SUPPLY CHAIN RESILIENCE – INFLUENCE OF SUPPLY CHAIN CAPABILITIES AND STRATEGIES ON AGILITY AND ROBUSTNESS

BY

CHRISTOPH ALEXANDER PICKERT

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF ENGINEERING (LOGISTICS AND SUPPLY CHAIN SYSTEM ENGINEERING)

SIRINDHORN INTERNATIONAL INSTITUTE OF TECHNOLOGY
THAMMASAT UNIVERSITY

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A Thesis Presented

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Abstract

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Recent catastrophic events such as the Japanese Earthquake, Hurricane Katarina or the Ukraine Crisis revealed the weaknesses of current supply chain configurations, which are often too lean and vulnerable to withstand frequent external shocks in today's uncertain business environment. While the need exists to develop more resilient supply chains, it is still unclear for managers and companies how resilience can be achieved and how different capabilities foster or decrease resilience in a supply chain network. This thesis investigates resilience by examine the effects of certain capabilities on the two dimensions of resilience, agility and robustness, and the effect resilience, has on the performance of the supply chain. Survey data from Thailand based companies have been collected in order to test the hypothesized relations of the conceptual framework by employing Structured Equation Modeling (SEM). The analysis showed that certain capabilities have a strong positive effect on the resilience of a supply chain and that agility as well as robustness shows strong positive influence on the supply chain performance. The empirical results help practitioners to understand how a more resilient supply chain can be established by fostering the development of certain identified capabilities.

Keywords: Agility, Robustness, Structured Equation Modeling (SEM), Supply Chain Resilience, Supply Chain Management

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Abbreviations

AGFI	Adjusted-Goodness-of-Fit-Index
AGT	Agility
AVE	Average Variance Extracted
CFA	Confirmatory Factor Analysis
CFI	Comparative-Fit-Index
CITC	Corrected Item-to-Total Correlation
CR	Critical Ratio
d.f.	Degrees of Freedom
EFA	Exploratory Factor Analysis
EM	Expectation-Maximization
FIML	Full Information Maximum Likelihood
FR	Factor Reliability
GFI	Goodness-of-Fit-Index
GLS	Generalized Least Squares
IFI	Incremental-Fit-Index
IIC	Inter-Item Correlation
IMC	Information Management Capabilities
ITC	Item-to-Total Correlation
KMO	Kaiser-Meyer-Olkin
KS	Kolmogorov-Smirnov
LISREL	Linear Structural Relations
MAR	Missing at Random
MCAR	Missing Completely at Random
ML	Maximum Likelihood
MSA	Measure of Sampling Adequacy
NFI	Normed-Fit-Index
NMAR	Not Missing at Random
PCA	Principal Component Analysis
PLS	Partial Least Squares
RBN	Robustness

RMC	Risk Management Capabilities
RMR	Root Mean Square Residual
RNI	Relative-Noncentrality-Index
RSMEA	Root-Mean-Square-Error of approximation
SC	Supply Chain
SCM	Supply Chain Management
SCO	Supply Chain Orientation
SCP	Supply Chain Performance
SCPV	Supply Chain Process Variability
SCRI	Supply Chain Resilience Index
SCS	Supply Chain Strategies
SE	Standard Error of Estimates
SEM	Structured Equation Modeling
SMC	Squared Multiple Correlation
SRMR	Standardized Root Mean Square Residual
SW	Shapiro-Wilk
TLI	Tucker-Lewis-Index

Chapter 1
Introduction

In March 2011 TOYOTA and a big number of other companies, which were focusing on tightly managed supply chains and disciplined operations received a wake-up call, when an earthquake reaching the magnitude of 9.0 on the Richter scale in conjunction with an enormous tsunami struck Japan. While worldwide news coverage was focusing on the impending danger of the melting down nuclear power plant of Fukushima, companies like TOYOTA slowly began to realize the degree to what this natural disaster compromises its global business. The company has focused for years on an efficiency driven operation management and a strictly managed supply chain. Thus slack and waste were removed from its operations, just-in-time delivery became standard and inventory levels were reduced to a minimum. However these practices enabled TOYOTA to become the bestselling car manufacturer worldwide, the company was now more prone to supply chain disruptions than it has ever expected. A reduction of its supply base, single sourcing initiatives and minimum buffer stocks have been payed off in a stable environment but now caused severe problems. The shutdown of a few car part suppliers grounded TOYOTA's assembly lines worldwide within a few days and lead to a global decline in March production of about 30%. It took TOYOTA more than six month to recover from the disruption and return to the pre-disaster stage by delivering products in required volumes (Marchese and Lam, 2014; SC Digest, 2012).

Although the 2011 earthquake and the subsequent tsunami stand out due to their severity and the regional focus on one of world's economic centers, other similar events clearly show, that companies have to operate in an increasingly unpredictable and risky environment (Christopher and Peck, 2004). Among others some of the recent disruptions were natural disasters such as Hurricane Katrina 2005, Turkey earthquake 2012, Thailand flood 2011, diseases like SARS 2003, bird flu 2005, swine flu 2009, terrorist attacks in New York 2001, Madrid 2004, London 2005 political risks like the Arab Spring 2010 or the Ukraine Crisis 2014 as well as economic recessions or the global financial crisis 2008 (PWC, 2013; Soni, Jain and Kumar, 2014). Among researchers and practitioners general acceptance exists, that the increasing global interconnectedness and complexity of supply chains, shortened product life cycles as well as the strong focus on operational efficiency make supply chains increasingly prone and vulnerable to disruptions (Bogataj and Borgata, 2007; Myers, Borghesi and Russo, 2006). Owing to these developments the concept of supply chain resilience, which describes the ability of a supply chains to resist external shocks and return quickly to its desired state, emerged and has increasingly become more important among professionals as well as researchers (Marchese and Lam, 2014; Wieland and Wallenburg, 2013).

Having experienced the major influences of a supply chain disruption TOYOTA began to reconsider its approach of efficiency driven supply chains and redesigned its supply chain in a way to reduce recovery time from disruptions to a maximum of two weeks. In order to fulfill this goal TOYOTA's supply system did not just have to be better and faster in recovering from disasters, above all it has to obtain the ability to anticipate problems in order to become more resilient against certain catastrophic events. The automaker's answer to these experiences was an initiative to make its supply chain more robust and to reduce its exposure to vulnerabilities. Potential vulnerabilities and threats were analyzed and ranked according to their impact and likelihood. The firm closely worked together with about 500 suppliers to develop a better visibility throughout the entire supply chain, to distribute production across several locations and companies as well as to increase buffer stock. Furthermore TOYOTA redesigned about 5000 car components and increased the commonality of these parts to be assembled for different products. By doing so TOYOTA increased the order volumes and encouraged the supplier to build additional production facilities, serving as a hedge if one production sides breaks down (Chang-Ran, 2011; Marchese and Lam, 2014).

By pursuing these measures TOYOTA developed a more anticipatory, prepared and agile supply network. However the case of the car manufacturer provides an extreme example of a problem many other companies are also experiencing, which have also been exposed to disruptions and suffered from their consequences. Companies throughout all different kinds of industries try to rework their supply chains, which were once incidentally formed and subsequently optimized, with the aim to design and reconfigure them for a better anticipation for disturbances and mitigation of their impacts (Marchese and Lam, 2014). Key drivers for this trend are certainly progresses in information and communication technology, as well as an increasingly volatile business environment and a strong globalization and interconnectedness of supply chain networks (Sheffi and Rice, 2005). The trend of building more resilient and anticipatory supply chains reflects a growing belief among professionals and scholars that supply chain management in recent years has focused to long on optimization. A decade long focus on optimization in order to reduce costs lead to supply networks, which are too lean and vulnerable to withstand frequent external shocks in today's uncertain business environment (Marchese and Lam, 2014). For companies, the implication is very clear: The competitiveness of an organization will heavily depend on the extent to which it can keep pace with the trend of designing and operating more robust and anticipatory supply chains. The need exists to develop more resilient supply chains, but it is still unclear for managers how the resilience can be achieved and how different capabilities foster or decrease resilience in a supply chain network (Ponomarov and Holcomb, 2009). Especially due to the fact that it is difficult to measure the return of investments in resilient SC measures and that it can took years until these measures are really needed, it is important for practitioners to have a sound understanding of the cause and effect relationships within the field of resilience. Practitioners need improved knowledge to analyze the elements that define and significantly influence the resilience of supply chains towards disruptions (Sheffi and Rice, 2005; Tang, 2006). The concept of resilient supply chain represents an alternative paradigm, which aims at enabling organizations to reduce the vulnerability of their supply chains. In contrast to the principles of the lean supply chain management, resilient supply chain management strategies promote a company's ability to compensate expected and unexpected risks and to quickly respond to disruptions and to minimize their negative impact (Park, 2011).

For the last 15 years studies from different disciplines have investigated the concept of resilience in academic research. Particular attention was usually placed on how an organization can manage its business processes and supply chain to make them robust and less prone to disruptions (Rice and Caniato, 2003; Tang, 2006). However most of the research about supply chain resilience has been focusing on the definition of the resilience domain, highlighting its relevance, and determine certain characteristics of resilient and robust supply chains and companies (Ponomarov and Holcomb, 2009; Sheffi and Rice, 2005; Hendricks and Singhal, 2005). According to Wieland and Wallenburg (2013) there is still a lack of understanding concerning the key elements of supply chain resilience and their relationships between each other.

In addition, only a small amount of studies, are dealing with the investigation and identification of antecedents of resilience and address the consequences of and contributions of resilient measures on corporate success (Hohenstein et al., 2015). According to Ponomarov (2012) the academic literature lacks a substantiated theoretical foundation for the resilient frameworks as well as a quantitative justification due to their relative novelty. Wieland and Wallenburg (2013) are consistent with this perception and emphasize that a missing conceptualization of complex cause-effect relations between the antecedents and consequences as well as between related elements constitutes a serious gap in academic research. Based on the previous insights, a deeper appreciation of an organization's supply chain resilience, as well as its most important antecedents and consequences is needed. (Ponomarov, 2012).

1.1. Statement of Purpose

Researchers like Durach, Wieland and Machuca (2015), Ponomarov and Holcomb (2009) or Hohenstein et al. (2015) call for more quantitative examination of qualitative proposed conceptual and theoretic frameworks of resilience in order to obtain reasonable guidelines and justification for the implementation in business practices. They claim that the future research should especially focus on the validation of the hypothetical relationships as well as their respective strength. Therefore the aim of this thesis is to make a contribution to these research issues by the development and empirical testing of an extensive conceptual model, which is combining the main antecedents of supply chain resilience as well as their consequences on the organizational level.

Hence this work examines the issue of resilience, which is of great importance in the field of supply chain management. In order to do so the study examines the causal effects certain organizational capabilities have on resilience and the impact resilience has on the performance of a supply chain. A purposefully distinction is made between the proactive (robustness) and reactive (agility) component of resilience. Thereby the thesis should provide practitioners and scholars with a better understanding of the supply chain resilience domain by answering the following research questions.

1) What is the relative relevance of certain capabilities for establishing the proactive (robustness) and reactive (agility) dimension of supply chain resilience?
2) What effect do certain resilient supply chain strategies have on agility and robustness?
3) What influences do the resilience dimensions agility and robustness have on supply chain performance?

1.2. Contribution of the Thesis

As described in the previous chapters this thesis will make a contribution to the body of literature by suggesting and assessing a conceptual model of SC-resilience. It will extend the theoretical models and frameworks of previous researchers by incorporating the influence of supply chain strategies and by an explicit distinction between agility and robustness and the influence of these dimensions on the performance of the supply chain. By empirically assessing the impact certain organizational capabilities have on the resilience of a supply chain practitioners will be able to understand how to establish a more resilient supply chain by fostering the development of certain identified capabilities. Furthermore the incorporation of supply chain strategies will enable companies to revise their supply chain strategy and align it with the desired resilience goals. The explicit distinction between robustness and agility furthermore helps practitioners to better align capabilities and strategies to their business environment. If companies are operating in an environment with fast moving customer and market requirements they could intensify investments in capabilities aimed at increasing agility rather than spending money for measures increasing robustness, which may be the wrong feature in the respective environment. By means of this research practitioners might thus be able to identify the influence certain capabilities and strategies have on the resilience and establish an individual mix of those to obtain a competency mix tailored to the specific business requirements. Professional researchers will benefit from a new theoretical framework linking antecedents and consequences of supply chain resilience and thus contributing to a better and deeper understanding of the complex topic of resilience. Especially the consideration of strategies and the empirical testing of their influence on resilience will increase understanding and allow further studies in this field. By testing the influence of a wide variety of influential factors researchers benefit by obtaining a holistic picture of the resilience and also a more detailed view regarding the effect of agility and robustness on the supply chain performance. Overall the research will lead to a better understanding of the resilience domain and thus help companies establishing more resilient supply chains as well as enable researchers with a holistic picture to better address further topics within the field of supply chain resilience.

1.3. Thesis Organization

The thesis is organized in six chapters and follows a 7-step approach of structured equation modeling as proposed by Weiber and Mühlhaus (2014).

The first chapter serves as an introduction and explains the motivation and objectives of the study. The second chapter provides an overview of selected scientific papers in the field of supply chain resilience is provided. Based on the relevant literature the hypotheses are developed and summarized in a conceptual framework at the end of the second chapter. The third chapter describes the applied scientific method of SEM and explains the experimental setup and the conduct of the investigation.

Subsequently in the fourth chapter the data is analyzed as well as evaluated and the results are presented. These results are critically discussed in chapter five. The sixth chapter presents a summary of the work and gives an outlook on further research areas as well as the contributions of this thesis.

According to Weiber & Mühlhaus (2014) this work follows a 7-step approach for application of SEM, which is also reflected in the chapter organization. In a first step, the hypotheses are developed (Chapter 2.3), which are transferred into a conceptual model (Chapter 2.4). Then, the developed constructs are operationalized in order to raise the data with the help of a survey (Chapter 3.3.2). After the data has been collected, the structural equation model is firstly assessed based on the quality of the measurement model (Chapter 4.3) and secondly based on the quality of the structural model (Chapter 4.4). After the testing of the quality criteria the actual model estimations and evaluations are conducted (Chapter 4.6) and the obtained results are eventually interpreted (Chapter 5).

Chapter 2
Literature Review

2.1. Definitions

2.1.1. Supply Chain Management

The term supply chain management (SCM) was coined by the logistics consultants Oliver and Webber and first mentioned in the literature in the 1980s (Gomm, 2008). The authors emphasize that the supply chain should be seen as a cohesive units and that strategic decisions on a high hierarchical level is needed to efficiently control the chain (Oliver and Webber, 2012). However, research dealing with the integration and coordination of various functional units along the supply chain, began long before the term SCM was coined (Felea and Albăstroiu, 2013). In the scientific literature, these approaches are identified by specific theoretical contributions of some authors in various research areas such as logistics, marketing, or operations research.

Particularly noteworthy are the publications of Bowersox (1969) concerning collaboration and cooperation, Hanssmann (1959) for inventory management in production and distribution networks or Forrester's (1958) well-known publication on dynamic systems in production- and distribution networks. Since the coining of the SCM concept in the 1980s, however, the interest of researchers and practitioners has continuously increased with respect to the research area of SCM (La Londe, 1997).

This is mainly due to the intensification of global competition and the recognition of companies that can no longer stay competitive isolated from their suppliers and that a cross-company cooperation represents a significant competitive advantage (Felea and Albăstroiu, 2013). The applicability of the SCM has been heavily explored during the last two decades, which led to the emergence of a variety of different approaches and definitions (Gomm, 2008).

Some authors define SCM in operational terms while taking into account the material and product flows, other define it as management philosophy and others refer to SCM as a of the management process (Tyndall et al., 1998). According to Christopher (1994) a supply chain is a network of organizations, which are involved in the various processes and activities that create added value in the form of products or services to the end customer through upstream and downstream connections. Chopra and Meindl (2007) write that a supply chain is made up of all parties who are directly or indirectly involved in meeting customer demand. Mentzer et al. (2001) describe a supply chain as an assembly of three or more instances that are directly involved in the upstream or downstream flows of products, services, finance or information from a source to the customer. Since the introduction of SCM in the 1980s and the original motivation to control the goods and information flows along the supply chain, the SCM has however consistently developed and more and more aspects are taken into account in the management of supply chains (Russel and Taylor, 2009).

2.1.2. Supply Chain Resilience

As Resilience is an emerging field in the SCM a generally accepted and commonly used definition for this multi-disciplinary and multi-faceted does not exist (Hohenstein et al., 2015). Rice and Caniato (2003, p. 25) took the first attempts to explain the resilience within the field SCM and developed their definition from an organizational point of view from. According to their definition resilience in SCM can be regarded as the "ability to react to an unexpected disruption, such as one caused by a terrorist attack or a natural disaster, and restore normal operations." In contrast Christopher and Peck (2004) as well as Sheffi and Rice (2005) define resilience as the ability of a system to withstand external shocks and quickly restore the initial state or even achieve a more aspirational state in the aftermath of a disturbance. The probably most extensive and theoretically founded definition of resilience has been established by Ponomarov and Holcomb (2009), who follow a multidisciplinary approach. According to Ponomarov and Holcomb (2009, p. 131) supply chain resilience is defined as "The adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function."

Hohenstein et al. (2015) found out in an extensive literature review about supply chain resilience that although numerous other researcher have suggested their own definitions of supply chain resilience, these definitions consists only of slight modifications or combinations of previous definitions (Jüttner and Maklan, 2011; Ponis and Koronis, 2012; Wieland, 2013) or relate to other authors (Blackhurst, Kaitlin and Craighead, 2011; Golgeci and Ponomarov, 2013; Pettit, Croxton and Fiksel, 2013). Thus in this paper follows the definition provided by Ponomarov and Holcomb (2009, p. 131) and regards resilience mainly as the ability to „prepare for unexpected events, respond to disruptions, and recover from them". According to these three stages of preparing, responding and recovering a fourth stage of improving (achieving a more desirable state after disruption) is emphasized by Christopher and Peck (2004). Most of the research concerning supply chain resilience stresses the differentiation into these stages, whereas response and recovery can be regarded as the reactive dimension, while readiness and improvement or growth can be regarded as the proactive dimension (Hohenstein et al., 2015). This study follows the concept of a separation of resilience in a proactive and reactive dimension and according to Wieland and Wallenburg (2013) refers to these two dimensions in the following as agility and robustness. Agility is defined as a concept, which is mainly based on flexibility and responsiveness (Braunscheidel and Suresh, 2009) and marked by obligatory information enrichment consultative forecast mechanism in order to react quickly to changing requirements or scenarios (Fernie, Sparks and McKinnon, 2010). Important elements of agility are visibility (e.g. communication, information sharing), velocity in order to achieve responsiveness as well as recovery (Christopher and Peck, 2004; Blackhurst, Kaitlin and Craighead, 2011).

Robustness in contrast is defined as the proactive dimension of resilience (Shukla, Lalit and Venkatasubramanian, 2011) and as „the ability of a supply chain to resist change without adapting its initial stable configuration“ (Wieland and Wallenburg, 2012, p. 890). Furthermore robustness enables a supply chain to stay operational in the presence of disruptions (Meepetchdee and Shah, 2007) and it helps a supply chain to maintain a high level of performance under various scenarios (Harrison, 2005).

2.2. Research related to Resilience in Supply Chain Management

The literature related to the resilience domain of supply chains is extensive and covers several different areas of academic research. A strong scientific interest in the study of supply chain resilience could be observed after major disruptions like the 9/11 terror attacks or the tsunami in Thailand, which significantly affected the global economy (Christopher and Peck, 2004; Rice and Caniato, 2003; Sheffi and Rice, 2005). In the light of following disorders such as Hurricane Katrina or the nuclear catastrophe in Fukushima, it is not surprising that the resilience of supply chains is increasingly considered in scientific publications. According to Hohenstein et al. (2015) these developments show that the exploration of resilience will likely be intensified over the next years as supply chain resilience proved to be an important factor for companies' competitiveness.

A huge share of this body of literature is trying to define the concept of resilience, highlighting its importance, as well as identifying components and characteristics, which foster the resilience of a supply chain or a company (Ponomarov, 2012). In one of the first papers on SC-Resilience Sheffi and Rice (2005) provided a basis for further research in the field of resilience by discovering the commonalities between companies and supply chains that performed well during disruptions and distinguishing them from those that did not. The authors established a disruption profile, which allows graduating each disruption in eight distinct stages. Sheffi and Rice (2005) furthermore found out that redundancy and flexibility increase SC-Resilience and that increasing their flexibility is the most important step companies can take to fundamentally and efficiently increase their resilience. Hendricks and Singhal (2005) contribute to the understanding of supply chain disruptions by investigating the time pattern of abnormal stock price behavior caused by disruptions in terms of when it starts, how long it lasts and whether companies can recover quickly from such disruption. The paper examines, which effects disruptions of a company's supply chain have on the long-term stock price and the equity risks of the respective company. The authors conducted empirical research on the basis of a sample of 827 disruptions, which were communicated by companies from 1989-2000 and investigated the correlation between announced disruptions and stock price performance. By this empirical research they found out that the average abnormal stock returns of firms that experienced disruptions is about 40% lower than the stock returns of benchmark companies, that it does not matter what the cause of disruptions is and that disruptions have negative effects across all industry groups. A couple of years later, Hendricks, Singhal & Zhang (2009) similarly examined the effect of SC disturbances on operational slack, diversification and vertical relatedness on the stock market reaction. The outcomes result from the analysis of 307 SC disturbances that were announced within 1987-1998. Findings were that organizations that deal with more operational slacks in their SC had few negative stock market experience, while the scope of a business diversification seems to had no effect on stock market reaction. Organizations with geographically diversified experience tend to have a negative reaction, while organizations with a high vertical relatedness have less negative reaction. The two applied methods to evaluate abnormal returns, i.e. market model and portfolio matching model have similar outcomes, demonstrating that the stock market responds negatively to supply chain disturbances.

Ponomarov and Holcomb (2009) approach the topic of resilience from a more theoretical perspective and present an integrated perspective and a conceptual framework of resilience by conducting an extensive literature review in a multidisciplinary and multidimensional way. Their research contributes to a better understanding of the concept of resilience as well as to identify and address theoretical gaps in the existing literature. They developed a theoretical basis of resilience and came to the result, that the main elements of supply chain resilience and their relationships and the methodologies for managing these key elements lack a sound understanding. Another paper that deals with research concerning risk and resilience in supply chains by examining a case of the agri-food supply chain of ASDA PorkLink in Scotland was published by Leat and Revoredo-Giha (2013). The objective of the paper was to identify and classify the major risks that take part in establishing and maintaining a resilient agri-food SC with the main focus on the supply of a primary product and the inherent challenges that are faced. The paper demonstrates how risk management and cooperation with stakeholders lead to an increased SC-Resilience as well as that horizontal & vertical collaboration lead to reduced SC-vulnerability. Wagner and Bode (2006) investigate supply chain risks in greater detail and assess the relationship between supply chain vulnerability and supply chain risk in a cross-sectional survey among German companies. The authors examined the relationship between different supply chain characteristics -which are considered to increase the SC-vulnerability - and the impact on the performance from three kinds of supply chain disruptions. The study revealed that SC-characteristics, like a company's dependence on designated customers and suppliers, the extent of single sourcing, or the reliance on global sourcing initiatives are reasons for an organization's exposure to supply chain risks. Therefore the paper gives reason to ask for an acceptable risk-benefit trade-off for every company or supply chain setup.

Another focus of researchers within the topic of supply chain risk management and resilience is the identification and proposal of strategies for implementing resilient measures in supply chains. One early paper regarding this topic was published by

Christopher & Peck (2004). The paper focuses on the development of a managerial agenda for identification and management of supply chain risks while giving recommendations how to improve the overall resilience of supply chains. By following the guidelines developed in the paper companies should be able to better categorize risks and implement resilient SC-measures. Christopher & Peck (2004) applied a survey and case study approach and highlight the importance of collaboration, agility and the creation of a risk management culture as key enablers for SC-resilience. In contrast to the previous paper Tang (2006) applied a literature review and caste study methodology to determine different measures, which helped companies to increase the resilience of their supply chain and proceeding from that to propose a set of nine strategies, such as postponement, strategic stock or a flexible supply base, capable to foster the robustness of a company's supply chain. Although the resilience is increases by applying one or more of the mentioned strategies when disruptions occur, companies still have to reduce their exposure to risk according to Tang (2006).

A third stream within the field of resilience research is aiming at the evaluation of the effects different measures have on the overall resilience of a supply chain. In order to do so Carvalho, Azevedo and Cruz-Machado (2012) developed a conceptual framework that aims to analyze the coherences among agile and resilient approaches and SC performance and competitiveness. For the purpose of the conceptual framework, the performance of a supply chain is measured according to the operational performance, i.e. the assessment of its flexibility and responsiveness and the economic performance, meaning the evaluation of costs regarding inventory and redundancies in resources. The paper shows that the agile supply chain management approach pursues faster response to changes in markets and customer requirements, while the resilient approach is better designed to cope with disturbances in order to sustain supply chain competitiveness.
In a previous study Carvalho et al. (2011) already evaluate alternative supply chain scenarios for improving resilience and robustness in order to understand how mitigation strategies affect each supply chain's performance. For this purpose Carvalho et al. (2011) used simulation for the redesign of supply chain resilience and

testing flexibility (e.g. restructuring existing transport) as well as redundancy (e.g. additional stock) strategies. As a result, 6 scenarios were designed indicating the actual SC with and without redundancy and flexibility as well as the SC when affected by disruption with and without flexibility and redundancy. The performances were measured with total cost and the lead-time ratio, which is the ratio between actual and planned lead-time. The authors concluded that both strategies have a positive impact in reducing the effects of a disruption on a supply chain's performance, however flexibility strategies result in lower total costs for the supply chain compared to redundancy strategies. Roath et al. (1998) similarly simulate and benchmark supply chain performances considering varying circumstances of uncertainty and information exchange. For the simulation, an anticipatory and response-based supply chain is examined, both to be simulated under high and low demand. The to be compared variables within the supply chain are customer service, inventory performance by supply chain stage and total system inventory. The simulation demonstrated that the response-based supply chain resulted in having a better performance than the anticipatory and given a minimized demand uncertainty, a better supply chain performance can be achieved having a good customer service and fewer inventories. Qiang and Nagurney (2009) developed a supply chain model that analyses the demand and supply-side risks. Within this model, the demand was set random and the supply risks uncertain in the subjacent cost functions. The model is based on a generalization of available models adding several transportation techniques from manufacturers to retailers onwards to the demand markets. Furthermore, the study suggests a weighted SC performance and robustness measure that relies on the deduced network performance. Thun and Hoenig (2011) investigate the relevance of different risks in terms of their probability of occurrence and their potential impact on the supply chain in an empirical study in the German automobile industry. The results reveal that internal supply chain risks are regarded as being more likely to occur and that they would also have a greater impact on the SC than external risks. Furthermore, the results show that reactive supply chain risk management results in higher average value for disruptions resilience, whereas preventive supply chain risk management has higher values regarding flexibility or safety stocks. Companies having a low implementation degree of SC-Risk management instruments have lower average values in all of the investigated performance criteria. In a more recent study Soni, Jain & Kumar (2014) develop a single measure for quantifying supply chain resilience in order to facilitating the comparison between different supply chains. The merging of several factors into one single measure, the supply chain resilience index (SCRI), advocates the consideration of resilience aspects in supply chain design. Furthermore it enables practitioners and researchers to better compare and assess the resilience of supply chains and different companies, thus giving a decision support aid for evaluating and implementing resilience into supply chain management.

Although an extensive body of literature exists on the topic of resilience the majority of the published research on this topic concentrated on defining the concept of resilience (Sheffi and Rice, 2005), highlighting its importance (Hendricks and Singhal, 2005; Hendricks, Singhal and Zhang, 2009) or identifying certain characteristics, which have influence on the resilience of a supply chain (Thun and Hoenig, 2011). Most of the studies however examine certain characteristics, fostering SC-Resilience in an isolated research setup and do not link them with other important factors. Therefore there is still a lack of understanding concerning the most important components of the supply chain resilience and the relations between them (Wieland and Wallenburg, 2013). Moreover, only a small number of papers exist that deals with the identification and examination of antecedents and relates those capabilities with the results of resilience (Carvalho et al., 2011). According to Ponomarov (2012) the literature also lacks theoretical justification for the established frameworks of resilient supply chains and most of the research regarding the establishing of a deeper understanding of the resilience domain remains to be qualitative in nature (Ponomarov, 2012). Obvious gaps are the missing conceptualization of the complex cause-effect relationships between the different characteristics fostering resilience and the analysis between antecedents and consequences of supply chain resilience, as well as a necessity for an quantitative testing of suggested conceptual models (Ponomarov, 2012; Wieland and Wallenburg, 2013).

In recent years a few papers were published, which try to conceptualize resilience in supply chain management and empirically test the hypotheses by means of structural equation modeling, in order to contribute to a holistic understanding of complex cause-effect relationships. Wieland and Wallenburg (2013) investigate the effects logistic and supply chain competencies and capabilities of a company have on the resilience of their supply chain as well as the effect of resilience on supply chain's customer value. They distinguish between the proactive and reactive dimension of resilience and empirically test effect communication, cooperation, and integration have on agility and robustness. Wieland and Wallenburg (2013) showed that both communication and cooperation have a positive influence on agility, while robustness is only supported by communication capabilities and that integration does not have an effect on either one of the resilience dimensions. Furthermore they came to the conclusion that enhanced resilience, facilitated by investments in agility and robustness, increases customer value of a supply chain.

Lavastre, Gunasekaran, Spalanzani (2012) conducted a survey among 50 French companies with the aim to better understand and analyze management of business risks associated with supply chains. The authors investigated the effects the attitude towards risk, tools used in SC-Risk Management as well as techniques to minimize risk in supply chains have on the resilience and supply chain risk management of a company. The paper reveals that supply chain risk management has to be regarded as an inter-organizational management function and closely related to strategic and operational reality. Important antecedents of an effective risk management fostering resilience are collaboration and the establishment of joint and cross-company processes. Ponomarov (2012) also developed a conceptual model of supply chain resilience and tested the relation between antecedents of resilience and their impact on supply chain performance on the company level. He especially focused on the influence of certain capabilities on the overall resilience and performance of a supply chain and additionally integrated moderating factors in the holistic framework. Ponomarov (2012) proofed, that SC-Capabilities and information sharing capabilities have a direct positive influence on SC-Resilience and SC-Resilience in turn on SC-Performance. However the paper could not find out how supply chain risk management is linked with Resilience. Therefore the model proposes and proofs the fundamental interrelations between capabilities, resilience and performance, but still lacks he integration of risk management measures as well as other capabilities, which might have influence on the SC-Resilience.

This paper builds upon the conceptual frameworks developed by Ponomarov (2012), Wieland and Wallenburg (2013), Carvalho et al. (2012) as well as Lavastre, Gunasekaran, Spalanzani (2012). However the model of this paper is based on the work of the previously mentioned authors it combines the different approaches and findings and thereby establishes a new and improved conceptual framework of SC resilience. The originality of this thesis arises from the extension of Ponomarov's (2012) framework by the integration of two factors, namely Supply Chain Strategies and Risk Management Capabilities. Furthermore factors and moderating variables were excluded from the conceptual model as no influence of moderating effect on resilience could be observed in previous papers. The division of resilience in the agility and robustness dimension is a further new element in resilience research, as Wieland and Wallenburg (2013) only investigated the effect of integration, cooperation and communication on agility and robustness. Last but not least the thesis investigated the resilience domain in a different business environment. While previous studies focused on companies in developed countries, namely Germany and the US, this thesis focuses on companies from Thailand and thus a country with a higher risk profile due to its economic differences as well as geographical location.

2.3. Hypotheses Development

2.3.1. Antecedents of Supply Chain Resilience

The basis of this work is constituted by previous studies, which are investigating and considering supply chain capabilities in the context of a resource-oriented perspective (Zhao, Droge and Stank, 2001; Lynch, Keller and Ozment, 2000). In the existing Literature several logistics and supply chain-related functions are discussed and analyzed, which contribute to improvements in company performance and thereby create a sustainable competitive advantage (Lynch, Keller and Ozment, 2000; Zhao, Droge and Stank, 2001; Esper, Fugate and Davis, 2007; Olavarrieta and Ellinger, 1997). According to Ponomarov (2012) top companies purposefully promote and create this kind of supply chain capabilities to foster the performance and maintain advantages in competition. The empirical research results of Zhao et al. (2001) for example show that customer-oriented and information-oriented capabilities contribute substantially to the company's success. Interestingly, the research discovered that the information-oriented skills alone are not a distinguishing factor directly linked to the company's success. These are rather used for creating other features, which are harder to imitate for competitors. Merely the right combination of these skills enables the supply chain of a company to react appropriately to SC-interruptions and other challenges caused by an uncertain external business environment (Ponomarov, 2012). Christopher and Peck (2004, p. 13) also came to the conclusion that resilience should be purposefully designed in a supply chain and that „ ... there are certain features that, if engineered into a supply chain, can improve its resilience." This paper therefore investigates how the existence, the manifestation and the combination of certain supply chain capabilities influence the resilience of a supply chain and subsequently the firms' performance. The following section will review several capabilities which are mentioned in previous research and which are assumed to foster the resilience and hence the performance of the supply chain.

H1: Supply Chain capabilities and competencies have a positive effect on Agility.
H2: Supply Chain capabilities and competencies have a positive effect on Robustness.

2.3.1.1. Information System Capabilities

In order to achieve a high degree of agility and robustness, a company needs visibility to improve the identification of potential changes as well as speed to be able to respond quickly (Christopher and Peck, 2004). Therefore achieving this visibility is an important precondition for enabling companies to recognize and accurately respond to changes. Barratt and Oke (2007) show that visibility can be facilitated by investments in information management capabilities. Information sharing can foster both the visibility of changes or disruption as well as the speed managers can respond to them (Holweg and Pil, 2008; Wieland and Wallenburg, 2013). Information sharing can be described as “the extent to which critical and proprietary information is communicated to supply chain partners” (Li, 2005, p. 625). Especially against the background of more complex and global supply chains companies need to communicate for properly managing diverse risks within their networks (Wieland and Wallenburg, 2013). For this reason, the effective exchange of information between companies in a supply chain plays an important role for the internal and external risk reduction (Hallikas et al., 2004). Exchange of information on demand, supply, inventory and production schedules allows companies to establish a better understanding and visibility, which in turn promotes the general resilience of a supply chain (Christopher and Peck, 2004). According to Durach, Wieland & Machuca (2015) the degree of interaction and information exchange between the various supply chain partners is essential for establishing of robustness. Lavastre et al. (2012) indicate that efforts to improve transparency in the supply chain through the exchange of risk-related information is resulting in an increasing ability of a supply chain to avoid risk and enhance robustness.

H1a: Information System capabilities have a positive effect on Agility.
H1b: Information System capabilities have a positive effect on Robustness.

2.3.1.2. Supply Chain Orientation

For sufficiently taking into account the increasing complexity and uncertainty in today’s business environment as well as for enhancing efficiency and effectiveness, companies increasingly apply cooperative organizational structures (Achrol and Louis, 1988; Stank, Davis and Fugate, 2005). According to the resource dependency theory stronger relationships enable companies in uncertain times to skim off required resources from supply chain partners in order to effectively use resources and maintain competitiveness (Fynes, Burca and Marshall, 2004). Within a supply chain forming closer sustainable partnerships, e.g. with lead suppliers, can be regarded as an option of establishing governance mechanisms and to diminish uncertainty. In this way, a strategic supply chain orientation is becoming increasingly significant (Ponomarov, 2012). However it is important not to use the terms Supply Chain

Orientation and Supply Chain Management interchangeably. Mentzer et al. (2001) claim that those firms have a SC orientation that are able to detect and properly asses which systematic, strategic impact and scope tactical activities have that are required for controlling the distinct flows of goods, information and money in a supply chain. Thus, an organization with SC-Orientation recognizes and comprehends, the magnitude and the impact of the controlling and managing product, service, finance, and information flows along their up- and downstream supply chain. Furthermore Supply Chain Orientation is regarded as a management philosophy, which is characterized by cultural norms and procedures of the company to develop the necessary skills aiming at creating competitive advantages on the tactical as well as the strategic level (Mello and Stank, 2005). Additionally SC-Orientation is a multi-layered formation, which contains items like trust, commitment, cooperation, organizational compatibility as well as top management support (Mentzer et al., 2001; Min, Mentzer and Ladd, 2007; Ponomarov, 2012).

H1b: Supply Chain Orientation has a positive effect on Agility.
H2b: Supply Chain Orientation has a positive effect on Robustness.

2.3.1.3. Supply Chain Strategies

According to Yang et al. (2009) it is essential for companies to be able to anticipate and prepare for possible future disturbances. In order to reduce risk and disruption vulnerability by a robust set-up, the members of a SC must be in a position to proactively anticipate different scenarios and implement reliable solutions and strategies that prevent their supply chains from the negative effects in the future (Hendricks, Singhal and Zhang, 2009; Zsidisin and Wagner, 2010). Thus the anticipation as well as the readiness and the strategies fostering these capabilities are essential factors of resilient supply chains (Wieland and Wallenburg, 2013). The creation of redundancies as well as an enhanced flexibility allows companies to reduce the impact and likelihood of potential disruptions and in turn enhance the resilience of a supply chain. Strategies aiming at achieving resilience by redundancy are for example safety stocks, extra inventory, multiple sourcing, back-up sites and slack capacity (Park, 2011). However redundant strategies add costs to operations (Sheffi and Rice, 2005) these strategies achieve resilience and reduce the overall supply chain risk (Tang, 2008). Christopher and Peck (2004) argue that opting for supply chain strategies that leave several options open may be more expensive for a company in the short term than lean and efficient practices but reduce the likelihood and impact of disruptions and therefore pay out in the long-term.

H1c: Supply Chain Management Strategies have a positive effect on Agility.
H2c: Supply Chain Management Strategies have a positive effect on Robustness.

2.3.1.4. Risk Management Capabilities

Although risk management capabilities are equally important as other capabilities, the link to resilience is not as well entrenched in the relevant scientific literature as information management capabilities or supply chain strategies (Ponomarov, 2012). However risk management capabilities play an important role with regard to resilience as the creation of a risk management culture in the organization can enhance or even facilitate the resilience component in the supply chain (Christopher and Peck, 2004).

According to Wieland and Wallenburg (2012) risk management at supply chain stages can mitigate cascading failures of the supply chain. Strong risk management capabilities foster the implementation of proactive risk measures and support organizational learning from previous events (Lin and Wang, 2011; Schmitt, 2011).

According to Zsidisin und Wagner (2010) a better understanding of the risk tendency of a company contributes to implementing better measures that minimize or even avoid the consequences of disruptions. Increased risk management orientation thus leads to a promotion of robustness within the supply chain (Wieland and Wallenburg, 2013). Christopher & Peck (2004) revealed in their research that many companies lack the awareness of considering resilience within the scope of risk management and that several risk management tools should be applied in order to increase resilience by a better identification and management of supply chain risk.

H1d: Risk Management capabilities have a positive effect on Agility.
H2d: Risk Management capabilities have a positive effect on Robustness

2.3.2. Effects of Supply Chain Resilience on SC-Performance

2.3.2.1. Agility

If a disruption has occurred at some point of the supply chain, agility ensures an adequate response and adaptation to the disturbances and enables a supply chain to start the recovery as soon as possible (Hohenstein et al., 2015). A rapid response to a disturbance allows a supply chain to quickly recover and can reduce the total negative effects of a disruption considerably (Manuj and Mentzer, 2008). The more time a company needs to react and to carry out its countermeasures, the longer disruption may exert its negative influence on the performance of a supply chain (Blackhurst et al., 2005). Furthermore Blackhurst et al. (2011) highlights the positive effect the agile components of resilient capabilities have on the performance of a supply chain by considerably reducing the recovery time after a disturbance occurred. Thus it is hypothesized that the agile capabilities of the resilience dimension contribute to the overall supply chain performance in a positive way.

H3a: A higher level of Supply Chain Agility results in a higher level of Supply Chain Performance.

2.3.2.2. Robustness

Hohenstein et al. (2015) consider robustness is the fundament of a resilient capability and as a robust supply chain setup reduces the probability of disruptions and absorbs its potential negative effects. Thus in addition to the mentioned capabilities in section 2.3.2.1 companies need to ensure also a proactive approach to resilience in order to absorb and mitigate potential disturbances and to not only return to the original condition but to exceed the performance of a supply chain after a disruption by the development of specific elements and capabilities (Hohenstein et al., 2015).

According to Yang et al. (2009) it is essential for organizations how potential disturbances can be anticipated and to find ways how to effectively prepare and deal with prospective disruptions. For reducing the associated risks of disruptions by means of a robust supply chain design, companies have to implement robust strategies like slack capacities, redundancies or safety stocks in their supply chain, which will decrease the impact of negative effects on the performance (Hendricks, Singhal and Zhang, 2009; Zsidisin and Wagner, 2010). Hamel and Välikangas (2003) have emphasized the significance of forward-looking capabilities that can identify trends and risks that may sustainably affect the profitability of the core business. Especially by anticipating future uncertainties, which is an important part of a proactive supply chain strategy, positive effects on the overall performance of a supply chain can be achieved according to (Hallikas et al., 2004). This is due to the assumption, that predictive and forward-looking features grants an organization with more time and scope to react in the case of an unexpected disruption (Wieland and Wallenburg, 2013). Hendricks and Singhal (2005) demonstrate that organizations which have been exposed to disruptions are need a long time to recover from the negative consequences, while companies that have implemented robust capabilities in their supply chain recover more quickly and show weaker stock market responses to disturbances (Hendricks, Singhal and Zhang, 2009).

Due to the mentioned points it is hypothesized that robust capabilities have a positive effect on the supply chain performance as they can significantly reduce the negative effects of disruptions.

H3a: A higher level of Supply Chain Robustness results in a higher level of Supply Chain Performance.

2.4. Conceptual Model

According to the literature review a conceptual model; linking antecedents of resilience and their influence on agility and robustness, as well as the influence of those two factors on the performance of the supply chain is developed. Figure 1 describes the model, while Table 1 shows the adopted hypothesizes.

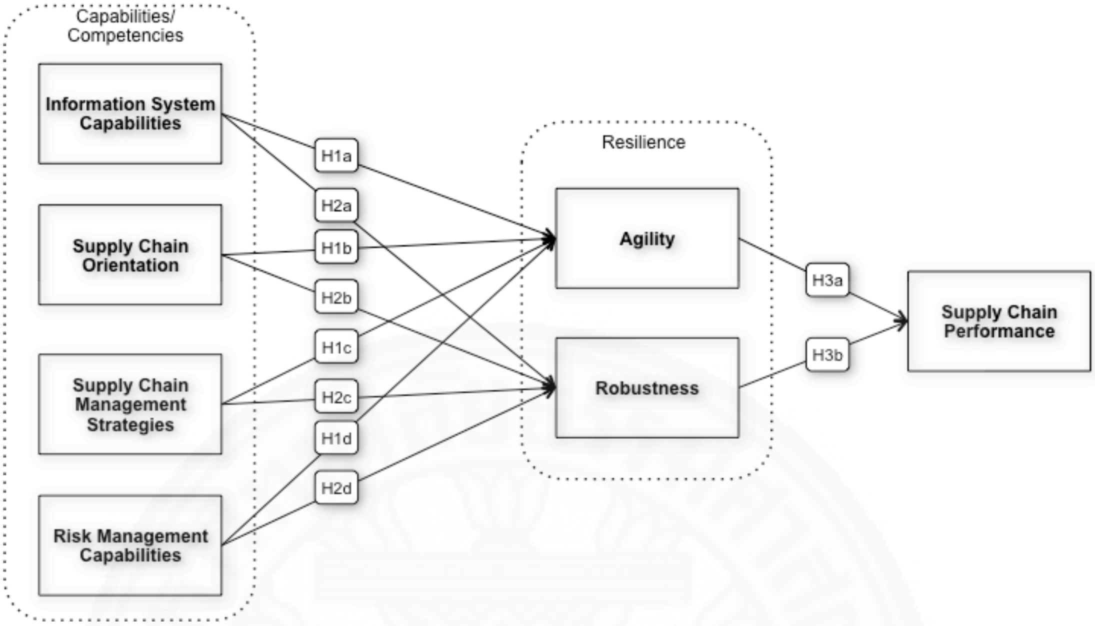

Figure 1: Conceptual Model

Table 1: List of Hypotheses

No.	Hypothesis
H1	Supply Chain Capabilities and Competencies have a positive effect on Agility.
H1a	Information Management Capabilities have a positive effect on Agility.
H1b	Supply Chain Orientation has a positive effect on Agility.
H1c	Supply Chain Strategies have a positive effect on Agility.
H1d	Risk Management capabilities have a positive effect on Agility.
H2	Supply Chain capabilities and competencies have a positive effect on Robustness.
H2a	Information System capabilities have a positive effect on Robustness.
H2b	Supply Chain Orientation has a positive effect on Robustness.
H2c	Supply Management Strategies have a positive effect on Robustness.
H2d	Risk Management capabilities have a positive effect on Robustness.
H3	A higher level of Supply Chain Resilience results in a higher level of Supply Chain Performance.
H3a	A higher level of Supply Chain Agility results in a higher level of Supply Chain Performance.
H3b	A higher level of Supply Chain Robustness results in a higher level of Supply Chain Performance.

Chapter 3
Methodology

3.1. Methodological Approach

The methodological approach is empirical and is pursuing a confirmatory character, which is theoretically founded by the resource-based view of Pfeffer and Salancik (1978) and Prahalad and Hamel (1990). Survey data from Thailand based manufacturing companies is collected and subsequently analyzed by means of Structural Equation Modeling (SEM). In order to collect the necessary data for evaluating the developed hypotheses of the conceptual model a survey methodology was used (see appendix A). The survey methodology was employed as it is a relatively cost-efficient option for collecting a large number of data (Kerlinger and Lee, 2000) allowing an easy quantification and subsequent analysis of the responses by applying statistical methods (Ponomarov, 2012).

3.2. Applied Research Method

The investigations of causal dependencies, which are characterized by a network of cause-effect relationships, are in the center of many business issues in research and practice (Riekeberg, 2002). Complex methods for the multivariate analysis of empirically researching such effect relationships have been developed within economic and social research in the past, which are referred to as causal analysis or as a structural equation analysis (Ringle, 2004). The structural equation methodology for multivariate empirical data analysis has become firmly established in the field of business and supply chain management in the last two decades (Homburg and Baumgartner, 1995; Wallenburg and Weber, 2005). The analysis of complex cause-effect relationships using Structural equation modeling is not only limited to this field of business research but also widely applied in areas such as economics, psychology, sociology or behavioral genetics (Fergusson, 1995).

This trend was particularly favored by the much-improved availability of the method in powerful statistical software packages. In the 80s the program LISREL (LInear Structural Relations (Jöreskog and Sörbom, 1993)) set the standard for the analysis of structural equation modeling, thus this term LISREL models is often used synonymously for structural equation models. Since the early 90s, however, the number of alternative SEM software is constantly growing (Hildebrand and Görtz, 1999). In contrast to early versions the more recent editions of the these software packages now allow less experienced users to specify complex structural equation models without deeper knowledge of methods due to their user-friendly Windows interface (Nachtigall et al., 2003).

Multivariate analysis methods are used for empirical testing of theoretically derived statements about complex cause-effect relationships (Fuchs, 2011). Structural equation analysis is a method which allows conclusions on dependency relationships between underlying latent variables based on empirically measured variances and covariances of indicator variables by parameter estimations (Homburg, 1989). This opens up the possibility to examine causality, which in the strict epistemological sense is only possible by means of controlled experiments (Homburg and Hildebrandt, 1998). The causal analysis combines elements of regression and factor analysis, however, is superior to these classical methods in terms of their applications and their result quality (Ringle, 2004). Thus, it is possible to map even complex dependency structures and causal chains by means of causal models, which can be tested formalized in the form of a linear equation system. Fuchs (2011) mentions that probably no other method supports the theory building process to such a high degree.
The structural equation methodology is assigned to the confirmatory analysis techniques (Hildebrand, 1983).
Characteristic for SEM models is the explicit distinction between the measurement theory (measurement model) and the theory of substance (structural model) (Homburg and Hildebrandt, 1998). The measurement model describes the relationships between the unobservable theoretical constructs (latent variables) and their indicators (observable variables) that are modeled as a factor structure. The structural model,

however, constitutes the assumed causal relations on the level of theoretical constructs (Hildebrand and Görtz, 1999).

3.2.1. Areas for possible application

Since the method of causal analysis only allows drawing conclusions about causal relationships under very specific conditions, the more appropriate term of structural equation analysis is often used (Herrmann, 2008). The assumption of causality is essential for the structural equation modeling. Although the concept of causality is sometimes discussed very controversially in the scientific literature, a causal cause-effect relationship according to always exists if the following three conditions are being satisfied (Cook and Campell, 1979):

- Changes in the independent variables cause changes in the dependent variable, so that a systematic relationship is present.
- There is a time sequence in such a way that the change of the independent variable is prior in time to the change of the dependent variable.
- The independent variable is the only plausible explanation for the change in the dependent variable that can be substantiated in a theoretical or logical way.

Hence a necessary and a sufficient condition have to be fulfilled for the presence of causality. The necessary condition for the existence of a causal relationship is a statistical dependence between the variables under consideration. The conclusion of a statistically proven dependence on a causal cause, however, is only possible if previously intensive proper logical considerations were made regarding the relationships between the variables under consideration (sufficient condition) (Weiber and Mühlhaus, 2014). The special feature of structural equation modeling in the context of causal-analytical approach is the fact that they allow a separation between manifest and latent variables. Thereby manifest variables are directly observable (i.e. measurable), while latent variables evade from being measured directly (Backhaus et al., 2006). Another feature of linear structural equation models is the explicit consideration of measurement errors, which is not the case with other classical multivariate analysis methods in that particular way. This integral model component allows a better approximation to real world problems and thus enables to constitute a more accurate picture of reality (Steenkamp and Baumgartner, 2000; Chin and Newsted, 1999).

3.2.2. Advantages and Disadvantages of SEM

Compared to other multivariate methods of analysis, the benefits of the structural equation methodology arise primarily from the explicit modeling of the measurement error for both the dependent and independent variable (Hildebrand and Görtz, 1999). The most important advantage of linear structural equation models with latent variables is that by using latent variable measurement error in the analysis are explicitly taken into account (Schumacker and Lomax, 2010). As a result, the relationships in the structural model can be estimate more accurately than, for example, correlation, regression and path analysis can, which are only based on the observation of observed (faulty) variables.

Furthermore, structural equation models allow conducting an empirical verification (model testing) of complex theories for measurement and associated structures among variables. This also allows comparing various competing models statistically (Geiser, 2010). The estimation of measurement errors proportion allows assessing the reliability of the measurement model. Furthermore another advantage of structured equation modeling is its flexibility, as it not only calculated a single simple or multiple linear regressions but rather a whole system of regression equations (Nachtigall et al., 2003)

The structural equation methodology is especially suitable for analyzing complex relationships since it analyses all relationships between the variables in the model simultaneously, which is not possible with any other of the multivariate analysis techniques established in business research (Hildebrand and Görtz, 1999).

According to Fergusson (1995, p. 18) the "… advantages of structured equation modeling are almost self-evident … ". As long as the researcher has a well founded conceptual theory as well as that the theory can be fairly realistically represented by a number of linear equations and that data is available in sufficient quality and quantity to test the hypotheses SEM constitutes a powerful methodology for hypothesis testing and theory generation. Furthermore the strict conditions concerning data quantity, quality and distributions (see Table 2) are another disadvantages of SEM compared to other multivariate techniques, such as PLS (Fuchs, 2011).

Table 2: Preconditions for the Deployment of SEM

Preconditions for the deployment of SEM
• Theoretically founded hypothesis system
• Sample size: usually n> = 100; but sometimes n> = 200 or n> = 5 * q (q is the number of parameters to be estimated)
• Multivariate normal distribution: If not present, special procedures are necessary; In principle there are problems with "out of range values".
• Linearity and additivity of the constructs and measurement hypotheses
• No correlation between measurement errors and residuals of the structural equations
• No correlation between the residuals in the structural model and the exogenous latent variables
• Independence of observations

(Fuchs, 2011; Schumacker and Lomax, 2010; Nachtigall et al., 2003)

3.3. Research Design

3.3.1. Data Collection & Sampling

In order to collect the desired data an online survey was developed according to the operationalization of Chapter 3.3.2. The web-based approach was favored as it provides several advantages over a paper-based survey such as easy access to potential respondents, more efficient distribution and data evaluation as well as lower costs (Dillman, 2007; Ponomarov, 2012). The web-based survey was creates using the SoSci Survey software package, which was specifically developed for scientific surveys and is free for academic purposes (SoSci Survey GmbH, 2014). According to the recommendations of Ponomarov (2012) the target group were senior-level employees of manufacturing companies working in the field of supply chain management, logistics, risk management or with direct involvement in company decision making processes. Subsequently a link to the online survey, both in Thai and English language, was send to the potential respondents. The survey was conducted in Thailand and data was collected for 5 months between December 2014 and April 2015.

3.3.2. Survey Items/ Construct Measurement

After the hypothetical constructs have been described on the theoretical level in a next step their "empirical counterweights", i.e. observable indicators to measure them, have to be identified on the observation level. In the context of structural equation modeling the operationalization corresponds to the formulation of the measurement models for latent exogenous and endogenous variables (Weiber and Mühlhaus, 2014). As some of the utilized constructs in this paper have already been applied in previous papers and have already been subject to empirical tests, firstly a review of related studies and literature was conducted in order to identify suitable operationalization. According to Weiber & Mühlhaus (2014) the consultation of the related literature is especially relevant in the context of the "scientific progress", as an independent construct operationalization for each research, would lead to a "construct overload". A comparison of different studies would thus no longer be guaranteed or only merely possible. Furthermore the identification and exposure of superordinate causal relations would not be possible anymore (Diller, 2006; Jacoby, 1978).

The supply chain capabilities, information sharing capabilities and supply chain performance have been adapted from Ponomarov (2012), while agility and robustness have been operationalized according to the proposed scales of Wieland and Wallenburg (2012). While the scales for risk management capabilities and the scale for supply chain strategies was newly developed upon suggestions from adapted from Lavastre, Gunasekaran, Spalanzani (2012), respectively Tang (2006). According to the suggestions of Thun and Hoenig (2011) as well as Wagner and Bode (2006) Five-point Likert-type items were applied in order to operationalize the constructs. The items were scored in a way that higher numbers indicate increases in the underlying constructs. As Weiber & Mühlhaus (2014) recommend the use of 3-6 observable items per latent construct, the constructs of this paper are operationalized with 5 respectively 6 items for each latent variable.

3.3.2.1. Measuring Information System Capabilities

The operationalization of Information System Capabilities have been adapted from Wieland and Wallenburg (2013) as well as Ponomarov (2012), who in turn adapted the items from Zhao, Droge and Stank (2001) and Mentzer Min and Bobbits (2004). According to Zhao et al. (2001) the level of information system capabilities is characterized by the level of information sharing, the quality of information and connectivity. While the sharing of information is operationalized by the first two questions, the quality of information is operationalized by the third and the connectivity by the fourth and fifth question.

Table 3: Operationalization of Information Management Capabilities

Question	Scale	Abbreviation
Our firm effectively shares operational information between departments frequently and in a timely manner.		IMC_IIS
Our firm effectively shares operational information externally with selected customers frequently and in a timely manner.		IMC_EIS
The information available in our firm is accurate.	Strongly Disagree – Strongly Agree	IMC_ACC
Our firm maintains an integrated database to facilitate information sharing with customers as well as for internal information sharing.		IMC_IDB
We have full access to joint planning systems along the supply chain.		IMC_JPS

3.3.2.2. Measuring Supply Chain Orientation

The items for Supply Chain Orientation have been adapted from Ponomarov (2012). According to Min, Mentzner and Ladd (2007), whose work formed the basis for Ponomarov's operationalization, supply chain orientation can be characterized by trust, commitment, organizational compatibility and top management support.

Furthermore collaboration and integration were also regarded as characterizations of Supply Chain Operation, based on the work of Wieland and Wallenburg (2013).

Table 4: Operationalization of Supply Chain Orientation

Question	Scale	Abbreviation
Our firm is actively implementing and pursuing activities that increase collaboration with customers (e.g. joint decision making, CPFR, knowledge sharing, benefit sharing, VMI, etc.).	Strongly Disagree – Strongly Agree	SCO_COL
We trust our key customers.		SCO_TRST
Our objectives are consistent with those of our key customers.		SCO_OBJ
Top managers reinforce the need of building, maintain and enhance long-term relationships with our customers and the need of sharing valuable information.		SCO_MNGT
Our supply chain forms an integrated environment that provides end-to-end interaction of orders, inventory, transportation and distribution to facilitate supply chain transparency.		IMC_INT

3.3.2.3. Measuring Supply Chain Strategies

The Supply Chain Strategies capability described the extent to which companies implement and apply sophisticated strategies in order to increase their resilience. Tang (2006) describes and categorizes several supply chain strategies, which increase the ability of an organization to efficiently manage demand and supply during normal conditions as well as improve the ability to maintain the operations during the time of severe disruptions. According to these categorizations, the Supply Chain Capabilities are newly operationalized by items measuring the degree of implementation of postponement, strategic stock, flexible supply base, flexibly transportation and slack capacity. Furthermore a sixth item was added in order to assess whether Lean supply chain practices contradict or support the robustness of supply chain strategies.

Table 5: Operationalization of Supply Chain Strategies

Question	Scale	Abbreviation
Our firm uses a flexible supply base strategy for key and critical components (dual-sourcing, multiple sourcing).	Strongly Disagree – Strongly Agree	SCS_FSUP
Our firm is carrying additional “just in case” safety stock inventories of certain critical components.		SCS_SS
Our firm has slack capacity or redundancies in operations to cope with uncertainties.		SCS_SCAP
Postponement techniques such as standardisation, commonality, and modular design approaches are applied to delay the point of product differentiation.		SCS_POST
Our company applies flexible transportation techniques (multi-modal transportation, multi-carrier transportation or multiple routes).		SCS_FTRA
Our company strongly applies Lean and Just-in-Time techniques (e.g. 5S, Six Sigma, Kanban, One-Piece-Flow, etc.) and is continuously focusing on improving the efficiency by removing waste from operations.		SCS_LEAN

3.3.2.4. Measuring Risk Management Capabilities

The items for measuring and operationalize Risk Management Capabilities have been developed based on the study of Lavastre, Gunasekaran, Spalanzani (2012), who conceptualized the risk management within a supply chain. According to their conceptualization risk management can be characterized by four generic steps, risk identification, risk assessment (risk calculation), risk management implementation as well as risk monitoring. These generic steps of risk management have been used to operationalize the risk management capabilities by question 1-4. Additionally the independent and position within the company and dedication of resources to risk management was added according to the suggestion of Ponomarov (2012)

Table 6: Operationalization of Risk Management capabilities

Question	Scale	Abbreviation
In our firm, an employee or a team is dedicated to supply chain risk management.		RMC_DEDR
Our firm applies risk identification & analysis techniques (What if Analysis, Scenario Planning, Value Stream Mapping).		RMC_ID
Our firm applies risk assessment techniques (Pareto diagrams, ABC Ranking, FMECA - Failure Mode, Effects, and Criticality Analysis).	Strongly Disagree – Strongly Agree	RMC_ASS
Our firm applies techniques to support the decision and implementation of risk management actions (Business Continuity Plans, etc.).		RMC_IMPL
Our firm proactively monitors risks (Audits, Project Risk Reviews).		RMC_MON

3.3.2.5. Measuring Agility

According to Swafford, Gosh and Murthy (2006) agility represents the capability of a supply chain to adapt to certain changes or situation in a quickly manner. Thus Agility can be characterized by the speed the supply chain can adapt different performance measures (such as lead-time, or customer service level). For the operationalization the items developed by Wieland and Wallenburg (2013) has been used, as they showed very good results and a valid and reliable operationalization. Furthermore the fifth item was added according to Ponomarov (2012) in order to include the performance after a disruption into the operationalization.

Table 7: Operationalization of Agility

Question	Scale	Abbreviation
Adapt manufacturing leadtimes with customers.	Slow– Fast	AGT_MLT
Adapt level of customer service.		AGT_CSL
Adapt delivery reliability with customers.		AGT_DLRE
Adapt responsiveness to changing market needs.		AGT_RESP
Restoring product flow to its original state after being disrupted.		AGT_RPF

3.3.2.6. Measuring Robustness

According to Wieland and Wallenburg (2013) Supply Chain Robustness was operationalized by the capabilities of a supply chain to be resistant to external disruptions and to retain its functionality over a wide range of scenarios. Therefore the empirically tested item by Wieland and Wallenburg (2013) were adopted in order to operationalize the robustness of a supply chain.

Table 8: Operationalization of Robustness

Question	Scale	Abbreviation
For a long time, our supply chain retains the same stable situation as it had before changes occur.	Strongly Disagree – Strongly Agree	RBN_RSS
When changes occur, our supply chain grants us much time to consider a reasonable reaction.		RBN_GRT
Without adaptations being necessary, our supply chain performs well over a wide variety of possible scenarios.		RBN_DSC
For a long time, our supply chain is able to carry out its functions despite some damage done to it.		RBN_COF
Our firm's supply chain has the ability to maintain a desired level of connectedness among its members at the time of disruption.		RBN_MLC

3.3.2.7. Measuring Supply Chain Performance

Concerning the performance of a supply chain it was found that conventional performance indicators are not necessarily describing the value creation in a comprehensive sense in order to enable a proper assessment; therefore, great emphasis is placed on research into alternative value-based performance indicators (Stank, Davis and Fugate, 2005). According to Ponomarov (2012) a special construct aiming at measuring the performance of the supply chain resilience is the supply chain process variability (SCPV). SCPV measures the consistency or volatility of the flow of goods within the input, throughput and output of a company (Germain, Claycomb and Dröge, 2008). This approach is more comprehensive compared to the already much-documented production process variability. It includes the internal variability of cycle time and throughput, but also includes the inconsistencies in inbound and outbound operations. Thus the Supply Chain Performance is operationalized by its process variability and the items developed by Ponomarov (2012) are used.

Table 9: Operationalization of Supply Chain Performance

Question	Scale	Abbreviation
Amount of time for shipments to reach our key customers.		SCP_SHIP
Manufacturing time based on a fixed production schedule.		SCP_MLT
Response to the everyday needs of key customers.	Very Inconsistent – Very Consistent	SCP_RCN
Meeting as promised delivery dates with customers.		SCP_DD
Providing desired quantities on a consistent basis.		SCP_QNT

Chapter 4
Findings and Data-Analysis

4.1. Descriptive Statistics

137 responses from companies have been collecting consisting of small, medium and large Thai organizations. The responding companies are mainly manufacturing companies as well as companies operating in transportation and logistics. According to the numbers of employees and total assets it can be stated that the companies show different characteristics concerning size.

Table 10: Properties of respondents

Business Function	General Management	49
	Logistics	9
	Supply Chain Mngmt.	16
	Risk Management	6
	Purchasing	6
	Production	10
	Other	31
	n	127

Total Assets	< 300,000 THB	0
	300,000 - 750,000 THB	4
	750,000 - 1.5m THB	8
	1.5 – 2.25m THB	16
	2.25 - 3m THB	15
	3 - 15m THB	15
	15 - 30m THB	18
	30 - 150m THB	15
	150 - 300m THB	8
	> 300m THB	17
	n	116

Industry	Agriculture & Forestry	11
	Mining	0
	Construction	8
	Manufacturing	45
	Transportation,	21
	Wholesale Trade	6
	Retail Trade	12
	Finance, Insurance, And Real Estate	3

Employees	1-19	26
	20 - 49	31
	50 - 99	33
	100 - 199	16
	200 - 299	5

	Services	14
	Public Administration	0
	Other	12
	n	132

Supply Chain Stage	OEM	11
	1st Tier Supplier	36
	2nd Tier Supplier	35
	Other	39
	n	121

	300 - 399	5
	400 - 499	1
	500 - 999	2
	1,000 - 1,499	2
	1,500 - 1,999	0
	More than 2,000	5
	n	126

4.2. Data Preparation

As preparation for the model estimation, the collected data is first reviewed for missing values and outliers. In Addition the data is subsequently tested for multi-normal distribution, as the Maximum Likelihood (ML) method is desired for the estimations.

4.2.1. Missing Values

The problem of missing values or the handling of those is omnipresent in empirical sciences and in particular in the application of structural equation models since the SEM requires the existence of a complete data matrix (Schumacker and Lomax, 2010). Marsh (1998, p. 22) emphasized that: "Missing data are a problem in most structural equation modeling studies" and Backhaus and Blechschmidt (2009) reveal that many of the published empirical studies in SEM don't broach the issue of missing values adequately. Ignoring or non-consideration of missing values, which do not occur randomly, but systematically, can cause the entire examination findings to be not useful and systematically distorted. Also the guileless replacing of missing values (e.g. by the means, medians or the corresponding mode of the indicator variable) has a significant effect on the achievable results within the causal analysis, which is reflected in particular in distorted and inefficient estimators (Weiber and Mühlhaus, 2014).

There are a variety of different missing values, whereas Rubin (1976) categorizes them in three distinct types of missing values. Not Missing at Random (NMAR) data show a systematic failure mechanism, which is also referred to as "non ignorable missing data" (Kim, 2003). This is given when the probability of missing particulars in variable x depends on their "true", but unobservable value itself. For the second type Missing Completely at Random (MCAR) the missing values occur at random, i.e. the absence of values is not related to the missing or existing values. For Missing at Random (MAR) the probability of a missing particular for variable x depends on the information of one or more variables y, not on the variable x itself.

Depending on the type of missing values different approaches exist of how to deal with these issues. In general however NMAR missing values pose more significant problems for a subsequent SEM due to their systematic character compared to the two other error types (Weiber and Mühlhaus, 2014).

Table 11: Overview of Missing Values (Univariate Statistics)

	N	Mean	Std. Deviation	Missing		No. of Extremes[a]	
				Count	Percent	Low	High
SCO_COL	137	3.16	1.031	0	.0	0	0
SCO_TRST	137	3.55	.962	0	.0	1	0
SCO_OBJ	137	3.29	1.051	0	.0	3	0
SCO_MNGT	135	3.19	1.066	2	1.5	0	0
SCO_INT	137	3.20	1.104	0	.0	0	0
IMC_IIS	137	3.27	1.204	0	.0	0	0
IMC_EIS	136	3.40	1.244	1	.7	0	0
IMC_ACC	134	3.53	1.218	3	2.2	0	0
IMC_IDB	135	3.37	1.232	2	1.5	0	0
IMC_JPS	137	3.34	1.250	0	.0	0	0
SCS_FSUP	137	3.32	1.150	0	.0	8	0
SCS_SS	136	3.49	1.161	1	.7	0	0
SCS_SCAP	135	3.41	1.224	2	1.5	0	0
SCS_POST	137	3.36	1.169	0	.0	8	0
SCS_FTRA	137	3.39	1.209	0	.0	0	0

SCS_LEAN	137	2.87	1.282	0	.0	0	0
RMC_DEDR	137	3.04	1.248	0	.0	0	0
RMC_ID	137	3.18	1.296	0	.0	0	0
RMC_ASS	135	3.13	1.320	2	1.5	0	0
RMC_IMPL	136	3.17	1.347	1	.7	0	0
RMC_MON	137	3.04	1.353	0	.0	0	0
AGT_MLT	137	3.36	1.194	0	.0	0	0
AGT_CSL	135	3.39	1.165	2	1.5	0	0
AGT_DLRE	137	3.35	1.252	0	.0	0	0
AGT_RESP	137	3.42	1.161	0	.0	6	0
AGT_RPF	137	3.22	1.229	0	.0	0	0
RBN_RSS	137	3.32	1.218	0	.0	0	0
RBN_GRT	137	3.52	1.189	0	.0	0	0
RBN_DSC	136	3.35	1.352	1	.7	0	0
RBN_COF	136	3.42	1.184	1	.7	0	0
RBN_MLC	137	3.49	1.119	0	.0	6	0
SCP_SHIP	137	3.34	1.088	0	.0	6	0
SCP_MLT	135	3.53	1.092	2	1.5	3	0
SCP_RCN	137	3.31	1.090	0	.0	0	0
SCP_DD	137	3.43	.984	0	.0	1	0
SCP_QNT	137	3.30	1.046	0	.0	5	0

a. Number of cases outside the range (Q1 - 1.5*IQR, Q3 + 1.5*IQR).

The first evidence for systematically missing information can be obtained on the basis of the frequencies of missing values per variable or indicator. As displayed in table 11 none of the investigated variables show a high proportion of missing values. This indicates no systematic failure and thus no NMAR missing values. Furthermore the absolute number of missing values is comparatively small and significantly below the threshold value of 10% that Kline (1998) constitutes for a large and questionable amount of missing values. Due to the very low total number and the unremarkable frequency distribution of the missing values concerning the indicators it can be assumed that the missing values are of the MCAR or MAR type.

As the missing values are assumed to be MCAR or MAR methods that use the Maximum Likelihood estimates for estimating the missing values can be applied (Baltes-Götz, 2013). The best-known approach here is the so-called EM algorithm

(Dempster, Laird and Rubin, 1977), which has excellent features (Malhotra, 1987), however the procedures are not without criticism (Allison, 2002; von Hippel, 2004). Beyond that AMOS also offers the possibility of imputation of missing values with its Full Information Maximum Likelihood (FIML) estimation (Arbuckle, 1996). The special feature of FIML technique is the fact that it replaces missing values directly within the parameter estimation of a model. According to Weiber & Mühlhaus (2014) FIML estimated provide consistent and statistically efficient estimations for MCAR values. In the case of MAR estimators are asymptotically unbiased and even if the MAR condition is not completely satisfied, the use of the FIML estimate shows the least distortion (Little and Rubin, 1989; Backhaus and Blechschmidt, 2009).
Since the FIML technique is characterized by excellent properties (Arbuckle, 2012; Baltes-Götz, 2013), it will be applied for the further analysis of the causal model with AMOS in this thesis. A disadvantage of this procedure however is that AMOS is not able to calculate Modification Indices with incomplete data sets (Weiber and Mühlhaus, 2014). For analyses in AMOS that require a complete dataset without missing values, but do not allow the application of the FIML method, the missing values were calculated using the EM algorithm in SPSS. Since, as already mentioned, the FIML method is preferred in the literature, this method has been applied whenever possible.

4.2.2. Outliers

Outliers are observed values, which can be referred to as unusual, implausible and inconsistent from a proper logical point of view and therefore do not match the rest of observed values of a variable and its distribution (Weiber and Mühlhaus, 2014). In order to identify outliners in the data set the Outliner Labeling Rule analysis according to Hoaglin, Iglewicz and Tuckey (1986) was applied. This method identifies outliners according to their relative distance from the lower 0.25 respectively the upper 0.75 percentile. The analysis conducted with a g-value of 2.2 as proposed by Hoaglin and Iglewicz (1987) showed no considerable outliners in the dataset, which is not unusual as all variables were operationalized using a 5-point Likert Scale, providing relatively consistent data without extreme values. However, it should be noted that an exact threshold for outliers couldn't generally be specified, so that the identification and existence of outliers strongly depends on the chosen threshold value (Weiber and Mühlhaus, 2014).

4.2.3. Normal distribution

Out of the frequently used estimation methods for the covariance structure analysis, Maximum Likelihood and the Generalized Least Squares (GLS) algorithm require a multi-normal distribution of the underlying data (Schumacker and Lomax, 2010). If this multi-normal distribution is not given, severe distortion of both the model quality and the parameter estimates could be the consequence, which may lead to wrong substantive conclusions (Urban and Mayerl, 2013). The examination of the assumption of normal distribution of individual variables is usually carried out with the help of skewness and kurtosis measures and statistical tests. A perfectly normally distributed variable exists when skewness and kurtosis of a manifest variable have a value of zero (Blunch, 2013). At what point a significant violation of normality assumptions within the SEM is assumed is controversial discussed in the literature. Thus, some authors take a conservative approach and require that both the skewness and kurtosis measurements magnitude should not be greater than 1 (Temme and Hildebrandt, 2009). In contrast, West, Finch and Curran (1995) propose only values $| > 2 |$ for the skewness and $| > 7 |$ for the kurtosis coefficient as substantial deviation from the normal distribution.

To test the univariate normal distribution assumption with the help of statistical tests, a modification of the Kolmogorov-Smirnov test (KS) or the Shapiro-Wilk test (SW) can be used. In the KS test, the observed frequencies of individual values are compared with those which would be expected if the presence of normal distribution (Weiber and Mühlhaus, 2014). High deviations indicate that the data is not normally distributed. The SW test explicitly tests the null hypothesis that a variable x is normally distributed. This test however is very sensitive to the sample size and should only be applied with samples greater than 30 (Hair et al., 2010).

In addition to the distribution coefficients of skewness and kurtosis its standard error can be estimated. By dividing the empirically determined coefficient by the standard error, the so-called Critical Ratios (CR) can be obtained. If strictly conservatively interpreted CR-values greater than 1.96 indicate that the normal distribution assumption is violated on the 5% significance level. More moderate interpretation suggest a violation only from CR-values greater than 2.57 (Weiber and Mühlhaus, 2014).

Although the statistical tests (KS, SW) are used frequently in practical applications due to their objectivity, it has to be mentioned that data collected from rating scales rarely meet the "strict" test criteria (Janssen and Laatz, 2013). As the distortions of the quality measures and standard errors of the parameter estimates caused by a violation of normality distribution occur only at a significant deviation from the normal distribution, the mentioned test criteria appear to be too restrictive in the context of the SEM (Weiber and Mühlhaus, 2014). In order to assess whether a significant violation of the normality assumption exists skewness and kurtosis measures will be considered. However it should be noted, that the prerequisite for multivariate-normally distributed data in most papers involving rating scales is rarely satisfied (Scholderer and Balderjahn, 2006). Therefore, it is more important to evaluate the "strength" of the violation of the normality distribution assumption. According to Bollen (1989) Maximum Likelihood and Generalized Least Square estimations can be used, as long the violation is only moderate.

Table 12 shows the results for both in SPSS conducted univariate KS- and SW-Tests. The test shows that that the assumption of univariate normal distribution cannot be maintained for any of the 35 variables as all variables show significance below 0.05. This result, however, is hardly surprising, since the variables were collected using rating scales, which usually leads to non-normally distributed data (Weiber and Mühlhaus, 2014). Since these tests are based on a very "strict understanding" of normal distribution which is not absolutely necessary for the application of structural equation modeling, the skewness and kurtosis values were investigated for a further investigation of normality.

Table 12: Test of Normality (KS & SW Test)

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
SCO_COL	.186	137	.000	.905	137	.000
SCO_TRST	.226	137	.000	.890	137	.000
SCO_OBJ	.201	137	.000	.900	137	.000
SCO_MNGT	.199	135	.000	.906	135	.000
SCO_INT	.191	137	.000	.911	137	.000
IMC_IIS	.159	137	.000	.910	137	.000
IMC_EIS	.162	136	.000	.892	136	.000
IMC_ACC	.195	134	.000	.883	134	.000
IMC_IDB	.177	135	.000	.899	135	.000
IMC_JPS	.179	137	.000	.878	137	.000
SCS_FSUP	.179	137	.000	.908	137	.000
SCS_SS	.169	136	.000	.894	136	.000
SCS_SCAP	.180	135	.000	.881	135	.000
SCS_POST	.192	137	.000	.901	137	.000
SCS_FTRA	.204	137	.000	.887	137	.000
RMC_DEDR	.172	137	.000	.911	137	.000
RMC_ID	.162	137	.000	.896	137	.000
RMC_ASS	.152	135	.000	.903	135	.000
RMC_IMPL	.168	136	.000	.892	136	.000
RMC_MON	.165	137	.000	.898	137	.000
AGT_MLT	.199	137	.000	.903	137	.000
AGT_CSL	.183	135	.000	.890	135	.000
AGT_DLRE	.187	137	.000	.897	137	.000
AGT_RESP	.168	137	.000	.900	137	.000
AGT_RPF	.168	137	.000	.904	137	.000
RBN_RSS	.208	137	.000	.901	137	.000
RBN_GRT	.178	137	.000	.852	137	.000
RBN_DSC	.208	136	.000	.882	136	.000
RBN_COF	.210	136	.000	.899	136	.000
RBN_MLC	.209	137	.000	.900	137	.000
SCP_SHIP	.180	137	.000	.910	137	.000
SCP_MLT	.189	135	.000	.893	135	.000
SCP_RCN	.181	137	.000	.903	137	.000
SCP_DD	.209	137	.000	.893	137	.000
SCP_QNT	.189	137	.000	.909	137	.000

a. Lilliefors Significance Correction

The skewness (see Table 13) consistently show no values greater than | 1 |, which generally indicates that no substantial deviation from the normal distribution exists (Temme and Hildebrandt, 2009). The kurtosis values are also predominantly smaller than | 1 | or only slightly above this value. However, even the highest kurtosis values lie far within the required threshold of | 7 | stated by West, Finch and Curran (1995). The C.R. values for the skewness coefficients are only showing slightly higher values than | 2.57 | for the five variables RBN_DSC, RBN_GRT, IMC_JPS, RMC_IMPL, SCS_SCAP, while the remaining variables show smaller values.

The assessment on the indicators level overall suggest only a moderate violation of the assumption of normal distribution. In the light of these results it is assumed for the following discussion that no significant violation of the multi-normal distribution assumption exists. Thus a model estimation based on the ML-method can be applied in the further steps of this thesis. According to Bollen (1989) the ML-method should only be rejected if an extreme violation of the multi-normal distribution assumption exists - which is according to this section not the case for the analyzed data.

Table 13: Assessment of Normality (Kurtosis & Skewness)

Variable	min	max	skew	c.r.	kurtosis	c.r.
SCO_INT	1.000	5.000	.003	.014	-.782	-1.726
RBN_MLC	1.000	5.000	-.280	-1.235	-.734	-1.620
RBN_COF	1.000	5.000	-.339	-1.498	-.910	-2.008
RBN_DSC	1.000	5.000	-.270	-1.192	-1.187	-2.621
RBN_GRT	1.000	5.000	.006	.026	-1.429	-3.156
RBN_RSS	1.000	5.000	-.198	-.876	-.993	-2.193
IMC_JPS	1.000	5.000	.068	.300	-1.316	-2.905
IMC_IDB	1.000	5.000	-.135	-.598	-1.023	-2.259
IMC_ACC	1.000	5.000	-.318	-1.402	-1.062	-2.346
IMC_EIS	1.000	5.000	-.101	-.446	-1.089	-2.404
IMC_IIS	1.000	5.000	-.095	-.419	-.915	-2.020
SCO_MNGT	1.000	5.000	.114	.505	-.782	-1.726
SCO_OBJ	1.000	5.000	.085	.374	-.925	-2.041
SCO_TRST	1.000	5.000	-.215	-.951	-.728	-1.607

Variable	min	max	skew	c.r.	kurtosis	c.r.
SCO_COL	1.000	5.000	-.006	-.024	-.794	-1.753
SCP_QNT	1.000	5.000	-.062	-.275	-.691	-1.525
SCP_DD	1.000	5.000	.003	.015	-.894	-1.975
SCP_RCN	1.000	5.000	-.004	-.019	-.963	-2.126
SCP_MLT	1.000	5.000	-.159	-.702	-.950	-2.096
SCP_SHIP	1.000	5.000	-.138	-.611	-.733	-1.617
AGT_RPF	1.000	5.000	-.109	-.481	-1.098	-2.425
AGT_RESP	1.000	5.000	-.085	-.376	-.935	-2.065
AGT_DLRE	1.000	5.000	-.066	-.291	-1.162	-2.566
AGT_CSL	1.000	5.000	-.067	-.296	-1.164	-2.570
AGT_MLT	1.000	5.000	-.295	-1.301	-.884	-1.952
RMC_MON	1.000	5.000	.137	.606	-1.122	-2.477
RMC_IMPL	1.000	5.000	.065	.289	-1.187	-2.620
RMC_ASS	1.000	5.000	-.007	-.031	-1.142	-2.521
RMC_ID	1.000	5.000	.103	.454	-1.087	-2.400
RMC_DEDR	1.000	5.000	.025	.109	-1.009	-2.228
SCS_FTRA	1.000	5.000	-.026	-.116	-1.015	-2.242
SCS_POST	1.000	5.000	-.101	-.446	-.803	-1.772
SCS_SCAP	1.000	5.000	-.017	-.075	-1.283	-2.832
SCS_SS	1.000	5.000	-.188	-.830	-.933	-2.060
SCS_FSUP	1.000	5.000	-.087	-.386	-.776	-1.714

4.3. Testing of the measurement model

Primary objective of structured equation modeling is the empirical examination of the theoretically presumed relationships constituted by the structural model (Schumacker and Lomax, 2010). As part of the causal analysis, the structural model includes the relationship structure between hypothetical constructs, i.e. between unobservable variables. The quality of the estimated parameters of the structural model will be significantly determined by the quality of the measurement models, since according to the principle of "garbage in - garbage out" faulty measured constructs also lead to errors in the estimates of construct relations. The quality inspection of the

measurement models therefore has a prominent role in the causal analysis (Weiber and Mühlhaus, 2014).
In the following this section focuses on the reliability and validity testing of reflective measurement models and a distinction is made between the test of the indicators and the test of the construct level.

While reliability reflects the accuracy of a measuring instrument, validity refers to which extent a measuring instrument measures the things that it should measure and thus describes the validity or conceptual accuracy of a measuring instrument (Walker and Maddan, 2012). According to Fornell (1982) the quality criteria for testing validity and reliability are differentiated in the literature in quality or goodness criteria of the first and second generation: The quality criteria of the first generation were developed primarily in the psychometric research and are mainly based on correlation analyses for reliability testing (Cronbach and Meehl, 1955; Campell, 1960). An essential prerequisite for the application of these criteria is the one-dimensionality of the observed constructs, which can be verified by Exploratory Factor Analysis (EFA). The large deficit of the criteria of the first generation is the fact that they do not allow estimation of measurement errors and model parameters cannot be verified by means of inferential statistics (Weiber and Mühlhaus, 2014). In contrast, the quality criteria of the second generation are based on the application of Confirmatory Factor Analysis (CFA) and also allow the testing of validity. By applying CFA measurement error can be taken into account and statistical tests can be conducted (Fornell, 1982).

In order to assess and evaluate the measurement model several tests and analyses will be conducted in the following sub-chapter. First of all the one-dimensionality is tested by means of an EFA. Subsequently the goodness criteria of the first generation will be applied to examine the indicator and construct reliability. Finally conducting a CFA further tests the measurement model according to the quality criteria of the second generation.

4.3.1. Exploratory Factor Analysis

As part of the operationalization of a reflective measurement models as many measurement indicators as possible should be derived in the first step, which subsequently have to be subject to reliability testing. The objective of this test step is to eliminate those indicators that are not suitable to measure a reflective construct and whose measurement can be regarded as "not reliable“ (Gorsuch, 1988). The assumption that reflective measurement indicators represent different consequences or implications of a construct implies, that the constructs are considered one-dimensional. Therefore, the examination of the one-dimensionality of a construct is a prerequisite for further reliability testing of reflective indicators and is conducted using the Exploratory Factor Analysis (EFA) (Gerbing and Anderson, 1988). By means of the EFA it should be determined whether factors can be extracted based on the data and the resulting correlation structure of the measurement indicators. This structure should be corresponding to the assignments of the measurement indicators to the hypothetical constructs in the context of operationalization (Eckstein, 2008). If the assignments are confirmed, the substantive interpretation of the factors corresponding to construct meanings is considered justified and the factors are considered as the causal variables for the correlation of the measured indicators (Thompson, 2004). However, this procedure is only "quasi" exploratory, since the user uses the results of the EFA to eliminate such measurement indicators that are not correlated in accordance with its putative associations with a factor (Weiber and Mühlhaus, 2014).
The test with the aid of the EFA may be conducted either separately for each set of indicators of a construct or with several or all of the considered sets of indicators of the respective construct at the same time. While conducting separate EFA explicitly aims to confirm a single-factor structure, i.e. one-dimensionality, the simultaneous observation try to confirm the theoretically derived relationships of indicators to their assigned constructs. In the latter case those indicators should have high loadings on those constructs, which they have been assigned to at the conceptual level (Homburg and Giering, 1996).

The application of factor analysis is only useful if there are sufficiently high correlations between the output variables (Weiber and Mühlhaus, 2014). This assumption in the context of EFA can be verified by a number of criteria (Backhaus et al., 2011). The most important test parameters at the variable level are the Measure of Sampling Adequacy (MSA) as well as the communalities. The variable specific MSA-values are reported by SPSS in the anti-image correlation matrix and indicate the extent to which a variable must be considered as "belonging together“ with the other variables. In contrast, the commonality of a variable gives information about which percentage of the variable scattering can be explained by the extracted factors. MSA values and commonalities are in the interval [0, 1]. Variables with values less than 0.5 should be excluded from the EFA because they have less in common with the other variables or only a small fraction of the variance of these variables can be explained by the factors (Weiber and Mühlhaus, 2014).

For the whole population of variable the Kaiser-Meyer-Olkin criterion (KMO) as well as the Bartlett's test provide information on the links between the variables. The KMO criterion is determined by aggregation of the MSA values and should not be less than 0.6 (Kaiser and Rice, 1974). The Bartlett test checks the null hypothesis that the variables are derived from an uncorrelated population and should be rejected (Dziuban and Shirkey, 1974). To determine the number of factors to be extracted the widespread Kaiser criterion is applied. According to the Kaiser criterion a factor has to be extracted, whose eigenvalues is greater than 1 (Kaiser, 1974). This means that only those factors have a "significant" explanatory power that can explain more variance than a single standardized indicator variable itself, which (after standardization) has a variance of 1 (Weiber and Mühlhaus, 2014).

According to Costello and Osborne (2005) who argue that the default Principal Component Analysis (PCA) of SPPS is only a data reduction method and does not take into consideration the underlying structure caused by the latent variables, Maximum Likelihood was chosen as extraction method. Fabrigar, et al. (1999, p. 277) recommend Maximum Likelihood method as it „allows for the computation of a wide range of indexes of the goodness of fit of the model [and] permits statistical significance testing of factor loadings and correlations among factors and the computation of confidence intervals.” The normality distribution prerequisite for applying ML-estimation, as postulated by Costello and Osborne (2005) is given according to the analysis in chapter 4.2.3, which suggest only a moderate violation of the assumption of normal distribution.

In order to simplify and clarify the data structure oblique rotation was applied in this paper as this rotation technique allows the factors to be correlated with each other. Orthogonal rotation like Varimax or Quartimax however is the most widely used technique as it produces easily interpretable results. But due to the fact that we expect some correlation between the factors (e.g. high levels of Supply Chain Orientation may influence the Level of Information Management Capabilities throughout the supply chain) orthogonal rotation results in a loss of valuable information and oblique techniques provide a more accurate picture (Costello and Osborne, 2005). For this thesis Direct Oblimin (with a default value for delta (0)) was applied as Fabrigar et al. (1999) states that all oblique techniques provide similar results.

Table 14: EFA - KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.864
	Approx. Chi-Square	3428.377
Bartlett's Test of Sphericity	df	630
	Sig.	.000

Table 15: EFA - Communalities

	Initial	Extraction
SCO_COL	.496	.538
SCO_TRST	.392	.356
SCO_OBJ	.445	.407
SCO_MNGT	.449	.435
SCO_INT	.529	.485
IMC_IIS	.704	.674
IMC_EIS	.776	.730
IMC_ACC	.801	.785
IMC_IDB	.804	.794
IMC_JPS	.800	.822

SCS_FSUP	.685	.657
SCS_SS	.747	.783
SCS_SCAP	.704	.755
SCS_POST	.688	.673
SCS_FTRA	.694	.638
SCS_LEAN	.379	.093
RMC_DEDR	.736	.669
RMC_ID	.820	.783
RMC_ASS	.782	.831
RMC_IMPL	.762	.693
RMC_MON	.762	.772
AGT_MLT	.721	.727
AGT_CSL	.764	.770
AGT_DLRE	.720	.698
AGT_RESP	.668	.587
AGT_RPF	.776	.777
RBN_RSS	.807	.803
RBN_GRT	.794	.870
RBN_DSC	.763	.684
RBN_COF	.706	.678
RBN_MLC	.641	.566
SCP_SHIP	.711	.721
SCP_MLT	.635	.522
SCP_RCN	.743	.740
SCP_DD	.693	.624
SCP_QNT	.688	.670

Extraction Method: Maximum Likelihood.

The KMO criterion of 0.864 and the rejection of Bartlett's tests indicate sufficient correlations of the reflective measurement indicators (see Table 14), thereby supporting the adoption of the concept of multiple items. Most of the communalities (see Table 15) show high values with values > 0.5 and thus can be considered adequate. Only the values for the items for Supply Chain Orientation (SCO) show little lower values but still close to 0.5, however SCS_LEAN shows a significantly lower value of 0.093.

Table 16: EFA - Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	11.585	32.181	32.181	11.239	31.220	31.220	5.951
2	4.393	12.202	44.383	4.105	11.402	42.622	5.535
3	2.858	7.939	52.322	2.539	7.052	49.674	5.798
4	2.202	6.115	58.438	1.580	4.389	54.063	6.121
5	1.883	5.231	63.669	1.429	3.969	58.032	6.306
6	1.484	4.122	67.791	1.236	3.433	61.465	6.548
7	1.270	3.527	71.318	1.255	3.485	64.950	2.657
8	1.028	2.855	74.173	.428	1.189	66.138	.562
9	.776	2.155	76.328				
10	.694	1.927	78.255				
11	.660	1.834	80.089				
12	.570	1.583	81.672				
13	.559	1.553	83.225				
14	.535	1.485	84.710				
15	.474	1.317	86.027				
16	.443	1.230	87.257				
17	.427	1.186	88.442				
18	.393	1.091	89.534				
19	.370	1.027	90.561				
20	.342	.950	91.511				
21	.320	.890	92.400				
22	.301	.836	93.236				
23	.275	.765	94.001				
24	.268	.745	94.746				
25	.235	.652	95.398				
26	.226	.627	96.025				
27	.212	.589	96.614				

28	.205	.570	97.184				
29	.184	.512	97.696				
30	.157	.436	98.131				
31	.151	.420	98.551				
32	.130	.361	98.912				
33	.123	.341	99.253				
34	.107	.296	99.549				
35	.087	.241	99.790				
36	.076	.210	100.000				

Extraction Method: Maximum Likelihood.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

As displayed in Table 16, eight factors show an Eigenvalue of greater than 1. Therefore 8 factors can be extracted according to the Kaiser criterion. These eight factors together explain about 66% of the total variance of the model, which is a rather good value referred to the number of 36 variables.

Table 17: EFA – Pattern Matrix

	Factor							
	1	2	3	4	5	6	7	8
RMC_ASS	.906	-.081	.069	-.112	.117	-.148	-.021	-.042
RMC_MON	.857	.066	-.092	.149	-.078	-.009	-.001	.004
RMC_DEDR	.780	.099	-.076	-.031	.012	.086	.030	-.007
RMC_ID	.765	-.047	.043	-.111	-.176	.000	.007	-.016
RMC_IMPL	.717	-.022	.004	-.139	-.103	.054	.030	.062
IMC_JPS	.084	.884	-.086	.003	.041	-.010	.036	-.047
IMC_ACC	-.006	.793	.093	-.063	-.018	-.121	.080	.116
IMC_EIS	.078	.777	.087	.021	-.076	-.052	.066	-.070
IMC_IIS	-.091	.755	-.039	-.063	-.126	-.076	-.125	.033
IMC_IDB	-.087	.661	.031	-.001	-.229	-.212	.030	-.166
SCO_INT	.061	.559	-.083	.023	-.044	-.095	.158	.056
SCS_SCAP	.167	.164	-.801	-.067	.078	.006	-.087	-.126
SCS_SS	.045	.057	-.785	-.040	-.074	-.075	-.068	.095
SCS_FSUP	-.040	-.035	-.761	-.029	.025	-.113	.025	.036

SCS_FTRA	-.090	-.054	-.659	-.193	-.095	-.035	.131	-.073
SCS_POST	.030	-.095	-.631	-.111	-.063	-.076	.229	.048
SCS_LEAN	-.079	.139	.182	-.040	.112	.048	.021	-.029
RBN_GRT	-.017	-.034	-.044	-.867	-.098	-.075	.012	-.205
RBN_RSS	.044	-.028	-.038	-.795	-.084	-.116	.006	-.050
RBN_DSC	.058	.040	-.049	-.734	-.073	.027	.016	.101
RBN_COF	.167	.144	-.083	-.685	.119	.015	-.097	.181
RBN_MLC	.110	-.031	-.169	-.529	-.074	-.027	.155	.074
SCP_RCN	.060	.032	-.031	-.120	-.763	.012	-.051	-.178
SCP_SHIP	-.013	.080	-.193	.109	-.727	-.088	.030	-.097
SCP_QNT	.104	.041	-.053	.025	-.694	-.079	.055	.109
SCP_DD	.021	.014	.021	-.152	-.657	-.030	-.018	.260
SCP_MLT	.087	.143	.102	-.102	-.627	.027	-.004	-.022
AGT_CSL	-.018	.039	-.109	-.039	.017	-.810	-.055	-.102
AGT_MLT	.062	.072	-.089	.088	-.034	-.783	-.035	.121
AGT_RPF	.104	.097	.045	.056	-.117	-.756	.108	-.154
AGT_DLRE	-.077	.077	-.051	-.124	.012	-.736	-.005	.176
AGT_RESP	-.010	.110	-.024	-.166	.009	-.624	.073	-.058
SCO_COL	.081	.035	.065	-.032	.010	.039	.725	-.058
SCO_OBJ	.019	-.109	.058	-.033	-.019	-.143	.621	.082
SCO_MNGT	-.024	.159	-.113	.013	-.010	.142	.599	.095
SCO_TRST	-.054	.050	-.069	.040	.027	-.031	.556	-.115

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.[a]
a. Rotation converged in 12 iterations.

Table 17 shows the pattern matrix of the extracted factors after Direct Oblimin rotation. For better visibility the items belonging to one of the extracted factors were highlighted. The Pattern Matrix shows clearly that 7 distinct factors were extracted from the underlying data. The items belonging to one of the factors show high loadings on only one factor and low loadings on the other extracted factors. While most of the assignments of items to factors are according to the theoretical model the items SCS_LEAN and SCO_INT constitute exceptions. SCO_INT seems to belong to the factor constituting the Information Management Capabilities (IMC) rather then to the factor constituting Supply Chain Orientation (SCO), due to its higher correlation with the items of IMC. SCS_LEAN in comparison does not show high correlation with either the other items of Supply Chain Strategy (SCS) or with any other extracted factor. Thus SCS_LEAN will be removed for the subsequent analysis, while SCO_INT should be integrated into the Information Management Capabilities measurement model.

With correlations in the range of about 0.6 to 0.9 on the propagated factor and values in the range of less than 0.3 for the other factors, the EFA provides that all constructs are one-dimensional and a high suitability for the subsequent analysis steps is generally given (Weiber and Mühlhaus, 2014). In summary it can be stated that the hypothetically assumed structure of seven factors can be confirmed on the basis of the EFA.

4.3.2. Examination of indicator and construct reliability

Subsequent to examining the one-dimensionality of the item structure for the hypothetical constructs the actual test of reliability of the measurement indicators has to be conducted. The proof of reliability of the measured variables refers to the estimation of the random error. According to classical test theory the reliability corresponds to the squared correlation between the (observed) measurements and the true value of a variable. The greater the squared correlation is, the greater the proportion of shared variance between the measurements and the true value. However, since the true value of a variable is unknown, the reliability has to be estimated, for which various options are available (Schnell, Hill and Esser, 2011).

For practical application primarily the examination of the measurement equivalence in the form of the so-called Cronbach's Alpha is of importance. According to Churchill (1979, p. 68) Cronbach’s Alpha is „ ... absolutely [...] the first measure one calculates to asses the quality of the instrument“. The more Cronbach's Alpha approaches the value 1, the higher is the internal consistency reliability (Weiber and Mühlhaus, 2014). Nunnally and Bernstein (1994) recommend using a set of indicators only if it has a value of $\alpha \geq 0.7$. However, in the literature, very high values of Cronbach's alpha close to 1 are also considered problematic, as this could be an indication that the items are congruent in content and / or linguistics (Peter, 1979).

Another measure for estimating the reliability on the level of total construct measurement is the so-called Inter-Item Correlation (IIC). The IIC here represents the average correlation of all items that are assigned to a construct. The values are required by ≥ 0.3, to assume an adequate construct measurement (Revelle, 1979; Robinson, Shaver and Wrightsman, 1991). If the values of Cronbach's Alpha (and also the IIC) show an acceptable value for the respective constructs, the indicator variables can in principle be maintained, i.e. a change in the indicators or the reduction or enlargement of the indicator set is not required (Weiber and Mühlhaus, 2014). Nevertheless, sometimes it is advisable, to remove individual variables even if they show a high alpha. This is due to the fact that Cronbach's Alpha increases dramatically with the number indicator (Homburg and Giering, 1996).

The internal consistency of a construct can possibly be improved, if indicators that contribute little to the construct measurement are eliminated from the analysis, which can be determined in the first step using the so-called Item-to-total-correlation (ITC). To determine the ITC, the correlation of an indicator with the sum of the indicators of a construct is calculated with a threshold for good reliability of ITC ≥ 0.5 (Nunnally, 1967; Bearden, Netemeyer and Teel, 1989). Since for the calculation of this measure each variable partially correlate with itself, because it is a constituent part of the overall scale, the Corrected Item-to-Total Correlation (CITC) is often used. An indicator should be excluded from the analysis if the ITC or CITC shows values < 0.5 (Zaichkowsky, 1985; Shimp and Sharma, 1987).

Table 18: Reliability Statistics (Cronbach's Alpha)

Factor	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
SCO (Supply Chain Orientation)	.733	.733	4
IMC (Information Management Capabilities)	.924	.924	6
SCS (Supply Chain Strategy)	.905	.905	5
RMC (Risk Management Capabilities)	.928	.929	5
AGT (Agility)	.909	.909	5
RBN (Robustness)	.909	.909	5
SCP (Supply Chain Performance)	.880	.880	5

Table 19: Inter-Item Correlation Matrix

SCO

	SCO_COL	SCO_TRST	SCO_OBJ	SCO_MNGT
SCO_COL	1.000	.389	.489	.452
SCO_TRST	.389	1.000	.363	.383
SCO_OBJ	.489	.363	1.000	.363
SCO_MNGT	.452	.383	.363	1.000

IMC

	SCO_INT	IMC_IIS	IMC_EIS	IMC_ACC	IMC_IDB	IMC_JPS
SCO_INT	1.000	.512	.524	.594	.571	.593
IMC_IIS	.512	1.000	.694	.686	.704	.678
IMC_EIS	.524	.694	1.000	.753	.714	.771
IMC_ACC	.594	.686	.753	1.000	.698	.771
IMC_IDB	.571	.704	.714	.698	1.000	.758
IMC_JPS	.593	.678	.771	.771	.758	1.000

SCS

	SCS_FSUP	SCS_SS	SCS_SCAP	SCS_POST	SCS_FTRA
SCS_FSUP	1.000	.662	.659	.615	.657
SCS_SS	.662	1.000	.739	.662	.662
SCS_SCAP	.659	.739	1.000	.630	.610
SCS_POST	.615	.662	.630	1.000	.671
SCS_FTRA	.657	.662	.610	.671	1.000

RMC

	RMC_DEDR	RMC_ID	RMC_ASS	RMC_IMPL	RMC_MON
RMC_DEDR	1.000	.741	.700	.688	.688

RMC_ID	.741	1.000	.765	.715	.743
RMC_ASS	.700	.765	1.000	.725	.754
RMC_IMPL	.688	.715	.725	1.000	.704
RMC_MON	.688	.743	.754	.704	1.000

AGT

	AGT_MLT	AGT_CSL	AGT_DLRE	AGT_RESP	AGT_RPF
AGT_MLT	1.000	.718	.671	.602	.709
AGT_CSL	.718	1.000	.694	.633	.721
AGT_DLRE	.671	.694	1.000	.635	.639
AGT_RESP	.602	.633	.635	1.000	.642
AGT_RPF	.709	.721	.639	.642	1.000

RBN

	RBN_RSS	RBN_GRT	RBN_DSC	RBN_COF	RBN_MLC
RBN_RSS	1.000	.819	.715	.704	.617
RBN_GRT	.819	1.000	.740	.641	.637
RBN_DSC	.715	.740	1.000	.619	.591
RBN_COF	.704	.641	.619	1.000	.590
RBN_MLC	.617	.637	.591	.590	1.000

SCP

	SCP_SHIP	SCP_MLT	SCP_RCN	SCP_DD	SCP_QNT
SCP_SHIP	1.000	.564	.659	.550	.673
SCP_MLT	.564	1.000	.598	.480	.545
SCP_RCN	.659	.598	1.000	.612	.666
SCP_DD	.550	.480	.612	1.000	.587
SCP_QNT	.673	.545	.666	.587	1.000

First, the quality criteria Cronbach's Alpha and the Inter-Item Correlation are considered. The value of Cronbach's Alpha for all constructs is above the normal threshold values of 0.7 (see Table 18), which also applies to the standardized alphas, while both measures yield very similar results for every factor. With the exception of SCO all constructs show considerably higher values for Cronbach’s Alpha as required and even though SCO shows the lowest value it is still above the required threshold value. The similar values of Cronbach’s Alpha and the standardized Cronbach’s Alpha have been foreseeable, since the Likert-Scale for all items has been the same and thus the variances were expected to be within the same range. Based on the IIC, indicating the average correlations of indicators that are assigned to a construct, a similar picture emerges (see Table 19). All values are far above the required threshold value of 0.3 while SCO again shows the lowest values but still above the threshold.

Thus it can be concluded, that the usual minimum requirements for a reliable measurement model are fulfilled and both Cronbach’s Alpha as well as the Inter-Item-Correlation show a strong reliability for all constructs, however SCO shows smaller values then the other tested constructs.

The alpha values as well as the IIC proofed the principle suitability of a set of indicators for measuring a certain construct. But beyond that it should also be investigated to what extent individual indicator variables represent a "problem" or are not well suited for the construct measurement. For this purpose, the CITC and Cronbach's Alpha (if item deleted) are applied. Cronbach's Alpha (if item deleted) shows the alpha values of the total scale, which would have been achieved by elimination of the corresponding items and can thus be used to identify unsuitable variables (Weiber and Mühlhaus, 2014).
According to Table 20 all items, except of SCO_TRST show CITC values higher then the required threshold value of 0.5. However SCO_TRST shows a value, which is very close to the threshold value (0.480). Especially with regard to the fact that the construct of SCO is only measured by 4 items and the Cronbach’s Alpha (if item deleted) would significantly decrease with the exclusion of SCO_TRST will not be excluded for the further analysis. As all the other items would not significantly increase Cronbach’s Alpha by being excluded the test proofs that these items are well suited for measuring the constructs.

Table 20: Item Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
SCO_COL	10.04	5.520	.584	.348	.637
SCO_TRST	9.65	6.184	.480	.230	.697
SCO_OBJ	9.92	5.702	.521	.288	.674
SCO_MNGT	10.03	5.686	.511	.269	.680
SCO_INT	16.90	29.859	.634	.417	.929
IMC_IIS	16.84	27.551	.763	.598	.913
IMC_EIS	16.69	26.647	.814	.689	.906
IMC_ACC	16.58	26.784	.825	.692	.905
IMC_IDB	16.72	26.773	.810	.667	.907
IMC_JPS	16.77	26.224	.845	.729	.902
SCS_FSUP	13.75	16.743	.750	.566	.886
SCS_SS	13.59	16.319	.798	.650	.876
SCS_SCAP	13.69	15.973	.765	.614	.883
SCS_POST	13.71	16.659	.745	.562	.887
SCS_FTRA	13.70	16.166	.752	.578	.886
RMC_DEDR	12.46	22.641	.787	.625	.917
RMC_ID	12.34	21.804	.838	.705	.907
RMC_ASS	12.37	21.647	.831	.695	.908
RMC_IMPL	12.34	21.851	.792	.628	.916
RMC_MON	12.49	21.665	.812	.664	.912
AGT_MLT	13.33	17.224	.782	.624	.886
AGT_CSL	13.30	17.288	.806	.655	.881
AGT_DLRE	13.36	17.037	.760	.584	.891
AGT_RESP	13.28	18.040	.717	.519	.899
AGT_RPF	13.48	16.998	.785	.628	.885
RBN_RSS	13.77	17.178	.837	.736	.874
RBN_GRT	13.58	17.485	.833	.732	.875
RBN_DSC	13.73	16.824	.769	.606	.890
RBN_COF	13.67	18.356	.730	.548	.897
RBN_MLC	13.60	19.137	.689	.478	.905
SCP_SHIP	13.57	12.247	.739	.559	.847
SCP_MLT	13.40	12.734	.647	.426	.870
SCP_RCN	13.61	11.925	.771	.596	.839
SCP_DD	13.50	13.237	.660	.448	.866
SCP_QNT	13.62	12.371	.748	.571	.845

As limitation, however, it should be noted that the threshold values given are only guidelines that should not be accepted uncritically. Especially the first generation goodness criteria have some considerable weaknesses concerning the reliability assessment (Homburg and Giering, 1996; Bagozzi and Phillips, 1982). Gerbing and Anderson (1988) as well as Hildebrandt and Temme (2006) mention that they are party based on very restrictive assumptions. Cronbach's Alpha for example assumes, that all indicators of a factor are having the same reliability and uni-dimensionality, which however strongly depends on the number of indicators. Furthermore the goodness criteria are based on relatively intransparent determined threshold values that may only represent "rules of thumb" and they do not consider measurement errors (Hildebrandt, 1984).

4.3.3. Confirmatory Factor Analysis

The previously discussed goodness criteria of the first generation for testing the reliability does not allow explicit estimates of measurement error and also does not allow statistical assessments for validity. First with the work of Jöreskog (1967; 1969; 1970) for confirmatory factor analysis (CFA) a way was opened to estimate measurement error variances of reflective measurement models and to examine the discriminant validity of hypothetical constructs in particular. Since the work of Fornell (1982) the goodness criteria derived from CFA are referred to as goodness criteria of the second generation. Thereby it is possible, especially to check the reliability of the construct measurement as well as to examine the construct validity.

The reliability test criteria of the second generation are primarily conducting a comparison between the variance of an indicator and the variance of the measurement error. The respective reliability criterion is better, the greater the share of the explained variance is. All test criteria of the second generation are derived from the results of the CFA, which is a special case of a complete structural equation model (Weiber and Mühlhaus, 2014). Thereby the CFA represents a special case of a complete causal model because it only analyzed the measurement models of the hypothetical constructs and is an integral part of the complete SEM with focus on the quality inspection of reflective measurement models (Backhaus, Erichson and Weiber, 2013). In contrast to the already conducted EFA, CFA differs fundamentally, although both are based on the fundamental theorem of factor analysis and both use similar methods of estimation. In contrast to the EFA the number of factors (constructs) and the assignment of empirical indicators to the factors in the CFA is defined by the user a-priori and not extracted from the data structure. These decisions based upon theoretical or logical point of views are tested using the CFA, whereby the CFA belongs to the structure-testing methods of multivariate data analysis (Brown and Moore, 2013).

To calculate the reliability criteria of the second generation, the reflective measurement models of the constructs are jointly investigated in a CFA. Using the results of the CFA the indicator reliability (squared multiple correlation), the factor reliability (FR) or composite reliability as well as the average variance extracted for each factor (AVE) can be calculated (Weiber and Mühlhaus, 2014).

The indicator reliability is the proportion of the variance of an indicator that is explained by the construct. They are issued in AMOS under the name Squared Multiple Correlation (SMC). The indicator reliability should thereby show values greater than 0.4 in order to assume an at least acceptable suitability of the corresponding indicator variables (Bagozzi and Yi, 1988). In addition to this, the loadings are often directly observed and assessed (Homburg and Giering, 1996). Overall, it is required on the indicator level that the loadings should be statistically significantly different from zero and significant in terms of indicator reliability. Because this test is significantly less restrictive, it can serve as a minimum requirement, which should lead to the exclusion of the corresponding indicator and therefore a new calibration of the measurement model in case of non-compliance. (Hildebrandt and Temme, 2006).

Analogously to Cronbach's Alpha the following two criteria can be understood as a measure of reliability of the sum of all indicators, which form a construct. The so-called FR corresponds to the Indicator Reliability on the construct level and should according Bagozzi und Yi (1988) assume values greater than 0.6.

In addition to the FR the Average Variance Extracted for each factor is often considered in the literature (Bruner and Kumar, 2005; Gillenson and Sherrell, 2002). The AVE indicates what percentage of the scattering of the latent construct is explained on average by the indicators. Here values greater than 0.5 are required in the literature (Fornell and Larcker, 1981).

To conduct a CFA initially a path diagram with the seven measurement models was created using the program package AMOS 21 and the Amos Graphics module. The procedure for creating the path diagram is identical to the creation of a complete causal model (= measurement models and structural model) only without the causal relationships between the latent variables. Figure 2 shows the path diagram of the CFA, in which case the estimation results are already displayed. In order to estimate the parameters (factor loadings and correlation of the constructs) the ML-method was used, and the missing data were supplemented using the „Estimate Means and Intercepts“ function.

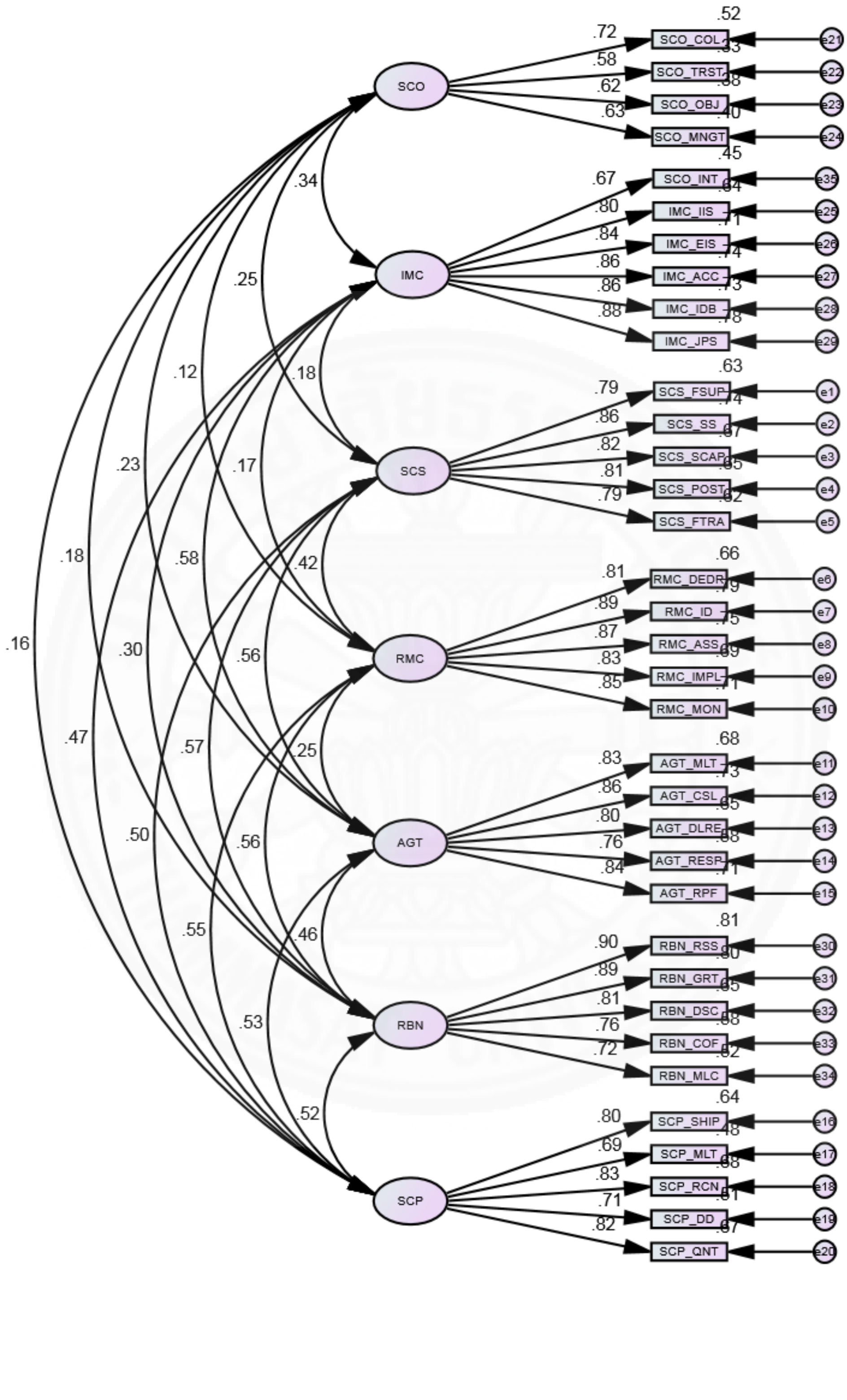

Figure 2: Confirmatory Factor Analysis (with standardized estimates)

To calculate the reliability criteria of the second generation, which are not reported directly from AMOS, the estimation results of the CFA have been transferred to an Excel spread sheet model. The necessary calculations have been carried out subsequently in accordance with the described formulas by Weiber and Mühlhaus (2014). Table 21 shows the result of the calculations, wherein the values for Factor Loading and SMC have been adopted from CFA estimates. The error variance of an indicator is calculated in the case of standardized estimation results as "1- Squared Multiple Correlation" and the indicator reliability corresponds to Squared Multiple Correlation.

Table 21: Reliability Calculations

		Results CFA			**Reliability Calculation**		
Factor	**Indicator**	**Factor Loading**	**Squared Multiple Correlation**	**Error Variance**	**Indicator Reliability**	**Factor Reliability**	**AVE**
SCO	SCO_COL	0,72	0,52	0,48	0,52	0,733	0,418
	SCO_TRST	0,58	0,33	0,67	0,33		
	SCO_OBJ	0,62	0,40	0,60	0,40		
	SCO_MNGT	0,63	0,45	0,55	0,45		
IMC	SCO_INT	0,67	0,45	0,55	0,45	0,925	0,675
	IMC_IIS	0,80	0,64	0,36	0,64		
	IMC_EIS	0,84	0,71	0,29	0,71		
	IMC_ACC	0,86	0,74	0,26	0,74		
	IMC_IDB	0,86	0,73	0,27	0,73		
	IMC_JPS	0,88	0,78	0,22	0,78		
SCS	SCS_FSUP	0,79	0,63	0,37	0,63	0,908	0,663
	SCS_SS	0,86	0,74	0,26	0,74		
	SCS_SCAP	0,82	0,67	0,33	0,67		
	SCS_POST	0,81	0,65	0,35	0,65		
	SCS_FTRA	0,79	0,62	0,38	0,62		
RMC	RMC_DEDR	0,81	0,66	0,34	0,66	0,929	0,722
	RMC_ID	0,89	0,79	0,21	0,79		
	RMC_ASS	0,87	0,75	0,25	0,75		
	RMC_IMPL	0,83	0,69	0,31	0,69		
	RMC_MON	0,85	0,71	0,29	0,71		
AGT	AGT_MLT	0,83	0,68	0,32	0,68	0,910	0,670
	AGT_CSL	0,86	0,73	0,27	0,73		
	AGT_DLRE	0,80	0,65	0,35	0,65		

	AGT_RESP	0,76	0,58	0,42	0,58		
	AGT_RPF	0,84	0,71	0,29	0,71		
RBN	RBN_RSS	0,90	0,81	0,19	0,81	0,910	0,671
	RBN_GRT	0,89	0,80	0,20	0,80		
	RBN_DSC	0,81	0,65	0,35	0,65		
	RBN_COF	0,76	0,58	0,42	0,58		
	RBN_MLC	0,72	0,52	0,48	0,52		
SCP	SCP_SHIP	0,80	0,64	0,36	0,64	0,880	0,596
	SCP_MLT	0,69	0,48	0,52	0,48		
	SCP_RCN	0,83	0,68	0,32	0,68		
	SCP_DD	0,71	0,51	0,49	0,51		
	SCP_QNT	0,82	0,67	0,33	0,67		

If the results shown in Table 22 are considered, it becomes apparent that all factor loadings (unstandardized loadings = Estimate, standardized loadings = Estimate*) are significantly different from zero and that they show high values. For this purpose AMOS shows the p-Values in the column P. The three asterisks (***) state that all indicator variables are significantly different from zero at a level of 0.01%.

Table 22: CFA Parameter Estimation

			Estimate	S.E.	C.R.	P	Estimate *
SCS_FSUP	<---	SCS	1				0,793
SCS_SS	<---	SCS	1,094	0,098	11,203	***	0,861
SCS_SCAP	<---	SCS	1,108	0,106	10,498	***	0,820
SCS_POST	<---	SCS	1,032	0,100	10,313	***	0,806
SCS_FTRA	<---	SCS	1,046	0,104	10,049	***	0,790
RMC_DEDR	<---	RMC	1				0,812
RMC_ID	<---	RMC	1,138	0,091	12,518	***	0,890
RMC_ASS	<---	RMC	1,131	0,094	12,000	***	0,867
RMC_IMPL	<---	RMC	1,098	0,098	11,238	***	0,828
RMC_MON	<---	RMC	1,128	0,097	11,604	***	0,845
AGT_MLT	<---	AGT	1				0,827
AGT_CSL	<---	AGT	1,009	0,085	11,920	***	0,855
AGT_DLRE	<---	AGT	1,018	0,093	10,913	***	0,803
AGT_RESP	<---	AGT	0,897	0,088	10,132	***	0,763
AGT_RPF	<---	AGT	1,045	0,090	11,652	***	0,840
SCP_SHIP	<---	SCP	1				0,803
SCP_MLT	<---	SCP	0,869	0,103	8,474	***	0,695

SCP_RCN	<---	SCP	1,032	0,098	10,568	***	0,826
SCP_DD	<---	SCP	0,805	0,091	8,807	***	0,714
SCP_QNT	<---	SCP	0,981	0,094	10,446	***	0,819
SCO_COL	<---	SCO	1				0,719
SCO_TRST	<---	SCO	0,749	0,142	5,284	***	0,577
SCO_OBJ	<---	SCO	0,879	0,158	5,552	***	0,619
SCO_MNGT	<---	SCO	0,909	0,162	5,610	***	0,633
IMC_IIS	<---	IMC	1				0,799
IMC_EIS	<---	IMC	1,088	0,096	11,282	***	0,843
IMC_ACC	<---	IMC	1,084	0,094	11,569	***	0,860
IMC_IDB	<---	IMC	1,098	0,095	11,515	***	0,857
IMC_JPS	<---	IMC	1,146	0,095	12,028	***	0,881
RBN_RSS	<---	RBN	1				0,902
RBN_GRT	<---	RBN	0,965	0,063	15,344	***	0,893
RBN_DSC	<---	RBN	0,994	0,079	12,560	***	0,809
RBN_COF	<---	RBN	0,816	0,073	11,194	***	0,759
RBN_MLC	<---	RBN	0,737	0,071	10,379	***	0,724
SCO_INT	<---	IMC	0,771	0,092	8,403	***	0,672

In addition, the loadings are assessed as significant as the respective indicator reliabilities values (SMC) show values between 0.40 and 0.81 (see Table 20) and are thus above the required minimum level of 0.4 (Bagozzi and Baumgartner, 1994) and below the maximum level of 0.90 (Netemeyer, Bearden and Sharma, 2003). Only the item SCO_TRST is located below the minimum level with a value of 0.33. These results thus confirm the previous examinations, so a high suitability of each manifest variable can be assumed even with the explicit consideration of measurement errors. Only SCO_TRST cannot be considered as suitable for the subsequent analysis and thus will be deleted.

The analysis on the construct level yields a similar result. Thus, the above-mentioned minimum values of 0.6 for FR (Bagozzi and Yi, 1988) as well as the 0.5 for AVE (Fornell and Larcker, 1981) are significantly exceeded with values from 0.733 to 0.929 for FR respectively 0.596 to 0.722 for AVE. Hence a very good reliability of the seven construct measurements may be assumed.

4.4. Structural Equation Modeling

For the analysis of causal relationships using the SEM, it is assumed that the indicators SCO_COL, IMC_IDB, RMC_ID, SCS_FSUP, AGT_CSL, RBN_GRT and SCP_MLT reflect the corresponding constructs particularly well. For this reason, they are selected as reference indicators to determine the respective construct metrics and their path coefficient is fixed to 1. For the parameter estimation furthermore the regression weight is set to 1 between the error terms and the constructs (e1-e39). All other parameters to be estimated are constituted as free parameters. As the CFA (see Figure 2) revealed low to medium covariances between SCO & IMC (0.34), SCS & SCO (0.25) as well as RMC & SCS (0.42) these covariances are added to the structural model. The remaining pairs of variables (IMC & RMC, IMC & SCS, RMC & SCO) are regarded as uncorrelated as they show only very low covariances (<0.2). These covariances seem to be appropriate from a proper logical consideration as the level of Supply Chain Orientation is likely to correlate with the level of Information Management Capabilities and Supply Chain Strategies within a Supply Chain. Furthermore the medium covariance between Risk Management Capabilities and Supply Chain Strategies can be explained due to the fact that companies which focus in a forward looking and proactive risk management are also likely to have certain strategies implemented in their supply chain to support the risk management measures.

As a necessary condition for identifiability of the model the number of model parameters must be less than the number of empirically determined variances and covariances. In the present model the measured variables provide a total of 595 empirical variances and covariances while the number of distinct parameters to be estimated is 81. Thus, the number of degrees of freedom is 595-81 = 514, so that the identifiability of the model is given. The ratio of degrees of freedom to the number of parameters can therefore be classified overall as appropriate, however the model is over identified and thus the model fit will be not as good as with an just identified model (Weiber and Mühlhaus, 2014).

For evaluation of the model the ML-method is used as a method of estimation. The ML-method maximizes the likelihood that the theoretical covariance or correlation matrix has generated the respective empirical covariance or correlation matrix. The use of the ML method is here mainly justified by the fact that it is the most frequently applied methods practice for the causal analysis, that it allows the calculation of inferential statistics and that it provides the most precise estimates in the present of multi-normal distribution of the measured variables (Weiber and Mühlhaus, 2014).

The evaluation of a causal model is the central goal of causal analysis, as it examines whether it is possible to empirically confirm the theoretical considerations formulated hypothesis system on the basis of the collected data. Basically, the evaluation of a model refers to the assessment partial structures, as well as the evaluation of the overall model (Schumacker and Lomax, 2010). The assessment of the partial structures is aiming primarily at the reliability- and validity of the measurement models of the latent variables and has already been conducted in chapter 4.3. Therefore the considerations below only focus on the assessment of the causal model (measurement models + structural model) in its entirety. In order to assess the model fit of the overall model first a plausibility check the parameter estimates is conducted. In a second step the model is assessed based on selected inferential statistical as well as descriptive goodness of fit criteria, while the latter is again subdivided into absolute fit indices as well as goodness of fit indices.

4.4.1. Plausibility check of parameter estimates

The parameter estimates of a causal model are generally considered "implausible" if negative variances, communalities > 1 or correlations > 1 occur. This means that parameter matrices are not "positive definite" and therefore not invertible. The result is that certain quality criteria cannot be calculated and the estimation algorithm may terminate (Blunch, 2013). Such Heywood cases are an indication that the estimation algorithm has not found a reasonable solution. In these cases an interpretation of the results should be refrained and modifications of the model have to be made (West, Finch and Curran, 1995). Generally, problem cases can also be detected on the basis of the standardized solution, since both the path coefficients and the error variances and covariances between the constructs are normalized to the interval [-1; 1]. Values beyond this range indicate that no reliable estimate could be determined (Weiber and Mühlhaus, 2014).

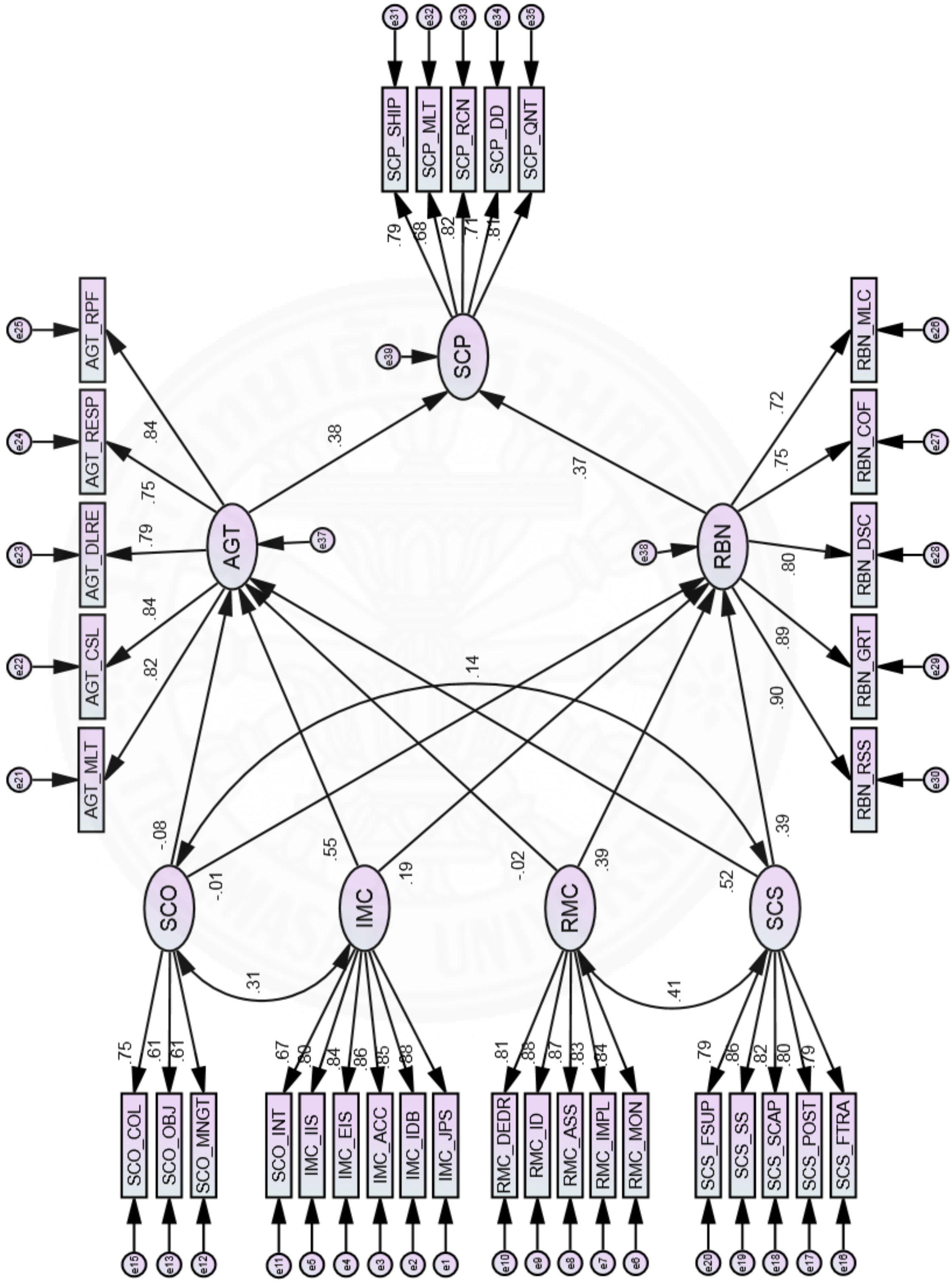

Figure 3: Structured Equation Model (with standardized estimates)

In the present model no Heywood cases occurred, and all goodness criteria has been calculated. The reliability assessment conducted for the complete model in chapter 4.3.2 provided satisfactory overall reliabilities of the indicators and the latent variables show no evidence that the causal model is misspecified. The standardized solution (see Figure 3) thereby confirmed the theoretically formulated relationships.
All prefixes of the factor loadings (Standardized Regression Weights) are positive and show acceptable loadings with values > 0.5. The parameter estimates are all plausible and consistent with the hypotheses formulated.

4.4.2. Assessment bases on goodness criteria

A high quality of a causal model (so-called model fit) is generally given when calculated variances and covariances using the parameter estimates match as closely as possible with the variances and covariances empirically obtained (Hooper, Coughlan and Mullen, 2008). To evaluate the model fit, a variety of criteria is available that can be distinguished into inferential goodness criteria that represent the statistical tests of the model fit as well as descriptive goodness criteria. The latter are based primarily on experience and stimulation studies and make decisions whether a model should be adopted or rejected due to so-called cut-off criteria (rules of thumb) (Weiber and Mühlhaus, 2014).

4.4.2.1. Inferential statistical goodness criteria

The most important inferential goodness criterion is the so-called Chi-square test (or Likelihood Ratio Test) (Weiber and Mühlhaus, 2014). This test corresponds to a chi-square goodness of fit test, and tests the null hypothesis, that the theoretical model variance-covariance matrix corresponds to the true values of the population alternative hypothesis that the theoretical model variance-covariance matrix corresponds to an arbitrary positive definite matrix (Hooper, Coughlan and Mullen, 2008). The smaller the difference of the deviations between the empirical variance-covariance matrix and model-theoretically calculated variance-covariance matrix, the lower is the χ^2 value (Reinecke, 2005). According to Weiber and Mühlhaus (2014) the chi-square value, however has to be interpreted with caution. This is particularly true in the context that it is a measure of the goodness of fit of the entire model, thus it may even show high values when complex models differ only in parts of the empirical variance-covariance matrix. In addition, it is testing the full compliance of the empirical and theoretical calculated variance-covariance matrix (perfect fit) and also responds very strongly to an increase in the sample size. As a result, models that are validated against a large data set are usually rejected on the basis of the χ^2-value (Bentler and Bonnet, 1980).

For these reasons Browne and Mels (1992, p. 78) suggest to refrain from the use of the chi-square test (with a zero hypothesis of perfect fit) because "it does not help much to know whether or not the statistical test has been able to detect that it is false." In addition, the calculation of the chi-square value is linked to a number of conditions, and it is only a suitable test statistic when these are met (Reinecke, 2005). However these conditions are rarely fulfilled in practical applications, so that adjustments in the chi-square test statistic have to be made or more goodness criteria has to be used, which can support the quality test of a model (Weiber and Mühlhaus, 2014). In order to circumvent the problems of the χ^2 tests of the Root-Mean-Square-Error of approximation (RMSEA) can be investigated. RMSEA is also a inferential statistical measure, and checks whether a model can approximate the reality well, making it less strictly formulated than the χ^2 test, which checks the "correctness" of a model (Steiger, 1990). According to Brown and Cudeck (1993) the values for the RMSEA ≤ 0.05 indicate a good or close model fit, while values ≤ 0.08 indicate a reasonable model fit and models with a RMSEA of ≥ 0.10 are inacceptable. Additionally PCLOSE-values in AMOS indicate the error probability for the null hypothesis that the RMSEA is ≤ 0.05. If this probability is less than a predetermined error probability (e.g. $\alpha = 0.05$) a good model fit can be concluded. In addition the 90% confidence interval with the lower limit LO90 and the upper limit HI90 is reported.

Weiber & Mühlhaus (2014) suggest that for practical applications where the conditions of the chi-square test statistics are often not met, to interpret the chi-square value only as a descriptive criterion and set in ratio to the degrees of freedom (d.f.).

AMOS issues this quotient as "CMIN / DF" (Arbuckle, 2012). According to Homburg and Baumgartner (1995) the ratio between the χ^2 value and the degrees of freedom should be less or equal to 2.5. Byrne (1989) requires a more restrictive requirement, after which this value should not be greater than 2. Furthermore the question of "sufficient" sample size plays a central role in the use of the chi-square statistic, as the chi-square value reacts extremely sensitive to a change of the sample size and deviations from the normal distribution assumption. The chances that a model is accepted are increasing with a decreasing sample size, and vice versa (Backhaus et al., 2006; Bearden, Sharma and Teel, 1982).
The HOELTER test in AMOS indicates the "critical" sample size with which the model under consideration would just get accepted using the chi-square test with a significance level of $\alpha = 0, 01$ respectively 0.05. Greater samples in this case lead to a rejection of the chi-square test's null hypothesis (Hoelter, 1983; Arbuckle, 2012). Due to the sensitivity of the χ^2-value in terms of degrees of freedom such an "absolute statement" for HOELTER test, however, is highly doubtful (Weiber and Mühlhaus, 2014).

For the present model 595 empirical variances and covariances were calculated, while 81 parameters have to be estimated. This results in a total of 595- 81 = 514 degrees of freedom (d.f.) (see Table 23). The ML-discrepancy reached its minimum after 9 iterations with a value of 5.442 (reported as „FMIN“) and the chi-square shows a high value of 740.148. As probability level p = 0.000 is reported, which means that the null hypothesis (empirical and model-theoretical covariance matrices are equal) must be discarded as a rejection with a probability of 0.000 would be a mistake. Therefore the model cannot be regarded as a good fit to the reality according to the chi-square test, since only a small equivalence between empirical and theoretical modeling variance-covariance matrix exists.
However if the chi-square value is divided by the number of degrees of freedom, we obtain the descriptive goodness measure of CMIN/DF with a value of 1.440, which according to Byrne (1989) indicates a good overall model fit. In addition, the RMSEA value of 0.057 shows a good to acceptable model fit, following the recommendations of Browne and Cudeck (1993). For PCLOSE AMOS reports a value of 0.110, which

suggests that the "true" RMSEA is only slightly greater than 0.05, which is confirmed by the specified confidence interval of [0.048; 0.066]. According to HOELTER the minimum sample size for the two error probabilities of 1% and 5% is below the actual sample size of 137. This again confirms the results of chi-square tests and shows that only with a much reduced sample size, the model would be confirmed. Overall the χ^2-test and HOELTER test contradict the validity of the causal model, whereas the RMSEA and the descriptive χ^2 / d.f. measure show a good to acceptable suitability of the model.

Table 23: Notes for Model

Computation of degrees of freedom (Default model)		**Result (Default model)**
Number of distinct sample moments:	595	Minimum was achieved; Chi-square = 740.148
Number of distinct parameters to be estimated:	81	Degrees of freedom = 514
Degrees of freedom (595 - 81):	514	Probability level = .000

Table 24: Model Fit Summary (CMIN, FMIN, RMSEA, HOELTER)

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	81	740.148	514	.000	1.440
Saturated model	595	.000	0		
Independence model	34	3811.686	561	.000	6.794

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	5.442	1.663	1.160	2.224
Saturated model	.000	.000	.000	.000
Independence model	28.027	23.902	22.491	25.367

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.057	.048	.066	.110
Independence model	.206	.200	.213	.000

HOELTER		
Model	HOELTER .05	HOELTER .01
Default model	105	109
Independence model	23	23

4.4.2.2. Descriptive goodness criteria

Descriptive goodness criteria answer the question of whether an existing difference between the empirical and the theoretical model variance-covariance matrix can be neglected. Based on simulation and comparative studies cut-off values are specified (rules of thumb), whose exceeding indicates a "good" model fit. Since these measurements are not statistical tests, they are independent of the sample size and relatively robust against violations of the assumption of multi normal distribution (Weiber and Mühlhaus, 2014). A variety of descriptive quality criteria have been developed in the literature, which can be distinguished by absolute fit indices and the so-called Goodness-of-fit measure. Absolute fit indices set the chi-square value in relation to the complexity of a model, which is expressed by the number of degrees of freedom, the number of model parameters, the number of manifest variables and / or the sample size (Hooper, Coughlan and Mullen, 2008). The two most frequently used absolute fit indices are the Root Mean Square Residuals (RMR) and the Standardized Root Mean Square Residual (SRMR).

The goodness measure of the root mean square residuals (RMR) is the sum of the squared deviations between the variances and covariances of the empirical and the theoretical model matrices in relation to the number of all collected indicators. The smaller the RMR values, the better the theoretical model adapts to the empirical data (Jöreskog and Sörbom, 1983). Concerning RMR it should however be noted that the scaling of the indicators affects the value of variances and covariances. This effect is avoided in the Standardized Root Mean Square Residual (SRMR), which according to Weston und Gore (2006), should always be taken into consideration for assessing the model fit. The threshold for a good model fit is a SRMR ≤ 0,10 as recommended by (Homburg, Klarmann and Pflesser, 2008).

In addition to the descriptive SRMR value the Goodness-of-Fit-Index (GFI) as well as the Adjusted-Goodness-of-Fit-Index (AGFI) have been often used in the past as „classical“ goodness-of-fit measures (Weiber and Mühlhaus, 2014). The GFI was developed by Jöreskog and Sörbom (1983) for Maximum Likelihood and Unweighted Least Square estimates and was extended to Generalized Least Squares estimates by Tanaka and Huba (1985). GFI measures the relative amount of variance and covariance, which are account for by the model and is independent of the sample size in contrast to the Chi-square test. The GFI can take values between 0 and 1 and a GFI of 1 indicated that all empirical variances and covariances are accurately reproduced by the model (perfect model fit) (Hooper, Coughlan and Mullen, 2008). Since the GFI is influenced by the model complexity the adjusted-Goodness-of-fit index (AGFI), which also forms a measure of the variance explained in the model, is applied. The AGFI "tries" to capture the model complexity by the number of model parameters and the number of degrees of freedom and to correct the GFI with these values (Weston and Gore, 2006). Both values should be above the threshold value of 0.9 to indicate a good model fit (Weiber and Mühlhaus, 2014).

Table 25: Model Fit Summary (RMR, GFI)

RMR, GFI				
Model	RMR	GFI	AGFI	PGFI
Default model	.128	.774	.738	.669
Saturated model	.000	1.000		
Independence model	.488	.195	.147	.184

According to Table 25 AMOS provides a value of 0.128 the RMR, resulting in a calculated SRMR value of 0.0904. This value shows an acceptable model fit corresponding to the cut-off criterion of 0.10 (Homburg, Klarmann and Pflesser, 2008), while the displayed values of GFI = 0.774 and AGFI = 0.738 suggest an unacceptable fit of the model considering the usual cut-off values (≥ 0,9). The performance of the GFI related measures however has been strongly questioned in current simulation studies, so that the use of these measures is no longer recommended in practical applications (Sharma et al., 2005). Due to this fact the GFI and AGFI values are reported in this study but are not considered as necessary condition for a good model fit and thus are not further examined.

4.4.3. Incremental fit indices for model comparison

In concrete application of structural model, there is often uncertainty as to which causal paths in the structural model in are truly significant reality. In these cases a decision support can be provide, by comparing causal models with the same constructs but different causal paths assessing them on the basis of quality criteria. Such a model comparison can be conducted in AMOS by comparing the formulated default model with the Independence model on the one hand and the saturated model on the other hand (Weiber and Mühlhaus, 2014). While the Independence model considers all manifest variables as statistically independent, the saturated model postulates that all model variables are correlated. The Independence model is the model worst adapted to the empirical data, which always achieves the worst model fit. Incremental fit indices between Default Model and Independence model reflect the percentage by which the default model outperforms the Independence model in terms of the chi-square value and the minimum value of discrepancy function. If the default model differs only slightly from the independence model, these measurements have a value close to zero. In contrast, a value of close to 1 indicates a "significant improvement" compared to the independence model (Blunch, 2013).

In the literature, a number of indices have been developed to make a comparison between Default Model and Independence Model and their significance has been tested in different simulation studies (Haughton, Oud and Jansen, 1997). While Normed Fit Index (NFI), developed by Bentler and Bonnet (1980), considers the simple difference of the χ^2 values of the default and independence model, the Tucker-Lewis-Index (TLI) additionally takes the degrees of freedom of the two models into consideration. The TLI can assume values greater than 1, which suggests that more parameters than necessary were specified in the formulated model (so-called over fitting) (Bollen, 1989). The Comparative Fit Index (CFI) by Bentler (1990) however takes into account the distortions of the distribution and is in contrast to the TLI also normalized within the interval [0, 1].

The Incremental Fit Index (IFI), which was proposed by Bollen (1989), compares the difference of the $\chi 2$- values in relation to the difference of the $\chi 2$ -value of the independence model and the degrees of freedom in the default model. In addition, also the Relative Noncentrality Index (RNI) is often quoted, which however is not reported by AMOS, but can be easily calculated with regular AMOS Output values (McDonald and Marsh, 1990). Threshold values for good model fit are values ≥ 0.9 for NFI (Arbuckle (2012), TLI, CFI (Homburg and Baumgartner, 1995), IFI (Weiber and Mühlhaus, 2014) and values ≥ 0.95 for RNI (Hu and Bentler, 1999).

Table 26 displays the relevant indices for the baseline comparison, which were calculated by AMOS. Additionally the RNI was calculated according the formula of Weiber & Mühlhaus (2014) resulting in a value of 0.93. Thus the incremental fit indices of TLI, CFI, IFI show values well above the required threshold of 0.9 and therefore indicate a very good fit of the causal model. However NFI value of 0.806 is considerably lower than the required threshold and contradicts a good model fit, while the calculated RNI value of 0.93 is just slightly smaller then the suggested threshold value and indicated a just sufficient model fit. As the investigated model is highly complex it is argued that the IFI, TLI and CFI values are more meaningful than the NFI value, as they allow for consideration of the complexity. Therefore it can be concluded that the incremental fit indices overall indicate a good model fit.

Table 26: Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.806	.788	.931	.924	.930
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

4.5. Concluding overall assessment of the model fit

For the concluding overall assessment of the model it should first be noted that the model does not show an acceptable χ^2 value of 740.148. However the χ^2 value deteriorated „automatically“ with increasing sample size and it tests the very stringent hypothesis of full compliance of the empirical and theoretical calculated variance-covariance matrix (perfect fit) (Bentler and Bonnet, 1980). On the other hand the inferential RMSEA value of 0.057 indicates at a good model fit. If the central incremental fit indices TLI, IFI and CFI are additionally considered for the final evaluation, they all report values above the required cut-off values of 0.9 and thus also show a good model fit. This result is furthermore supported by the absolute descriptive fit indices SRMR (0.0904) and $\chi2$ / d.f. (1.440). Due to the proximity of the various fit indices to the required cut-off values the model fit of the present causal model is referred to as "acceptable" to „good“.

Finally, it should be noted that in the literature, different recommendations are given what criteria in any case should be used to assess the overall quality of a model (Homburg, Klarmann and Pflesser, 2008; Sharma et al., 2005; Hu and Bentler, 1999). In the past, a series of simulation studies have been conducted that examined the sensitivity of quality criteria under different conditions (e.g. sample size, model complexity, distribution of data, estimation methods) (Hu and Bentler, 1999; Sharma et al., 2005; Hoyle and Panter, 1995). This paper follows the key recommendations of Hu and Bentler (1999), which are referred to by Barrett (2007, p. 817) as the "'bible' for the threshold cut-offs by most SEM investigators". Using the ML-estimation the authors generally recommend the assessment of TLI, IFI, RNI or CFI in combination with SRMR. For low sample sizes ($n \leq 250$) the authors recommend the combinations of IFI, RNI, CFI as well as SRMR. According to the two proposed combinations of Hu and Bentler (1999) all required indices show values above the cut-off values (see Table 27) and thus result in a good overall model fit for the causal model of this paper.

Table 27: Overview of Obtained Goodness Criteria

Criterion	Cut-off Value	Source	Obtained	Model Fit
Inferential statistical goodness criteria				
χ^2 / d.f.	≤ 3 *	Homburg and Giering (1996)	1.440	very good fit
	≤ 2.5	Homburg and Baumgartner (1995)		
	≤ 2	Byrne (1989)		
RMSEA	≤ 0.05-0.08 *	Browne and Cudeck (1993)	0.057	good fit
	≤ 0.08	Hair et al. (2010)		
Descriptive (absolute) goodness criteria				
SRMR	≤ 0.09	Hair et al. (2010)	0.0904	good fit
	≤ 0.10 *	Homburg, Klarmann and Pflesser (2008)		
GFI	≥ 0.90	Bentler and Bonnet (1980)	0.774	insufficient fit
AGFI	≥ 0.90	Bentler and Bonnet (1980)	0.738	insufficient fit
Incremental fit indices for model comparison				
NFI	≥ 0,90 *	Arbuckle (2012)	0.806	insufficient fit
TLI	≥ 0,90 *	Homburg and Baumgartner (1995)	0.924	good fit
	≥ 0,92	Hair et al. (2010)		
CFI	≥ 0,90 *	Homburg and Baumgartner (1995)	0.930	good fit
	≥ 0,92	Hair et al. (2010)		
IFI	≥ 0,90 *	Weiber and Mühlhaus (2014)	0.931	good fit
RNI	≥ 0,95	Hu and Bentler (1999)	0.930	acceptable fit
	≥ 0,92	Hair et al. (2010)		

Adapted from (Weiber and Mühlhaus, 2014)

* Cut-off values that are commonly used in the literature

4.6. Interpretation of the structural model

The interpretation of the estimated parameter is carried out against the background of the formulated causal model with the goal of an empirical confirmation of the proposed hypothesis system. In the context of the interpretation of the results the estimated parameters will be tested according to their significance and consistency with the formulated hypotheses. Subsequently the analysis of causal effects will be conducted.

4.6.1. Plausibility test and parameter assessment by means of statistical criteria

As part of the plausibility test it is initially verified whether the prefixed of the model parameters are consistent with the established hypotheses in the first step of structural equation. Subsequently the plausibility test is supplemented by the assessment of parameter estimation using statistical criteria. It should be noted that the parameter estimates represent so-called point estimates, which means that for each parameter only a specific value is calculated. However, since the empirical survey only represents one of many conceivable samples from the population, these estimates may vary if other samples had been drawn from the population (Weiber and Mühlhaus, 2014). Therefore, the standard error of estimates (SE) will be issued for all estimated parameters in the unstandardized solution and indicates which scattering is expected in the respective parameter estimates. If the standard error is very large, this is an indication that the parameter estimates are not very reliable (Fuchs, 2011).
Furthermore the so-called Critical Ratio (CR) values are calculated for all estimated parameters in the model. Using the CR values as test statistic, the null hypothesis, that the estimated values are not significantly different from zero can be examined by means of a t-test. If the absolute CR value is above 1,96, this null hypothesis can be rejected at a significance level of 5%. Values above 1.96 indicate that the corresponding parameters provide an important contribution to the formation of the model structure (Weiber and Mühlhaus, 2014).

In addition to the CR values AMOS also calculates the P probability of a two-sided test that one model parameter in the population is zero. If the P-value is < 0.001, AMOS displays three asterisks (***), indicating that the model parameter is significantly different from zero at a significance level of 0.1%. It should be noted that the P-values require normally distributed parameter estimates and a large sample size for accurate calculations. However, the P values do not allow conclusions about the strength of a relationship, so additionally the standardized regression weights should be considered (Blunch, 2013). Standardized regression weights (path coefficients), which show higher absolute values than 0.2, are referred to as meaningful by Chin (1998a). The theoretical benefit of smaller values, even if they are statistically significant or even highly significantly different from zero, however have been doubted by Chin (1998a, p. 8), who argues that these paths are „theoretically not interesting".

As a further statistical criteria AMOS reports the Squared Multiple Correlations (SMC) for the constructs. The SMC of the constructs indicate what percentage of the variance of the latent endogenous variable is explained by the other latent variables. Thus they can be interpreted and evaluated analogous to the coefficient of determination in linear regression (R^2). As there are no recommendations for the interpretation of R^2 values in covariance structural analysis, the recommended values for the application of PLS models is used as a guideline (Weiber and Mühlhaus, 2014). Chin (1998b) for example refers to R^2 values smaller than 0.19 as „weak", between 0.19 and 0.33 as "moderate" and higher than 0.66 as "substantial".

Table 28 Unstandardized Parameter Estimations (Regression Weights)

			Estimate	S.E.	C.R.	P
AGT	<---	SCO	-.101	.109	-.928	.353
AGT	<---	IMC	.477	.072	6.586	***
AGT	<---	RMC	-.014	.064	-.222	.825
AGT	<---	SCS	.501	.085	5.886	***
RBN	<---	SCS	.409	.089	4.583	***
RBN	<---	RMC	.351	.074	4.714	***
RBN	<---	IMC	.175	.073	2.407	.016

			Estimate	S.E.	C.R.	P
RBN	<---	SCO	-.007	.119	-.059	.953
SCP	<---	AGT	.349	.084	4.136	***
SCP	<---	RBN	.313	.076	4.090	***
IMC_JPS	<---	IMC	1.000			
IMC_IDB	<---	IMC	.952	.070	13.554	***
IMC_ACC	<---	IMC	.948	.068	13.865	***
IMC_IIS	<---	IMC	.870	.072	12.034	***
RMC_MON	<---	RMC	.987	.076	12.995	***
RMC_IMPL	<---	RMC	.962	.077	12.503	***
RMC_ASS	<---	RMC	1.000			
RMC_ID	<---	RMC	.991	.070	14.188	***
RMC_DEDR	<---	RMC	.877	.072	12.160	***
SCO_MNGT	<---	SCO	.839	.174	4.818	***
SCO_OBJ	<---	SCO	.827	.172	4.823	***
SCO_COL	<---	SCO	1.000			
SCS_FTRA	<---	SCS	.958	.087	11.016	***
SCS_POST	<---	SCS	.945	.083	11.372	***
SCS_SCAP	<---	SCS	1.016	.087	11.637	***
SCS_SS	<---	SCS	1.000			
SCS_FSUP	<---	SCS	.919	.082	11.158	***
AGT_MLT	<---	AGT	.997	.088	11.357	***
AGT_CSL	<---	AGT	1.000			
AGT_DLRE	<---	AGT	1.006	.094	10.696	***
AGT_RESP	<---	AGT	.887	.090	9.909	***
AGT_RPF	<---	AGT	1.047	.089	11.707	***
RBN_MLC	<---	RBN	.768	.076	10.040	***
RBN_COF	<---	RBN	.847	.079	10.727	***
RBN_DSC	<---	RBN	1.034	.086	12.042	***
RBN_GRT	<---	RBN	1.000			
RBN_RSS	<---	RBN	1.035	.070	14.748	***
SCP_SHIP	<---	SCP	.966	.095	10.203	***
SCP_MLT	<---	SCP	.836	.100	8.367	***
SCP_RCN	<---	SCP	1.000			
SCP_DD	<---	SCP	.783	.089	8.841	***
SCP_QNT	<---	SCP	.947	.091	10.458	***
IMC_EIS	<---	IMC	.947	.071	13.279	***

			Estimate	S.E.	C.R.	P
SCO_INT	<---	IMC	.669	.074	9.104	***

Firstly the column S.E. shows that the standard errors of the variables are relatively small and quite homogeneous (in a range from 0,064 to 0.174). However, it is noticeable that the higher standard errors (> 0.100) were measured only in constructs of SCO. The CR levels can be interpreted in conjunction with the probability P. It can be observed that with the exception of the path coefficients between AGT <-- SCO, AGT <-- RMC, RBN <-- IMC and RBN <-- SCO all CR are significantly higher than 1.96 and due to the P value of 0.001 (***) highly significant (different from zero). While the path coefficients AGT <-- SCO, AGT <-- RMC and RBN <-- SCO show both a smaller CR value than 1.96 and a high P-value, the path coefficient RBN <-- IMC shows an acceptable CR with 2,407 and a significant P-value of 0.016.

Table 29 lists the standardized regression weights as well as the Squared Multiple Correlations. Concerning the regression weights AGT <-- IMC, AGT <-- SCS, RBN <-- RMC, SCP <-- AGT and SCP <-- RBN show values greater than 0.2 and thus can be referred to as meaningful. Furthermore all three latent endogenous variables show high SMC values. This lead to the conclusion that the causal effects between AGT <-- SCO, AGT <-- RMC and RBN <-- SCO do not provide an important contribution to the formation of the model structure, while RBN <-- IMC provide only a limited contribution to the model structure!

Table 29 Standardized Regression Weights & Square Multiple Correlation

			Estimates*
AGT	<---	SCO	-.082
AGT	<---	IMC	.553
AGT	<---	RMC	-.017
AGT	<---	SCS	.521
RBN	<---	SCS	.392
RBN	<---	RMC	.392
RBN	<---	IMC	.187
RBN	<---	SCO	-.005

	SMC
RBN	.467
AGT	.537
SCP	.379
SCP_QNT	.657
SCP_DD	.505
SCP_RCN	.676
SCP_MLT	.466
SCP_SHIP	.632

			Estimates*
SCP	<---	AGT	.378
SCP	<---	RBN	.366
IMC_JPS	<---	IMC	.883
IMC_IDB	<---	IMC	.853
IMC_ACC	<---	IMC	.864
IMC_IIS	<---	IMC	.798
RMC_MON	<---	RMC	.844
RMC_IMPL	<---	RMC	.827
RMC_ASS	<---	RMC	.875
RMC_ID	<---	RMC	.884
RMC_DEDR	<---	RMC	.813
SCO_MNGT	<---	SCO	.610
SCO_OBJ	<---	SCO	.609
SCO_COL	<---	SCO	.751
SCS_FTRA	<---	SCS	.788
SCS_POST	<---	SCS	.804
SCS_SCAP	<---	SCS	.819
SCS_SS	<---	SCS	.858
SCS_FSUP	<---	SCS	.795
AGT_MLT	<---	AGT	.819
AGT_CSL	<---	AGT	.842
AGT_DLRE	<---	AGT	.786
AGT_RESP	<---	AGT	.745
AGT_RPF	<---	AGT	.835
RBN_MLC	<---	RBN	.718
RBN_COF	<---	RBN	.750
RBN_DSC	<---	RBN	.803
RBN_GRT	<---	RBN	.886
RBN_RSS	<---	RBN	.895
SCP_SHIP	<---	SCP	.795
SCP_MLT	<---	SCP	.683
SCP_RCN	<---	SCP	.822
SCP_DD	<---	SCP	.710
SCP_QNT	<---	SCP	.811
IMC_EIS	<---	IMC	.843
SCO_INT	<---	IMC	.670

	SMC
RBN_RSS	.801
RBN_GRT	.785
RBN_DSC	.645
RBN_COF	.563
RBN_MLC	.516
AGT_RPF	.698
AGT_RESP	.555
AGT_DLRE	.618
AGT_CSL	.709
AGT_MLT	.670
SCS_FSUP	.631
SCS_SS	.736
SCS_SCAP	.670
SCS_POST	.647
SCS_FTRA	.621
SCO_COL	.564
SCO_OBJ	.370
SCO_MNGT	.372
SCO_INT	.449
RMC_DEDR	.661
RMC_ID	.782
RMC_ASS	.765
RMC_IMPL	.684
RMC_MON	.712
IMC_IIS	.637
IMC_EIS	.710
IMC_ACC	.746
IMC_IDB	.727
IMC_JPS	.780

4.6.2. Testing of causal hypothesis and analysis of causal effects

The testing of causal hypotheses focuses on the structural model of a complete causal model system and is conducted in comparison to the in Chapter 2.3 formulated system of theoretically hypotheses.

4.6.2.1. Testing of causal hypothesis

For the analysis of causal effects it is initially examined whether the estimated parameters can be considered as confirmation of they hypothesized system due to their prefixes and value. For causal models this assessment is only performed for the structural model containing the presumed relations between hypothetical constructs. Appropriately for this purpose only the standardized solution will be considered. The standardized parameter estimates are listed in Table 30 in the last column (Estimate*), while first columns again displays the estimates of the unstandardized solution. These estimates serve the basis fort he following considerations.

If the prefixes of the paths coefficients compared to the hypotheses developed in Figure 1 it can be seen that except for the relations between AGT <-- SCO, AGT <-- RMC as well as RBN <-- SCO all prefixed of the model parameters correspond to the assumed hypotheses. For example, a high Information System Capabilities lead to a higher Agility (0.553) or an increasing level of Robustness results in a higher level of Supply Chain Performance (0.366).

Since both the prefixes of the estimated model correspond with the hypothetical model and the effects are highly significant (p-value of ***), the hypotheses (H1c, H1d, H2b, H2c, H3a, H3b) cannot be rejected. Although hypothesis H2a (Information System Capabilities have a positive effect on Robustness) does not show a p-value of 0.001 but is still significantly different from zero with a small p-value of 0.016. However, the hypotheses H1a (Supply Chain Capabilities have a positive effect on Agility), H1b (Supply Chain Capabilities have a positive effect on Robustness) & H2d (Information System Capabilities have a positive effect on Robustness) cannot be maintained as these three show high p-values and prefixes not corresponding to the hypothesized effects.

Referring to Chin (1998a) only standardized regression weights ≥ 0.2 are considered as meaningful. Thus, the path coefficients originating from the construct IMC to RBN with a value of 0.187 cannot be regarded as substantial. The other, not yet excluded relationships between the latent constructs in contrast, are of relevance. In particular the effects of IMC to AGT with 0.553 and SCS to AGT with 0.521 have high effects.

A value of 0.467 for RBN for example implies that 46.2% of its variance can be explained by the assigned latent variables SCO, IMC, SCS and RMC. While the causal effects explained by the model for RBN (0.467) and SCP (0.379) can be considered as moderate, the explained causal effects for AGT (0.537) can be considered as moderate to substantial (Chin, 1998b).

Table 30 Estimated parameter of the structural model

Regression Weights/Standardized Regression Weights: (Group number 1 - Default model)							
			Estimate	S.E.	C.R.	P	Estimate*
AGT	<---	SCO	-.101	.109	-.928	.353	-.082
AGT	<---	IMC	.477	.072	6.586	***	.553
AGT	<---	RMC	-.014	.064	-.222	.825	-.017
AGT	<---	SCS	.501	.085	5.886	***	.521
RBN	<---	SCS	.409	.089	4.583	***	.392
RBN	<---	RMC	.351	.074	4.714	***	.392
RBN	<---	IMC	.175	.073	2.407	.016	.187
RBN	<---	SCO	-.007	.119	-.059	.953	-.005
SCP	<---	AGT	.349	.084	4.136	***	.378
SCP	<---	RBN	.313	.076	4.090	***	.366

Covariances/Correlations: (Group number 1 - Default model)							
			Estimate	S.E.	C.R.	P	Estimate*
SCS	<-->	SCO	.108	.074	1.464	.143	.143
SCS	<-->	RMC	.463	.117	3.971	***	.407
IMC	<-->	SCO	.264	.095	2.789	.005	.312

Squared Multiple Correlations: (Group number 1 - Default model)

Regression Weights/Standardized Regression Weights: (Group number 1 - Default model)						
		Estimate	S.E.	C.R.	P	Estimate*
	SMC					
RBN	.467					
AGT	.537					
SCP	.379					

4.6.2.2. Analysis of causal effects

The effects that are observable between the constructs of a causal model (structural model) can be divided into direct, indirect and total causal effects (Weiber and Mühlhaus, 2014). To determine the effects the standardized solution, which is illustrated in a simplified way for the structural model in Figure 4, is analyzed, as it is more suitable because of the ease of interpretability compared to the determination of the non-standardized effects. Direct causal effects exist whenever a construct influences another construct directly, which is indicated by causal arrows between constructs in the path diagram. In contrast, indirect causal effects between constructs arise if a latent variable affects another one via one or more "intermediate variables". Direct and indirect effects together form the total causal effect between constructs (Kline, 1998).

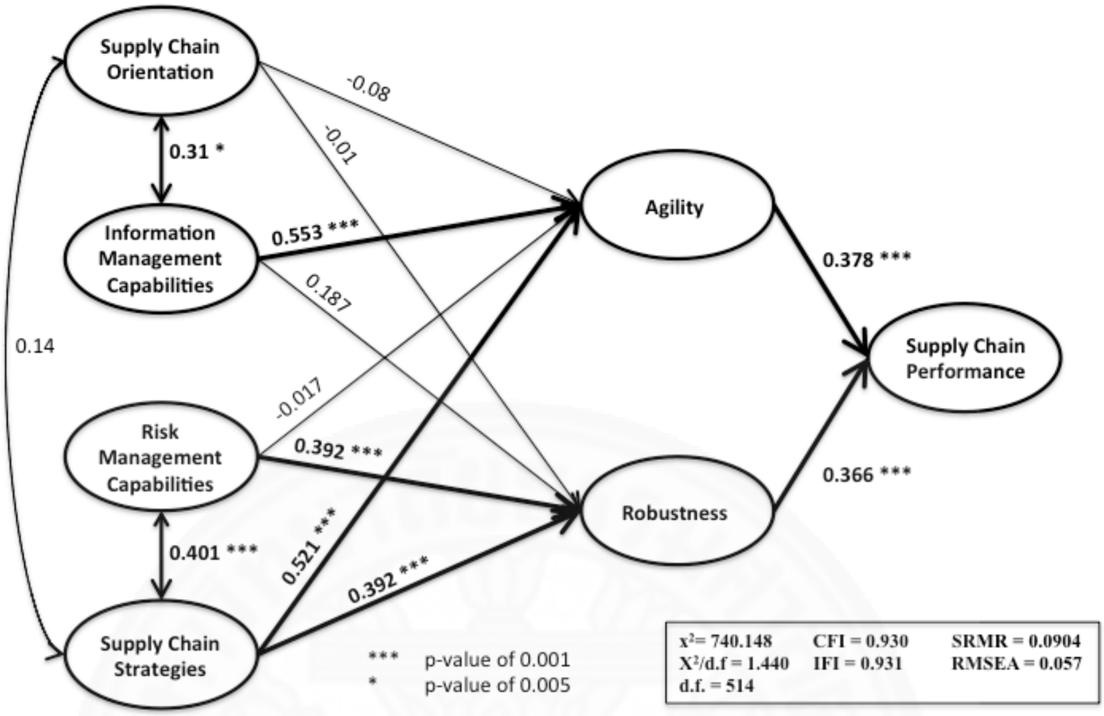

Figure 4: Direct causal effects (standardized estimates)

While the strength of direct causal effects can be directly obtained from the reported parameter estimates on the causal arrows in Figure 4, the indirect effects can be calculated by multiplying the corresponding coefficients. Thus Risk Management Capabilities (RMC) show an indirect effect on Supply Chain Performance (SCP) via the two endogenous variables Agility (AGT) and Robustness (RBN) with a value of -0.017 * 0.378 + 0.392 * 0.366 = 0.137. So overall supply chain performance is positively influenced by Information System Capabilities. Table 31 shows the standardized total effects between the constructs of the structural model. It can be seen that especially IMC and SCS have high standardized total effects on the Supply Chain Performance (SCP). A value of 0.277 between IMC and SCP explains that SCP increases by 0.277 standard deviations if IMC goes up by one standard deviation (Kline, 1998).

Table 31 Standardized Total Effects between latent variables

	SCO	RMC	IMC	SCS	RBN	AGT	SCP
RBN	-.005	.392	.187	.392	.000	.000	.000
AGT	-.082	-.017	.553	.521	.000	.000	.000
SCP	-.033	.137	.277	.340	.366	.378	.000

Table 32 Hypotheses Testing Results

Model Fit

χ^2 = 740.148	CFI = 0.930	SRMR = 0.0904
χ^2/d.f. = 1.440	IFI = 0.931	RMSEA = 0.057
d.f. = 514		

Hypotheses	Relation			Estimates	Result
H1a	Information Management capabilities (IMC)	→ (+)	Agility (AGT)	.553 ***	Supported
H1b	Supply Chain Orientation (SCO)	→ (+)	Agility (AGT)	-.082 *	Not supported
H1c	Supply Chain Strategies (SCS)	→ (+)	Agility (AGT)	.521***	Supported
H1d	Risk Management Capabilities (RMC)	→ (+)	Agility (AGT)	-.017 *	Not supported
H2a	Information Management capabilities (IMC)	→ (+)	Robustness (RBN)	.187 **	Not supported
H2b	Supply Chain Orientation (SCO)	→ (+)	Robustness (RBN)	-.005 *	Not supported
H2c	Supply Chain Strategies (SCS)	→ (+)	Robustness (RBN)	.392 ***	Supported
H2d	Risk Management Capabilities (RMC)	→ (+)	Robustness (RBN)	.392 ***	Supported
H3a	Agility (AGT)	→ (+)	Supply Chain	.378 ***	Supported

			Performance (SCP)		
H3b	Robustness (RBN)	→ (+)	Supply Chain Performance (SCP)	.366 ***	Supported

* p > 0.05; ** p < 0.01; *** p < 0.001

Chapter 5
Discussion

In this chapter the results of the SEM and the implication of the findings on the proposed hypotheses will be discussed. Furthermore a critical examination of the work and its result is conducted.

First the hypothesized positive effect of supply chain capabilities (SCO, SCS, IMC and RMC) on Agility is discussed (H1). The analysis of the structural model reveals that Information System Capabilities as well as Supply Chain Strategies show high and significant causal effects on Agility. However Supply Chain Orientation as well as Risk Management Capabilities only show small negative effects on Agility. As the strength of the effects of SCO and RMO on Agility is not significant and exhibits values below 0.2 they can be regarded as not meaningful. Thus it can be concluded that H1 is supported and that supply chain capabilities have a positive impact on the agility of a supply chain.

The research suggests that promoting sophisticated information systems and the capabilities of sharing the information effectively across the supply chain as well as the implementation of certain supply chain strategies companies are able to considerably increase their SC agility. These results correspond to the requirements of an agile supply chain to establish visibility (Christopher and Peck, 2004), flexibility (Swafford, Ghosh and Murthy, 2006) and a high degree of connectedness between supply chain partners (Braunscheidel and Suresh, 2009) in order to be able to respond quickly and efficiently to changes. According to the conducted study Information

System Capabilities can thus be regarded as the foundation for agility, especially because the required visibility and connectedness can be achieved through a targeted promotion and development of information systems. These abilities are the requirements for a prompt and efficient detection of demand fluctuations or external disturbances and for enable a company to quickly initiate targeted countermeasures (Wieland and Wallenburg, 2013; Holweg and Pil, 2008). These countermeasures however depend strongly on the companies' type and implementation of supply chain strategies. If flexibility-oriented strategies such as postponement, slack capacities or just-in-case stock form an integral component of the supply chain strategies, the agility of a supply chain can be significantly increased. While both IMC and SCS already have a positive impact on the agility, the analysis reveals that the full potential will only be exploited by the interaction of both capabilities. Risk Management Capabilities in this connection may indeed be regarded as capabilities that can identify risks and potential disruptions early (Craighead et al., 2007), but do not contribution to increase the speed of response to occurring disorders.

A similar picture emerges with regard to the second hypothesis (H2) that supply chain capabilities have a positive impact on the robustness of a supply chain. According to the conducted analysis SCS and RMC have a significant and strong effect on the robustness while SCO does not show any significant effect. Although IMC does have a moderately significant influence on robustness, which however must be evaluated as almost negligible due to the low value. Therefore Hypothesis H2 can also be considered as supported by the empirical findings.

The requirements of a robust supply chain, to be relatively resistant to external disruptions (Meepetchdee and Shah, 2007) and to master a variety of situations without showing significant adverse effects (Harrison, 2005) are thus mainly driven by the factors risk management capabilities and supply chain strategies. Similar as with Agility it can be argued that strong and sophisticated risk management capabilities provide the ability to anticipate potential disruptions or changes in advance, due to its foresighted planning involving a huge number of eventualities (Winter and Knemeyer, 2013; Bakshi and Kleindorfer, 2009). Once risks are adequately identified and evaluated they might be prevented or mitigated by the application or implementation of appropriate strategies. These findings correspond to the work of (Blackhurst, Kaitlin and Craighead, 2011; Wu et al., 2013), who propose that proactive supply chain strategies, like safety stocks, are able to mitigate or reduce the impact of unexpected events and increase the robustness of a supply chain. Thus, the combination of a sophisticated risk management and the subsequent implementation of strategies designed to increase the flexibility and resistance, such as a flexible supply base or alternative and flexible transportation, pose a significant contribution to enhancing the robustness of a supply chain.

Concerning the hypothesized positive effects of resilience (agility + robustness) on the supply chain performance (H3) both Agility and Robustness show high and significant causal effects on the performance. Hypothesis 3 can therefore be considered as supported by the analysis as agility and robustness are interpreted as two dimensions of resilience according to Wieland and Wallenburg (2012) and Hohenstein et al. (2015). These findings indicate that resilience has a positive contribution to the performance of a supply chain and that both dimensions robustness and agility contribute to this by equally strong proportions. A high resilience is expressed by the ability to better mitigate disruptions by the supply chain (Rice and Caniato, 2003) and that production can be maintained even in the presence of disturbances and unexpected events (Ponomarov and Holcomb, 2009). In addition, market or customer requirements can be fulfilled during a wide range of scenarios and the supply chain shows a high adaptability (Ponomarov and Holcomb, 2009). The combination of this adaptability with the ability to keep a supply chain operational under different situations has a direct impact on the performance or the success of a supply chain according to our empirical evaluation. On the one hand competitive advantages can arise, especially in volatile markets or in disruptive environments (Hohenstein et al., 2015), on the other hand existing customers are maintained and losses due to production downtime can be avoided (Manuj and Mentzer, 2008). Besides others these mentioned issues are the reason why resilient supply chains constitutes an important component for establishing an efficient and productive supply chain management.

On the capabilities level the total effects clearly show that especially the Supply Chain Strategies capabilities have a high impact on the supply chain performance. This is not surprising, since it has already been demonstrated in the preceding paragraph that the SCS show a strong causal effect on both agility as well as on robustness. Furthermore also Information System Capabilities affect performance of the supply chain strongly, whereas Risk Management Capabilities only have a moderate effect on performance. Surprisingly Supply Chain Orientation provides no substantial contribution to the explanation of the SC resilience and also has no notable total effects on the performance of a supply chain according to the results of the SEM. Thus, the data suggest that a cooperative supply chain management culture aligned with joint goal setting and mutual commitment on its own has no significant causal influences on the resilience and the performance of a supply chain. An explanation of this surprising result may be provided by Ponomarov (2012) who suggested that the collaborative and supply chain oriented alignment of companies may not be regarded as a capability directly affecting supply chain resilience but rather can be regarded as a precondition and enabler for other supply chain capabilities like Information System or Supply Chain Strategies. This conception also corresponds with the structural equation model of this paper, as a moderately significant covariance with a meaningful effect exists between SCO and IMS as well as a low but insignificant covariance between SCO and SCS. Thus this study shows that specific capabilities need to be present to make a supply chain resistant to external influences and increase their performance, while supply chain orientation can only be regarded as an enabler, which supports the implementation of effective supply chain capabilities.

In order to critically evaluate the results an assessment of the weaknesses and limitations of this thesis and its methodology has to be conducted. Especially the weaknesses and limitations of the nature and scope of the survey, as well as the restrictions of the SEM model have to be highlighted.

The sample size of 137 is at the lower end of the scale, which is required for the use of SEM methods in the literature. While Gorsuch (1983) and Kline (1979) require a minimum number of 100 samples, other authors require at least 150 (Hatcher, 1994) or even significantly higher numbers (Comrey and Lee, 1992). In addition, the sample is limited only to Thai companies and therefore is only partially suitable for the overall analysis of the phenomenon of supply chain resilience. In addition, the database comprises not necessarily a representative population for Thai manufacturing industries, due to the comparatively simple sampling procedure.

Concerning the experimental arrangement it has to be noted that the assessment of the observable variables (and thus the values of the latent variables) merely constitute subjective evaluations of single informant representatives of the respective companies. Since the respondents have made the assessment of individual items by themselves the rating may have resulted in a significant bias, which is based on misconceptions, lack of objectivity or deliberate positive assessment of the company's own performance. Particularly with regard to the operationalization of the supply chain performance, the agility and robustness this subjectivity of the results should be taken into account. In addition, it should be noted that the supply chain performance was interpreted as process variability according to the definition of Ponomarov (2012). The supply chain performance in this study thus represents only a narrow performance evaluation without consideration of financial or customer-related criteria.

In terms of the present model, the database and the implementation of SEM a number of further limitations arise. Thus the collected data is not normally distributed (which is a requirement for the use of the SEM) but only shows no substantial violation of the assumption of a normal distribution. In addition, the model has a high number of degrees of freedom and is therefore strongly over-identified, which reduces the quality of the estimates in comparison to a just-identified model. It should also be noted that most fit values are close to the Cut-off values or in the case of NFI, GFI and AGFI even below. Although an acceptable fit can thus be assumed in general these values are a clear indicator that the established and tested model cannot explain the phenomenon of resilience in its entirety. An optimization of the model fits based on the modification indices could not be carried out in this work, since the FIML method (which does not calculated modification-indices) was used to estimate the missing values in AMOS. Due to the small sample size exclusion of records with missing values and thus the avoidance of FIML estimates, however, was not an option.

Chapter 6
Conclusion

6.1. Summary

The present work contributes with a quantitative study to an improved understanding of the elusive and complex phenomenon of supply chain resilience. Both by confirmation of pre-established hypotheses as well as by the refutation substantial contributions to further scientific description could be made. On the one hand the positive impact of information system and risk management capabilities as well as the supply chain strategies on the resilience of supply chain could be proven. On the other hand, the positive causal connection of resilience to the performance of a supply chain was shown. Moreover, it was demonstrated that the various capabilities have different impacts on the proactive and reactive dimension of resilience. While it could be proven that information system capabilities especially increase the agility component of resilience, risk management capabilities especially have a strong positive impact on the robustness component. Supply chain strategies promote both dimensions equally strong whereas a direct influence of the supply chain orientation on resilience could not be verified. Due to the fact that Supply Chain Strategies show the highest total effects on the performance it is advised that companies place their priority on the implementation of resilient strategies followed by the establishment of Information System Capabilities and Risk Management Capabilities in order to increase the performance of their Supply Chain.

6.2. Implications

This paper is one of few empirical SEM studies on supply chain resilience and is the first paper linking Risk Management Capabilities, Supply Chain Strategies, Information System Capabilities and Supply Chain Orientation with Resilience and Supply Chain Performance. The paper provides several theoretical as well as managerial implications, which are described subsequently:

Firstly this study provides a better understanding of how resilience is achieved in a supply chain and how resilience in turn influences the performance. Also the causal effects between selected capabilities of a supply and their effect on agility and robustness have been evaluated.

Secondly this study is explicitly focusing on the resilience and its antecedents in Thailand based companies. Due to the fact that the country experienced severe supply chain disruptions during recent time (Haraguchi and Lall, 2014; Abe, 2013) the study provides insights from companies that have already experienced the effects of disruptions. This fact provides a new perspective from previous studies, which mostly focused on American or European companies (Wieland and Wallenburg, 2013; Ponomarov, 2012; Park, 2011).

Although various papers have examined the effect of supply chain capabilities on resilience, the effect of these capabilities on the performance of the supply chain and the effect robustness and agility have on the overall performance has mainly remained unclear. This paper provides empirical evidence about these relationships by linking the capabilities and the resilience dimensions with the supply chain performance.

In order to assess the antecedents the constructs of Supply Chain Strategies and Risk Management Capabilities were newly developed and operationalized. Due to the fact that these latent measures show a high reliability and validity the operationalization can be used for further research in the area of supply chain resilience.

The identified and tested framework helps both managers and researchers to better understand the impact and interactions of different supply chain related capabilities on resilience and supply chain performance. The theoretical derived framework provides value to managers by identifying capabilities that foster the building of resilience within a supply chain. Furthermore the separation of resilience in its two dimensions agility and robustness offer better and more precise evaluations of the effects different capabilities have and how resilience is achieved. By systematically analyzing the causal effects within the structural model this thesis provides guidance for companies that seek to establish a more resilient supply chain. Especially against the background of scare resources managers can better assess which measures a company should take and which capabilities should be fostered in order to optimally achieve resilience. The distinction between the proactive and reactive dimension has the advantage that managers can customize the measures for achieving resilience according to their needs and specific business environment. Thus companies operating in an environment with rapid changes in demand pattern, changing customer needs or fast product life cycles may prefer to specifically fostering the agility dimension. According to the empirical results these companies should especially focus on establishing sophisticated Information System Capabilities in combination with flexible Supply Chain Strategies. The study findings also revealed that companies operating in an environment characterized by a high likelihood of disruptions or if a disruption would be extremely harmful to their supply chain should focus on establishing Risk Management Capabilities in combination with a set of robust Supply Chain Strategies. In addition investments in an intensified collaboration across the supply chain and the establishing of a supply chain culture do not show considerable benefits for the resilience level of a supply chain.

In order to achieve resilience companies especially have to focus on the implementation of robust and agile supply chain strategies as this capability showed high effects on both resilience dimensions. Thus managers aiming at increasing the resilience of their supply chains should foster the establishment of agile strategies like postponement, flexible transportation or flexible supply base (dual sourcing, multiple sourcing) as well as the establishment of robust strategies like implementing redundancies like slack capacity or just-in-case inventory.

6.3. Suggestions for Further Research

Based on the results of this study and identified weaknesses and unanswered questions a variety of approaches for further scientific research arise. Due to the subjective rating of the items in the survey a more objective approach for assessing the robustness, agility and SC-performance is recommended for further studies. These requirements could either be implemented by the use of company data e.g. customer service levels, delivery delays or downtimes or by assessing the performance not by the company itself but rather by letting customers or suppliers conduct the ratings. Furthermore subsequent studies can concentrate on a broader and more holistic assessment of SC-performance by including more performance criteria (e.g. financial criteria, customer satisfaction, etc.) in the operationalization of the performance construct. Another interesting field of research would be the contextual extension of the model by comparing results from different industries or countries. These comparisons could lead to valuable insights, how the implementation and consideration of resilience depends on different business environments or cultural issues. According to the limited sample size of this research a large scale quantitative study based on the established operationalization would be advisable in order to prove the obtained results. By collecting a bigger data set modification indices could be applied to modify the model and improve the overall model fit, which was not possible in this research due to the small sample size. Along with the modification other capabilities could be integrated and investigated in regard of their effect on resilience, agility and robustness. This study especially calls for a further investigation of the role of supply chain orientation either as condition for other capabilities or as a moderator. In a different methodological approach simulation studies could be conducted in order to assess the influence of different elements of the resilience framework under different scenarios and supply chain configurations.

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APPENDIX A
Survey Questionaire

Supply Chain Orientation– adapted from Ponomarov 2012, Wieland and Wallenburg (2013)	**Strongly Disagree**		**Neutral**		**Strongly Agree**
1. Our firm is actively implementing and pursuing activities that increase collaboration with customers (e.g. joint decision making, CPFR, knowledge sharing, benefit sharing, VMI, etc.).	1	2	3	4	5
2. We trust our key customers.	1	2	3	4	5
3. Our objectives are consistent with those of our key customers.	1	2	3	4	5
4. Top managers reinforce the need of building, maintain and enhance long-term relationships with our customers and the need of sharing valuable information.	1	2	3	4	5
5. Our supply chain forms an integrated environment that provides end-to-end interaction of orders, inventory, transportation and distribution to facilitate supply chain transparency.	1	2	3	4	5

Information Management Capabilities – adapted from Ponomarov 2012, Wieland & Wallenburg 2013	**Strongly Disagree**		**Neutral**		**Strongly Agree**
1. Our firm effectively shares operational information between departments frequently and in a timely manner.	1	2	3	4	5
2. Our firm effectively shares operational information externally with selected customers frequently and in a timely manner.	1	2	3	4	5
3. The information available in our firm is accurate.	1	2	3	4	5
4. Our firm maintains an integrated database to facilitate information sharing with customers as well as for internal information sharing.	1	2	3	4	5
5. We have full access to joint planning systems along the supply chain.	1	2	3	4	5

Supply Chain Management Strategies – adapted from Tang 2006, Christopher & Peck (2004), Ponomarov & Holcomb (2009)	Strongly Disagree		Neutral		Strongly Agree
1. Our firm uses a flexible supply base strategy for key and critical components (dual-sourcing, multiple sourcing).	**1**	**2**	**3**	**4**	**5**
2. Our firm is carrying additional "just in case" safety stock inventories of certain critical components.	**1**	**2**	**3**	**4**	**5**
3. Our firm has slack capacity or redundancies in operations to cope with uncertainties.	**1**	**2**	**3**	**4**	**5**
4. Postponement techniques such as standardisation, commonality, and modular design approaches are applied to delay the point of product differentiation.	**1**	**2**	**3**	**4**	**5**
5. Our company applies flexible transportation techniques (multi-modal transportation, multi-carrier transportation or multiple routes).	**1**	**2**	**3**	**4**	**5**
6. Our company strongly applies Lean and Just-in-Time techniques (e.g. 5S, Six Sigma, Kanban, One-Piece-Flow, etc.) and is continuously focusing on improving the efficiency by removing waste from operations.	**1**	**2**	**3**	**4**	**5**

Risk Management Capabilities– adapted from Ponomarov 2012, Lavastre, Gunasekaran, Spalanzani 2012	Strongly Disagree		Neutral		Strongly Agree
1. In our firm, an employee or a team is dedicated to supply chain risk management.	**1**	**2**	**3**	**4**	**5**
2. Our firm applies risk identification & analysis techniques (What if Analysis, Scenario Planning, Value Stream Mapping)	**1**	**2**	**3**	**4**	**5**
3. Our firm applies risk assessment techniques (Pareto diagrams, ABC Ranking, FMECA - Failure Mode, Effects, and Criticality Analysis)	**1**	**2**	**3**	**4**	**5**
4. Our firm applies techniques to support the decision and implementation of risk management actions (Business Continuity Plans, etc.)	**1**	**2**	**3**	**4**	**5**
5. Our firm proactively monitors risks (Audits, Project Risk Reviews)	**1**	**2**	**3**	**4**	**5**

Agility– adapted from Wieland & Wallenburg (2013), Ponomarov 2012 **Please indicate the speed of reaction with which your company can engage in the following activities should changes occur.**	Slow				Fast
1. Adapt manufacturing leadtimes with customers	1	2	3	4	5
2. Adapt level of customer service	1	2	3	4	5
3. Adapt delivery reliability with customers	1	2	3	4	5
4. Adapt responsiveness to changing market needs	1	2	3	4	5
5. Restoring product flow to its original state after being disrupted	1	2	3	4	5

Robustness– adapted from Wieland & Wallenburg (2013), Ponomarov 2012 **To what extent do the statements apply to your supply chain?**	Strongly Disagree		Neutral		Strongly Agree
1. For a long time, our supply chain retains the same stable situation as it had before changes occur.	1	2	3	4	5
2. When changes occur, our supply chain grants us much time to consider a reasonable reaction.	1	2	3	4	5
3. Without adaptations being necessary, our supply chain performs well over a wide variety of possible scenarios.	1	2	3	4	5
4. For a long time, our supply chain is able to carry out its functions despite some damage done to it.	1	2	3	4	5
5. Our firm’s supply chain has the ability to maintain a desired level of connectedness among its members at the time of disruption.	1	2	3	4	5

Supply Chain Performance– adapted from Ponomarov 2012					
	Very Inconsistent		**Neutral**		**Very Consistent**
1. Amount of time for shipments to reach our key customers.	**1**	**2**	**3**	**4**	**5**
2. Manufacturing time based on a fixed production schedule.	**1**	**2**	**3**	**4**	**5**
3. Response to the everyday needs of key customers.	**1**	**2**	**3**	**4**	**5**
4. Meeting as promised delivery dates with customers.	**1**	**2**	**3**	**4**	**5**
5. Providing desired quantities on a consistent basis.	**1**	**2**	**3**	**4**	**5**