Three Essays on Aligning Supply Chain Strategies with the Business Environment

Inauguraldissertation

zur Erlangung des akademischen Grades

eines Doktors der Wirtschaftswissenschaften

der Universität Mannheim

vorgelegt von

Christian Joachim
Freiherr von Falkenhausen

Mannheim

Dekan: Prof. Dr. Dieter Truxius

Referent: Prof. Dr. Moritz Fleischmann

Korreferent: Prof. Dr. Christoph Bode

Tag der mündlichen Prüfung: 15. Dezember 2017

Acknowledgements

Moritz Fleischmann, the supervisor of this thesis, and I engaged in our first conversation at the end of one of his lectures. Since I had arrived late and fallen asleep subsequently, he proposed that next time I would stay awake and arrive on time. I took his advice to heart, eventually enrolled in most of his courses, and ultimately discovered a passion for operations management that led me to take up my doctoral studies at his chair.

During this time, having Moritz as my supervisor was invaluable. His composed and well-thought-throughout manner provided not only a pleasant working environment, but also much-needed reassurance when I was unsure how to proceed with my studies. To this day, I am impressed by how quickly and thoroughly he comprehends the work I present to him and by the clear-cut guidance he gives concerning matters that require improvement. Most importantly to me though, over the past three years, I could always rely on Moritz' backing regarding issues that extended beyond the immediate needs of our research. Be it visiting a conference, joining a doctoral course at a different university, or aligning our projects with the timeline we had set when I joined the chair – knowing that I could confide in my supervisor to have these issues in mind provided a trustful and motivating basis for the pursuit of this thesis.

I also greatly appreciate the support I have received from Christoph Bode. Christoph has taught me the basics of empirical research, ranging from the need for theorizing, "setting the hook", to practical topics such as the dos and don'ts of writing an empirical research article. Further, he contributed greatly to my first research project. Christoph was not only a valuable source of reference regarding methodological questions, he also provided key ideas with regards to the structure of the article. Having a knowledgeable contact like Christoph only a knock-on-the-door away was extraordinary – I am truly grateful for his tremendous help.

Moreover, I would like to thank Christian Eich and Thomas Furtwängler for being my supervisors at BASF. Christian enabled me to set the foundation of my research. He facilitated access to data and ensured I participate in ongoing initiatives connected to my research. Thomas, who was my supervisor for the past two years, has played a major role in embedding my research into the supply chain governance of BASF. Working together with him was extremely rewarding, as it allowed me to experience first-hand how the approaches developed in this thesis can contribute to making a difference a practice.

In addition to the aforementioned contributors, there are many colleagues that have made the past three years exceptional. I will miss the workplace banter and the distractions from day-to-day work that I have enjoyed with my fellow doctoral students and the strategy development team at BASF. A special mention goes to Michael Westerburg, who not only excelled at providing such distractions, but also at giving valuable feedback that helped to improve this manuscript.

Finally, and most importantly, I am greatly indebted to my family, my girlfriend and my friends for their continuous encouragement and undoubting support over the past years. Knowing that I could count on their backing has kept me on track and, hence, rendered the completion of this undertaking possible. I dedicate this thesis to them.

Abstract

Aligning the competitive priorities of supply chains with the requirements of the business environment is critical for competing successfully in the marketplace. Nonetheless, many companies fail to develop supply chain strategies that provide a good "fit" to the characteristics of their business. The goal of the thesis at hand is therefore to provide insights for three steps that are key for attaining alignment: (1) capturing requirements of the business environment, (2) subdividing products and customers to obtain segments with distinct supply chain design requirements and (3) developing aligned supply chains strategies for each segment. The first study investigates which variables companies should analyse to capture the requirements their business. Specifically, it tests the effects hypothesized to be underlying the five most frequently cited contingency variables in the literature on supply chain strategy. The results indicate that demand variability and the customer lead time requirements are important for setting competitive priorities because they influence whether companies require market mediation capabilities to fulfil demand as requested by customers. Volume, variety and lifecycle duration are less important for this purpose, but may instead be used for analysing the causes of variable demand. The second study investigates how companies can subdivide a heterogeneous set of products or customers into groups ("segments") that require distinct supply chain strategies. The study uses clustering and classification to form segments quantitatively and compares the results to segments that were formed based on managers' tacit knowledge. The findings indicate that managers may choose segments that do not reflect the needs of their business environment, consequently pursuing supply chain strategies that adversely affect financial performance. Clustering and classification help managers detect such segment-environment mismatches and thus serve as valuable tools for challenging managers' judgment. Lastly, to facilitate the derivation of aligned supply chain strategies, the third study investigates in which business environments companies should prioritize responsiveness, i.e., the ability to fulfil orders within a time frame that is acceptable to the customer. As the extant literature provides inconsistent recommendations in this regard, the study analyses both the benefits and the costs of shorter lead times. The results suggest that responsiveness can increase financial performance in two distinct ways: either by matching supply and demand or by decreasing supply chain related costs depending on the characteristics of the products that are being sold.

Contents

List of Figures

List of Tables

Chapter 1 Introduction

1 Motivation

Contingency theory states that in order to maximize performance, companies need to align the structures of their organization with the context they operate in (Donaldson, 2001; van de Ven et al., 2013). The strategic management literature refers to the alignment between strategy and environment as “fit” (Venkatraman, 1989). The need to achieve “fit” between strategy and context is also widely recognized in the supply chain community (Sousa and Voss, 2008). Following the seminal article by Fisher (1997), a thrust of studies has highlighted the adverse effects of failing to align supply chain strategies with the requirements of the business environment (Childerhouse et al., 2002; Christopher et al., 2009; Lee, 2002; Qi et al., 2009; Randall and Ulrich, 2001). There are indeed many real-word examples where misalignment has eroded companies’ market positions.

Consider, for instance, the well-known case of Gap Inc. and Inditex S.A. Both companies operate in the fashion industry, i.e., a business environment where demand is hard to forecast because consumer preferences change quickly (Christopher et al., 2004). Despite operating in the same industry, the two companies pursue radically different supply chain strategies. Gap, on the one hand, orders products up to one year in advance (CNN, 2016). Inditex, on the other hand, pursues a strategy that emphasizes short lead times. At Zara, Inditex’ most prominent fashion brand, the time between the design of a new product and its arrival in stores can be as short as 15 days (Ferdows et al., 2004).

Since Inditex achieves these short lead times by relying on local production, frequent replenishments at stores, and the use of fast transportation modes, it incurs comparably high production and transportation costs (Chopra and Sodhi, 2014). Nonetheless, pursuing short lead times pays off for Inditex. Short lead times are important in the fashion industry, since they allow companies to operate with lower inventories and generate additional revenues by offering the latest trends (The Economist, 2015). Because Inditex’ supply chain strategy therefore closely matches the requirements of its business environment, the company has continuously gained market share over the past years (Reuters, 2017a). On the contrary, Gap has lost market share and struggles to be profitable (Forbes, 2015). Recently, the company has launched an initiative to reduce cycle times with the goal of reacting to changes in customer preferences more quickly (CNN, 2016).

Yet while a supply chain strategy that emphasizes flexibility and short lead times may be successful in the fashion industry, it does not guarantee success in other business environments as well. Consider, for instance, two of the largest bankruptcies in Germany that took place in the past decade: the semiconductors manufacturer Qimonda AG and the photovoltaics manufacturer Solarworld Industries AG (Amtsgericht Bonn, 2017; Amtsgericht München, 2009). Both companies had opened production facilities close to their customers in high-cost countries during a period of high market growth (Infineon Technologies AG, 2006; Solarworld Industries AG, 2009). However, for these companies, the benefits of local production did not outweigh the associated costs. When their respective markets saturated and the margins for their products dropped, Qimonda and Solarworld were unable to match the prices of competitors from Asia (Reuters, 2017b; The Economist, 2009). Both companies therefore had to close – at least in part – because they lacked supply chain fit.

Apart from anecdotal evidence, there are also several empirical studies that demonstrate the value of supply chain fit. Wagner et al. (2012), Gligor (2015) and Gligor (2017) highlight that aligning supply chain strategies with the requirements of the business environment is associated with a higher return on assets. Supply chain fit is also recognized by shareholders: companies that succeed in matching their supply chain strategy to their business environment on average have an 18.9% higher market capitalization (Grosse-Ruyken and Wagner, 2010).

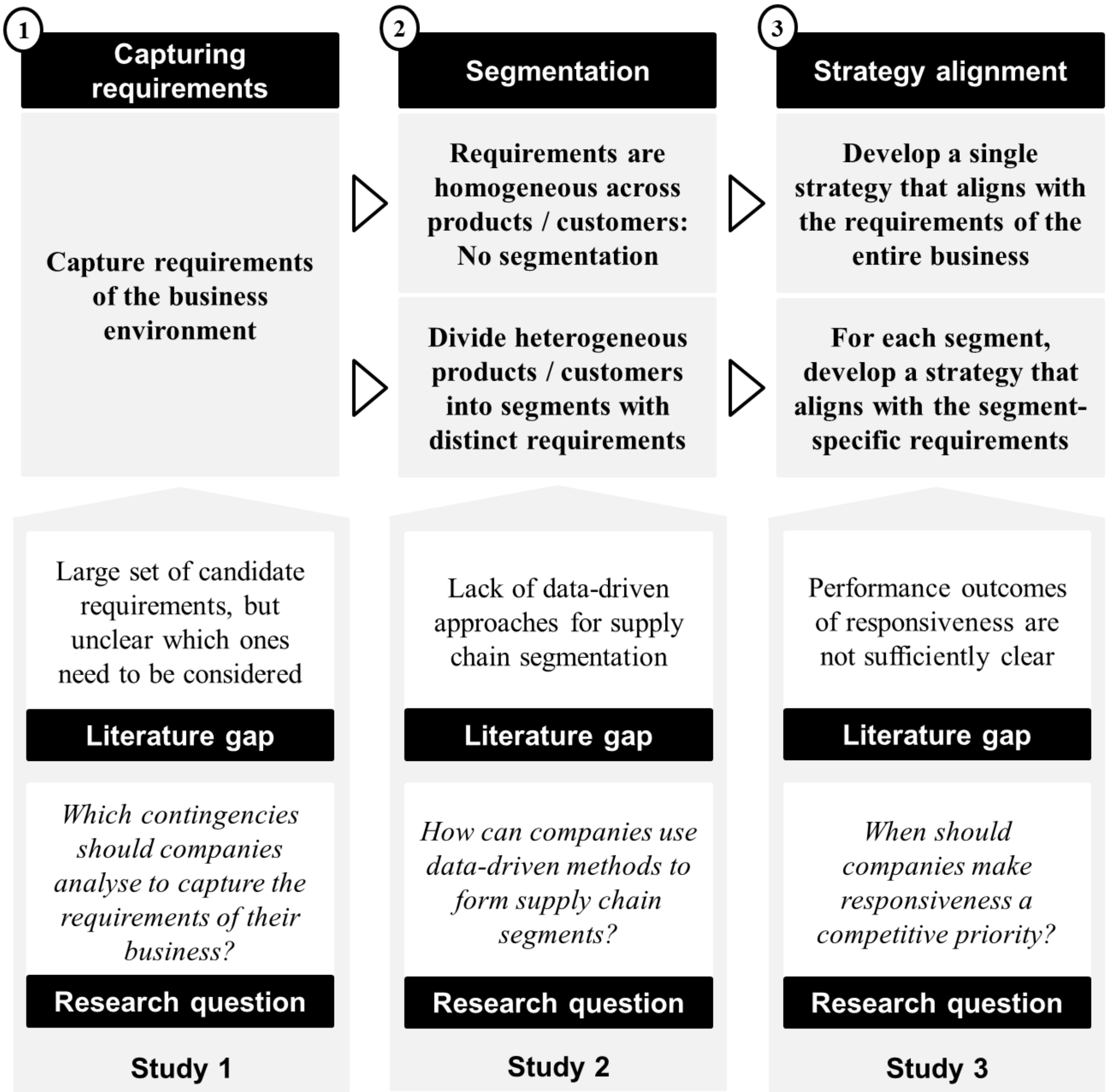
However, while these studies substantiate the importance of aligning supply chain strategies with the business environment, they also highlight that many companies fail in doing so. Gligor (2015) and Gligor (2017), for instance, only find a weak correlation between investments in market mediation capabilities and environmental uncertainty, even though market mediation capabilities are considered critical for achieving fit when uncertainty is high. Similarly, Wagner et al. (2012) find that almost 50% of companies significantly overinvest or underinvest in market mediation given the level of uncertainty they are confronted with. Finally, Selldin and Olhager (2007) concur that "there is not an overall clear match between product type and supply chain design".

We can therefore summarize the status quo in literature on supply chain fit as follows: (1) even though supply chain fit is critical for competing successfully in the marketplace, (2) many companies fail to align the setup of their supply chain with the requirements of their business. This finding reflects that despite decades of research on the topic, key challenges companies face when seeking alignment remain unresolved (Basnet and Seuring, 2016). Consequently, this dissertation aims to contribute towards resolving challenges that prevent the attainment of supply chain fit, hence enabling companies to align their supply chain strategies with the requirements of their business.

2 Research questions

As indicated in Figure 1.1, aligning supply chain strategies with the requirements of the business environment is a three-step process. First, companies need to gain an understanding of the environment they operate in. For this purpose, they may gather information on supply-chain-relevant characteristics of their business. Second, companies need to assess to what extent the captured requirements diverge across their portfolio of products and customers. If their products and customers are relatively similar, companies may proceed with the third step and develop a single supply chain strategy that aligns with the characteristics of their business. However, if products and customers differ regarding the type of supply chain they require, companies need to create groups ("segments") of products or customers with distinct characteristics. For each segment, companies may then develop a supply chain strategy that fits the segment-specific requirements. In the following, we highlight gaps in the extant literature that prevent the execution of these steps and derive corresponding research questions.

Figure 1.1: Three-step process for achieving supply chain fit with corresponding literature gaps and research questions.



2.1 Research Question 1: Capturing requirements of the business environment

The importance of supply chain fit is widely acknowledged and nowadays resonates in practitioner frameworks and learning materials (APICS, 2016; Gartner, 2016b). Nonetheless, many companies fail to align their supply chains with the requirements of their business (Gligor, 2015, 2017; Wagner et al., 2012). One likely reason for this seemingly paradoxical observation is that business environments are complex: managers need to consider many different factors when setting the competitive priorities of their supply chains.

To help managers decide on supply chain strategies, the extant literature has introduced a variety of contingency variables. Contingency variables reflect characteristics of the business environment that influence the competitive priorities supply chains should pursue for maximizing profits. Fisher (1997), for instance, proposes that demand uncertainty increases the need for a market-responsive supply chain. A recent review article identifies 13 contingency variables mentioned at least twice in the literature (Basnet and Seuring, 2016). However, it can be put into question whether such a broad spectrum of contingency variables facilitates the development of aligned supply chain strategies.

On the one hand, covering all essential contingencies is important to ensure that relevant characteristics of the business environment are adequately reflected. On the other hand, managers have trouble analysing higher-order interactions of contingency variables; considering too many variables in the strategy formation process may thus prevent the best strategy from being found (Wedel, 2000). Similarly, if companies subdivide their product or customer portfolios into clusters that require similar supply chain strategies, considering irrelevant or redundant variables may lead to suboptimal results (Bacher et al., 2010; Brusco et al., 2017; Ketchen and Shook, 1996).

Given the resultant trade-off and the wide variety of proposed contingencies, there is a need to disambiguate which contingencies are important for setting the competitive priorities of supply chains. Accordingly, Basnet and Seuring (2016) call for "more work to identify a parsimonious set of contingency variables". As a response to this call, Study 1 in Chapter 2 aims to answer the following research question:

Question 1: *Which contingency variables should companies analyse in order to capture supply-chain-relevant requirements of their business?*

2.2 Research Question 2: Data-driven supply chain segmentation

Once companies have captured the supply-chain-relevant requirements of their business, they may attempt to develop a supply chain strategy that meets these requirements. However, many companies offer a wide variety of products to a range of different customers. Oftentimes, these products and customers are heterogeneous regarding the type of supply chain they require.

Consider, for instance, the well-known difference between innovative and functional products: while the former require a supply chain that excels at matching supply and demand in a challenging operating environment, the latter require a supply chain that emphasizes efficiency (Fisher, 1997). Yet it is not uncommon for companies to sell both innovative and functional products (Childerhouse et al., 2002). Given the resultant heterogeneity in companies' product and customer portfolios, supply chain segmentation has become an emergent practice. It describes the process of dividing a heterogeneous set of products or customers into groups ("segments") that impose similar requirements on the supply chain. For each of these segments, a tailored supply chain strategy is developed.

Supply chain segmentation, therefore, allows companies to more accurately align their supply chain capabilities and structures to the requirements of their business. Compared to a company with a single supply chain strategy, a company with a tailored strategy for each segment may operate some parts of its business at lower cost and extract higher revenues from other parts. As a result, supply chain segmentation is considered one of the most effective levers for improving supply chain performance (Rexhausen et al., 2012) and has been linked to lower inventories, higher service levels and lower logistics cost (Mayer et al., 2009). A recent survey by Gartner, a consultancy, concludes that "an overwhelming 95% of [chief supply chain officers] expect to invest in supply chain segmentation in 2016, with 35% calling it a top priority" (Gartner, 2016a).

Despite practitioners' interest in the topic, the number of corresponding studies is limited so far. A key characteristic of the extant literature on supply chain segmentation is a qualitative approach to segment formation: segments are formed using managers' tacit knowledge, without a systematic data analysis.

This approach has its drawbacks. Managers' tacit knowledge is subjective; relevant clusters of products or customers may remain undetected as a result (Foedermayr and Diamantopoulos, 2008). Especially if product or customer portfolios are broad and heterogeneous, it is unlikely that managers will have a comprehensive overview of all relevant segmentation criteria and objects (Wedel, 2000). A supply chain segmentation initiative that exclusively relies on managers' tacit knowledge can thus only provide limited insights.

Consequently, authors of segmentation methodologies in marketing urge practitioners to refrain from solely relying on the qualitative approach (Foedermayr and Diamantopoulos, 2008; Wedel, 2000). There are many examples of segmentation initiatives in other areas of business research that employ data analysis to derive segments (Ngai et al., 2009). The supply chain community, however, appears to be lagging behind in this regard: with one exception (Langenberg et al., 2012), articles in scholarly journals exclusively rely on managers' tacit knowledge for this purpose. Strikingly, the two most commonly employed methods for deriving segments in other areas of business research – clustering and classification (Ngai et al., 2009)

– have not been used in studies on supply chain segmentation so far. Study 2 in Chapter 3 therefore examines how clustering and classification can be used to form supply chain segments quantitatively. In doing so, the study aims to answer the following research questions:

Question 2a: *How can companies use data-driven methods to form supply chain segments quantitatively?*

Question 2b: *What insights do these data-driven methods generate relative to qualitative approaches?*

2.3 Research Question 3: Performance outcomes of responsiveness

Study 3 in Chapter 4 aims to provide insights that facilitate the derivation of supply chain strategies that fit to segment-specific requirements of the business environment. For this purpose, the study investigates the performance outcomes of responsiveness. In supply chain management, responsiveness describes the ability of a supply chain to fulfil orders within a time frame that is acceptable to the customer (Chen et al., 2004; Holweg, 2005). As this ability is considered critical for competing successfully in the marketplace, setting lead-time-related targets is imperative when developing supply chain strategies (APICS, 2016).

However, there are two conflicting perspectives regarding the performance outcomes of responsiveness. On the one hand, studies on the value of shorter lead times argue that responsiveness entails a cost premium and, hence, purport that responsiveness is primarily important for innovative products (Blackburn, 2012; de Treville et al., 2014a; de Treville et al., 2014b). On the other hand, studies on lean management and just-in-time practices assert that shorter lead times reduce supply-chain-related costs, especially in stable operating environments that are typical for functional products (Mackelprang and Nair, 2010; Narasimhan et al., 2006; Shah and Ward, 2003). To determine in which contexts companies should make responsiveness a competitive priority, we formulate the following research question:

Question 3: *When should companies make supply chain responsiveness a competitive priority?*

3 Empirical basis

3.1 Data requirements

Answering the research questions formulated in the previous section requires two types of data: archival data from company databases and data on qualitatively derived supply chain segments.

The need for archival data from company databases is inherent to all studies in this thesis. Study 1 aims to provide companies a better understanding as to which characteristics of their business they should gather information on when developing a supply chain strategy. To ensure practical relevance, the study focuses its analysis on contingencies that companies can attain information on without a large data gathering effort, i.e., where data is available in company databases. Study 2 investigates how companies can use clustering and classification to subdivide their business into segments that are distinct regarding supply-chain-relevant characteristics. Consequently, the study requires data on the characteristics of potential segmentation objects (e.g., products, customers, or business units) from a company that operates in a broad set of business environments. Finally, Study 3 analyses how different contextual factors affect the performance outcomes of responsiveness. Since data on responsiveness (i.e., lead times and customer expectations), performance outcomes (e.g., financial performance or supply-chain-related costs) and supply-chain-relevant contingencies is available in company databases, using archival company data is a natural choice for this study as well.

In addition, Study 2 requires data on qualitatively derived supply chain segments. The study investigates how supply chain segments formed with company data compare to segments formed based on managers' judgment. For this purpose, it requires not only archival company data for deriving segments quantitatively, but also information on qualitatively formed segments.

3.2 Case company

The case company of this thesis is BASF, the largest chemicals company worldwide with revenues in excess of 50 billion Euros annually (American Chemical Society, 2017). The company is highly diverse regarding the business environments it operates in, since it embraces the "Verbund"-concept: BASF controls multiple value streams that span from basic chemicals to high-value-added products such as coating and crop protection agents (BASF SE, 2016b). Business units producing basic chemicals, for example, typically operate in stable low-margin environments. On the contrary, business units producing high-value crop protection or coatings for the automotive industry operate in volatile high-margin environments.

As a result of its size and diversity, the company fulfils both requirements outlined in the previous section. First, its broad and diverse portfolio of products and business units provides this thesis a large sample of archival data with considerable variance. Second, to comprehend the diverse requirements of its business units, BASF has formed a set of supply chain segments based on managers' tacit knowledge, hence allowing for a comparison of qualitatively and quantitatively formed segments.

3.3 Data characteristics

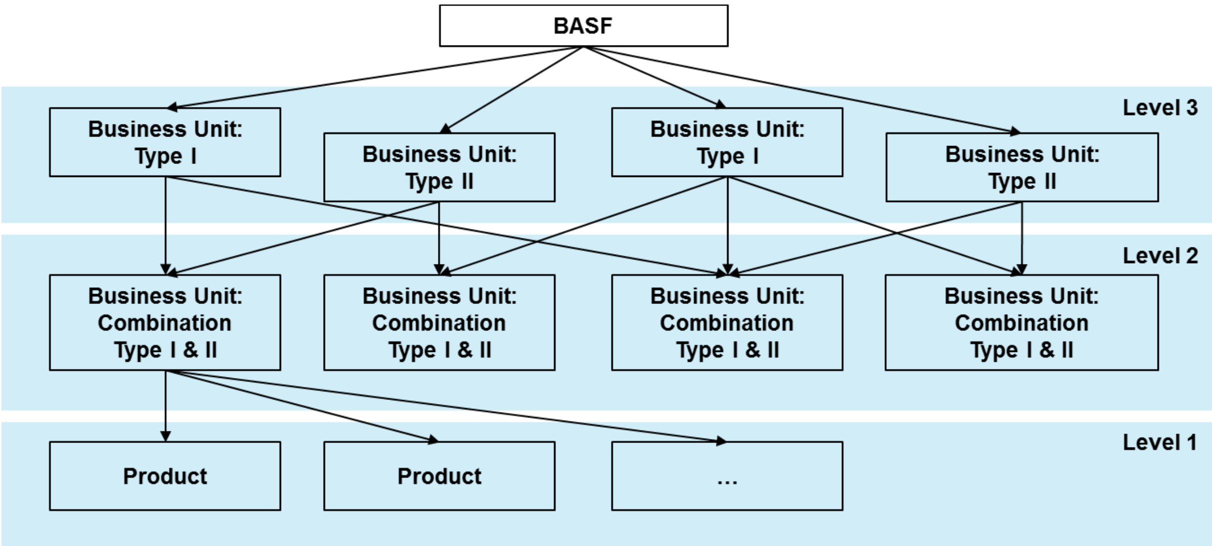
As indicated by Figure 1.2, the studies in this thesis analyse two cross-sectional datasets. The first dataset is used by all studies and covers the years 2013 and 2014. It comprises archival data and BASF's qualitative supply chain segments which were formed during this time period. The second dataset is used only by Study 2 and comprises archival data from the year 2015. Both datasets cover the entire company except for its oil and gas business and thus approximately 80% of the its revenues (BASF SE, 2015).

The datasets have a multilevel structure due to the hierarchical organization of the company. As indicated by Figure 1.3, there are two types of upper-level (Level 3) business units. While the first type of Level 3 business unit indicates the region of a business, the second type of Level 3 business unit indicates the market that is being served. Level 2 business units are combinations of Level 3 business units (region and market); a hypothetical example of a Level 2 business unit is "Specialty Petrochemicals Europe" which is a combination of the Level 3 business units "Petrochemicals Europe" (Type I) and "Specialty Petrochemicals" (Type II). Finally, products (Level 1) are nested within Level 2 business units.

Figure 1.2: Data characteristics.

First dataset		**Second dataset**	
Analysed period:	2013 and 2014	**Analysed period:**	2015
Used by:	Study 1, 2 and 3	**Used by:**	Study 2
Type of data:	Archival data and qualitative segments	**Type of data:**	Archival
Unit of analysis:	Level 1 and Level 2 (Study 2 only Level 2)	**Unit of analysis:**	Level 2

Figure 1.3: Multilevel data structure.



Study 1 and 3 use the first dataset as their empirical basis. The studies focus their analyses on Level 1 and Level 2, as these levels provide sufficient observations for testing hypothesis. Study 2 uses data from both datasets. The study focuses its analyses on business units at Level 2 to ensure comparability with BASF's qualitative supply chain segments which the company has formed at same level of aggregation. The study employs the first dataset to form segments with a cluster analysis and to compare the results to BASF's qualitatively formed segments; the second dataset is employed to demonstrate how classification algorithms can be used for updating quantitatively formed segments.

The first dataset comprises 228 observations at Level 2. Some of the business units at that level have few supply-chain-related activities (e.g., research and design business units). These business units exhibit extreme values for financial performance (due to low sales) or supply chain variables (due to few orders). Consequently, the studies in this thesis exclude business units with annual sales below 1 million Euros or fewer than 1,000 orders annually. In addition, the studies exclude one business unit that is not reliably integrated into BASF databases and one business unit with missing financial data. Study 3 further excludes one business unit with missing data for logistics costs and three business units with extreme values for financial performance. The final sample of business units from the first dataset located at Level 2 therefore comprises 181 observations for Study 1 and 2, and 177 observations for Study 3.

At Level 1, the dataset comprises 133,687 products that can be uniquely assigned to the remaining 181 Level 2 business units (132,476 products can be uniquely to the 177 Level 2 business units of Study 3). Following the removal of products with missing data or negative values, the final sample of products comprises 101,071 observations for Study 1 and 77,710 observations for Study 3.

Finally, the second dataset comprises 216 observations at Level 2. Again, we remove all business units with annual sales below 1 million Euros, fewer than 1,000 orders annually or missing values. As a result, the final sample of Level 2 business units in the second dataset used for Study 2 comprises 151 observations.

Chapter 2 Contingency variables for developing supply chain strategies: An analysis of the DWV3 framework

Co-author:

Moritz Fleischmann

Chair of Logistics and Supply Chain Management, Business School, University of Mannheim, Germany

Abstract

Contingency variables are characteristics of the business environment that influence the competitive priorities supply chains should pursue for maximizing profits. But which contingency variables should managers focus on when developing a supply chain strategy? On the one hand, if important variables are omitted, the selected strategy may fail to fulfil the needs of the business environment. On the other hand, considering irrelevant variables unnecessarily complicates the strategy formation process, hence preventing well-suited strategies from being found. As a first step towards resolving this trade-off, our study empirically examines the effects hypothesized to be underlying the five most frequently cited contingency variables in supply chain strategy literature that are referred to as **DWV3** (product lifecycle **D**uration, customer lead time requirements / delivery time **W**indow, demand **V**ariability, demand **V**olume, product **V**ariety). We test the hypothesis on archival data from a leading chemical manufacturer using multilevel regression and multilevel structural equation modelling. Our findings indicate that demand variability and customer lead time requirements are important for strategy development because they indicate whether companies require market mediation capabilities to fulfil demand as requested by customers. Volume, variety and lifecycle duration are less important for this purpose, but may instead be used for analysing the causes of variable demand. Yet, as our study examines only a subset of the contingencies proposed in the extant literature, additional research is needed to further disambiguate which contingencies companies should focus on when developing supply chain strategies.

1 Motivation

In the last two decades, a thrust of studies has analysed trade-offs companies face when deciding on a supply chain strategy (Aitken et al., 2005; Childerhouse et al., 2002; Fisher, 1997; Lee, 2002; Olhager, 2003; Qi et al., 2009; Randall and Ulrich, 2001). Put simply, these studies conclude that there is no one-size-fits-all supply chain strategy. As a result, the importance of trade-offs is widely acknowledged and nowadays resonates in practitioner frameworks and learning materials (APICS, 2016; Gartner, 2016b). However, despite this widespread awareness, many companies operate supply chains that underserve or overserve the needs of their business (Gligor, 2015; Wagner et al., 2012). One likely explanation for this seemingly paradoxical observation is that business environments are complex: managers need to consider many different factors when setting the competitive priorities of their supply chains.

To help managers decide on supply chain strategies, the extant literature has introduced a variety of contingency variables. Contingency variables are characteristics of the business environment that influence the competitive priorities supply chains should pursue for maximizing profits. Fisher (1997), for instance, proposes that demand uncertainty increases the need for a market-responsive supply chain. A recent review article identifies 13 contingencies mentioned at least twice in the literature (Basnet and Seuring, 2016). However, it can be put into question whether such a broad spectrum of contingency variables is helpful to managers.

On the one hand, covering all essential contingencies is important to ensure that relevant characteristics of the business environment are adequately reflected. On the other hand, however, managers have trouble analysing higher-order interactions of contingency variables; considering too many variables in the strategy formation process may thus prevent the best strategy from being found (Wedel, 2000). Similarly, if companies subdivide their product or customer portfolios into clusters that require similar supply chain strategies, considering irrelevant or redundant variables may lead to suboptimal results (Bacher et al., 2010; Brusco et al., 2017; Ketchen and Shook, 1996). Consequently, there is a "need for more work to identify a parsimonious set of contingency variables" (Basnet and Seuring, 2016).

An established practice in marketing strategy for obtaining a parsimonious set of contingencies is to empirically examine the effects that are assumed to be underlying the variables of interest. Cooil et al. (2007) and Wangenheim and Bayon (2004), for instance, examine the relevance of different customer characteristics for tailoring marketing actions by testing whether they are significant moderators of the link between customer satisfaction and loyalty. However, we are not aware of any studies that empirically examine the effects hypothesized to be underlying contingencies that are potentially important for developing supply chain strategies. As a first step towards filling this gap, our study examines the effects of the five most frequently cited contingency variables in literature on supply chain strategy that are referred to as **DWV3** (product lifecycle **D**uration, customer lead time requirement / delivery time **W**indow, demand **V**ariability, demand **V**olume, product **V**ariety) (Christopher et al., 2009). Specifically, we use archival data from the chemicals company BASF to test to what extent the DWV3 variables necessitate investments in market mediation for demand to be fulfilled as requested by customers. In doing so, our study contributes by taking a first step towards disambiguating which contingencies are important for setting the competitive priorities of supply chains.[1]

The remainder of this article proceeds as follows. Section 2 provides an overview of the contingency variables proposed in the extant literature by grouping together contingencies with similar effects. Section 3 introduces the variables examined as part of our study. Section 4 provides further theoretical background for deriving hypothesis. Section 5 outlines the dataset and specifies the measures used. Section 6 introduces the methodology. The results of our analysis are outlined in Section 7 and discussed in Section 8. Section 9 derives implications and concludes with the limitations of our work and suggestions for future research.

2 Categorizing contingency variables

Supply chains have two distinct functions: the *physical function* and the *market mediation function* (Fisher, 1997). The former minimizes the costs of supply-chain-related activities such as production, distribution and warehousing. The latter ensures the reliable fulfilment of demand according to customer specification in order to avoid lost sales. Two types of contingency variables influence the relative importance of these functions.

Challenges in the operating environment are contingencies that make it harder to fulfil demand as requested by customers, *ceteris paribus*. In a stable environment with few uncertainties, supply chains may adopt practices that allow reliable operations at low costs (Azadegan et al., 2013; Browning and Heath, 2009). However, in environments characterized by uncertainty and time pressure, supply chains require market mediation capabilities such as responsiveness, flexibility or agility in order to fulfil demand according to customer specifications (de Treville et al., 2014a; Gligor et al., 2015; Wagner et al., 2012). Since many

[1] Further research is needed in this regard, since the DWV3 variables comprise only five of thirteen contingencies identified as potentially relevant for developing supply chain strategies by Basnet and Seuring (2016).

measures that facilitate market mediation are costly, challenges in the operating environment therefore indicate whether there is a trade-off between efficiency and market mediation (Randall and Ulrich, 2001).

The second type of contingency variables influences the *value of market mediation*. Even though investments in market mediation capabilities are a prerequisite for reliably fulfilling demand in a challenging operating environment, this does not imply that such investments should necessarily be taken: companies need to ensure that the financial reward of better fulfilling demand clearly outweigh the associated costs. Hence, when deciding whether or not to invest in market mediation in a challenging operating environment, companies may need to consider contingencies influencing the effect of lost sales on the bottom line.

In the following, we outline challenges in the operating environment and contingencies affecting the value of market mediation that have been proposed in the extant literature.

2.1 Challenges in the operating environment

By making it harder to reliably fulfil demand, *ceteris paribus*, contingencies of this type influence to what extent companies require market mediation capabilities to avoid lost sales. As indicated by Table 2.1, challenges in the operating environment can be categorized as demand-related, time-related and supply-related.

Table 2.1: Contingency variables (adapted from Basnet and Seuring, 2016).

	Source: Basnet and Seuring (2016)			Source: this study
	Contingency	**Definition**	**Count (*n* = 55)**	**Type of contingency**
DWV3 variables: examined by this study	Demand **V**ariability / uncertainty	This contingency refers to the inability to forecast product demand accurately, which results in possible obsolescence and mark-down of prices.	42	Challenge in the operating environment: Demand-related
	Product **V**ariety	Products may be characterized as being standard (less variety) or customized (high variety).	36	Challenge in the operating environment: Demand-related
	Customer lead time [requirement] [DWV3: "delivery time **W**indow"]	Customer lead time refers to the importance placed by the customer on quick delivery.	26	Challenge in the operating environment: Time-related
	Length of product life cycle [DWV3: "product lifecycle **D**uration"]	A short product life accentuates the risk of obsolescence.	12	Challenge in the operating environment: Demand-related
	Volume of production [DWV3: "demand **V**olume"]	Large production runs can take advantage of economy of scale, whereas small production runs require rapid reconfiguration.	11	Challenge in the operating environment: Demand-related
Not examined by this study	Supply uncertainty	Raw material supplies to the focal firm may be disrupted by various causes, such as natural disaster, yield losses, quality issues, etc.	8	Challenge in the operating environment: Supply-related
	Customer service	Customer service refers to the ability to fill rate, the proportion of customer demand that is filled from stock.	7	–[1]
	Contribution margin	When the mark-up on a product is low, there is more emphasis on cost-efficiency of production.	6	Value of market mediation
	Stage of product life cycle	The demand for a product changes with the stage of its product life cycle, the demand at the introduction stage is small and uncertain, but at the mature stage the demand is high and stable.	4	Challenge in the operating environment: Demand-related
	Rate of market growth	Rate of market growth changes with the stage of the product life cycle.	4	Challenge in the operating environment: Demand-related

Not examined by this study	Complexity of product structure	The bill of material of a product may be simple or complex, with multiple components and sub-assemblies.	3	Challenge in the operating environment: Supply-related
	Markdowns	Markdowns occur when prices are reduced because of stocking higher than demand.	3	Value of market mediation
	Value density	The ratio of product value to product weight.	2	Challenge in the operating environment: Supply-related
	Uniqueness	The degree of difficulty in replicating a product by competitors.	2	Value of market mediation

1: Challenges in the operating environment make it harder to achieve high service levels. Consequently, a number of studies consider service levels a characteristic of challenging operating environments. However, service levels are not only influenced by the business environment, but also by the market mediation capabilities of a supply chain. We therefore consider service levels a performance outcome rather than a contingency variable. For completeness, service levels are included in the table nonetheless.

2.1.1 Demand-related challenges

Expected and unexpected changes in demand require corresponding changes in the supply of finished goods for orders to be fulfilled according to customer specifications. Several empirical studies indicate that companies obtain higher financial rewards from market mediation capabilities such as responsiveness, agility or flexibility if demand is variable or uncertain. Gligor et al. (2015), for instance, use Compustat data to show that unstable demand amplifies the positive effect of supply chain agility on customer-related and financial performance. Similarly, Merschmann and Thonemann (2011) and Wagner et al. (2012) highlight that perceived demand uncertainty increases the financial rewards companies obtain from market mediation capabilities like flexibility and responsiveness. However, since industry-level Compustat data and measures of perceived uncertainty are not available in company databases, managers cannot rely on the measures used in these studies for assessing demand-related challenges in their organization.

Yet several demand-related contingency variables that can be measured using company databases have been proposed in conceptual literature. As indicated by Table 2.1, a recent review article has identified six demand-related challenges in the operating environment: high demand variability, low demand volumes, high product variety, short product lifecycles, challenging product lifecycle stages and high market growth (Basnet and Seuring, 2016). Even though these contingencies have been referenced multiple times in the extant literature, we are not aware of any studies that empirically test whether they significantly affect the ability to fulfil demand as requested by customers. Consequently, it remains unclear which of these variables should be considered in the strategy development process.

2.1.2 Time-related challenges

Reliably fulfilling demand is also more difficult if customers require off-the-shelf availability or quick delivery. The shorter the period between order placement and requested delivery date, the less time is available for reacting to unexpected changes in demand. The emphasis customers place on short-notice delivery is therefore considered a critical contingency for strategic decisions such as selecting sourcing locations (de Treville et al., 2014a), setting the decoupling point (Olhager, 2003) and deciding on a transportation mode (Verma and Verter, 2010).

The measurement of time-related challenges depends on the supply chain design decision in question. The ratio between lead times accepted by the customer and the production lead time indicates whether make-to-order production is feasible (Olhager, 2003). The customer lead time requirement – i.e., the time between order placement and requested delivery – is considered a key determinant for valuing lead times in sourcing decisions (de Treville et al., 2014a) and when choosing transportation modes (Verma and Verter, 2010). The authors of the DWV3 framework, whilst referring to the customer lead time requirement as the “delivery time window”, concur that lead time requirements are important for deciding on supply chain strategies (Christopher et al., 2009).[2] However, similar to the introduced demand-related challenges, we are not aware of any studies that empirically test whether the proposed time-related challenges significantly affect the ability to fulfil demand as requested by customers.

2.1.3 Supply-related challenges

The fulfilment of demand may also be disrupted by unexpected changes in the ability to provide finished goods to customers. Supply-related challenges in the operating environment increase the likelihood of disruptions in source, make or deliver processes.

Disruptions in the supply of critical materials starve the production and thus prevent the fulfilment of customer demand. Contingencies affecting the likelihood of disruptions in the supply of materials relate to supplier performance (e.g., variance of material supply lead time),

[2] Contrary to the DWV3 framework, we will henceforth refer to the time between order placement and requested delivery date as the “customer lead time requirement”. We thereby aim to emphasize that customers’ preferences regarding lead times impose requirements on supply chains that are potentially important for developing supply chain strategies.

substitutability of suppliers (e.g., number of critical material suppliers) or material criticality (e.g., time-specificity of materials) (Ho et al., 2005).

Further, disruptions in manufacturing may prevent customer demand from being fulfilled as well. Contingencies affecting the likelihood of disruptions in the production of finished goods relate to product complexity (e.g., product modularity), the degree of process interaction (e.g., degree of pre-process output on post-process performance) or product redesigns (e.g., frequency of redesigns) (Ho et al., 2005).

Finally, there are contingencies that make the delivery of finished goods more challenging. Low product value density (i.e., low value products with high weight) renders the usage of fast transportation modes prohibitively expensive (Lovell et al., 2005). Similarly, difficult terrain and unreliable transportation infrastructure increase the likelihood of disruptions in transportation (Simangunsong et al., 2012).

However, there is little research examining the effects of supply-related challenges in the operating environment. Ho et al. (2005) highlight that companies facing supply-related challenges are more likely to invest in supply chain flexibility. Yet to what extent variables of this type affect the ability to fulfil demand as requested by customers has not been empirically analysed so far.

2.2 Value of market mediation

In challenging operating environments, market mediation capabilities generate additional sales by preventing shortages. However, preventing lost sales comes at the expense of lower physical efficiency, since many capabilities that facilitate market mediation are costly (Randall and Ulrich, 2001). To evaluate whether the financial reward of preventing shortages outweighs the cost of market mediation, managers may therefore need to consider contingencies that affect the value of fulfilling demand more reliably when developing supply chain strategies.

The most frequently-cited contingency of this category is the contribution margin. Contribution margins are a key determinant of the value of market mediation because they influence the effect of lost sales on the bottom line (Randall et al., 2003). If contribution margins are high, managers should be willing to incur higher market mediation costs, since the cost of lost sales is also higher (Hendricks and Singhal, 2003). However, other variables are potentially important for determining value of market mediation as well. Contract penalties and goodwill loss in case of late delivery, for instance, may also incentivize companies to invest in market mediation by increasing the cost of shortages (Langenberg et al., 2012).

3 Focus of this study: DWV3 variables

The previous chapter highlights that (1) there is a broad spectrum of potentially relevant contingency variables, (2) these variables are hypothesized to affect the relative importance of competitive priorities in different ways, yet (3) these hypothesized effects have not been empirically validated so far. As a result, companies are confronted with a wide variety of potentially relevant contingency variables, but with little guidance as to which of these variables they should take into consideration when developing supply chain strategies. Our study therefore takes a first step towards disambiguating which contingencies companies need to consider for this purpose by testing the effects hypothesized to be underlying a set of variables that has been termed DWV3: product lifecycle **D**uration, customer lead time requirement (delivery time **W**indow), demand **V**ariability, demand **V**olume, product **V**ariety (Christopher et al., 2009).

We restrict our analysis to the DWV3 variables, since supply chain strategy literature perpetuates that these variables are the most important contingencies. Aitken et al. (2005), for example, refer to the DWV3 variables as the "five key […] characteristics that should influence decision making". Christopher et al. (2009) devote an entire article to the DWV3 variables, stating that they are the "five key characteristics that influence decision making on the design of value stream delivery strategies". In line with these statements, Table 2.1 indicates that the DWV3 variables are by far the most frequently cited contingency variables. The DWV3 variables are thus a natural starting point for both practitioners and researchers enquiring which contingencies need to be taken into consideration when setting the competitive priorities of supply chains.

Nonetheless, this study constitutes only a first step towards disambiguating which contingencies are important for setting competitive priorities, as the DWV3 variables comprise solely demand-related and time-related challenges in the operating environment. Yet two other types of variables are potentially relevant as well. First, supply-related challenges in the operating environment may necessitate higher investments in the market mediation than indicated by the DWV3 variables for demand to be fulfilled reliably. Second, variables influencing the effect of lost sales on the bottom line might be important for determining whether the financial rewards of better fulfilling demand outweigh the associated costs.

Consequently, in order to provide companies a parsimonious set of contingencies that conveys a holistic picture of the business environment, further research needs to investigate the effects of these two types of variables.

4 Hypothesis development

4.1 Conceptual framework

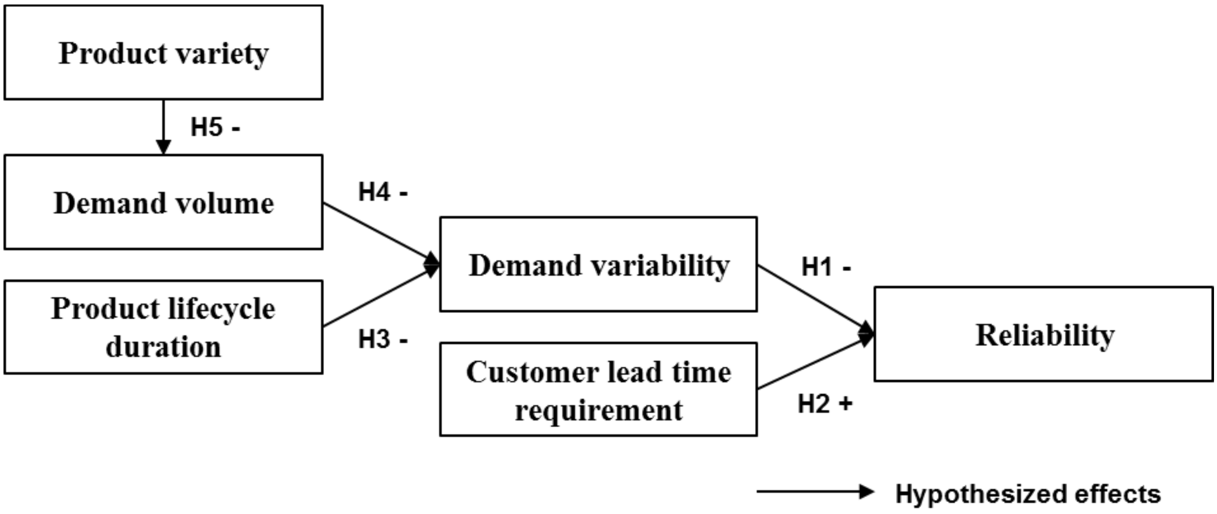
The DWV3 variables reflect challenges in the operating environment. Hence, we expect these variables to (1) make it harder to fulfil demand as requested by customers, *ceteris paribus*, and (2) increase the financial rewards companies can obtain from market mediation capabilities, as there are more opportunities for reducing lost sales when it is hard to fulfil demand as requested.

Consequently, there are two possible approaches for evaluating whether the DWV3 variables necessitate investments in market mediation. First, we may test to what extent the DWV3 variables reduce the ability of companies to fulfil demand as requested by customers, *ceteris paribus*. Second, we may test to what extent the DWV3 variables increase the financial rewards companies can obtain from market mediation capabilities.

Empirical articles in the extant literature have largely opted for the second modelling approach. These articles examine how uncertainty-related contingencies affect the link between individual market mediation capabilities and financial performance. Gligor et al. (2015), for example, highlight that the positive effect of supply chain agility on financial performance increases with different types of environmental uncertainty. Merschmann and Thonemann (2011) present similar findings for supply chain flexibility. However, while this approach is feasible for *individual* market mediation capabilities, it is less suitable for examining how contingencies affect the performance outcomes of market mediation capabilities *in general*, as it is not sufficiently clear which capabilities one would have to evaluate for this purpose (Basnet and Seuring, 2016). Proposed market mediation capabilities range from different aspects of responsiveness (e.g., Bernardes and Hanna, 2009), agility (e.g., Gligor et al., 2013), flexibility (e.g., Swafford et al., 2006) to different sources of resilience (e.g., Pettit et al., 2010). Given the resultant ambiguity as to which capabilities are important for market mediation and how these capabilities should be operationalized, we have opted for the first modelling approach described in the previous paragraph. Specifically, our study tests the direct and indirect effects of the DWV3 variables on the ability of supply chains to fulfil demand according to customer specifications.

The examined relationships are illustrated in Figure 2.1.

Figure 2.1: Conceptual framework.



4.2 Hypothesis

Expected and unexpected changes in demand require corresponding changes in the supply of goods for demand to be fulfilled. As a result, *demand variability* increases the risk of lost sales, *ceteris paribus* (Christopher et al., 2009). Consequently, we expect a negative and direct relationship between demand variability and the ability to fulfil demand as requested by the customer.

A standard measure of the ability to fulfil demand as requested by customers is *reliability* which reflects the proportion of orders where customer expectations have been met with respect to time (on time), quantity (in full) and condition (in quality) (APICS, 2016; Shepherd and Günter, 2006). We thus use reliability to approximate the ability of a supply chain to fulfil demand as requested by customers and hypothesize a negative and direct relationship between demand variability and reliability.

Hypothesis 1: *There is a negative and direct relationship between demand variability and reliability.*

Short *customer lead time requirements* necessitate a "rapid response" as competitive pressures give the supply chain less time to fulfil demand as requested (Christopher et al., 2009). As a result, they increase the need for market mediation capabilities such as responsiveness and agility (Aitken et al., 2005; de Treville et al., 2014a). We therefore hypothesize a positive and direct relationship between the length of lead time requirements and reliability.

Hypothesis 2: *There is a positive and direct relationship between the length of customer lead time requirements and reliability.*

As indicated by Table 2.1, the extant literature also considers the remaining DWV3 variables important for determining whether companies require market mediation capabilities to reliably fulfil demand. One might thus be inclined to hypothesize a direct relationship between the remaining DWV3 variables and reliability as well. However, upon closer examination, it becomes clear that "small production volumes, short product life, large product variety, all add to the variability of product demand" (Basnet and Seuring, 2016). Consequently, we expect these variables to affect reliability indirectly by increasing the demand variability.

Products with short *lifecycles* require supply chains that are "able to 'fast track' […] manufacturing and logistics" (Christopher et al., 2009). The underlying reason is that they spend relatively large shares of their lives in the introduction and growth stages where demand is variable and uncertain (Childerhouse et al., 2002). Consequently, we expect short lifecycles to reduce reliability indirectly by increasing demand variability, *ceteris paribus*. Accordingly, we hypothesize a direct relationship between product lifecycle duration and demand variability. In addition, we analyse whether this relationship also leads to an indirect effect on reliability.

Hypothesis 3: There is a negative and direct relationship between product lifecycle duration and demand variability.

Low *volume* products are more likely to have demand that is sporadic and uncertain. Vice versa, high volume products more often allow make-to-forecast production, as demand tends to be more stable (Christopher et al., 2009; Zotteri and Kalchschmidt, 2007). Consequently, we expect higher demand volumes to increase reliability by reducing demand variability, *ceteris paribus*. Accordingly, we hypothesize a direct relationship between demand volume and demand variability. In addition, we analyse whether this relationship also leads to an indirect effect on reliability.

Hypothesis 4: There is a negative and direct relationship between demand volume and demand variability.

Regarding *product variety*, the authors of the DWV3 framework state that "greater variety results in a larger number of stock keeping units because the volume is split between alternatives" (Christopher et al., 2009). We therefore expect product variety to decrease reliability by reducing the volume per product which we in turn expect to increase demand variability, *ceteris paribus*. Accordingly, we hypothesize a direct relationship between variety and volume. In addition, we analyse whether this relationship also leads to indirect effects on demand variability and reliability.

Hypothesis 5: There is a negative and direct relationship between product variety and demand volume.

5 Dataset

5.1 Data collection and sampling

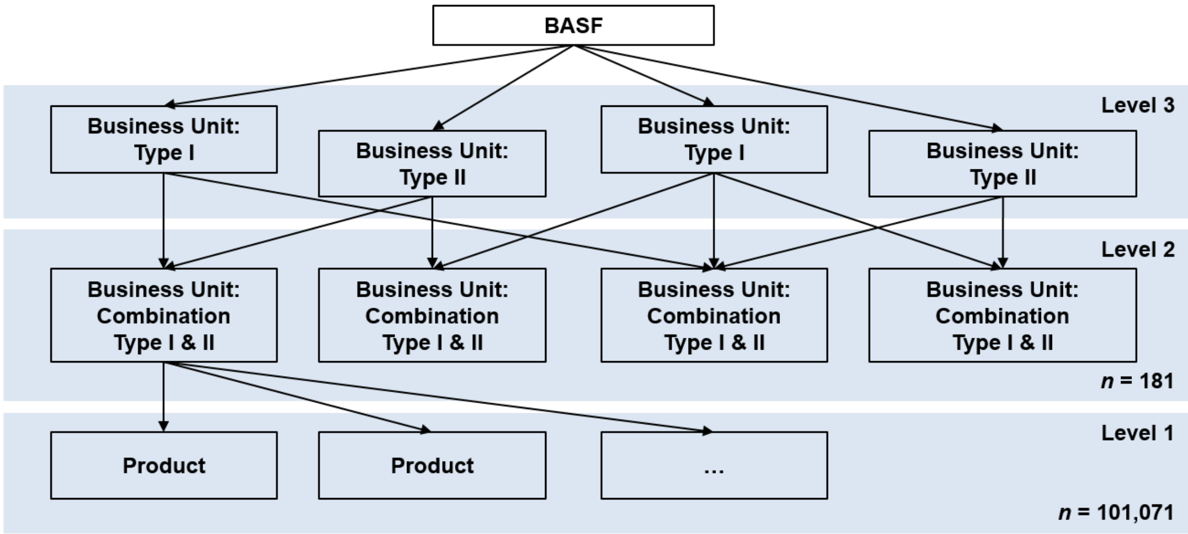
This study is conducted in cooperation with BASF, one of the world's leading chemicals manufacturers. The company is a well-suited subject for our investigation because it embraces the "Verbund"-concept: the company controls multiple value streams that span from basic chemicals to high-value-added products such as coatings and crop protection agents (BASF SE, 2016b). As a result, supply-chain-relevant characteristics of the business environment differ considerably across the company. Business units producing basic chemicals, for example, typically operate in stable low-margin environments. On the contrary, business units producing high-value crop protection or coatings for the automotive industry operate in volatile high-margin environments. Given the resultant diversity of BASF's portfolio of products and business units, we consider it plausible that our dataset provides sufficient variance in the examined contingency variables to warrant the generalization of our findings.

To align the competitive priorities of its supply chains with the diverse requirements of its business unit portfolio, BASF launched a supply chain segmentation initiative in the years 2013 and 2014: business units were assigned to a set of four segments, each with a distinct supply chain strategy (Cecere, 2017). As part of the initiative, BASF commissioned this research project to examine which contingency variables should be considered when assigning business units to segments. Accordingly, our study is based on a dataset from the 2013 and 2014 that covers the entire company except for its Oil&Gas business, hence capturing approximately 80% of its revenues (BASF SE, 2015).

The data has a multilevel structure due to the hierarchical organization of the company. Figure 2.2 indicates that there are two types of upper-level (Level 3) business units. While the first type of Level 3 business unit indicates the region of a business, the second type of Level 3 business unit indicates the market that is being served. Level 2 business units are combinations of Level 3 business units (region and market); a hypothetical example of a Level 2 business unit is "Specialty Petrochemicals Europe" which is a combination of the Level 3 business units

"Petrochemicals Europe" (Type I) and "Specialty Petrochemicals" (Type II). Finally, products (Level 1) are nested within Level 2 business units.

Figure 2.2: Multilevel data structure.



The units of analysis of this study are Level 1 and Level 2, as the sample size is sufficiently large to test our hypothesis at these levels.

At Level 2, our sample comprises 228 observations. We exclude business units at Level 2 with annual sales below 1 million € or fewer than 1,000 orders annually to ensure that only business units with sufficient supply-chain-related activities are included. Further, we exclude one business unit with missing data and one business that was not reliably integrated in the company's databases at the time. The examination of Cook's distance and Mahalanobis distance plots does not reveal any outliers. The final sample therefore comprises 181 observations at Level 2.

At Level 1, 133,687 products can be uniquely assigned to the remaining 181 Level 2 business units. We exclude products with missing data (19,424) or negative values for demand volume, customer lead time requirements, or order fulfilment lead times (13,192). The final sample used for this study therefore consists of 101,071 observations at Level 1.

5.2 Dependent and independent variables

A standard measure for approximating the *reliability* in fulfilling demand as requested by customers is the proportion of orders delivered on-time, in-full and in-quality (APICS, 2016). An order is classified as on-time and in-full, if the order arrives within the time window set by the customer and in the requested quantity. It is recorded as in-quality if the customer voices no complaints regarding aspects such as product quality, documentation or packaging.

For operationalizing the DWV3 variables, we follow the propositions by Aitken et al. (2005). *Demand variability* is measured by the coefficient of variation of weekly sales. The *customer lead time requirement* is measured by the average number of days customers grant between the initial order entry and the requested delivery date. *Demand volume* is measured by the average sales volume per product in Euros over the examined time period per product. *Product variety* is measured by the number of products in a business unit's portfolio. *Product lifecycle duration* is measured by the product age.

As the DWV3 variables are highly skewed, we employ natural logarithm transformations. In addition, we standardize the DWV3 variables to render their scales comparable.

The correlation matrixes in Table 2.2 and Table 2.3 illustrate the relationships between the examined variables. Means and standard deviations are not provided due to the confidential nature of the data.

Table 2.2: Pearson correlation coefficients at Level 1.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
(1) Demand variability	1.00***						
(2) Demand volume	-0.68***	1.00***					
(3) Product variety	0.17***	-0.31***	1.00***				
(4) Product lifecycle duration	-0.17***	0.12***	-0.21***	1.00***			
(5) Customer lead time requirement	0.09***	0.16***	-0.02***	0.06***	1.00***		
(6) Order fulfilment lead times	0.09***	0.18***	-0.11***	0.07***	0.78***	1.00***	
(7) Reliability	-0.17***	0.04***	0.12***	-0.01***	-0.18***	-0.31***	1.00***

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed).

Table 2.3: Pearson correlation coefficients at Level 2.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
(1) Demand variability	1.00***						
(2) Demand volume	-0.38***	1.00***					
(3) Product variety	0.37***	-0.69***	1.00***				
(4) Product lifecycle duration	-0.38***	0.59***	-0.55***	1.00***			
(5) Customer lead time requirement	-0.12	0.36***	-0.29***	0.37***	1.00***		
(6) Order fulfilment lead times	0.01	0.24***	-0.25***	0.30***	0.89***	1.00***	
(7) Reliability	-0.18*	0.05	0.02	0.02	-0.02	-0.13	1.00***

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed).

5.3 Control variables

Order fulfilment lead times (natural logarithm) are included as a control variable when assessing the relationship between the customer lead time requirements and reliability. Customers are assumed to grant longer lead times when it is hard to fulfil orders quickly. Order fulfilment lead times indeed correlate with customer lead time requirements and reliability as indicated by Table 2.2 and Table 2.3.

In addition, it is likely that industry-specific effects have an impact on the examined relationships (Bozarth et al., 2009). Level 2 business units nested within a Level 3 business unit are likely to be similar in ways that are otherwise not explicitly accounted for by our models. As outlined in Section 5.1, the Level 3 business unit "Petrochemicals Europe" for instance contains two Level 2 business units that produce different types of petrochemicals (standard and specialty petrochemicals). These two business units that operate in the same industry are likely to have similar competitive and operating environments. The multilevel models we use for our analysis contain *random intercepts* to account for similarities of Level 2 business units nested within a Level 3 business unit. They thus implicitly control for industry-specific effects. As will be demonstrated in the next section, random intercepts explain between 15.0% and 75.6% of the variance in our models.

6 Methodology

Due to the multilevel structure of our data, we cannot make inferences from an ordinary structural equation model, as this would violate the assumption of independent observations (Hofmann, 1997). In order to analyse the effects of predictors at Level 2, we need to account for the fact that observations at this level are nested within Level 3 business units. We thus assess the relationships at Level 2 using a multilevel structural equation model (*gsem* command in Stata 14). Predictors are located at Level 2 and random intercepts at Level 3. To avoid the violation of model assumptions when testing indirect effects, we conduct a non-parametric bootstrap with 1,000 resamples (Preacher et al., 2010). The parameter estimates obtained from this procedure are presented in Table 2.4, along with *p*-values and 95% bias-corrected confidence intervals.[3]

[3] For a detailed description of methodological decisions regarding random intercepts and the resampling levels of the non-parametric bootstrap, we refer the reader to Sections 3 and 4 in Chapter 4.

At Level 1, we test the hypothesized effects using a set of multilevel regressions (*mixed* command in Stata 14), as the sample size is too large for solving a multilevel structural equation model. Predictors are located at Level 1 and random intercepts at Level 2 and Level 3.

The results of the regression with reliability as the dependent variable are heteroskedastic. The heteroscedasticity is caused by the high proportion of products with a reliability of 0% or 100%; most of these products were ordered only a few times during the time period under consideration. Since they are more likely to exhibit extreme values for reliability (a product that was only sold once by default has a value for reliability of either 0% or 100%), their values for reliability are distributed differently from those of the rest of the sample (Cook et al., 2008). Zero-or-one inflated beta regression models could serve as a remedy, since they assume that the response variable has a mixed continuous–discrete distribution with probability mass at zero or one (Ospina and Ferrari, 2012). However, beta regressions are not yet available for multilevel models. To be able to draw inferences nonetheless, we conduct non-parametric bootstraps with 1,000 resamples for the regressions at Level 1, as standard errors obtained from non-parametric bootstrapping are still consistent under heteroscedasticity (Godfrey, 2009; van der Leeden et al., 2008). The indirect effects are tested with Monte Carlo simulations using the results of the bootstrapping as input (Selig and Preacher, 2008). The results of these procedures are presented in Table 2.5.

Table 2.4: Results at Level 1.

Independent variables	**Dependent variables**		
	Service levels	**Demand variability**	**Demand volume**
Demand variability	-0.055*** [-0.057, -0.053]		
Demand volume		-0.782*** [-0.787, -0.777]	
Product variety			-0.200*** [-0.206, -0.189]
Product lifecycle duration		-0.095*** [-0.099, -0.090]	
Customer lead time requirement	0.045*** [0.042, 0.049]		
Order fulfilment lead time	-0.121*** [-0.125, -0.117]		
Wald χ^2	13410.02***	120993.41***	29.82***
ICC	0.152***	0.150***	0.325***
Pseudo-R^2	0.109	0.479	0.070
VIF	2.60	1.01	1.00
Type of analysis	Regression	Regression	Regression

Table 2.5: Results at Level 2.

Independent variables	**Dependent variables**		
	Service levels	**Demand variability**	**Demand volume**
Demand variability	-0.022* [-0.041, -0.003]		
Demand volume		-0.264*** [-0.366, -0.095]	
Product variety			-0.614*** [-0.713, -0.518]
Product lifecycle duration		-0.216** [-0.365, -0.115]	
Customer lead time requirement	0.092*** [0.038, 0.134]		
Order fulfilment lead time	-0.101*** [-0.150, -0.066]		
Wald χ^2	31.00***	33.12***	113.99***
ICC	0.465***	0.243***	0.751***
Pseudo-R^2	0.083	0.180	0.544
VIF	5.17	1.52	1.00
Type of analysis	Structural equation model	Structural equation model	Structural equation model

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed). Bias corrected confidence intervals are shown.

7 Results

Multicollinearity is unlikely to be an issue, as the variance inflation factor (VIF) is within a tolerable range (maximum VIF = 5.17). The residuals of the model at Level 2 are approximately normally distributed and homoscedastic. The residuals of the regression at Level 1 are also approximately normally distributed. For the regression with reliability as the dependent variable, the residuals are, as expected, heteroskedastic. The intraclass correlation coefficients (ICC) in Table 2.4 and Table 2.5 indicate that the random intercepts explain a significant proportion of the variance in our models. At Level 2, the ICC is 0.465 for reliability, 0.243 for demand variability and 0.751 for demand volume. At Level 1, the ICC is 0.150 for reliability, 0.148 for demand variability and 0.321 for demand volume.[4]

To assess the level of variance explained by the predictors, we compute a Pseudo-R^2 measure for the change in the total variance explained at all levels with and without the predictors (LaHuis et al., 2014). For the model at Level 2, Table 2.4 indicates that the predictors explain a significant proportion of the variance in reliability (Pseudo-R^2 = 0.083 and Wald χ^2 = 31.00, $p < 0.001$), demand variability (Pseudo-R^2 = 0.180 and Wald χ^2 = 33.12, $p < 0.001$) and demand volume (Pseudo-R^2 = 0.544 and Wald χ^2 = 113.99, $p < 0.001$). For the regressions at Level 1, Table 2.5 also indicates that the predictors explain a significant proportion of the variance in reliability (Pseudo-R^2 = 0.109 and Wald χ^2 = 13410.02, $p < 0.001$), demand variability (Pseudo-R^2 = 0.479 and Wald χ^2 = 120993.41, $p < 0.001$) and demand volume (Pseudo-R^2 = 0.007 and Wald χ^2 = 29.82, $p < 0.001$).

7.1 Endogeneity

As endogeneity can lead to biased and inconsistent estimates, this study addresses three main causes of endogeneity: measurement error, omitted variables, and simultaneity (Roberts and Whited, 2013). Concerns regarding measurement error are addressed by minimizing the risk of common method bias, as it is one of the main sources of measurement error (Podsakoff et al., 2003). Common method bias is unlikely to be an issue for our study, as it relies exclusively on archival data that is free from respondents' perceptions and originates from multiple data sources (supply chain databases and Material Master Data).

[4] The *gsem* command in Stata does not yet provide ICC or Pseudo-R^2 measures. To obtain these measures for the structural equation model at Level 2 nonetheless, we computed ICC and Pseudo-R^2 measures at Level 2 by running regressions with the *mixed* command. As the parameter estimates from the regressions are very similar to those of the structural equation model, we are confident that the computed measures provide an appropriate approximation for the goodness of fit in the structural equation model.

Concerns regarding omitted variables arise for the competitive priorities of the examined supply chains. Our model does not evaluate whether business units prioritize market mediation or physical efficiency. This is of concern, since business units facing demand uncertainty or time pressure are more likely to invest in market mediation (de Treville et al., 2004; Ho et al., 2005). At the same time, it is likely that these business units have a lower reliability because of the challenging environment they operate in. Consequently, we would most likely observe stronger relationships between the DWV3 variables and reliability if we were to control for the competitive priorities of the examined supply chains. However, while omitting competitive priorities from our model might systematically reduce (absolute) effect sizes, we expect the relative strengths of effects to remain unchanged. In addition to evaluating significance levels and absolute effect sizes, we therefore also take into consideration how effect sizes differ among the examined relationships when discussing our findings in Section 8.

Concerns regarding simultaneity do not arise for the hypothesized relationships. We consider demand variability and customer lead time requirements exogenous predictors of reliability. Time pressure and volatile demand lead to low reliability *ceteris paribus*, but it is unlikely that low reliability has a significant effect on customers' preferences regarding lead times or demand variability. Similarly, we consider product lifecycle duration an exogenous predictor of demand variability: product age – which we use as a proxy for lifecycle duration – is determined by the date of the product introduction and not by the variability of demand that occurs once the product has been introduced. Further, demand volume is a plausibly exogenous predictor of demand variability, as it is unlikely that changes in the standard deviation of demand systematically affect the average demand volume. Finally, product variety is an exogenous predictor of demand volume, as the number of products decreases the demand per product rather than vice versa.

7.2 Hypothesis testing

First, the proposed conceptual framework posits that high demand variability (Hypothesis 1) and short customer lead time requirements (Hypothesis 2) reduce reliability. A one-standard-deviation increase in demand variability is associated with a 5.5-percentage-point (ppt) decrease in reliability at Level 1 (β_1 = -0.055, $p < 0.001$) and with a 2.2ppt decrease at Level 2 (β_2 = -0.022, $p < 0.05$). Similarly, a one-standard-deviation decrease of lead time requirements is associated with a 4.5ppt decrease in reliability at Level 1 (β_3 = 0.045, $p < 0.001$) and with a 9.2ppt decrease at Level 2 (β_4 = 0.092, $p < 0.001$). Hypothesis 1 and Hypothesis 2 are thus supported.

Second, the proposed conceptual framework posits that short product lifecycles (Hypothesis 3) and low demand volumes (Hypothesis 4) are antecedents of demand variability. A one-standard-deviation increase in product age is associated with a statistically significant decrease in demand variability at both Level 1 (β_5 = -0.095, p < 0.001) and Level 2 (β_6 = -0.216, p < 0.01). Similarly, a one-standard-deviation increase in demand volume is associated with a statistically significant decrease in demand variability at both Level 1 (β_7 = -0.782, p < 0.001) and Level 2 (β_8 = -0.264, p < 0.001). Hypothesis 3 and Hypothesis 4 are thus supported.

Third, the proposed conceptual framework posits that high product variety is an antecedent of low demand volumes (Hypothesis 5). A one-standard-deviation increase in product variety is associated with a statistically significant decrease in demand volume at both Level 1 (β_9 = -0.200, p < 0.001) and Level 2 (β_{10} = -0.614, p < 0.001). Hypothesis 5 is thus supported.

7.3 Direct and indirect effects on reliability

Our findings indicate that high demand variability and short customer lead time requirements are both linked to lower reliability. This section examines how the remaining DWV3 variables (demand volume, product lifecycle duration, and product variety) affect reliability. To estimate indirect and total effects, we test the proposed conceptual framework again, but allow for direct effects between the independent and the dependent variables. As indicated by Figure 2.3, we extend our model to include direct links between all DWV3 variables and reliability, as well as a direct link between product variety and demand variability. The results are shown in Table 2.6 and Table 2.7.

Figure 2.3: Extended conceptual framework.

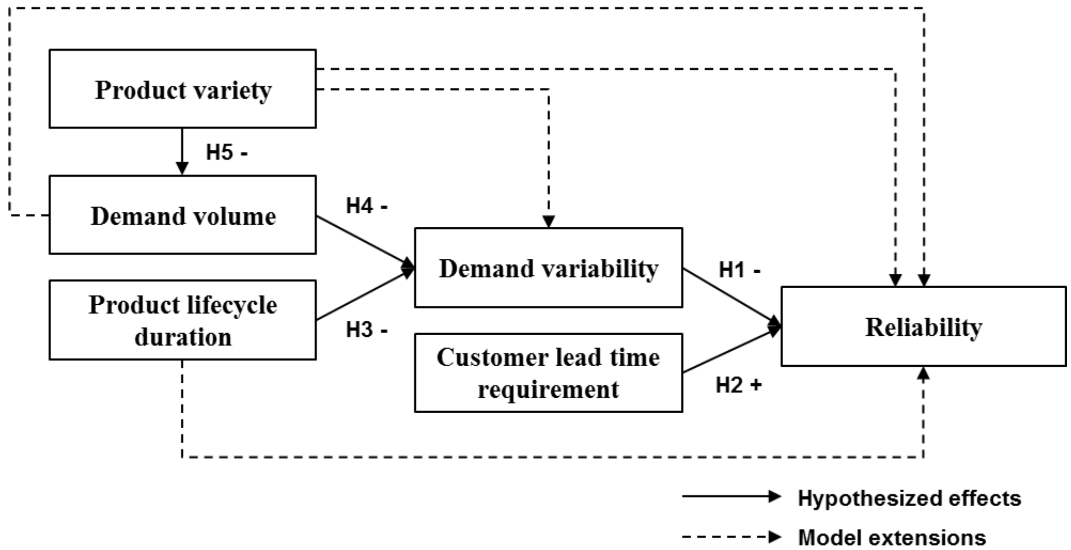


Table 2.6: Results of the extended model at Level 1.

Independent variables	**Dependent variables**		
	Service levels	**Demand variability**	**Demand volume**
Demand variability	-0.044*** [-0.047, -0.041]		
Demand volume	0.014*** [0.011, 0.018]	-0.783*** [-0.787, -0.777]	
Product variety	-0.002 [-0.004, 0.002]	-0.074** [-0.082, -0.070]	-0.200*** [-0.206, -0.189]
Product lifecycle duration	0.006*** [0.004, 0.008]	-0.095*** [-0.099, -0.091]	
Customer lead time requirement	0.045*** [0.041, 0.048]		
Order fulfilment lead time	-0.123*** [-0.127, -0.119]		
Wald χ^2	13551.18***	121000.86***	29.82***
ICC	0.152***	0.150***	0.325***
Pseudo-R^2	0.107	0.494	0.070
VIF	2.73	1.14	1.00
Type of analysis	Regression	Regression	Regression

Table 2.7: Results of the extended model at Level 2.

Independent variables	**Dependent variables**		
	Service levels	**Demand variability**	**Demand volume**
Demand variability	-0.022* [-0.044, -0.003]		
Demand volume	0.009 [-0.034, 0.050]	-0.154 [-0.311, 0.029]	
Product variety	0.008 [-0.027, 0.041]	0.173 [-0.106, 0.334]	-0.612*** [-0.712, -0.518]
Product lifecycle duration	0.002 [-0.020, 0.018]	-0.193* [-0.338, -0.068]	
Customer lead time requirement	0.089** [0.024, 0.137]		
Order fulfilment lead time	-0.098*** [-0.150, -0.055]		
Wald χ^2	31.44***	36.04***	113.99***
ICC	0.465***	0.243***	0.751***
Pseudo-R^2	0.068	0.178	0.544
VIF	5.63	2.16	1.00
Type of analysis	Structural equation model	Structural equation model	Structural equation model

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed). Bias corrected confidence intervals are shown.

Regarding *demand volume*, our findings confirm statistically significant direct, indirect and total effects on reliability at Level 1. Demand volume has an indirect and positive link to reliability that is mediated by demand variability (β_{11} = 0.035, p < 0.001). As the direct relationship between demand volume and reliability also is positive and statistically significant (β_{12} = 0.014, p < 0.001), the total effect of demand volume on reliability is positive and statistically significant as well (β_{13} = 0.049, p < 0.001).

At Level 2, however, none of the examined relationships between demand volume and reliability are statistically significant. When controlling for product variety, the link between demand volume and demand variability is no longer statistically significant (β_{14} = -0.154, p = 0.082). One likely reason is that the strong correlations between product variety, demand volume and product lifecycle duration at Level 2 (> 50%) lead to a loss of power. As a result, the indirect link between demand volume and reliability is not statistically significant (β_{15} = 0.003, p = 0.253). Since the direct effect of demand volume on reliability is not statistically significant either (β_{16} = 0.009, p = 0.673), there is no statistically significant total effect of demand volume on reliability at Level 2 (β_{17} = 0.012, p = 0.553).

Regarding *product lifecycle duration*, our findings are very similar to the link between demand volume and reliability. At Level 1, product lifecycle duration has statistically significant direct, indirect and total effects on reliability. Product lifecycle duration has an indirect and positive link to reliability that is mediated by demand variability (β_{18} = 0.004, p < 0.001). As the direct relationship between product lifecycle duration and reliability is also positive and statistically significant (β_{19} = 0.006, p < 0.001), the total effect of product lifecycle duration on reliability is positive and statistically significant as well (β_{20} = 0.010, p < 0.001). However, at Level 2, neither the direct effect (β_{21} = 0.002, p = 0.882), the indirect effect (β_{22} = 0.004, p = 0.122) nor the total effect (β_{23} = 0.006, p = 0.558) of product lifecycle duration on reliability are statistically significant.

Regarding *product variety*, our findings indicate that higher product variety is indirectly linked to higher demand variability at both Level 1 and Level 2. At Level 1, both the indirect effect via demand volume (β_{24} = 0.156, p < 0.001) and the total effect (β_{25} = 0.080, p < 0.01) on demand variability are statistically significant. At Level 2, the effect of product variety on demand variability is only partially mediated by demand volume. As a result, only the total effect is positive and significant (β_{26} = 0.288, p < 0.01) whereas the indirect effect is positive but not statistically significant (β_{27} = 0.095, p = 0.158). Our findings therefore indicate that product variety – similar to demand volume and product lifecycle duration – is an antecedent of demand variability.

However, we do not find support for a significant relationship between product variety and reliability. At Level 1, there is a statistically significant indirect link between product variety and reliability that is mediated by demand variability (β_{28} = -0.004, p < 0.01). Nonetheless, the total effect of product variety on reliability fails to be significant (β_{29} = 0.000, p = 0.978), since there is no significant direct link between the two variables (β_{30} = 0.002, p = 0.822). At Level 2, neither the direct effect (β_{31} = 0.008, p = 0.666), the indirect effect via demand variability (β_{32} = -0.006, p = 0.132) nor the total effect (β_{33} = 0.001, p = 0.942) of product variety on reliability are significant.

8 Discussion

8.1 Demand variability and customer lead time requirements

Our findings link high *demand variability* and short *customer lead time requirements* to significantly lower reliability. At Level 1, high demand variability and short lead time requirements are associated with approximately 4.4ppt lower reliability. At Level 2, the effect of customer lead time requirements on reliability is even higher: a one standard deviation decrease in lead time requirements is associated with a 9.2ppt decrease in reliability. The effect of demand variability on reliability is lower at Level 2 than at Level 1 (2.2ppt), but it is still significant at the 95% level. Our findings therefore consistently indicate that both high demand and short customer lead time requirements make it harder to fulfil demand according to customer specifications, *ceteris paribus*.

8.2 Demand volume and product lifecycle duration

On the contrary, our findings fail to consistently link low *demand volumes* and short *product lifecycles* to lower reliability. At Level 2, there are no statistically significant direct effects of demand volumes and product lifecycles on reliability. At Level 1, the effects are statistically significant, but much lower than the effect of demand variability on reliability. Compared to the effect demand variability, the direct effect of demand volume on reliability is more than three times lower (1.4ppt instead of 4.4ppt). Similarly, the direct effect of product lifecycle duration on reliability is more than seven times lower (0.6ppt instead of 4.4ppt). Low demand volumes and short product lifecycle therefore only marginally decrease the ability of supply chains to fulfil demand as requested, *ceteris paribus*.

However, our findings consistently link lower demand volumes and short product lifecycles to higher demand variability. The tested effects are statistically significant and have similar effect sizes with one exception: the link between demand volume and demand variability is particularly strong at Level 1. A one-standard-deviation decrease in volume is associated with a 0.8-standard-deviation increase in demand variability at that level of analysis. Our findings therefore confirm that low demand volumes and short product lifecycles are antecedent of demand variability.

8.3 Product variety

Our findings indicate a strong link between product variety and volume at both levels of analysis. As a result, there is also an indirect link between product variety and demand variability that is mediated by demand volume. Consequently, high product variety is associated with significantly lower demand variability at both Level 1 and Level 2. Our findings therefore indicate that product variety is an antecedent of demand variability as well.

9 Conclusion

9.1 Implications

This study intends to take a first step towards disambiguating which contingencies are important for setting the competitive priorities of supply chains. For this purpose, we have examined the effects hypothesized to be underlying the five most frequently cited contingency variables that are referred to as DWV3.

Our findings consistently link high demand variability and short customer lead time requirements to significantly lower reliability. Companies therefore need to consider these variables when developing supply chain strategies to evaluate whether they require market mediation capabilities to fulfil demand as requested by customers.

However, for the remaining DWV3 variables, we do not find a consistent direct link to reliability. We therefore propose that managers seeking to determine whether they require market mediation capabilities to reliably fulfil demand focus on examining the level of demand variability and the length of lead time requirements in their organization. Analysing demand volume, product variety and product lifecycle duration for this purpose as well will likely lead to only few additional insights at the expense of a more complex strategy formation process.

Hence, we instead propose that companies use these variables for verifying and analysing the causes of variable demand.

If companies cluster products or business units that are similar regarding the contingency variables of interest, they require additional variables for establishing external validity (Bacher et al., 2010; Brusco et al., 2017; Ketchen and Shook, 1996). In case a cluster of products is characterized by, for instance, high values for demand variability, it is important to rule out that these values are not caused by measurement error or statistical artefacts. Since our findings indicate that volume, variety and lifecycle duration are antecedents of demand variability, they are candidate variables for this purpose. In addition, companies may also use these variables to analyse the causes of high demand variability and for designing corresponding mitigation strategies, as different causes of variability may require different kinds of responses (Slack, 1987).

Yet besides the insights our study provides for the roles of the DWV3 variables in the strategy formation process, the typology introduced in Section 2 highlights that two types of variables not examined as part of this research might also be relevant for setting competitive priorities.

First, in addition to demand variability and short customer lead time requirements, supply-related challenges in the operating environment may also make it harder to fulfil demand as requested by customers. They may therefore necessitate higher investments in the market mediation than indicated by demand variability and customer lead time requirements for demand to be fulfilled reliably.

Second, contingencies influencing value of market mediation are potentially important for deciding whether or not to invest in market mediation in a challenging operating environment. Supply chain strategy literature typically assumes that volatility and higher margins go hand-in-hand (e.g., Childerhouse and Towill, 2000; Mason-Jones et al., 2000). However, as we will demonstrate in Study 3, the correlations between contribution margins and challenges in the operating environment at our case company are low. Before investing in market mediation, companies may therefore evaluate variables of this type to ensure that the financial reward of avoiding shortages outweighs the associated costs.

9.2 Limitations and future research

Our study has two key methodological limitations. First, we have analysed a single time period. Even though we consider the DWV3 variables plausibly exogenous predictors, we cannot rule out the threat of simultaneity completely (Ketokivi and McIntosh, 2017). Second, we have analysed data from a single company. Even though our dataset provides considerable variance, we cannot rule out that one might observe a change in effects when analysing data from a different company or a different industry. As a result, there is a need for replication and validation studies.

Further research is also needed to examine the effects underlying supply-related challenges in the operating environment and variables influencing the value of market mediation. Ho et al. (2005), for instance, propose that companies measure manufacturing-related and supplier-related uncertainties using a set of seven reflective indicators. Future studies may analyse whether a more parsimonious set of measures that is available in company databases suffices for this purpose as well. Similarly, future studies may evaluate which contingencies are important for approximating the value of market mediation and how these contingencies could be measured.

Chapter 3 Supply chain segmentation: A data-driven approach

Co-author:

Moritz Fleischmann

Chair of Logistics and Supply Chain Management, Business School, University of Mannheim, Germany

Abstract

For many companies, a single supply chain setup is not sufficient for fulfilling the divergent needs of a heterogeneous product and customer portfolio. An emergent practice is thus to “segment” supply chains: companies develop different supply chain strategies for different parts of their business. While the extant literature largely forms supply chain segments qualitatively, our study introduces two quantitative methods: clustering and classification. We employ these methods at a leading chemicals manufacturer and compare our results to segments the company had formed using managers’ tacit knowledge. Our findings indicate that managers may choose segments that do not reflect the needs of their business environment, consequently pursuing supply chain strategies that adversely affect financial performance. Clustering and classification help managers detect such segment-environment mismatches and thus serve as valuable tools for challenging managers’ judgment when conducting a supply chain segmentation.

1 Motivation

Companies frequently offer a wide variety of products to a range of different customers. Oftentimes, these products and customers are heterogeneous regarding the type of supply chain they require. Consider, for instance, the well-known difference between innovative and functional products: while the former require a supply chain that excels at matching supply and demand in a challenging operating environment, the latter require a supply chain that emphasizes efficiency (Fisher, 1997). Yet it is not uncommon for companies to sell both innovative and functional products (Childerhouse et al., 2002). As a result, supply chain segmentation (SCS) has become an emergent practice. It describes the process of dividing a heterogeneous set of products or customers into groups ("segments") that impose similar requirements on the supply chain. For each of these segments, a tailored supply chain strategy is developed.

SCS, therefore, allows companies to more accurately tailor their supply chain capabilities and structures to the requirements of their business. Compared to a company with a single supply chain strategy, a company with a tailored strategy for each segment may operate some parts of its business at lower cost (e.g., functional products or cost-conscious customers) and extract higher revenues from other parts of its business (e.g., additional service for service-oriented customers or innovative products). As a result, SCS is considered one of the most effective levers for improving supply chain performance (Rexhausen et al., 2012) and has been linked to lower inventories, higher service levels and lower logistics cost (Mayer et al., 2009). A recent survey by Gartner, a consultancy, concludes that "an overwhelming 95% of [chief supply chain officers] expect to invest in supply chain segmentation in 2016, with 35% calling it a top priority" (Gartner, 2016a).

Despite practitioners' interest in the topic, the number of corresponding studies is limited so far. A key characteristic of the extant literature on SCS is a qualitative approach to segment formation: segments are formed using managers' tacit knowledge, without a systematic data analysis.

This approach has drawbacks. Managers' tacit knowledge is subjective; relevant clusters of products or customers may remain undetected as a result (Foedermayr and Diamantopoulos, 2008). Especially if product or customer portfolios are broad and heterogeneous, it is unlikely that managers will have a comprehensive overview of all relevant segmentation criteria and objects (Wedel, 2000). A SCS initiative that exclusively relies on managers' tacit knowledge can thus only provide limited insights.

Consequently, authors of segmentation methodologies in marketing urge practitioners to refrain from solely relying on the qualitative approach (Foedermayr and Diamantopoulos, 2008; Wedel, 2000). There are many examples of segmentation initiatives in other areas of business research that employ data analysis to derive segments (Ngai et al., 2009). The supply chain community, however, appears to be lagging behind in this regard: with one exception (Langenberg et al., 2012), all reviewed articles in scholarly journals on SCS exclusively rely on managers' tacit knowledge for this purpose. Strikingly, the two most commonly employed methods for deriving segments in other areas of business research – clustering and classification (Ngai et al., 2009) – have not been used in studies on SCS so far.

Our study thus employs clustering and classification to form supply chain segments. Specifically, we use data from the chemicals manufacturer BASF to form segments quantitatively and compare our results to segments the company had previously formed without data analysis. Based on our findings, we are able to deduce several managerial insights on this issue. In particular, we address the following questions. How can companies use clustering and classification for a SCS? What insights do these methods generate relative to qualitative approaches?

The remainder of this article proceeds as follows. In Section 2, we review extant qualitative and quantitative approaches in SCS literature and outline how clustering and classification can remedy their shortcomings. Section 3 introduces the case company and outlines its qualitative approach to forming segments. In Section 4, we form segments using clustering, and we compare the results to the company's qualitative segments in Section 5. In Section 6, we highlight the need to update segments periodically and demonstrate how classification can be employed for this purpose. Section 7 discusses the implications of our findings and the limitations of our work.

2 Related literature

This section reviews the extant approaches to forming supply chain segments and outlines how clustering and classification may help remedy their shortcomings.

2.1 Qualitative approaches

The vast majority of studies on SCS forms segments without data analysis. The first study on the topic introduces a qualitative approach claiming that "clustering is more an art than a science" (Fuller et al., 1993). It advises managers to examine for each product successively whether a distinct supply chain setup is needed, and to form a new segment only if the expected benefits outweigh the additional complexity costs.

Aitken et al. (2005), Childerhouse et al. (2002) and Godsell et al. (2011) advocate a different case-by-case approach. First, managers collectively decide on a set of segments. Second, they assess for each product individually which segment fits best. Variables such as demand variability and contribution margins (Godsell et al., 2011) or the stage of the product lifecycle (Aitken et al., 2005; Childerhouse et al., 2002) are taken into account for this purpose.

Christopher et al. (2006) and Christopher and Towill (2002) neither outline how they form segments nor how they allocate products or customers to segments. Instead, they introduce a set of generic supply chain strategies and describe how companies have adopted these strategies for different parts of their business (e.g., 80% of the business is “lean” and 20% is “agile”). However, in a later study, the authors disclose that the introduced strategies were determined by “hunch” rather than data analysis, and call for the use of “advanced analytics” for SCS (Christopher et al., 2009).

Roscoe and Baker (2014) present a special case, where a company has formed supply chain segments that correspond to its market segments. As each market segment is served with a distinct product offering at the case company, products are allocated to supply chain segments depending on the market segment that they serve.

Finally, a stream of publications proposes a narrower approach to SCS (Langenberg et al., 2012; Lovell et al., 2005; Payne and Peters, 2004). Rather than differentiating supply chain strategies between segments, these publications only differentiate individual design choices such as the speed of the transportation mode or sourcing locations. With one exception (Langenberg et al., 2012), the number and type of segments is determined based on managers’ judgment. Products are then allocated to segments based on threshold values. Lovell et al. (2005) determine whether a product should be shipped by sea or air based on its value and chargeable weight. Similarly, Payne and Peters (2004) establish thresholds (e.g., the minimum number of order lines per year) that determine whether products should be held centrally or locally.

The main advantage of the outlined qualitative approaches is that they require neither the availability of data nor the knowledge of statistics software. However, segments formed based on managers’ judgment alone can only provide limited new insights, as no new information enters the segment formation process (Foedermayr and Diamantopoulos, 2008). Especially if a large number of criteria needs to be analysed when forming segments, managers tend to have trouble identifying products or customers that are similar with respect to the criteria of interest (Wedel, 2000). Consequently, segmentation procedures without data analysis are considered “probably the simplest but least effective” (Wedel, 2000).

2.2 Quantitative approach

Langenberg et al. (2012) are the first to recognize the resulting need for “profound quantitative analysis”. They introduce a model that matches the product portfolio of a company with a set of supply chains. It assumes that companies hold a diverse portfolio of functional and innovative products for which product characteristics related to cost (holding, stockout, procurement and order setup), demand (mean and standard deviation) and production lead times are known. Further, the model assumes that companies have a portfolio of supply chain options at their disposal with known supply-chain-specific lead times and procurement cost. To form segments, Langenberg et al. (2012) employ a branch-and-bound algorithm that selects a subset of the supply chain portfolio and allocates products to these supply chains with the goal of minimizing total cost.

An advantage of this approach is that it finds the “optimal” set of segments, i.e., segments that minimize the sum of all considered costs. However, it presumes that managers have a portfolio of supply chain design options with quantifiable performance implications at their disposal. This assumption holds only if the SCS focuses on isolated design decisions: in their study, Langenberg et al. (2012) assess a set of 20 different sourcing and shipment options with quantified implications for lead times, procurement and transportation costs. Yet, if the goal of the SCS is to assess different strategic directions, a broader set of performance measures is affected and performance implications are harder to quantify (APICS, 2016).

Langenberg et al. (2012) acknowledge this limitation and highlight that their model provides guidance “at the tactical [rather than the strategic] level of decision-making”. Consequently, as most studies on SCS seek to form segments that serve as a basis for tailored supply chain strategies, there is a need to introduce a different set of quantitative methods to SCS.

2.3 Clustering

Clustering is the unsupervised learning task of subdividing a set of heterogeneous objects into groups that are internally homogenous and heterogeneous amongst each other (Bacher et al., 2010; Clarke et al., 2009) . When conducting a cluster analysis, critical decisions include *selecting segmentation criteria, selecting a clustering procedure* and *assessing cluster solutions*.

Selecting segmentation criteria for a cluster analysis entails a trade-off. On the one hand, if important criteria are omitted, the obtained solutions fail to adequately reflect the context of interest. On the other hand, irrelevant or redundant criteria may distort the cluster analysis and thus prevent meaningful solutions from being found (Ketchen and Shook, 1996; Milligan, 1996). The screening and pre-testing of candidate criteria is therefore a critical part of a cluster analysis (Brusco et al., 2017).

Clustering procedures are either heuristics or model-based (Bacher et al., 2010). Heuristic clustering procedures such as K-Means or Ward's method are the most popular in the operations management area. However, in recent years, model-based procedures are being increasingly employed as well (Brusco et al., 2012). Whereas heuristic procedures aim to find a local optimum within a reasonable amount of time, model-based procedures assume a probability model underlying the data. As a result, most heuristic procedures require a distinct classification of objects to clusters, whereas model-based procedures allow objects to belong to multiple clusters (Bacher et al., 2010). The choice of the clustering method therefore depends on how clearly clusters are separated in the data and on whether overlapping clusters are permissible (Everitt et al., 2011).

Finally, the *assessment of cluster solutions* evaluates whether the obtained solutions suffice for reaching the goal of the analysis (Bacher et al., 2010). The assessment comprises the examination of technical features such as within-cluster heterogeneity and between-cluster homogeneity. It also evaluates the interpretability of clusters and tests their stability.

Performing a cluster analysis therefore not only requires knowledge of the technical features of the analysis, but also of the context in which the analysis takes place. Despite these requirements, cluster analysis is the most popular method for data-driven segmentation initiatives in business research (Ngai et al., 2009) and popular for market segmentation in particular (Wedel, 2000). When conducting a market segmentation, companies may use cluster analysis to group customers that are similar regarding their response to marketing activities (Foedermayr and Diamantopoulos, 2008). When conducting a SCS, companies may use cluster analysis to group products or customers that are similar regarding the type of supply chain they require. In doing so, cluster analysis may discover groups of similar products or customers that managers would not have discovered using tacit knowledge alone. Unlike the quantitative approach by Langenberg et al. (2012), managers do not need to specify supply chain designs or strategies upfront.

2.4 Classification

Contrary to clustering, classification is a *supervised* learning task (Duda et al., 2012). Whereas clustering aims to uncover hidden patterns in the data, classification assigns objects to a predetermined set of classes (Breiman, 2001). First, the classification algorithm is trained using a “training dataset” with a pre-established allocation of objects to classes. The trained algorithm then allocates objects to classes for a “test dataset” where the allocation of objects to classes is unknown.

Available classification procedures range from probabilistic methods, decision trees, rule-based methods, instance-based methods, support vector machines to neural networks (Aggarwal, 2015). They differ regarding a number of characteristics such as predictive accuracy, training speed, the ability to handle missing data or the amount of parameter tuning required. K-Nearest Neighbours (KNN) algorithms, for instance, are instance-based methods that are simple to implement and make few assumptions about the underlying data structure, but they are resource-intensive. Neural networks are fast to run once they are trained, but require considerable tuning of input parameters and it is hard to understand how these algorithms arrive at classifications (Kotsiantis, 2007). Similar to clustering, the choice of the classification method therefore depends on the dataset and the application scenario.

In the operations management area, classification currently receives significant attention due to the trend topic “Internet of Things”. Application areas include the prediction of machine failures (Peng et al., 2010) and the large-scale analysis of sensor data (Perera et al., 2014). In the context of a SCS, classification algorithms are of interest once companies have established a preliminary set of segments via clustering or a qualitative approach.

Companies may use classification to review the allocation of objects to segments that they have established qualitatively. When managers allocate objects to segments as part of a qualitative approach, they implicitly consider a set of segmentation criteria (e.g., *“does the product that needs to be allocated have a low or a high contribution margin?”*). If data is available for these criteria, managers may compose a training dataset of archetype objects (e.g., products or customers) for each segment and then classify the remaining objects using a classification algorithm.

Similarly, companies may use classification algorithms to update segments obtained from clustering. Companies' product and customer portfolios are constantly changing – accordingly the allocation of objects to segments needs to be reviewed periodically. As products mature, for instance, demand variability and contribution margins are likely to decrease (Aitken et al., 2005). Once the segmentation criteria of the objects in a company's portfolio change, the company may employ a classification algorithm to review the allocation of objects to segments using the results of the initial cluster analysis as the training dataset. Finally, classification algorithms are also useful to allocate new products or customers to existing supply chain segments.

Companies may thus use classification procedures to update or challenge existing segments. The extant literature acknowledges the importance of regularly reviewing supply chain segments (Godsell et al., 2011; Seifert and Langenberg, 2011). Nonetheless, we are not aware of any studies on SCS that employ classification.

3 Case company

3.1 Company profile

Arguably, one of the best-suited companies to examine how companies can use clustering and classification for a SCS is the chemicals manufacturer BASF. Contrary to its competitors, BASF embraces the "Verbund"-concept: the company controls value streams that span from basic chemicals to high-value-added products such as coatings and crop protection agents (BASF SE, 2016b). While this diversity achieves annual cost savings in excess of 1€ billion in logistics and production, it aggravates supply chain complexity: a business unit producing basic chemicals requires a different supply chain than a business unit producing high-value crop protection. The former operates in a stable low-margin environment and thus prioritizes cost-efficiency. The latter operates in a volatile high-margin environment and thus requires capabilities for matching demand and supply (Fisher, 1997). Due to the scope of its operations, BASF is considerably diverse regarding the type of supply chain different parts of its business require.

To remedy this diversity, BASF initiated a SCS in the years 2013 and 2014. Goals included finding a common terminology to communicate supply chain needs, obtaining a better overview of how supply chain needs are distributed across the business unit portfolio, and helping business units tailor their supply chains to the needs of their business environment. As quantitative approaches to deriving supply chain segments were missing at that time, the company decided to form segments based on managers' judgment.

3.2 Qualitative segments

BASF's SCS project initially consisted of two phases. First, to come up with a set of supply chain segments, the company put together a focus group consisting of their supply chain strategy team, external consultants and supply chain leaders of business units. Second, after the focus group had decided on a set of four segments, business unit supply chain leaders were asked to assign their business unit to one of the supply chain segments. If they considered their product or customer portfolio too diverse for a single segment, they had the option of subdividing their business unit and choosing different segments for different parts.

Three of the segments identified by the qualitative approach have been widely discussed in textbooks and supply chain strategy literature: Lean, Leagile and Agile (e.g., Agarwal et al., 2006; Mason-Jones et al., 2000; Naylor et al., 1999).

The "Lean" segment comprises cost-sensitive business units with a stable operating environment. Consequently, the goal of these business units is to ensure reliable supply at competitive costs through practices such as level scheduling and just-in-time production.

The "Leagile" and the "Agile" segments comprise business units that operate in a volatile environment with customers willing to pay a premium. In the Agile segment, customers tolerate relatively long lead times. Business units in the Agile segment can therefore use flexible make-to-order production to deal with uncertainties. In the Leagile segment, customers only tolerate short lead times. Business units in the Leagile segment therefore rely on a postponement strategy that emphasizes cost-efficiency upstream and flexibility downstream of the decoupling point.

The fourth segment is company-specific. We refrain from discussing it in this paper to protect the proprietary information of BASF. However, it is also only relevant for a small minority of business units (fewer than 2% of the company's business units). When comparing the qualitative to the quantitative approach, we will focus on the former three supply chain segments.

4 Clustering

4.1 Dataset

4.1.1 Unit of analysis

Studies on SCS differ regarding the unit of analysis they choose for subdividing businesses into groups that require distinct supply chain strategies. Some studies segment *products* (Aitken et al., 2005; Childerhouse et al., 2002; Christopher et al., 2006; Christopher and Towill, 2002; Christopher et al., 2009; Langenberg et al., 2012; Lovell et al., 2005; Payne and Peters, 2004), whereas others segment *customers* (Christopher and Gattorna, 2005; Godsell et al., 2006).

We choose a more aggregated unit of analysis by clustering *business units*. We cluster business units rather than products or customers for three reasons. First, clustering business units ensures comparability to the company's qualitative approach. Second, data on contribution margins – a critical segmentation criterion – is only available at the business-unit-level. Third, the business units in our dataset are organized according to the products they sell (e.g., herbicides versus fungicides) and according to the markets they serve (e.g., Europe or Asia) (BASF SE, 2017). Clustering business units therefore takes into consideration that supply chain strategies account for both product and customer/market characteristics.

4.1.2 Sampling

Our dataset covers the entire company except for its oil and gas division for the years 2013 and 2014. As a result, it captures approximately 80% of the company's revenues during the examined period (BASF SE, 2015). In total, the dataset comprises 228 business units.

We exclude business units with annual sales below 1 million € or fewer than 1,000 orders annually to ensure that only business units with sufficient supply-chain-related activities are included. Further, we exclude one business unit with missing data and one business unit that was not reliably integrated in the company's databases at the time. The final sample therefore comprises 181 observations and is identical to sample of business units employed in Chapter 2.

4.2 Segmentation criteria

Segmentation criteria are contingency variables considered important for deciding which supply chain strategy to pursue. Arguably the most prominent framework of such variables is the distinction between functional and innovative products (Fisher, 1997). The previous chapter has subdivided the characteristics of functional and innovative products into two categories:

challenges in the operating environment and variables influencing the *value of matching supply and demand*. We use this categorization as guidance for selecting segmentation criteria.

4.2.1 Challenges in the operating environment

Challenges in the operating environment inhibit the ability to match supply and demand, *ceteris paribus*. An operating environment characterized by unexpected changes in demand, for example, requires a supply chain that emphasizes flexibility and agility (Gligor, 2015; Merschmann and Thonemann, 2011). Similarly, if customers demand short lead times, supply chains need to be sufficiently responsive to achieve on-time delivery nonetheless (de Treville et al., 2014a).

An examination of frameworks for supply chain or manufacturing strategies reveals that demand uncertainty and time pressure are indeed two of the most important challenges imposed by operating environments. According to Fisher (1997), challenges in the operating environment comprise different causes of demand uncertainty (short lifecycles, forecast error and high product variety) as well as the time granted by customers to fulfil orders. The same is true for the DWV3 framework by Christopher et al. (2009) which also considers different sources of demand uncertainty (demand variability and volume, product variety and the product lifecycle) as well as the customer lead time requirement. Olhager (2003) explicitly maps challenges of the operating environment along a time-related and a demand-related dimension. In line with these frameworks, we include variables that approximate demand uncertainty and time pressure as segmentation criteria in the cluster analysis.

Contingency variables proposed in the extant literature for approximating time pressure include the time window for delivery (Christopher et al., 2009), market standards for lead times (Fisher, 1997) and the ratio between customers' lead time requirements and the production lead time (Olhager, 2003). As our dataset does not feature information on production lead times, we use customers' lead time requirements to approximate time-related challenges. We measure lead time requirements by the number of days customers grant between order placement and the requested delivery date.

The most frequently proposed variable in the extant literature on supply chain strategy for approximating demand uncertainty using company data is demand variability (Basnet and Seuring, 2016). Demand variability captures both expected and unexpected changes in demand. Following Aitken et al. (2005) and Christopher et al. (2009), we measure demand variability as the coefficient of variation of weekly sales.

4.2.2 Value of matching supply and demand

Even if demand uncertainty and time pressure increase the need to invest in capabilities that improve the match between supply and demand, this does not imply that such investments should necessarily be taken. Managers need to ensure that the benefits of preventing supply and demand mismatches clearly outweigh the associated costs.

Variables approximating the value of matching supply and demand include contribution margins, contract penalties, goodwill loss and the salvage value of products (Langenberg et al., 2012). Due to data availability, this study focuses on contribution margins. Segmentation criteria used in the main body of this study are thus demand variability, customer lead time requirements and contribution margins. Table 3.1 provides a summary of all measures.

Table 3.1: Variable descriptions and measurement.

	Variable	**Measurement**
Segmentation criteria	Demand variability	Coefficient of variation of weekly sales (logarithm, standardized)
	Customer lead time requirements	Average number of days customers grant between the initial order entry and the requested delivery date (logarithm, standardized)
	Contribution margins	Average selling price minus the average variable cost per unit (standardized)
	Demand uncertainty (Appendix B)	Factor analysis output
	Time pressure (Appendix B)	Factor analysis output
External validity	Product lifecycle duration	Average product age (logarithm, standardized)
	Demand volume	Average sales per product (logarithm, standardized)
	Product variety	Number of products in the business unit’s portfolio (logarithm, standardized)
Mismatch-performance link	Self-assigned segments	Proportion of the business unit’s sales assigned to the Lean, Leagile or Agile segment by managers
	Segments proposed by the cluster analysis	Lean, Leagile, Agile or Basic Service (categorical)
	Mismatches	Proportion of the business unit’s sales for which the self-assigned segment does not correspond to the segment proposed by the cluster analysis
	Business unit size	Business unit revenues during the examined period (logarithm, standardized)
	Financial performance	Return on sales

Variables with diminishing marginal effects are logarithmized. Variables used as segmentation criteria or for assessing external validity are standardized to render their scales comparable.

4.3 Clustering procedure

Visual inspection of the data does not reveal a clear cluster structure. To deal with this issue – which is common in segmentation initiatives – model-based procedures that allow overlapping clusters have been developed (Brusco et al., 2012). We therefore perform the cluster analysis using the model-based clustering algorithm Mclust. We select the Mclust algorithm because it is available free of charge and offers a wide range of diagnostic tools (Fraley and Raftery, 2002).

4.4 Assessing cluster solutions

We follow a four-step approach to determine the number of clusters and evaluate cluster solutions (Bacher et al., 2010).

4.4.1 Preselecting candidate solutions

We preselect a candidate set of cluster solutions by assessing measures of within-cluster homogeneity, between-cluster heterogeneity and explained variance. The Bayesian Information Criterion (BIC) weighs the incremental increase in the proportion of variance explained by an additional cluster against the risk of overfitting the cluster solution to the data. As shown in Table 3.2, the BIC proposes solutions with two, three or four clusters. In addition to the BIC, we employ two standard metrics for assessing within-cluster homogeneity and between-cluster heterogeneity (Brock et al., 2011). The Silhouette metric proposes a solution with two or four clusters; the Dunn Index proposes a solution with two, three or four clusters.

Table 3.2: Statistical properties of the cluster solutions.

Statistical properties	Number of clusters					
	1	2	3	4	5	6
BIC	-1558.753	**-1548.338**	**-1548.675**	**-1552.244**	-1556.325	-1571.711
Silhouette		**0.318**	0.250	**0.312**	0.269	0.259
Dunn Index		**0.053**	**0.055**	**0.055**	0.040	0.032

Note: Bolded values indicate preferred solutions

4.4.2 Nominating the final solution

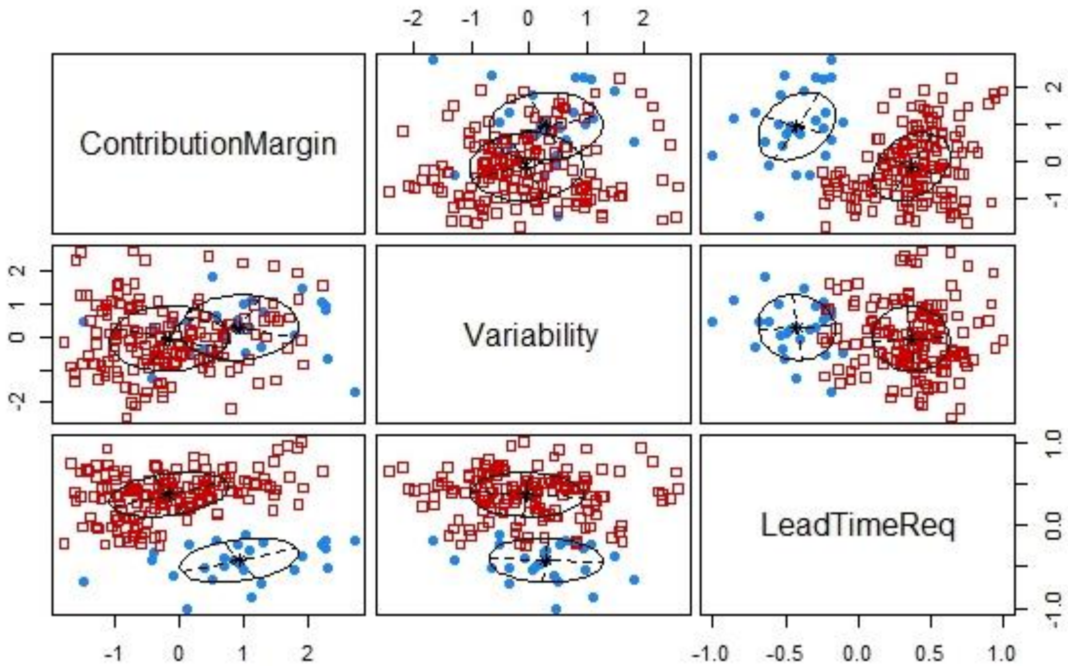
The goal of segmentation initiatives is to arrive at an *actionable* set of segments (Foedermayr and Diamantopoulos, 2008): segments must be sufficiently homogeneous regarding the examined criteria for determining the type of action required. In a quantitative SCS, clusters therefore need to be sufficiently homogeneous for determining which supply chain strategy is needed.

For this purpose, we evaluate the two-dimensional scatter plots in Figures 3.1-3.3. Each figure shows one of the candidate solutions. The axis of the scatters depict the examined criteria.

Since we cluster analyse three criteria, there are six scatters in each figure. The colour and shape of the objects in the scatters depict the business units' cluster membership. If one of the clusters stretches across large parts of a scatter, the cluster is heterogeneous regarding the examined criteria and the solution therefore fails to be actionable.

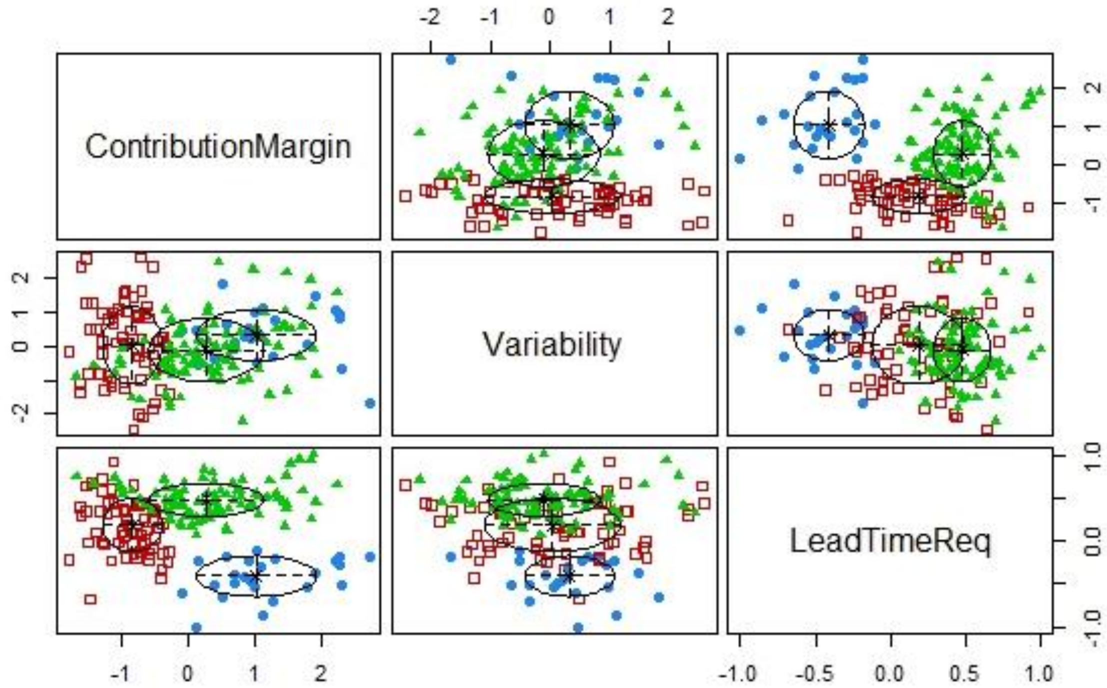
The red squares in top-left scatters of Figure 3.1 indicate that the two-cluster-solution contains a large cluster that is heterogeneous regarding demand variability and contribution margins. Some business units in this cluster thus require an efficient supply chain (low demand variability and low contribution margins) whereas others require a supply chain that focuses on matching supply and demand (high demand variability and high contribution margins). The green triangles in Figure 3.2 indicate that the three-cluster-solution contains a similarly heterogeneous cluster. Neither the two-cluster-solution nor the three-cluster-solution are thus actionable. The four-cluster-solution shown in Figure 3.3, however, is sufficiently actionable.

Figure 3.1: Scatter plots of the two-cluster-solution.



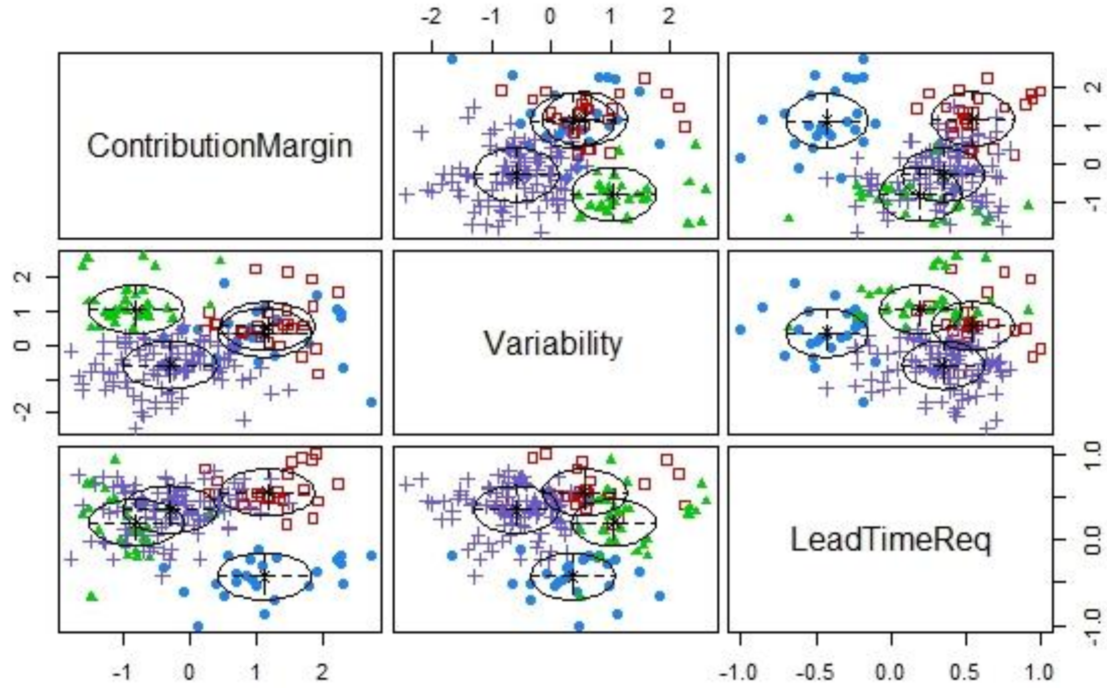
Note: The colour and shape of the objects in the scatters depict business units' cluster membership.

Figure 3.2: Scatter plots of the three-cluster-solution.



Note: The colour and shape of the objects in the scatters depict business units' cluster membership.

Figure 3.3: Scatter plots of the four-cluster-solution.



Note: The colour and shape of the objects in the scatters depict business units' cluster membership.

As indicated by Table 3.3 and Figure 3.3, the first cluster of this solution (pink crosses) is characterized by low demand variability and customers granting relatively long lead time requirements. The need to invest in capabilities for matching supply and demand is thus limited. As contribution margins are low, such investments would also fail to pay off. Consequently, the competitive priority of business units in this cluster should be cost efficiency while ensuring that service levels are sufficiently high. As the first cluster is thus similar to the Lean segment derived by the judgmental approach, we will refer to this cluster as “Lean”.

The second cluster (red squares) and the third cluster (blue dots) both have above average demand variability and contribution margins. Consequently, they require capabilities for matching supply and demand such as responsiveness or agility (de Treville et al., 2014a; Gligor et al., 2015). Customer lead time requirements are relatively short in the second cluster and relatively long in the third cluster. Business units in the second cluster thus require capabilities for matching supply and demand at short notice, whereas business units in the third cluster may for instance employ flexible make-to-order production to deal with the variable demand. Since the two clusters are therefore similar to the Leagile and the Agile segments derived by the qualitative approach, we will refer to the second cluster as “Leagile” and to the third as “Agile”.

High demand variability also characterizes business units in the fourth cluster (green triangles). However, since contribution margins are low, the scope for investments in capabilities for matching supply and demand is limited. The extant literature proposes two strategies for such a context. First, business units may follow a portfolio alignment strategy by eliminating low-margin and high-variability products from the portfolio (Barksdale and Harris, 1982; Godsell et al., 2011). Second, business units may distinguish between predictable “base” demand and volatile “surge” demand: base demand is met with a cost-efficient supply chain and surge demand is neglected at the expense of lower service levels (Christopher et al., 2006; Christopher and Towill, 2002). In line with the latter strategy, we will refer to the fourth cluster as “Basic Service”.

Table 3.3: Criteria and covariates of the four-cluster-solution (standardized).

		Lean	Leagile	Agile	Basic Service
Criteria	Contribution margins	-0.31	1.10	1.16	-0.81
	Demand variability	-0.58	0.37	0.58	1.05
	Customer lead time requirements	0.25	-1.75	0.76	-0.10
Covariates	Product lifecycle duration	0.35	-1.04	-0.46	0.04
	Demand volume	0.35	-1.04	-0.23	-0.18
	Product variety	-0.36	1.19	0.53	-0.16
Number of business units		102	24	25	30

4.4.3 External validity

Apart from being actionable, high-quality segments require external validity: the interpretation of the clusters needs to be remain valid when assessing characteristics of the dataset not considered in the clustering process (Brusco et al., 2017). For this purpose, we assess the remaining demand-related contingency variables in our dataset, i.e., demand volume, product lifecycle length and product variety. Demand volume is measured by the average sales per product. Product lifecycle length is measured by the average product age. Product variety is measured by the number of product in a business unit’s portfolio.

We expect business units in the Leagile, Agile and Basic Service clusters to face a more challenging operating environment than business units in the Lean cluster. Consequently, business units in the former clusters should exhibit a broader product portfolio with short lifecycle products and lower demand volumes per product than business units in the Lean cluster (Childerhouse et al., 2002). Table 3.3 indicates that this is the case. Business units in the Leagile, Agile and Basic Service clusters indeed have broader product portfolios with newer products and lower demand volumes per product compared to business units in the Lean cluster. The external validity assessment thus confirms that business units in the Leagile or the Agile cluster should focus on matching supply and demand whereas business units in the Lean cluster need to make cost-efficiency a competitive priority. For the Basic Service cluster, the assessment confirms the combination of a challenging operating environment and low contribution margins.

4.4.4 Stability

Cluster solutions need to be stable with respect to observations, variables, clustering method and the number of clusters (Bacher et al., 2010). Assessing stability ensures that the cluster solution is not an artefact of a small fraction of observations, a certain variable or the method employed for establishing clusters.

The results of stability assessment indicate that the four-cluster-solution is sufficiently stable regarding the removal of observations, the measurement of variables, the clustering method and the number of clusters. For details on the assessment, we refer the reader to Appendix A and B.

In summary, the four-cluster-solution is actionable, externally valid and sufficiently stable. Its clusters thus constitute the quantitative supply chain segments used in this research.

5 Comparing quantitative and qualitative segments

The cluster analysis largely confirms the results of BASF's qualitative approach: three clusters correspond to the segments derived qualitatively (Lean, Leagile and Agile). However, it also provides two novel insights. First, the qualitative approach does not identify the Basic Service cluster. Second, the self-assignment of business units to segments often does not correspond to the segment proposed by the cluster analysis. Such a mismatch occurs, for instance, if a business unit assigns itself to the Leagile segment even though the cluster analysis suggests that the Lean segment would be a better fit.

5.1 Mismatch-performance link

There are two potential causes for mismatches between self-assigned segments and segments proposed by the cluster analysis.

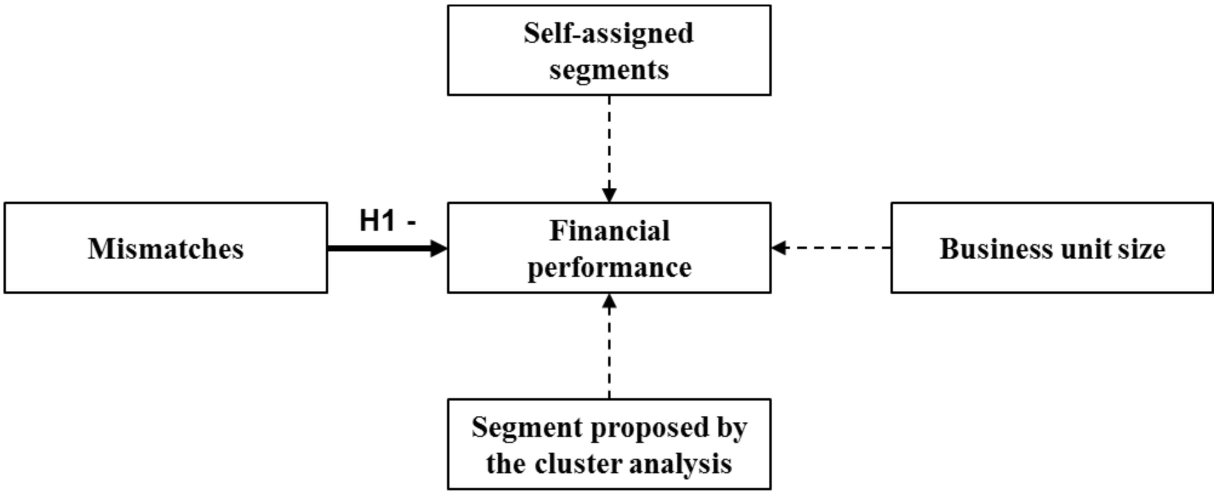
On the one hand, falsely omitted segmentation criteria may have distorted the results of the cluster analysis. For example, the segment propositions by the cluster analysis might be inaccurate for business units in our sample supplying the automotive industry, since delivering as requested is important in that industry regardless of contribution margins (Guiffrida and Nagi, 2006). Thus, if falsely omitted criteria have caused mismatches between the self-assigned and the proposed segments, these mismatches simply indicate that the segments derived quantitatively are inadequate.

On the other hand, however, if mismatches result from business units selecting segments that do not reflect the requirements of their business environment, adverse effects are likely. In such cases, business units are pursuing supply chain strategies that overcharge or underserve customers, which in turn leads to either unnecessarily high costs or lost sales (Fuller et al., 1993). A mismatch between the self-assigned and the proposed segment caused by managers' misjudgement should thus manifest itself in lower financial performance (Gligor, 2015; Wagner et al., 2012).

Given the diligent criteria selection and given the stability of the derived segments, we hypothesize that a significant proportion of mismatches indicates managers' misjudgement as illustrated by Figure 3.4.

Hypothesis 1: *There is a negative relationship between mismatches and financial performance.*

Figure 3.4: Effect of mismatches on financial performance.



5.2 Dataset and variables

We test the hypothesized relationship for all business units that have assigned themselves to the Lean, Leagile or Agile segments and that are assigned by the cluster analysis to one of the corresponding clusters. Following the examination of Mahalanobis and Cook's distance plots, we remove one outlier with an extreme value for financial performance. As a result, the final sample comprises 92 business units.

Financial performance is measured by the return on sales. Mismatches are measured by the proportion of a business unit's sales for which the self-assigned segment does not correspond to the segment proposed by the cluster analysis.[5]

We control for the self-assigned segments and the segments proposed by the cluster analysis, as they correlate with both financial performance and mismatches. The correlation matrix in Table 3.4 shows that business units self-assigned to the Leagile segment, for example, not only have higher financial performance but also more frequent mismatches.

In addition, we control for business unit size. Larger business units might achieve a higher financial performance by leveraging economies of scale. At the same time, they have more resources to build up supply chain capabilities that help avoid mismatches (Damanpour, 1992; Mansfield, 1993; Vijayasarathy, 2010). Table 3.4 shows that larger business units indeed have a higher financial performance and fewer mismatches. Business unit size is measured by the logarithm of business units' revenues during the examined period.

[5] Recall that business units have the option of selecting different segments for different parts of their business. Consequently, the variable measuring mismatches is bounded between zero and one.

Table 3.4: Pearson correlation coefficients.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Financial performance	1***								
(2) Mismatches	-0.1	1***							
(3) Cluster Lean	-0.03	0.16	1***						
(4) Cluster Leagile	0.11	-0.28**	-0.59***	1***					
(5) Cluster Agile	-0.06	0.08	-0.63***	-0.26*	1***				
(6) Self-assigned Lean	-0.17	-0.57***	0.31**	-0.12	-0.26*	1***			
(7) Self-assigned Leagile	0.19	0.46***	-0.06	-0.04	0.11	-0.64***	1***		
(8) Self-assigned Agile	-0.06	0.02	-0.24*	0.17	0.13	-0.25*	-0.59***	1.00***	
(9) Business unit size	0.34***	-0.13	0.04	0.05	-0.10	0.11	-0.10	0.01	1***

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed).

5.3 Endogeneity

As endogeneity can lead to biased and inconsistent estimates, this study addresses three main causes of endogeneity: measurement error, omitted variables and simultaneity (Roberts and Whited, 2013). The control variables specified in the previous section address concerns related to omitted variables. Concerns regarding measurement error are addressed by minimizing the risk of common method bias, as it is one of the main sources of measurement error (Podsakoff et al., 2003). Common method bias is unlikely to be an issue for our study, as it relies on both qualitative data (self-assigned segments) and archival data from multiple sources (financial and supply chain databases).

Simultaneity concerns may arise for the relationship between mismatches and financial performance. We hypothesize a positive relationship between these two constructs, arguing that mismatches decrease financial performance. Yet, one might also argue that business units with a higher financial performance have more resources to invest in capabilities that prevent mismatches. However, upon closer examination, it becomes clear that such reverse causality is unlikely for two reasons. First, by controlling for business unit size, we ensure that the relationship between mismatches and financial performance is not driven by economies of scale. Second, the examined business units have the option of building up capabilities for preventing mismatches by drawing on centrally provided resources such as the company-wide pool of experts and shared information systems. Since these resources are available irrespective of financial performance, the examined business units are relatively unconstrained in their ability to prevent mismatches, especially when compared to a sample of independent companies. Consequently, we consider mismatches a *plausibly* exogenous predictor of financial performance (Ketokivi and McIntosh, 2017).

5.4 Results

We employ a multilevel regression that accounts for the multilevel structure of the data (*mixed* command in *Stata 14*). Even though visual inspection of diagnostic plots does not indicate the violation of model assumptions, we conduct a non-parametric bootstrap with 1,000 resamples to ensure that our results are robust. Table 3.5 indicates the derived parameter estimates, *p*-values and 95% bias-corrected confidence intervals.

Multicollinearity is within a tolerable range (maximum variance inflation factor = 2.96). The intra-class correlation coefficient (ICC) indicates that a significant proportion of the variance is explained by the multilevel structure of the data (ICC = 0.359) (Firebaugh, 1978). We compute a Pseudo-R^2 for the change in the total variance explained at all levels with and without the predictors (LaHuis et al., 2014). A significant percentage of the variance is explained (Pseudo-R^2 = 0.224, and Wald χ^2 = 28.89, $p < 0.001$). Mismatches between the self-assigned and the proposed segment that affect entire business units are associated with a 5.5.-percentage-point decrease in the return on sales (β_1 = -0.055, $p < 0.01$). Hypothesis 1 is therefore supported.

Our results thus indicate that a mismatch between the self-assigned and the proposed segment suggests that managers are pursuing a supply chain strategy that does not reflect the needs of their product and customer portfolio. This in turn highlights the value of conducting a cluster analysis for a SCS. A cluster analysis not only challenges number and type of segments required, but also the allocation of objects to segments.

Table 3.5: Regression results with *p*-values and bias-corrected confidence intervals.

Independent variables	Dependent variable			
	Financial Performance	Financial Performance	Financial Performance	Financial Performance
Cluster Leagile	0.004 [-0.023, 0.034]	-0.018 [-0.040, 0.012]	0.010 [-0.016, 0.038]	-0.011 [-0.032, 0.017]
Cluster Agile	-0.001 [-0.039, 0.042]	-0.013 [-0.047, 0.028]	0.005 [-0.034, 0.040]	-0.007 [-0.041, 0.027]
Self-assigned Leagile	0.038 [-0.001, 0.083]	0.081^{***} [0.033, 0.122]	0.043^{*} [0.006, 0.094]	0.083^{***} [0.041, 0.127]
Self-assigned Agile	0.010 [-0.035, 0.061]	0.058^{**} [0.014, 0.091]	0.007 [-0.039, 0.059]	0.051^{*} [0.008, 0.087]
Business unit size			0.026^{***} [0.013, 0.041]	0.025^{***} [0.013, 0.040]
Mismatches		-0.059^{**} [-0.097, -0.020]		-0.055^{**} [-0.088, -0.017]
Wald χ^2	5.59	14.48^{*}	19.23^{**}	28.89^{***}
ICC	0.359^{***}	0.359^{***}	0.359^{***}	0.359^{***}
Pseudo-R^2	0.055	0.115	0.172	0.224

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed).

6 Classification

All previous analysis in this study relies on data from the years 2013 and 2014, as the case company launched its segmentation initiative during that time. In 2016, however, it became apparent that the assignment of business units to segments required review for two reasons. First, a change in the reporting structure resulted in a number of new business units that had not been assigned to a segment yet. Second, a strong decline of the oil price had affected contribution margins (BASF SE, 2016a) which in turn had changed the value of matching supply and demand for many business units.

To review the assignment of business units to the segments, we use classification. Due to limited resources and capabilities, companies prefer easy-to-use algorithms with transparent classification decisions for segmentation initiatives (Verhoef et al., 2003). Three classification methods available free of charge in *R* that require little parameter tuning are random forests, K-Nearest-Neighbours and multinomial logistic regression (Aggarwal, 2015; Kotsiantis, 2007). As the former is the most popular classification algorithm for segmentation initiatives (Ngai et al., 2009), we use a random forest (*randomForest* in *R*) to classify business units. K-Nearest-Neighbours (*class* in *R*) and logistic regression (*nnet* in *R*) are used to evaluate the stability of the classification.

The random forest algorithm is trained by growing 100,000 trees with the results of the cluster analysis as the training dataset. The trained algorithm then classifies the test dataset which comprises all BASF business units from the year 2015 with more than 1,000 orders and sales greater than 1 million € except for the oil and gas division. In total, 151 business units are classified. The classification is stable regarding the method used: K-Nearest Neighbour assigns 89% of the observations to the same segment and logistic regression assigns 95% to the same segment. Visual inspection of variable importance plots confirms that all three segmentation criteria significantly contribute to the classification (Liaw and Wiener, 2002).

Table 3.6 indicates that the random forest algorithm assigns 21% of the business units that are part of both datasets to a different segment when classifying the 2015 data. While the Lean and Leagile clusters remain comparably stable (9% and 17% different classification respectively), the segment assignment of business units originally assigned to the Agile and Basic Service clusters changes more frequently (25% and 65% different classification respectively).

Two changes in the assignment of business units to segments stand out. First, a migration of business units from the Basic Service to the Lean cluster caused by margin improvements and lower demand variability. This migration is expected, as it indicates that business units in the Basic Service cluster embrace the portfolio alignment strategy proposed in Section 5. Second, there is migration from the Lean and Leagile clusters to the Agile cluster. While the migration from the Lean cluster is caused by margin improvements and higher demand variability, the migration from the Leagile cluster is caused by longer customers granting longer lead times.

Table 3.6: Changes in the allocation of business units to segments due to the re-classification.

		Data 2015				Percentage change
		Lean	Leagile	Agile	Basic Service	
Data 2013/14	Lean	67	0	**5**	**2**	9%
	Leagile	0	19	**4**	0	17%
	Agile	**3**	0	12	**1**	25%
	Basic Service	**13**	0	**0**	7	65%

Note: Bolded values indicate changes in the allocation of business units to segments

Our findings demonstrate that the allocation of business units to segments requires periodic review, as the contexts in which supply chains operate continuously change. While some business units deliberately change their business environment by adjusting their product portfolio, others face externally induced changes caused by the oil price or changes in demand. The need to revise supply chain segments is particularly high in the chemicals industry due to cyclical demand, inflexible supply and oil price dependency (de Paepe et al., 2015; Hong et al., 2015). Nonetheless, reviewing the allocation of objects (e.g., business units, products or customers) will also be of interest in more stable industries. If, for example, companies segment products instead of business units, the need for review increases further, as the product lifecycle stage affects the type of supply chain that is needed (Childerhouse et al., 2002). Classification algorithms therefore play an important role for SCS because they allow companies to track dynamics in their business environment and – if necessary – to adjust the allocation of objects to segments.

7 Discussion and conclusion

7.1 Implications

Until now, two barriers have prevented the adoption of quantitative approaches to SCS. First, a perceived lack of capabilities or resources (Dibb and Simkin, 2009). Second, concerns that quantitatively formed segments may not adequately reflect requirements of the business environment (Childerhouse et al., 2002). Our study demonstrates that these barriers can be overcome.

A lack of capabilities or resources should not prevent practitioners from forming supply chain segments quantitatively. Our study has successfully formed supply chain segments quantitatively using data that is commonly available in company databases and algorithms that are available free of charge. Our study also provides practitioners guidelines on how to use these algorithms for deriving supply chain segments. Consequently, the cost of conducting a quantitative SCS is limited.

The benefits of a quantitative SCS, however, can be substantial. First, our results show that clustering identifies segments not discovered by the management team. At the case company, the cluster analysis confirms three qualitatively derived segments (Lean, Leagile and Agile), but also detects one new segment (Basic Service). Second, in many cases managers assign their business unit to a segment that does not reflect the needs of the business environment, consequently pursuing a supply chain strategy that adversely affects financial performance. Clustering and classification help detect such segment-environment mismatches and thus serve as a valuable tool for challenging managers' judgment when forming segments. Third, the case company's business unit portfolio highlights the need to periodically review the allocation of business units to segments. Our study demonstrates that classification algorithms are a suitable tool for this purpose. Given these benefits and the limited cost, we recommend companies use clustering and classification when conducting a SCS.

7.2 Limitations and future research

Despite the outlined benefits, there are limits to the use of clustering and classification for SCS. Foremost, these methods do not substitute for managers' tacit knowledge. Interviews with supply chain leaders from the examined business units reveal that there may be valid reasons for assigning a business unit to a segment different from the one proposed by the cluster analysis. In our sample, some business units have schedule agreements with their customers in place, allowing them much more time to plan ahead than indicated by the customer lead time requirement (Tuli and Shankar, 2015). Others are supplying the automotive industry and have to ensure high service levels regardless of the level of contribution margins (Guiffrida and Nagi, 2006). For these business units, the quantitatively derived segments fail to reflect the requirements of the business environment. Consequently, we advise practitioners to complement clustering and classification with managers' tacit knowledge when conducting a SCS.

Further, replication and validation studies are needed to scrutinize the benefits of clustering and classification outlined by this research. In particular, they may address the following questions. Will other companies discover a similar set of segments when conducting a cluster analysis? If their analysis yields a different set of segments, is the solution still actionable? How do cluster solutions change when segmenting products or customers instead of business units? Replication studies are also needed to rule out the risk of a systematic measurement error.

Finally, future studies may examine the antecedents of segment-environment mismatches. Misjudgement by managers is a likely explanation of the adverse effects associated with segment-environment mismatches. However, other explanations such as inflexible structures that are outside managers' span of control are plausible as well. Since knowing what has caused mismatches is a prerequisite for crafting solutions that help resolve them, further work is needed in this area.

Appendix A

The four-cluster-solution is stable with respect to the removal observations. We draw 100 random subsets of the data that contain 80% of the original observations. Cluster membership changes on average for less than 8% of the observations.

The solution is also stable regarding the measurement of variables. In Appendix B, we use different measures for demand-related and time-related challenges in the operating environment. Even though the change of measurement affects the number of clusters in the final solution, both the interpretation of the clusters and the allocation of business units to clusters remains largely unchanged.

The solution is unstable regarding the removal of variables though. Omitting one variable causes on average 41.4% of observations to change cluster membership. This is not surprising, since we only cluster analyse three variables. Removing one of these variables eliminates an important factor for determining the right supply chain strategy which makes it impossible to find an actionable set of clusters. Consequently, stability with respect to the removal of variables is less important in our case.

The solution is stable regarding the clustering method used. The P-Median and K-Means methods qualify as benchmarks because of their emergent (P-Median) or established (K-Means) popularity in the operations management area (Brusco et al., 2012). The interpretation of the clusters remains the same for these methods: the clusters are again Lean, Leagile, Agile and Basic Service. Table 3.7a and Table 3.7b indicate that business units originally assigned by Mclust to the Leagile, Agile or Low-Cost cluster all maintain their cluster membership except for two observations. However, some of the business units originally assigned to the Lean cluster are now assigned differently. These are business units located in an area where the Lean cluster overlaps with the other clusters. Most likely, they are assigned differently because P-Median and K-Means assign observations uniquely to clusters whereas Mclust allows overlapping clusters. In total, both P-Median and K-Means assign 15% of the observations differently.

Table 3.7: Allocation of business units to clusters for different clustering methods.

Table 3.7a

		P-Median			
		Lean	Leagile	Agile	Basic Service
Mclust	Lean	75	**3**	**11**	**13**
	Leagile	0	24	0	0
	Agile	0	0	25	0
	Basic Service	0	**1**	0	29

Table 3.7b

		K-Means			
		Lean	Leagile	Agile	Basic Service
Mclust	Lean	76	**3**	**6**	**17**
	Leagile	0	24	0	0
	Agile	0	0	25	0
	Basic Service	0	0	**2**	28

Note: Bolded values indicate changes in the allocation of business units to clusters

Finally, we assess the stability of the cluster solution with respect to the number of clusters. Adding or removing a cluster changes the cluster membership of observations that are part of the new cluster or that have been part of the removed cluster. Cluster membership for the remaining observations should remain unchanged though.

In our case, if only three clusters are allowed, Table 3.8a indicates that the Lean cluster splits into two parts. The first part absorbs the Agile cluster and the second part absorbs the Basic Service cluster. The Capable cluster remains the same except for one observation. If we add a fifth cluster, Table 3.8b indicates that the Low-Cost cluster splits up into two parts. Low contribution margins and high demand variability characterize the first part, whereas low contribution margins and short lead time requirements characterize the second part. The cluster membership for the observations originally assigned to the other clusters is largely unaffected; only a proportion of the Lean cluster migrates to the second Basic Service cluster.

Thus, each time we allow a new cluster, two of the original clusters re-arrange to form an additional cluster. Since the remaining observations remain largely unchanged, the four-cluster-solution sufficiently stable with regarding number of clusters.

Table 3.8: Allocation of business units to clusters for different number of clusters.

Table 3.8a

		4 clusters			
		Lean	Leagile	Agile	Basic Service
3 clusters	Leagile	1	23	0	0
	Lean & BS	43	1	0	26
	Lean & Agile	58	0	25	4

Table 3.8b

		4 clusters			
		Lean	Leagile	Agile	Basic Service
5 clusters	Lean	81	0	3	5
	Leagile	0	23	0	0
	Agile	3	0	22	0
	BS I	0	0	0	13
	BS II	18	1	0	12

Appendix B

A common practice in segmentation initiatives is to reduce the number of criteria by conducting a factor analysis that combines single-item measures into reflective multi-item measures (Foedermayr and Diamantopoulos, 2008). Benefits of this approach are the reduced risk of measurement error and potentially simpler cluster solutions (Bacher et al., 2010). However, there is a key drawback: variables derived from a factor analysis are harder to interpret (Dolnicar and Grün, 2008). When discussing with managers the segment proposed by the cluster analysis for their business unit, we found it critical to graphically illustrate the data that had been used for arriving at the segment proposition. As this is much easier with untransformed variables, we have used single-item measures in the main body of the study.

In this section, however, we use factor variables to assess the stability of the cluster solution in the main body of this study with respect to the measurement of variables. In order to investigate the value of supply chain fit, Wagner et al. (2012) and Gligor (2015) conduct factor analyses to form reflective measurement constructs that approximate challenges in the operating environment. Following this approach, we conduct a factor analysis with promax rotation for the challenges in the operating environment in our dataset: demand variability, lead time requirements, product lifecycle duration, demand volume and product variety. As indicated by Table 3.9, the analysis yields a two-factor-solution.

The first factor comprises variance of demand-related challenges in the operating environment. We thus term it “demand uncertainty” and use it in place of demand variability for the cluster analysis. The second factor only has a high loading for lead time requirements. We thus term it “time pressure” and use it in place of lead time requirements. The segmentation criteria used in this section are thus demand uncertainty, time pressure and contribution margins.

Table 3.9: Factor loadings and communalities based on a factor analysis with promax rotation.

	Demand uncertainty	Time pressure
Demand variability	0.503	
Product lifecycle duration	-0.654	-0.111
Demand volume	-0.836	
Product variety	0.833	
Customer lead time requirements		-0.995

Note: Factor loadings < .1 are suppressed

We again follow a three-step approach to determine the number of clusters and evaluate cluster solutions (Bacher et al., 2010).

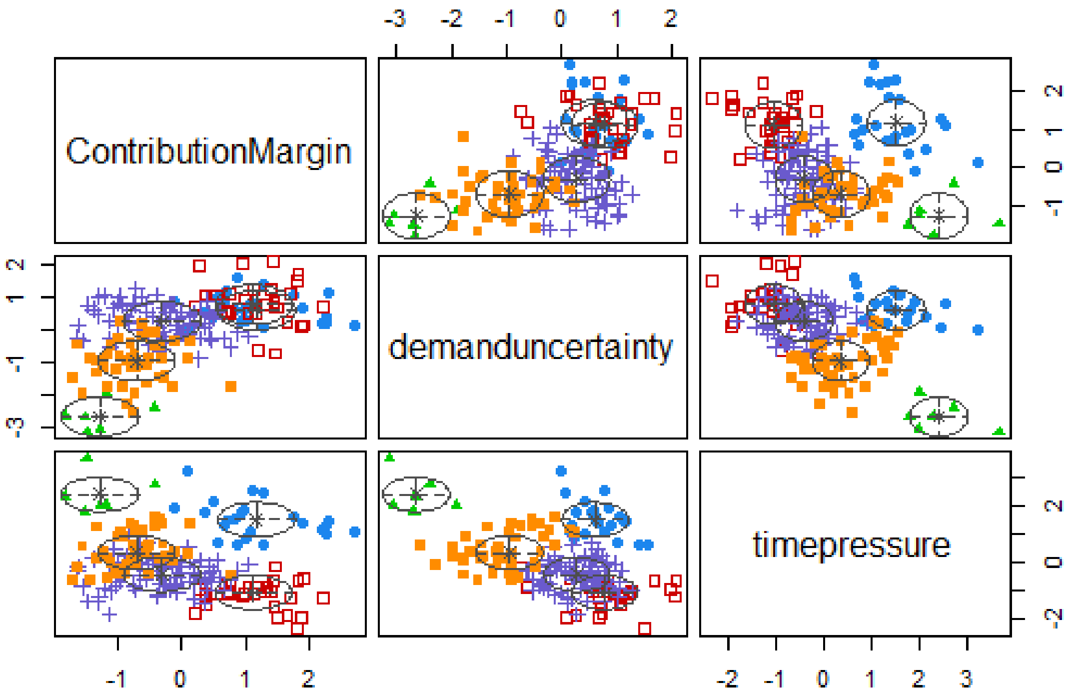
As shown in Table 3.10, the BIC proposes solutions with up to eight clusters. The Silhouette metric and the Dunn Index proposes solutions with five or seven clusters. We examine scatter plots to assess whether the solutions with five or seven clusters are actionable. Figure 3.5 indicates that the five-cluster-solution contains a large cluster that is characterized by low contribution margins, but contains some business units with high and some business units with low demand variability (pink crosses). As the five-cluster-solution therefore fails to be actionable, we focus on the seven-cluster-solution depicted in Figure 3.6.

Table 3.10: Statistical properties of the cluster solutions.

Statistical properties	Number of clusters							
	1	2	3	4	5	6	7	8
BIC	-1529.99	**-1508.55**	**-1490.49**	**-1497.08**	**-1484.25**	**-1498.90**	**-1500.82**	**-1517.32**
Silhouette		0.286	0.275	0.247	**0.317**	0.305	**0.308**	0.306
Dunn Index		0.029	0.032	0.014	**0.053**	0.027	**0.035**	0.028

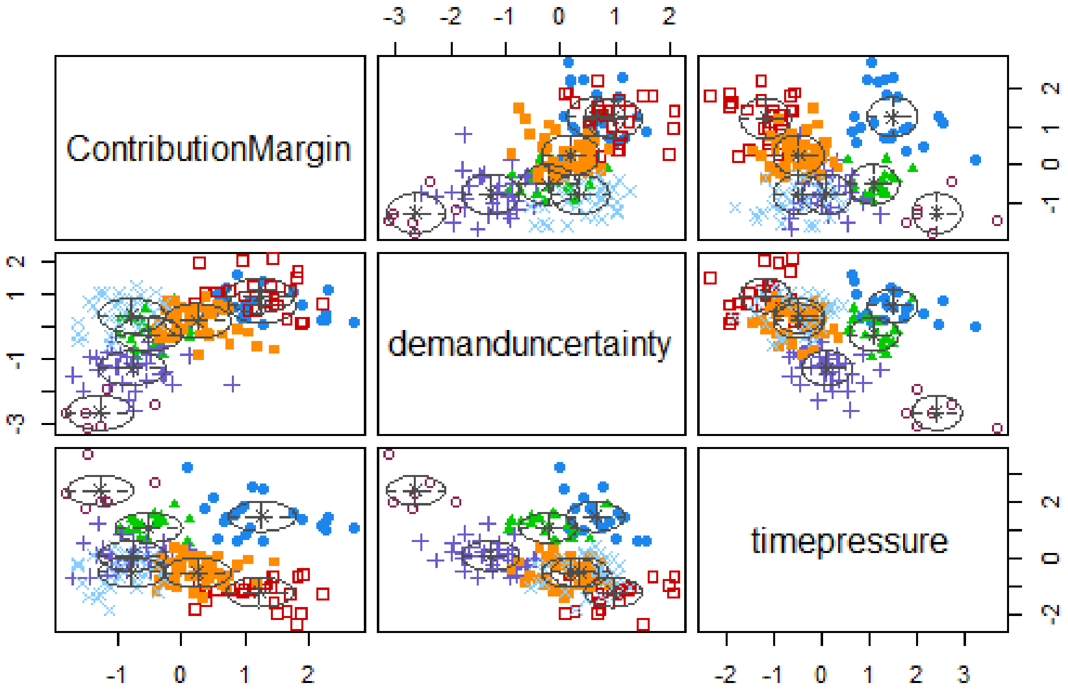
Note: Bolded values indicate preferred solutions

Figure 3.5: Scatter plots of the five-cluster-solution.



Note: The colour and shape of the objects in the scatters depict business units' cluster membership.

Figure 3.6: Scatter plots of the seven-cluster-solution.



Note: The colour and shape of the objects in the scatters depict business units' cluster membership.

Similar to the solution in Section 4, we will refer to the three clusters as "Leagile", "Agile" and "Basic Service". As indicated by Table 3.11, the Leagile cluster is characterized by high demand uncertainty, high time pressure and high contribution margins. The Agile cluster is characterized by high demand uncertainty, low time pressure and high contribution margins. The Basic Service cluster is characterized by high demand uncertainty and low contribution margins.

The remaining four clusters are all characterized by relatively low demand uncertainty when compared to the Leagile, Agile and Basic Service clusters. The need for investments in capabilities that match supply and demand is thus limited for these business units. Further, as the level of contribution margins is lower than in the Leagile and Agile clusters, the scope for such investments is thus limited as well. The remaining four clusters are thus all similar to the Lean segment in the main body of this study and will be referred to as "Lean I", "Lean II", "Lean III" and "Lean IV". The numbering of Lean clusters indicates the level of demand uncertainty and contribution margins, ranging from very low (Lean I) to moderate (Lean IV).

Table 3.11: Criteria of the seven-cluster-solution (standardized).

	Lean I	Lean II	Lean III	Lean IV	Leagile	Agile	Basic Service
Contribution margins	-1.27	-0.77	-0.51	0.26	1.26	1.23	-0.78
Demand uncertainty	-2.63	-1.30	-0.23	0.19	0.64	0.96	0.36
Time pressure	2.40	0.10	1.09	-0.50	1.49	-1.20	-0.49
Number of business units	6	32	18	46	22	25	32

The seven-cluster-solution is stable with respect to the removal of observations, the clustering method and the number of clusters. When drawing 100 random subsamples containing 80% of the observations, 4% of business units change cluster membership on average. 8% of business units change observations when forming clusters with the K-Means or the P-Median algorithm. When removing one cluster, the Lean IV and the Basic Service cluster merge; out of the business units originally assigned to one of the other clusters, 6% change cluster membership. When adding a cluster, the Lean II cluster splits up into two parts; out of the business units originally assigned to one of the other clusters, 2% change cluster membership.

As the seven-cluster-solution is therefore actionable and sufficiently stable, we can compare it to the four-cluster-solution in the main body of the study. Table 3.12 indicates that the allocation of business units to clusters is similar for the two solutions. Except for four business units, all observations assigned to the Leagile or Agile clusters in the four-cluster-solution are also assigned to the corresponding clusters in the seven-cluster-solution. There is, however, migration between the Basic Service and the Lean clusters. 13 business units originally assigned to the Basic Service cluster are assigned to the Lean clusters in the four-cluster-solution. Vice versa, 15 business units originally assigned to the Lean clusters are assigned to the Basic Service cluster in the seven-cluster solution. Nonetheless, the allocation of business units to clusters remains relatively stable overall: 81% of the observations are assigned to the same or corresponding clusters when comparing the four-cluster-solution and the seven-cluster-solution.

Further, the mismatch-performance link remains intact also for the seven-cluster solution. Table 3.13 outlines the results of the regression of mismatches on financial performance when controlling for cluster membership, self-assigned segments and business unit size. Multicollinearity is within a tolerable range (maximum variance inflation factor = 3.42) and a significant percentage of the variance is explained (Pseudo-R^2 = 0.236, and Wald χ^2 = 34.32, p

< 0.001). The link between mismatches and financial performance is significant and negative (β_1 = -0.067, p < 0.01), indicating that Hypothesis 1 also supported for the seven-cluster-solution.

In summary, the interpretation of clusters, the allocation of business unit to clusters, and the performance implications of segment-environment mismatches are similar for the four-cluster-solution in Section 4 and the seven-cluster-solution in the appendix. The solutions are therefore sufficiently stable regarding changes in the measurement of segmentation criteria.

Table 3.12: Allocation of business units to clusters for the four-cluster-solution and the seven-cluster-solution.

	Lean I	Lean II	Lean III	Lean IV	Leagile	Agile	Basic Service
Lean	5	10	42	29	0	**1**	**15**
Leagile	0	**2**	0	0	22	0	0
Agile	0	0	**2**	0	0	23	0
Basic Service	**1**	**6**	**2**	**3**	0	**1**	17

Note: Bolded values indicate changes in the allocation of business units to clusters

Table 3.13: Regression results with *p*-values and bias-corrected confidence intervals.

Independent variables	Dependent variable			
	Financial Performance	Financial Performance	Financial Performance	Financial Performance
Cluster Lean I	-0.044 [-0.104, 0.020]	-0.055 [-0.116, 0.003]	-0.067 [-0.159, 0.012]	-0.074 [-0.164, 0.004]
Cluster Lean II	-0.034 [-0.061, 0.013]	-0.041* [-0.067, -0.005]	-0.033 [-0.059, 0.010]	-0.038* [-0.064, -0.002]
Cluster Lean III	-0.031 [-0.114, 0.009]	-0.027 [-0.115, 0.016]	0.042* [-0.125, -0.002]	-0.039 [-0.124, 0.005]
Cluster Leagile	-0.016 [-0.056, 0.017]	-0.047** [-0.078, -0.016]	-0.009 [-0.046, 0.020]	-0.038* [-0.067, -0.007]
Cluster Agile	-0.011 [-0.053, 0.022]	-0.026 [-0.066, 0.005]	-0.007 [-0.051, 0.022]	-0.021 [-0.063, 0.008]
Self-assigned Leagile	0.012 [-0.022, 0.067]	0.060* [0.006, 0.113]	0.018 [-0.017, 0.067]	0.062* [0.011, 0.112]
Self-assigned Agile	-0.007 [-0.057, 0.047]	0.047* [0.006, 0.097]	-0.005 [-0.050, 0.048]	0.043* [0.001, 0.089]
Business unit size			0.026*** [0.010, 0.041]	0.023** [0.010, 0.040]
Mismatches		-0.074** [-0.118, -0.023]		-0.067** [-0.108, -0.022]
Wald χ^2	10.93	21.13**	24.17**	34.32***
ICC	0.389***	0.389***	0.389***	0.389***
Pseudo-R^2	0.058	0.113	0.183	0.236

Note: * p < 0.05, ** p < 0.01, *** p < 0.001 (two-tailed).

Chapter 4 Performance outcomes of responsiveness: When should supply chains be fast?

Co-authors:

Moritz Fleischmann

Chair of Logistics and Supply Chain Management, Business School, University of Mannheim, Germany

Christoph Bode

Endowed Chair of Procurement, Business School, University of Mannheim, Germany

Abstract

Responsiveness is considered a “basis of competition” attribute of supply chain performance (APICS, 2016). Nonetheless, there remains ambiguity under which conditions a supply chain that is fast enough to fulfil customers’ lead time requirements constitutes competitive advantage. We examine the benefits and costs associated with supply chain responsiveness using secondary data from a leading chemicals manufacturer. Our results indicate that responsiveness can improve financial performance in two distinct ways: either by matching supply and demand or by decreasing supply-chain-related costs depending on the characteristics of the products that are being sold. Based on these findings, this study aims to contribute to supply chain strategy literature by providing managers guidance on when their supply chains should be fast.

1 Introduction

The *Cambridge Dictionary* defines *responsiveness* as "how quickly and well a person or organization reacts to something" (Cambridge Dictionary, 2016). In supply chain management, responsiveness describes the ability of a supply chain to fulfil orders within a time frame that is acceptable to the customer (Chen et al., 2004; Holweg, 2005). It is considered a "basis of competition" attribute of supply chain performance that has been linked to higher revenues (APICS, 2016; Elgazzar et al., 2012). So why have empirical studies failed to find a link between shorter lead times – a popular measure of responsiveness – and financial performance (Croom et al., 2007; Droge et al., 2004)? The answer is simple: there are clear limits to time-based competition, as the value of reducing lead times to better meet customer requirements is often too low to warrant higher costs (Blackburn, 2012). Cost premiums associated with shorter lead times explain why some companies deliberately extend lead times through practices such as "slow steaming" or offshoring production (Cariou, 2011; Kinkel and Maloca, 2009). As a more responsive supply chain is thus not only a potential source of value, but may also be a source of higher costs, managers need to carefully consider both the benefits and costs of shorter lead times. Our goal is therefore to support managers confronted with lead-time-related decisions by analysing the performance outcomes of responsiveness. In doing so, we aim to answer the following research question: when should supply chains be fast?

Assessing the performance outcomes of responsiveness is challenging because of the many factors that influence the benefits and costs associated with shorter lead times. A simple yet powerful framework for assessing responsiveness has been proposed by Fisher (1997): companies selling innovative products will perform best with a responsive supply chain, whereas companies selling functional products should instead adopt a supply chain that focuses on efficiency. Fisher's framework thus suggests that companies selling innovative products should make lead time reductions a competitive priority, whereas companies selling functional products should not.

Several studies have found support for Fisher's framework regarding the benefits of shorter lead times. Based on a simulation study, Blackburn (2012) finds that the marginal value of lead time reductions is low for functional products. Using real options theory, de Treville et al. (2014a) and de Treville et al. (2014b) highlight that the marginal value of lead time reductions is much higher for innovative products with characteristics such as high demand variability, demand clustering, tender loss risk or low salvage values. However, while these studies provide valuable insights by highlighting the context-dependency of the benefits of shorter lead times, they rely on overly simplistic assumptions regarding the costs that lead time reductions entail.

Existing models analysing the benefits of shorter lead times assume that lead time compression entails a cost premium (Blackburn, 2012; de Treville et al., 2014a; de Treville et al., 2014b). Jian et al. (2015) model the benefits and costs of shorter lead times, assuming that costs related to lead time compression are a linear function of lead times.[6] Many levers for reducing lead times like airfreight or shipping less-than-full truckloads are indeed costly. However, there are also levers that reduce supply-chain-related costs by cutting lead times. Lean practice bundles, for instance, are associated with *both lead time and cost reductions* (Mackelprang and Nair, 2010; Narasimhan et al., 2006; Shah and Ward, 2003). The classic assumption that responsiveness entails a cost premium is thus overly simplistic and needs to be challenged. Apart from examining the context-dependency of the benefits of responsiveness, we therefore also analyse the conditions under which shorter lead times are associated with higher or lower costs. Based on the findings of our empirical analysis, this article contributes to the supply chain strategy literature by offering managers guidance as to when they should make responsiveness a competitive priority.

The remainder of the paper is organized as follows. Section 2 provides the theoretical background for deriving hypotheses. Section 3 describes the dataset and specifies the measures used in this study. Section 4 introduces the methodology. In Section 5 the results of the analysis are outlined; the implications for managers and researchers are presented in Section 6. Finally, Section 7 concludes with the limitations of our work and suggestions for future research.

2 Conceptual model

2.1 The responsiveness-performance link

Several empirical studies have analysed the link between responsiveness and financial performance, but they found no empirical support for a strong, direct relationship (Croom et al., 2007; Droge et al., 2004). Two reasons are likely: (1) measuring responsiveness purely based on the length of lead times may not be appropriate and (2) there are opposing intermediate performance outcomes (mediation) that need to be accounted for.

---

[6] According to Jian et al. (2015), lead time compression incurs crashing costs which comprise of expenditures on equipment improvement, information technology, order expedite, special shipping and handling.

2.1.1 Measuring responsiveness

Shorter lead times are assumed to positively affect companies' top-line performance (Elgazzar et al., 2012). The underlying reasoning is that if a company's lead times exceed its customers' willingness to wait for a product, customers will buy elsewhere and the company will in turn loose sales. Both theoretical and empirical models have thus used different measures of lead times to assess the value of responsiveness (Blackburn, 2012; de Treville et al., 2014a; Droge et al., 2004). The SCOR framework – a "standard" performance management model for operational performance (de Leeuw and van den Berg, 2011) – also uses end-to-end cycle times to measure supply chain responsiveness. Order fulfilment lead times (i.e., the time between order placement and the *actual* delivery date) indeed measure how long the customer needs to wait for the order to arrive. However, whether a supply chain is perceived as "fast" or "slow" also depends on the lead time requirement of the customer.

To illustrate this point, consider two examples. First, let us assume the case of a custom-made product. Customers grant 30 days until delivery, as this product cannot easily be obtained from a different supplier. In this example, a delivery after 29 days would be perceived as fast enough and delivery after 33 days would be perceived as too slow. Second, consider an off-the-shelf product that the customer expects to receive within 5 days, as it can be sourced from different suppliers. In this second example, a delivery after 4 days would be perceived as fast enough and delivery after 7 days would be perceived as too slow. The ability of shorter lead times to improve financial performance by avoiding lost sales thus depends on the lead time requirement of customers (i.e., the time between order placement and *requested* delivery date).

When examining the ability of shorter lead times to improve financial performance by avoiding lost sales, we thus need to assess order fulfilment lead times relative to the lead time requirements of customers. Accordingly, we measure supply chain responsiveness as the difference between the customer lead time requirement and the order fulfilment lead time. In the first example above, the supply chain that is perceived as fast enough would have a responsiveness of 1, whereas the too slow supply chain would have a responsiveness of -3 (in the second example, the respective values are 1 and -2). By incorporating both customer lead time requirements and order fulfilment lead times in our measure of responsiveness, we aim to generate more accurate insights on the performance outcomes of shorter lead times and time-based competition.

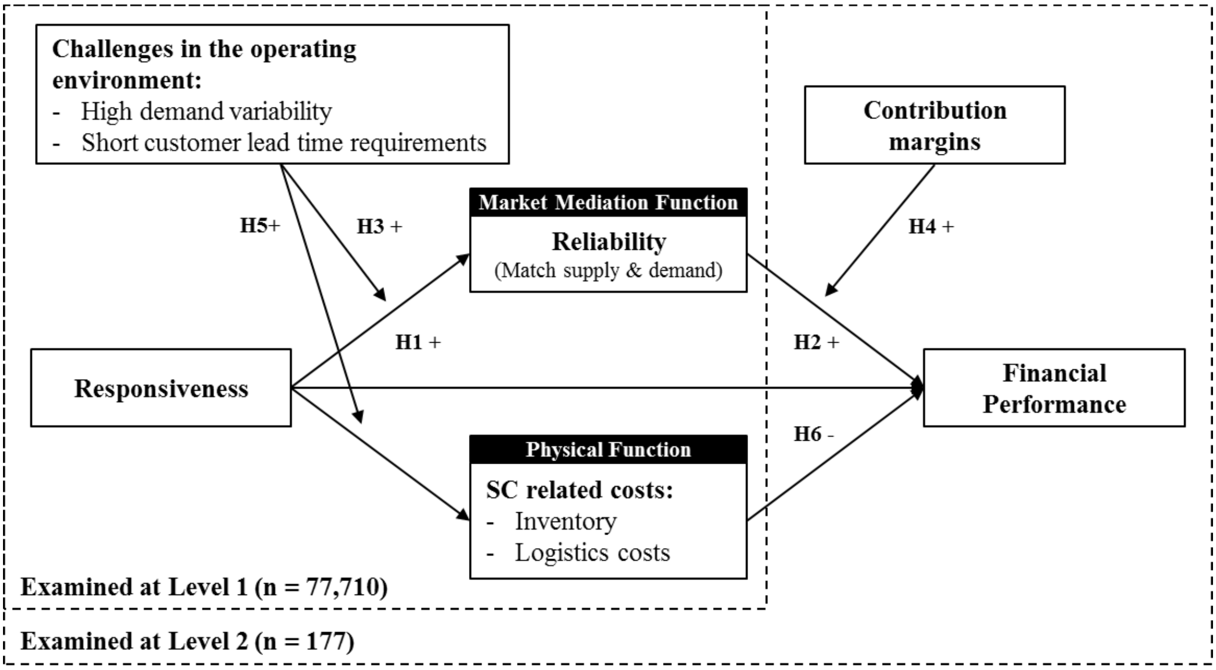
2.1.2 Intermediate performance outcomes of responsiveness

There are two points of view on the performance outcomes of responsiveness in the literature. According to the first, responsiveness has a direct and positive effect on financial performance. This view is reflected by the SCOR model which classifies responsiveness as one of the key performance attributes for "measur[ing] how successful [a supply chain] is in achieving its desired positioning within the competitive market space" (APICS, 2016). Responsiveness has also been linked to higher revenues in the conceptual literature (Elgazzar et al., 2012). However, empirical studies examining the direct link between shorter lead times and financial performance failed to find a significant relationship (Croom et al., 2007; Droge et al., 2004).

According to the second, a set of intermediate performance outcomes mediates the effect of responsiveness on financial performance. On the one hand, responsiveness helps to match supply and demand and thereby prevents lost sales. On the other hand, responsiveness is often associated with higher supply-chain-related costs. The notion of opposing intermediate performance outcomes may explain why previous studies failed to establish a direct link between responsiveness and financial performance: in many cases the benefits of better meeting customers' lead time requirements do not outweigh the associated costs.

Proponents of the latter perspective include Fisher (1997), who recognizes that supply chains have two functions: (1) to match supply and demand ("market mediation function") and (2) to efficiently provide products to customers ("physical function"). According to Fisher, responsiveness is a lever for improving the market mediation function, although this often comes at the expense of lower physical efficiency. Similarly, theoretical models on the value of shorter lead times measure the benefits of a faster supply chain based on avoided demand and supply mismatches (Blackburn, 2012; de Treville et al., 2014a; de Treville et al., 2014b). Following this line of thought, this study asks how responsiveness is linked to financial performance via the match between supply and demand (market mediation function), as well as supply-chain-related costs (physical function). The examined relationships are illustrated in Figure 4.1.

Figure 4.1: Conceptual framework (Level 1 and Level 2 are explained in Section 3).



2.2 Responsiveness and the market mediation function

2.2.1 Direct effects

Responsiveness helps to avoid lost sales by matching supply and demand. An indicator of the match between supply and demand is *reliability* which reflects the proportion of orders where customer expectations have been met with respect to time (on time), quantity (in full) and condition (in quality) (APICS, 2016; Shepherd and Günter, 2006). An order is considered on time, if it arrives within the delivery window specified by the customer. As responsiveness is thus a key determinant of the on time performance, we hypothesize a positive relationship between responsiveness and reliability:

Hypothesis 1: *There is a positive relationship between responsiveness and reliability.*

Supply chain reliability has major implications for the financial performance of a company. A failure to deliver as promised may at best result in a negative customer experience with no adverse financial effects. It is more likely, however, that a failure to deliver as promised will result in penalty payments, lost sales, and foregone contribution margins (Langenberg et al., 2012). A large scale supply chain disruption or recurring unreliability will damage customer relationships and eventually result in disappointed customers leaving for good (Craighead et al., 2007; Habermann et al., 2015; Hendricks and Singhal, 2005). Hence, we posit:

Hypothesis 2: *There is a positive relationship between reliability and financial performance.*

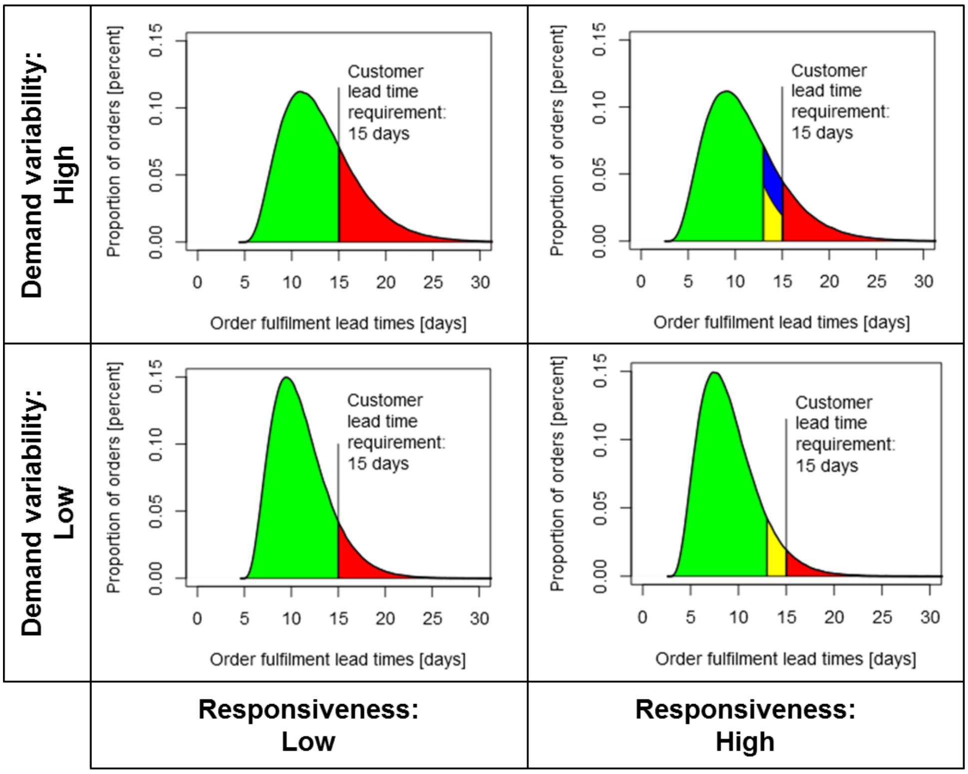
2.2.2 *Moderating effects*

According to Fisher (1997), being responsive is more important for "innovative" products than for "functional" products. With respect to their influence on the importance of responsiveness, characteristics of innovative products can be grouped into two categories: *challenges in the operating environment* and factors influencing the *value of matching supply and demand*. The former make it more difficult to match supply and demand and thereby increase the need for responsiveness. The latter affect the cost of overage and underage and therefore the value of matching supply and demand.

Challenges in the operating environment inhibit the ability to match supply and demand, *ceteris paribus*. Frameworks for supply chain or manufacturing strategies typically comprise demand-related and time-related challenges. According to Fisher (1997), challenges in the operating environment comprise different causes of demand uncertainty (short lifecycles, forecast error and high product variety) as well as the time granted by customers to fulfil orders. The same is true for the DWV3 framework by Christopher et al. (2009) which also considers different sources of demand uncertainty (demand variability and volume, product variety and the product lifecycle) as well as the customer lead time requirement. Olhager (2003) explicitly maps challenges of the operating environment along a time-related and a demand-related dimension. Following these frameworks, our study evaluates how demand variability – which we use as a proxy for demand-related challenges – and customer lead time requirements moderate the relationship between responsiveness and reliability.

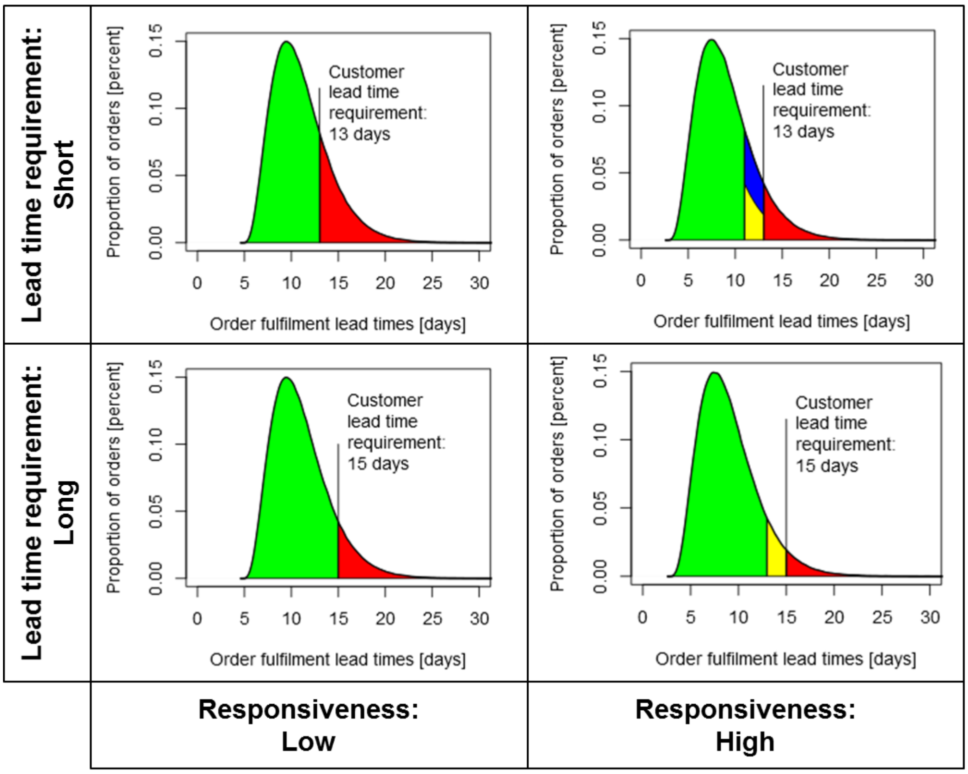
In environments characterized by recurring demand peaks, the ability to react to customer needs in a timely manner can be a valuable buffer that allows on time delivery nonetheless. When demand is stable, this buffer will not be used and thus does not contribute to reliability. Similarly, if customers demand short lead times, there is less time to react to unexpected changes in demand. Consequently, capabilities that allow supply chains to react quickly will have a larger effect than in an environment where most orders are delivered on time anyways. We thus expect the need for responsiveness to be higher in operating environments characterized by high demand variability and short customer lead time requirements.

Figure 4.2: Moderating effect of demand variability on the relationship between responsiveness and reliability.



Note: For the purpose of illustration, we assume gamma-distributed order fulfilment lead times with shape and scale parameters (4, 1.5) in the low-variability scenario. In the high-variability scenario, a larger scale parameter (4, 2) indicates that a higher proportion of orders arrives late (larger red areas under the curves). When increasing responsiveness, the curves shift left causing a higher proportion of orders to arrive on time. In the low-variability scenario, orders arriving on time due to higher responsiveness are highlighted in yellow. In the high-variability scenario, also the orders highlighted in blue arrive on time due to the higher responsiveness.

Figure 4.3: Moderating effect of customer lead time requirements on the relationship between responsiveness and reliability.



Note: For the purpose of illustration, we assume gamma-distributed order fulfilment lead times with shape and scale parameters (4, 1.5). In the scenario with short lead time requirements, a higher proportion of orders arrives late (larger red areas under the curves). When increasing responsiveness, the curves shift left causing a higher proportion of orders to arrive on time. In the low-variability scenario, orders arriving on time due to higher responsiveness are highlighted in yellow. In the high-variability scenario, also the orders highlighted in blue arrive on time due to the higher responsiveness.

To illustrate these arguments, Figure 4.2 and Figure 4.3 show – as hypothetical examples – the gamma distributed fulfilment lead times of the orders for a fictitious product given different levels of responsiveness, demand variability and customer lead time requirements. The left-hand side of Figure 4.2 comprises two scenarios: in the lower graph, demand is stable and hence most orders arrive on time (green area under the curve). In the upper graph, demand variability is high causing the right tail of the graph to be heavier and a higher proportion of orders to arrive later than requested by the customer (red area under the curve). The right-hand side of Figure 4.2 indicates the effect of a two-day increase in responsiveness (i.e., two-day decrease in order fulfilment lead times) on reliability for both scenarios. In the low-variability-scenario, shorter lead times have a relatively low effect on reliability, as most orders were already arriving on time before the increase in responsiveness (yellow area under the curve). However, in the high-variability-scenario, shorter lead times have a higher effect on reliability, as a higher share of orders arrives on time because of the increase in responsiveness: in addition to the orders highlighted in yellow, also the orders highlighted in blue are now classified as on time instead of delayed. Figure 4.2 therefore provides further support for our assumption that the effect of responsiveness on reliability increases with demand variability. Figure 4.3 indicates that short customer lead times requirements have a similar moderating effect. A comparison of the graphs on the right-hand side reveals that responsiveness has a stronger effect on reliability if lead time requirements are short; the increase of the effect is again marked in blue.

In summary, we expect high demand variability and short customer lead time requirements to positively moderate the relationship between responsiveness and reliability:

Hypothesis 3: *The positive relationship between responsiveness and reliability is stronger when the level of challenges in the operating environment is high (high demand variability and short customer lead time requirements) than when it is low (low demand variability and long customer lead time requirements).*

Challenges in the operating environment make it harder to match supply and demand, ceteris paribus. In environments characterized by uncertainty and time pressure, supply chain responsiveness is particularly important for preventing supply-and-demand mismatches. Yet, before investing in responsiveness to cope with a challenging operating environment, managers need to ensure that the benefits of responsiveness clearly outweigh the associated costs. For this purpose, contribution margins have to be considered, because they influence the effect of lost sales on the bottom line (Randall et al., 2003). If contribution margins are high, managers should be willing to incur higher market mediation costs, since the cost of lost sales is also higher (Hendricks and Singhal, 2003). In contrast, if contributions margins are low, the incentive to match supply and demand will also be lower. Hence, contribution margins are decisive for the willingness to invest in capabilities that help to match supply and demand such as responsiveness:

Hypothesis 4: *The positive relationship between reliability and financial performance is stronger when contribution margins are high than when they are low.*

2.3 Responsiveness and the physical function

The relationship between responsiveness and supply-chain-related costs is also subject to moderating factors. Challenges in the operating environment are critical for determining whether responsiveness leads to higher or lower supply-chain-related costs.

Several studies have linked process improvements and waste reduction (lean) initiatives to both shorter lead times and lower supply-chain-related costs (Mackelprang and Nair, 2010; Narasimhan et al., 2006; Shah and Ward, 2003). The concept of just-in-time production, for instance, includes practices such as the elimination of bottlenecks and the reduction of batch sizes which aim to minimize work-in-progress inventory by reducing throughput times (Sugimori et al., 1977). Yet a prerequisite for just-in-time production is a level production schedule which is hard to achieve when demand is variable. Practices that cut lead times in order to achieve a higher cost efficiency therefore fail to reap the expected benefits in environments characterized by dynamism or technological turbulence (Azadegan et al., 2013; Chavez et al., 2015). It is also more challenging to improve the efficiency and responsiveness of processes in environments characterized by instability and uncertainty, as such environments inhibit learning (Browning and Heath, 2009). Consequently, we only expect responsiveness to be associated with *lower supply-chain-related costs* in an operating environment characterized by stable demand and customers granting sufficient time to react to uncertainties.

In an environment characterized by volatile demand or time pressure, we expect responsiveness to be associated with *higher supply-chain-related costs*. Companies may build inventory buffers to remain responsive to customer orders even when demand is volatile. They may also resort to costly options for decreasing delivery lead times such as less-than-full truckload shipments or airfreight when under time pressure. Responsiveness therefore entails a cost premium if it is used as a market mediation capability that mitigates the adverse effects of challenges in the operating environment on reliability.

This study focusses on two types of supply-chain-related costs: inventory and logistics costs.[7] These cost types are not only assumed to be affected by process improvements and waste reduction initiatives (Goldsby and Martichenko, 2005; Mackelprang and Nair, 2010), but also by costly enablers of responsiveness such as inventory buffers and airfreight. Accordingly, we posit:

Hypothesis 5: *The relationship between responsiveness and supply-chain-related costs (inventory and logistics costs) is*

(a) positive when the level of challenges in the operating environment is high (high demand variability and short customer lead time requirements).

[7] Inventory is measured by days in inventory. Logistics costs comprise of all costs related to freight, distribution, warehousing order management and materials management as a percentage of sales.

(b) *negative when the level of challenges in the operating environment is low (low demand variability and long customer lead time requirements).*

Hypothesis 6: *There is a negative relationship between supply-chain-related costs (inventory levels and logistics costs) and financial performance.*

3 Dataset

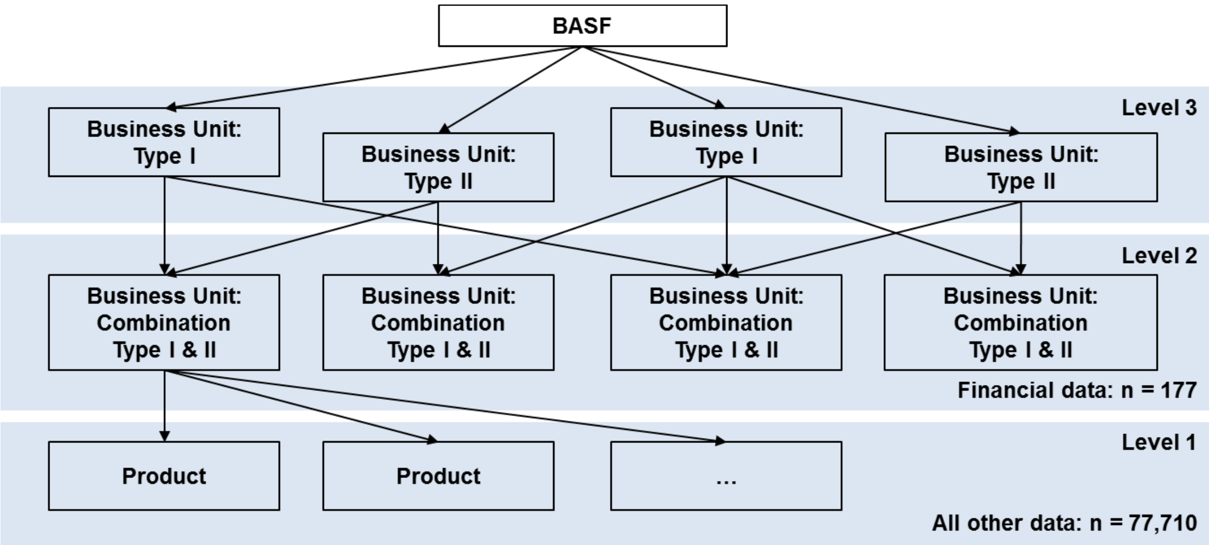
3.1 Data collection and sampling

This study is conducted in cooperation with BASF, one of the world's largest chemicals manufacturers. The company is a well-suited subject for our investigation because it embraces the "Verbund"-concept: BASF controls multiple value streams that span from basic chemicals to high-value added products such as coating and crop protection agents (BASF SE, 2016b). As a result, it not only offers a large sample of business units and products, but also considerable diversity in terms operating environments, margins and supply chain structures.

As BASF operates with a standardized reporting structure, we were able to gather data from supply chain and financial databases for the years 2013 and 2014 covering the whole company except for the oil and gas business and thus approximately 80% of the company's revenues (BASF SE, 2015). We focus our analysis on this timeframe, since the study was conducted as part of a company-wide initiative for differentiating supply chain strategies that commenced in 2013 and 2014 (Cecere, 2017).

The data has a multilevel structure due to the hierarchical organization of the company. As indicated in Figure 4.4, there are two types of upper-level (Level 3) business units. While the first type of Level 3 business unit indicates the region of a business, the second type of Level 3 business unit indicates the market that is being served. Level 2 business units are combinations of Level 3 business units (region and market); a hypothetical example of a Level 2 business unit is "Specialty Petrochemicals Europe" which is a combination of the Level 3 business units "Petrochemicals Europe" (Type I) and "Specialty Petrochemicals" (Type II). Finally, products (Level 1) are nested within Level 2 business units. While financial data is available at Level 2, all supply-chain-related and demand-related data is available at both Level 1 and Level 2. The units of analysis of this study are Level 1 and Level 2.

Figure 4.4: Multilevel data structure.



At Level 2, our sample comprises 228 observations. An examination of the dataset revealed some small business units that have few supply chain activities (e.g., research and design business units). These business units exhibit extreme values for financial performance (due to low sales) or supply chain variables (due to few orders). Consequently, we exclude business units with annual sales below 1 million € or fewer than 1,000 orders annually. In addition, we exclude one business unit that is not reliably integrated into BASF databases and two observations with missing data. The remaining 180 observations were examined for outliers using Cook's distance and Mahalanobis distance plots. Three observations with extreme values for financial performance are excluded. The final sample for this study therefore consists of 177 observations at Level 2.

At Level 1, 132,476 products could be uniquely assigned to the remaining 177 Level 2 business units. We exclude products with missing data (45,935) or negative values for inventory levels, logistics costs, customer lead time requirements or order fulfilment lead times (8,831). The final sample used for this study therefore consists of 77,710 observations at Level 1.

Table 4.1: Pearson correlation coefficients at Level 1.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
(8) Responsiveness	1.00***					
(9) Reliability	0.26***	1.00***				
(10) Logistics costs	0.08***	0.00	1.00***			
(11) Inventory	0.06***	-0.03***	0.15***	1.00***		
(12) Demand variability	0.03***	-0.20***	0.09***	0.26***	1.00***	
(13) Lead time requirement	-0.13***	-0.17***	-0.02***	-0.11***	0.06***	1.00***

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed).

Table 4.2: Pearson correlation coefficients at Level 2.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Financial performance	1.00***							
(2) Contribution margin	0.41***	1.00***						
(3) Responsiveness	0.05	0.03	1.00***					
(4) Reliability	0.14	-0.10	0.23***	1.00***				
(5) Logistics costs	-0.04	0.31***	0.11	0.00	1.00***			
(6) Inventory	-0.14	0.26***	-0.17**	-0.20***	0.08	1.00***		
(7) Demand variability	-0.13	0.10	-0.23**	-0.18**	-0.16*	0.14*	1.00***	
(8) Lead time requirement	0.09	-0.10	-0.34***	-0.04	-0.09	-0.02	-0.12	1.00***

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed).

The correlation matrixes in Table 4.1 and Table 4.2 provide information on the relationships between the examined variables at both levels. Means and standard deviations are not provided because of the confidential nature of the data. The tables indicate that the zero-order correlations are within tolerable ranges (maximum: 0.41).

3.2 Dependent and independent variables

Financial performance is measured by the return on sales (ROS) of a business unit. The ROS measures the ratio of the net income before interest and tax to the revenues of a business unit. It is also commonly referred to as the EBIT-Margin and has already been used in a previous study to assess the effect of supply and demand mismatches on financial performance (Hendricks and Singhal, 2005).

Contribution margins indicate the average selling price minus the average variable cost per unit sold for a business unit. Variable cost includes cost types such as raw material cost and variable production cost. It thus reflects the percentage of sales a business unit has at its disposal to recover its fixed costs.

As proposed by the SCOR model, *reliability* is measured as the percentage of orders that arrive on time, in full and in quality (APICS 2016). An order is classified as on time and in full, if the order arrives within the time window set by the customer and in the requested quantity. It is recorded as in quality if the customer voices no complaints regarding aspects such as product quality, documentation or packaging.

Responsiveness describes the ability of a supply chain to respond to customer orders in a timely manner. We thus measure responsiveness as the difference between the customer lead time requirement and the order fulfilment lead time in days.

As demand uncertainty is hard to measure with archival data, we use *demand variability* as a proxy. Demand variability has been suggested as an appropriate measure of demand-related challenges in the operating environment, since it captures both expected and unexpected changes in demand (Aitken et al., 2005). We measure it as the coefficient of variation of weekly sales (Christopher et al. 2009).

The *customer lead time requirement* is measured by the average number of days customers grant between the initial order entry and the requested delivery date.

Inventory levels are measured by days in inventory (DIV) which indicates how long it takes the business unit to turn its inventory into sales. *Logistics costs* capture all costs related to freight, distribution, warehousing, order management and materials management as a percentage of sales.

The variables for responsiveness, demand variability, customer lead time requirements, inventory levels, and logistics costs are highly skewed. To reduce the influence of extreme values on parameter estimates, we have transformed these variables. For responsiveness, we employ the inverse hyperbolic sine transformation for responsiveness because it reduces the skewness of variables that comprise both positive and non-positive values (Burbidge et al., 1988). For demand variability, customer lead time requirements, inventory levels and logistics costs, we use the natural logarithm, because these variables are strictly positive. To render the scales of the transformed variables more comparable, they are also standardized. All other variables (financial performance, contribution margins and reliability) are centered at the grand mean to ease the interpretation of interaction effects.

3.3 Control variables

The *customer lead time requirement* is included as a control variable when assessing the relationship between responsiveness and financial performance. On the one hand, long customer lead time requirements indicate that products are more difficult to deliver or produce. On the other hand, long customer lead time requirements also indicate that the business unit has a unique selling proposition which increases customers' willing to wait. As a consequence, Table 4.2 shows that the length of customer lead time requirements is negatively correlated with responsiveness and positively correlated with financial performance.

Finally, it is likely that industry-specific effects have an impact on the examined performance attributes (Bozarth et al., 2009). Level 2 business units nested within a Level 3 business unit are likely to be similar in ways that are otherwise not explicitly accounted for by our models. As demonstrated in Section 3.1, the Level 3 business unit "Petrochemicals Europe" for instance contains two Level 2 business units that produce different types of petrochemicals (standard and specialty petrochemicals). These two business units that operate in the same industry are likely to have similar competitive and operating environments. The multilevel models we use for our analysis contain *random intercepts* to account for similarities of Level 2 business units nested within a Level 3 business unit regarding the examined performance attributes. They thus implicitly control for industry-specific effects. As will be demonstrated in the next section, random intercepts explain between 16.6% and 59.8% of the variance in our models.

4 Methodology

As indicated by Figure 4.1, we test the hypothesized relationships at two levels. First, we examine all hypothesized relationships at Level 2. Since financial data is available at that level, we estimate the direct, indirect and total effects of responsiveness on financial performance. Second, we analyse the relationships that do not require financial data at Level 1. The goal is to generate additional insights, as the sample size at Level 1 (n = 77,710) is much higher than at Level 2 (n = 177).

4.1 Analysis at Level 2

4.1.1 Model description

Due to the multilevel structure of our data, we cannot make inferences from an ordinary structural equation model, as this would violate the assumption of independent observations (Hofmann, 1997). In order to analyse the effects of predictors at Level 2, we need to account for the fact that observations at this level are nested within Level 3 business units. We thus assess the relationships at Level 2 using a multilevel structural equation model (*gsem* command in Stata 14).

The model allows the intercept to vary according to Level 3 business units (Steele and Goldstein, 2006). Level 2 observations can be attributed to two types of Level 3 observations (Type I or Type II). Ideally, we would estimate a crossed model that controls for both types of Level 3 observations (Snijders, 2011). However, there is only one Level 2 observation per combination of Level 3 observations (e.g., for "Petrochemicals Europe" and "Specialty Petrochemicals" there is only one Level 2 observation "Specialty Petrochemicals Europe"). As a consequence, a crossed model would be underidentified. We thus estimated the model twice, once with random intercepts for Level 3 observations of Type I (regions such as “Petrochemicals Europe”) and once with random intercepts for Level 3 observations of Type II (markets such as “Specialty Petrochemicals”). The parameter estimates are similar, but a higher percentage of the variance was explained by the random intercepts in the former model.[8] We thus report the results of the model with random intercepts for Level 3 observations of Type I in Table 4.3 and Table 4.4.

[8] The percentage of variance explained by random intercepts is measured by the intraclass correlation coefficient (Firebaugh, 1978).

Table 4.3: Results at Level 2 for financial performance.

Independent variables	Dependent variable
	Financial performance
Reliability	0.093** [0.040, 0.145]
Responsiveness	0.003 [-0.008, 0.011]
Inventory	-0.020** [-0.033, -0.011]
Logistics Costs	-0.016*** [-0.024, -0.006]
Customer lead time requirement	0.019*** [0.010, 0.029]
Contribution margins	0.374*** [0.280, 0.444]
Contribution margins × Reliability	0.618*** [0.264, 0.910]
Wald χ^2	87.01***
ICC	0.326***
Pseudo-R^2	0.315
Type of analysis	Structural equation model

Table 4.4: Results at Level 2 for intermediate performance outcomes.

Independent variables	Dependent variables		
	Reliability	**Inventory**	**Logistics costs**
Customer lead time requirement	0.015 [-0.027, 0.039]	-0.064 [-0.195, 0.039]	-0.057 [-0.210, 0.101]
Demand variability	-0.026** [-0.045, -0.010]	0.072 [-0.075, 0.228]	-0.057 [-0.183, 0.050]
Responsiveness	0.048*** [0.029, 0.077]	-0.218*** [-0.342, -0.094]	0.107 [-0.028, 0.243]
Cust. lead time requirement × Responsiveness	-0.016* [-0.035, -0.002]	-0.139** [-0.235, -0.050]	-0.061 [-0.154, 0.039]
Demand variability × Responsiveness	0.012 [-0.007, 0.033]	-0.020 [-0.140, 0.088]	-0.105 [-0.221, 0.017]
Wald χ^2	34.53***	16.46**	10.38
ICC	0.458***	0.200***	0.598***
Pseudo-R^2	0.178	0.077	0.075
Type of analysis	Structural equation model	Structural equation model	Structural equation model

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed). Bias-corrected confidence intervals are shown.

Table 4.5: Indirect and total effects.

Challenges in the operating environment	Contribution margins		
	M –1 *SD*	*M*	*M* + 1*SD*
Demand variability: *M* +1*SD* Lead time requirement: *M* –1*SD*	Indirect eff. reliability: 0.000 [-0.005, 0.004] Indirect eff. cost: -0.002 [-0.006, 0.004] Total effect: 0.001 [-0.007, 0.011]	Indirect eff. reliability: **0.007 [0.003, 0.014]** Indirect eff. cost: -0.002 [-0.006, 0.004] Total effect: 0.009 [-0.001, 0.017]	Indirect eff. reliability: **0.014 [0.006, 0.025]** Indirect eff. cost: -0.002 [-0.006, 0.004] Total effect: **0.016 [0.005, 0.028]**
Demand variability: *M* Lead time requirement: *M*	Indirect eff. reliability: 0.000 [-0.003, 0.003] Indirect eff. cost: 0.003 [-0.002, 0.007] Total effect: 0.006 [-0.004, 0.013]	Indirect eff. reliability: **0.004 [0.002, 0.010]** Indirect eff. cost: 0.003 [-0.002, 0.007] Total effect: **0.010 [0.001, 0.017]**	Indirect eff. reliability: **0.009 [0.004, 0.017]** Indirect eff. cost: 0.003 [-0.002, 0.007] Total effect: **0.015 [0.005, 0.022]**
Demand variability: *M* –1*SD* Lead time requirement: *M* +1*SD*	Indirect eff. reliability: 0.000 [-0.002, 0.003] Indirect eff. cost: **0.006 [0.001, 0.013]** Total effect: 0.010 [-0.001, 0.018]	Indirect eff. reliability: 0.002 [-0.001, 0.009] Indirect eff. cost: **0.006 [0.001, 0.013]** Total effect: **0.012 [0.002, 0.019]**	Indirect eff. reliability: 0.004 [-0.004, 0.016] Indirect eff. cost: **0.006 [0.001, 0.013]** Total effect: **0.014 [0.001, 0.021]**

Note: Bolded rows indicate statistical significance at the 95% level. Bias-corrected confidence intervals are shown.

4.1.2 Non-parametric bootstrap

We conduct a non-parametric (cases) bootstrap with 1,000 resamples to check the robustness of our results and to assess indirect effects. Bootstrapped standard errors are consistent under heteroscedasticity; in addition, the bias-corrected confidence intervals obtained from the bootstrap do not require an asymptotic normal distribution of estimators (Godfrey, 2009; van der Leeden et al., 2008). Because of these characteristics, non-parametric bootstrapping has been recommended for assessing indirect effects in multilevel structural equation models (Preacher et al., 2010).

When bootstrapping multilevel models, one has to decide at which level the data should be resampled. In our case, the intraclass correlation coefficient (ICC) – a measure of the percentage of total variance explained by the random intercepts (Firebaugh, 1978) – indicates that the majority of variance is located at Level 2 (ICC < 50% for inventory, reliability and financial performance). As a consequence, we resample Level 2 observations (van der Leeden et al., 2008). More specifically, for each Level 3 observation a random sample of the Level 2 observations belonging to that Level 3 observation is drawn. Once a random sample of Level 2 observations has been drawn for each Level 3 observation, the parameters are estimated and the procedure is repeated. The parameter estimates obtained from this procedure are presented in

Table 4.3, Table 4.4 and Table 4.5, along with *p*-values and 95% bias-corrected confidence intervals.

4.2 Analysis at Level 1

We examine the relationships at Level 1 via a set of multilevel regressions with maximum likelihood estimators (*mixed* command in Stata 14). The predictors are located at Level 1 and the random intercepts at Level 2 and Level 3 (Type I). Since reliability is measured as a fraction (bounded between 0 and 1), the regression results are heteroskedastic (Ferrari and Cribari-Neto, 2004). A frequently proposed remedy is to employ generalized multilevel linear models with a logit link function and the binomial distribution (Baum, 2008; Papke and Woolridge, 1996). However, this did not resolve the problem in our case, as a high proportion of products has a reliability of 0% or 100%; most of these are products which were only ordered only a few times during the time period under consideration. Since they are more likely to exhibit extreme values for reliability (a product that was only sold once by default has a value for reliability of either 0% or 100%), their values for reliability are distributed differently from those of the rest of the sample (Cook et al., 2008). For this reason, the zero-or-one inflated beta regression has been introduced (Ospina and Ferrari, 2012). However, beta regressions are not yet available for multilevel models. To be able to draw inferences nonetheless, we use non-parametric bootstrapping with 1,000 resamples for each regression, because bootstrapped standard errors are still consistent under heteroscedasticity, as highlighted above. Observations are resampled at Level 1, as the majority of variance is located at that level for all regressions. The results are presented in Table 4.6.

Table 4.6: Results at Level 1 for intermediate performance outcomes.

Independent variables	Dependent variables		
	Reliability	Inventory	Logistics costs
Customer lead time requirement	-0.041^{***} [-0.042, -0.038]	-0.300^{***} [-0.315, -0.285]	-0.061^{***} [-0.072, -0.050]
Demand variability	-0.059^{***} [-0.061, -0.057]	0.537^{***} [0.522, 0.551]	0.131^{***} [0.121, 0.141]
Responsiveness	0.074^{***} [0.072, 0.077]	0.093^{***} [0.077, 0.108]	0.028^{***} [0.018, 0.038]
Customer lead time requirement × Responsiveness	-0.044^{***} [-0.046, -0.041]	-0.077^{***} [-0.091, -0.063]	-0.025^{***} [-0.035, -0.016]
Demand variability × Responsiveness	0.017^{***} [0.014, 0.019]	0.140^{***} [0.124, 0.156]	0.039^{***} [0.029, 0.050]
Wald χ^2	13010.60^{***}	9221.61^{***}	1267.57^{***}
ICC	0.166^{***}	0.246^{***}	0.281^{***}
Pseudo-R^2	0.136	0.129	0.018
Type of analysis	Regression	Regression	Regression

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed). Bias-corrected confidence intervals are shown.

5 Results

Multicollinearity is unlikely to be an issue, as the maximum variance inflation factor (VIF) is 1.30. The residuals in the model at Level 2 are homoscedastic and approximately normally distributed. At Level 1, the errors of the regression on reliability are, as expected, heteroskedastic. Further, the distribution of the residuals of the regressions on inventory and logistics costs exhibit heavy tails. To resolve these issues, Table 4.6 displays confidence intervals and *p*-values obtained from non-parametric bootstrapping.

Evaluating the goodness-of-fit for multilevel models can be problematic, since the variance is distributed across multiple levels. We employ two measures for this purpose. The ICC indicates the need for a multilevel model by measuring the percentage of total variance explained by the random intercepts in the model (Firebaugh, 1978). To assess the level of variance explained by the predictors, we compute a Pseudo-R^2 measure for the change in the total variance explained at all levels with and without the predictors (LaHuis et al., 2014).

Table 4.3 and Table 4.4 indicate the ICC or Pseudo-R^2 measures for the structural equation model.[9] A significant proportion of the variance is explained by the random intercepts

[9] The *gsem* command in Stata does not yet provide ICC or Pseudo-R^2 measures. To obtain these measures for the structural equation model at Level 2 nonetheless, we computed ICC and Pseudo-R^2 measures at Level 2 by running regressions with the *mixed* command. As the parameter estimates from the regressions are very similar to those of the structural equation model, we are confident that the computed measures provide an appropriate approximation for the goodness of fit in the structural equation model.

at Level 3 with an ICC of 0.337 for financial performance, 0.458 for reliability, 0.200 for inventory and 0.598 for logistics costs. A statistically significant proportion of the variance is explained for financial performance (Pseudo-R^2 = 0.315 and Wald χ^2 = 87.01, $p < 0.001$), reliability (Pseudo-R^2 = 0.178 and Wald χ^2 = 34.53, $p < 0.001$) and inventory (Pseudo-R^2 = 0.077 and Wald χ^2 = 16.46, $p < 0.01$). However, the proportion of variance explained for logistics costs is not statistically significant at the 5% level (Pseudo-R^2 = 0.075 and Wald χ^2 = 10.38, $p = 0.07$).

For the regressions at Level 1, Table 4.6 indicates that a significant proportion of the variance is explained by the random intercepts at Level 2 and Level 3 for all three regression. The ICC is 0.166 for reliability, 0.246 for inventory and 0.281 for logistics costs. The proportion of variance explained is similar to the analysis at Level 2 for reliability (Pseudo-R^2 = 0.136 and Wald χ^2 = 13010.60, $p < 0.001$), but higher for inventory (Pseudo-R^2 = 0.129 and Wald χ^2 = 9221.61, $p < 0.001$) and lower for logistics costs (Pseudo-R^2 = 0.018 and Wald χ^2 = 1267.57, $p < 0.001$).

As endogeneity can lead to biased and inconsistent estimates, this study addresses three main causes of endogeneity: measurement error, omitted variables and simultaneity (Roberts and Whited, 2013). The control variables specified in Section 3.3 address concerns related to omitted variables. Concerns regarding measurement error are addressed by minimizing the risk of common method bias, as it is one of the main sources of measurement error (Podsakoff et al., 2003). Common method bias is unlikely to be an issue for our study, as it relies exclusively on archival data that is free from respondents' perceptions and originates from multiple data sources (financial and supply chain databases).

Concerns regarding simultaneity arise for the relationship between reliability and financial performance. Hypothesis 2 suggests a positive relationship between these two constructs, based on the argument that reliability increases financial performance by preventing lost sales. However, one might also argue that the link between the two constructs is reverse: business units with higher financial performance have more resources to invest in reliability. For this reason, we conduct a Wu-Hausman specification test to assess whether reliability is an exogenous estimator of financial performance (Hausman, 1978). Demand variability is used as an instrumental variable for reliability for two reasons: (1) it is associated with lower reliability as indicated by Table 4.5 and (2) it is not assumed to influence financial performance apart from its negative effect on reliability. The residuals of the multilevel regression of demand variability on reliability are not a statistically significant predictor of financial performance at the 95% level. This result suggests that reliability is an exogenous estimator of financial performance.

For the remaining hypothesized relationships, simultaneity is unlikely to be an issue. Supply chain related costs are exogenous predictors of financial performance, as costs decrease profits and not vice versa (IASB, 2016). Similarly, responsiveness is an exogenous predictor of supply-chain-related costs, as costs do not determine how fast a supply chain is. Finally, responsiveness is an exogenous predictor of reliability, as delivery within the timeframe requested by the customer is a prerequisite for an order to be considered on time (APICS, 2016). Endogeneity concerns regarding measurement error, omitted variables and simultaneity are thus addressed in this study.

In the following, we evaluate whether or not our models offer support for the postulated hypotheses. Table 4.7 provides an overview of the results.

Table 4.7: Summary of hypotheses tests and results.

Hypo-thesis	**Relationship**	**Level**	**Beta and bias corrected CI**	**Support for hypothesis**
H1	Responsiveness → Reliability	Level 1	$\beta_1 = 0.074^{***}$ [0.072, 0.077]	YES
		Level 2	$\beta_2 = 0.048^{***}$ [0.029, 0.077]	YES
H2	Reliability → Financial Performance	Level 2	$\beta_3 = 0.093^{***}$ [0.040, 0.148]	YES
H3	Moderation of demand variability on Responsiveness → Reliability	Level 1	$\beta_7 = 0.017^{***}$ [0.014, 0.019]	YES
		Level 2	$\beta_8 = 0.012$ [-0.007, 0.033]	NO
	Moderation of lead time requirements on Responsiveness → Reliability	Level 1	$\beta_5 = -0.044^{***}$ [-0.046, -0.041]	YES
		Level 2	$\beta_6 = -0.016^{*}$ [-0.035, -0.002]	YES
H4	Moderation of contribution margins on Reliability → Financial Performance	Level 2	$\beta_9 = 0.618^{***}$ [0.264, 0.910]	YES
H5a	Cumulative indirect effect responsiveness → supply-chain-related costs → financial performance if demand variability is one standard deviation above the mean and lead time requirements are one standard deviation below the mean	Level 2	$\beta_{21} = -0.002$ [-0.006, 0.004]	NO
H5b	Cumulative indirect effect responsiveness → supply-chain-related costs → financial performance if demand variability is one standard deviation below the mean and lead time requirements are one standard deviation above the mean	Level 2	$\beta_{22} = 0.006^{*}$ [0.001, 0.013]	YES
H5	Moderation of demand variability on Responsiveness → Inventory	Level 1	$\beta_{27} = 0.140^{***}$ [0.124, 0.156]	YES
		Level 2	$\beta_{36} = -0.020$ [-0.140, 0.088]	NO

	Moderation of lead time requirement on Responsiveness → Inventory	Level 1	$\beta_{25} = -0.077^{***}$ [-0.091, -0.063]	YES
		Level 2	$\beta_{20} = -0.139^{**}$ [-0.235, -0.050]	YES
H5	Moderation of demand variability requirement on Responsiveness → Logistics Costs	Level 1	$\beta_{28} = 0.039^{***}$ [0.029, 0.050]	YES
		Level 2	$\beta_{37} = -0.105$ [-0.221, 0.017]	NO
	Moderation of lead time requirement on Responsiveness → Logistics Costs	Level 1	$\beta_{26} = -0.025^{***}$ [-0.035, -0.016]	YES
		Level 2	$\beta_{38} = -0.061$ [-0.154, 0.039]	NO
H6	Inventory → Financial Performance	Level 2	$\beta_{15} = -0.020^{**}$ [-0.030, -0.010]	YES
	Logistics Costs → Financial Performance	Level 2	$\beta_{16} = -0.016^{***}$ [-0.024, -0.006]	YES

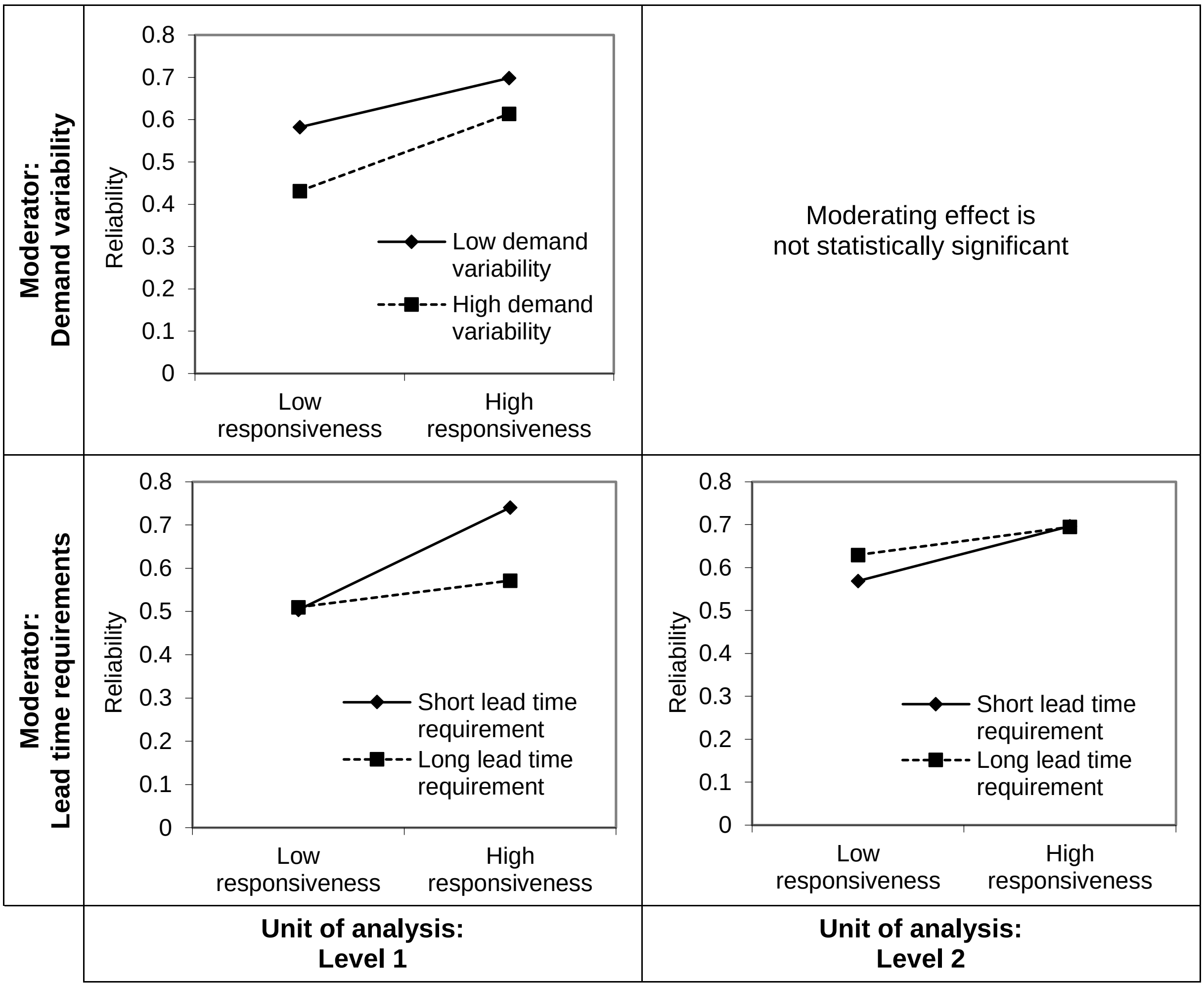
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed)

5.1 Responsiveness and the market mediation function

The proposed conceptual framework posits that responsiveness helps to match supply and demand (Hypothesis 1) which prevents lost sales and therefore improves financial performance (Hypothesis 2). Hypothesis 1 receives support at both Level 1 ($\beta_1 = 0.074$, $p < 0.001$) and Level 2 ($\beta_2 = 0.048$, $p < 0.001$). A one-standard-deviation change in responsiveness is associated with a 7.4-percentage-point (ppt) increase in reliability at Level 1 and a 4.8ppt increase at Level 2. Likewise, Hypothesis 2 is supported ($\beta_3 = 0.093$, $p < 0.01$); a one-standard-deviation increase in reliability (plus 14.4ppt) is associated with a 1.3ppt increase in the return on sales.

The theoretical model further states that these direct relationships are subject to several moderating factors. Hypothesis 3 suggests that challenges in the operating environment (high demand variability and short lead time requirements) increase the need for responsiveness and thus positively moderate the relationship between responsiveness and reliability. As hypothesized, the results indicate that the longer the customer lead time requirements (i.e., lower challenges), the weaker the relationship between responsiveness and reliability at Level 1 ($\beta_5 = -0.044$, $p < 0.001$) and Level 2 ($\beta_6 = -0.016$, $p < 0.05$). In the same vein, demand variability positively moderates the relationship between responsiveness and reliability at Level 1 ($\beta_7 = 0.017$, $p < 0.001$) and Level 2 ($\beta_8 = 0.012$, $p = 0.209$). There is strong support for Hypothesis 3, as three out of the four examined relationships are as hypothesized and statistically significant. To better understand the statistically significant moderating effects of lead time requirements and demand variability at both levels, Figure 4.5 shows the corresponding interaction plots.

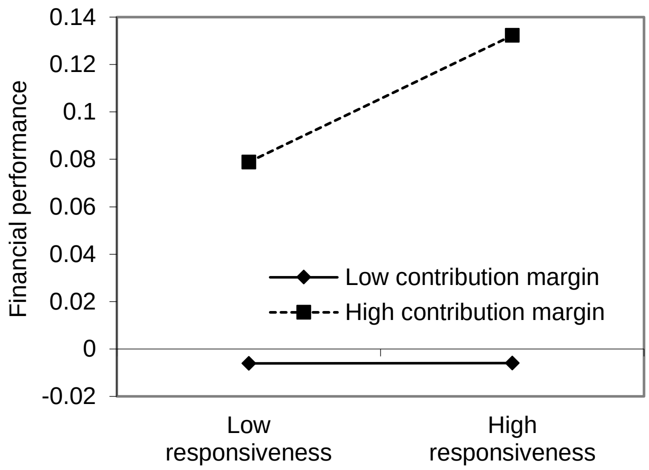
Figure 4.5: Moderating effects of challenges in the operating environment on the relationship between responsiveness and reliability.



Note: Moderating effects are assessed at one standard deviation above and below the mean.

Hypothesis 4 posits that the value of matching supply and demand increases with contribution margins. As illustrated by Figure 4.6, the corresponding moderating effect is positive and statistically different from zero (β_9 = 0.618, p < 0.001). If contribution margins are high, business units with high reliability have a 5.34ppt higher return on sales than business units with low reliability. If contribution margins are low, the return on sales is nearly the same for business units with high or low reliability. Hypothesis 4 is thus supported.

Figure 4.6: Moderating effect of contribution margins on the relationship between reliability and financial performance.



Note: Moderating effect is assessed at one standard deviation above and below the mean.

5.2 Responsiveness and the physical function

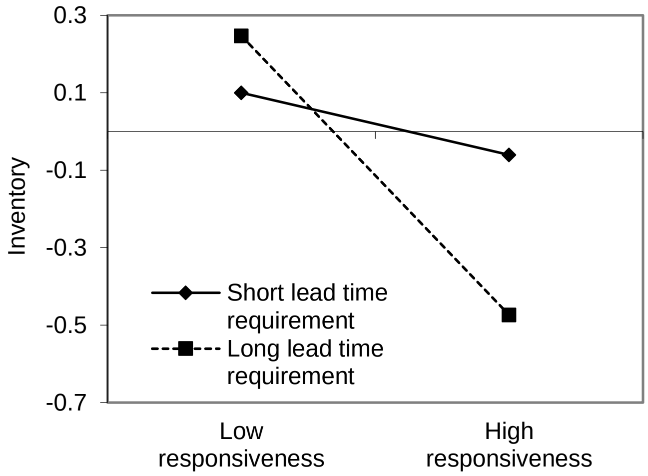
5.2.1 Analysis at Level 2

Our study considers two types of supply-chain-related costs: inventory and logistics costs. Both inventory (β_{15} = -0.020, $p < 0.01$) and logistics costs (β_{16} = -0.016, $p < 0.001$) are associated with lower financial performance. Hypothesis 6 is thus supported.

At Level 2, we receive mixed results for the direct effects of responsiveness on inventory and logistics. Our analysis suggests that responsiveness has a positive direct effect on inventory (β_{17} = -0.218, $p < 0.001$) but a negative direct effect on logistics costs (β_{18} = 0.107 p = 0.145). These results reflect the finding of a previous study: initiatives designed to increase responsiveness are often able to decrease inventories but at the expense of higher logistics costs (Holweg and Miemczyk, 2003). To determine whether the net effect of responsiveness on both cost types is positive or negative, we scrutinize the cumulative indirect effect of responsiveness via both cost types on financial performance. The cumulative indirect effect is positive but statistically insignificant (β_{19} = 0.003, p = 0.258), which suggests that responsiveness is associated with slightly lower supply-chain-related costs on average.

Hypothesis 5 focusses on how a more or a less challenging environment moderates the relationship between responsiveness and both cost types: Hypothesis 5a suggests that this relationship is positive when the operating environment is highly challenging while Hypothesis 5b suggests that this relationship is negative when the operating environment is less challenging. To test these predictions at Level 2, we evaluate how challenges in the operating environment moderate the cumulative indirect effect of responsiveness via both cost types on financial performance. Out of the moderating effects examined here, only the effect of customer lead time requirements on the relationship between responsiveness and inventory, shown in Figure 4.7, is statistically significant (β_{20} = -0.140, $p < 0.01$). As a result, the cumulative indirect effects of responsiveness via both cost types on financial performance is negative in a more challenging operating environment (β_{21} = -0.002, p = 0.503) and positive in a less challenging one (β_{22} = 0.006, $p < 0.05$). Responsiveness is thus associated with slightly higher costs in a more challenging operating environment, but with lower costs in a less challenging operating environment. Hypothesis 5 is therefore supported, but with two limitations.

Figure 4.7: Moderating effect of customer lead time requirements on the relationship between responsiveness and inventory at Level 2.



Note: Moderating effect is assessed at one standard deviation above and below the mean.

First, there is only partial support for Hypothesis 5a, as the indirect effect between responsiveness and financial performance is not statistically significant for a high level of challenges in the operating environment. Business units with a more responsive supply chain thus do not appear to incur significantly higher costs even if they operate in a challenging environment. This is surprising, since levers for improving responsiveness that are used to deal with challenges in the operating environment (e.g., airfreight or safety stock buffers) are assumed to be costly.

Second, Hypothesis 5 claims that demand variability and customer lead time requirements moderate the relationship between responsiveness and the two cost types. As we hypothesize that there are two relevant moderators for each of the relationships between responsiveness and the two cost types, there should be four statistically significant moderating effects. However, only one out of the four hypothesized moderating effects is statistically significant.

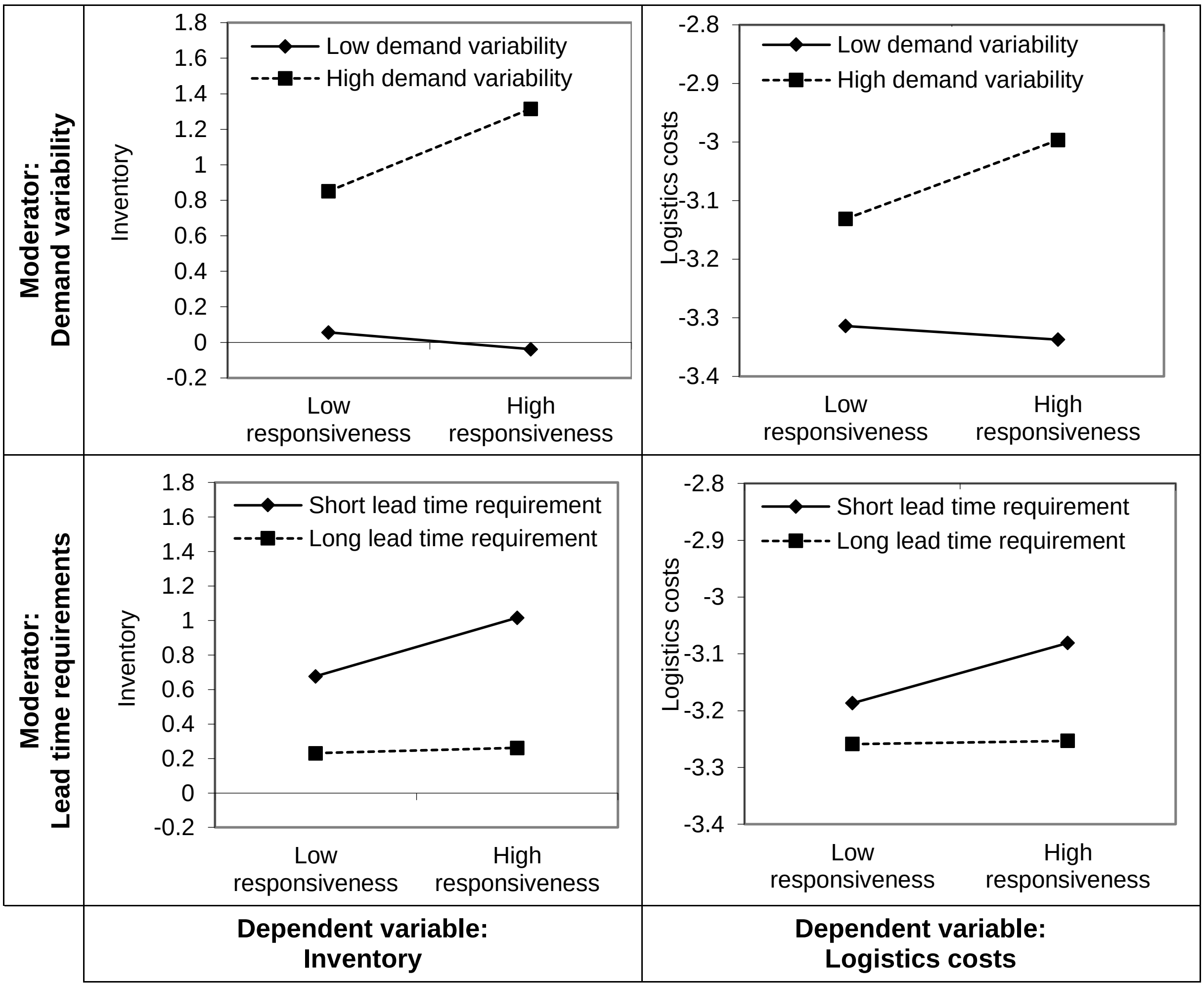
To find out whether there are additional moderating effects at Level 1 that were not discovered at Level 2, and to determine whether there are conditions given which higher responsiveness is clearly associated with higher supply-chain-related costs, we examine Hypothesis 5 at Level 1 as well.

5.2.2 Analysis at Level 1

There is a positive and statistically significant relationship between responsiveness and logistics costs at Level 1 ($\beta_{23} = 0.028$, $p < 0.001$). Like the effect at Level 2, responsiveness is on average associated with higher logistics costs at the product level.

For inventory, however, interpreting the direct effect is less straightforward. Although the relationship between responsiveness and inventory is negative and statistically significant at Level 2 ($\beta_{17} = -0.218$, $p < 0.001$), there is a positive and statistically significant relationship between responsiveness and inventory at Level 1 ($\beta_{24} = 0.093$, $p < 0.001$). The difference between the findings at Level 1 and Level 2 can be explained by the fact that practices designed to reduce inventory by cutting lead times are typically adopted at the plant level (Shah and Ward, 2003). The negative effect of responsiveness on inventory levels will therefore be hard to observe at the product level, as products are often produced in several plants. Further, if managers want to offer shorter lead times for a single product, it is more likely that they allocate additional inventory to warehouses close to customers for that product than to initiate structural changes in the supply chain. Consequently, it is not surprising that shorter lead times are on average associated with higher inventories at a product level (e.g., due to build-up of safety stock) and lower inventories at a business unit level (e.g., due to the effect of practices that aim to reduce inventories at the business unit's plants).

Figure 4.8: Moderating effect of challenges in the operating environment on the relationship between responsiveness and both cost types at Level 1.



Note: Moderating effects are assessed at one standard deviation above and below the mean.

As illustrated by Figure 4.8, challenges in the operating environment moderate the relationship between responsiveness and both cost types at Level 1. The length of customer lead time requirements negatively moderates both the relationship between responsiveness and inventory (β_{25} = -0.077, $p < 0.001$) and the relationship between responsiveness and logistics costs (β_{26} = -0.025, $p < 0.001$). Demand variability further positively moderates both the relationship between responsiveness and inventory (β_{27} = 0.140, $p < 0.001$) and the relationship between responsiveness and logistics costs (β_{28} = 0.039, $p < 0.001$).

At Level 1, Hypothesis 5a is supported. If demand variability is one standard deviation above the mean, both the relationship between responsiveness and inventory (β_{29} = 0.232, $p <$ 0.001) and the relationship between responsiveness and logistics costs (β_{30} = 0.067, $p < 0.001$) are positive and statistically significant. The same holds for short customer lead time requirements. If they are one standard deviation below the mean, the relationship between responsiveness and inventory (β_{30} = 0.167, $p < 0.001$) and the relationship between responsiveness and logistics costs (β_{31} = 0.053, p < 0.001) are also positive and statistically significant. Our results thus indicate that managers who aim to increase the responsiveness for individual products are likely to incur higher supply-chain-related costs in a more challenging operating environment.

Hypothesis 5b is only partially supported at Level 1. If demand variability is one standard deviation below the mean, the relationship between responsiveness and inventory (β_{32} = -0.047, p < 0.001) is negative and statistically significant. The relationship between responsiveness and logistics costs is also negative but not statistically significant at the 95% level for low levels of demand variability (β_{33} = -0.012, p = 0.07). If customer lead time requirements are below the mean, both the relationship between responsiveness and inventory (β_{34} = 0.015, p = 0.06) and the relationship between responsiveness and logistics costs (β_{35} = 0.003, p = 0.597) cease to be statistically significant at the 95% level. While it thus might be difficult to achieve cost savings by increasing the responsiveness of individual products in a less challenging operating environment, there does not appear to be a trade-off between responsiveness and costs either.

In summary, our results support Hypothesis 5. Both demand variability and customer lead time requirements are important moderators of the relationship between responsiveness and the examined cost types. Hypothesis 5a is supported, as responsiveness is associated with significantly higher supply-chain-related costs at Level 1 and slightly higher supply-chain-related costs at Level 2 in a more challenging operating environment. Further, there is support for Hypothesis 5b at Level 2, as business units' responsiveness is associated with lower supply-chain-related costs in a less challenging operating environment. At Level 1, there is partial support for Hypothesis 5b, as there does not appear to be a trade-off between responsiveness and costs for individual products in a less challenging operating environment. Our results thus indicate that responsiveness entails a cost premium in a more challenging operating environment and is associated with cost reductions in a less challenging operating environment.

6 Discussion and implications

A popular framework for assessing the value of responsiveness has been proposed by Fisher (1997): the importance of matching supply and demand is higher for innovative products – accordingly responsiveness is more important for innovative products as well.

Our results, however, indicate that responsiveness is important for *both* functional and innovative products. On the one hand, challenges in the operating environment positively moderate the relationship between responsiveness and reliability; contribution margins further positively moderate the relationship between reliability and financial performance. As a consequence, there is a strong indirect link between responsiveness and financial performance via reliability for innovative products (top right quadrant in Table 4.5). On the other hand, however, challenges in the operating environment also positively moderate the relationship between responsiveness and supply-chain-related costs. Consequently, there is an indirect link between responsiveness and financial performance via supply-chain-related costs for functional products as well (bottom left quadrant in Table 4.5). As shorter lead times therefore contribute to the bottom line for both functional and innovative products, it is necessary to sharpen the performance objective set by Fisher's framework with respect to responsiveness.

Fisher (1997) proposes an "efficient" supply chain for functional products and a "responsive" supply chain for innovative products. One might thus be led to assume that shorter lead times are important only for "responsive" supply chains. However, our results show that being responsive to customer orders is also important for "efficient" supply chains. "Efficient" and "responsive" supply chains should both emphasize responsiveness, but by using different means and for pursuing different goals. The former emphasize practices and capabilities that reduce both costs and lead times, while the latter focus on costly enablers of responsiveness to match supply to demand. Hence, to eliminate the equivocality of the "efficient"/"responsive" dichotomy, we label the strategy in the top right quadrant of Figure 4.10 "market mediation" instead of "responsive", as the market mediation function (i.e., the ability to match supply and demand) is especially important for innovative products.

Given our claim that shorter lead times are important for both functional and innovative products, one might now be inclined to ask "when should supply chains *not* be fast?"

The correlations shown in Table 4.2 suggest that other product types exist besides functional and innovative. Fisher's framework assumes that low-margin commodity products are sold in a stable operating environment and high-margin specialty products in a challenging one. This view is frequently echoed in the supply chain strategy literature (e.g., Childerhouse and Towill, 2000; Mason-Jones et al., 2000). In our data, however, contribution margins are neither strongly correlated with demand variability (r = 0.10) nor with customer lead time requirements (r = -0.10). A certain contribution margin is therefore not necessarily matched with a certain type of operating environment. There is thus a need to extend Fisher's (1997) functional-innovative dichotomy to give more meaningful propositions of when supply chains should be fast.

Figure 4.9: Scatter plot of contribution margins and challenges in the operating environment.

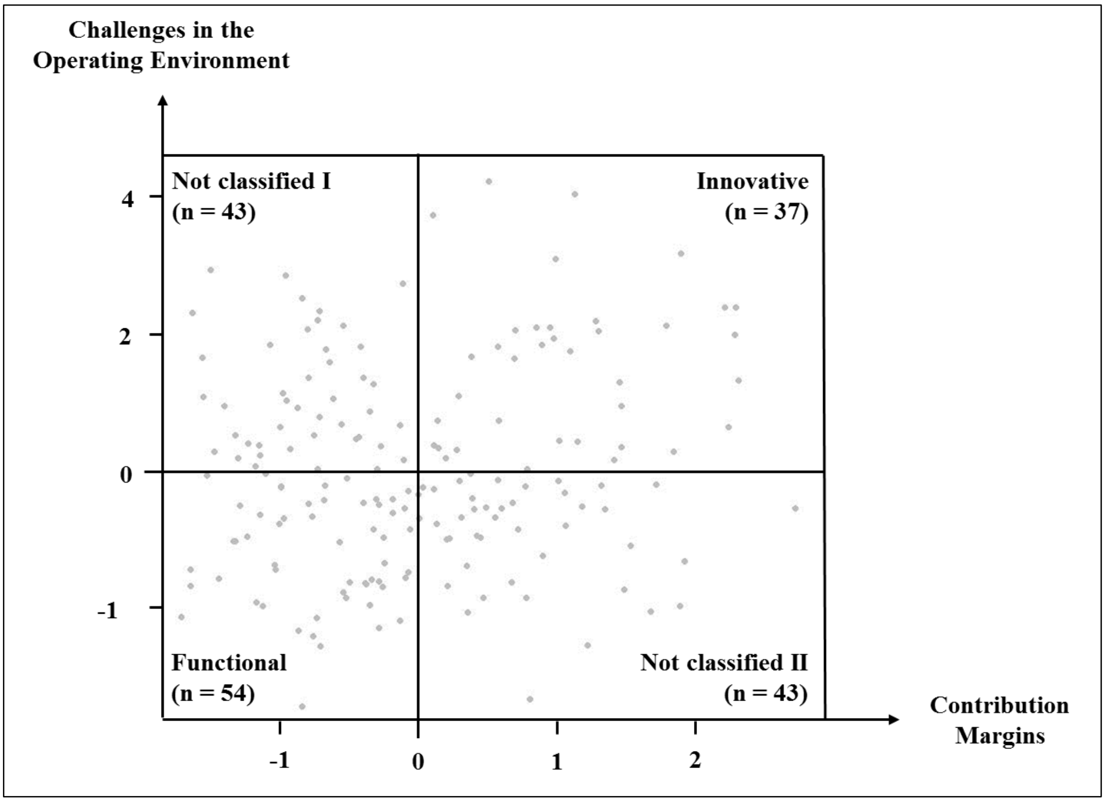


Figure 4.10: Extended and modified version of Fisher's framework.

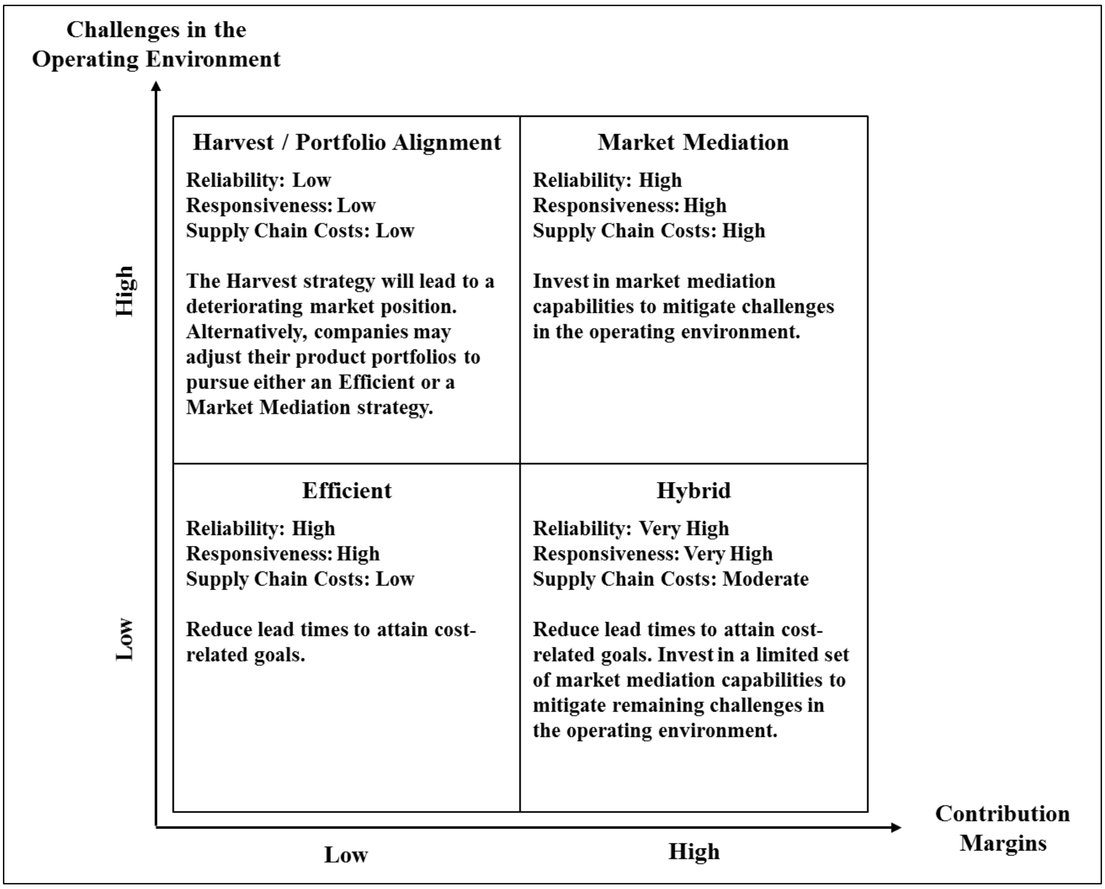


Figure 4.9 illustrates that the distribution of business units in our sample according to contribution margins and challenges in the operating environment. As with the left-hand side of Table 4.5, challenges in the operating environment are measured by the standardized logarithm of demand variability minus the standardized logarithm of customer lead time requirements.[10] Although there is a positive correlation between contribution margins and challenges in the operating environment (r = 0.14), there are many business units that cannot be classified as manufacturers of functional or innovative products. Business units in the bottom-left quadrant (n = 54) can be classified as manufacturers of functional products and business units in the top-right quadrant (n = 37) as manufacturers of innovative products. However, for manufacturers of low-margin products with high challenges in the operating environment (n = 43), no classification is provided by Fisher's framework. The same is true for business units in the bottom-right quadrant (n = 43) that manufacture high margins products in a less challenging operating environment.

To clarify the role of the responsiveness for these unclassified business units, we extend Fisher's framework by the two additional supply chain strategies shown in Figure 4.10. Based on our findings, the strategies not only indicate whether supply chains should be fast, but also specify targets for the match been supply and demand (reliability) and supply-chain-related costs. The four strategies are detailed next.

The "**market mediation**" strategy in the top-right quadrant applies to companies selling high-margin products in a challenging operating environment (e.g., fashion retailers). They should aim for a high level of reliability, since high contribution margins increase the adverse effect of lost sales on profitability. Given the high level of demand variability and/or short customer lead time requirements, they need to invest in matching supply and demand. Our findings indicate that improving responsiveness is effective for this task. Other capabilities for matching supply and demand such as agility or flexibility could also fit well with this strategy (Anand and Ward, 2004; Gligor et al., 2015; Gligor, 2015; Merschmann and Thonemann, 2011; Qi et al., 2009; Qi et al., 2011; Wagner et al., 2012). However, we focus our recommendations for this strategy on reliability, responsiveness and cost-related targets, since agility and flexibility were not examined as part of our study. Accordingly, we advise managers pursuing a market mediation strategy to set ambitious targets for reliability and responsiveness, but also to accept higher supply chain costs.

[10] We take the logarithm of both variables, as we assume diminishing effects. The two variables are standardized to make their scales comparable.

The "**efficient**" strategy in the bottom-left quadrant applies to manufacturers of low-margin products operating in an environment with few challenges (e.g., producers of canned soup). Since demand is stable and customer grant sufficient time to react to uncertainties, reliability should be high even without investments in capabilities that match supply and demand. Low contribution margins also leave little room for such investments. Thus, managers should aim for a high level of reliability at relatively low cost. Our findings highlight that shorter lead times are a key enabler of this strategy, because they help to both reduce supply-chain-related costs and increase reliability in an operating environment with few challenges. Consequently, we advise managers pursuing a physically efficient supply chain to aim for high levels of reliability and responsiveness while keeping supply-chain-related costs relatively low.

The "**hybrid**" strategy in the bottom-right quadrant is applicable to companies that offer high-margin products in an operating environment with few challenges (e.g., producers of patent-protected pharmaceuticals). It is a hybrid of the "market mediation" and the "efficient" strategy. High contribution margins incentivize managers to aim for high reliability. However, since demand is relatively stable and/or customer grant sufficient time to react to uncertainties, there is only a limited need to invest in capabilities that match supply and demand. Similar to the "efficient" strategy, shorter lead times enable the attainment of cost-related goals, as the level of challenges in the operating environment is low. In addition, managers may invest in a limited set of capabilities for matching supply and demand if there are remaining challenges in their operating environment that need to be mitigated. Managers pursuing this strategy are advised to aim for very high levels of reliability and responsiveness (via practices that improve both efficiency and responsiveness and – if necessary – costly enablers of lead time reductions) at moderate supply chain costs.

The "**harvest**" and the "**portfolio alignment**" strategies in the top-left quadrant apply to companies that offer low-margin products in an operating environment characterized by time pressure and demand volatility. They are caught in an unfortunate situation, since challenges in the operating environment create a need for investing in capabilities such as responsiveness to match supply and demand. However, investments of this type would not pay off because of low contribution margins. As reflected by the results in the top-left quadrant of Table 4.5, the value of responsiveness is thus low for companies operating in such an environment. To deal with this issue, managers can either implement a low-cost supply chain that fails to reliably meet customer demand. This would be equivalent of adopting a "harvest" strategy for "dogs" of the BCG Matrix, where costs are reduced at the expense of a deteriorating market position

(Barksdale and Harris, 1982). Alternatively, managers may adjust their product portfolio. So far we have matched supply chain strategies to the requirements of the operating environment although decisions regarding the product portfolio and supply chain strategy are interdependent (Seifert and Langenberg, 2011; Seifert et al., 2016). Managers can remove products with low margins or sporadic demand from their portfolio (Godsell et al., 2011). Removing the former from the product portfolio would render the pursuit of a market mediation strategy attractive, while removing the latter would enable the setting up of a physically efficient supply chain.

7 Limitations and future research directions

When interpreting the findings of this research, one must be aware of its methodological limitations. First, our data was gathered for a single period which limits the extent to which cause-and-effect relationships can be inferred. Second, we examined data only from a single company (BASF). Although the company is diverse in terms of the operational and competitive environments its business units face, the relationships among the examined variables might be different for other companies and other industries. The moderating effect of contribution margins, for example, might be less pronounced for tier-one suppliers in the automotive industry, as they require nearly perfect reliability regardless of their contribution margins due to the high penalty costs charged by OEMs for late deliveries (Guiffrida and Nagi, 2006). Third, this study has relied exclusively on secondary data from BASF databases. An advantage of secondary data is its objectivity, as there is no risk of diluted respondent perception (Calantone and Vickery, 2009). However, although we trust the data used for this study, the risk of a systematic measurement error by the company's databases cannot be ruled out completely; replication and validation studies are therefore needed. Finally, our strict reliance on secondary data has limited the scope of our study and therefore presents opportunities for future research.

In particular, future studies may evaluate additional intermediate performance outcomes of supply chain responsiveness. This study assessed the implications of responsiveness for inventory and logistics costs. However, shorter lead times are also associated with costs of, for instance, procurement or manufacturing (de Treville et al., 2014b; Mackelprang and Nair, 2010). The remaining positive (but not statistically significant) direct effect of responsiveness on financial performance indicates that other cost types might be affected by shorter lead times. Benefits of responsiveness not considered in this study such as a shorter time-to-market are also a potential cause of the remaining direct effect. Assessing additional benefits and costs associated with shorter lead times would thus provide a fuller picture of the performance outcomes of responsiveness.

Chapter 5 Summary, limitations and outlook

This chapter summarizes the main results of this thesis with regards to the research questions formulated in Chapter 1. Further, it highlights the limitations of our studies and outlines potentials for future research.

1 Summary of the research questions

Aligning the competitive priorities of supply chains with the requirements of the business environment is critical for competing successfully in the marketplace. Nonetheless, misalignment is frequent in practice, as key challenges companies face when seeking alignment remain unresolved. The introductory chapter identified three of these challenges and formulated corresponding research questions. The studies in Chapter 2, 3 and 4 intended to answer these questions; the results are summarized in the following.

1.1 Research Question 1: Capturing requirements of the business environment

Companies are confronted with a wide variety of potentially relevant contingency variables, but with little guidance as to which of these variables they should take into consideration when developing supply chain strategies. Consequently, Research Question 1 was concerned with disambiguating which contingencies are important for setting the competitive priorities of supply chains. The research question was:

> **Question 1:** *Which contingency variables should companies analyse in order to capture supply-chain-relevant requirements of their business?*

Answering this question required a two-step approach. First, given the wide variety of contingencies, there was a need to clarify why the contingencies proposed in the extant literature are potentially relevant for achieving alignment. For this purpose, we categorized proposed contingencies based on how they affect the relative importance of competitive priorities. Second, to determine which of these contingencies should be considered for deriving strategies, we tested whether their proposed effects on the relative importance of competitive priorities are large enough to be taken into consideration when developing strategies.

Hence, at first, Chapter 2 developed a typology in order to clarify why different types of contingencies are potentially relevant for developing supply chain strategies. It highlights that contingencies may affect the relative importance of competitive priorities in two distinct ways.

On the one hand, *challenges in the operating environment* make it harder to fulfil demand as requested by customers, *ceteris paribus*. As a result, contingency variables of this type indicate to what extent companies require market mediation capabilities to avoid lost sales. Challenges in the operating environment can be further subclassified into demand-related (e.g., demand variability), time-related (e.g., customer lead time requirements) and supply-related (e.g., time-specificity of input-materials). On the other hand, contingencies affecting the *value of market mediation* indicate to what extent a failure to fulfil demand as requested by customers adversely affects a company's bottom line. Consequently, contingencies of this type determine whether the benefits of investing in market mediation capabilities in a challenging operating environment outweigh the associated costs.

For a subset of the categorized contingencies, Chapter 2 then tested whether the effects put forward by the typology are large enough for these variables to be taken into consideration when developing strategies. Specifically, the chapter analysed to what extent five challenges in the operating environment that are referred to as DWV3 affect the ability to fulfil demand as requested by customers. The chapter restricted its analysis to the DWV3 variables (product lifecycle **D**uration, customer lead time requirements / delivery time **W**indow, demand **V**ariability, demand **V**olume, product **V**ariety), since they are the most frequently cited variables in the literature on supply chain strategy (Christopher et al., 2009). We hypothesized that these variables affect the ability to reliably fulfil demand as requested in different ways: whereas demand variability and customer lead time requirements were expected to affect reliability directly, we hypothesized that the remaining DWV3 variables would affect reliability indirectly by increasing demand variability.

The analysis was conducted at two levels: the hypotheses were tested with a multilevel structural equation models at the business-unit-level and with multilevel regressions at the product-level. As expected, the findings linked high demand variability and short lead time requirements directly and consistently to lower reliability. For the remaining variables, the link to reliability was mostly indirect: apart from being associated with higher demand variability, these variables only marginally affected the ability of supply chains to fulfil demand as requested by customers. Consequently, we concluded that demand variability and customer lead time requirements need to be taken into consideration when developing supply chain strategies, as they indicate to what extent companies require market mediation capabilities to reliably fulfil demand. Volume, variety and lifecycle duration are less important for this purpose, but may instead be used for analysing the causes of variable demand.

Finally, in addition to the challenges in the operating environment analysed in Chapter 2, Chapter 4 examined whether contribution margins need to be taken into consideration when developing supply chain strategies. As part of an analysis on the performance outcomes of responsiveness, the chapter tested whether contribution margins increase the positive effect of reliability on financial performance. The results indicated a significant and positive moderating effect, hence demonstrating that contribution margins are a key determinant of the value of market mediation.

1.2 Research Question 2: Data-driven supply chain segmentation

Supply chain segmentation describes the process of dividing a heterogeneous set of products, customers or business units into groups (“segments”) that impose similar requirements on the supply chain. Because such a segmentation allows companies to tailor their supply chains more closely to the requirements of their business, the topic currently receives significant attention from practitioners (Gartner, 2016a). Despite this attention, extant studies on supply chain segmentation almost exclusively form segments qualitatively, even though this approach is considered “probably the […] least effective” (Wedel, 2000). Given the resultant need for alternative approaches to forming supply chain segments, Research Questions 2a and 2b were formulated as follows:

Question 2a: *How can companies use data-driven methods to form supply chain segments quantitatively?*

Question 2b: *What insights do these data-driven methods generate relative to qualitative approaches?*

As a first step towards answering this question, Chapter 3 highlighted the shortcomings of approaches to forming supply chain segments proposed by extant studies on the topic. Qualitative approaches – which are prevalent in the literature – are subjective and, hence, may cause relevant clusters of products or customers to remain undetected. The quantitative approach introduced by Langenberg et al. (2012) requires companies to specify potential supply chain design options with quantifiable performance implications before the segmentation. As a result, it provides guidance at the tactical rather than the strategic level of decision making. Given these shortcomings, the research in Chapter 3 then proceeded to demonstrate how companies can conduct a supply chain segmentation using two data-driven methods that are popular in other areas of business research: clustering and classification.

First, we conducted a cluster analysis to form an initial set of segments. For this purpose, the clustering algorithm Mclust was used for grouping together business units that were similar with respect to demand variability, customer lead time requirements and contribution margins. We employed the Mclust algorithm, since the examined business units did not exhibit a clear cluster structure and the algorithm allows for overlapping clusters. The cluster analysis was conducted with data on business units from the years 2013 and 2014 to enable a comparison with a set of supply chain segments BASF had formed qualitatively during the same time period and using the same level of aggregation. The analysed contingency variables were chosen based on the results of this thesis for Research Question 1.

The cluster analysis identified a set of four actionable, stable and externally valid supply chain segments. In accordance to strategies that match the characteristics of these segments, they were labelled “Lean” (low variability and low margins), “Agile” (high variability, high margins and long lead time requirements), “Leagile” (high variability, high margins and short lead time requirements), and “Basic Service” (high variability and low margins). The characteristics of the first three segments corresponded to BASF’s qualitative segments, hence allowing for a comparison between quantitative and the qualitative segments. For this purpose, we examined the link between mismatches (i.e., business units that had assigned themselves to a segment different from the one proposed by the cluster analysis) and financial performance. The results linked mismatches to significantly lower financial performance. The findings therefore implied that clustering is a feasible approach for developing supply chain segments and for detecting cases where managers have selected segments that do not adequately reflect the requirements of their business.

Finally, Chapter 3 examined how classification can be used to update and review existing segments. For this purpose, the segments established by the cluster analysis for data from the years 2013 and 2014 was used to train a random forest algorithm. The algorithm then classified data on BASF business units from the years 2015. 21% of business units were assigned to a different segment by the algorithm, in most cases because of a change in the level of contribution margins or demand variability. We therefore concluded that classification algorithms are important for sustaining a portfolio of supply chain segments, since the contexts in which supply chains operate change over time.

1.3 Research Question 3: Performance outcomes of responsiveness

In supply chain management, responsiveness describes the ability of a supply chain to fulfil orders within a time frame that is acceptable to the customer. Even though setting lead-time-related targets is considered critical for achieving aligned alignment, there are conflicting perspectives as to when short lead times should be prioritized. Consequently, Research Question 3 was concerned with the performance outcomes of responsiveness. The research question was:

Question 3: *When should companies make supply chain responsiveness a competitive priority?*

The conflicting perspectives regarding the performance outcomes of responsiveness emanate from two – largely disconnected – literature streams. On the one hand, studies on the value of shorter lead times argue that responsiveness entails a cost premium and, hence, purport that responsiveness is primarily important for innovative products (e.g., de Treville et al., 2014a). On the other hand, studies on lean management and just-in-time practices assert that shorter lead times reduce supply-chain-related costs (e.g., Shah and Ward, 2003). To clarify in which contexts shorter lead times positively contribute to a company's bottom line, the research in Chapter 4 examined both the benefits and the costs of responsiveness.

Regarding the benefits of responsiveness, we hypothesized that shorter lead times enable companies to fulfil demand as requested by customers and, hence, positively impacts the bottom line by preventing lost sales. Further, we hypothesized that the benefits are higher in contexts that are characteristic of innovative products – i.e., challenging operating environments with high margins – for two reasons. First, we suspected more opportunities for reducing lost sales by decreasing lead times in environments characterized by volatile demand and time pressure. Second, we expected high contribution margins to increase the positive effect of avoiding lost sales on the bottom line.

Regarding the costs of responsiveness, we hypothesized that companies can leverage lean management and just-in-time practices to achieve both lead time and cost savings in contexts that are characteristic of functional products, i.e., where demand is stable and lead time requirements are long. For challenging operating environments, we hypothesized that responsiveness entails a cost premium.

Similar to the research in Chapter 2, we conducted our analyses at two levels: the hypotheses were tested with a multilevel structural equation models at the business-unit-level and with multilevel regressions at the product-level. As expected, the findings indicated that responsiveness can increase financial performance for both innovative and functional products. In challenging operating environments with high contribution margins, shorter lead times increase financial performance by matching supply and demand, hence preventing the loss of high-margin sales. In environments characterized by stable demand and long lead time requirements, shorter lead times contribute to the bottom line by reducing supply-chain-related costs.

Further, as our sample comprised business units that could be classified neither as manufacturers of innovative products nor as manufacturers of functional products, we extended our propositions to two additional contexts. For high-margin businesses facing little time pressure and stable demand, we proposed leveraging responsiveness to reduce costs and for mitigating remaining challenges in the operating environment. For low-margin businesses facing a challenging operating environment, we proposed that managers refrain from prioritizing responsiveness, as the resulting increase in low-margin sales might fail to offset the associated increase in costs.

2 Limitations

When interpreting the findings of this thesis, one must be aware of its methodological limitations.

First, our research analysed cross-sectional data which limits the extent to which cause-and-effect relationships can be inferred. All relationships tested in the studies of this thesis were scrutinized for simultaneity. For one relationship where simultaneity was considered plausible – the relationship between reliability and financial performance in Chapter 4 – the results of a Wu-Hausman specification test suggested that the analysed predictor is exogenous. Nonetheless, the threats of simultaneity and reverse causality cannot be ruled out entirely.

Second, this thesis has analysed data from a single company (BASF). Although BASF is diverse in terms of the operational and competitive environments its business units face, the relationships among the examined variables might be different for other companies and other industries. The link between mismatches and financial performance, for instance, might be different for companies operating in a different industry, as the relationship between fit and performance is subject to a number of industry-level moderators (Gligor, 2017). Similarly, companies using clustering to form supply chain segments quantitatively may arrive at a different set of segments, as characteristics of product and business unit portfolios differ between firms (Protopappa-Sieke and Thonemann, 2017). Hence, even though the BASF data used in this thesis constitutes a sufficiently broad and heterogeneous empirical basis to warrant the generalization of our findings, replication and validation studies are needed.

Third, given our reliance on archival company data, the studies in this thesis were at risk of omitting variables that (1) affect the examined relationships, but (2) are not available in company databases. The research in Chapter 2, for instance, did not account for the competitive priorities of the business units in our sample, even though they might have systematically affected the (absolute) effect sizes of the examined relationships. Similarly, when assessing the mismatch-performance link in Chapter 3, we would have liked to control for the resources the examined business units had available for preventing mismatches, since they might have affected both mismatches and performance. While our studies were able to draw inferences nonetheless – Chapter 2 examined relative effect sizes and Chapter 3 used business unit size as a proxy for resource availability – additional qualitative information would have rendered our findings more robust.

Fourth, the regressions in Chapter 2 and 4 employed maximum likelihood estimators even though one of the dependent variables (reliability) was bounded between zero and one. Since maximum likelihood estimators assume a continuous distribution of the dependent variable, the regression results were heteroskedastic. Zero-or-one inflated beta regressions – a potential remedy when response variables follow a mixed continuous–discrete distribution with probability mass at zero or one – are not yet available for multilevel models. To be able to draw inferences nonetheless, we obtained heteroscedasticity-robust standard errors from non-parametric bootstrapping. However, once methods for conducting zero-or-one inflated beta regressions with multilevel data are available, validation studies are needed to review the robustness of our results.

Finally, in addition to the outlined methodological limitations, the thesis at hand is subject to conceptual limitations that are addressed in the following section.

3 Outlook

The introductory chapter identified three key challenges that prevent companies from attaining supply chain fit. While the studies in this thesis have contributed towards filling these gaps, opportunities for future research remain.

Contingency variables affect the relative importance of competitive priorities in different ways. This thesis has investigated the effects hypothesized to be underlying variables of three types: demand-related challenges in the operating environment, time-related challenges in the operating environment and contingencies affecting the value of market mediation. However, the effects underlying supply-related challenges in the operating environment have not been empirically examined so far. Contingencies of this type are increasingly receiving attention in the extant literature (Ho et al., 2015), yet it is not sufficiently clear which variables need to be considered when developing supply chain strategies. Ho et al. (2005), for instance, propose that companies should analyse a set of seven reflective measures of manufacturing-related and supplier-related uncertainties for this purpose. However, most of the proposed measurement items are not available in company databases and so far there has been no empirical examination to what extent these measures affect the ability to fulfil demand as requested by customers.

Further research is also needed on data-driven approaches for supply chain segmentation. On the one hand, replication and validation studies may scrutinize the benefits of clustering and classification outlined by this research. As the characteristics of product and customer portfolios vary between companies, it would be worthwhile to enquire whether other firms would also be able to find an actionable set of segments with the proposed methods. On the other hand, there are opportunities for advancing the research presented in Chapter 3. Possible extensions include the use of a wider range of clustering and classification methods, cluster analysing products or customers instead of business units, or the development of approaches that explicitly combine qualitative and quantitative information from the beginning. Given the attention the topic currently receives from practitioners and the benefits of conducting a data-driven segmentation outlined by this thesis, we are confident that further research on this issue will emerge.

Finally, out of the examined research questions, arguably the largest potential for future studies lies in enabling managers to derive strategies that align with the (segment-specific) requirements of their business. This thesis has investigated the context-dependency of benefits and costs associated with responsiveness. Future research may extend this analysis by considering additional contingencies, benefits or costs. However, disambiguating the performance outcomes of responsiveness constitutes only a first step towards enabling companies to achieve alignment. In particular, further work is needed to (1) delineate which capabilities are important for achieving alignment, (2) how these capabilities should be operationalized and (3) what their antecedents and consequences are.

Consider, for instance, the case of supply chain agility, a market mediation capability that is considered critical for competing successfully in a turbulent business environment (Lee, 2004). A recent literature review identified 26 different definitions of supply chain agility that exhibit considerable overlap to closely related constructs such as flexibility (Sharma et al., 2017). The review also identified a lack of consensus as to what relevant antecedents of supply chain agility are. Further, there are inconsistent propositions regarding the performance outcomes of supply chain agility. Even though most studies find that supply chain agility is a market mediation capability that entails a cost premium (Agarwal et al., 2006; Goldsby et al., 2006; Narasimhan et al., 2006), an empirical study by Gligor et al. (2015) suggests that agility can improve both efficiency and customer effectiveness. Hence, in spite of being considered critical for achieving alignment, it is not sufficiently clear what supply chain agility is, how it can be achieved and when it should be pursued.

The fact that recent literature reviews have made similar findings for other market mediation capabilities such as flexibility and resilience (Tukamuhabwa et al., 2015; Yu et al., 2015) highlights that there is significant ambiguity as to which capabilities are important for achieving alignment. As stated in Chapter 2, proposed market mediation capabilities range from different aspects of responsiveness (e.g., Bernardes and Hanna, 2009), agility (e.g., Gligor et al., 2013), flexibility (e.g., Swafford et al., 2006) to different sources of resilience (e.g., Pettit et al., 2010). Consequently, further research is needed to delineate which capabilities are relevant for aligning supply chain strategies and how these capabilities should be operationalized.

Once a set of well-defined market mediation capabilities has been specified, future studies may investigate its antecedents and consequences. Comprehending the consequences of market mediation capabilities is critical for determining when they should be prioritized; investigating their antecedents is imperative for enabling companies to put their strategies into practice. It is only if the antecedents and consequences of a well-defined set of market mediation capabilities are unambiguous that this area of research will be able to adequately support companies in developing aligned supply chain strategies.

References

Agarwal, A., Shankar, R., Tiwari, M.K., 2006. Modeling the metrics of lean, agile and leagile supply chain: An ANP-based approach. European Journal of Operational Research 173 (1), 211–225.

Aggarwal, C.C., 2015. Data Classification: Algorithms and Applications. CRC Press, Boca Ranton, USA.

Aitken, J., Childerhouse, P., Christopher, M., Towill, D., 2005. Designing and managing multiple pipelines. Journal of Business Logistics 26 (2), 73–96.

American Chemical Society, 2017. Global Top 50 Chemical Companies 2017. Chemical & Engineering News. https://cen.acs.org/articles/95/i30/CENs-Global-Top-50.html?type=paidArticleContent. Accessed 16 October 2017.

Amtsgericht Bonn, 2017. Insolvenzbekanntmachung SolarWorld AG. https://www.insolvenzbekanntmachungen.de/cgi-bin/bl_aufruf.pl?PHPSESSID=689b9651f8be4f20186102d010c5de53&datei=gerichte/nw/agbonn/17/0099_IN00079_17/2017_08_01__11_21_30_Eroeffnung_Insolvenzverfahren.htm. Accessed 5 September 2017.

Amtsgericht München, 2009. Insolvenzbekanntmachung Qimonda AG. https://www.insolvenzbekanntmachungen.de/cgi-bin/bl_aufruf.pl?PHPSESSID=aa19c6b8c8cb84a773bacc6a91c1cbeb&datei=gerichte/by/agmuenchen/09/1542_IN_209_09/2009_08_06__15_20_02_Termine.htm. Accessed 5 September 2017.

Anand, G., Ward, P.T., 2004. Fit, flexibility and performance in manufacturing: coping with dynamic environments. Production and Operations Management 13 (4), 369–385.

APICS, 2016. Supply Chain Operations Reference Model: SCOR Model - Version 11. Accessed 18 October 2016.

Azadegan, A., Patel, P.C., Zangoueinezhad, A., Linderman, K., 2013. The effect of environmental complexity and environmental dynamism on lean practices. Journal of Operations Management 31 (4), 193–212.

Bacher, J., Pöge, A., Wenzig, K., 2010. Clusteranalyse: Anwendungsorientierte Einführung in Klassifikationsverfahren. Oldenbourg Verlag, Munich, Germany.

Barksdale, H.C., Harris, C.E., 1982. Portfolio analysis and the product life cycle. Long Range Planning 15 (6), 74–83.

BASF SE, 2015. BASF Annual Report 2014. http://bericht.basf.com/2014/en/. Accessed 10 March 2016.

BASF SE, 2016a. BASF Annual Report 2015. http://bericht.basf.com/2015/en/. Accessed 18 October 2016.

BASF SE, 2016b. Verbund. https://www.basf.com/en/company/about-us/strategy-and-organization/verbund.html. Accessed 1 February 2017.

BASF SE, 2017. Segments. https://www.basf.com/en/company/investor-relations/basf-at-a-glance/business-segments.html. Accessed 21 April 2017.

Basnet, C., Seuring, S., 2016. Demand-Oriented Supply Chain Strategies - A Review of Literature. Operations and Supply Chain Management 9 (2), 73–89.

Baum, C.F., 2008. Stata tip 63: Modeling proportions. Stata Journal 8 (2), 299.

Bernardes, E., Hanna, M.D., 2009. A theoretical review of flexibility, agility and responsiveness in the operations management literature: Toward a conceptual definition of customer responsiveness. International Journal of Operations & Production Management 29 (1), 30–53.

Blackburn, J., 2012. Valuing time in supply chains: establishing limits of time-based competition. Journal of Operations Management 30 (5), 396–405.

Bozarth, C.C., Warsing, D.P., Flynn, B.B., Flynn, E.J., 2009. The impact of supply chain complexity on manufacturing plant performance. Journal of Operations Management 27 (1), 78–93.

Breiman, L., 2001. Random forests. Machine learning 45 (1), 5–32.

Brock, G., Pihur, V., Datta, S., Datta, S., 2011. clValid: An R package for cluster validation. Journal of Statistical Software 25 (4), 1–22.

Browning, T.R., Heath, R.D., 2009. Reconceptualizing the effects of lean on production costs with evidence from the F-22 program. Journal of Operations Management 27 (1), 23–44.

Brusco, M., Singh, R., Cradit, J.D., Steinley, D., 2017. Cluster analysis in empirical OM research: survey and recommendations. International Journal of Operations & Production Management 37 (3), 300–320.

Brusco, M., Steinley, D., Cradit, J.D., Singh, R., 2012. Emergent clustering methods for empirical OM research. Journal of Operations Management 30 (6), 454–466.

Burbidge, J.B., Magee, L., Robb, A.L., 1988. Alternative transformations to handle extreme values of the dependent variable. Journal of the American Statistical Association 83 (401), 123–127.

Calantone, R., Vickery, S.K., 2009. Special topic forum on using archival and secondary data sources in supply chain management research. Journal of Supply Chain Management 45 (2), 94–95.

Cambridge Dictionary, 2016. Meaning of “responsiveness” in the English Dictionary. http://dictionary.cambridge.org/dictionary/english/responsiveness. Accessed 28 August 2016.

Cariou, P., 2011. Is slow steaming a sustainable means of reducing CO2 emissions from container shipping? Transportation Research Part D: Transport and Environment 16 (3), 260–264.

Cecere, L., 2017. BASF: A Story of a Supply Chain Leader. http://www.supplychainshaman.com/supply-chain-2/supply-chain-excellence/basf-a-story-of-a-supply-chain-leader/. Accessed 13 April 2017.

Chavez, R., Yu, W., Jacobs, M., Fynes, B., Wiengarten, F., Lecuna, A., 2015. Internal lean practices and performance: The role of technological turbulence. International Journal of Production Economics 160, 157–171.

Chen, I.J., Paulraj, A., Lado, A.A., 2004. Strategic purchasing, supply management, and firm performance. Journal of Operations Management 22 (5), 505–523.

Childerhouse, P., Aitken, J., Towill, D., 2002. Analysis and design of focused demand chains. Journal of Operations Management 20 (6), 675–689.

Childerhouse, P., Towill, D., 2000. Engineering supply chains to match customer requirements. Logistics Information Management 13 (6), 337–346.

Chopra, S., Sodhi, M.S., 2014. Reducing the risk of supply chain disruptions. MIT Sloan Management Review 55 (3), 73–80.

Christopher, M., Gattorna, J., 2005. Supply chain cost management and value-based pricing. Industrial Marketing Management 34 (2), 115–121.

Christopher, M., Lowson, R., Peck, H., 2004. Creating agile supply chains in the fashion industry. International Journal of Retail & Distribution Management 32 (8), 367–376.

Christopher, M., Peck, H., Towill, D., 2006. A taxonomy for selecting global supply chain strategies. The International Journal of Logistics Management 17 (2), 277–287.

Christopher, M., Towill, D., 2002. Developing market specific supply chain strategies. The International Journal of Logistics Management 13 (1), 1–14.

Christopher, M., Towill, D., Aitken, J., Childerhouse, P., 2009. Value stream classification. Journal of Manufacturing Technology Management 20 (4), 460–474.

Clarke, B., Fokoue, E., Zhang, H.H., 2009. Principles and theory for data mining and machine learning. Springer, New York, USA.

CNN, 2016. Gap still getting clobbered by 'fast fashion'. http://money.cnn.com/2016/05/09/news/companies/gap-sales-decline/index.html. Accessed 4 September 2017.

Cooil, B., Keiningham, T.L., Aksoy, L., Hsu, M., 2007. A longitudinal analysis of customer satisfaction and share of wallet: Investigating the moderating effect of customer characteristics. Journal of Marketing 71 (1), 67–83.

Cook, D.O., Kieschnick, R., McCullough, B.D., 2008. Regression analysis of proportions in finance with self selection. Journal of Empirical Finance 15 (5), 860–867.

Craighead, C.W., Blackhurst, J., Rungtusanatham, M.J., Handfield, R.B., 2007. The severity of supply chain disruptions: design characteristics and mitigation capabilities. Decision Sciences 38 (1), 131–156.

Croom, S., Christensen, W.J., Germain, R., Birou, L., 2007. Variance vs average: supply chain lead-time as a predictor of financial performance. Supply Chain Management: An International Journal 12 (5), 349–357.

Damanpour, F., 1992. Organizational size and innovation. Organization studies 13 (3), 375–402.

de Leeuw, S., van den Berg, J., 2011. Improving operational performance by influencing shopfloor behavior via performance management practices. Journal of Operations Management 29 (3), 224–235.

de Paepe, P., McLinn, J., Porter, M., 2015. Responding to oil price volatility in the chemical industry. http://www.bain.com/publications/articles/responding-to-oil-price-volatility-in-the-chemical-industry.aspx. Accessed 5 April 2017.

de Treville, S., Biçer, I., Chavez-Demoulin, V., Hagspiel, V., Schürhoff, N., Tasserit, C., Wager, S., 2014a. Valuing lead time. Journal of Operations Management 32 (6), 337–346.

de Treville, S., Schürhoff, N., Trigeorgis, L., Avanzi, B., 2014b. Optimal Sourcing and Lead-Time Reduction under Evolutionary Demand Risk. Production and Operations Management 23 (12), 2103–2117.

de Treville, S., Shapiro, R.D., Hameri, A.-P., 2004. From supply chain to demand chain: the role of lead time reduction in improving demand chain performance. Journal of Operations Management 21 (6), 613–627.

Dibb, S., Simkin, L., 2009. Implementation rules to bridge the theory/practice divide in market segmentation. Journal of Marketing Management 25 (3-4), 375–396.

Dolnicar, S., Grün, B., 2008. Challenging “factor–cluster segmentation”. Journal of Travel Research 47 (1), 63–71.

Donaldson, L., 2001. The contingency theory of organizations. Sage, Thousand Oaks, CA.

Droge, C., Jayaram, J., Vickery, S.K., 2004. The effects of internal versus external integration practices on time-based performance and overall firm performance. Journal of Operations Management 22 (6), 557–573.

Duda, R.O., Hart, P.E., Stork, D.G., 2012. Pattern classification. John Wiley & Sons, New York, USA.

Elgazzar, S.H., Tipi, N.S., Hubbard, N.J., Leach, D.Z., 2012. Linking supply chain processes’ performance to a company’s financial strategic objectives. European Journal of Operational Research 223 (1), 276–289.

Everitt, B., Landau, S., Leese, M., Stahl, D., 2011. Cluster Analysis. Wiley, Chichester, UK.

Ferdows, K., Lewis, M.A., Machuca, J.A.D., 2004. Rapid-fire fulfillment. Harvard Business Review 82 (11), 104–110.

Ferrari, S., Cribari-Neto, F., 2004. Beta regression for modelling rates and proportions. Journal of Applied Statistics 31 (7), 799–815.

Firebaugh, G., 1978. A rule for inferring individual-level relationships from aggregate data. American sociological review 43 (4), 557–572.

Fisher, M.L., 1997. "What is the right supply chain for your product?". Harvard Business Review 75 (2), 105–117.

Foedermayr, E.K., Diamantopoulos, A., 2008. Market segmentation in practice: Review of empirical studies, methodological assessment, and agenda for future research. Journal of Strategic Marketing 16 (3), 223–265.

Forbes, 2015. Gap Inc Is Gradually Losing Its Share In The U.S. Apparel Market To Fast-Fashion Counterparts. https://www.forbes.com/sites/greatspeculations/2015/07/15/gap-inc-is-gradually-losing-its-share-in-the-u-s-apparel-market-to-fast-fashion-counterparts/#72735552b0e1. Accessed 5 September 2017.

Fraley, C., Raftery, A.E., 2002. Model-based Clustering, Discriminant Analysis and Density Estimation. Journal of the American Statistical Association 97 (458), 611–663.

Fuller, J., O'Conor, J., Rawlinson, R., 1993. Tailored logistics: the next advantage. Harvard Business Review 71 (3), 87–98.

Gartner, I., 2016a. For Supply Chain Executives: How Segmentation Supports New Growth and Efficiencies. https://www.gartner.com/doc/3270717/supply-chain-executives-segmentation-supports. Accessed 5 October 2016.

Gartner, I., 2016b. The Hierarchy of Supply Chain Metrics: Diagnosing Your Supply Chain Health. https://www.gartner.com/doc/3083323/hierarchy-supply-chain-metrics-diagnosing. Accessed 10 July 2016.

Gligor, D., Esmark, C.L., Holcomb, M.C., 2015. Performance outcomes of supply chain agility: when should you be agile? Journal of Operations Management 33 (1), 71–82.

Gligor, D., Holcomb, M.C., Stank, T.P., 2013. A multidisciplinary approach to supply chain agility: Conceptualization and scale development. Journal of Business Logistics 34 (2), 94–108.

Gligor, D., 2015. The Role of Supply Chain Agility in Achieving Supply Chain Fit. Decision Sciences 47 (3), 524–553.

Gligor, D., 2017. Re-Examining Supply Chain Fit: An Assessment of Moderating Factors. Journal of Business Logistics.

Godfrey, L., 2009. Bootstrap Methods for Regression Models with Non-IID Errors, in: Godfrey, L. (Ed.), Bootstrap Tests for Regression Models. Springer, Cham, Switzerland, pp. 177–217.

Godsell, J., Diefenbach, T., Clemmow, C., Towill, D., Christopher, M., 2011. Enabling supply chain segmentation through demand profiling. International Journal of Physical Distribution & Logistics Management 41 (3), 296–314.

Godsell, J., Harrison, A., Emberson, C., Storey, J., 2006. Customer responsive supply chain strategy: An unnatural act? International Journal of Logistics 9 (1), 47–56.

Goldsby, T.J., Griffis, S.E., Roath, A.S., 2006. Modeling lean, agile, and leagile supply chain strategies. Journal of Business Logistics 27 (1), 57–80.

Goldsby, T.J., Martichenko, R., 2005. Lean six sigma logistics: Strategic development to operational success. J. Ross, Plantation, USA.

Grosse-Ruyken, P.T., Wagner, S.M., 2010. Does supply chain “Fit” matter to investors. Supply Chain Quarterly 4 (4), 44–50.

Guiffrida, A.L., Nagi, R., 2006. Cost characterizations of supply chain delivery performance. International Journal of Production Economics 102 (1), 22–36.

Habermann, M., Blackhurst, J., Metcalf, A.Y., 2015. Keep your friends close? Supply chain design and disruption risk. Decision Sciences 46 (3), 491–526.

Hausman, J.A., 1978. Specification tests in econometrics. Econometrica 46 (6), 1251–1271.

Hendricks, K.B., Singhal, V.R., 2003. The effect of supply chain glitches on shareholder wealth. Journal of Operations Management 21 (5), 501–522.

Hendricks, K.B., Singhal, V.R., 2005. Association between supply chain glitches and operating performance. Management Science 51 (5), 695–711.

Ho, C.-F., Tai, Y.-M., Chi, Y.-P., 2005. A structural approach to measuring uncertainty in supply chains. International Journal of Electronic Commerce 9 (3), 91–114.

Ho, W., Zheng, T., Yildiz, H., Talluri, S., 2015. Supply chain risk management: a literature review. International Journal of Production Research 53 (16), 5031–5069.

Hofmann, D.A., 1997. An overview of the logic and rationale of hierarchical linear models. Journal of Management 23 (6), 723–744.

Holweg, M., Miemczyk, J., 2003. Delivering the ‘3-day car’—the strategic implications for automotive logistics operations. Journal of Purchasing and Supply Management 9 (2), 63–71.

Holweg, M., 2005. The three dimensions of responsiveness. International Journal of Operations & Production Management 25 (7), 603–622.

Hong, S., Musso, C., Simons, T.J., 2015. Oil-price shocks and the chemical industry: Preparing for a volatile environment. http://www.mckinsey.com/industries/chemicals/our-insights/oil-price-shocks-and-the-chemical-industry-preparing-for-a-volatile-environment. Accessed 5 April 2017.

IASB, 2016. IAS Standard 1: Presentation of Financial Statements. http://www.ifrs.org/IFRSs/Pages/IFRS.aspx. Accessed 22 November 2016.

Infineon Technologies AG, 2006. Annual Report. https://www.infineon.com/dgdl/2006_IFX_20-F.pdf?fileId=db3a3043324cae8c01326323efe339cc. Accessed 5 September 2017.

Jian, M., Fang, X., Jin, L.-q., Rajapov, A., 2015. The impact of lead time compression on demand forecasting risk and production cost: A newsvendor model. Transportation Research Part E: Logistics and Transportation Review 84, 61–72.

Ketchen, D.J., Shook, C.L., 1996. The application of cluster analysis in strategic management research: an analysis and critique. Strategic Management Journal 17 (6), 441–458.

Ketokivi, M., McIntosh, C.N., 2017. Addressing the endogeneity dilemma in operations management research: Theoretical, empirical, and pragmatic considerations. Journal of Operations Management 52, 1–14.

Kinkel, S., Maloca, S., 2009. Drivers and antecedents of manufacturing offshoring and backshoring - A German perspective. Journal of Purchasing and Supply Management 15 (3), 154–165.

Kotsiantis, S.B., 2007. Supervised Machine Learning: A Review of Classification Techniques, in: Proceedings of the 2007 conference on Emerging Artificial Intelligence Applications in Computer Engineering: Real Word AI Systems with Applications in eHealth, HCI, Information Retrieval and Pervasive Technologies. IOS Press, Amsterdam, The Netherlands, pp. 3–24.

LaHuis, D.M., Hartman, M.J., Hakoyama, S., Clark, P.C., 2014. Explained variance measures for multilevel models. Organizational Research Methods 17 (4), 433–451.

Langenberg, K.U., Seifert, R.W., Tancrez, J.-S., 2012. Aligning supply chain portfolios with product portfolios. International Journal of Production Economics 135 (1), 500–513.

Lee, H.L., 2002. Aligning Supply Chain Strategies with Product Uncertainties. California Management Review 44 (3), 105–119.

Lee, H.L., 2004. The triple-A supply chain. Harvard Business Review 82 (10), 102–113.

Liaw, A., Wiener, M., 2002. Classification and regression by randomforest. R News 2 (3), 18–22.

Lovell, A., Saw, R., Stimson, J., 2005. Product value-density: managing diversity through supply chain segmentation. The International Journal of Logistics Management 16 (1), 142–158.

Mackelprang, A.W., Nair, A., 2010. Relationship between just-in-time manufacturing practices and performance: A meta-analytic investigation. Journal of Operations Management 28 (4), 283–302.

Mansfield, E., 1993. The diffusion of flexible manufacturing systems in Japan, Europe and the United States. Management Science 39 (2), 149–159.

Mason-Jones, R., Naylor, B., Towill, D., 2000. Lean, agile or leagile? Matching your supply chain to the marketplace. International Journal of Production Research 38 (17), 4061–4070.

Mayer, S., Thiry, E., Frank, C.B., 2009. 6th European AT Kearney/ELA Logistics Study 2008/2009: Supply Chain Excellence Amidst the Global Economic Crisis.

Merschmann, U., Thonemann, U.W., 2011. Supply chain flexibility, uncertainty and firm performance: An empirical analysis of German manufacturing firms. International Journal of Production Economics 130 (1), 43–53.

Milligan, G.W., 1996. Clustering validation: results and implications for applied analyses, in: Arabie, P., Hubert, L.J., de Soete, G. (Eds.), Clustering and classification. World Scientific, Singapore, pp. 341–375.

Narasimhan, R., Swink, M., Kim, S.W., 2006. Disentangling leanness and agility: an empirical investigation. Journal of Operations Management 24 (5), 440–457.

Naylor, B., Naim, M.M., Berry, D., 1999. Leagility: integrating the lean and agile manufacturing paradigms in the total supply chain. International Journal of Production Economics 62 (1), 107–118.

Ngai, E.W.T., Xiu, L., Chau, D.C.K., 2009. Application of data mining techniques in customer relationship management: A literature review and classification. Expert Systems with Applications 36 (2), 2592–2602.

Olhager, J., 2003. Strategic positioning of the order penetration point. International Journal of Production Economics 85 (3), 319–329.

Ospina, R., Ferrari, S., 2012. A general class of zero-or-one inflated beta regression models. Computational Statistics & Data Analysis 56 (6), 1609–1623.

Papke, L., Woolridge, J., 1996. Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. Journal of Applied Econometrics 11, 619–632.

Payne, T., Peters, M.J., 2004. What is the right supply chain for your products? The International Journal of Logistics Management 15 (2), 77–92.

Peng, Y., Dong, M., Zuo, M.J., 2010. Current status of machine prognostics in condition-based maintenance: a review. The International Journal of Advanced Manufacturing Technology 50 (1), 297–313.

Perera, C., Zaslavsky, A., Christen, P., Georgakopoulos, D., 2014. Context aware computing for the internet of things: A survey. IEEE Communications Surveys & Tutorials 16 (1), 414–454.

Pettit, T.J., Fiksel, J., Croxton, K.L., 2010. Ensuring supply chain resilience: development of a conceptual framework. Journal of Business Logistics 31 (1), 1–21.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y., Podsakoff, N.P., 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. Journal of Applied Psychology 88 (5), 879–903.

Preacher, K.J., Zyphur, M.J., Zhang, Z., 2010. A general multilevel SEM framework for assessing multilevel mediation. Psychological Methods 15 (3), 209.

Protopappa-Sieke, M., Thonemann, U.W., 2017. Supply Chain Segmentation: Best-in-Class Cases, Practical Insights and Foundations. Springer, Cham, Switzerland.

Qi, Y., Boyer, K.K., Zhao, X., 2009. Supply chain strategy, product characteristics, and performance impact: Evidence from Chinese manufacturers. Decision Sciences 40 (4), 667–695.

Qi, Y., Zhao, X., Sheu, C., 2011. The Impact of Competitive Strategy and Supply Chain Strategy on Business Performance: The Role of Environmental Uncertainty. Decision Sciences 42 (2), 371–389.

Randall, T., Morgan, R.M., Morton, A.R., 2003. Efficient versus Responsive Supply Chain Choice: An Empirical Examination of Influential Factors. Journal of Product Innovation Management 20 (6), 430–443.

Randall, T., Ulrich, K., 2001. Product Variety, Supply Chain Structure, and Firm Performance: Analysis of the US Bicycle Industry. Management Science 47 (12), 1588–1604.

Reuters, 2017a. Emerging markets, online growth help Zara-owner Inditex outpace H&M. http://www.reuters.com/article/us-inditex-results/emerging-markets-online-growth-help-zara-owner-inditex-outpace-hm-idUSKBN16M0YP. Accessed 5 September 2017.

Reuters, 2017b. SolarWorld collapses as Europe's solar industry eclipsed by China. http://www.reuters.com/article/us-sma-solar-results/solarworld-collapses-as-europes-solar-industry-eclipsed-by-china-idUSKBN1870ZV. Accessed 5 September 2017.

Rexhausen, D., Pibernik, R., Kaiser, G., 2012. Customer-facing supply chain practices - The impact of demand and distribution management on supply chain success. Journal of Operations Management 30 (4), 269–281.

Roberts, M.R., Whited, T.M., 2013. Endogeneity in Empirical Corporate Finance, in: Constantinides, G.M., Harris, M., Stulz, R.M. (Eds.), Handbook of the Economics of Finance, Volume 2, Part A. Elsevier, Amsterdam, Netherlands, pp. 493–572.

Roscoe, S., Baker, P., 2014. Supply chain segmentation in the sporting goods industry. International Journal of Logistics Research and Applications 17 (2), 136–155.

Seifert, R.W., Langenberg, K.U., 2011. Managing business dynamics with adaptive supply chain portfolios. European Journal of Operational Research 215 (3), 551–562.

Seifert, R.W., Tancrez, J.-S., Biçer, I., 2016. Dynamic product portfolio management with life cycle considerations. International Journal of Production Economics 171, 71–83.

Selig, J.P., Preacher, K.J., 2008. Monte Carlo method for assessing mediation: An interactive tool for creating confidence intervals for indirect effects [Computer software]. http://quantpsy.org/. Accessed 26 May 2017.

Selldin, E., Olhager, J., 2007. Linking products with supply chains: testing Fisher's model. Supply Chain Management: An International Journal 12 (1), 42–51.

Shah, R., Ward, P.T., 2003. Lean manufacturing: context, practice bundles, and performance. Journal of Operations Management 21 (2), 129–149.

Sharma, N., Sahay, B.S., Shankar, R., Sarma, P.R., 2017. Supply chain agility: review, classification and synthesis. International Journal of Logistics Research and Applications 20 (6), 532–559.

Shepherd, C., Günter, H., 2006. Measuring supply chain performance: current research and future directions. International Journal of Productivity and Performance Management 55 (3/4), 242–258.

Simangunsong, E., Hendry, L.C., Stevenson, M., 2012. Supply-chain uncertainty: a review and theoretical foundation for future research. International Journal of Production Research 50 (16), 4493–4523.

Snijders, T.A.B., 2011. Multilevel analysis. Springer, Heidelberg, Germany.

Solarworld Industries AG, 2009. U.S. headquarters and largest solar module production facility in the Americas. https://www.solarworld-usa.com/about-solarworld/locations. Accessed 5 September 2017.

Sousa, R., Voss, C.A., 2008. Contingency research in operations management practices. Journal of Operations Management 26 (6), 697–713.

Steele, F., Goldstein, H., 2006. Multilevel models in psychometrics, in: C.R. Rao, S. Sinharay (Eds.), Psychometrics, vol. 26. Elsevier, Amsterdam, Netherlands, pp. 401–420.

Sugimori, Y., Kusunoki, K., Cho, F., Uchikawa, S., 1977. Toyota production system and kanban system materialization of just-in-time and respect-for-human system. The International Journal of Production Research 15 (6), 553–564.

Swafford, P., Ghosh, S., Murthy, N., 2006. The antecedents of supply chain agility of a firm: Scale development and model testing. Journal of Operations Management 24 (2), 170–188.

The Economist, 2009. The semiconductor industry - Under new management. http://www.economist.com/node/13405279. Accessed 5 September 2017.

The Economist, 2015. Faster, cheaper fashion. https://www.economist.com/news/business/21663221-rapidly-rising-super-cheap-irish-clothes-retailer-prepares-conquer-america-rivals-should. Accessed 4 September 2017.

Tukamuhabwa, B.R., Stevenson, M., Busby, J., Zorzini, M., 2015. Supply chain resilience: definition, review and theoretical foundations for further study. International Journal of Production Research 53 (18), 5592–5623.

Tuli, P., Shankar, R., 2015. Collaborative and lean new product development approach: a case study in the automotive product design. International Journal of Production Research 53 (8), 2457–2471.

van de Ven, A., Ganco, M., Hinings, C., 2013. Returning to the frontier of contingency theory of organizational and institutional designs. Academy of Management Annals 7 (1), 393–440.

van der Leeden, R., Meijer, E., Busing, F., 2008. Resampling multilevel models, in: de Leeuw, J., Meijer, E. (Eds.), Handbook of Multilevel Analysis. Springer, New York City, USA, pp. 401–433.

Venkatraman, N., 1989. The concept of fit in strategy research: Toward verbal and statistical correspondence. Academy of management Review 14 (3), 423–444.

Verhoef, P.C., Spring, P.N., Hoekstra, J.C., Leeflang, P.S.H., 2003. The commercial use of segmentation and predictive modeling techniques for database marketing in the Netherlands. Decision Support Systems 34 (4), 471–481.

Verma, M., Verter, V., 2010. A lead-time based approach for planning rail–truck intermodal transportation of dangerous goods. European Journal of Operational Research 202 (3), 696–706.

Vijayasarathy, L.R., 2010. Supply integration: An investigation of its multi-dimensionality and relational antecedents. International Journal of Production Economics 124 (2), 489–505.

Wagner, S.M., Grosse-Ruyken, P.T., Erhun, F., 2012. The link between supply chain fit and financial performance of the firm. Journal of Operations Management 30 (4), 340–353.

Wangenheim, F., Bayon, T., 2004. Satisfaction, loyalty and word of mouth within the customer base of a utility provider: Differences between stayers, switchers and referral switchers. Journal of Consumer Behaviour 3 (3), 211–220.

Wedel, M., 2000. Market segmentation: Conceptual and methodological foundations. Springer, New York, USA.

Yu, K., Cadeaux, J., Luo, B.N., 2015. Operational flexibility: Review and meta-analysis. International Journal of Production Economics 169, 190–202.

Zotteri, G., Kalchschmidt, M., 2007. A model for selecting the appropriate level of aggregation in forecasting processes. International Journal of Production Economics 108 (1), 74–83.

Curriculum Vitae

Christian Joachim Freiherr von Falkenhausen accomplished his secondary education at the Brentwood College School in Mill Bay, British Columbia, Canada in 2008. Subsequently, he studied business and economics at the University of Exeter, UK. After receiving his Bachelor's degree in 2011, he enrolled at the University of Mannheim, Germany, to purse a Master's degree in business studies. Following his graduation in 2014, he commenced his doctoral studies at the Chair of Logistics and Supply Chain Management of the University of Mannheim where he was employed as a research assistant.