 6

Summary and conclusions

This thesis focuses on how to solve warehouse challenges in global supply chain management (SCM) that is characterized by large volume uncertainty, great responsiveness needs and complex order-fulfilment collaboration with other functionalities. We employ data analytic methods to exploit the rich data information obtained from detailed registration of daily warehouse operations to address these challenges. By providing actual application examples in real-world situations we showcase the potency of such data-driven warehouse management.

The empirical study in chapter 2 examines distance effects on cross-border electronic commerce, in particular, the critical importance of express-delivery for reductions in distance. E-commerce provides suppliers with a range of opportunities to reduce distance from the on-line buyer standpoint. Psychological barriers to cross-border demand melt down by websites that simplify the search and comparison of products and suppliers across countries. Cost barriers shrink under pricing strategies that leverage transportation costs, and time barriers compress via express delivery services. This study for 721 regions in five countries of the European Union shows that 'distance still matters' in e-commerce, that express delivery reduces distance for cross-border demand, and that rush orders satisfied by express services are more time-sensitive and less price-sensitive than e-demand fulfilled by standard delivery. The willingness of e-customers to pay for express services is shown to be income-sensitive as buyers weigh relative lead-time utility versus the express cost. Further, the adoption of express delivery is positively linked with e-loyalty in terms of enhanced repurchase ratios. The results confirm the importance for e-suppliers to cleverly craft delivery services to reduce distance in order to attract on-line customers across borders.

Chapter 3 considers the question how manufacturers should choose the lot size in the final production run to cover spare part demand during the end-of-life phase. This decision is best informed by forecasting expected replacement demand. Forecasts can be obtained from the installed base of the product reflecting the number of products in use. Consumer choices regarding expired goods depend on the specific product and spare part. Users may also vary in their decisions for products featuring rapid innovations amid changing social trends. Consumer behavior can be anticipated using appropriate types of installed base, one type being a full lifetime installed base for cheap but essential spare parts in costly systems and another comprising a warranty installed base for expensive spare parts in products with short lifecycles. The chapter presents a general methodology for installed base forecasting of end-of-life spare part demand and formulates research hypotheses on which of four installed base types performs best for which conditions. The methodology is illustrated by case studies of eighteen spare parts for six products from a consumer electronics company. Research hypotheses are supported in most cases, and the forecasts obtained from correct installed bases are substantially better than those obtained by black-box methods. Incorporating past sales via installed base supports final production decisions to satisfy spare part demand.

Chapter 4 studies the ways in which outbound warehouse efficiency depends on the management of mid-term demand forecasts and associated labour planning. The outbound process of a case study in consumer electronics consists of the consecutive stages of picking, packing, and loading. The current management system tends to over-forecast actual orders, and a time series model corrects for this bias and provides the benchmark for selecting an optimal level of bias to maximise labour productivity. For picking and loading, optimal biases range from 30-70 percent yielding labour efficiency gains of 5-10 percent, whereas packing does not benefit from bias. Applying similar methodologies, managers can tailor the degree of intentional forecast bias that works best for their situation. The required information for this kind of evidence-based labour management consists of historical data on order sizes, forecasts, and worker productivity. Optimal implementation depends on hiring strategies available to the firm and on prevailing cost structures.

Chapter 5 addresses "order cut-off time" effects. To satisfy consumer expectations, these cut-off times are gradually delayed to improve order responsiveness. Warehouses must therefore allocate jobs more efficiently to meet compressed response times. Though priority job management by means of flow shop modelling has been used mainly for production, these methods can also be applied for warehouse job scheduling to accommodate tighter cut-off times. This chapter investigates which priority rule performs best under what circumstances. The performance of each rule is evaluated in terms of a common cost criterion that integrates goals of low earliness, low tardiness, low labour idleness, and low work-in-process stocks. A real-world case of a warehouse distribution centre for an original equipment manufacturer in consumer electronics provides input parameters for simulation. Results validate several strategies for improved responsiveness. The critical ratio rule offers the fastest flow time and performs best for warehouse contexts with expensive products and high labour costs.

The investigations presented in this thesis lead to the following conclusions. Globalization of SCM will accelerate and warehouse logistics should address the corresponding challenges. Warehouses should adopt data-driven management into their daily operations to gain insight in operational uncertainties. Chapter 2 shows long-term opportunities (for the coming years) for expanding cross-border e-commerce in the European Union. Chapter 3 illustrates how to satisfy mid-term demand for spare parts during the end-of-life phase (of several months) by means of data-driven forecasts. Chapter 4 shows how to employ detailed productivity data to control short-term (weekly or daily) labour cost, helping to sustain effective operation of variable warehouse resources. Chapter 5 considers imminent-term (hourly or shorter) data applications for job priority allocation to improve daily responsiveness in warehouse order fulfilment. All these data analytic methods can be incorporated in warehouse management systems where managers can tune the specific strategies according to their warehouse constraints, including location cost, labour cost, time criticality, and freight company flexibility. In this way, data analytics at the warehouse level offers great opportunities for managing increasing uncertainties and performance requirements in global SCM.

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Nederlandse samenvatting (Summary in Dutch)

Dit proefschrift onderzoekt op welke manier distributiecentra de uitdagingen kunnen oplossen die optreden in het beheer van mondiale toevoerketens ("global supply chains") die worden gekarakteriseerd door grote onzekerheid in volumes, de noodzaak om snel te reageren en ingewikkelde samenwerking voor het voldoen van bestellingen. Om deze uitdagingen het hoofd te bieden maken we gebruik van data analysemethoden voor het benutten van de rijke informatie die voortkomt uit een gedetailleerde registratie van de dagelijkse werkzaamheden in distributiecentra. We laten de potentiële mogelijkheden van dergelijk data gestuurd beheer zien door daadwerkelijke toepassingen in de praktijk.

De empirische studie in hoofdstuk 2 onderzoekt afstandseffecten in de internationale handel via internet en vooral de cruciale betekenis van spoedlevering om afstand te verkleinen. Het aanbod van producten via internet biedt een waaier aan mogelijkheden om de door de internetklant ervaren afstand te verkleinen. Psychologische obstakels voor buitenlandse vraag verdwijnen door websites die het gemakkelijk maken om producten en aanbieders van verschillende landen te vinden en met elkaar te vergelijken. Kostenobstakels worden kleiner door vervoerskosten te verrekenen in prijzen en tijdsobstakels verdwijnen door spoedlevering. Deze studie voor 721 regio's in vijf landen van de Europese Unie toont aan dat afstand nog steeds een rol speelt maar dat spoedleveringen de ervaren afstand voor internationale vraag verkleinen en dat deze meer tijdsgevoelig en minder prijsgevoelig zijn dan internetbestellingen met standaard aflevering. De bereidheid van klanten om te betalen voor spoedlevering blijkt samen te hangen met het inkomen omdat de relatieve tijdswinst wordt afgewogen tegen de extra kosten. De neiging om te kiezen voor spoedlevering hangt positief samen met klantloyaliteit gemeten in termen van herhaalde aankopen. De resultaten bevestigen dat het voor aanbieders via internet belangrijk is om hun leveringsdiensten zorgvuldig te kiezen voor het verkleinen van de ervaren afstand om internetklanten uit het buitenland te trekken.

Hoofdstuk 3 gaat in op de vraag op welke manier producenten de omvang van de finale productieronde moeten kiezen om te kunnen voldoen aan de vraag naar reserve onderdelen in de laatste fase van de levenscyclus. Deze beslissing kan het beste worden bepaald door de verwachte vervangingsvraag te voorspellen. Deze voorspellingen kunnen worden gebaseerd op de zogenoemde “installed base”, een maatstaf voor het aantal producten dat nog in gebruik is. De beslissingen van consumenten bij niet langer geproduceerde goederen hangen af van het specifieke product en onderdeel. Gebruikers verschillen ook in hun beslissingen voor producten met snelle innovaties en in hun gevoeligheid voor sociale trends. Er kan rekening worden gehouden met het gedrag van consumenten door een geschikt type “installed base” te gebruiken, zoals gebaseerd op volle levensduur voor goedkope maar onmisbare onderdelen van kostbare producten en op garantietermijn voor dure onderdelen van producten met een korte levensduur. Het hoofdstuk biedt een algemene methodologie voor het gebruik van dit concept voor het voorspellen van de vraag naar reserve onderdelen gedurende de laatste fase van de levenscyclus en formuleert onderzoekshypothesen over welk type het beste presteert in welke omstandigheden. De methodologie wordt toegelicht door toepassingen voor achttien reserve onderdelen van zes producten van een bedrijf in consumentenelektronica. De meeste gevallen leveren ondersteuning voor de onderzoekshypothesen en de voorspellingen verkregen door toepassing van “installed base” zijn aanzienlijk beter dan die worden verkregen door zogenoemde black-box methoden. Het meenemen van verkopen uit het verleden helpt bij de beslissing over de finale productieronde voor het voldoen aan de vraag naar reserve onderdelen.

Hoofdstuk 4 bestudeert hoe de efficiëntie van uitgaande activiteiten in distributiecentra samenhangt met het beheer van middellange termijn vraagvoorspellingen en de daarmee verbonden werkplanning. Het uitgaande proces van een voorbeeld distributiecentrum in consumentenelektronica bestaat uit de opeenvolgende activiteiten van order verzamelen, inpakken en inladen. Het huidige beheersysteem overschat de werkelijke vraag meestal en een tijdreeksmodel corrigeert deze vertekening en geeft de grondslag voor de keuze van de beste vertekening die leidt tot de grootste arbeidsproductiviteit. Voor verzamelen en inladen ligt de optimale vertekening tussen de 30 en 70 procent met winsten van 5 tot 10 procent in arbeidsproductiviteit, terwijl zulke vertekening het inpakken niet versnelt. Beheerders kunnen deze methodologie toepassen door de gewenste vertekening aan te passen aan hun situatie. De benodigde informatie voor dit soort ervaring gedreven arbeidsbeleid bestaat uit historische gegevens over vraagomvang, voorspellingen en arbeidsproductiviteit. De optimale uitvoering hangt af van de kostenstructuur en van de beschikbare arbeidsopties van het bedrijf.

Hoofdstuk 5 gaat over het effect van het gekozen tijdsmoment waarna bestellingen niet meer direct worden verwerkt. Om tegemoet te komen aan verwachtingen van consumenten wordt dit moment geleidelijk uitgesteld om sneller te kunnen leveren. Distributiecentra moeten daarom hun taken efficiënter ordenen om te voldoen aan een krappere reactietermijn. Hoewel prioriteringsregels vooral zijn ontwikkeld voor productie op assemblagelijnen kunnen deze methoden ook worden gebruikt voor het ordenen van taken in distributiecentra om te voldoen aan strakkere tijdslimieten. Dit hoofdstuk onderzoekt welke prioriteitsregels het beste werken onder welke omstandigheden. De kwaliteit van elke regel wordt uitgedrukt in een gezamenlijk geïntegreerd kostencriterium voor vier doelen: de taken moeten noch te vroeg noch te laat zijn afgerond, er moet geen arbeidstijd verloren gaan, en wachtvoorraden tijdens het werkproces moeten klein zijn. Een voorbeeldstudie van een distributiecentrum van een producent van consumentenelektronica levert de parameters voor simulaties. De resultaten bevestigen diverse strategieën voor het verkorten van reactietijden. Zo geeft de zogenoemde kritieke verhoudingsregel de snelste doorstroom en is dit de beste regel voor distributiecentra met dure producten en kostbare arbeid.

Het onderzoek in dit proefschrift leidt tot de volgende conclusies. De mondialisering van toevoerketens zal toenemen en distributiecentra moeten de daarmee samenhangende logistieke uitdagingen oplossen. Beheerders van distributiecentra moeten in de dagelijkse praktijk gebruik maken van waarnemingsgegevens om beter inzicht te krijgen in operationele onzekerheden. Hoofdstuk 2 toont lange termijn mogelijkheden (voor de komende jaren) voor het uitbreiden van buitenlandse handel via internet in de Europese Unie. Hoofdstuk 3 laat zien hoe voldaan kan worden aan de vraag op middellange termijn naar reserve onderdelen in de laatste fase van de levenscyclus (van enige maanden of jaren) met voorspellingen gebaseerd op historische gegevens. Hoofdstuk 4 beschrijft hoe gedetailleerde productiviteitsgegevens gebruikt kunnen worden voor het in toom houden van arbeidskosten op de korte termijn (wekelijks of dagelijks) voor de efficiënte inzet van aanpasbare middelen in distributiecentra. Hoofdstuk 5 beziet het onmiddellijk gebruik van gegevens (per uur of korter) voor het ordenen van taken die de dagelijkse reactiesnelheid in het voldoen van bestellingen verhogen. Deze door waarnemingsgegevens aangestuurde methoden kunnen allemaal worden opgenomen in het beheersysteem van distributiecentra, waarbij beheerders de strategieën kunnen toespitsen op de specifieke situatie van hun centrum zoals locatiekosten, arbeidskosten, tijdsbeperkingen en flexibiliteit van vervoerders. Op deze manier levert de analyse van waarnemingsgegevens op het niveau van distributiecentra grote mogelijkheden voor het opvangen van toenemende onzekerheid en voor het voldoen aan hogere prestatie-eisen in het beheer van mondiale toevoerketens.

Curriculum Vitae

Thai Young Kim (1974) obtained his Bachelor's degree in electrical engineering from Yonsei University in Seoul, South Korea in 2001. In 2007 he received his master's degree in marketing communication at the same university. In 2010 he received another master's degree in maritime economics and logistics from Erasmus University Rotterdam.

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During his PhD he presented his research at the Dutch expert group symposium including Bigdata from science to practice (hosted by Erasmus Q-intelligence), Service Logistics Forum (hosted by Dinalog).

Portfolio

PUBLICATIONS

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• **Thai Young Kim.** (2018). Improving warehouse responsiveness by job priority

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PRESENTATIONS

• Big Data : Science to practice Q-intelligence symposium, Erasmus University Rotterdam, 29th August 2016, Rotterdam, The Netherlands

• Spare part demand forecasting from installed based for consumer goods Service logistics forum & Dutch institute for advanced logistics, 9th October 2014, Breda, The Netherlands

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Warehouse management has emerged as a determinant for success of global supply chain management. This thesis focuses on how to solve warehouse challenges in global supply chain management (SCM) that is characterized by large volume uncertainty, great responsiveness needs and complex order-fulfilment collaboration with other functionalities. We employ data analytic methods to exploit the rich data information obtained from detailed registration of daily warehouse operations to address these challenges. By providing actual application examples in real-world situations we showcase the potency of such data-driven warehouse management.

In this dissertation, data-driven warehouse management is presented by four-steps in the time horizon of warehouse operations: Long-term opportunities (for the coming years) are examined by predictive analytics for expanding cross-border e-commerce in the European Union. Mid-term demand for spare parts during the end-of-life phase (of several months) are forecasted by means of data-driven modelling for installed base. Short-term operational opportunity (weekly or daily) are presented by employing detailed productivity data to sustain effective operation of variable warehouse resources. Real-time (hourly or shorter) data applications are introduced for job priority allocation to improve daily responsiveness in warehouse order fulfilment.

All these data analytic methods can be incorporated in warehouse management systems where practitioners can tune the specific strategies according to their warehouse constraints, including location cost, labour cost, time criticality, and freight company flexibility. In this way, data analytics at the warehouse level offers great opportunities for managing increasing uncertainties and performance requirements in global SCM.

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