From Supply Chain Integration to Operational Performance: The Moderating Effect of Demand Uncertainty

by

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Table of Abbreviations

AGFI	Adjusted Goodness-of-Fit Index
AJG	Academic Journal Guide
AVE	Average Variance Extracted
BSREC	Biomedical & Scientific Research Ethics Committee
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CI	Customer Integration
CMB	Common Method Bias
CT	Configuration Theory
DS	Decision Science
DU	Demand Uncertainty
EFA	Exploratory Factor Analysis
EI	External Integration
GFI	Goodness-of-Fit Index
HRA	Hierarchical Regression Analysis
II	Internal Integration
IJOPM	International Journal of Operations and Production Management
IJPDLM	International Journal of Physical Distribution and Logistic Management
IJPE	International Journal of Production Economics
IMM	Industrial Marketing Management
JIT	Just-in-time
JOM	Journal of Operations Management
KMO	Kaiser-Meyer-Olkin
OEM	Original Equipment Manufacturer
OIPT	Organizational Information Processing Theory
OLS	Ordinary Least Square
OP	Operational Performance
RBV	Resource Based View
RMSEA	Root Mean Error of Approximation
SCI	Supply Chain Integration
SCM	Supply Chain Management
SCMAIJ	Supply Chain Management: An International Journal
SE	Standard Error
SEM	Structural Equation Modelling
SI	Supplier Integration
SLR	Systematic Literature Review
TCT	Transaction Cost Theory
TJ	Transportation Journal
TRA	Threshold Regression Analysis

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Abstract

The aim of this study is to examine the moderating effect of demand uncertainty on the relationship between supply chain integration and operational performance of automotive supply chains in China. Several studies have previously been performed by providing empirical evidence to examine the supply chain integration to operational performance relationship. However, their empirical findings are inconsistent. Some authors investigated the supply chain integration from an aggregated level and explicitly indicated that the degree of integration always improves the operational performance. On the other hand, some studies indicate negative and non-significant relationships between supply chain integration and operational performance in sub-dimensions. Some even support that there are curved relationships. Scholars have modelled different types of these relationships; however, none appear to provide a satisfactory explanation of the inconsistencies among the current findings. To bridge the gap, and based on the contingency theory, this study argues that there is no single best model of supply chains' integration. Instead, it is the fitness between the supply chain integration model and the environmental factors that optimises the operational performance. Hypotheses were developed and tested to create a new conceptual model. In particular, the modelling process re-examines such relationship under the moderating effect of an external environmental factor – demand uncertainty. An empirical survey instrument has been designed and applied to gather data from a wide spectrum of aspects of the automotive industry in China. After testing for reliability and validity of the collected data, exploratory factor analysis, confirmatory factor analysis, hierarchical regression analysis and threshold regression analysis were applied as primary research methodologies to test the proposed research hypotheses. As a result, strong empirical evidence has been found to support most of the hypotheses, which leads to the findings that the relationship between supply chain integration and operational performance is

non-linear, and the nature of this non-linearity can be significantly moderated by demand uncertainty. This study extends the current literature by contributing an analytical model that represents the relationship between supply chain integration and operational performance with respect to external environmental factors.

Chapter 1 Introduction

The first chapter presents an introduction of theoretical context and objectives of this study. First, to better understand the research aim and objectives, general background information on how demand uncertainty may impact the relationship between supply chain integration and operational performance is described. The contingency theory in a supply chain context as the core concept for supply chain management and operations management is also introduced. Second, an overview of the research context (China's automotive industry) is presented. Thus, the first chapter seeks to reveal the two areas examined in this study:

- The direct relationship between supply chain integration and operational performance.
- The moderating effect of demand uncertainty on the relationship between supply chain integration and operational performance.

Lastly, the aim, objectives, research questions and methodologies of this study are presented, followed by an outline of research significance.

1.1 Supply Chains with Uncertain Demand

Supply chain management (SCM) was developed in the 1980s, enabling organizations to more effectively integrate their business processes (Towill and Christopher, 2002). During the past four decades, SCM has attracted great attention from both academics and practitioners alike. *SCM has been defined as the flow of materials, products, information within a company, as well as across organization from suppliers to manufacturers and from manufacturers to customers in order to improve the long-term performance of the organizations and the supply chain as a whole* (Mentzer et al., 2001). Supply chain integration (SCI) is one of the key indicator of SCM, and its enablers and outcomes have been studied quite extensively (Bennett and Klug, 2012).

Unlike SCM, SCI is merely a recent entry on the agenda of researchers. Studies have been focused on developing definitions and dimensions of SCI. In particular, for the purpose of examining the contribution of SCI to OP, some studies view SCI as a single concept (Vereecke and Muylle, 2006, Sezen, 2008), however, the majority of the studies constructed SCI from multiple dimensions. For example, according to Gimenez and Ventura (2005), SCI studies can be classified into three categories according to whether they study the relation between internal integration (II) and performance, between external integration (EI) and performance or between both types of SCI with regards to performance. For instance, studies of Gimenez and Ventura (2005), Flynn et al. (2010), Wong et al. (2011b) have examined the effects of both internal and external integration on supply chain performance. In the meantime, other literature has argued that the role of II has been overlooked, and the importance of EI has not been well studied and emphasised (Power, 2005, Stevenson and Spring, 2007). For these reasons, numerous studies elaborate the sole role of EI into supplier integration (SI) and customer integration (CI), which is a further taxonomy of EI (Petersen et al., 2005, Das et al., 2006, Koufteros et al., 2007).

Researchers have long articulated the necessity for close integration of supply chain participants for the propose of improving supply chain performance (Cao et al., 2015, Flynn et al., 2016). Strategies and knowledge of supply chain integration that have been used to develop effective collaboration and partnership between supply chain participants are now widely accepted as one of the most indisputable factors for supply chain success (Graham et al., 2005, Brewer and Speh, 2000). However, by witnessing the increased supply chain environmental complexity, especially the sprawling demand uncertainty over the last decade largely due to specialisation, there has been a call to rethink ‘common sense’, which is the understanding and validity of SCI that it highly acclaims contribution to OP (Prajogo et al., 2015, Ebrahimi, 2015, Zhao et al., 2015, Beske-Janssen et al., 2015, Yang et al., 2015, Yu et al., 2014).

This study starts with the doubts of 'common sense' that SCI will always be positively correlated with the optimum OP (Jonsson et al., 2011, Terjesen et al., 2012). This is because that many previous studies appear to be inconsistent or even conflicting with one another about their findings on the nature of this correlation (Devaraj et al., 2007, Gimenez et al., 2012, Sousa et al., 2012). Some of the positive relationship findings might be restricted to certain specific conditions or might instead be dependent on a specific factor or control parameter (Morash and Clinton, 1998, Stank et al., 2001b), while many others were intended to be general (Bowersox et al., 1999, Frohlich and Westbrook, 2001, Frohlich and Westbrook, 2002, Fawcett and Magnan, 2002). With the advent of a large number of empirical studies which evidence such a positive relationship, inevitable or expected empirical results in terms of an insignificant (Gimenez and Ventura, 2005, Devaraj et al., 2007) and even negative relationship (Swink et al., 2007) emerged. Such inconsistent empirical results have motivated researchers to re-investigate the theoretical foundation of such 'common sense' (Halldórsson et al., 2007, Van der Vaart and van Donk, 2008). They also motivated researchers to discover unknown mechanisms and try to perfect theoretical foundations.

To consolidate the theoretical foundation, researchers have attempted to use the contingency theory in the context of SCM to explain the inconsistence. Contingency theory's view is that a single most effective method to manage an organization or a supply chain does not exist, instead, the optimal management method is contingent on both internal and external factors (Cao et al., 2015). In addition, contingency theory also suggests that a proper fitness level between the SCM and its internal and external factors tends to improve performance (Flynn et al., 2010). By introducing contingency theory, extant literature indicated that the contribution of the level of SCI to the manufacturer's OP is subject to the influence of various environmental factors (Turkulainen, 2008, Wong et al., 2011b, Gimenez et al., 2012). These factors may include ones such as market uncertainty, national culture, political uncertainty and so on. Under the effects of mixed environmental factors, what may be agreeable without too much controversy is that any attempt to construct a universally applicable relationship model between SCI and OP is theoretically doomed before conception. However, what has not been agreed upon, or still remains inconclusive, is how the relationship between SCI and OP may be influenced and by which factors (Van der Vaart and van Donk, 2008, Waller et al., 2008). This inconclusiveness therefore logically gives rise to the research gap in the SCI-related subject domain.

The research gap through which this study enters is that there is a lack of research which provides analytical models and theories to explain why, in some instances, environmental factors have no effect on the SCI-OP relationship but, in other instances, an SCI-OP relationship can be enhanced or weakened under the moderating environmental effects, especially within a focused industry. Without an analytical model or theory, the research findings on the relationship between SCI and OP tend to be fragmented and inconsistent (Flynn et al., 2010, Turkulainen and Ketokivi, 2012). Arguably, a properly derived analytical model, if achievable, will provide a more holistic and detailed explanation than a formative evaluation on how those constructs affect each other.

1.2 Research Objectives

In the light of addressing the identified research gap and the described research context, the objective of this study is to take a small step towards bridging the aforementioned gap in the research context. This study defines a manageable scope of investigation in between SCI, OP and a selected key exogenous factor: demand uncertainty (DU). This study also attempts to analytically model the relationship between these concepts. The validity of the choices of the three key constructs for this study will be discussed in Chapter 3.

For the above reasons, the objective of this study can be stated as revisiting the relationship between the SCI and the OEMs' OP under the full spectrum of DU as the moderator by using an empirical instrument to create an analytical model that further explains the inter-play of these three constructs. The unit of analysis in this study is the manufacturer that acts as the OEMs in China's automotive industry. The level of the research focus is pitched at the dynamic non-linear relationship among the three constructs.

1.3 Research Methodology

This research reviews the literature about SCI and OP in order to clearly define and measure the key constructs which are under examination. Based on the research gaps identified in a systematic literature review, a theoretical framework with three direct hypotheses and three moderating hypotheses on the SCI-OP relationships were established for this study. Data were collected through a questionnaire survey and validated by statistical techniques including exploratory factor analysis, confirmatory factor analysis and ANOVA. A group of management experts from China's automotive industry and several professors of operations management reviewed the survey questionnaire. After passing through the ethical approval process via the Biomedical & Scientific Research Ethics Committee (BSREC), the final version of the survey questionnaire was confirmed after a pilot and a test run within a small sample of the management experts. Finally, the questionnaire was directly emailed to the potential respondents who were identified as experienced managers in China's automotive industry. A quantitative approach using hierarchical regression analysis and threshold regression analysis was utilised to test the proposed hypotheses.

1.4 Research Significance

This study adopts a contingency approach in order to analyse the moderating effects of DU on the SCI-OP relationship. Using a data sample from China's automotive industry, this study expects to contribute to SCM and operations management theories.

First, this study examines the direct relationship among the three dimensions of SCI (internal integration, supplier integration and customer integration) and OP.

Second, by utilising a data sample from China's automotive industry, this study empirically reveals the moderating effects of DU on the SCI-OP relationships.

Third, by categorising DU into three regimes, including 'low uncertain demand', 'middle uncertain demand' and 'high uncertain demand', this study provides empirical evidence on how DU moderates the SCI-OP relationships in each regime of DU. The obtained empirical results also indicate that DU does not moderate the relationship between internal integration and OP.

Fourth, by using the theoretical framework established in this study, an optimal supply chain integration configuration strategy is proposed. Accordingly, such strategy argues that, in China's automotive industry, more integration on the customer side is encouraged when the demand is highly uncertain and, conversely, close integration with suppliers is favoured as the demand becomes anticipatable.

The empirical findings are highly significant for supply chain daily managers and organizational decision makers of Chinese automotive supply chains, since they require practical knowledge for implementing SCI. Thus, instead of perceiving SCI in a closed supply chain context, this study endorses an extended perspective by including an environmental factor (DU) when approaching SCI to improve OP in China's automotive industry.

1.5 Thesis Structure

The remainder of the thesis is structured as follows. The first chapter provides a brief introduction to this study. A general background of the relationships between SCI and OP is presented, followed by a short discussion on the moderating effects of DU. The remaining sections report the main research gaps, research objectives, research methodologies and research significances.

Chapter 2 describes the research context, which is China's automotive industry, with its developmental and industrial challenges which have arisen in recent years with the inclusion of sufficient industrial figures.

Chapter 3 is carried out based on a systematic literature review and provides a detailed summary of relevant theoretical arguments and empirical supports on the SCI-OP relationships. Accordingly, a discussion on the systematic literature review results is presented to clearly identify the research gaps. To overcome the identified gaps, Chapter 3 establishes a theoretical framework with the six research hypotheses which are under examination.

Chapter 4 presents a discussion on the choice of appropriate research philosophies, followed by reports on the process of designing the questionnaire, how the key theoretical constructs were measured and how data were collected and validated. In addition, this chapter introduces the primary data-analysing method – threshold regression analysis with its estimation, inference and computation processes. Lastly, a section is presented to reveal the theoretical model establishment.

The fifth chapter reports the results of the data analysis. The results of examining the direct relationships (hypotheses 1 – 3) are reported first, and the non-linear results of examining the moderating effects (hypotheses 4 – 6) obtained by adopting the threshold regression analysis are reported in the following sections. Importantly, an additional section compares models based on the author-introduced method of analysis and the literature-favoured method of analysis to reveal the significant advantage of using the threshold regression analysis.

The sixth and final chapter discuss the empirical findings and indicates the contribution to the body of knowledge, research limitations and recommendations for future empirical studies.

Chapter 2 Research Context: The China Automotive Industry

2.1 Chapter Introduction

Chapter 1 introduced the research background, objectives and rationale. To represent the research objective, this study aims to examine the moderating effect of demand uncertainty on the relationship between SCI and OP in automotive supply chains of China. There exist a number of reasons to examine such relationships in the context of automotive supply chains in China, the most significant of which are as follows:

- Based on the contingent argument, prior studies have examined the moderating or mediating effect of environmental factors on the SCI-OP relationship. However, the majority of such studies have been conducted based on mixed manufacturing industries (Huang et al., 2014, Koufteros et al., 2005, Wong et al., 2011a, Flynn et al., 2010). Lockstroem et al. (2010) argued that the automotive industry is one of the largest manufacturing industries, which has been considered the basic engine of economy. Its products (vehicle) are essential elements in supporting flows of goods and personnel. Thus, a sector-focused empirical investigation seems to be necessary in understanding its significance in the operations management domain.

- With the economic depression in the USA, Europe and Japan, the attention of the automotive industry has now been shifted focus to China, where there is a rapidly growing economy along with a great domestic market (Aller and Carlos, 2010). China's automotive industry has experienced dramatic growth from 1949 to now. However, uncertain issues in terms of expanding demand, quickly changing customer preferences on vehicle type, rising petrol prices, increasing level of urban traffic congestion, political encouragement on hybrid vehicles and, most importantly, China's economic deceleration have made requirements for automotive OEMs to effectively manage their supply chains and production flows. Such uncertainties will eventually result in challenges to understand and predict future market demand for the automotive OEMs (Lockstroem et al., 2010). Therefore, the Chinese automotive industry and the challenges it is facing indicate the need for improved understanding on how demand uncertainty affects supply chain operations from scholars and supply chain managers.

- Another major issue in the Chinese automotive industry is the overcapacity which has existed among OEMs in recent years. Such overcapacity clearly reflected the prior inefficiency of their supply chain management (Holweg et al., 2008). It is argued that inappropriate integration could expose OEMs' risk of effectively sharing information, strategically using resources and controlling costs. This may result in failure of production capacity management by facing an unpredictable market demand. Thus, it becomes important to investigate how the demand challenges moderate the relationship between SCI and OP in such association.
- From a theoretical perspective, existing theories in the domain of supply chain management and operations management have not been widely tested and validated in an emerging economy like China's (Cai et al., 2010). Especially with China's economy quickly opening up to the rest of the world, China's manufacturing supply chain developed its unique mechanism on linking overseas supply chains (Mozur, 2014). Endorsed by government policy protection and a fast-growing domestic market, the question of how China's manufactures manage their integrations within and across the board became a focus in academia (Wei and Qingfen, 2015). In addition, the question of how existing theories should be adjusted to demonstrate and understand manufacturers' integration mechanism in China also calls for more field research (Li et al., 2014).

Therefore, the Chinese automotive industry exists as a proper case to examine the SCI-OP relationship based on the contingent argument. Prior empirical studies have been conducted based on mixed manufacturing industries. Consequently, this study provides a new perspective to the current debates on the SCI-OP relationship by focusing on China's automotive industry.

2.2 The Importance of the Automotive Industry in China's Manufacturing Industries

The past decades witnessed China's significant economic growth, and the automotive industry acted as a vital role in supporting this growth (Lockstroem et al., 2010). This means that China's economic growth is tied closely to the contribution made by the automotive industry. Figure 1 provides an illustration of the annual total assets of all manufacturing industries in China from 2012 to 2014, measured in billion yuan. Apart from the computers and communications industry, the automotive industry ranked the second largest manufacturing industry across those three years. Like most of these manufacturing industries, the automotive industry has achieved stable growth year by year, and its total assets reached approximately 4400 billion yuan in 2014. Next is Figure 2, which further presents the monthly stable growth of the automotive industry and its proportion to all manufacturing industries in a cumulative standard from 2013.07 to 2016.04. From this figure, it is visible that the automotive industry's total asset growth grew to approximately 6000 billion yuan in 2016.04. In addition, its proportion to all manufacturing industries grew from 5.5% (2013.07) to 6.1% (2016.04). Such statistics further indicate a seasonal feature of the economic cycle of the automotive industry's growth proportion. The economic cycle is defined as the natural fluctuation of the factors between periods of expansion (growth) and contraction (recession) (Barras, 1994). However, its proportion's growth or recession does not necessarily equal the automotive industry's overall growth or recession.

As argued above, the automotive industry forms an important portion of China's manufacturing industries. Its stable growth of operational asset scales produces a great number of working positions along automotive supply chains. Also, as customers of metal, instrument, chemical fibre, rubber, plastic, leather and many other industries, the automotive industry underpins more working opportunities across manufacturing industries.

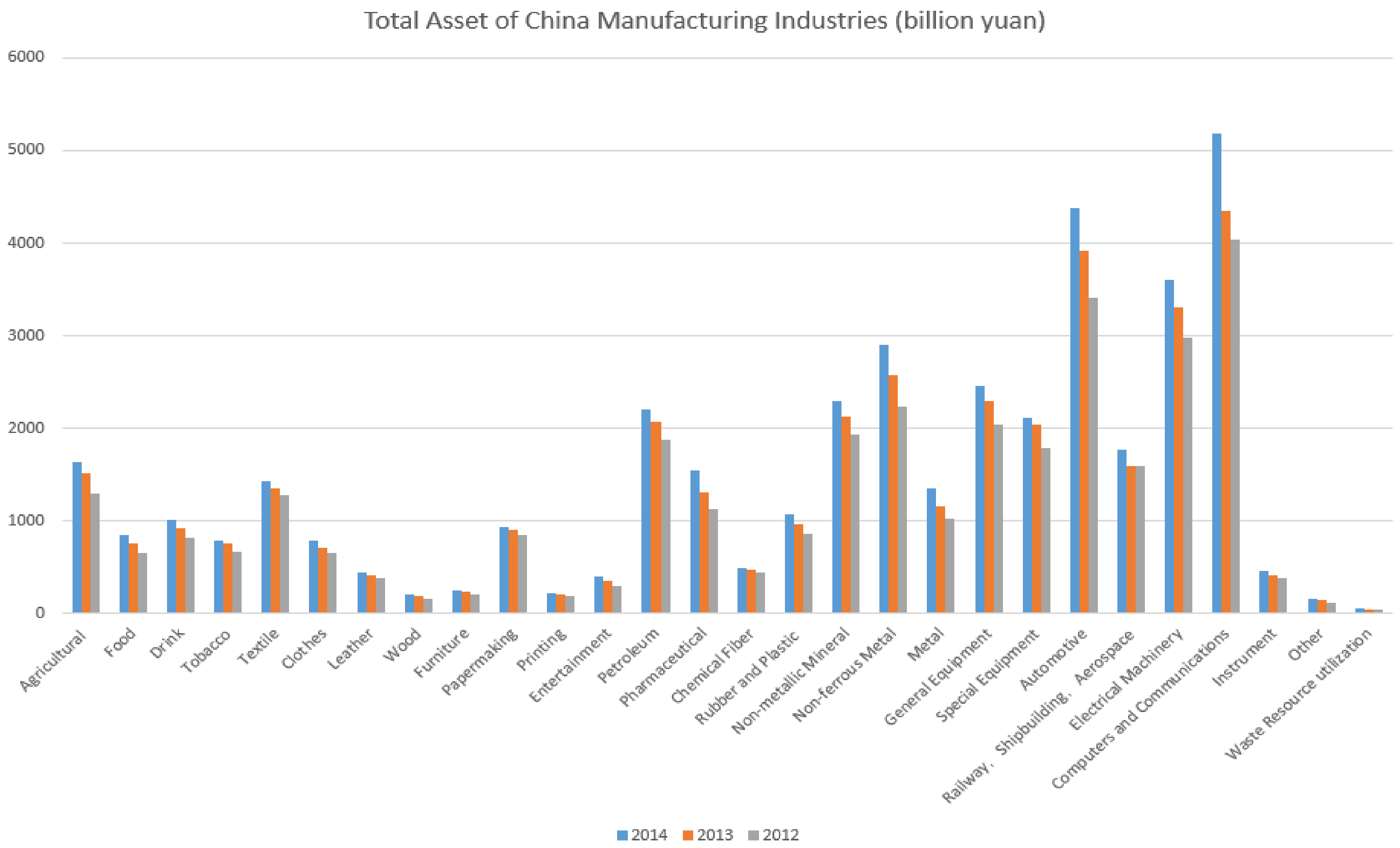

Figure 1 Total asset of China's manufacturing industries from 2012 to 2014.
Data source: National Bureau of Statistics of China.

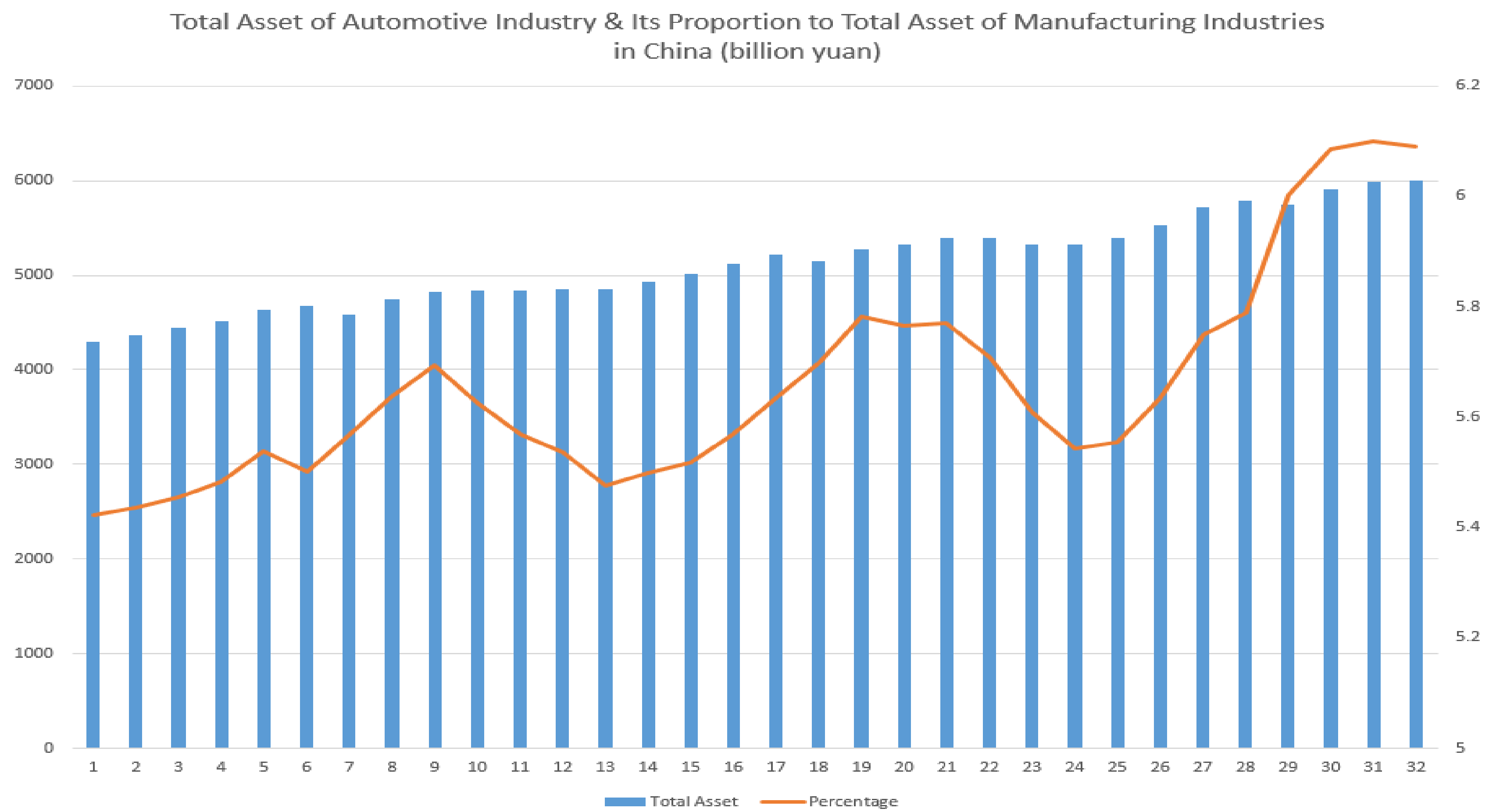

Figure 2 Total asset of China's automotive industry and its proportion to the total asset of all manufacturing industries.
Note: time line starts from 1 (2013.07) to 32 (2016.04); total asset figures are cumulative and monthly data.
Data source: National Bureau of Statistics of China.

2.3 Characteristics of the Chinese Automotive Industry

China's automotive industry has experienced dramatic growth since 1949. Following this timeline, there was virtually no automotive industry before 1956. Hundreds of trucks were assembled in 1956, which was the first milestone of China's automotive industry. After 30 years of growth, China began its production of civilian vehicles. The first joint venture with Volkswagen in 1991 gave a boost to China's automotive industry development. To prevent international shocks to the achieved development, China's automotive market was protected by high tariffs and the central government's pricing policy in the 1990s. The government-controlled market mechanism was to mediate the balance between demand and supply, which enabled small domestic manufacturers to survive. Later, China joined WTO in 2002 and, from this, followed a number of steps to open up its automotive market, including tariff reduction and a gradual reduction of government controls. After entering the 21^{st} century, the automotive industry began to grow faster, achieving a 38.8% and 36.7% increase on overall production in 2002 and 2003 (see Figure 3), respectively, ranking China as the fourth largest auto producer and third largest auto market in the world.

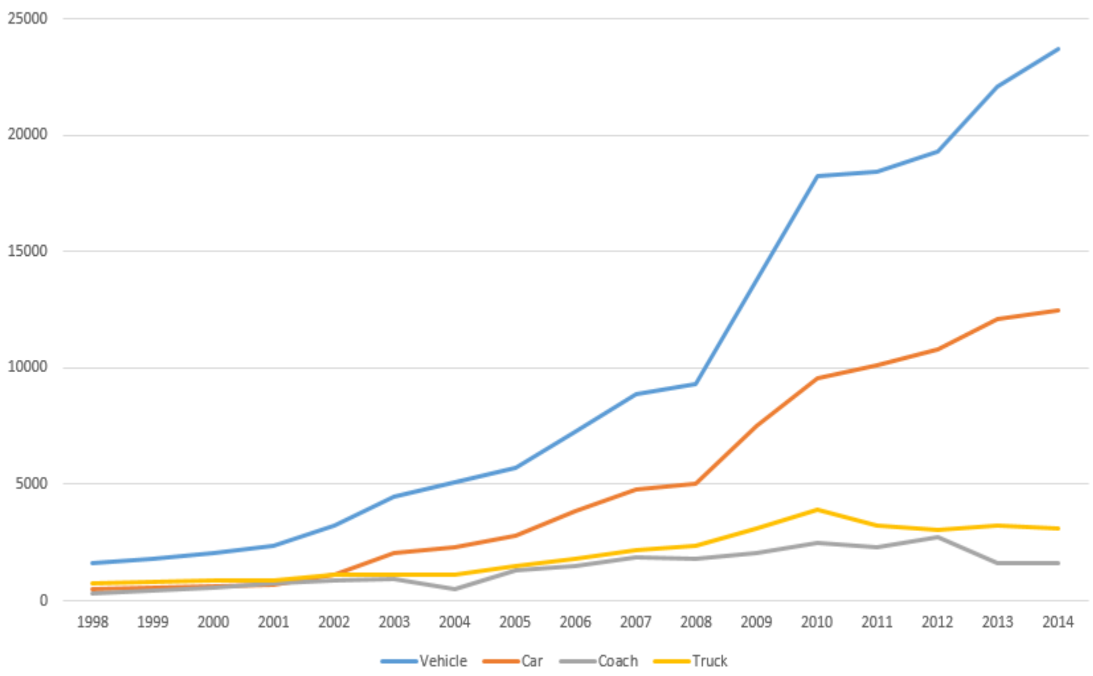

Figure 3 China annual vehicle production in thousands from 1998 to 2014.

Note: vehicle = car + truck + coach.

Data source: National Bureau of Statistics of China Data, 2016.

2.4 Supply and Demand

The production of total privately owned cars grew from 11.33 million vehicles in 2002 (see Figure 4) to 17.82 million in 2004 and 1.21 billion in 2014. In general, China's auto production grew 15% on average every year from 2002 on. As shown in Figure 5, among the production levels, privately owned passenger vehicles count as the majority of the total production, and it also gains more significant increasing rates than the privately owned trucks across the decade. In particular, passenger vehicle production reached approximately 122 million units in 2014, which is about seven times greater than truck production.

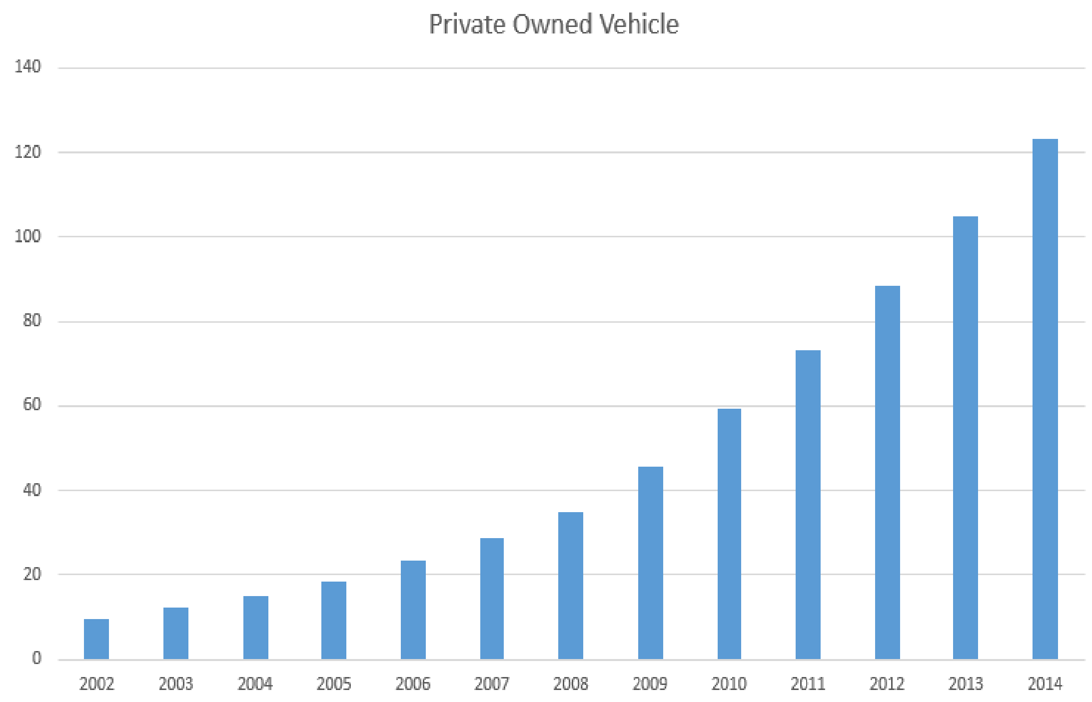

Figure 4 China's number of private owned vehicle from 2002 to 2014 million units.

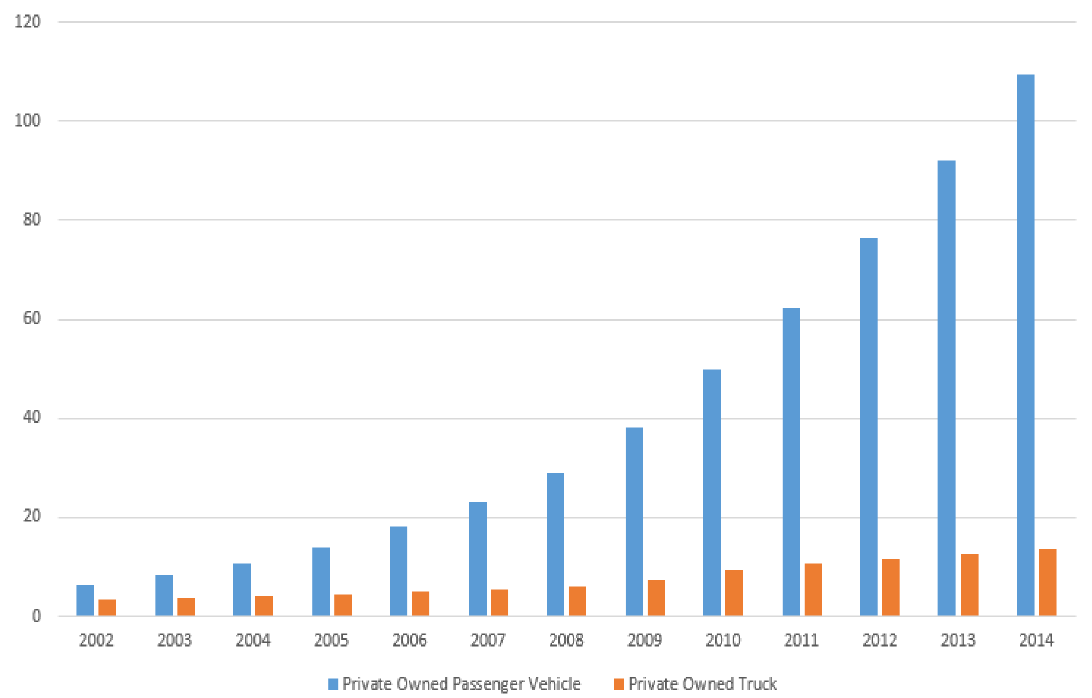

Figure 5 China's number of private owned passenger vehicle vs private owned truck from 2002 to 2014 in million units.

By focusing on the privately owned passenger vehicle production, Figure 6 tells an interesting story, which is that the production of small sized (5-9 seats) passenger vehicle acts as the determining role in the total passenger vehicle production (89%) (2014). On the other hand, Figure 7 tells another similar story that small-sized trucks (1.8-6 tons) accounts for 61.7% of the total production of privately owned trucks. With such huge expansion in supply, in particular for passenger vehicles, China's auto market comprised 86% sedans, 10% SUVs and 4% MPVs in 2010. Comparing this body type structure in 2016, the auto market was made up of 52% sedans, 37% SUVs and 11% MPVs. The decreasing line of sedans and the increasing line of SUVs are likely to cross in the very near future, as shown in Figure 8. However, no matter if these two lines cross or not, one cannot predict their future trends, since it is unsure whether the demand of sedans and the demand of SUVs will reach a stable equilibrium or if SUVs progressively will replace sedans. In addition, although the demand of MPVs merely counts a small portion at the moment, it still cannot be concluded that the demand of MPVs will not be a majority in near future.

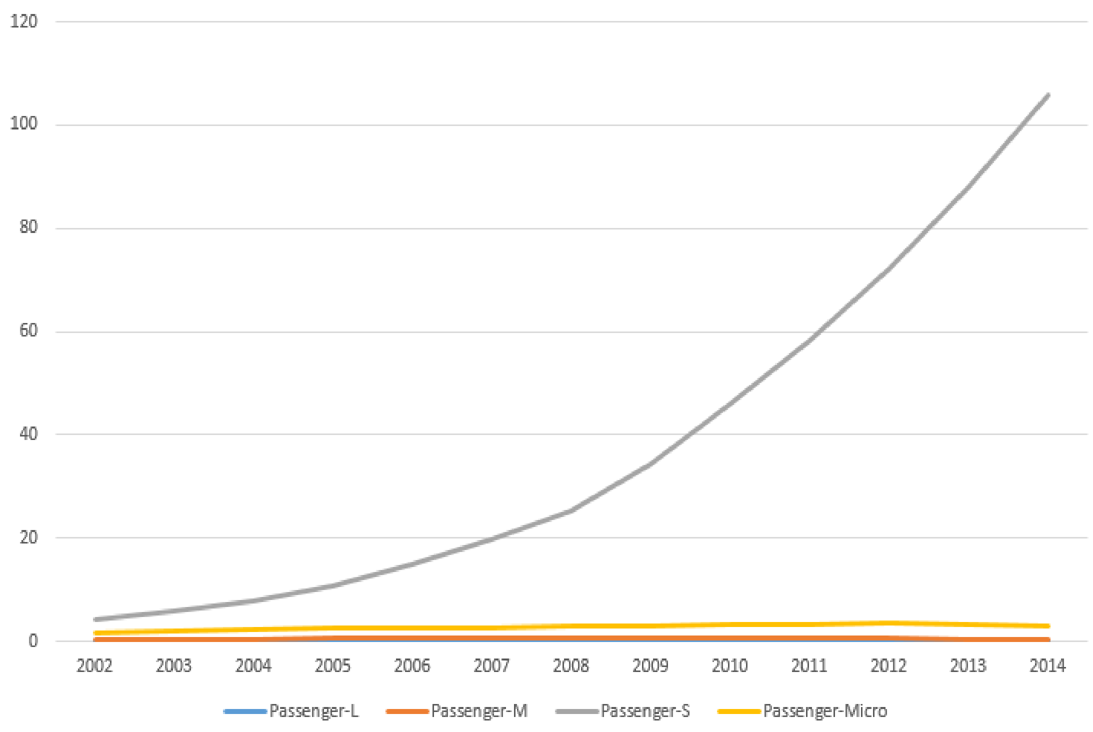

Figure 6 Categories of private owned passenger vehicles from 2002 to 2014 in million units.

Notes: L-Large; M-Middle; S-Small; Large: more than 40 seats; Middle: 9-40 seats; Small:5-9 seats; Micro: less than 5 seats.

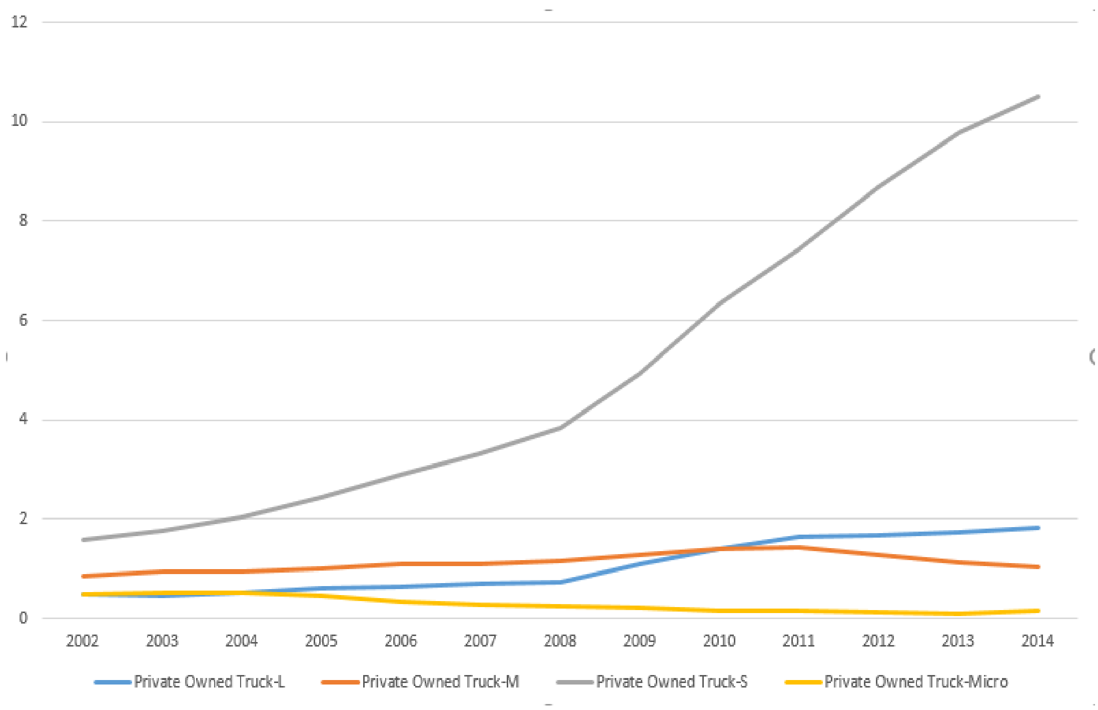

Figure 7 Categories of private owned truck from 2002 to 2014 in million units.

Notes: L-Large; M-Middle; S-Small; Large: total mass more than 14 tons; Middle: 6-14 tons; Small:1.8-6 tons; Micro: less than 1.8 tons.

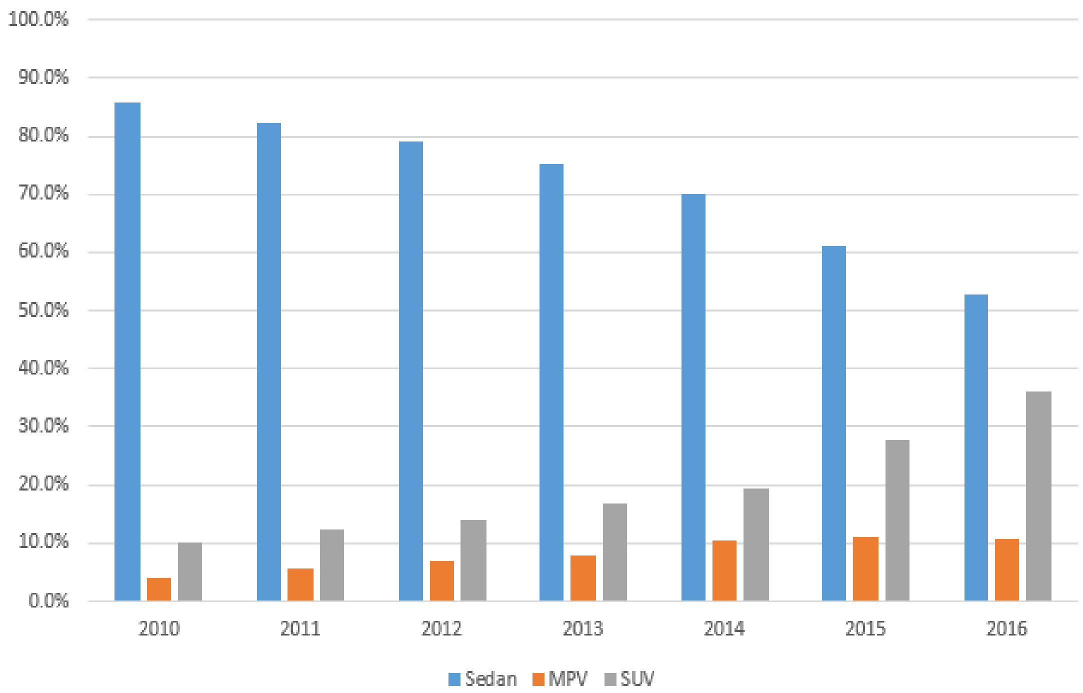

Figure 8 Body type categories of private owned small passenger vehicle with their annual market share of sale from 2010 to 2016.

From an engine size perspective of the small-sized passenger vehicle, as shown in Figure 9, 1.6L performed as the most popular engine size, followed by 1.5L, 2L and the rest. The market shares of 1.5L and 1.8-2LT are monotonically increasing along the entire time period. In contrast, the market demand tended not to recognise the 1.3-1.4L, 1.8L, 2.3-2.5L, 1.0-1.1L, 0.8-0.9L and above 2.5L engines. There exist three key features in Figure 9. First, we witnessed a big drop of the 1.6L engine market share between 2014-2015; second, the market shares of 1.5L engine vehicles is likely to catch up to 1.6L; third, the market share of electric cares grew dramatically from 0% in 2013 to approximately 11% in 2016.

The significant market share growth of electric vehicles was due to the Chinese government believing that electric battery-powered vehicles will come to play a major role in the future auto market. In 2009, the Chinese government arranged more governmental funding to encourage domestic auto manufacturers to improve their own R&D capabilities, in particular for energy-saving and green-power technologies (Tang, 2009). To further encourage auto manufacturers’ willingness to research and produce electric vehicles and to enhance customers’ purchasing preference on electric vehicles, the Chinese government offered tax subsidies to auto manufacturers and offered a purchase tax exemption to electric vehicle customers. Especially in Beijing and Shanghai, cities with rules of limited registration, electric vehicles have been listed as exceptions, which has further encouraged the demand for electric vehicles (Kumaraswamy et al., 2012).

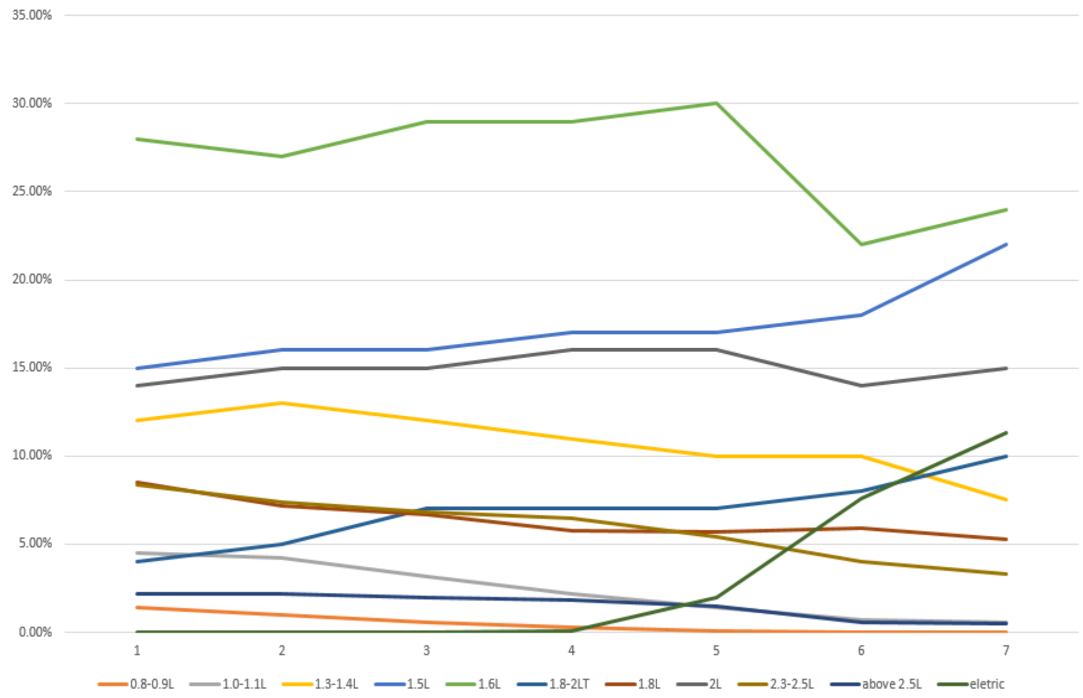

Figure 9 Engine size categories of private owned small passenger vehicle with their annual market share of sale from 2010 to 2016.

Not only the demand structure change was considered as a challenge to the automotive OEMs, but another challenge has been also associated with such significant industry: with plenty of investment into the automotive industry from both of domestic and external sources, the issue of overcapacity existed in early 2007, although it seems surprising in the most dynamically expanding market in the world. For example, General Motors (GM) (in China) achieved a capacity utilisation of 80% in 2005; in 2010, its capacity utilisation was around 50%-60% (Chinen et al., 2014). Monthly reports from China Passenger Car Association (CPCA) provided detailed figures of China passenger vehicle production, sale and inventory. Figure 10 shows the amount of passenger vehicle production and sales from December 2012 to December 2015. As can be seen, the production line lays above the sale line for a majority of the time, in which the difference between production and sales constructs inventory. Figure 11 further provides details of the amount of inventory held by OEMs and dealers, as there generally existed more positive inventory than negative inventory for both OEMs and dealers. By summarising their inventory, Figure 12 shows the total inventory of passenger vehicle in China's automotive market. The orange line represents the six-month-based weighted average inventory. Although it fluctuated up and down cross the time period, it stayed positive after January 2014. These features of inventory clearly reflect the issue of overcapacity in China's automotive industry.

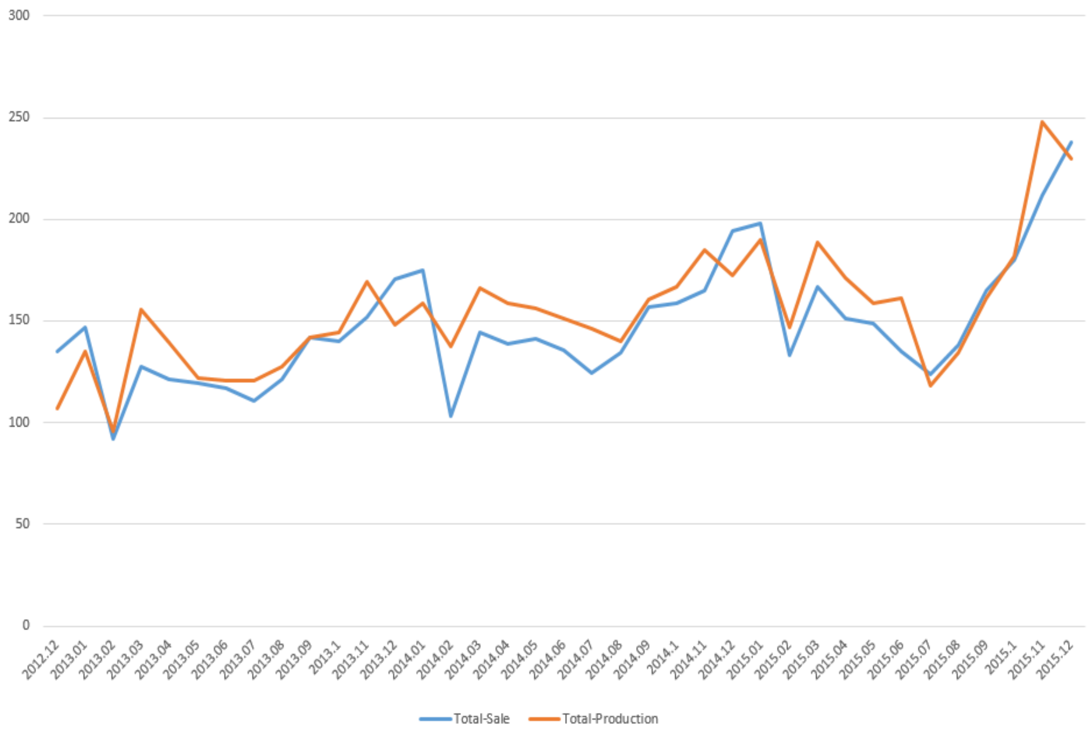

Figure 10 Total monthly sales and production of private owned small passenger vehicle from 2012.12 to 2015.12 in 10 thousand units.

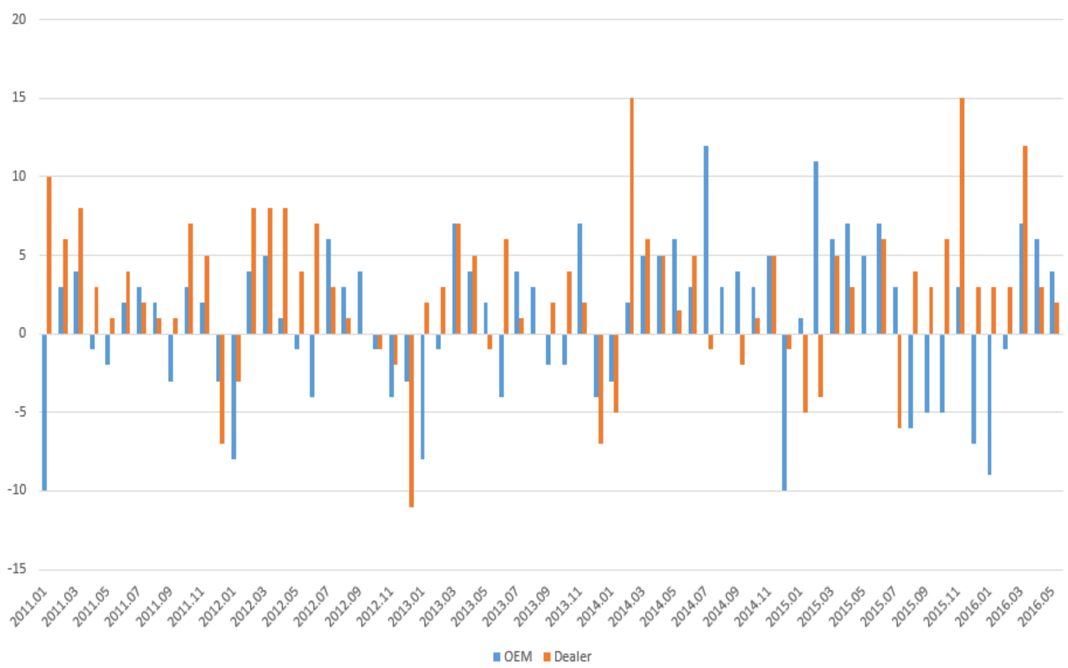

Figure 11 Total monthly small passenger vehicle inventory held by OEMs and Dealers from 2011.01 to 2016.05 in 10 thousand units.

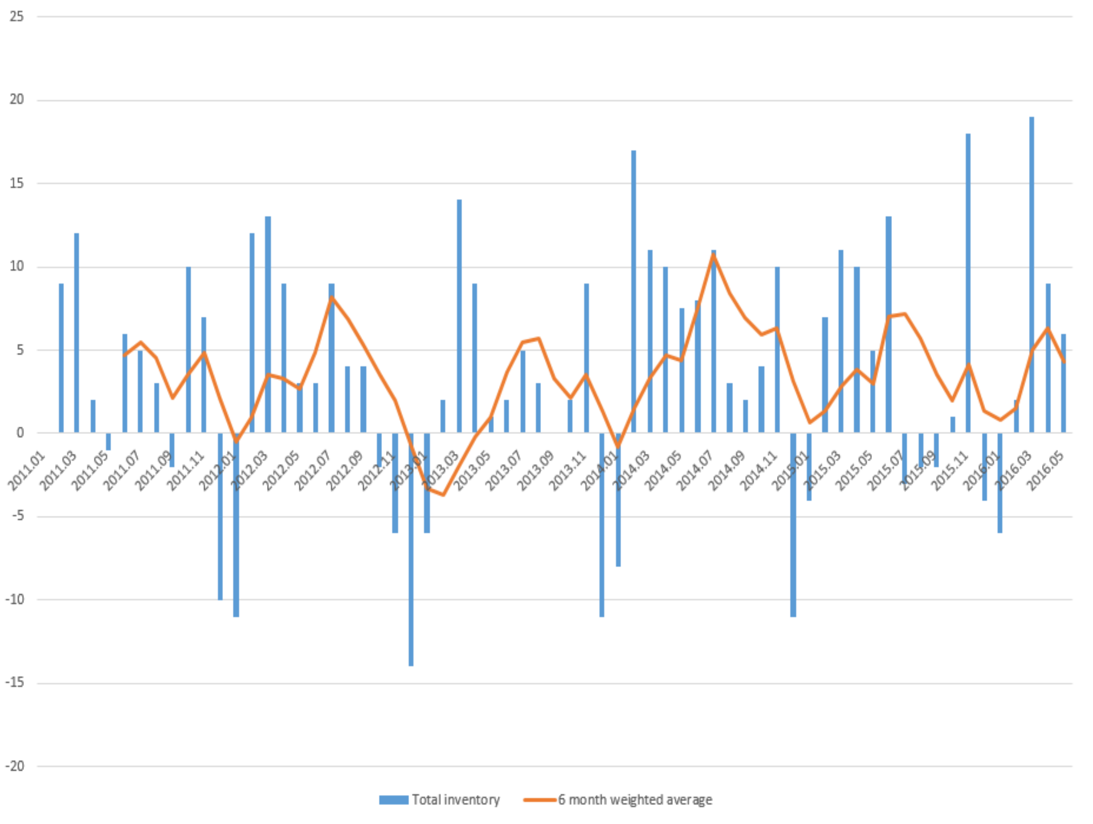

Figure 12 Total monthly small passenger vehicle inventory with its 6-month based weighted average line from 2011.01 to 2016.05 in 10 thousand units.

An accompanying effect of the overcapacity was that competition increased considerably. Many price-sensitive consumers delayed their vehicle-purchasing plans as prices continued to fall. This resulted in an effect known as the ‘liquidity trap’ (Krugman et al., 1998), which is when a price war happened between OEMs in order to divest inventory. By witnessing the price fall, consumers further delayed their purchasing plan, which reduced market demand, and the demand reduction further intensified the price war. Not surprisingly, such price falls also forced changes in the demand structure, making the market demand more unpredictable.

Accordingly, there are five points which can be concluded at the end of this section. First, the total vehicle market supply grew at approximately 15% every year, and it was the supply growth of small-sized passenger vehicle which comprised the majority of the total supply. Second, in regard to small-sized passenger vehicles, the demand preferences on body type are approaching a crossroads. In particular, the decreasing preference line of sedans and the increasing line of SUVs are likely to reach an equilibrium, accompanied by the steady growth of MPVs. Additionally, it is possible to witness a market position rotation after such equilibrium. Third, the 1.5L, 1.6L and 2L engines gained the majority of recognition from market demand, and demand preference on electric vehicle has been taking shape in recent years with an unknown future trend. Fourth, the monthly production generally exceeded monthly sales, which led to the issue of overproduction. Fifth, the overproduction forced an inventory rise, which reflected the rising issue of overcapacity in OEMs. In addition, rising inventory increased OMEs' managing cost and reduced asset turnover (Harford, 2005). In order to maximise OEMs' OP, reducing inventories became necessary and important. However, such inventory reduction activities would cause pricing war in the automotive market, which might further compress OEMs' profit space. As discussed above, the pricing war would also lead to the emergence of the liquidity trap. The effect of liquidity trap would bias the demand preference curve, so that future demand would be even more difficult to anticipate.

2.5 Supply Chain Management in the Automotive Industry

Generally speaking, OEMs in the automotive industry have very complex supply chains with upstream suppliers and downstream customers. In a general manufacturing supply chain, OEMs obtain demand information from downstream and estimate order quantities without pre-communication upstream. In such a circumstance, suppliers are unlikely able to fulfil the received orders due to lack of materials, which often leads to overtime production. To achieve just-in-time (JIT) production, automotive manufacturers have been establishing closely integrated collaborations with suppliers who have a willingness to deliver production upgrades together with OEMs (You and Zhu, 2005).

To achieve JIT production at a certain cost level becomes the primary objective of

OEMs' SCM, for their final aim is avoiding both being out of stock and having a massive inventory (Power, 2005). Wei and Qingfen (2015) indicated that automotive OEMs in China were pursuing consumer-demand-driven strategies. By applying such strategies, OEMs are expected to achieve higher operational profits and market share. Many automotive OEMs expend effort to learn consumers' demand preferences on vehicle body type, design, engine size, number of seats, entertainment and other features (Zhang and Chen, 2006). For example, both Volvo and Ford established their build-to-order online system for consumers to design personalised vehicles. In a different way, domestic OEMs such as BYD and Geely also have their 'build-up-now' systems. The aim of launching these systems is to maximally learn consumers' demand preferences on vehicles.

The OEMs' online vehicle design systems were not the only way to learn consumers' demand preferences. Khoong et al. (1997) indicated that OEMs designed their aftermarket services as a part of their downstream. In this way, closely integrated downstream customers are more likely to satisfy consumers' need and then gain consumer loyalty. In addition, downstream customers geographically close to and more directly communicate with consumers, which makes information about consumer demand preference more easily collectable (Lyons et al., 2004). As stated by Mills et al. (2004): *"accurate visible real-time information, such as demand information and consumer requirements for all activities in the supply chain, from procurement,* *transport, produce to store etc. can improve demand forecast and price fluctuations, stimulate the efficiency of upstream operations and result in faster system response time."*

2.6 Automotive Supply Chain Challenges

By observing the uncertain future trends of market demand preferences, demand uncertainty is a challenge in China's automotive supply chains. Demand uncertainty is an issue related to un-anticipatable future demand trends regarding a specific vehicle product. Unlike other manufacturing industries, given that it often takes several years to build a vehicle from its starting design, a failure to anticipate future demand will directly lead to inappropriate vehicle design. Production on such inappropriately designed vehicles usually exceeds market sale, which then forms overstock and eventually depreciates OP for a considerably long period. Therefore, demand information transformation from downstream to OEMs becomes the main objective of downstream supply chain management (Das et al., 2006) for the purpose of accurately anticipate future demand preferences. In particular, for the automotive industry in China, there exists a high need of demand information for anticipation, while the future demand preferences on body type and engine size are getting fuzzy.

Another significant challenge is to adjust the gradual excess capacity based on anticipated future demand. This challenge is formed by three industrial features in terms of steady growing total demand, uncertain future demand preferences and gradually rising inventory. Stocked inventory caused by inappropriate capacity adjustment decisions will lead to higher operational costs and a loss in market share. The production capacity is aligned with upstream in that it is the collaboration between OEMs and suppliers which delivers production. Consequently, from the SCM perspective, the collaboration strength between OEMs and suppliers determines their supply chain production capacity.

To overcome the challenges in China's automotive industry, a clear understanding of SCI contributes to OP under the moderating effect of demand uncertainty will be beneficial. This is particularly the case because both of the challenges are related to how OEMs should collaborate with suppliers and customers by facing uncertain demand.

2.7 Chapter Conclusion

Chapter 2 presented a brief introduction to the context of China's automotive industry. The chapter began with a discussion on the importance of the automotive industry to China's other manufacturing industries. It was argued that the automotive industry is vital for sustaining and developing China's economy. A descriptive analysis of China's annual vehicle production statistics revealed that China's automotive industry has experienced dramatic growth since 1998 and been ranked as one of the largest auto producers and auto markets in the world. Additionally, it was argued that auto production grew steady in the past years and is expected to continue growing. However, it was demonstrated that the demand preferences on vehicle features are approaching a crossover and may become uncertain to predict in the future. The chapter also introduced how automotive supply chain works differently to other manufacturing supply chains. In the later part of the chapter, challenges facing automotive supply chains were also presented. Under this study, it was suggested that the un-anticipatable demand uncertainty observed in China's automotive industry brings operational challenges.

In order to overcome the identified challenges, it was argued that automotive OEMs would require more appropriate adjustment on their collaborations with suppliers and customers when facing different demand conditions. Without observing how OEMs in China actually adjust their collaborations, however, it was argued that the automotive OEMs in China have been adopting consumer-demand-driven strategies in recent years. This could be associated to OEMs' attention to market changes, the existing demand uncertainties ahead, as well as risk and time constraints in auto vehicle productions. This therefore presents an interesting context to observe the moderating effect of DU on the SCI-OP relationship in China's automotive supply chains.

Chapter 3 Relationship between Supply Chain Integration (SCI) and Operational Performance (OP)

3.1 Chapter Introduction

Supply chain management has many definitions in academia, most of which are related to integration: *"the entire concept of SCM is really predicted on integration"* (Pagell, 2004). Integration plays a strategic role in SCM (Stank et al., 2001a), both in research and in practice. There is a 'common sense' belief that integration always positively contributes to operational performance, and it has been widely discussed and evidenced on an empirical basis (Sousa et al., 2012, Graham et al., 2005, Wook Kim, 2006). Somewhat in contrast, existing literature reveals disagreements and contradictions regarding the universal understanding of integration of 'the more the better'. Some studies found insignificant relationships (Devaraj et al., 2007, Gimenez et al., 2012, Stank et al., 2001b, Cousins and Menguc, 2006), while other studies recommend positive relationships with differentiated magnitudes or even negative relationships (Koufteros et al., 2005, Van der Vaart and van Donk, 2008).

By receiving the above inconsistent empirical findings, it is intuitively imaginable to view a more intricate web of the relationships by expanding the literature review's scale and scope. Given that terminologies of SCI and OP were introduced in Chapter 1, this chapter further studies the SCI-OP relationship by reviewing plentiful literature to identify a research gap and establish research hypotheses. As discussed in Chapter 1, this study attempts to answer the following research questions:

1. What is the relationship between SCI and OP?
2. Do the supply chain environmental factors moderate the relationship between SCI and OP?
3. How will the SCI-OP relationship be moderated by the environmental factors and to what extent?

To address the first research question, this chapter begins with a systematic literature review (SLR) on SCI in the SCM and operations management domain. The abundance of SCI studies, diverse methodologies used and different conceptualisations of SCI sub-dimensions have consequently led to diversified empirical findings (Pagell, 2004, Halldórsson et al., 2007). To address these findings, an SLR approach (Power, 2005) is applied for the purpose of clarifying the intricate current understanding of sub-dimensions of SCI and how these sub-dimensions of SCI individually affect OP. The SLR reported in this chapter focuses on prior empirical findings on the subject of the SCI-OP relationship.

To address the second and third research questions, which explore the moderating effect of the supply chain environmental factors on the SCI-OP relationship, this research reviews and discusses conflicts within theoretical arguments from operations management theories and from contingency theory. Reviewing the literature in the above areas enables this study to identify the current gaps in knowledge and, therefore, propose research hypotheses.

The rest of this chapter is structured as follows: the second section describes methodology followed for the SLR; the third section analyses findings obtained from the SLR; the fourth section discusses theoretical arguments; the theoretical framework and research hypotheses are presented in the final section.

3.2 The Systematic Review

This study follows the SLR method originally proposed by Tranfield et al. (2003a), (Thomas and Harden, 2008): planning, conducting and reporting the review. As discussed above, SCI is a developing concept with numerous and sometimes varying definitions, and the opinions of its relationship with OP are not unified. The aims of systematic literature are to locate, select and evaluate research question-related literature (Tranfield et al., 2003b). Thus, the systematic literature review in this study is established based on the following questions:

- *To what extent has the concept of SCI been developed thus far?*
- *What has been found in terms of the impact of SCI on operational performance?*
- *Does SCI always improve operational performance?*

The review protocol was developed first, as an initial step, and describes the review aim, strategy, selection criteria, data extraction and synthesis. This review was carried out based on Google Scholar. The reason for choosing Google Scholar is that it includes most of the journals in the fields of SCM and OM which are relevant to this study. This search was originally conducted in July of 2014 and was updated in January of 2016.

The search string was as follows:

Supply chain

OR Suppl* OR Custom* OR Internal

AND integrat*

AND Operat*

AND Performance

AND (data OR empirical OR test OR statistical OR finding* OR result* OR evidence OR case* OR stud* OR review*)

The keyword *supply chain* aims at the supply chain management context; *Suppl**, *Custom** and *Internal* were to cover studies which might focus on a specific integration dimension rather than treating SCI as an aggregated construct; while *integrat** was used to include integrate, integrating and integration; *Operat** aims to limit the search scope to operations research; *Performance* was used to target at all types of supply chain performance; the final keyword string aimed to select articles with empirical contents. By using the above search strings to screen article titles, **294** articles were identified from Google Scholar. Thereafter, the following inclusion and exclusion criteria were applied before relevancy analysis:

- **Exclude articles before year 2000 (include articles from 2000-2016).** Since SCI is a developing concept, it is necessary to include the most recent studies and arguments (Van der Vaart and van Donk, 2008), hence this study excluded articles prior to 2000. This step reduced the number of articles to **247**.
- **Only include journal papers.** Stevenson and Spring (2007) indicated that a systematic review should be conducted by implementing a standard selection method. This study only includes journal papers, which are peer-reviewed, because peer feedback guarantees a high standard of reporting and contributions. After applying this inculcation criterion, the number of articles was reduced to **222**.
- **Journal selection.** The previous step of exclusion still concluded with a large number of articles. Journals with greater a journal impact factor are considered to have better quality, thus this study only included articles with more than 2 stars that were under the high journal categories of the Academic Journal Guide (AJG). This step ended up with selecting eight journals which had published a significant amount of papers relevant to this topic, including (Table 1):

Journal	Abbreviation	AJG Ranking
Journal of Supply Chain Management	JSCM	4*+
Journal of Operations Management	JOM	4*+
Production and Operations Management	POM	4*
International Journal of Operations & Production Management	IJOPM	4*
Supply Chain Management: An International Journal	SCMAIJ	3*
International Journal of Production Economics	IJPE	3*
Industrial Marketing Management	IMM	3*
Decision Science	SD	3*
Transportation Journal	TJ	3*
International Journal of Physical Distribution & Logistics Management	IJPDLM	2*

Table 1 Selected journals with their abbreviations and ranking in AJG.

The journal selection step narrows down the number of journal papers to **46**.

The remaining 46 journal papers were then evaluated based on a set of quality criteria such as theory robustness, methodology, generalisability and contribution (Power, 2005). Thereafter, the 46 journal papers were categorised as:

- Studies on SCI which had clarity in relation to SCI sub-dimensions and OP. It is then important to have conceptual accuracy before theoretical discussion.
- Clearly presented measures of SCI and OP. In order to better understand the findings from past studies, it is important to be clear on how they measure SCI and OP.
- The majority of the 46 journal papers were conducted in general areas of manufacturing supply chains. Specific supply chains such as fresh food and military supply chains were excluded to avoid the effect of particular supply chain features.

- Studies about SCI that examined different dimensions of SCI including internal, external, supplier, customer integration, etc.

Obviously, the larger the number of criteria met, the higher the relevance of the journal paper. To achieve a balance, the author decided that journal papers which meet at least three criteria were included, as shown in Table 2, 35 journal papers were included. Among the 35 journal papers, as shown in Table 3, five used ANOVA analysis, 14 used regression analysis, and the remaining 16 were conducted by applying structural equation modelling (SEM). In addition, by categorising the selected journal papers in relation to their measurement methodologies, all of the 35 selected journal papers are survey-based empirical studies. This result is in line with other literature reviews in the SCM domain (Van der Vaart and van Donk, 2008, Power, 2005). As argued by Van der Vaart and van Donk (2008), reviewing articles with different methodologies definitely provides a better understanding of the SCI conceptualisation.

Criteria	Number of paper	Relevant to study
Studies meeting all four criteria	24	Included
Studies meeting at least three criteria	**35**	Included
Studies meeting at least two criteria	38	Excluded
Studies meeting at least one criteria	46	Excluded

Table 2 Criteria for further selecting relevant journal papers

Primary Methodology	Number of Papers	Percentage (%)
ANOVA	5	16.1
Regression Analysis	14	38.7
SEM	16	45.2
Total	31	100

Table 3 Summary of primary methodologies applied in the selected 31 journal papers.

Eventually, the breakdowns of the 35 selected journal papers were as follows (see Table 4): 10 studies from the *Journal of Operations Management (JOM)*; 3 from the *Journal of Supply Chain Management (JSCM)*; 1 from the *Production and Operations Management (POM)*; 5 from the *International Journal of Operations & Production Management (IJOPM)*; 6 from the *Supply Chain Management: An International Journal (SCMAIJ)*, 2 from the *International Journal of Production Economics (IJPE)*; 3 from the *Decision Science (DS)*; 1 from the *Transportation Journal (TJ)*; 1 from the *Industrial Marketing Management (IMM)*; 3 from the *International Journal of Physical Distribution & Logistics Management (IJPDLM)*.

Journal	Number of papers	Percentage (%)
JOM	10	28.6
IJOPM	5	14.3
SCMAIJ	6	17.1
IJPE	2	5.7
JSCM	3	8.6
DS	3	8.6
POM	1	2.8
TJ	1	2.8
IMM	1	2.8
IJPDLM	3	8.6

Table 4 Summary of Journals with number of papers included.

The applied filters narrowed the initial searching results of 294 articles to 35 journal papers. The selected 35 journal papers were then read and analysed in depth, with basis in four aspects:

- The way SCI was defined or measured;
- The way OP was defined or measured;
- The detailed methodologies applied;
- Types of relations found between SCI and OP;
- The ‘answer’ given to the key question: ‘What has been found in terms of the impact of SCI on OP?’

For the purpose of reviewing the above aspects, the selected journal papers were systematically classified based on a framework developed in the study of Ebrahimi (2015). The framework was developed multi-dimensionally with the basis in an iterative approach. The resulting framework is based on:

- Four overall dimensions of SCI including supply chain integration from an aggregate level, internal integration (II), supplier integration (SI) and customer integration (CI);
- An aggregate dimension of OP;
- Methodological approaches;
- Selected industries;
- Findings on the nature of the relationship;

- Given answers to the review question: ‘Does SCI always improve OP?’

SCI and sub-dimensions.

The understanding of SCI requires clear definitions and proper measures (Waller et al., 2008). Strategic collaboration and interdependence are two key characteristics of SCI which respond to flows in a supply chain, and SCI has been broadly defined as a process of strategic interaction and collaboration across firms that incorporate customers and suppliers into a cohesive supply network (Van der Vaart and van Donk, 2008). Thus, the general propose of SCI is to remove barriers of communication by coordinating, monitoring and controlling processes (Power, 2005). Based on this definition, with a highly purposive integrated supply chain, organizations can shape the attraction and the selection of supply chain members (Gulati et al., 2005). Another characteristic of SCI is interdependence (Huang et al., 2014). Both the relationship between supplier and manufacturer and the relationship between manufacturer and customer require interdependent efforts to coordinate material transfer and production operations (Lazzarini et al., 2008). A high level of synchronisation within the interdependent efforts guarantees the joint benefit of organizations engaged in SCI activities (Simatupang et al., 2002). In this way, SCI can also be defined as the level of information processing and the interdependence which exists among organizations (Das et al., 2006). By combining the above two definitions, Flynn et al. (2010) define SCI as the strategic collaboration of both intra-organizational and inter-organizational processes. Without too much argument, the definition of SCI used in this study refers to Flynn et al. (2010).

There are extant studies which examine the SCI-OP relationship while considering SCI as an aggregate construct and emphasising its effects on few aspects, such as supply chain collaborative practices (De Toni and Nassimbeni, 2000, Frohlich and Westbrook, 2001), attitudinal issues (Johnston et al., 2004) and communication technologies (Devaraj et al., 2007). However, it is increasingly accepted that SCI is a multi-dimensional concept (Das et al., 2006).

The literature provides many different classifications of SCI. A fundamental distinction is between internal and external integration (Stank et al., 2001b). Similarly, Frohlich and Westbrook (2001) proposed a distinction which is between upstream and downstream integration. Lee and Whang (2004) argued that SCI can be analysed in three ways in terms of operational integration, functional integration and relational integration. By expanding Lee and Whang (2004)'s argument, Das et al. (2006) further considered enterprise resource planning and relational initiatives. In a recent view, Flynn et al. (2010) argued that "*the diverse dimensions of SCI can ultimately be collapsed into three dimensions: customer, supplier and internal*". This study follows this very recent SCI classification. In addition, the aggregate SCI is also used in the SLR to include more SCI studies.

The following dimensions were included:

- Aggregate: considering supply chain integration at an aggregated level.
- Internal integration: integration within a company and across different departments.
- Supplier integration: upstream integration between an OEM and its suppliers.
- Customer integration: downstream integration between an OEM and its customers.

With regards to the discussion of the SCI sub-dimensions (see Table 5), 13 (38.7%) papers are limited at an aggregated level, the remaining 22 (61.3%) papers considered specific sub-dimensions of SCI. With regards to the latter 22 papers, there are 2 (6.5%) papers which only focused on supplier integration in their studies; 5 (9.7%) papers included both supplier integration and customer integration; the final 15 (41.9%) papers studied on all three sub-dimensions of SCI. It can thus be concluded that there are significant variations regarding the inclusion of SCI sub-dimensions, and recent studies have a tendency to include all three sub-dimensions.

OP and Sub-dimensions

To understand the SCI-OP relationships, this study draws upon existing knowledge from total quality management (TQM) literature. As suggested by the TQM literature, the successful implementation of TQM requires a consistent goal and barrier removal across internal functions and between the upstream-downstream supply chain (Talib and Rahman, 2010). Without an appropriate level of integration, functions and supply chain participators may work at multiple goals and thus waste resources, which will have a detrimental influence on cost and quality performance (Wang et al., 2012). From the production literature, there are arguments that integration enables the information share along the supply chains (Narasimhan and Kim, 2002) and slows for higher level of production coordination for improving production flexibility and delivery performances (Jonsson et al., 2011). These theoretical arguments have been empirically evident by many studies which found positive relationships between SCI and logistic performance (Gimenez and Ventura, 2005), delivery performance (Jonsson et al., 2011), quality performance (Wang et al., 2012) and cost performance (Waller et al., 2008). All of these empirical findings suggest a four-dimension category of OP (Wong et al., 2011a, Flynn et al., 2010).

- Aggregate: considering operational performance at an aggregated level.
- Delivery performance: provide on-time and reliable quantity products to customers.
- Production cost: produce products with low inventory and overhead costs.
- Product quality: produce consistent quality and high performance products that meet customer needs.
- Production flexibility: produce customized product features and able to rapidly change production volume.

As shown in Table 6, there are 24 (68.6%) studies which measured OP from an aggregated level; 10 (28.6%) studies measured OP in sub-dimensions and 1 (2.8%) study did not measure OP. From a timeline perspective, OP has been generally measured from an aggregated level before the year 2006. Then, scholars tended to measure OP in sub-dimensions within the period of 2006-2012, and the measurement preferences of OP returned from sub-dimensions to the aggregated level after 2012. This trend indicates a tendency of OP measurements' development in literature.

Author	Year	Journal	SCI			
			Aggregate	SI	CI	II
Markham T Frohlich, Roy Westbrook	2001	JOM		√	√	
Markham T Frohlich, Roy Westbrook	2002	JOM		√	√	
Theodore P Stank, Scott B Keller, David J Close	2002	TJ		√	√	√
Stanley E Fawcett, Gregory M Magnan	2002	IJPDLM	√			
Cristina Gimenez, Eva Ventura	2005	IJOPM		√	√	√
Xenophon A Koufteros, Mark Vonderembse, Jayanth Jayaram	2005	DS		√	√	√
Paul D. Cousins, Bulent Menguc	2006	JOM	√			
Ajay Das, Ram Narasimhan, Srinivas Talluri	2006	JOM		√		
Soo Wook Kim	2006	SCMAIJ	√			
Xenophon A Koufteros, T C Edwin Cheng, Kee Huang Lai	2007	JOM		√		
Sarv Devaraj, Lee Krajewski, Jerry C Wei	2007	JOM		√	√	
Morgan Swink, Ram Narasimhan, Cynthia Wang	2007	JOM		√	√	√
Chang Won Lee, Ik-Whan G Kwon, Dennis Severance	2007	SCMAIJ		√	√	√
Buleny Sezen	2008	SCMAIJ		√	√	
Soo Wook Kim	2009	IJPE		√	√	√
Veronica H Villena, Luis R Gomez Mejia, Elena Revilla	2009	DS	√			
Barbara B. Flynn, Baofeng Huo, Xiande Zhao	2010	JOM		√	√	√
Chee Yew Wong, Sakun Boon, Christina Wong	2011	JOM		√	√	√
Sakun Boon-itt, Chee Yew Wong	2011	IJPDLM		√	√	√
Cristina Gimenez, Taco van der Vaart and Dirk Pieter van Donk	2012	IJOPM	√			
Baofeng Huo	2012	SCMAIJ		√	√	√
Daniel Prajogo, Jan Olhager	2012	IJPE		√	√	√
Tobias Schoenherr, Morgan Swink	2012	JOM		√	√	√
Taco van der Vaar and Dirk Pieter van Donk, Cristina Gimenez, Vicenta Sierra	2012	IJOPM	√			
Siri Terjesen, Pankaj C Patel, Nada R Sanders	2012	DS	√			
Virpi Turkulainen, Mikko Ketokivi	2012	IJOPM	√			
Yao Henry Jin, Amydee M Fawcett, Stanley E Fawcett	2013	IJPDLM	√			
Li Zhao, Baofeng Huo, Linyan Sun, Xiande Zhao	2013	SCMAIJ		√	√	√
David X. Peng, Anto Verghese, Rachna Shan and Roger G.s Schroeder	2013	JSCM		√	√	
Ming-Chang Huang, Ghi-Feng Yen and Tzu-Chuan Liu	2014	SCMAIJ	√			
Baofeng Huo; Xiande Zhao; Honggeng Zhou	2014	POM		√	√	√
Gang Zhao, Taiwen Feng, Dan Wang	2015	IMM		√	√	√
Peter M. Raiston	2015	JSCM		√	√	
Daiel Prajogo, Adegoke Oke, Jan Olhager	2016	IJOPM	√			
Barbara, Flynn, Xenophon Koufteros, Guanyi Lu	2016	JSCM		√	√	√

Table 5 Sub-dimensions of SCI involved in the selected paper

Author	Year	Journal	OP				
			Aggregate	Delivery	Costs	Quality	Flexibility
Markham T Frohlich, Roy Westbrook	2001	JOM		√		√	√
Markham T Frohlich, Roy Westbrook	2002	JOM		√	√		√
Theodore P Stank, Scott B Keller, David J Close	2002	TJ	√				
Stanley E Fawcett, Gregory M Magnan	2002	IJPDLM	√				
Cristina Gimenez, Eva Ventura	2005	IJOPM	√				
Xenophon A Koufteros, Mark Vonderembse, Jayanth Jayaram	2005	DS	√				
Paul D. Cousins, Bulent Menguc	2006	JOM	√				
Ajay Das, Ram Narasimhan, Srinivas Talluri	2006	JOM	√				
Soo Wook Kim	2006	SCMAIJ	√				
Xenophon A Koufteros, T C Edwin Cheng, Kee Huang Lai	2007	JOM				√	
Sarv Devaraj, Lee Krajewski, Jerry C Wei	2007	JOM	√				
Morgan Swink, Ram Narasimhan, Cynthia Wang	2007	JOM		√	√	√	√
Chang Won Lee, Ik-Whan G Kwon, Dennis Severance	2007	SCMAIJ	√				
Buleny Sezen	2008	SCMAIJ	√				
Soo Wook Kim	2009	IJPE	√				
Veronica H Villena, Luis R Gomez Mejia, Elena Revilla	2009	DS		√			
Barbara B. Flynn, Baofeng Huo, Xiande Zhao	2010	JOM	√				
Chee Yew Wong, Sakun Boon, Christina Wong	2011	JOM		√	√	√	√
Sakun Boon-itt, Chee Yew Wong	2011	IJPDLM		√			
Cristina Gimenez, Taco van der Vaart and Dirk Pieter van Donk	2012	IJOPM		√	√	√	√
Baofeng Huo	2012	SCMAIJ	√				
Daniel Prajogo, Jan Olhager	2012	IJPE	√				
Tobias Schoenherr, Morgan Swink	2012	JOM		√	√	√	√
Taco van der Vaar and Dirk Pieter van Donk, Cristina Gimenez, Vicenta Sierra	2012	IJOPM	√				
Siri Terjesen, Pankaj C Patel, Nada R Sanders	2012	DS	√				
Virpi Turkulainen, Mikko Ketokivi	2012	IJOPM		√	√	√	√
Yao Henry Jin, Amydee M Fawcett, Stanley E Fawcett	2013	IJPDLM	√				
Li Zhao, Baofeng Huo, Linyan Sun, Xiande Zhao	2013	SCMAIJ	√				
David X. Peng, Anto Verghese, Rachna Shan and Roger G.s Schroeder	2013	JSCM	√				
Ming-Chang Huang, Ghi-Feng Yen and Tzu-Chuan Liu	2014	SCMAIJ	√				
Baofeng Huo; Xiande Zhao; Honggeng Zhou	2014	POM	√				
Gang Zhao, Taiwen Feng, Dan Wang	2015	IMM	√				
Peter M. Raiston	2015	JSCM	√				
Daiel Prajogo, Adegoke Oke, Jan Olhager	2016	IJOPM	√				
Barbara, Flynn, Xenophon Koufteros, Guanyi Lu	2016	JSCM	NA				

Table 6 Sub-dimensions of OP involved in the selected paper

Author	Year	Journal	Findings SCI-OP
Markham T Frohlich, Roy Westbrook	2001	JOM	SI+Quality, SI+Flexibility, CI+Delivery, CI+Flexibility
Markham T Frohlich, Roy Westbrook	2002	JOM	SI+Flexibility, SI+Cost, CI+Delivery
Theodore P Stank, Scott B Keller, David J Close	2002	TJ	CI+OP, II+OP, SI|OP
Stanley E Fawcett, Gregory M Magnan	2002	IJPDLM	SCI+OP
Cristina Gimenez, Eva Ventura	2005	IJOPM	SI+OP, CI+OP, II|OP
Xenophon A Koufteros, Mark Vonderembse, Jayanth Jayaram	2005	DS	II+competitive performance, CI+quality performance, SI+competitve&quality performance
Paul D. Cousins, Bulent Menguc	2006	JOM	SCI+OP
Ajay Das, Ram Narasimhan, Srinivas Talluri	2006	JOM	SI-bell-OP
Soo Wook Kim	2006	SCMAIJ	SCI+OP
Xenophon A Koufteros, T C Edwin Cheng, Kee Huang Lai	2007	JOM	SI+Quality performance
Sarv Devaraj, Lee Krajewski, Jerry C Wei	2007	JOM	SI+OP, CI|OP
Morgan Swink, Ram Narasimhan, Cynthia Wang	2007	JOM	CI+quality performance, II+all performance dimensions, SI+cost performance
Chang Won Lee, Ik-Whan G Kwon, Dennis Severance	2007	SCMAIJ	SI+OP, II+OP, CI+OP
Buleny Sezen	2008	SCMAIJ	SI+OP, CI+OP
Soo Wook Kim	2009	IJPE	SI+OP, II+OP, CI+OP
Veronica H Villena, Luis R Gomez Mejia, Elena Revilla	2009	DS	SCI+OP
Barbara B. Flynn, Baofeng Huo, Xiande Zhao	2010	JOM	SI+OP, II+OP, CI+OP
Chee Yew Wong, Sakun Boon, Christina Wong	2011	JOM	SI, II, CI + all performance dimensions
Sakun Boon-itt, Chee Yew Wong	2011	IJPDLM	SI+OP, II+OP, CI+OP
Cristina Gimenez, Taco van der Vaart and Dirk Pieter van Donk	2012	IJOPM	SCI+OP
Baofeng Huo	2012	SCMAIJ	II directly + OP, CI & SI indirectly + OP
Daniel Prajogo, Jan Olhager	2012	IJPE	SI+OP, II+OP, CI+OP
Tobias Schoenherr, Morgan Swink	2012	JOM	SI,CI+quality&cost performance，II | quality&costs performance.
Taco van der Vaar and Dirk Pieter van Donk, Cristina Gimenez, Vicenta Sierra	2012	IJOPM	SCI+OP
Siri Terjesen, Pankaj C Patel, Nada R Sanders	2012	DS	SCI-Bell-OP
Virpi Turkulainen, Mikko Ketokivi	2012	IJOPM	SCI+all performance dimensions
Yao Henry Jin, Amydee M Fawcett, Stanley E Fawcett	2013	IJPDLM	SCI+OP
Li Zhao, Baofeng Huo, Linyan Sun, Xiande Zhao	2013	SCMAIJ	SI+OP, II+OP, CI+OP
David X. Peng, Anto Verghese, Rachna Shan and Roger G.s Schroeder	2013	JSCM	SI+OP, CI+OP
Ming-Chang Huang, Ghi-Feng Yen and Tzu-Chuan Liu	2014	SCMAIJ	SCI+OP
Baofeng Huo; Xiande Zhao; Honggeng Zhou	2014	POM	II+OP, CI+OP, SI | OP
Gang Zhao, Taiwen Feng, Dan Wang	2015	IMM	SI, II, CI - bell- OP
Peter M. Raiston	2015	JSCM	SI-OP, CI-OP positive
Daiel Prajogo, Adegoke Oke, Jan Olhager	2016	IJOPM	SCI+OP
Barbara, Flynn, Xenophon Koufteros, Guanyi Lu	2016	JSCM	NA

Note: '+' represents positive relationship, '-' represents negative relationship, 'bell' represents inverse-U shaped relationship，'|' represents non-significant relationship

Table 7 Empirical findings of the SCI-OP relationships in the selected paper

	Author	Year	SCI				OP					Findings SCI-OP
			Aggre	SI	CI	II	Aggre	Delivery	Costs	Quality	Flexibility	
SCI & OP at aggregated level	Stanley E Fawcett, Gregory M Magnan	2002	√				√					SCI+OP
	Paul D. Cousins, Bulent Menguc	2006	√				√					SCI+OP
	Soo Wook Kim	2006	√				√					SCI+OP
	Taco van der Vaar and Dirk Pieter van Donk, Cristina Gimenez	2012	√				√					SCI+OP
	Siri Terjesen, Pankaj C Patel, Nada R Sanders	2012	√				√					SCI-Bell-OP
	Yao Henry Jin, Amydee M Fawcett, Stanley E Fawcett	2013	√				√					SCI+OP
	Ming-Chang Huang, Ghi-Feng Yen and Tzu-Chuan Liu	2014	√				√					SCI+OP
	Daiel Prajogo, Adegoke Oke, Jan Olhager	2016	√				√					SCI+OP
SCI at aggregated level, OP in multi-dimensions	Veronica H Villena, Luis R Gomez Mejia, Elena Revilla	2009	√					√				SCI+delivery performance
	Cristina Gimenez, Taco van der Vaart and Dirk Pieter van Donk	2012	√					√	√	√	√	SCI+ all performance dimensions
	Virpi Turkulainen, Mikko Ketokivi	2012	√					√	√	√	√	SCI+all performance dimensions
SCI in multi-dimensions , OP at aggregated level	Theodore P Stank, Scott B Keller, David J Close	2001		√	√	√	√					CI+OP, II+OP, SI|OP
	Cristina Gimenez, Eva Ventura	2005		√	√	√	√					SI+OP, CI+OP, II|OP
	Ajay Das, Ram Narasimhan, Srinivas Talluri	2006		√			√					SI-bell-OP
	Sarv Devaraj, Lee Krajewski, Jerry C Wei	2007		√	√		√					SI+OP, CI|OP
	Chang Won Lee, Ik-Whan G Kwon, Dennis Severance	2007		√	√	√	√					SI+OP, II+OP, CI+OP
	Buleny Sezen	2008		√	√		√					SI+OP, CI+OP
	Soo Wook Kim	2009		√	√	√	√					SI+OP, II+OP, CI+OP
	Barbara B. Flynn, Baofeng Huo, Xiande Zhao	2010		√	√	√	√					SI+OP, II+OP, CI+OP
	Baofeng Huo	2012		√	√	√	√					II directly + OP, CI & SI indirectly + OP
	Daniel Prajogo, Jan Olhager	2012		√	√	√	√					SI+OP, II+OP, CI+OP
	Li Zhao, Baofeng Huo, Linyan Sun, Xiande Zhao	2013		√	√	√	√					SI+OP, II+OP, CI+OP
	David X. Peng, Anto Verghese, Rachna Shan	2013		√	√		√					SI+OP, CI+OP
	Baofeng Huo; Xiande Zhao; Honggeng Zhou	2014		√	√	√	√					II+OP, CI+OP, SI | OP
	Gang Zhao, Taiwen Feng, Dan Wang	2015		√	√	√	√					SI, II, CI - bell curve- OP
	Peter M. Raiston	2015		√	√		√					SI+OP, CI+OP
SCI&OP in multi-dimensions	Markham T Frohlich, Roy Westbrook	2001		√	√			√		√	√	SI+Quality, SI+Flexibility, CI+Delivery, CI+Flexibility
	Markham T Frohlich, Roy Westbrook	2002		√	√			√	√		√	SI+Flexibility, SI+Cost, CI+Delivery
	Xenophon A Koufteros, Mark Vonderembse, Jayanth Jayaram	2005		√	√	√		√	√	√	√	II+competitive performance, CI+quality performance, SI+competitve&quality performance
	Xenophon A Koufteros, T C Edwin Cheng, Kee Huang Lai	2007		√						√		SI+Quality performance
	Morgan Swink, Ram Narasimhan, Cynthia Wang	2007		√	√	√		√	√	√	√	CI+quality performance, II+all performance dimensions, SI+cost performance
	Chee Yew Wong, Sakun Boon, Christina Wong	2011		√	√	√		√	√	√	√	SI, II, CI + all performance dimensions
	Sakun Boon-itt, Chee Yew Wong	2011		√	√	√		√				SI,II,CI+delivery performance
	Tobias Schoenherr, Morgan Swink	2012		√	√	√		√	√	√	√	SI,CI+quality&costperformance, II | quality&costs performance.
	Barbara, Flynn, Xenophon Koufteros, Guanyi Lu	2016		√	√	√						NA

Table 8 Segmented empirical findings of the SCI-OP relationships in the selected paper

Relationship between SCI and OP

One review question is ‘what has been found in terms of the impact of SCI on OP?’ It is therefore relevant to determine what kinds of relationships between SCI and OP have been argued and empirically proven in the selected papers, and whether they explicitly or implicitly discussed such relationships. Furthermore, the selected papers were coded on the nature of the relationship of the findings in Table 7. However, these findings are not suitable to be compared directly because SCI and OP were measured at different levels. Thus these findings were segmented into four scenarios in terms of:

- Both SCI and OP are measured from an aggregated level.
- SCI is measured in three sub-dimensions, and OP is measured from an aggregated level.
- SCI is measured from an aggregated level, and OP is measured from four sub-dimensions.
- Both SCI and OP are measured in sub-dimensions.

Based on the same measurement of the theoretical constructs, this study can compare the findings in each segmented scenario. The four scenarios are coloured differently in Table 8. In the first scenario, apart from the study of Terjesen et al. (2012) which obtained a bell-shaped relationship between SCI and OP, all other relationship findings are positive and consistent. Following the second scenario, although OP is collapsed into four sub-dimensions, empirical results tend to support an overall positive relationship. Inconsistent findings were observed in the third scenario, in that Stank et al. (2001b) and Huo et al. (2014) found an insignificant relationship between SI and OP; Devaraj et al. (2007) empirically evidenced that CI does not contribute to OP; Huo (2012) argued that II directly contributes to OP but SI and CI indirectly contribute to OP; Zhao et al. (2015) and Das et al. (2006) claimed bell-shaped relationships.

Although most findings still tend to support a positive SCI-OP relationship, indeed there are certain inconsistent results. The forth scenario shows expanded inconsistency along with OP measured in sub-dimensions. For example, Koufteros et al. (2014) found in their study that II only contributes to competitive performance, CI positively correlates with quality performance and SI significantly loads to both competitive and quality performance. Likewise, Schoenherr and Swink (2012) demonstrated an insignificant relationship between II and quality and cost performance. In contrast, Wong et al. (2011a) and Jonsson et al. (2011) published results which support overall positive relationships among any sub-dimensions.

One can see, it is the classification of SCI rather than OP which brings inconsistent findings. Further classification merely brings more complex and confused results, which creates more difficulty for scholars to induce existing results into a theory. Flynn et al. (2016) claimed that further studies should contribute to including more factors rather than making more classifications.

Author	Year	Journal	Moderator	Findings Moderating effect
Paul D. Cousins, Bulent Menguc	2006	JOM	Socialization	Socialization positively moderates SCI-OP
Soo Wook Kim	2006	SCMAIJ	Firm size	Firm size positively moderates SCI-OP.
Xenophon A Koufteros, T C Edwin Cheng, Kee Huang Lai	2007	JOM	Firm size	Firm size negatively moderates SI-OP
Sarv Devaraj, Lee Krajewski, Jerry C Wei	2007	JOM	eBusiness technology	eBusiness positively moderates both of SI and CI
Veronica H Villena, Luis R Gomez Mejia, Elena Revilla	2009	DS	Environmental volatility	Environmental volatility negatively moderates SCI-OP
Barbara B. Flynn, Baofeng Huo, Xiande Zhao	2010	JOM	Customer learning	Customer learning positively moderate SI, II, and CI with OP
Chee Yew Wong, Sakun Boon, Christina Wong	2011	JOM	Environmental Uncertainty	Environmental uncertainty negatively moderates SCI-OP
Sakun Boon-itt, Chee Yew Wong	2011	IJPDLM	Demand Uncertainty & Technology uncertainty	Technology uncertainty positively moderates SI-OP, negatively moderates II-OP, insignificant on CI; demand uncertainty negatively moderates SI and II, insignificant on CI.
Cristina Gimenez, Taco van der Vaart and Dirk Pieter van Donk	2012	IJOPM	Supply complexity	Supply chain complexity negatively moderates SCI-all performance dimensions
Tobias Schoenherr, Morgan Swink	2012	JOM	II	II positively moderates SI and CI on both delivery and flexibility, insignificant on either quality or costs.
Taco van der Vaar and Dirk Pieter van Donk, Cristina Gimenez, Vicenta Sierra	2012	IJOPM	Supply complexity	Supply chain complexity negatively moderates SCI-OP
Siri Terjesen, Pankaj C Patel, Nada R Sanders	2012	DS	Environmental Uncertainty	Environmental uncertainty negatively moderates SCI-bell-OP.
Li Zhao, Baofeng Huo, Linyan Sun, Xiande Zhao	2013	SCMAIJ	Supply delivery risk & Demand variability risk	SI CI II all positive relate to OP; supply delivery risk negatively moderates SI CI and II; demand variability risk negatively moderates CI.
David X. Peng, Anto Verghese, Rachna Shan and Roger G.s Schroeder	2013	JSCM	Product Clockspeed	Product clockspeed positively moderate CI-OP, non-significant on SI-OP
Ming-Chang Huang, Ghi-Feng Yen and Tzu-Chuan Liu	2014	SCMAIJ	Demand Uncertainty & Technology uncertainty	Demand uncertainty positively moderates SCI-OP, technology uncertainty negatively moderates SCI-OP
Baofeng Huo; Xiande Zhao; Honggeng Zhou	2014	POM	Local competition	No moderating effect from local competition
Gang Zhao, Taiwen Feng, Dan Wang	2015	IMM	Top management support	Top management support positively moderates either SI CI and II -bell- financial performance.
Peter M. Raiston	2015	JSCM	Demand response	Demand response positively moderate CI-OP, negatively moderate SI-OP
Daiel Prajogo, Adegoke Oke, Jan Olhager	2016	IJOPM	Lean strategy	Lean strategy positively moderate SCI-OP
Barbara, Flynn, Xenophon Koufteros, Guanyi Lu	2016	JSCM	Micro-Meso-Macro uncertainty	Micro-uncertainty positively moderate CI, Meso-Macro-uncertainty negatively moderate CI; Micro-uncertainty negatively moderate II and SI, Meso-Macro-uncertainty does not moderate on II and SI

Table 9 Empirical findings of the Moderating effects on SCI-OP relationships in the selected paper

Relationship between SCI and OP with Moderating Effects

To reconcile the observed inconsistency of SCI-OP relationships, Flynn et al. (2010) first introduced contingency theory and argued that the contribution level of an integration dimension to OP should be contingent on other integration dimensions. Their study explicitly demonstrated that the relationship between external integration and OP is contingent upon the level of II. Following this intuition, Wong et al. (2011a) extended the contingency argument and claimed that it is the fitness between integration strategy and the external environment which will eventually deliver optimal OP. Empirical studies built on the argument by Wong et al. (2011a) have tested many moderators effect on the SCI-OP relationships. As shown in Table 10, the moderators can be generally categorised into two groups in terms of endogenous moderator and exogenous moderator. By comparing the moderating effects between similar moderators, there is still inconsistency. For example, firm size's moderating effects have been found positive in the study by Kim (2009) and negative in that by Koufteros et al. (2007); environment uncertainty's moderating effects were proven to be negative in the studies of Villena et al. (2009), Wong et al. (2011a) and Terjesen et al. (2012); likewise, Jonsson et al. (2011) and Huang et al. (2014) divided the environment uncertainty into sub-dimensions of demand uncertainty and technology uncertainty, and their findings of the moderating effects were conflict with each other. Furthermore, Ralston et al. (2015) stepped on prior studies and found that demand uncertainty positively moderates CI-OP but negatively moderates the SI-OP relationship.

By observing an inconsistency in the moderating effects, Flynn et al. (2016) suggested that environment uncertainty should be considered in different levels of uncertainty which would have varied moderating mechanisms on integration strategies. Flynn et al.

(2016) measured the environment uncertainty into three sub-dimensions: micro-uncertainty, meso-uncertainty and macro-uncertainty, and empirically proved that diverse levels of uncertainty indeed influence integration strategies differently. However, their study did not include OP measurement, which brings a call for future studies to improve environmental moderators' measurement for better understanding the moderating effects.

3.3 Theoretical Background and Hypothesis Development

According to the discussions in Section 3.2, inconsistent empirical findings have been compared and contrasted. We observed that each single empirical finding has its theoretical explanation. However, no one single theory can explain the overall inconsistency. This section starts with frequently discussed theories in the SCI domain in order to reveal why and how the inconsistency exists.

3.3.1 The SCI-OP Relationships

This study integrated the resource-based view (RBV), organizational information processing theory (OIPT), transaction cost theory (TCT) and contingency theory (CT) to discuss the moderating effect of DU on the SCI-OP relationship.

Resource-based View (RBV)

The primary focus of the RBV is representing the role of strategic resources and capabilities within an organization as sustainable competitive advantage (Cousins and Menguc, 2006). Such resources and capabilities are usually treated as tangible and intangible assets as primary inputs of operational strategy (Koufteros et al., 2007).

Simpson and Power (2005) argued that strategic resources are non-tradable and shall be accumulated within the organization. For instance, an organization's brand value is non-tradable and should be established internally and over a certain period of time. Simpson and Power (2005) further argued that an organization's competitiveness can only be generated based on non-tradable assets.

However, recent studies argued that strategic resources might lie beyond organizations' edge, that the level of integration of a supply chain also has a certain explanatory ability to organizations' competitiveness (Lavie, 2006). Such arguments extended the understanding of a firm's competitiveness from an individual perspective to a network perspective. This extension has been termed the 'extended resource-based view' (Lavie, 2006).

Recognising the extended RBV, scholars have focused on the role of supply chain integration as a means of gaining external resources (Schoenherr and Swink, 2012). Thus, supply chain integration becomes a strategic tool for firms to fill gaps between their current circumstances and their strategic goals. Based on this theoretical rationale, it is reasonable to argue that supply chain integration as a kind of strategic resources is non-tradable and will lead to higher levels of supply chain collaboration.

Organizational Information Processing Theory (OIPT)

A deeper explanation of the effects of strategic integration activities is provided by OIPT. With intensive communication and information sharing occurring within supply chain participants, especially among the supply chain daily managers, value-added activities and events are more easily recognised and reached (Wong, 2013). Such rich information and knowledge processing as externally gathered resources also relates to the manufacturers' capability of strategic management and advanced technology, which will eventually lead to greater ability for cost reduction (Cai et al., 2010). In addition, information processing is a critical factor of SCI that formulates a platform through which organizations are able to gain engagement in problem solving capabilities by behaving jointly (Prajogo and Olhager, 2012). In particular, JIT (Kang and Bekkers, 2015) and build-to-order practices (Volling et al., 2013) are results of implementing such joint behaviour. An example from which Ambrosio and Schurr (2014) observed this is that the designing and production processes of smart electric vehicles are highly dependent on the information processing between component suppliers and manufacturers.

In the same vein, information processing has endowed OEMs a greater ability to predict and anticipate changing markets. Thus, from the OIPT's perspective, it is suggested that integrative activities should lead to superior manufacturing competitive capabilities and, therefore, improve operational performance (Prajogo and Olhager, 2012). Additionally, OIPT recognises that, as an open social economical system, an organization operates within and beyond organizational edges, which requires distinction of internal and external collaborations (Galbraith, 1973).

Both the RBV and OIPT tend to support the idea that performance improvement depends on leveraging organizational capabilities, strategic resources and information processing ability, which belongs to the principal subjects usually including suppliers, manufacturers and customers. Accordingly, SCI enables supply chain participants to gain capabilities, strategic resources and information processing abilities for sustained competitiveness (Schoenherr and Swink, 2012, Wong, 2013). As reported in the previous sections, recent literature has considered SCI as an important enabler for organizations to improve their OP.

Contingency Theory (CT)

Contingency theory might further provide an explanation into the existence of inconsistent research findings of the SCI-OP relationship. According to Vokurka and O'Leary-Kelly (2000), CT argues that there is no theory or method which can be applied in all cases. In other words, there is no single best way to design a supply chains' structure and operation strategy (Flynn et al., 2010). The rational proposition given is that a supply chain designs its structure and plans its activities with the potential requirements of fitting the environment in which it operates. This proposition suggests that supply chain participants, especially the focal companies, should match their structures and strategies to the external environment.

Transaction Cost Theory (TCT)

Considerable attention has been given to TCT from scholars in various disciplines of business, yet little use has been made of it in OM literature. In particular, with the increasing importance of SCI within the OM literature, there exists more necessity for understanding the explanation of TCT to OM issues. Williamson (1975) puts the notion of 'transactions' of exchange units as the core point of the theory. Transaction costs are the expenses generated by identifying fair product prices and negotiating and carrying out exchanges (Williamson, 1975). Thus, TCT suggests that organizations should operate better if they properly adjust their collaboration mechanisms to the transaction activities (Williamson, 2008).

Clemons et al. (1993) indicated that coordination costs and transaction risks are the two major characteristics of TCT. Coordination costs refer to the cost of exchanging information and converting information into decisions. In particular, it generally includes costs of exchanging production-oriented information in terms of design, material, availability, market demand and market price and operation-oriented information such as production plan, meeting, visiting, training and marketing. Transaction risk is associated with the risk that other collaborators' default upon their responsibilities and the risk of their inability to switch collaborators. For example, suppliers might provide inferior components if they know manufacturers are lacking equipment for quality checking. Another example of transaction risk might be the capability of withdrawing from a current collaboration, as the withdrawal process can be complicated due to bi-directional investment in capital.

From the perspective of TCT, a higher level of SCI will lead to risking exposure and raising coordination costs (Das et al., 2006, Simpson and Power, 2005, Zhao et al., 2015). There exists a diminishing marginal utility of investing in the closer integrative collaborations, and the utility benefit which might be submerged by raising coordination costs thereafter turns negative. Swink et al. (2007) argued that firms integrating too closely with their supplier and customers might exposure themselves to risks including adverse selection, moral hazard and opportunity costs. For instance, suppliers might become less innovative and vigilant to the market if they operate in a stable environment which allows them a guaranteed performance. In addition, as organizations' integration level rises, their openness and corporation opportunity offered to new suppliers or customers will reduce, or they might face great switching costs which set barriers to participate in new businesses. These dilemmas limit supply chain participants from effectively and efficiently responding and adapting to external changes and thus negatively contribute to OP (Zhao et al., 2015, Ghoshal and Moran, 1996). The inherent trade-off in SCI has been applied by the literature to explain their insignificant research findings. As TCT argues, there should not be a universal suggestion of whether SCI might positively or negatively contribute to OP.

Summary of the Theories

Summarising the discussed theoretical arguments, the RBV and OIPT tend to support a positive correlation from SCI to OP. By contrast, the TCT described a trade-off circumstance in which a higher level of SCI also brings a higher level of risk exposure and transaction cost. Thus, there should not be a strictly positive or negative relationship between SCI and OP. The TCT provided agreeance to the joint supports of all other theories, which indicates possibilities of existence in any type of SCI-OP relationships. The CT then suggested that the contribution of SCI to OP should be contingent on environmental conditions, which gives collateral support for the reasonable existence of TCT's tolerance.

3.3.2 Selection of Environmental Factor – Demand Uncertainty (DU)

There exists a set of environmental factors in the literature such as socialisation (Gulati et al., 2005), integration investment (Das et al., 2006), eBusiness technology (Devaraj et al., 2007), environmental uncertainty (Wong et al., 2011a) and lean strategy (Prajogo et al., 2015). The environmental uncertainty factor might involve mixed consideration in terms of demand uncertainty, supply uncertainty, technology uncertainty, political uncertainty and so on, which is quite general and lacks focus. Empirical findings regarding these two environmental factors might contribute to the body of knowledge; however, it is difficult to apply their measurements to real supply chain activities. Different from these two environmental factors, the remaining environmental factors are endogenous factors which change as supply chain condition changes. Following the call from Flynn et al. (2016), this study focuses on the moderating effect of a specific exogenous uncertainty factor and attempts to measure it with the full spectrum.

Existing findings have conflicting information on the moderating effects of demand uncertainty and technology uncertainty. To re-examine such conflict, this study continues from the investigation of demand uncertainty and technology uncertainty's moderating effects. The selection of such exogenous uncertainty factors has been largely recommended by the challenges existing in China's automotive industry. The first challenge was the upcoming demand uncertainty, and the second challenge was the adjustment on supply chain collaborations based on the anticipated demand uncertainty to eliminate the issue of gradual overcapacity. Thus, the demand uncertainty has been selected as the exogenous environmental factor. It is exogenous because consumer demand preferences do not change with changing conditions in the automotive industry.

In the supply chain management context, the demand uncertainty (DU) can be defined as the inability to recognise demand changes or the difficulty to accurately predict demand preference. As an alternative environmental factor, the moderating effects of DU have not been studied yet; DU is considered to be a clearer and more specified exogenous factor.

These challenges provide a reasonable and valuable exogenous factor, thus the use of

DU is expected to provide clearer and more focused moderating effects in the following investigation. Evidently, DU has become the key variable which influences supply chain strategy and decision making (Bernstein and Federgruen, 2005, Frohlich and Westbrook, 2002). With the selection of DU as the exogenous construct to begin with, it is expected to present some directly relevant implications for management.

3.4 Theoretical Framework and Hypotheses

3.4.1 Relationship between SCI and OP

This study first examines the direct relationship between internal, supplier and customer integration and OP without taking into consideration the moderating effect of DU. As suggested by the total quality management literature, a valid application of quality management requires reducing communication limits between departments (Wang et al., 2012). In this way, a strengthened internal integration may enhance departments' working capability at cross-purposes and lead to a reduction of resource consumption, which can positively impact operational performance for cost and quality (Schoenherr and Swink, 2012). From the strategic management literature, there are arguments that internal integration promotes the strategic collaboration and knowledge sharing across functions and manufacturers, which permits advanced responding capabilities to improve flexibility to markets and delivery performance (Kim, 2009, Swink et al., 2007). These arguments suggest a positive correlation between internal integration and operational performance. Thus, this study comes to the first hypothesis:

Hypothesis 1. *Internal integration is positively correlated with operational performance.*

Based on the OIPT introduced in Section 3.3.1, supplier integration allows for a better capability of collecting accurate supplier information. Likewise, customer integration enables the supply chain to gather valuable information from the customer's side. The gathered information from both the supplier side and customer side is essential for collaboration within supply chains (Vachon et al., 2009, Lockstroem et al., 2010). A higher level of external integration will hence generally produce better production plans, inventory performance and operation reliability (Gallear et al., 2014). In addition, a highly integrated supply chain from either the supplier side or customer side promotes a cross-functional problem-solving ability, which generates more understanding of production planning (Turkulainen and Ketokivi, 2012). This helps to minimise supply chain wastage in both resource usage and management efforts (Jin et al., 2013). Furthermore, investment in external integration also provides the benefit of efficiently aligning various operation objectives within supply chains and effectively adjusting coordinate direction in cost reduction (Zhao et al., 2013), quality improvement (Huang et al., 2014), delivery in time (Sousa et al., 2012) and flexibility to market changes (Cao et al., 2015). Thus, all of the above arguments converge to the second and third hypotheses:

Hypothesis 2. *Supplier integration is positively correlated with operational performance.*

Hypothesis 3. *Customer integration is positively correlated with operational performance.*

3.4.2 Relationship between SCI and OP under DU

Based on the proposed hypotheses 1-3, all dimensions of SCI are supposed to be positively correlated to OP. Whether DU moderates the multiple SCI-OP relationships is reflected in the sensitivity of SCI dimensions to DU. This study 。argues that, under a highly uncertain demand, circumstances which require more needs of scanning the demand features, integration on the customer side is likely to enhance ability to recognise and read information for supply chains (Vachon et al., 2009). This helps supply chains to better understand the changes of market demand and, therefore, improve their responsiveness (Wu et al., 2010). When a market becomes stable, demand is predictable, the payoff of continuing to invest in customer integration may show out because the marginal utility of improving customer integration decreases (Parkhe, 1993). This marginal utility is reflected as the difference between the increasing information-gathering ability and the increasing transaction cost and management effort inputs. Such utility is argued to turn negative when the level of customer integration exceeds a certain point (Thompson, 2011). Thus, a high DU strength the contribution from customer integration to OP and a low DU weakens such contribution.

On the other hand, the marginal utility of enhancing SI is considered to be lower when DU is high. Since suppliers are located at the far end of supply chain information flow, integration of suppliers is helpless in understanding the changing market conditions (Yigin et al., 2007). However, just like a reversed way of comparing customer integration, there is a great need for integration on suppliers when a market is stable and predictable (Bennett and Klug, 2012). Development of a strong strategic partnership with suppliers will significantly reduce production cost and improve production quality (Vanpoucke et al., 2014). This study then argues that a high DU negatively moderates the effect of supplier integration on operational performance, and a low DU provides a positive moderating effect.

Anticipated demand uncertain will subsequently raise the need for OEMs to alter manufacturing plans and strategies (Vokurka and O'Leary-Kelly, 2000). Intuitively, enhanced information-processing abilities across OEM functions will improve the efficiency and effectiveness of altering manufacturing plans and strategies and respond more accurately and in-time to changing demands (Flynn et al., 2010). This means highly integrated OEM functions with a greater ability to process information is more able to satisfy uncertain market demand. In contrast, when demand is anticipatable, OEMs will have more possibility to reach operational goals (Bernstein and Federgruen, 2005). Especially for OEMs who operate JIT productions (Kang and Bekkers, 2015), integrated functions allow engaged information sharing to be effective collaboration with upstream, which will enhance their production planning accuracy and inventory management. This means OEMs are expected to perform better in JIT production with anticipatable demand, which implies DU will positively moderate internal integration on operational performance. With the above arguments, three additional hypotheses are established as follows:

Hypothesis 4. *DU positively moderates the correlation between internal integration and operational performance.*

Hypothesis 5. *A high (low)* DU *negatively (positively) moderates the positive correlation between supplier integration and operational performance.*

Hypothesis 6. *A high (low)* DU *positively (negatively) moderates the positive correlation between customer integration and operational performance.*

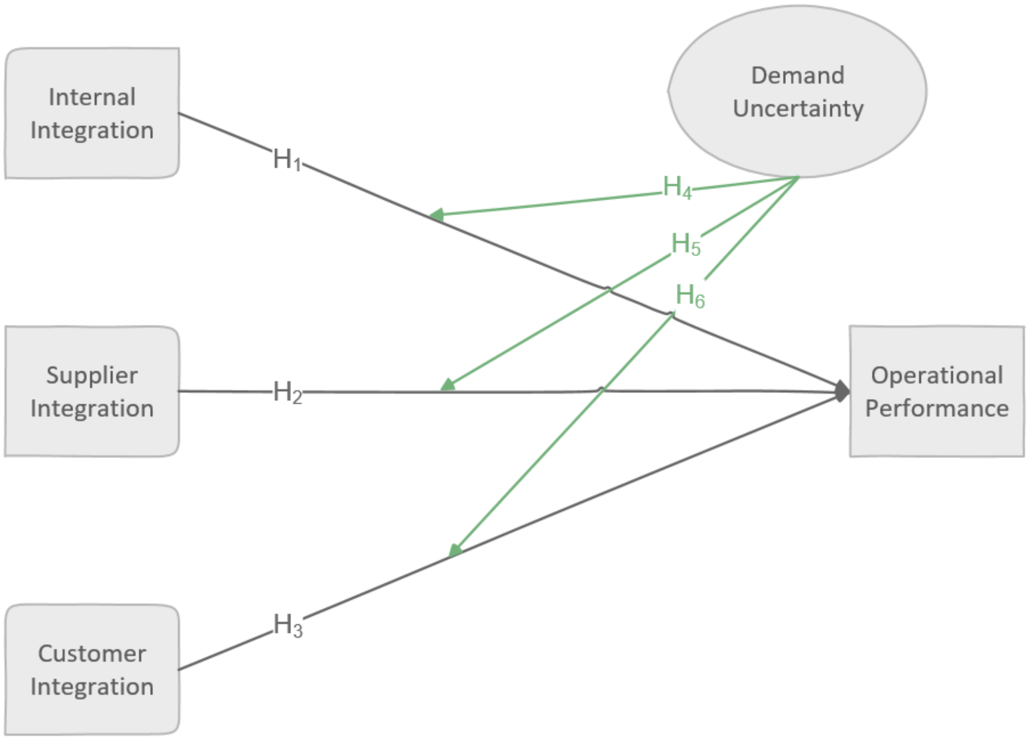

Figure 13 Theoretical framework.

Figure 14 illustrates the theoretical framework which summarises the proposed six hypotheses of the three SCI dimensions on OP's moderating effect on DU.

3.5 Chapter Conclusion

Chapter 3 started with an SLR and discussion on the theoretical constructs under investigation. In particular, this chapter systematically reviewed and discussed background information and definitions on the three constructs of SCI, OP and DU. The review also helps to identify and establish the appropriate dimensions associated with the theoretical constructs. The most relevant dimensions of SCI (II, SI, CI) were identified in examining their relationships with OP. Despite the terminologies, the review compared and contrasted the existing empirical findings on the SCI-OP relationships. The comparison clearly indicated the inconsistency within the existing findings. Contingency theory has been used to associate the inconsistent findings with the moderating effects from exogenous environmental factors. Finally, Section 3.2 ended with the argument that current examinations on the moderating effects of environmental factors on SCI-OP relationships tend to be general and lacking in industrial focus. In addition, there is still no analytical model which can explicitly indicate how theoretical constructs inter-play with each other.

To explore the potential mechanism of SCI-OP relationships, Section 3.3 started with an introduction on frequently applied theories in the OM domain. Such theories include RBV, OIPT, TCT and CT. Accordingly, a number of debates were presented based on these theories. From the resource utilisation and information process points of view, RBV and OIPT jointly suggest the 'common sense' approach. The TCT discussion added cost consideration into the debate and suggested that the increasing costs along with amounts of capital and managerial effort put in might eventually exceed benefits gained through integrative activities. Facing this dilemma, CT provides a guidance to what determines the balance mechanism between the integrative activities' costs and benefits. Based on the contingency argument and research context introduced in Chapter 2, this section also presented the selection of the environmental factor – DU.

By carrying out the discussions on existing empirical findings and theoretical arguments, Section 3.4 indicated research gaps and established the theoretical framework with six developed hypotheses.

Chapter 4 Methodology

4.1 Chapter Introduction

Chapter 3 presented the SLR and theoretical framework, and six research hypotheses were proposed in line with the research question. This chapter provides an overview of the research methodology adopted for this study. The main research epistemologies and ontologies are reviewed to provide justifications for the *interpositivist* and *deductive* approaches adopted in this study. Furthermore, this chapter discusses how measurements for the three main constructs were recognised and developed. Discussions are also provided on the research unit selection, questionnaire design and data collection process. Accordingly, the collected data are tested to ensure reliability and validity before analysis. Finally, this chapter summarises a discussion on the selection of threshold regression analysis (TRA) as the prime analysis technique used to test the hypotheses.

4.2 Research Philosophy

Most research questions can be examined from either a quantitative, qualitative or mixed perspective. An appropriate research methodology is therefore surely associated with the choice of research paradigm. Research paradigm is defined as the principles or views which enable a scholar to make informed choices on the appropriate method, epistemology and ontology (Crossan, 2003). As argued by Hammersley (1993), an appropriate choice of research paradigm helps scholars to better explain why the selected methodology is more appropriate than others. Social science philosophies include positivism, interpretivism and realism (Hughes and Sharrock, 1980). The selection of research philosophy in this study determines the manner in which the relationships between SCI and OP under the moderating effects of DU are examined quantitatively, and such selection further determines the method chosen to conduct this study.

4.2.1 Research Epistemology

Epistemology is a concept that represents what can be thought as 'knowledge' in a given research domain, and such concept argues whether it is appropriate to apply natural science approaches on social science studies (Hammersley, 1993). Positivists believe that *"reality can be observed and described from using an objective method, rather than being inferred subjectively through sensation, reflection or intuition"* (Levin, 1988). They proposed that a phenomenon can be isolated from others and an observation can be repeatable (Easterby-Smith et al., 1991). Positivists then study problems and concepts by quantifying observations. Findings are usually obtained by using a mathematical approach and are reported in statistical terminology (Hammersley, 1993).

In contrast, the interpretivists believe that the world is as people think it to be, thus the interpretivists aim to *"uncover the socially constructed meaning as it is understood by an individual or a group of individuals"* (Cavana et al., 2001), and to *"describe it in a way that is meaningful for these research participants"* (Saunders, 2011). Saunders (2011) indicated that the main objective of interpretivist studies is to make sense of people's actions and intentions by understanding their subjective reality. In this way, interpretivism can also be interpreted as the idea that reality is constructed by people's subjective understandings.

Realism bridges the two extremes reached by the positivism and interpretivism (Stiles, 2003). Realism claims that existing knowledge might be partial or incomplete, therefore such knowledge must be completed by applying theoretical frameworks to reflect the underling mechanisms (Stiles, 2003).

As previously stated, the objective of this study is to examine the moderating effect of DU on the relationship between SCI and OP in the automotive industry of China and explore potential mechanisms and suggestions of how OEMs should adjust their collaborations by facing different levels of demand uncertainty for the propose of maximising their OP. This study is of an exploratory nature which is a way of observing the mechanism, and thus this study can be classified as positivistic. However, the data used in this study will be collected through survey questionnaire, and the survey questionnaire is an instrument that quantifies people's view and understandings on a given issue, which is of an interpretivist nature. Even though the major components of this study design are from a positivist approach, overall, this study can be best classified as positivistic.

4.2.2 Research Approach

There are generally two approaches to designing a study: deductive and inductive. The deductive approach develops a theory or hypothesis based on existing facts and theories in a particular area (Saunders, 2011). Comparably, the inductive approach looks like a reverse way of the deductive approach, as it suggests collecting and analysing data to consequently develop a theory based on the results of the analysis (Hepp et al., 2007, Noy and Musen, 2004). In other words, the deductive approach goes from theory to practice, and the inductive approach does from practice to theory. The deductive approach is considered the most appropriate for this study, since proposed hypotheses have been established based on existing OM theories. Thus, this study follows the deductive approach.

The deductive approach is mainly used to examine causal relationships between model constructs, followed by hypothesis development and a verification process (Stojanovic et al., 2002). As indicated by Stojanovic, a deductive approach should have five main stages:

- Developing research hypotheses with a strong theoretical foundation
- Establishing a theoretical framework and specifying construct measurements
- Estimating the theoretical model and testing the proposed hypotheses
- Discussing the model outcome
- Adjusting the theory in relation to research findings

Quantitative studies are frequently referred to as the deductive approach, and this approach is indeed used by all reviewed empirical studies which generate numerical data from survey questions. In addition, scholars argued that the deductive approach should provide a well-structured methodology which allows other scholars to repeat the research process (Stojanovic et al., 2002, Maedche et al., 2003).

4.3 Research Design

To test the research hypotheses proposed in the literature review chapter, this study takes a quantitative approach to collecting, validating and analysing the data sample. This section introduces how the theoretical constructs are measured and how the data sample was collected and analysed. A discussion on identifying the most appropriate methods of data analysis is also presented. For the data-gathering field, the automotive manufacturing industry in China was selected since China is argued to be the largest automotive market and the largest automotive-producing country in the world (Bennett and Klug, 2012, Lockstroem et al., 2010). China has experienced a profound transformation over the last two decades (Aller and Carlos, 2010, Flynn et al., 2010). The scope and scale of China's automotive industry have made it suitable for the data-gathering field of this study. In addition, the maturing automotive market in China has established extensive collaborations with major global automotive supply chains (Bennett and Klug, 2012). Such engagement will certainly produce more specified research implications. The reason for choosing a single industry is to conduct a focused study to avoid obtaining findings based on mixed average values. This is because different manufacturing industries may have different behaviour preferences and managerial patterns (Lockstroem et al., 2010), which could be argued as additional exogenous factors with moderating effects and may further confound the already complicated theoretical framework.

4.3.1 Questionnaire Design and Measures

This study used a questionnaire as one of the main empirical instruments for data gathering from the selected sample group of Chinese automotive OEMs. The unit of analysis of this study is defined as the manufacturers who act as the OEMs in automotive supply chains. The questionnaires were developed in three stages. In the first stage, the measurements of the three key constructs in terms of SCI, OP and DU were developed based on what has been already established from the literature. Since this study does not aim to contribute to the term measurements, measurements from existing literature were borrowed and modified as necessary. Accordingly, as shown in Appendix D, for the three dimensions of SCI, supplier integration was measured by 13 observable factors; customer integration was measured by 11 observable factors; internal integration was measured by 9 observable factors； and the OP was measured by 6 observable factors. Those measures of SCI and OP were borrowed from the study of Flynn et al. (2010). Following the literature's suggestion, this study measured OP from an aggregated level rather than measuring OP in sub-dimensions. By doing so, it is expected to have obtained less complex results, which can be easily converted into theory and management tools. Referring to the studies from (He and Zhao, 2012), there were four observable factors which could jointly measure DU. There were 43 indicative items in total. The 43 items were all measured using a seven-point Likert scale (Brown, 2015, Tang and Lan, 2015).

Control Variables

Control variables are frequently used in empirical studies to test whether there are determinant effects of research units' characteristics (Koufteros et al., 2007). The research unit in this study is the OEMs in automotive supply chains in China. Characteristics of OEMs in terms of firm size, number of employees, revenue, firm age and region are often used in supply chain empirical studies (Jonsson et al., 2011, Flynn et al., 2010, Zhao et al., 2008). However, in most cases, the determinant effects of these control variables are not observable. Although they have been significantly loaded to OP in infrequent cases (Terjesen et al., 2012, Huang et al., 2014), the loading magnitudes were negligible. Instead, most scholars use the characteristic variables in the survey data validation process but not in the analysing process (Huo, 2012, Flynn et al., 2010, Wong et al., 2011a). This study follows the latter approach.

4.3.2 Questionnaire Test and Validation

In the second stage, a list of all registered automotive manufacturers was obtained via contacting the Automotive Association of China, so all OEMs on the list jointly form a pool. From this pool, 10 OEMs were randomly selected and contacted. With their support, several online video meetings were held with the OEMs' R&D directors and managers to validate the survey questionnaire and the measurement items. Few words were modified to use lay language rather than academic language, which made the survey questions easier to be accurately understood. The survey questionnaire used in this study was originally developed in English, then translated into simplified Chinese (for mainland China use) by three Chinese operations management professors. Then, the questionnaires were translated back into English by another three operations management professors. The final English version was checked against the original English version for discrepancies to ensure its validity. To further ensure the ethical validity, the survey questionnaire has been approved by Biomedical & Scientific Research Ethics Committee (BSREC) of the University of Warwick, reference code: REGO-2016-1770.

In the final stage, differing from the previously random selected 10 OEMs, another group including 20 OEMs were randomly selected from the registered manufacturer pool. A pre-test process of the survey questionnaire was carried out with the 20 OEMs. The author sent a total of 60 questionnaires to the 20 OEMs' directors and managers, of which 45 questionnaires were returned, making a response rate of 75%. A set of analyses in terms of Cronbach's alpha measure, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were performed on the 45 returned questionnaires to test reliability and validity. This analysis was used to further examine whether the number and content of the key constructs borrowed from the existing literature could be verified empirically.

Checking Reliability

As introduced previously, the initial questionnaire design used a 11-item strategy for SI and CI; a 9-item strategy for II; a 6-item strategy for OP and a 4-item strategy for DU, which jointly forms the original measurement model (say measurement model 1). Adjustments were made to the measurement model 1 as suggested by the reliability analyses results until a final factor matrix emerged for each construct. Cronbach's alpha measures the internal consistency of a group of factors (Cronbach, 1951). Internal consistency is defined as the existence of no co-linearity issue between each two of input variables. Thus, the number of observations has no restriction in the Cronbach's alpha test. A low Cronbach's alpha score indicates that the data sample of items performs poorly in capturing the construct and a high level of alpha indicates that the correlations between items and constructs were well established with significant coefficients. As suggested by the literature, a minimum acceptable level for Cronbach's alpha is 0.7 in operations management research (Brown, 2015, Tang and Lan, 2015, Sousa et al., 2012). The Cronbach's alpha measurement has been applied on two dimensions of the five individual constructs and the whole measurement model, respectively, in order to test composite reliability and total reliability.

Table 8 lists the five theoretical constructs with their scale factors, in which each scale factor has been marked with a label, such as SI1. These labels will be used in later tables to represent the scale items.

Table 9 shows the Cronbach's alpha measure on items relating to the five constructs in terms of SI, CI, II, OP and DU and on the whole measurement model. Cronbach's alpha values for the individual constructs were 0.832 for SI, 0.811 for CI, 0.906 for II, 0.841 for OP and 0.779 for DU, and the values were all deemed acceptable based on the benchmark value of 0.7. However, in order to achieve a higher composite reliability (Raykov, 1997), it is observed that the corrected item-total correlation values of SI4, SI6, SI10, CI3, CI11, II6, II9 and OP6 are relatively low compared to other scale factors subject to their own construct. This means that the Cronbach's Alpha of the theoretical constructs will be improved by deleting the above scale items. For example, Cronbach's alpha will increase from 0.832 to 0.839 if SI4 is deleted, *ceteris paribus*. Therefore, these scale items have been removed from the measurement model 1. Removing these scale items optimises the measurement model to achieve a greater composite reliability. However, by looking at the obtained Cronbach's alpha values for either the individual construct or the whole measurement model, the composite reliability and total reliability are acceptable even without removing the above-mentioned scale items.

Construct	Scale factors
Supplier integration	SI1 – the level of information exchange with our major supplier through information network
	SI2 – the establishment of quick ordering system with our major supplier
	SI3 – the level of strategic partnership with our major supplier
	SI4 – stable procurement through network with our major supplier
	SI5 – the participation level of our major supplier in the process of procurement and production
	SI6 – the participation level of our major supplier the design stage
	SI7 – our major supplier shares their production schedule with us
	SI8 – our major supplier shares their production capacity with us
	SI9 – our major supplier shares available inventory with us
	SI10 – we share our production plans with our major supplier
	SI11 – we share our demand forecasts with our major supplier
	SI12 – we share our inventory levels with our major supplier
	SI13 – we help our major supplier to improve its process to better meet our needs
Customer integration	CI1 – the level of linkage with our major customer through information networks
	CI2 – the level of computerization for our major customer’s ordering
	CI3 – the level of sharing of market information from our major customer
	CI4 – the level of communication with our major customer
	CI5 – the establishment of quick ordering systems with our major customer
	CI6 – follow-up with our major customer for feedback
	CI7 – the frequency of period contacts with our major customer
	CI8 – our major customer share point of sales information with us
	CI9 – our major customer shares demand forecast with us
	CI10 – we share our available inventory with our major customer
	CI11 – we share our production plan with our major customer
Internal integration	II1 – data integration among internal functions
	II2 – enterprise application integration among internal functions
	II3 – integrative inventory management
	II4 – real-time searching of the level of inventory
	II5 – real-time searching of logistic-related operating data
	II6 – the utilization of periodic interdepartmental meetings among internal functions
	II7 – the use of cross functional teams in process improvement
	II8 – the use of cross functional teams in new product development
	II9 – real-time integration and connection among all internal functions from raw material management through production shipping and sales
Operational performance	OP1 – our company can quickly modify products to meet our major customer’s requirements
	OP2 – our company can quickly introduce new products into the markets
	OP3 – our company can quickly respond to changes in market demand
	OP4 – our company has an outstanding on-time delivery record to our major customer
	OP5 – the lead time for fulfilling customers’ orders is short
	OP6 – our company provides a high level of customer service to our major customer
Demand uncertainty	DU1 – order change frequency
	DU2 – order volume unpredictable
	DU3 – order preference change
	DU4 – product life cycle change

Table 10 Theoretical constructs with measurement items

	Items	Corrected item-total correlation	Cronbach's Alpha if item deleted	Cronbach Alpha of constructs	Cronbach Alpha
SI	SI1	0.498	0.771	0.832	0.877
	SI2	0.628	0.630		
	SI3	0.575	0.722		
	SI4	**0.365**	**0.839**		
	SI5	0.499	0.799		
	SI6	**0.408**	**0.841**		
	SI7	0.506	0.752		
	SI8	0.613	0.644		
	SI9	0.639	0.623		
	SI10	**0.479**	**0.855**		
	SI11	0.594	0.703		
	SI12	0.599	0.685		
	SI13	0.610	0.635		
CI	CI1	0.504	0.793	0.811	
	CI2	0.539	0.773		
	CI3	**0.409**	**0.830**		
	CI4	0.584	0.746		
	CI5	0.608	0.742		
	CI6	0.498	0.801		
	CI7	0.565	0.766		
	CI8	0.526	0.784		
	CI9	0.561	0.769		
	CI10	0.567	0.751		
	CI11	**0.401**	**0.836**		
II	II1	0.554	0.863	0.906	
	II2	0.579	0.852		
	II3	0.432	0.892		
	II4	0.499	0.881		
	II5	0.616	0.831		
	II6	**0.388**	**0.922**		
	II7	0.656	0.822		
	II8	0.598	0.845		
	II9	**0.413**	**0.916**		
OP	OP1	0.516	0.833	0.841	
	OP2	0.563	0.819		
	OP3	0.558	0.820		
	OP4	0.634	0.812		
	OP5	0.634	0.811		
	OP6	**0.433**	**0.852**		
DU	DU1	0.548	0.775	0.779	
	DU2	0.609	0.763		
	DU3	0.586	0.768		
	DU4	0.661	0.755		

Table 11 Measurement model 1 with Cronbach's alpha measure.

After removing those scale items with lower corrected item-total correlation, the remaining scale items formed measurement model 2, as shown in Table 10. In measurement model 2, composite reliabilities of the five constructs have been re-tested. The estimated Cronbach's alpha of constructs range from 0.779 to 0.920, which are greater than the benchmark value of 0.7 and greater than the alpha values obtained in measurement model 1. In addition, the total reliability improved from 0.877 to 0.889. Thus, both of the improvements are indicative of an optimisation of the measurement model.

	Items	Corrected item-total correlation	Cronbach's Alpha if item deleted	Cronbach Alpha of constructs	Cronbach Alpha
SI	SI1	0.502	0.754	0.864	0.889
	SI2	0.633	0.623		
	SI3	0.585	0.714		
	SI5	0.510	0.780		
	SI7	0.517	0.747		
	SI8	0.605	0.639		
	SI9	0.599	0.685		
	SI11	0.603	0.674		
	SI12	0.610	0.671		
	SI13	0.614	0.671		
CI	CI1	0.512	0.788	0.855	
	CI2	0.541	0.780		
	CI4	0.613	0.755		
	CI5	0.625	0.711		
	CI6	0.516	0.784		
	CI7	0.584	0.741		
	CI8	0.526	0.785		
	CI9	0.581	0.732		
	CI10	0.567	0.718		
II	II1	0.565	0.868	0.920	
	II2	0.583	0.861		
	II3	0.441	0.905		
	II4	0.503	0.899		
	II5	0.624	0.841		
	II7	0.667	0.857		
	II8	0.615	0.861		
OP	OP1	0.533	0.813	0.852	
	OP2	0.573	0.805		
	OP3	0.565	0.811		
	OP4	0.644	0.807		
	OP5	0.645	0.805		
DU	DU1	0.548	0.775	0.779	
	DU2	0.609	0.763		
	DU3	0.586	0.768		
	DU4	0.661	0.755		

Table 12 Measurement Model 2

Exploratory Factor Analysis

The EFA in this study aimed to determine which group of distinct items is a measure for a specific construct. In other words, scale items which are significantly correlated with each other but are distinct from one another should be grouped into a construct. This step is to avoid the effect of collinearity (Cudeck, 2000). Its goal is to find out how items can be grouped and whether the grouped items differ in their positions in theoretical measurement model 1.

Based on measurement model 2 with 35 items, the discriminant validity test starts with the Kaiser-Meyer-Olkin (KMO) (Dziuban and Shirkey, 1974) measure and Bartlett's test of sphericity which test the null hypothesis to determine that the correlation matrix is not an identity matrix. The EFA test reported a KMO measure at sampling adequacy of 0.891. There exists strong evidence to reject the null hypothesis and, therefore, prefer the alternative hypothesis with chi-square (df = 560) = 4489.25, $P<0.001$. These results suggest that measurement model 2 is suitable for factor analysis.

A principle component analysis (PCA) with varimax rotation was carried out on the 35 items. Jolliffe (2002) indicated that varimax rotation maximised the total variance explained by scale items. Item loadings above 0.5 under corresponding constructs and below 0.5 under un-corresponding constructs are considered to have reliability (Brown, 2015). In addition, constructs are only extracted with eigenvalues exceeding 1. Table 11 reports the varimax rotation of item loadings based on the benchmark value of the 0.5 requirement; items SI1, SI5, CI1, CI6 and II3 were removed from the measurement model 2 due to the insignificant loadings (<0.5) of their own constructs. In addition, no item loads significantly to un-corresponding constructs. Thus, the remaining 30 items form measurement model 3. The PCA successfully extracted five constructs based on measurement model 3 (Table 12). The five extracted constructs cumulatively explained 70.61% variance. According to Jolliffe (2002), a total explained variance greater than 60% with item loadings greater than 0.6 jointly indicate adequate reliability. The rotated constructs matrix under this study illustrates a five-factor solution which could best explain the theoretical framework under investigation.

Item loadings	SI	CI	II	OP	DU
SI1	**->0.45<-**	0.09	0.28	0.11	0.18
SI2	**0.80**	0.19	-0.06	0.16	0.09
SI3	**0.63**	0.25	0.30	0.16	0.00
SI5	**->0.48<-**	0.19	0.12	0.10	0.02
SI7	**0.59**	0.11	0.06	0.07	0.40
SI8	**0.78**	0.37	0.01	0.16	-0.09
SI9	**0.81**	0.36	0.23	0.16	0.02
SI11	**0.68**	0.22	0.16	0.15	0.06
SI12	**0.72**	0.15	0.10	0.22	0.01
SI13	**0.75**	0.28	0.23	0.14	-0.06
CI1	0.20	**->0.41<-**	0.01	0.02	0.04
CI2	0.16	**0.70**	0.20	0.04	0.26
CI4	0.22	**0.72**	0.33	0.29	0.08
CI5	0.10	**0.77**	0.38	0.13	0.14
CI6	0.42	**->0.44<-**	0.01	-0.06	0.18
CI7	0.22	**0.72**	0.24	0.18	-0.06
CI8	0.12	**0.65**	0.32	0.18	0.04
CI9	0.07	**0.75**	0.05	0.39	-0.02
CI10	0.10	**0.75**	0.12	0.38	0.30
II1	0.16	0.03	**0.67**	0.10	0.26
II2	0.37	0.09	**0.71**	0.06	-0.06
II3	0.06	0.10	**->0.44<-**	0.19	0.07
II4	0.31	0.21	**0.65**	0.40	0.36
II5	0.22	0.06	**0.83**	0.11	-0.14
II7	0.01	0.35	**0.84**	0.18	0.36
II8	0.38	0.15	**0.80**	-0.09	0.15
OP1	0.25	0.01	0.12	**0.74**	0.38
OP2	0.36	0.34	0.17	**0.79**	0.11
OP3	0.27	0.22	0.34	**0.79**	0.07
OP4	0.13	0.26	0.35	**0.81**	0.39
OP5	0.18	0.13	0.10	**0.81**	-0.01
DU1	0.17	0.19	0.24	0.09	**0.74**
DU2	0.10	-0.01	0.04	0.07	**0.77**
DU3	0.10	0.23	0.28	0.17	**0.74**
DU4	0.35	0.22	0.06	0.22	**0.84**

Table 13 Rotated Item Matrix

Total Variance Explained			
Construct	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	34.133	47.339	47.339
2	6.488	8.710	56.049
3	5.196	7.318	63.367
4	3.331	4.445	67.812
5	1.660	2.799	70.611
6	0.719	1.002	71.613
7	0.555	0.080	71.693
8	0.500	0.033	71.726

Table 14 Total Variance Explained (PCA with Varimax Rotation)

Confirmatory Factor Analysis

The constructs' validity of measurement model 3 was assessed by CFA. Measurement model 3 provided an acceptable goodness-of-fit level to the data as shown in Table 13. First, the estimated coefficients of chi-square/degree of freedom range from 0.182 to 1.301, which were less than the literature-agreed maximum level of 2 (Prajogo et al., 2015, Cao et al., 2015, Ebrahimi, 2015, Zhao et al., 2015). Second, the indicator of adjusted goodness-of-fit (AGFI) became popular in recent years since it adjusts the goodness-of-fit (GFI) based upon degrees of freedom. Values of the AGFI range between 0 to 1, and generally accepted values are 0.90 or above, indicate a well-fitting model (Ivanov et al., 2014). The measurement model presented that all values of AGFI were close to 1. Third, another frequently used indicator, comparative fit index (CFI), assumes that all constructs are uncorrelated (null model). It compares the difference of covariance matrixes between the null and measurement model. A cut-off criterion of CFI greater than 0.90 is initially advanced (Zhao et al., 2013). Estimated values of CFI were very close and even partially equal to one in this study. The last exhibiting indicator is the root mean square error of approximation (RMSEA), which tells how well the model would fit the sample covariance matrix with unknown but optimally chosen parameter estimates (Brown, 2015). Recommendations for the RMSEA cut-off point is below 0.08 to show a good fit (Sousa et al., 2012). Accordingly, the estimated values of RMSEA ranged from 0.012 to 0.065. Further discussion on the desirable cut-off points can be found in (Brown, 2015, Doll et al., 1994, Schreiber et al., 2006).

Construct	Items	χ2	*df*	χ2/*df*	AGFI	CFI	RMSEA
SI	8	18.040	20	0.902	0.977	0.999	0.046
CI	7	18.214	14	1.301	0.966	0.998	0.065
II	6	4.671	9	0.519	0.990	1.000	0.021
OP	5	2.340	5	0.468	0.988	1.000	0.018
DU	4	0.363	2	0.182	0.998	1.000	0.012

Table 15 Construct validity.

As illustrated in Table 14, the estimated average variance extracted (AVE) should be greater than 0.5, indicating convergent validity. The lowest estimated AVE is 0.604, indicating that each construct explains more than half of its variance. Furthermore the model reliability, besides the Cronbach's alphas which have been tested previously, the composite reliability (CR) measures the overall reliability of heterogeneous items (Brown, 2015), indicated that each construct was above the required 0.7. In this way, the convergent validity is confirmed.

Construct	CR	AVE
SI	0.883	71.2%
CI	0.916	69.8%
II	0.870	75.8%
OP	0.851	63.4%
DU	0.814	60.4%

Table 16 Construct correlation matrix.

4.3.3 Sampling and Data Collection

The final step collects data in an extended scale of OEMs via spreading the survey questionnaire designed based on measurement model 3. This study uses a random sampling method as suggested by McIntyre (1952) and Csikszentmihalyi and Larson (2014) to select target OEMs in the OEM pool. As a result, 65 OEMs were selected, and follow-up contact was made via phone calls to their R&D directors initially. A profile of the selected 65 OEMs is presented in Table 15. These OEMs were more or less normally distributed according to the statistics of their employees' scale and annual income level.

Number of Employees	Count	Percent	Annual Income (billion Yuan)	Count	Percent
<200	9	14.3	10-20	15	23.1
200 – 500	15	23.6	20-40	12	18.8
500 - 1000	16	24.6	40-60	9	13.8
1000 – 2000	14	21.7	60-100	13	20.0
>2000	11	15.8	>100	16	24.3
Total	65	100.0		65	100.0

Table 17 Profile of sample companies.

A new 'network approach' was attempted in order to improve the questionnaire response rate. Firstly, the questionnaire with a cover letter highlighting the study's objectives and practical implications was made into a web version (activated by an email sent to the respondents) which can be easily accessed and filled in by using either a computer or a mobile phone at any time. Second, after all of the questionnaires were completed and approved by the relevant directors or CEOs of each of the 65 sample companies, several chat groups were set up involving all respondents via the Wechat (most widely used communication application in China) mobile application. The chat groups were aimed to gather further opinions regarding our questionnaire, but also significantly increased their response rate.

A total of 700 questionnaires were sent with 477 returned, achieving a return rate of 68.1%. Out of the 477 returned questionnaires, 92 were invalid because of missing values, yielding a total of 385 valid responses, which represented a valid response rate of 55%. The nonresponse bias was evaluated by comparing the data between the pre-test (45) (data sample 1) and the early response (first returned 193 questionnaires) (data sample 2), and between the early response and the late responses (the remaining 192 of returned 385 questionnaires) (data sample 3) using a one-way ANOVA test (Gimenez et al., 2012, Sousa et al., 2012). Appendix A shows a description of all items' mean value and standard deviation on each data sample; Appendix B shows the ANOVA test on all items in cases of between samples, within samples and total. The null hypothesis of the ANOVA test is that there is no difference between samples, thus a significant p-value (<0.1) rejects the null hypothesis. For this reason, the alternative hypothesis is preferred, which suggests that there is significant difference between data samples. In the case of Appendix B, we observed one significant p-value (0.072) which existed with item OP4, suggesting a significant difference existed between data samples. Given that such tests have been applied with three data samples, in order to know such difference existed between which two data samples, post hoc tests (Brown, 2005) were used for further exploration. As shown in Appendix C, the found difference exists between data samples 1 and 2, in which data samples 2 and 3 still maintain consistency. Such difference might be generated by the effect of common method bias during the trial run, however, we still have strong evidence to confirm the validity requirement of data collected in the final run. The later-collected 385 valid survey questionnaires have been put together to form the **final data sample**. A profile of the respondents is shown in Table 16. More than half of the respondents have been in their position for more than three years, which is a positive attribute to the credibility of the responses.

Position	% of respondents	Years in current position	% of respondents
Chief officer	10.9	Over 12 years	9.3
Director	22.9	7-12 years	14.1
Senior manager	36.4	3-7 years	36.3
Junior manager	29.8	1-3 years	40.3

Table 18 Respondent features.

4.3.4 Final Data Sample: Reliability and Validity

This section follows the reliability and validity testing steps presented in the last section. As shown in Table 17, the Cronbach's alpha measure has been re-performed on the final data sample to test whether there is significant difference of reliability between the trial data sample and the final data sample. The estimated Cronbach's alphas of constructs are 0.857 for SI, 0.841 for CI, 0.904 for II, 0.843 for OP and 0.799 for DU, respectively, and the Cronbach's alpha for all constructs is 0.861, indicating that all constructs met the internal consistency requirement.

To perform EFA, the KMO measure ranged from 0.771 to 0.882, and the null hypotheses of identity matrix has also been rejected with Chi-square (df = 464) = 399.044 ($p<0.001$), which satisfied the requirement of suitability of data for factor analysis.

	Items	Factor Loading	Corrected Item-Total Correlation	Cronbach's Alpha if Item deleted	Cronbach's Alpha of constructs	Cronbach's Alpha	KMO
SI	SI2	0.76	0.610	0.613	0.857	0.861	0.804
	SI3	0.68	0.593	0.724			
	SI7	0.57	0.522	0.778			
	SI8	0.81	0.611	0.663			
	SI9	0.83	0.627	0.699			
	SI11	0.63	0.633	0.683			
	SI12	0.70	0.635	0.661			
	SI13	0.83	0.636	0.632			
CI	CI2	0.77	0.539	0.799	0.841		0.771
	CI4	0.61	0.622	0.741			
	CI5	0.83	0.636	0.696			
	CI7	0.75	0.599	0.733			
	CI8	0.66	0.510	0.791			
	CI9	0.77	0.576	0.733			
	CI10	0.79	0.559	0.726			
II	II1	0.64	0.544	0.878	0.904		0.882
	II2	0.75	0.583	0.866			
	II4	0.69	0.499	0.900			
	II5	0.80	0.667	0.875			
	II7	0.87	0.615	0.842			
	II8	0.71	0.630	0.834			
OP	OP1	0.76	0.511	0.823	0.843		0.819
	OP2	0.79	0.582	0.808			
	OP3	0.74	0.555	0.816			
	OP4	0.84	0.631	0.798			
	OP5	0.87	0.644	0.793			
DU	DU1	0.74	0.584	0.766	0.799		0.801
	DU2	0.78	0.623	0.741			
	DU3	0.77	0.599	0.739			
	DU4	0.88	0.674	0.728			

Table 19 Reliability and validity tests on the measurement model 3 with final data sample.

By carrying out the PCA on 30 items, which extracted five constructs, 69.33% of the total variance was jointly explained. As shown in Table 18, there exist five constructs with an eigenvalue greater than 1.

Total Variance Explained			
Construct	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	32.559	44.961	44.961%
2	7.452	9.822	54.783%
3	4.997	7.118	61.901%
4	3.408	4.281	66.182%
5	1.496	3.155	69.337%
6	0.883	0.984	70.321%
7	0.431	0.094	70.415%

Table 20 Total Variance Explained (PCA with Varimax Rotation) performed on the final data sample

The rotated construct matrix (Table 19) also clearly indicates a five-construct solution, since items are significantly related to their own constructs and insignificantly related to other constructs.

Item loadings	SI	CI	II	OP	DU
SI2	**0.86**	0.15	-0.14	0.16	0.07
SI3	**0.64**	0.24	0.32	0.17	0.01
SI7	**0.61**	0.18	0.07	0.11	0.36
SI8	**0.77**	0.33	0.04	0.17	-0.15
SI9	**0.84**	0.35	0.23	0.17	0.05
SI11	**0.69**	0.24	0.17	0.19	0.07
SI12	**0.73**	0.18	0.10	0.33	0.03
SI13	**0.77**	0.21	0.24	0.15	-0.09
CI2	0.14	**0.74**	0.24	0.08	0.24
CI4	0.20	**0.71**	0.32	0.25	0.16
CI5	0.11	**0.75**	0.34	0.15	0.15
CI7	0.27	**0.75**	0.26	0.17	-0.08
CI8	0.15	**0.66**	0.30	0.17	0.05
CI9	0.13	**0.75**	0.11	0.35	-0.04
CI10	0.18	**0.78**	0.18	0.35	0.36
II1	0.15	0.09	**070**	0.18	0.26
II2	0.30	0.13	**0.73**	0.16	-0.09
II4	0.38	0.23	**0.62**	0.32	0.35
II5	0.18	0.09	**0.84**	0.18	-0.18
II7	0.05	0.32	**0.81**	0.19	0.28
II8	0.33	0.19	**0.80**	-0.16	0.19
OP1	0.24	0.08	0.17	**0.69**	0.33
OP2	0.29	0.34	0.20	**0.76**	0.22
OP3	0.28	0.17	0.34	**0.75**	0.14
OP4	0.16	0.22	0.36	**0.80**	0.25
OP5	0.19	0.16	0.18	**0.83**	-0.21
DU1	0.19	0.14	0.29	0.14	**0.78**
DU2	0.14	-0.07	0.15	0.05	**0.73**
DU3	0.15	0.26	0.32	0.19	**0.78**
DU4	0.30	0.28	0.12	0.28	**0.81**

Table 21 Rotated item matrix on final data sample.

CFA was employed to access the constructs' validity. A set of indices measuring the overall fit of the model are reported in Table 20. Assessing fit using the Chi-square method has raised criticism in relation to the sensitivity of such test to a large sample size (Brown, 2015). To overcome this issue, in addition to using other indices as suggested (Brown, 2015, Doll et al., 1994), scholars appear to have accepted a valid level of less than one hundredth of the sample size (Pagell, 2004, Sila, 2007). Following this acceptance, one hundredth of the final data sample is estimated as 3.85. All estimated values of Chi-square/df are lower than 3.85. In terms of the alternative indices, estimated values of AGFI and CFI are all above the benchmark value of 0.9, and RMSRA values are all below the cut-off point of 0.08. Thus, all constructs have discriminant validity.

Construct	Items	$\chi 2$	*df*	$\chi 2/df$	AGFI	CFI	RMSEA
SI	8	43.266	20	2.163	0.954	0.988	0.056
CI	7	38.214	14	2.729	0.931	0.974	0.067
II	6	18.563	9	2.062	0.956	0.977	0.043
OP	5	11.211	5	2.242	0.982	0.991	0.032
DU	4	5.884	2	2.942	0.976	0.989	0.022

Table 22 Construct validity.

In testing for convergent validity, the lowest AVE reported in Table 21 is 0.616, which is greater than its benchmark value of 0.5. Finally, the composite reliabilities of all constructs are also achieved with all CR greater than 0.7.

Construct	CR	AVE
SI	0.822	73.3%
CI	0.883	71.2%
II	0.855	73.8%
OP	0.840	62.1%
DU	0.789	61.6%

Table 23 Convergent validity

4.3.5 Common Method Bias

The common method bias (CMB) includes *"a potential problem in behavioural research if the same person is providing data on both the predictor and criterion variables in the same measurement context, [which] can have a serious effect on empirical results"* (Podsakoff and Organ, 1986). A three-step process was established in this study to avoid CMB. First, the potential respondents' positions in their company and their length of time working in the position were prequalified to ensure they have the relevant knowledge background (see Table 16) (Huang et al., 2014). Second, all potential respondents received a consent form in advance which informed them that their responses would be kept anonymous (Zacharia et al., 2011). Third, to further mitigate the CMB in the data sample, this study applied CFA (Huo, 2012, Gimenez et al., 2012) with the null model being that all measurement items were assigned to a single construct in order to check the CMB. The result comes to: χ^2 = 3997.532, df = 405, χ^2/df = 9.87, GFI = 0.652, AGFI = 0.48, CFI = 0.4 and RMSEA = 0.37, showing that the null model does not fit to the data at all. Thus, CMB is not an issue for the final data sample.

4.3.6 Dimension Reduction

A two-step approach (first dimension reduction and then regression analysis) suggested by Yusuf et al. (2004) was applied to analyse the final data sample. CFA is used to reduce the 30 measurement items to 5 constructs: operational performance (OP), supplier integration (SI), customer integration (CI), internal integration (II) and demand uncertainty (DU). The CFA provided a standardised *factor score* for each construct. The factor scores are used to determine a factor's relative standing on its corresponding construct (Brown, 2015, Yusuf et al., 2004). This study used the obtained factor scores (see Table 22) for all the observed factors to generate the data columns of the five constructs (Flynn et al., 2010, Won Lee et al., 2007, Sezen, 2008), on which all the remaining analysis will be based.

	Item	Factor loading	Factor score
SI	SI2	0.86	0.192
	SI3	0.64	0.133
	SI7	0.61	0.138
	SI8	0.77	0.145
	SI9	0.84	0.177
	SI11	0.69	0.162
	SI12	0.73	0.166
	SI13	0.77	0.168
CI	CI2	0.74	0.188
	CI4	0.71	0.185
	CI5	0.75	0.187
	CI7	0.75	0.187
	CI8	0.66	0.166
	CI9	0.75	0.194
	CI10	0.78	0.199
II	II1	070	0.197
	II2	0.73	0.205
	II4	0.62	0.188
	II5	0.84	0.266
	II7	0.81	0.226
	II8	0.80	0.223
OP	OP1	0.69	0.259
	OP2	0.76	0.257
	OP3	0.75	0.245
	OP4	0.80	0.251
	OP5	0.83	0.243
DU	DU1	0.78	0.350
	DU2	0.73	0.307
	DU3	0.78	0.309
	DU4	0.81	0.319

Table 24 Factor descriptive statistics.

As shown in Figure 15-17, the independent variable SI, CI and II were scatter-plotted against the dependent variable OP respectively, revealing little visual linear correlation but a heteroscedastic form of the data especially for SI and CI. However, the visual relationship becomes relatively clearer when the exogenous variable DU is shown on the third axis, which indicates statistically that DU has a certain explanatory ability on the relationship between OP and SI and between OP and CI.

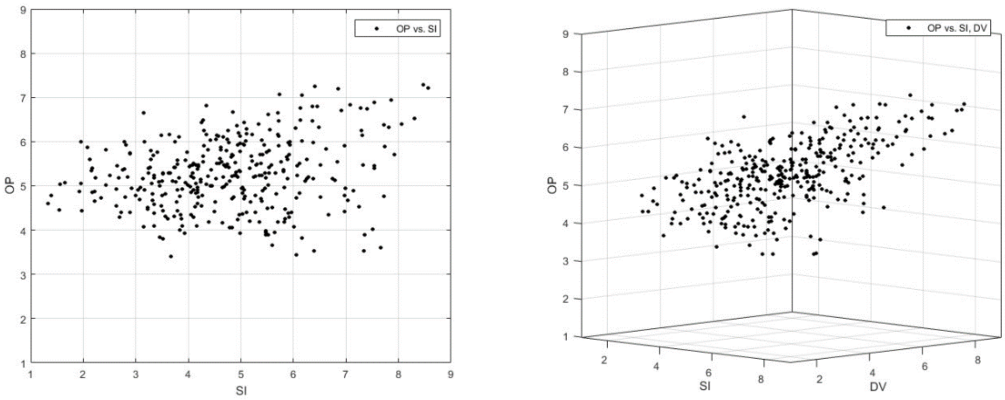

Figure 14 Scatter plot of OP against SI, with DU

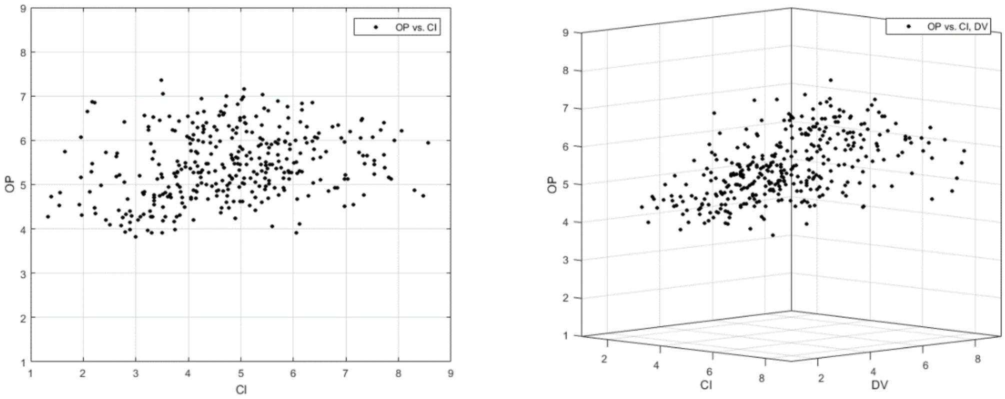

Figure 15 Scatter plot of OP against CI, with DU

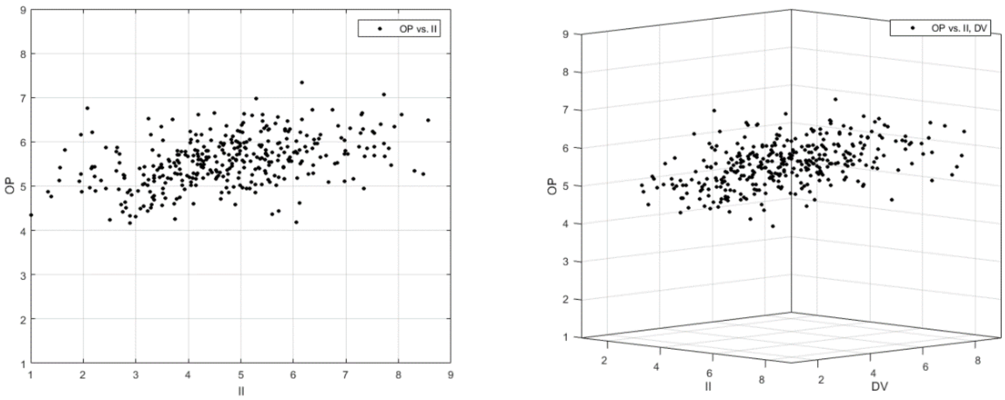

Figure 16 Scatter plot of OP against II, with DU

4.4 Analyzing Method

The proposed six research hypotheses can be divided into two groups. The first group includes the hypotheses 1 to 3, which generally hypothesised positive correlations between all SCI dimensions and OP. To test the first group of hypotheses, dimensions of SCI were examined to determine whether they directly and positively contribute to OP. On the other hand, the existence of moderating effects usually forms non-linear relationships, as suggested by the literature. For this reason, tests on the rest of the hypotheses, 3 to 6, which hypothesised that there may exist moderating effects from DU to the SCI-OP relationships, aimed to investigate whether non-linear SCI-OP relationships can be found under the effect of DU.

For reaching the differentiated hypothesis-testing objectives, linear and non-linear analysis methods were used in this study.

4.4.1 Linear Analyzing Method

By reviewing literature which concluded linear relationships between SCI and OP, the analysing methods of SEM and regression analysis exist as the mainstream method choices. Both of the path analyses from SEM and regression analysis have features to allow researchers to concisely evaluate the relationships between theoretical constructs (Klem, 2000). Besides SEM, hierarchical regression analysis (HRA) is a branch of regression analysis, and it is a wide-spread branch in management research (Rutter and Gatsonis, 2001). In addition to estimating direct and indirect correlations, HRA can also identify the most suitable model by comparing the null and alternative models. By doing so, the HRA is then fitted by the ordinary least square (OLS) algorithm, and all hypothesised relationships are fitted in as alternatives and estimated one by one. The statistical significance is tested through the t-test method with a p-value of the test below 0.1 specifying a significant relationship coefficient. The goodness of fit and explanation capability of HRA is revealed by adjusted R square which shows to what extend the estimated model can explain the data sample. The most suitable model is then identified as the one with significant coefficients and the highest adjusted R square. This study used HRA to test the first group of hypotheses.

Hypotheses 1 to 3 proposed that II, SI, CI and their interactions positively correlate to OP. The hypotheses were tested using HRA, and the fit model is specified as:

$$\boldsymbol{OP_i = \beta_0 + \beta_1 II_i + \beta_2 SI_i + \beta_3 CI_i + e_i} \qquad \textbf{Equation 1}$$

Where β_0 is intercept; β_1, β_2 and β_3 are regression coefficients of the regressors II_i, SI_i and CI_i respectively. Hierarchical regression is a stepwise model, the OEM's internal construct, II's linear effect is introduced first, and external constructs in terms of SI's and CI's effects are then introduced in the next step if II's relationship to OP is significant. Since hypotheses 1 to 3 are all hypothesised to be positive correlations, a statistically significant and positive coefficient would support an according hypothesis.

4.4.2 Non-linear Analyzing Method

On investigating the possibly non-linear OP-SCI relationship under the moderating effect of DU, literature provides examples and references for proper selection of the analysing method. In particular, the three studies conducted which have inverse U-shaped relationships have the highest value of the reference (see Table 23). Although

HRA has been applied in all of these three studies, the way in which they use HR to obtain the inverse U-shaped relationship differs from one another. Das et al. (2006) reported a mathematically inverse U-shaped relationship by analysing their original data sample and sub-samples and obtained different regression coefficients for the two samples. The sub-sample was created by moving the top 10% and bottom 10% performing firms. Likewise, for the purpose of examining the moderating effect of environmental uncertainty on SCI-OP relationship, Wong et al. (2011a) divided their data sample into high and low uncertainty groups based on the median of the uncertainty value. The authors subsequently discussed the difference of regression coefficients from SCI to OP between those two sample groups and concluded an inverse U-shaped relationship. Thus, it can be summarised that the comparison analysis across samples is the precondition of obtaining a non-linear research finding. Unexpectedly, without following the same path, Terjesen et al. (2012) directly hypothesised an inverse U-shaped relationship, and tested their hypothesis by applying a polynomial HRA method. However, one of the obvious weaknesses of their analysing methods is that they were highly subjective in nature. Neither the sample division nor the inverse U-shaped relationship hypothesis has rigorous theoretical support. Thus, to avoid the subjectivity in this study, this study attempted a *threshold regression method* instead (Hansen, 1999).

Reference	Research finding on SCI-OP relationship	Primary method
Das et al. (2006)	Inverse U-shaped	Hierarchical regression
Wong et al. (2011a)	Inverse U-shaped	Hierarchical regression
Terjesen et al. (2012)	Inverse U-shaped	Hierarchical regression

Table 25 List of inverse U-shaped relationship studies.

4.4.3 Threshold Regression Analysis (TRA)

The choice of threshold regression method is based on the fact that threshold regression is capable of identifying the underlying thresholds that partition the data into groups and to achieve their corresponding relationships through regressions. According to Hansen (1999), threshold analysis can avoid unpredictable errors caused by subjective division, and it can endogenously divide intervals based on the data characteristics, then estimate the relationships within each interval and eventually form the distinct shape of a relationship.

First, a model with a single threshold value was utilised before assuming a multi-threshold model. The observed data are from a balanced sample $[y_i, x_i, q_i: 1 \leq i \leq n]$. A balanced sample is defined as having an equal number of observations for all possible combinations of factor levels (Wansbeek and Kapteyn, 1983), however, it is unknown if the results extend to an unbalanced sample (Hansen, 1999). The subscript *i* index the individual. The dependent variable y_i is scalar, the threshold variable q_i is scalar and the regressor x_i is a k vector. The single threshold model is

$$\mathbf{y}_{\boldsymbol{i}} = \boldsymbol{\mu}_{\boldsymbol{i}} + \boldsymbol{\beta}_{\mathbf{1}} \boldsymbol{x}_{\boldsymbol{i}} \boldsymbol{I}(\boldsymbol{q}_{\boldsymbol{i}} \leq \boldsymbol{\gamma}) + \boldsymbol{\beta}_{\mathbf{2}} \boldsymbol{x}_{\boldsymbol{i}} \boldsymbol{I}(\boldsymbol{q}_{\boldsymbol{i}} > \boldsymbol{\gamma}) + \boldsymbol{e}_{\boldsymbol{i}} \qquad \textbf{Equation 2}$$

Where *I(*)* is the indicator function. And an alternative intuitive way of thinking (2) is:

$$y_i = \begin{cases} \mu_i + \beta_1 x_i + e_i, q_i \leq \gamma \\ \mu_i + \beta_2 x_i + e_i, q_i > \gamma \end{cases}$$

Another compact representation of (2) is to set

$$x_i(\gamma) = \begin{pmatrix} x_i I(q_i \leq \gamma) \\ x_i I(q_i > \gamma) \end{pmatrix}$$

And$\beta = (\beta_1, \beta_2)$, so that equation (2) equals to

$$\boldsymbol{y_i = \mu_i + \beta x_i(\gamma) + e_i} \quad \textbf{Equation 3}$$

The observations are divided into 'regimes' depending on whether the threshold variable q_i is smaller or larger than the threshold γ. The regimes are distinguished by differing regression slopes β_1 and β_2. The essential condition of identifying different regression slopes is that the elements of regressor x_i and threshold variable q_i are not time invariant. Given that the data sample used in this study is in cross-sectional format rather than a panel format (Wooldridge, 2010), which does not include time series, the time invariant therefore is not an issue. The residual term e_i is assumed to be independent and identically distributed (*iid*) with mean zero and finite variance σ^2. It is still unclear how to expand the current model to allow for heteroskedastic errors. This model is analysed asymptotically as *n* approaches infinity.

Estimation

In order to avoid individual effect μ_i, one traditional method is to remove individual-specific means (Hansen, 2000b). Note that taking averages of equation (3) produces

$$\boldsymbol{\bar{y}_i = \mu_i + \beta' \bar{x}_i(\gamma) + \bar{e}_i} \quad \textbf{Equation 4}$$

Where

$$\bar{y}_i = \frac{1}{N}\sum_{n=1}^{N} y_i$$

$$\bar{x}_i(\gamma) = \frac{1}{N}\sum_{n=1}^{N} x_i(\gamma) = \begin{cases} \frac{1}{N}\sum_{n=1}^{N} x_i I(q_i \leq \gamma) \\ \frac{1}{N}\sum_{n=1}^{N} x_i I(q_i > \gamma) \end{cases}$$

And

$$\overline{e_i} = \frac{1}{N}\sum_{n=1}^{N} e_i$$

Taking the difference between (3) and (4) yields

$$\mathbf{y}_{\boldsymbol{i}}{}^{*} = \boldsymbol{\beta}'\boldsymbol{x}_{\boldsymbol{i}}{}^{*}(\boldsymbol{\gamma}) + \boldsymbol{e}_{\boldsymbol{i}}{}^{*} \quad \textbf{Equation 5}$$

Where

$$\mathrm{y}_i{}^{*} = \mathrm{y}_i - \overline{\mathrm{y}_i}$$

$$x_i{}^{*}(\gamma) = x_i(\gamma) - \overline{x_i}(\gamma)$$

$$e_i{}^{*} = e_i - \overline{e_i}$$

Therefore

$$\mathrm{y}_i{}^{*} = \mathrm{y}_i - \frac{1}{N}\sum_{n=1}^{N} \mathrm{y}_i$$

The model after transformation is,

$$\mathbf{Y}^{*} = \widehat{\boldsymbol{\beta}}\boldsymbol{X}^{*}(\boldsymbol{\gamma}) + \boldsymbol{e}^{*} \quad \textbf{Equation 6}$$

For a given threshold value γ**,** the estimated value of β can be obtained by applying Ordinary Least Squares on equation (6),

$$\widehat{\boldsymbol{\beta}}(\boldsymbol{\gamma}) = (\boldsymbol{X}^*(\boldsymbol{\gamma})'\boldsymbol{X}^*(\boldsymbol{\gamma}))^{-1}\boldsymbol{X}^*(\boldsymbol{\gamma})'\boldsymbol{Y}^* \qquad \textbf{Equation 7}$$

The residual sum of square is,

$$\mathbf{S_1}(\boldsymbol{\gamma}) = \begin{cases} \hat{\boldsymbol{e}}^*(\boldsymbol{\gamma})'\hat{\boldsymbol{e}}^*(\boldsymbol{\gamma}) \\ \boldsymbol{Y}^{*\prime}(\boldsymbol{I} - \boldsymbol{X}^*(\boldsymbol{\gamma})'(\boldsymbol{X}^*(\boldsymbol{\gamma})'\boldsymbol{X}^*(\boldsymbol{\gamma}))^{-1}\boldsymbol{X}^*(\boldsymbol{\gamma})')\boldsymbol{Y}^* \end{cases} \quad \textbf{Equation 8}$$

Where $\hat{e}^*(\gamma)$is residual vector, as

$$\hat{\boldsymbol{e}}^*(\boldsymbol{\gamma}) = \boldsymbol{Y}^* - \boldsymbol{X}^*(\boldsymbol{\gamma})\widehat{\boldsymbol{\beta}}(\boldsymbol{\gamma}) \qquad \textbf{Equation 9}$$

Chan (1993) and Hansen (2000a) suggested to estimate γ by least squares. Perhaps this is the easiest way to achieve by minimisation of the concentrated residual sum of square (8), hence, by minimising $\mathrm{S}_1(\gamma)$ corresponding to (9), the estimated value of γ can be obtained,

$$\boldsymbol{\gamma}(\hat{\boldsymbol{\gamma}}) = \mathbf{arg}_{\boldsymbol{\gamma}}\boldsymbol{minS_1}(\boldsymbol{\gamma}) \qquad \textbf{Equation 10}$$

A situation of threshold $\hat{\gamma}$ is selected when it sorts too few observations into one regime, and this is absolutely undesirable. This potential can be excluded by restricting the search in (10) to values of γ such that a minimal percentage of the observations (1% or 5% for example) is collected in each regime. Once $\hat{\gamma}$ is obtained, the slope coefficient $\hat{\beta} = \hat{\beta}(\hat{\gamma})$ is obtained, as well as residual vector $\hat{e}^* = \hat{e}^*(\hat{\gamma})$ and residual variance $\widehat{\sigma}^2 = \frac{1}{n}\hat{e}^{*\prime}\hat{e}^* = \frac{1}{n}S_1(\hat{\gamma})$.

Estimation Issues

There is an un-ignored minimisation problem of the equation (10), which is involved in the estimation of the least squares of the threshold γ, because the residual sum of square function (8) depends on γ merely via the indicator function $I(q_i \leq \gamma)$. In addition, the residual sum of square function is a step function, in which steps exist at distinct values of the threshold variable q_i. Then, the minimisation problem of the equation (10) becomes the observation of values of γ equaling the distinct values of q_i.

The minimisation problem can be solved by taking the following procedures. Firstly, sort the distinct values of q_i, and reject the values of two tails of q_i distribution at 95% confidence interval. The remaining values of q_i constitute the database for searching $\hat{\gamma}$. Equation (7) is estimated to obtain the residual sum of square (8), thus $\hat{\gamma}$ is obtained by estimating equation (10).

Inference

Two individual tests must be taken after obtaining estimated values of parameters: first, determine whether the threshold effect is statistically significant; second, determine whether the estimated value of threshold equals its true value.

Testing for a Threshold

The null hypothesis and alternative hypothesis of the first test of no threshold against one threshold is

$$\mathbf{H_0}: \boldsymbol{\beta_1} = \boldsymbol{\beta_2}$$

$$\mathbf{H_1}: \boldsymbol{\beta_1} \neq \boldsymbol{\beta_2}$$

Under $\mathbf{H_0}$ the threshold γ is not identified, therefore classical tests cannot achieve normal distributions. This is named the 'Davies' problem' (Davies, 2002) and has been studied by (Donald and Ploberger, 1994) and (Hansen, 2000a). Hansen (2000a) suggests a bootstrap to simulate the asymptotic distribution of the likelihood ratio test.

Under the null hypothesis of no threshold, the model is

$$\mathbf{y}_i = \boldsymbol{\mu}_i + \boldsymbol{\beta} \boldsymbol{x}_i + \boldsymbol{e}_i \quad \textbf{Equation 11}$$

After transformation of (11), we have

$$\mathbf{y}_i^* = \boldsymbol{\beta}' \boldsymbol{x}_i^* + \boldsymbol{e}_i^* \quad \textbf{Equation 12}$$

The regression parameter β is estimated by OLS, which yields $\tilde{\beta}$, residual $\tilde{e}_i^*$ and residual sum of square $S_0 = \tilde{e}_i^{*\prime} \tilde{e}_i^*$. The likelihood ratio test of $\mathbf{H_0}$ is obtained via

$$\mathbf{F_1} = \frac{S_0 - S_1(\gamma)}{\hat{\sigma}^2} \qquad \textbf{Equation 13}$$

The distribution of F_1 is non-normal because the distribution depends generally upon cross sections of the data sample and therefore the P-value of F_1 cannot be obtained. Hansen (2000a) indicated that a bootstrap measurement can achieve the first-order asymptotic distribution, thus P-values can be constructed from the bootstrap and are asymptotically valid. Considering the cross-sectional nature of the data, the following procedure of bootstrap was implemented. Given the regressor x_i and threshold variable q_i, their values were fixed in multi-bootstrap sampling. The regression residuals $\hat{e}_i^* = (\hat{e}_1^*, \hat{e}_2^*, \ldots, \hat{e}_n^*)$ were grouped as the sample of empirical distribution.

A bootstrap sample was established under the null hypothesis (12), and it was estimated the theoretical model under the null (12) and alternative (13) hypotheses to obtain the bootstrap value of the likelihood ratio F_1. This operation was repeated hundreds of times, which was suggested by scholar (Hansen, 1999), and statistic the percentage of results for when simulated bootstrap values are greater than the true values. The combination of the above procedures is the bootstrap estimation of the asymptotic p-value for F_1 under the null hypothesis, and the null hypothesis of no threshold effect is rejected when the expected critical value is greater than the p-value.

The asymptotic distribution of threshold

When a hypothesis of no threshold effect is rejected ($\boldsymbol{\beta_1} \neq \boldsymbol{\beta_2}$), Hansen (1999) indicates that the asymptotic distribution of $\hat{\gamma}$ is highly non-normal. This is because $\hat{\gamma}$ is consistent for its true value. It is better to establish a non-reject interval for γ by applying the likelihood ratio statistic for testing γ. Therefore, the null hypothesis of the second test is $H_0: \hat{\gamma} = \gamma_0$, and its corresponding likelihood test statistics is

$$\boldsymbol{LR_1(\gamma)} = \frac{S_1(\gamma) - S_1(\hat{\gamma})}{\hat{\sigma}^2} \qquad \textbf{Equation 14}$$

Since this statistic is also non-normal, the technical assumptions borrowed from the change point literature indicate a rather unusual condition that the difference in the slope coefficients between regimes becomes smaller when sample size rises. This condition can be simplified as $(\boldsymbol{\beta_2} - \boldsymbol{\beta_1}) \rightarrow \mathbf{0}$ as $n \rightarrow \infty$. Given that the asymptotic distribution has to be used to establish confidence intervals, Bai (1997) offers a simple equation to estimate its non-reject interval, as we cannot reject the null hypothesis when $LR_1(\gamma) \leq c(\alpha)$

$$\mathbf{c}(\boldsymbol{\alpha}) = -\mathbf{2ln}(\mathbf{1} - \sqrt{\mathbf{1} - \boldsymbol{\alpha}}) \qquad \textbf{Equation 15}$$

α is the significant level. The hypothesis test $H_0: \hat{\gamma} = \gamma_0$ rejects at the value α when $LR_1(\gamma_0)$ is greater than $c(\alpha)$.

The confidence interval of γ is established when $LR_1(\gamma) \leq c(\alpha)$, $LR_1(\gamma)$ is formed in equation (14) and $c(\alpha)$ is formed in equation (15). Then it is observable by plotting $LR_1(\gamma)$ regressed by γ and drawing a flat line at $c(\alpha)$. Please note that the statistic (14) is a different hypothesis test from the statistic (15). $LR_1(\gamma_0)$ is testing $H_0: \hat{\gamma} = \gamma_0$, and F_1 is testing $\mathbf{H_0}: \boldsymbol{\beta_1} = \boldsymbol{\beta_2}$.

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Multiple Thresholds Model

The above model only assumes there is either a unique threshold or no threshold. In the previous section, F_1 was introduced as a test of no threshold against one threshold and the bootstrap method to conduct the asymptotic p-value of F_1. When the null hypothesis has been rejected, then equation (2) confirms there is one threshold. However, from a statistical point of view, there may exist two or more thresholds. Therefore, I introduce a double-thresholds model, and a model for more than two thresholds can be achieved easily by expanding the double-thresholds model. The double thresholds model takes the form

$$\boldsymbol{y_i = \mu_i + \beta_1 x_i I(q_i \leq \gamma_1) + \beta_2 x_i I(\gamma_1 < q_i \leq \gamma_2) + \beta_3 x_i I(q_i > \gamma_2) + e_i}$$
Equation 16

Where the thresholds are assumed that $\gamma_1 < \gamma_2$. There are three relevant issues which are discussed in this section: estimating, determining number of thresholds and generating confidence intervals for threshold parameters.

Estimation

For the threshold parameters γ_1 and γ_2, equation (16) has linear slope coefficients of $\beta_1, \beta_2, \beta_3,$ therefore the OLS method can be applied to approximate p-values of the slopes. For each threshold, the residual sum of the square can be estimated directly. However, the joint significance of the two thresholds γ_1 and γ_2 means the residual sum of square of both thresholds $S(\gamma_1, \gamma_2)$ is required to be jointly minimised. A grid search of γ_1 and γ_2 requires mathematically n^2 times of regressions, which is considered to be a heavy load for either manual calculation or computation.

The antidote of removing this heavy load has been found in the change-point literature (Bai, 1997, Bai and Perron, 1998), which indicates that sequential estimation is consistent. This proposition applies to multi-threshold models as well. The theoretical significance of this proposition is that, once the number of threshold has been determined, the residual sum of the square of the second threshold γ_2 can be searched for based on the estimation result of the first threshold, as $\hat{\gamma}_1$ is consistent for either γ_1 or γ_2.

The γ_2 estimation method is based on the obtained γ_1 in the single-threshold model to search for γ_2. After fixing the first threshold γ_1,

$$\boldsymbol{S_2(\gamma_2) = \begin{cases} S(\hat{\gamma}_1, \gamma_2), if\ \hat{\gamma}_1 < \gamma_2 \\ S(\gamma_2, \hat{\gamma}_1). if \gamma_2 < \hat{\gamma}_1 \end{cases}} \qquad \textbf{Equation 17}$$

And the estimation of the second threshold is

$$\hat{\gamma}_2 = arg_{\gamma_2} min S_2(\gamma_2) \qquad \textbf{Equation 18}$$

The two thresholds γ_1 and γ_2 divide the sample into three regimes. Statistically, it is unreasonable to have too few observations in any one of these three regimes. Therefore, there is a necessity to set a condition of at least 10% of total observations being located in each of these three regimes in the searching procedure of equation (18).

Hansen (1999) indicated that because $\hat{\gamma}_1$ is estimated base on a sample of lagged data, $\hat{\gamma}_1$ is therefore not as asymptotically significant as $\hat{\gamma}_2$. Hansen further introduced a remedial measure that the significant $\hat{\gamma}_1$ can be obtained by fixing the second threshold as

$$S_1(\gamma_1) = \begin{cases} S(\gamma_1, \hat{\gamma}_2), if\ \gamma_1 < \hat{\gamma}_2 \\ S(\hat{\gamma}_2, \gamma_1), if\ \hat{\gamma}_2 < \gamma_1 \end{cases} \qquad \textbf{Equation 19}$$

And the estimation of $\hat{\gamma}_1$ is

$$\hat{\gamma}_1 = arg_{\gamma_1} min S_1(\gamma_1) \qquad \textbf{Equation 20}$$

Determining Number of Thresholds

In the context of equation (16), there may exist 0, 1 or 2 thresholds. The previous section brings F_1 of equation (13) in to test whether there either 0 or 1 threshold exists. A bootstrap procedure was introduced thereafter to generate asymptotic p-value for F_1. When the alternative hypothesis of $\mathbf{H_1}: \boldsymbol{\beta_1} \neq \boldsymbol{\beta_2}$ is accepted as the critical value of

F_1 , which is greater than its p-value, then further tests must be done for one threshold against two thresholds.

The residual sum of square estimation $S_2(\hat{\gamma}_2)$ of the second threshold has its variance $\hat{\sigma}^2 = S_2(\hat{\gamma}_2)/n$. The likelihood ratio test of null hypothesis: 'there is a unique threshold' is based on

$$\mathbf{F_2} = \frac{S_1(\hat{\gamma}_1) - S_2(\hat{\gamma}_2)}{\hat{\sigma}^2} \qquad \textbf{Equation 21}$$

The null hypothesis of one threshold is rejected when F_2 is large, therefore we have strong evidence to say there are two thresholds rather than one threshold.

The asymptotic distribution of the likelihood ratio test should be achieved by applying a bootstrap procedure to fit the distribution of data sample. In order to generate the bootstrap samples, the independent variable x_i and threshold variable q_i are fixed in randomly repeated bootstrap samples. The residuals of the bootstrap are collected from the least square estimation of equation (16) under the alternative hypothesis. The regression residuals $\hat{e_i}^* as\ (\hat{e_1}^*, \hat{e_2}^*, \ldots, \hat{e_n}^*)$ was matrixed, and the theoretical model (16) was estimated to obtain the bootstrap value of the likelihood ratio F_2 (21). This operation was repeated hundreds of times and statistic the percentage of results for when simulated bootstrap values are greater than the true values. Additionally, the null hypothesis of one threshold effect is rejected when the expected critical value is greater than the p-value.

Confidence Interval Construction

If the two thresholds hypothesis has been accepted, there is necessity to consider the construction of confidence intervals for the two thresholds $[\gamma_1, \gamma_2]$. Literature from change-point models indicates that the estimators of equation (16) has the same asymptotic distributions as in the single-threshold model of (2) (Bai and Perron, 1998), which means the author is able to construct confidence intervals by using the same procedure in previous discussion.

Then,

$$LR'_2(\gamma) = \frac{S'_2(\gamma) - S'_2(\hat{\gamma}'_2)}{\hat{\sigma}^2}$$

And

$$LR'_1(\gamma) = \frac{S'_1(\gamma) - S'_1(\hat{\gamma}'_1)}{\hat{\sigma}^2}$$

Where$S'_2(\gamma)$ and $S'_1(\gamma)$ are defined in equation (17) and (19) respectively. Therefore, the constructed confidence intervals for γ_1 and γ_2 are the group of values of γ which meet conditions of $LR'_2(\gamma) \le c(\alpha)$ and $LR'_1(\gamma) \le c(\alpha)$ respectively.

4.5 Theoretical Model

The threshold regression analysis specified here concerns with the regression between the OP as the dependent variable; and the level of integration including SI, CI and II as the independent variables. The critical difference here is that the degree of demand uncertainty (DU) is now used as the threshold variable. For a single threshold scenario, following Hansen's (1999) study, the single threshold model should be constructed as:

$$\boldsymbol{OP_i = \begin{cases} u_i + \beta_1 SI_i I(DV_i \leq \gamma) + \beta_2 SI_i I(DV_i > \gamma) + e_i \\ u_i + \beta_1 CI_i I(DV_i \leq \gamma) + \beta_2 CI_i I(DV_i > \gamma) + e_i \\ u_i + \beta_1 II_i I(DV_i \leq \gamma) + \beta_2 II_i I(DV_i > \gamma) + e_i \end{cases}} \quad \textbf{Equation 22}$$

where β_1 and β_2 are the coefficients of the regressors *SI, CI* and *II*; *I(*)* is the indicator function; γ represents the unknown threshold to be estimated during the computing process. Based on this model, the observations have now been divided into two 'regimes' depending on whether the threshold variable DU is smaller or greater than the threshold γ. The regimes will then be distinguished by the two regression slopes β_1 and β_2. The residual term e_i are assumed to be independent and identically distributed with a zero mean and a finite variance of σ^2. And an alternative and more intuitive way of thinking (22) is:

$$\boldsymbol{OP_i = \begin{cases} u_i + \beta_1 SI_i + e_i, DV_i \leq \gamma \\ u_i + \beta_2 SI_i + e_i, DV_i > \gamma \end{cases}}$$

$$\boldsymbol{OP_i = \begin{cases} u_i + \beta_1 CI_i + e_i, DV_i \leq \gamma \\ u_i + \beta_2 CI_i + e_i, DV_i > \gamma \end{cases}} \quad \textbf{Equation 23}$$

$$\boldsymbol{OP_i = \begin{cases} u_i + \beta_1 II_i + e_i, DV_i \leq \gamma \\ u_i + \beta_2 II_i + e_i, DV_i > \gamma \end{cases}}$$

Again, to deal with the individual effect of u_i, taking averages of equation (23)

$$\overline{\boldsymbol{OP}}_i = \begin{cases} \boldsymbol{u_i + \beta'\overline{SI}_i(\gamma) + \bar{e}_i} \\ \boldsymbol{u_i + \beta'\overline{CI}_i(\gamma) + \bar{e}_i} \\ \boldsymbol{u_i + \beta'\overline{II}_i(\gamma) + \bar{e}_i} \end{cases}$$ **Equation 24**

Taking the difference between (23) and (24) yields

$$\boldsymbol{OP^*}_i = \begin{cases} \boldsymbol{\beta^*}_1\boldsymbol{SI^*}_i\boldsymbol{I(DV_i \le \gamma) + \beta^*}_2\boldsymbol{SI_i}^*\boldsymbol{I(DV_i > \gamma) + e_i}^* \\ \boldsymbol{\beta^*}_1\boldsymbol{CI^*}_i\boldsymbol{I(DV_i \le \gamma) + \beta^*}_2\boldsymbol{CI_i}^*\boldsymbol{I(DV_i > \gamma) + e_i}^* \\ \boldsymbol{\beta^*}_1\boldsymbol{II^*}_i\boldsymbol{I(DV_i \le \gamma) + \beta^*}_2\boldsymbol{II_i}^*\boldsymbol{I(DV_i > \gamma) + e_i}^* \end{cases}$$ **Equation 25**

With this model (25), it is hypothesized that there is a threshold effect, which forms an asymmetric non-linear relationship between the SCI and OP under the moderating effect of DU. It is therefore important to determine whether the threshold effect is statistically significant.

If there exist double thresholds, the model of equation (25) can be modified to become:

$$\boldsymbol{OP^*}_i = \boldsymbol{\beta^*}_1\boldsymbol{II^*}_i\boldsymbol{I(DV_i \le \gamma_1) + \beta^*}_2\boldsymbol{II_i}^*\boldsymbol{I(\gamma_1 < DV_i \le \gamma_2) + \beta^*}_3\boldsymbol{II_i}^*\boldsymbol{I(DV_i > \gamma_2) + e_i}^*$$
Equation 26

$$\boldsymbol{OP^*}_i = \boldsymbol{\beta^*}_1\boldsymbol{SI^*}_i\boldsymbol{I(DV_i \le \gamma_1) + \beta^*}_2\boldsymbol{SI_i}^*\boldsymbol{I(\gamma_1 < DV_i \le \gamma_2) + \beta^*}_3\boldsymbol{SI_i}^*\boldsymbol{I(DV_i > \gamma_2) + e_i}^*$$
Equation 27

$$\boldsymbol{OP^*}_i = \boldsymbol{\beta^*}_1\boldsymbol{CI^*}_i\boldsymbol{I(DV_i \le \gamma_1) + \beta^*}_2\boldsymbol{CI_i}^*\boldsymbol{I(\gamma_1 < DV_i \le \gamma_2) + \beta^*}_3\boldsymbol{CI_i}^*\boldsymbol{I(DV_i > \gamma_2) + e_i}^*$$
Equation 28

where the threshold value $\gamma_1 < \gamma_2$. This can be expended to multiple threshold models with $\gamma_1,\ \gamma_2,\ \gamma_3, \dots,\ \gamma_n$. Further specifications for the three or more thresholds models can be expanded similarly like the double thresholds model.

4.6 Chapter Conclusion

In this study, the six research hypotheses have been proposed to examine the moderating effects of DU on SCI-OP relationships of automotive supply chains in China. To empirically investigate the proposed hypotheses, an analysis of the key research philosophies and appropriate research design and analysis method were carried out. This chapter presented the philosophical stance of the research, the research design, research strategy and the selection of analysis methods. Additionally, this chapter revealed the sequences and steps of the estimation process in conducting the analysis.

According to the research epistemology, this study took an interpretivist stance because it allowed researchers to deeply understand the social network structures (Willcocks and Mingers, 2004). By doing so, a deductive approach was selected to assist in testing the research hypotheses and reach the research objectives. On the other hand, following the major approaches in literature, the survey questionnaire was designed and distributed to collect and sample data of measured constructs. A detailed process has also been presented on how the data samples were formed and tested for their validity and reliability. Furthermore, the selection of an appropriate analysis method which can be performed on the formed final data sample was also discussed. This used both HRA and threshold regression analysis (TRA) to test the two groups of hypotheses, respectively. As a new analysing method introduced in OM domain, TRA has been introduced in detail in terms of the model format, estimation, computing issues, inference and extension. Lastly, the theoretical constructs were combined with HRA and TRA to form the core theoretical model. The next chapter presents a report of the analysis conducted for this study.

Chapter 5 Results and Findings

5.1 Chapter Introduction

he HRA and TRA described in the methodology chapter were used to test the six proposed hypotheses formulated in the literature review chapter. The results of hypothesis testing are reported in two sections in this chapter. In particular, the first section reports the results of HRA by testing hypotheses 1 to 3, thereafter, the second section includes the results of testing hypotheses 4 to 6 by applying TRA. Specifically, the moderating effects of the threshold variable DU on the relationship between OP and SI, CI and II were assessed individually in order to determine whether there were moderating effects. This chapter also reports a competing model for the purpose of identifying an optimal model to best explain the data sample. To compute the estimation, the STATA 14 SE software was used.

5.2Results of Hierarchical Regression Analysis

To test hypotheses 1-3, HRA was used. In the first step, the direct effect of II on OP was assessed in Model 1 (see Table 24). In the second step, Model 2 assessed the relationship between SI and CI and OP, given that the relationship between II and OP was significant in Model 1. The results of HRA for OP indicate that there are statistically significant direct relationships between II, SI, CI and OP. In particular, II is positively correlate to OP with an estimated coefficient of 0.223 ($p<0.01$), which means OP will rise by 0.223 unit as II rises by 1 unit, *ceteris paribus*. Model 1 also reported a significant intercept 6.636 ($p<0.05$), indicating a natural level of OP without the effect of II. Based on the obtained significant relationship between II and OP, HRA was moved a step forward to model 2 to involve SI and CI. In Model 2, the estimated coefficients of

$\beta_1(II), \beta_2(SI), \beta_3(CI)$ are 0.173, 0.132 and 0.122, respectively, at 1% and 5% significance level, revealing significantly positive relationships between II, SI, CI and OP and **supporting hypotheses 1, 2 and 3**. One can see the estimated coefficients' magnitude decrease from II to CI, which indicates the relative contribution levels from SCI sub-dimensions to OP. Model 2 reported a valid intercept of 5.221 ($p<0.1$), which means OP equals to 5.221 when all integration constructs equal to 0. Importantly, adding SI and CI to Model 2 increased the predictive power of the regression analysis, with a delta adjusted R-square value of 0.054.

Regressor	Model 1:Direct Effect of II	Model 2: Direct Effects of II, SI, CI
II[β_1]	0.223***	0.173***
SI [β_2]		0.132**
CI [β_3]		0.122**
Intercept	6.636**	5.221*
Adjusted-R^2	0.211	0.265
ΔAdjusted-R^2		0.054
Notes: *p<0.1;**p<0.05,***p<0.01		

Table 26 Direct and interaction effects regression results.

5.3 Results of Moderating Effects on II-OP Relationships

To recall the equation (26) where DU acts as the threshold variable, a statistically significant threshold value of DU will lead to different regression coefficients of SCI on OP, which indicates the existence of DU's moderating effect on the SCI-OP relationships. Once a threshold has been found, it is necessary to hypothesise and test for an additional threshold. To determine the number of thresholds equation (26) was estimated by OLS, allowing for zero to multiple thresholds. As shown in Table 25, the test for the sole single threshold, the F value, cannot be rejected with a bootstrap *p*-value of 0.664 at the 5% significance level. Furthermore, the estimated *F*-statistics are all obtained after bootstrapping 2000 times. Therefore, it is concluded that there is no evidence that DU moderates the II-OP relationship, so **hypothesis 4 was rejected**. The same tests are also performed on SI-OP and CI-OP relationships in following sections. Additionally, without threshold effects, the linear coefficient of II has been estimated at 0.223 with a 10% significance level, which is the same as the hierarchical regression results. The linear regression analysis also reports a significant intercept of 6.634 and adjusted R-square 0.209. This means that such regression results explain 20.9% data in the sample. There exist slight differences of the estimated intercept and adjusted R-square between the reported results obtained from HRA and TRA, and these differences might be caused by different sampling methods applied by HRA and TRA. Figure 18 reveals the scatter plot of II-OP relationship with the regression line.

Test for single threshold	
F1	4.45
P-value	0.664
95% critical value	9.68
ß	0.223**
Intercept	6.634**
Adjusted R-square	0.209
Notes: bootstrap = 2000; *p<0.1;**p<0.05,***p<0.01	

Table 27 Tests for threshold effects on II-OP relationship.

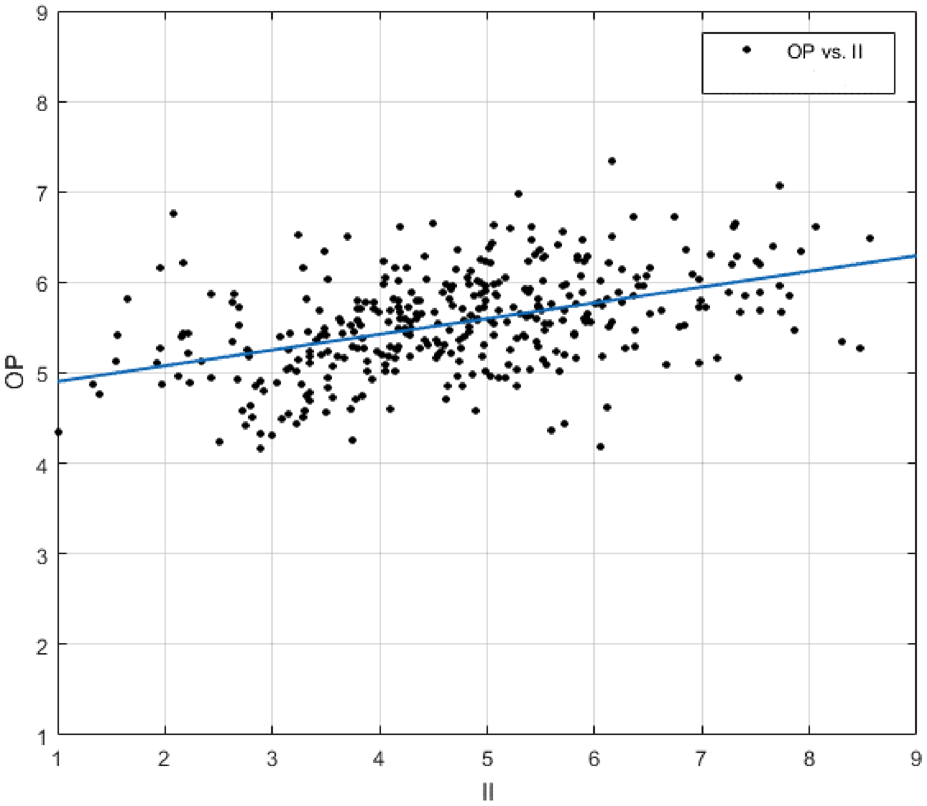

Figure 17 Scatter plot of OP against II with regression line.

5.4 Results of Moderating Effects on SI-OP Relationships

To test whether DU moderates SI-OP relationships, the *F*-test statistics F1, F2 and F3, along with their bootstrap *p*-values are reported in Table 26. The *F*-tests show that the single threshold effect is highly significant with a *p*-value of 0.000. In addition, the test of a double threshold effect is also strongly significant with a *p*-value of 0.003. By contrast, the test for a triple-threshold effect failed to show a strong significance. Thus, it is concluded that there is strong and statistically significant evidence to support the existence of two thresholds in the relationship between OP and SI. Furthermore, the estimated *F*-statistics were all obtained after bootstrapping for 2000 times.

Test for single threshold	
F1	99.8
P-value	0.000
95% critical value	11.06
Test for double threshold	
F2	67.2
P-value	0.003
95% critical value	11.06
Test for triple threshold	
F3	5.6
P-value	0.779
95% critical value	11.06
Notes: bootstrap = 2000	

Table 28 Tests for threshold effects on SI-OP relationship.

The two estimated threshold values and their 95% confidence intervals are reported in Table 27. The estimated threshold values are 3.88 and 6.28 respectively, which divided the data set into three regimes in terms of high uncertain demand (DU≦3.88), middle uncertain demand (3.88<DU≦6.28) and low uncertain demand (DU>6.28).

	Estimates	95% confidence interval
γ_1	3.88	[3.721, 3.956]
γ_2	6.28	[6.101. 6.346]

Table 29 Threshold estimates

Table 28 reports the number of respondents which fall into the three regimes. It can be seen that the number of respondents in the middle uncertain demand category counts the majority of data sample (48.4%). In addition, the size of 'low uncertain demand' respondents are approximately twice large compare to it of the 'high uncertain demand' respondents.

Respondents class	Number of respondent
DU≦3.88	65
3.88<DU≦6.28	184
DU>6.28	136

Table 30 Number of responses in each regime.

The regression slope estimates conventional OLS standard errors (SE), which are displayed in Table 29. The estimated results suggest that SI is negatively related to OP in the first regime. This could be unexpected finding to some researchers in that such finding seems to go against the 'common sense' idea on the positive relationship in many integration and performance studies. On the other hand, the estimated slopes become positive in the second and third regimes, and the magnitude of the slopes rise from 0.061 to 0.237 when it shifts from the second to the third regime. The estimated SI-OP relationship coefficients rise from negative to positive as the level of DU increases, which appears to squarely **support hypothesis 5**. To provide a more visual version of the regression result, the data sample was divided into three regimes based on the two estimated threshold values. The scatter plots with regression line in each regime are shown in Figure 19-21.

Regressor	Coefficient estimate	OLS SE
SI(DU≦3.88)	-0.196***	0.051
SI(3.88<DU≦6.28)	0.061***	0.031
SI(DU>6.28)	0.237***	0.025
Notes: *p<0.1;**p<0.05,***p<0.01		

Table 31 Regression estimates: double threshold model

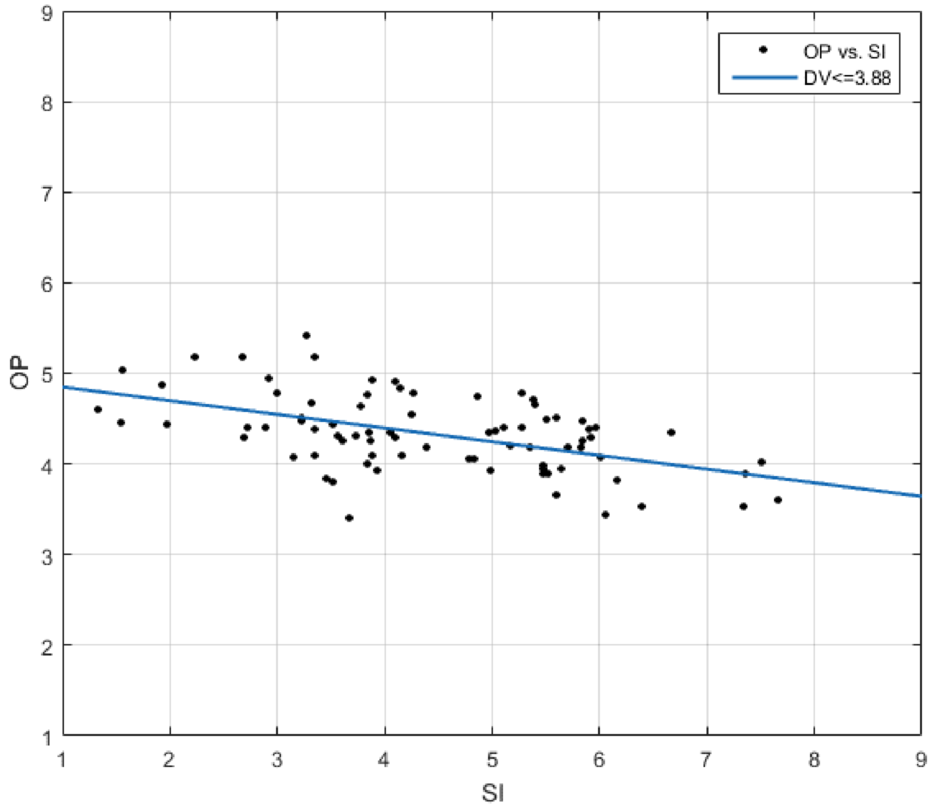

Figure 18 Scatter plot of OP against SI in high volatile demand interval with regression line.

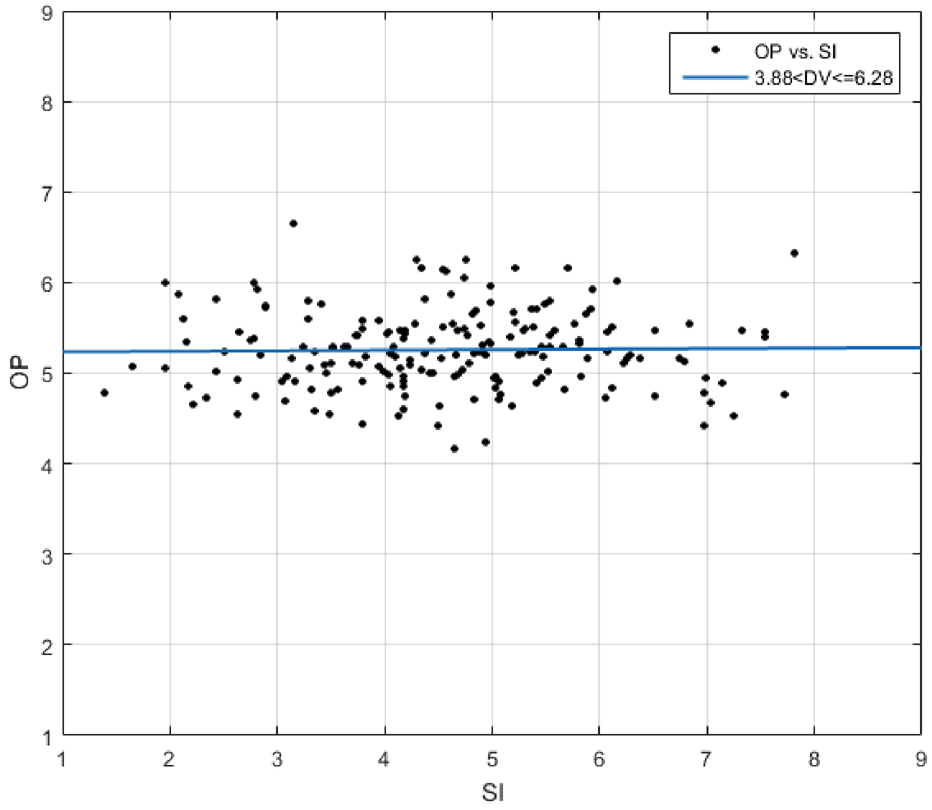

Figure 19 Scatter plot of OP against SI in middle volatile demand interval with regression line

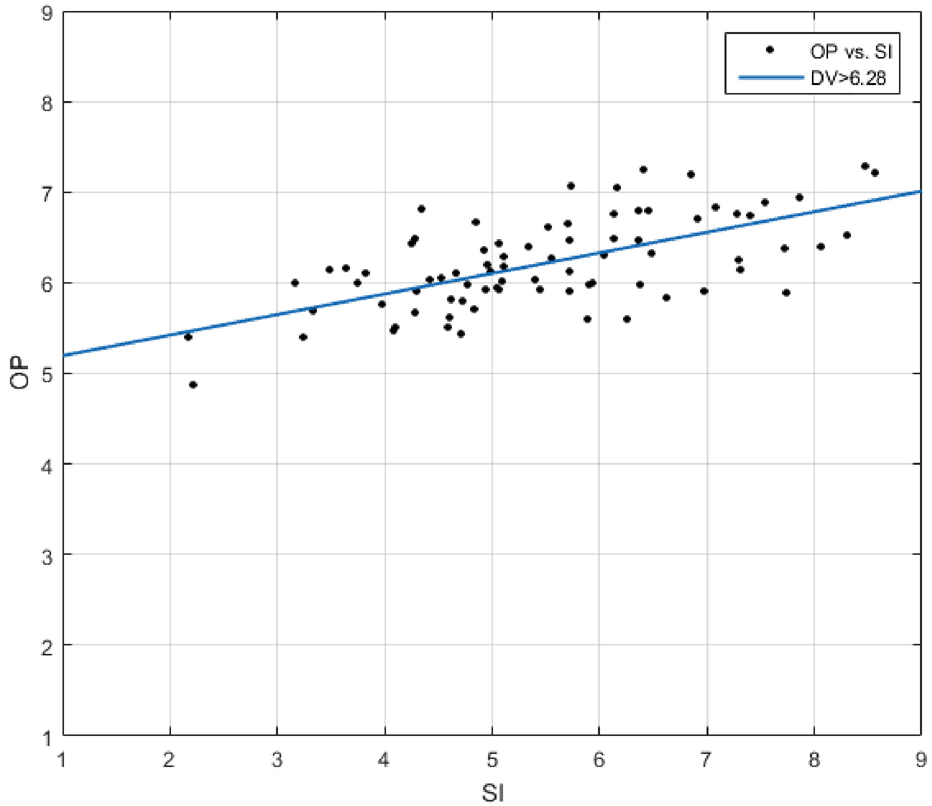

Figure 20 Scatter plot of OP against SI in low volatile demand interval with regression line.

The asymptotic confidence intervals for the estimated threshold values are very tight, which indicates that the non-determinacy of this division nature is considerably negligible. Additional knowledge according to the interval constructions can be learned from the threshold estimates plots of the likelihood ratio function in Figure 22-23, which shows the estimated $\hat{\gamma}_1$ and the refinement estimator $\hat{\gamma}_2$. The estimated values of the threshold are at points when the likelihood ratio shoots through the 95% confidence interval line (red line in the figure) and reaches the non-rejection area (below the red line).

It is always necessary to explore an additional threshold when a certain number of thresholds has been found significant. In this case, the first threshold value is computed by estimating a single threshold model, which is the point value where its likelihood ratio reaches the 95% critical line, as it appears at 3.88. However, Figure 22 shows there is a second significant drop in the likelihood ratio after 6. For this reason, the single threshold model delivered a message that there may exist a second threshold in the regression analysis. Following this suggestion, Figure 23 shows the confidence interval construction of $\hat{\gamma}_2$ by fixing the estimated first threshold $\hat{\gamma}_1$.

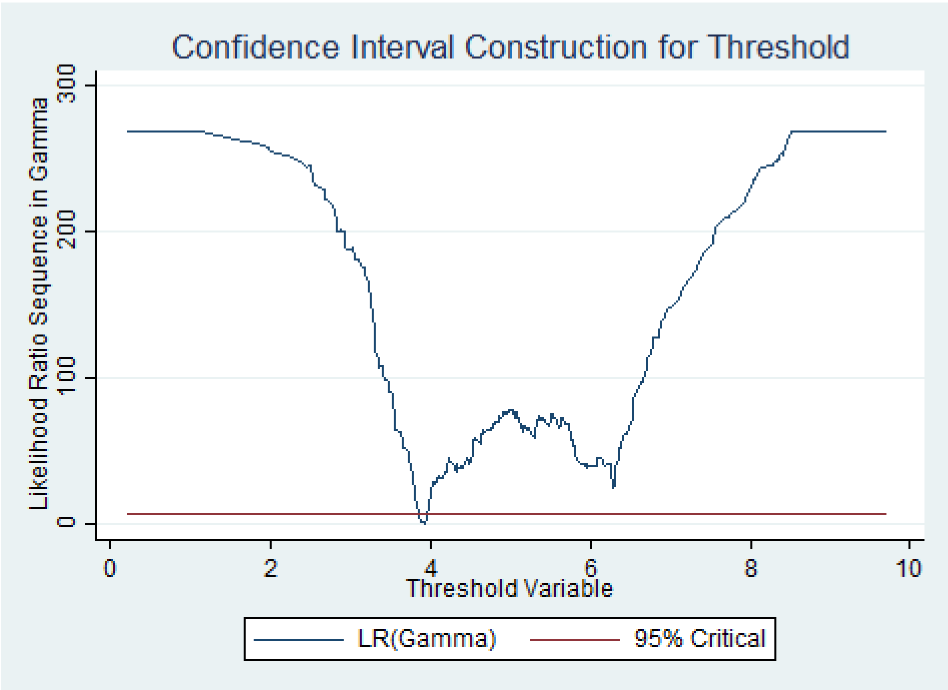

Figure 21 Confidence interval construction double threshold model

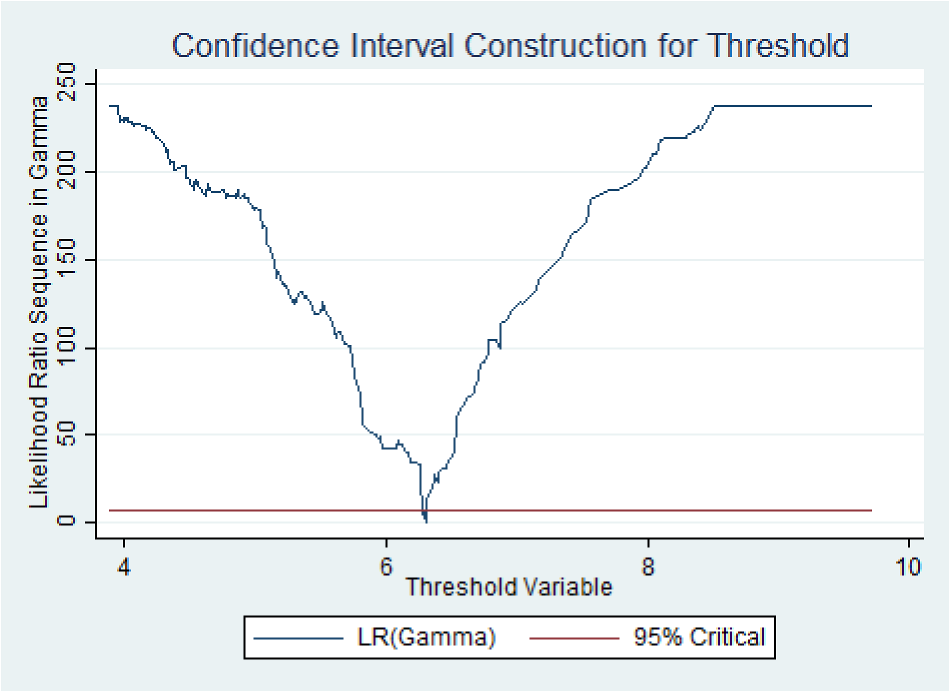

Figure 22 Confidence interval construction double threshold model by fixing the first threshold.

5.5 Results of Moderating Effects on CI-OP Relationships

The results of the moderating effects of DU on the relationship between CI and OP are presented in Table 30. The *F*-tests strongly support the significance of a double threshold model and reject additional hypotheses for more thresholds, since the *p*-value of F_3 was greater than 0.1. Thus, it is concluded that there is strong evidence in support of a two-threshold existence in the regression relationship of CI-OP. Accordingly, **hypothesis 6 is supported.**

Test for single threshold	
F1	58.03
P-value	0.000
95% critical value	11.58
Test for double threshold	
F2	23.16
P-value	0.003
95% critical value	11.58
Test for triple threshold	
F3	1.66
P-value	0.785
95% critical value	11.58
Notes: bootstrap = 2000	

Table 32 Tests for threshold effects on CI-OP relationship.

The estimated threshold values of 4.23 and 5.81 and their 95% confidence intervals are reported in Table 31. Based on the estimated threshold values, three categories are formed, including ‘high uncertain demand’, ‘medium uncertain demand’, and ‘low uncertain demand’. Such scenario of three regimes division is comparably the same to what has been obtained in analysing SI-OP relationships. The three regimes were divided based on a pair of estimated threshold values, however, the estimated threshold values (4.23, 5.81) in CI-OP model differ from them in SI-OP model (3.88. 6.28), and the former shows more togetherness than the latter.

	Estimates	95% confidence interval
γ_1	4.23	[4.121, 4.331]
γ_2	5.81	[5.699. 5.823]

Table 33 Threshold estimates

It is also interesting to note that the number of respondents falls into the three regimes in the CI-OP scenario are also distributed differently. Compare to the SI-OP scenario, lots of respondents in the 'medium uncertain demand' regime have now been relocated into the 'high uncertain demand' and 'low uncertain demand' regimes. The regime of 'low uncertain demand' includes the greatest number of respondents (177, 41%), while the 'low uncertain demand' (137, 32%) and 'medium uncertain demand' (116, 27%) regimes following closely (Table 32).

Respondents class	Number of respondent
$DU \leqq 4.23$	123
$4.23 < DU \leqq 5.81$	104
$DU > 5.81$	158

Table 34 Number of responses in each regime.

As shown in Table 33, all of the regime-dependent coefficients of CI are significant and plausibly signed. The coefficient in 'high uncertain demand' regime is 0.244, which indicates that CI is helpful for OP growth when demand uncertainty tends to be high. In particular, if CI increases 1 unit, OP will increase 0.244 unit, *ceteris paribus*. In the 'medium uncertain demand' regime, CI still has a positive impact but with lower magnitude (0.080) on OP. After the second threshold, unexpectedly, CI became harmful for the OP growth (-0.113). Note that the absolute size of CI's coefficient suggested that it may worsen OP's growth if CI gets too high. With views (Figure 27-28) to the tighten 95% asymptotic confidence intervals, this conclusion holds that the level of CI should not keep enhancing when DU is lower. Visual scatter plots with regression lines for the

CI-OP relationships in three divided regimes are provided below (Figure 24-26).

Regressor	Coefficient estimate	OLS SE
CI(DU≦4.23)	0.244***	0.032
CI(4.23<DU≦5.81)	0.080***	0.024
CI(DU>5.81)	-0.113***	0.048
Notes: *p<0.1;**p<0.05,***p<0.01		

Table 35 Regression estimates: double threshold model

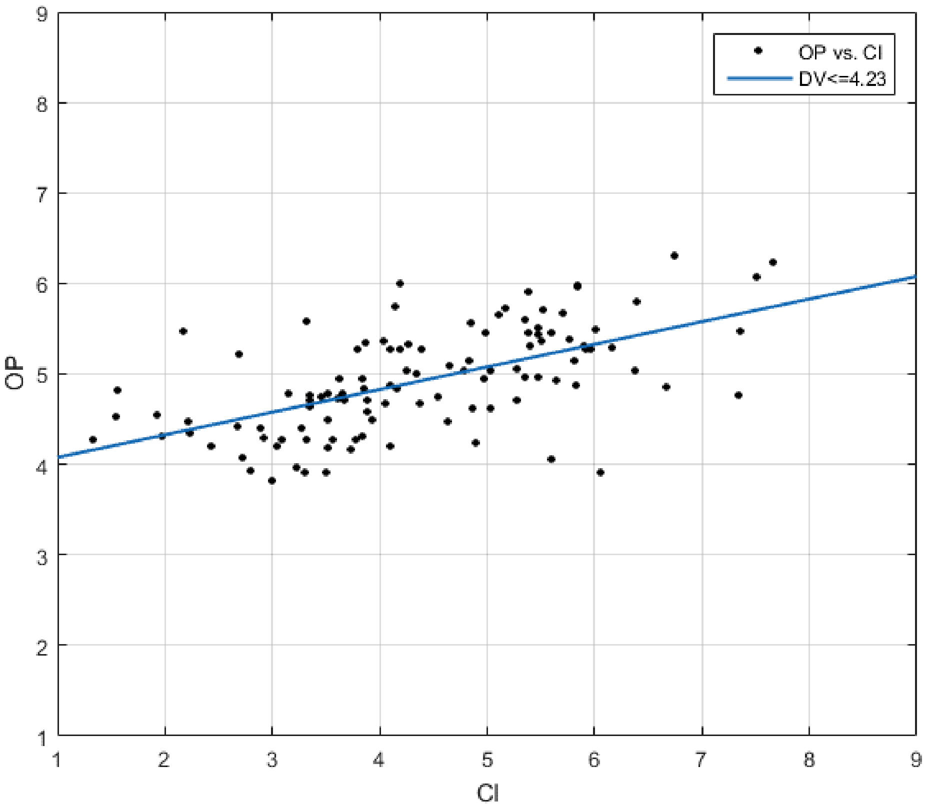

Figure 23 Scatter plot of OP against CI in high volatile demand interval with regression line

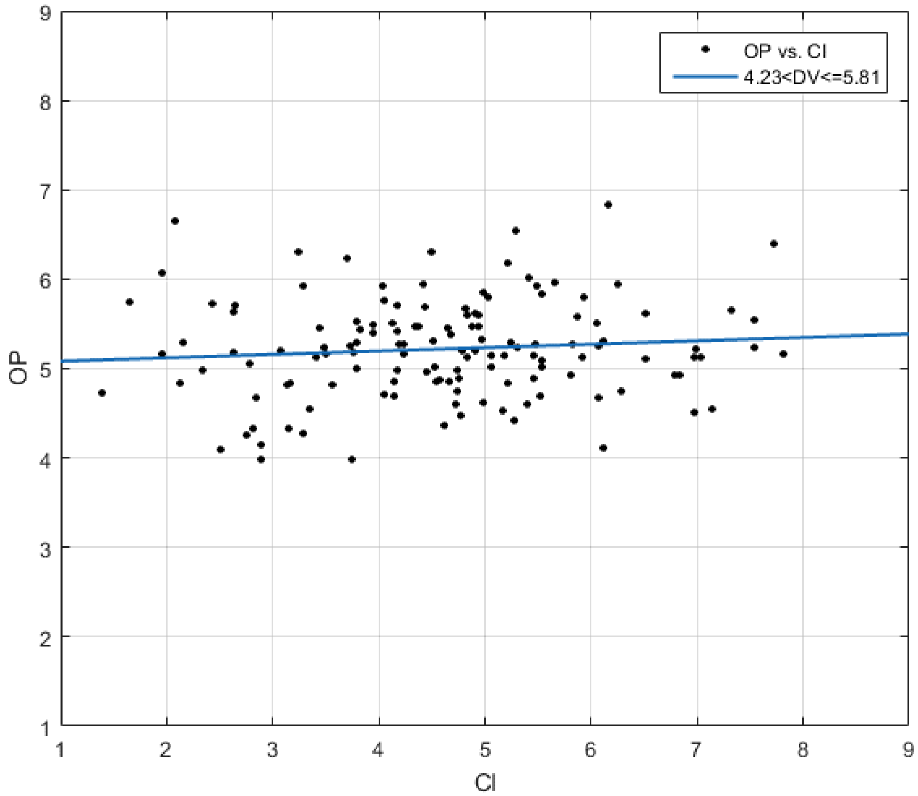

Figure 24 Scatter plot of OP against CI in middle volatile demand interval with regression line

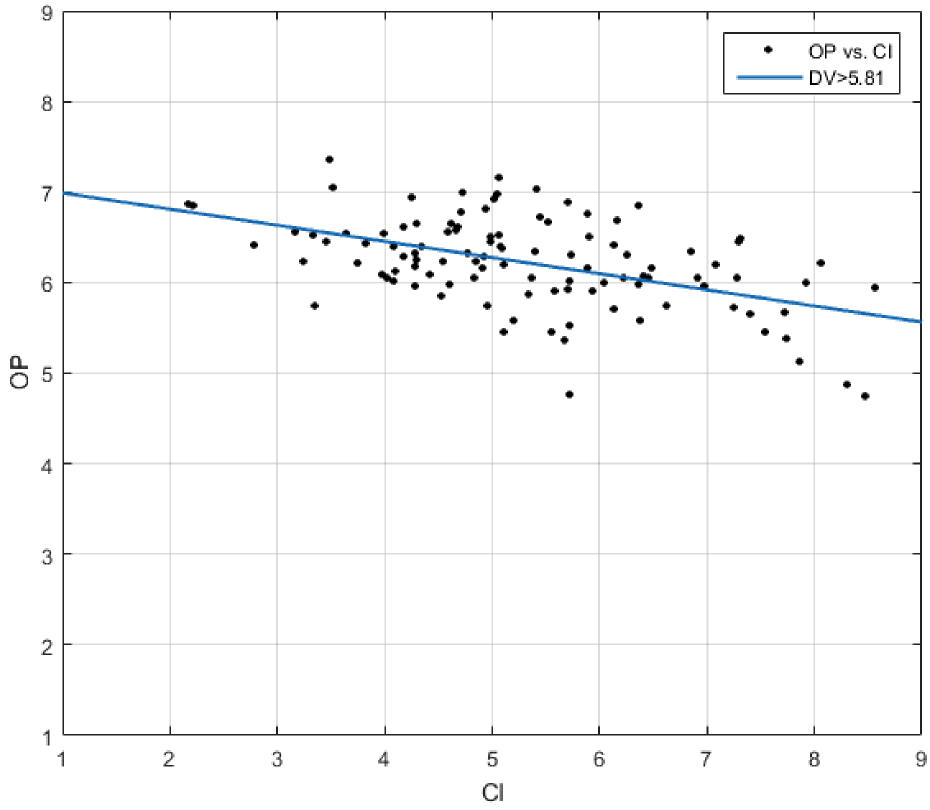

Figure 25 Scatter plot of OP against CI in low volatile demand interval with regression line.

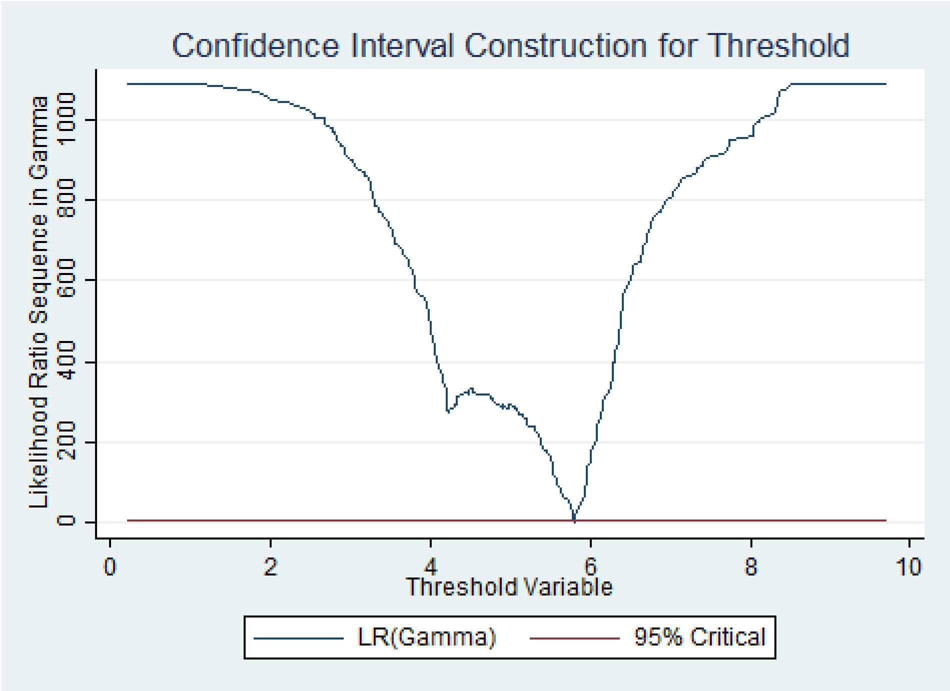

Figure 26 Confidence interval construction double threshold model

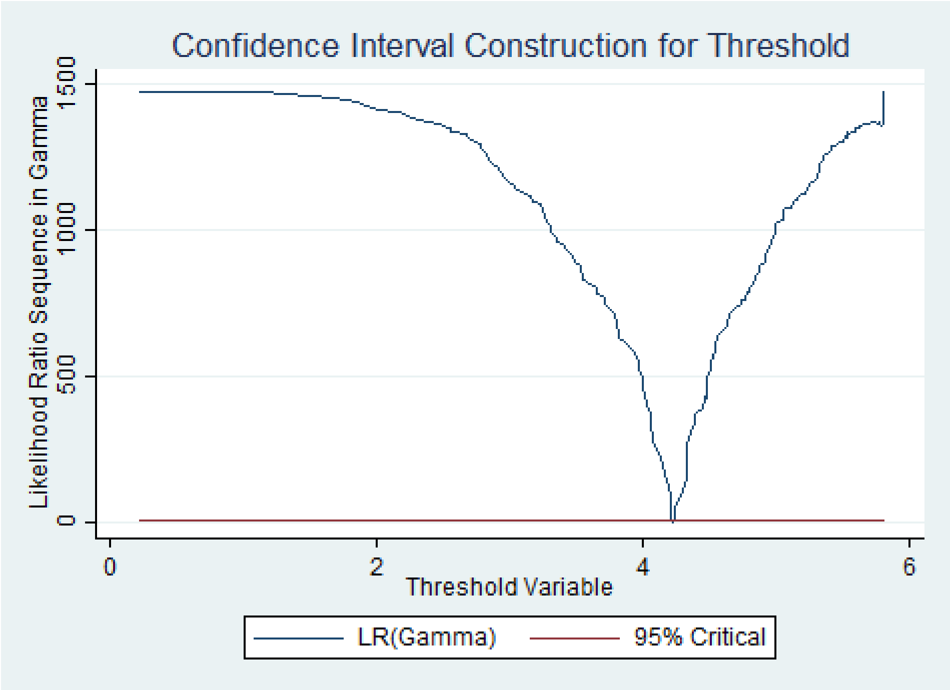

Figure 27 Confidence interval construction double threshold model by fixing the first threshold.

5.6 Competing Models

When introducing a new method of analysis to a specific research domain, such as introducing TRA into the OM domain, it is common practice to compare the proposed models to other literature-favoured models to clearly determine which model explains the data best. This section compares the proposed TRA models to the literature-favoured HRA model as the rival model to validate that the proposed TRA model is optimal. In the threshold regression models, DU has been found to fully moderate the SI-OP and CI-OP relationships. The moderating effects have been reflected by different regression coefficients which were obtained in different regimes divided by estimated threshold values of DU. These different regression coefficients eventually formed non-linear relationships. The rival model, the HRA model, was constructed and tested following the approach of a benchmark study by Terjesen et al. (2012), which added quadratic terms of SCI and interactions of these quadratic terms with the environmental factor DU into the direct effect model. The rival model can be specified as:

$$OP_i = \beta_0 + \beta_1 II_i + \beta_2 SI_i + \beta_3 CI_i + \beta_4 {II_i}^2 + \beta_5 {SI_i}^2 + \beta_6 {CI_i}^2 + \beta_7 {II_i}^2 * DV + \beta_8 {SI_i}^2 * DV + \beta_9 {CI_i}^2 * DV + e_i$$

Where $\beta_4, \beta_5\ and\ \beta_6$ are regression coefficients which test whether the relationships from II, SI and CI to OP are curved and $\beta_7, \beta_8\ and\ \beta_9$ are therefore the coefficients of curved relationships under the moderating effect of DU. Thus, in the rival model, the significant $\beta_7, \beta_8\ and\ \beta_9$ would be evidence to support hypotheses 4 to 6.

For the proposal of a competing optimal model, the criteria provided by Kleijnen (1998) is used. Such criteria include a model explanatory capability (Adjusted R-square, the more the better) and statistically significant coefficients (p<0.1, the smaller the better). As shown in Table 34, the rival model has several insignificant coefficients on the regressors of II_i^2, CI_i^2 and $II_i^2 * DV$. With the exception of the direct effects in the rival mode, which has been described in the previous section, the rival model obtained significant coefficients on SI_i^2, $SI_i^2 * DV$ and $CI_i^2 * DV$. In particular, the positive coefficients of SI_i^2 and $SI_i^2 * DV$ indicate that the relationship of SI-OP is a U-shaped curve ($\beta_5 = 0.013$) and its curvature increases under the moderating effect of DU ($\beta_8 = 0.074$). On the other hand, the negative coefficient of $CI_i^2 * DV$ reveals an inverse U-shaped CI-OP relationship, which is consistent with some previous research findings (Das et al., 2006, Terjesen et al., 2012). Compared to the rival model, the proposed model has higher significance levels of the major coefficients which were obtained. In addition, the most notable point is that the proposed model has a much higher explanatory power (adjusted R-square = 0.614) than it of the rival model (adjusted R-square = 0.233) with an increased adjusted R-square of 0.381. Furthermore, the proposed model provides significant and clear regression coefficients in all regimes divided by DU. Compared to the complicatedly explained and measured curved relationship, the clear regression coefficients with categories on the environmental factors are much easier for supply chain daily managers to learn and practice. For these reasons, these results support the proposed model as the model that best explains the data.

Regressor	Hierarchical Regression Model	Threshold Regression Model
II_i	0.173***	
SI_i	0.132***	
CI_i	0.122***	
${II_i}^2$	0.004	
${SI_i}^2$	0.013*	
${CI_i}^2$	0.002	
${II_i}^2 * DV$	0.017	
${SI_i}^2 * DV$	0.074*	
${CI_i}^2 * DV$	-0.082*	
$II_i(DV)$		0.174***
$SI_i(DV \leq 3.88)$		-0.196***
$SI_i(3.88 < DV \leq 6.28)$		0.061***
$SI_i(DV > 6.28)$		0.237***
$CI_i(DV \leq 4.23)$		0.244***
$CI_i(4.23 < DV \leq 5.81)$		0.080***
$CI_i(DV > 5.81)$		-0.113***
Intercept	4.636*	4.731**
Model fit statistics		
Adjusted *R*-square	0.233	0.614
ΔAdjusted *R*-square		0.381

Note: * *p*-value<0.1, ** *p*-value<0.05, *** *p*-value<0.01

5.7 Chapter Conclusion

The six proposed research hypotheses in the theoretical framework (literature review chapter) were subject to empirical examination under this chapter. In addition, this chapter applied the research design and methodologies introduced in Chapter 4. As a part of the analysis process, this research first tested the direct effects (hypotheses 1 to 3) of SCI dimensions on OP and then carried out the TRA in order to test hypotheses 4 to 6. All test results were presented in sub-chapters accordingly. It can be summarised that **hypotheses 1, 2, 3, 5 and 6** were supported with strong evidence, while **hypothesis 4** was rejected. Finally, the TRA results were compared with results of a rival model based on HRA, and, as expected, the former best fits the data.

Chapter 6 Discussion

6.1 Discussion on Linear Analyzing Results

Among the six proposed hypotheses, five of them were supported and one was rejected.; such results broadly indicate that SCI is related to OP. Specifically, by testing the direct effects, this research found that II, SI and CI are all directly and positively related to OP.

To compare the above results with findings from the relative literature, this research found that II was statistically significant and positively correlated to OP, which is consistent with several studies (Stank et al., 2001b, Fawcett and Magnan, 2002, Koufteros et al., 2005). Therefore, the findings of this study reinforce the evidence of the improvement of II on OP. Another finding, that SI positively correlates to OP, is supported by (Gimenez and Ventura, 2005, Koufteros et al., 2007, Devaraj et al., 2007). Lastly, the finding that CI positively correlates to OP is consistent with the findings of previous studies (Stank et al., 2001b, Wong et al., 2011a, Prajogo and Olhager, 2012). However, the literature provides mixed findings in general, such as suggesting an insignificant SI-OP relationship (Stank et al., 2001b), insignificant II-OP relationship (Gimenez and Ventura, 2005), insignificant CI-OP relationship (Devaraj et al., 2007) and even negative relationships (Swink and Song, 2007) can also be found.

The above comparison between the findings of this study and those of previous studies reveals that current investigations on the relationship between individual dimensions of SCI and OP are not sufficient. Scholars have argued that the relationship of SCI dimensions to OP should not be examined individually (Flynn et al., 2010, Terjesen et al., 2012). Ignoring the mediating role of II between SI, CI and OP would lead to biased or insignificant results. However, in order to maximise OP, whether the strength of the three dimensions should remain on equal levels is still unexplored.

6.2 Discussion on Non-linear Analyzing Results

The main objective of this research was to examine the moderating effect of DU on relationships from SCI dimensions to OP. The potential moderating effects have been hypothesised individually with each SCI dimension (hypothesis 4 to 6). Those hypotheses were tested through TRA, indicating SCI is non-linearly related to OP in terms of DU. However, the non-linearity here obtained by TRA should not be interpreted in strictly mathematical terms. It does not mean a polynomial with a degree higher than one or a non-linear system of differential equations. It simply means *not a directly proportional relationship*. In other words, the analytical relationships between SCI dimensions and OP in terms of DU at the given regimes separated by the estimated thresholds are only approximately linear with different slopes.

6.2.1 II-OP Relationship Subject to DU

The linear and direct effects analysis showed that II was positively related to OP. To refer to the contingency theory, it is argued that an organization or a supply chain designs its structure and plan its activities with the consideration of fitting external environments. However, it has been shown that the environmental changes usually happen on either the supplier side, such as technological uncertainty (Jonsson et al., 2011) and lean strategy (Prajogo et al., 2015), or on the customer side, such as political uncertainty and customer learning change (Flynn et al., 2010). Thus, one of the core capabilities of enhanced SI and CI is to provide more external information to the focal company by acting as sensors (Cao et al., 2015). The organizational information process theory supports such argumentation that the supply chain information flow is from the outside in (Wong, 2013). Based on the shared information, the focal company is capable of re-aligning the overall SCI structure (Prajogo and Olhager, 2012). Such argument suggests that II, as the management activities happened inside the focal company, does not necessarily be sensitive to external environmental changes. In particular, it is not necessarily sensitive to DU in this context.

Looking at the primary data of the three constructs, II, OP and DU, Figure 29 shows the observations of II to OP with DU collapsed; the correlation between II and OP is clearly discerned as a plane along the DU axis. Such plane is formed by scanning the regression line of the II-OP relationship across DU’s spectrum, indicating that the II-OP relationship is not moderated by DU. This evidence is similar to that from Devaraj et al. (2007), which showed the level of eBusiness does not moderate II-OP relationship, however, its moderating effects have been found significantly in relationships of SI and CI to OP.

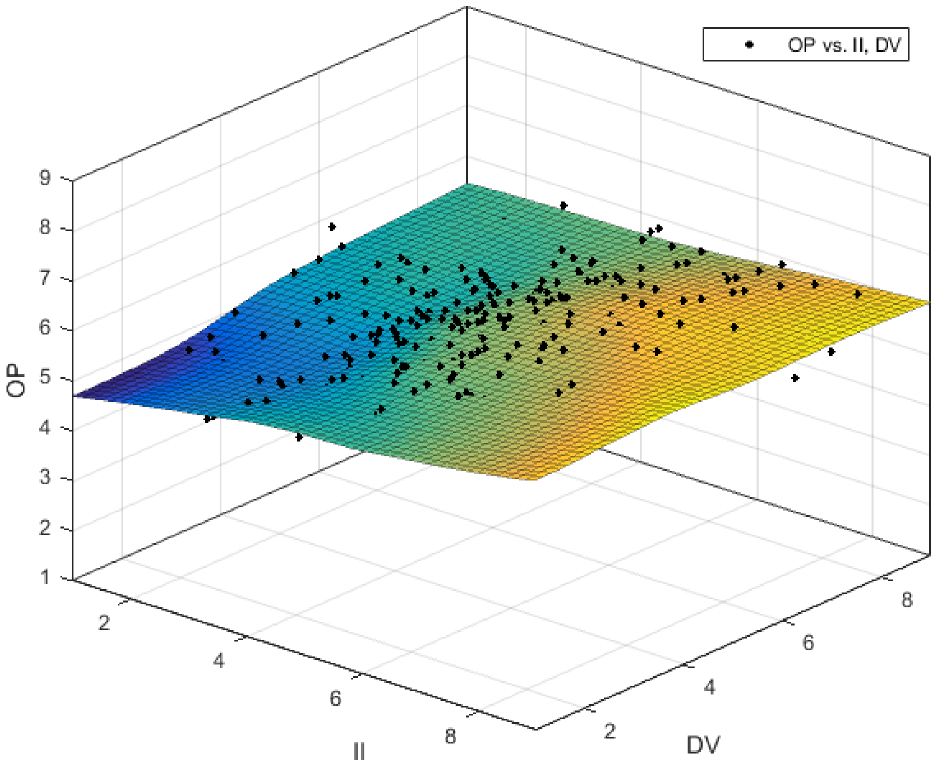

Figure 28 3D plot of the relationship from II to OP with DU, generated by LOWESS (Locally Weighted Scatterplot Smoothing)

When allocating the research findings in the Chinese automotive industry context, it is argued that OEMs as the supply chain decision makers are the core processors of information flow. In practice, it is generally accepted that OEMs do not have contact with consumers directly, and it is the customers who deal with consumers. Based on such circumstances, using cross-functional activities or meetings could lead to a better understanding and development of the organization, and as a result, the OEMs could produce knowledge beyond borders of a single department. However, even extremely strong connections between departments still cannot exceed the edge of the organization to reach the consumers. From another perspective, if II is sensitive enough to environmental changes and able to adjust operational strategies without information flow provided from supply chain partners, the importance of enhancing SI and CI thus becomes meaningless, which is contradictory to the majority of relative literature (Das et al., 2006, Flynn et al., 2010). These explanations are confirmed by further interviews with some responds who suggested that China’s automotive manufacturers embrace external integration to anticipate uncertainties by enhancing external collaboration amongst major customers in collecting information subject to consumers’ preference changes.

6.2.2 SI-OP Relationship Subject to DU

The LOWESS used in Figure 30 is a popular tool used in regression analysis that creates a smooth line through scatter plots. This provides researchers with a clear visual relationship between constructs and foreseeable trends (Cleveland, 1981). However, LOWESS cannot be used to obtain a simple equation for a set of data (Howarth and McArthur, 1997). In this study, the non-linear regression equations were obtained by applying TRA. Without specifying regression slopes, Figure 30 provides a visual relationship from SI to OP subject to DU.

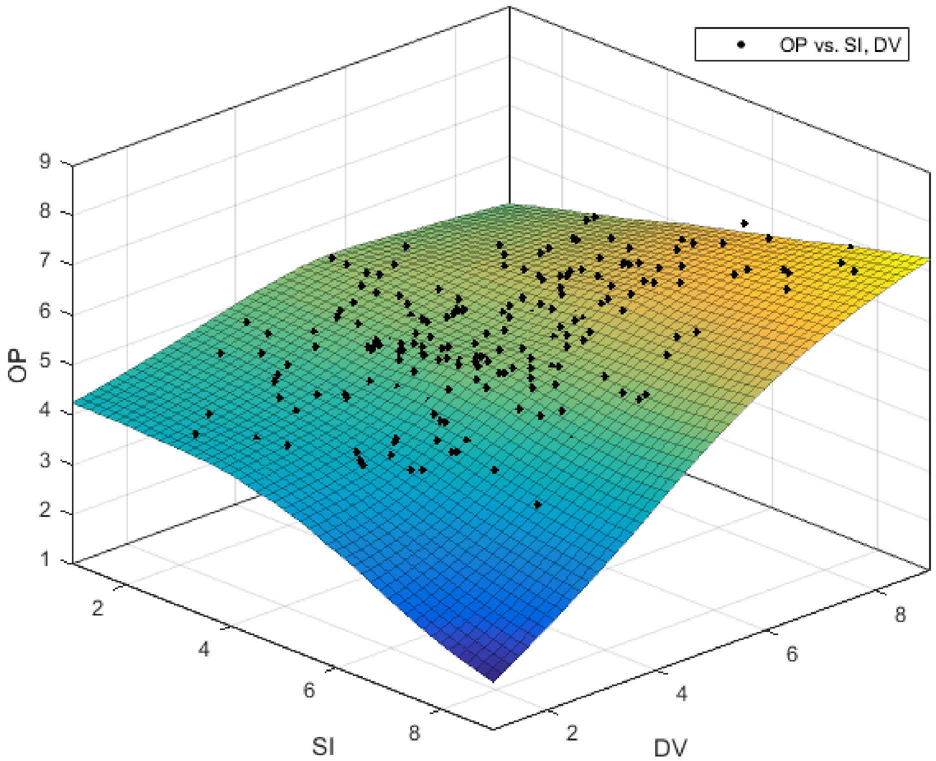

Figure 29 3D plot of the relationship from SI to OP with DU, generated by LOWESS (Locally Weighted Scatterplot Smoothing)

According to agile and lean supply chain strategies, a lean supply chain management is preferred when DU is low (please note the 7 for Low and 1 for High in DU dimension), which exactly represents that the closely integrated partnership between OEMs and their suppliers contributes positively to the OP (Prajogo and Olhager, 2012, Jin et al., 2013). In contrast, supply chains prefer to perform in an agile mode when DU is high, which produces difficulties in predicting future market conditions (Cousins and Menguc, 2006, Sanchez Rodrigues et al., 2015). Under an agile mode, a higher level of customer-oriented integration is encouraged in order to enhance supply chains' responsiveness, sensitivity and flexibility to market changes (Cao and Zhang, 2011, Hajmohammad et al., 2013). In this way, a higher integration of suppliers who stand at the end of information flow can produce the supply chains with a lower capability to quickly react (Vazquez-Bustelo et al., 2007, Goldsby et al., 2006). Further from a resource-based view, a highly uncertain demand exposes suppliers to high opportunity costs due to maladaptation (Kim, 2009, Huang et al., 2014). A high-level investment or collaboration forming tighter integration should not be better in any situations, since the payoff from closer integration is considered to be increased constraint for suppliers to respond to demand changes and to be overcautious in participating in new markets. Suppliers who developed a high level of integration within a market with highly uncertain demand would lead to higher switching costs and risk exposure (Ghoshal and Moran, 1996, Zhao et al., 2013). Therefore, the DU weakens the positive SI-OP relationship to even negative.

In addition, from the analytical results and the 3D figure, one can make some further important observations. First, for a given level of SI, the OP level is always negatively correlated with DU. This is in fact quite consistent with past research findings that DU is a negatively influencing factor to supply chain operational performance (He and Zhao, 2012, Huang et al., 2014). Second, given a fixed value of OP, for example, as a targeted operational performance, the 3D model can be reduced to a model that depicts the relationship between SI and DU. The model clearly shows the level of integration is somewhat negatively correlated with the level of DU. This also is evident in the past research, which shows that when in a marketplace with highly uncertain demand, the supply chain tends to strengthen its flexibility and responsiveness through outsourcing and virtual networks, but with reduced vertical integration (Stratton and Warburton, 2003). Third, given a fixed level of DU, the analytical model tends to show different patterns of relationship between SI and OP.

6.2.3 CI-OP Relationship Subject to DU

In terms of customer integration, ideally, customers are more sensitive than suppliers to DU as they are the front end of the information flow. Information sharing and collaboration across functions and with customers will enhance supply chains' ability to react accurately to a changing market (Jonsson et al., 2011, Zhao et al., 2008), which is what the agile strategy calls for (Gligor et al., 2015, Vazquez-Bustelo et al., 2007) when demand is highly uncertain. On the contrary, a lean strategy would be preferred when demand is stable with predictable conditions. Especially in the context of automotive industry, OEMs usually rely on JIT systems which require more integration with suppliers to deliver the necessary volume of parts (Goldsby et al., 2006, Bennett and Klug, 2012). Within such context, the demand of responsiveness reduces, the benefit from close integration with customers has been submerged by the unappreciated payoff of high transaction cost and thus creates lower operational performance for the OEMs. Therefore, it is expected to achieve a negative effect of CI on OP when DU is low.

Firstly, Figure 31 shows the level of CI is *positively* correlated with the manufacturer's performance, given that the DU is in the 'high uncertain demand' regime. This is consistent with many mainstream research findings in SCI (Prajogo and Olhager, 2012, Jin et al., 2013), although the general condition of highly uncertain demand is not always explicitly discussed. A large body of *agile* supply chain management research also postulates exactly the point that close partnerships and a high level of CI with the first-tier customers contributes positively to the supply chain's overall performance (Jin et al., 2013, Cao et al., 2015).

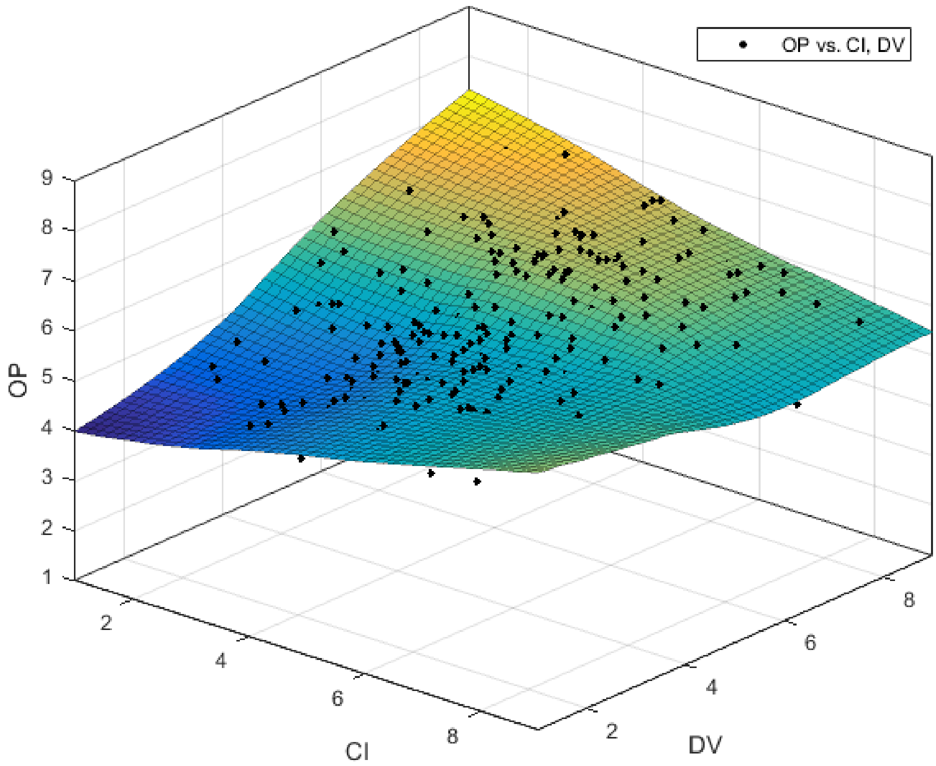

Figure 30 3D plot of the relationship from CI to OP with DU, generated by LOWESS (Locally Weighted Scatterplot Smoothing)

Second, Figure 31 shows the level of CI is slightly *negatively* correlated with the manufacturer's performance, given that the DU is in the 'low uncertain demand' regime. Many existing studies (Rodrigues et al., 2004, Cousins and Menguc, 2006) have also shown that CI does not really help when the supply chain is under a highly demand-predictable place. Instead, they prefer high level of collaboration with suppliers in order to improve the supply chain's cost performance and production quality. Research in the area of lean supply chain also echoed their findings in the same wavelength (Zhang, 2011, Vazquez-Bustelo et al., 2007). In particular, a lean supply chain prefers the management approach through vertical integration rather than virtual network (Agarwal et al., 2006). Transaction cost theory (Williamson, 1981, Parkhe, 1993) has long concluded that predictable demand will lead to higher transaction cost in terms of management effort input and investment on forecasting capability, thus resulting in lower economic performance for the organization if CI is high. It is, therefore, reasonable to argue that when DU is low (i.e. when a supply chain calls for more leanness than agility), a high level of CI can be costly or even detrimental to OP.

Lastly, Figure 18 shows that the relationship between CI and OP is somewhat of a mixture and undefined, given that the DU is in the 'medium uncertain demand' regime. This is consistent with the findings of "leagile" supply chains whereby the demand condition is at its transient level between high and low. Leagile supply chain considers and applies both lean and agile strategies complementarily (Agarwal et al., 2006, Goldsby et al., 2006). The research in this transition region is largely subject to other contingency factors, which could be an area of future work following this research.

6.3 Chapter Conclusion

It is now understood how the exogenous factor – demand uncertainty – moderates the relationship between SCI dimensions and OP. The 3D analytical model seems to be useful in explaining intuitively the inter-play of the key constructs. The 'non-linear' relationship discovered in this study could add to the literature of supply chain integration by explaining analytically how one of the exogenous factors may moderate or control the effect of integration on the operational performance. Furthermore, the seemingly inconsistent findings from past literature, in terms of 'positive', 'distinguished' and 'inverse U-shaped' (see Table 6) can be largely reconciled from the perspective of the moderating effect of exogenous factors; perhaps no one was wrong after all.

The interpretation of the results of this study can also be taken from a structural contingency theory (Sousa and Voss, 2008, Stonebraker and Afifi, 2004) perspective. External fit indicates consistency between an organizational structure and the strategy it pursues in response to its external environment. As its external environment, such as demand uncertainty, changes, a manufacturer should respond by developing, selecting and implementing strategies to maintain fit; not only among internal structural characteristics such as II, but also with its external environment (Hambrick, 1983, Kotha and Nair, 1995, Tushman and Nadler, 1978). This is precisely how this research's results and the analytical model will have implications on real-world business practices.

Chapter 7 Conclusions and Limitations

Recent literature in the subject area was critically reviewed and a number of inconsistencies and research gaps were identified. The goal of this study was to investigate the moderating effect of demand uncertainty on the relationship of supply chain integration and operational performance. Using Chinese automotive industry-based data with 385 valid respondents, this study first empirically examined the direct relationships between SCI dimensions and OP as statistical and logical foundations of the later research. The main goal of this study was reached in the second step by examining the moderating effect of DU. The TRA was used to validate a model of SCI-OP relationships that allows DU's moderating effects. To the author's best knowledge, TRA as the primary method of analysis has been introduced to analyse operation management issues for the first time. By doing so, I also compared the analysing results and model fitness between TRA and the literature-favoured HRA, and the comparison results showed the advanced nature of the TRA model.

7.1 Contribution to the Body of Knowledge

This study makes several empirical contributions to the existing literature. First, this study adds to the literature the moderating effect by empirically testing the relationship between SCI and OP under the influence of DU – an exogenous environmental factor. Second, while DU is an important external factor in supply chain management, this study found that DU moderates the SI-OP and CI-OP relationship, but does not moderate the II-OP relationship. This suggests that DU is necessary for consideration when managing SCI, but not sufficient in all SCI dimensions. Such findings provide empirical support for the proposition that the contribution levels of SI and CI to OP are contingent on the level of DU.

The third contribution lies with the embedding of the moderating effect of DU in the SI-OP and CI-OP relationship analysing models. This study empirically examined the influence of SI and CI to OP based on DU. The results showed that such moderating effects of DU to SI-OP and CI-OP are just the opposite. In particular, a negative SI-OP and positive CI-OP relationships were identified when DU is high, and such relationships switched when DU was low. This provides an SCI configuration approach while considering DU from an overall perspective.

The fourth contribution of this study lies in the analytically established 'non-linear' relationship between SCI and OP by applying, for likely the first time, the TRA method. This study also enriches the growing discussion of SCI in the literature by sharing empirical findings from automotive industries in China.

The fifth contribution of this study can be displayed in the renewed understanding on how SCI may be correlated with OP under the moderating power of DU; and as for the practical implication, one can expect more rational decision making in regard to the supply chain's appropriate level of integration and the desired competitive performance in respect to changing external demand.

7.2 Practical Implications

Based on contingency theory, a supply chain's optimal operational performance is achieved when there is a good fit between integration strategy and the external environment (Cao et al., 2015). Transactions cost theory further explains how managerial costs adjust integration strategy to cope with a changing environment (Makadok, 2001). This study suggests that demand uncertainty only moderates the contribution of external integration to operational performance. In the meantime, when uncertainty is monotonous, there is a trade-off between its moderating effects on the supplier side and customer side. Thus, managerial discretion with respect to addressing demand uncertainty is frequently reflected in supply chain managers' behaviours upon finding an optimal leveraging point within external integrations.

Several studies have stated that extensive integration may result in the loss of strategic competency and may compromise a supply chain's ability to meet its operational goals when demand uncertainty is turbulent (Terjesen et al., 2012). These studies also suggest loosening close and integrated supply chain collaborations by allowing supply chain participants to switch with flexibility, which allows for a rapid response to dynamic market requirements. Conversely, this study indicates that the adjustment of integration strategy depends on the change of overall benefit from integrations, and the overall benefits are associated with changing environmental conditions. Given a certain level of demand uncertainty, to simply enhance or weaken SCI is not an appropriate choice. Supply chain managers should adopt a trade-off strategy that emphasises resource value over integrations to achieve optimal operational performance by sustaining competitive advantage in the long term.

7.3 Research Limitations and Future Directions

This study has one limitation that should be addressed in future, which is that the findings of this study are based on Chinese automotive industry data. The choice to gather data from a single industry rather than mixed industries was done to avoid the potential bias of DU caused by different industrial preferences or features. Future research should gather data from cross rather than multiple industries, which could conduct a comparison study on the moderating effect of DU between different manufacturing industries. This would further validate the research findings.

Another limitation is an omission formed in the survey questionnaire design process. Such omission is a lack of explicit indication to respondents on whether they should respond to the questionnaire statements based on circumstances of their own supply chain or their understandings of automotive supply chains in general. This omission might have led to certain misunderstandings, which might have biased the empirical findings in this study. Future studies should fix this issue by adding a clear statement of the knowledge scope in the survey questionnaire introduction.

Despite the above claims on the research design, inevitable limitations can also be observed. This study used cross-sectional design, and the time dimension was largely ignored. As part of the future research agenda, a longitudinal study that observes the changes of the measures over time would likely shed new light on the SCI-OP relationship.

Future research should also focus on better understanding the measurement of theoretical constructs, given that the measurement validation may vary in different industries or supply chains. Future studies should focus on the following questions: Which measurement is the most effective in a single industry context and a mixed industry context? How can multiple environmental factors be measured in a mixed factor model?

As argued in the literature review chapter, even with the increasing attention that researchers have given to understand the correlation between integration and performance, there has been little research on the moderating effect of the increasingly important environmental factors. This study adds another level of insight about the SCI-OP relationships by considering DU as a moderator that seeks to understand the inter-workings of the constructs. Given the critical importance of demand change in today's business environment, a better understanding of the interaction mechanism which facilitates success in managing and aligning internal and external supply chain integration can contribute to the understanding of how organizations maintain competitive operational performance.

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Appendix A

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
SI2	1	45	4.40	2.005	.299	3.80	5.00	1	7
	2	193	3.97	2.010	.145	3.68	4.25	1	7
	3	192	3.98	1.944	.140	3.70	4.26	1	7
	Total	430	4.02	1.980	.095	3.83	4.21	1	7
SI3	1	45	3.96	1.918	.286	3.38	4.53	1	7
	2	193	3.77	2.005	.144	3.49	4.06	1	7
	3	192	3.91	2.060	.149	3.61	4.20	1	7
	Total	430	3.85	2.018	.097	3.66	4.04	1	7
SI7	1	45	4.42	1.852	.276	3.87	4.98	1	7
	2	193	3.99	2.054	.148	3.70	4.28	1	7
	3	192	4.35	1.881	.136	4.08	4.62	1	7
	Total	430	4.20	1.962	.095	4.01	4.38	1	7
SI8	1	45	4.67	2.011	.300	4.06	5.27	1	7
	2	193	4.16	1.960	.141	3.88	4.43	1	7
	3	192	4.08	1.995	.144	3.79	4.36	1	7
	Total	430	4.17	1.984	.096	3.99	4.36	1	7
SI9	1	45	4.13	1.984	.296	3.54	4.73	1	7
	2	193	4.08	1.981	.143	3.80	4.36	1	7
	3	192	3.91	2.021	.146	3.62	4.19	1	7
	Total	430	4.01	1.997	.096	3.82	4.20	1	7
SI11	1	45	4.09	1.893	.282	3.52	4.66	1	7
	2	193	4.00	2.008	.145	3.71	4.29	1	7
	3	192	4.23	2.029	.146	3.95	4.52	1	7
	Total	430	4.11	2.004	.097	3.92	4.30	1	7
SI12	1	45	4.53	1.817	.271	3.99	5.08	1	7
	2	193	4.29	2.046	.147	4.00	4.58	1	7
	3	192	4.07	2.050	.148	3.78	4.36	1	7
	Total	430	4.22	2.026	.098	4.03	4.41	1	7
SI13	1	45	3.78	2.044	.305	3.16	4.39	1	7
	2	193	3.69	2.066	.149	3.40	3.98	1	7
	3	192	3.81	2.023	.146	3.52	4.10	1	7
	Total	430	3.75	2.041	.098	3.56	3.94	1	7
CI2	1	45	4.00	2.011	.300	3.40	4.60	1	7
	2	193	3.89	2.068	.149	3.60	4.18	1	7
	3	192	4.01	1.964	.142	3.73	4.28	1	7
	Total	430	3.95	2.012	.097	3.76	4.14	1	7
CI4	1	45	4.07	2.178	.325	3.41	4.72	1	7
	2	193	3.89	2.055	.148	3.60	4.18	1	7
	3	192	3.94	2.121	.153	3.64	4.24	1	7
	Total	430	3.93	2.093	.101	3.73	4.13	1	7
CI5	1	45	4.18	1.992	.297	3.58	4.78	1	7
	2	193	3.90	2.061	.148	3.60	4.19	1	7
	3	192	4.16	2.071	.149	3.86	4.45	1	7
	Total	430	4.04	2.058	.099	3.85	4.24	1	7
CI7	1	45	4.13	1.804	.269	3.59	4.68	1	7
	2	193	3.99	1.947	.140	3.71	4.27	1	7
	3	192	4.13	1.949	.141	3.85	4.41	1	7
	Total	430	4.07	1.931	.093	3.88	4.25	1	7
CI8	1	45	4.31	1.856	.277	3.75	4.87	1	7
	2	193	3.96	1.972	.142	3.68	4.24	1	7
	3	192	3.79	1.947	.141	3.51	4.06	1	7
	Total	430	3.92	1.951	.094	3.74	4.11	1	7
CI9	1	45	4.09	2.043	.305	3.48	4.70	1	7
	2	193	4.06	1.828	.132	3.80	4.32	1	7
	3	192	3.73	1.984	.143	3.45	4.02	1	7
	Total	430	3.92	1.924	.093	3.74	4.10	1	7

CI10	1	45	3.84	2.044	.305	3.23	4.46	1	7
	2	193	4.04	2.080	.150	3.74	4.33	1	7
	3	192	3.91	1.993	.144	3.62	4.19	1	7
	Total	430	3.96	2.034	.098	3.77	4.15	1	7
II1	1	45	3.64	2.058	.307	3.03	4.26	1	7
	2	193	4.00	1.876	.135	3.73	4.27	1	7
	3	192	4.24	2.205	.159	3.93	4.55	1	7
	Total	430	4.07	2.052	.099	3.88	4.26	1	7
II2	1	45	4.07	2.230	.332	3.40	4.74	1	7
	2	193	4.18	1.967	.142	3.90	4.46	1	7
	3	192	4.06	2.039	.147	3.77	4.35	1	7
	Total	430	4.11	2.024	.098	3.92	4.31	1	7
II4	1	45	4.33	2.216	.330	3.67	5.00	1	7
	2	193	3.87	2.044	.147	3.58	4.16	1	7
	3	192	3.78	1.889	.136	3.51	4.04	1	7
	Total	430	3.87	1.997	.096	3.69	4.06	1	7
II5	1	45	3.69	2.141	.319	3.05	4.33	1	7
	2	193	4.01	1.934	.139	3.74	4.28	1	7
	3	192	4.21	1.979	.143	3.93	4.50	1	7
	Total	430	4.07	1.978	.095	3.88	4.25	1	7
II7	1	45	3.62	1.898	.283	3.05	4.19	1	7
	2	193	4.04	2.015	.145	3.76	4.33	1	7
	3	192	4.06	1.950	.141	3.78	4.33	1	7
	Total	430	4.00	1.974	.095	3.82	4.19	1	7
II8	1	45	4.04	2.011	.300	3.44	4.65	1	7
	2	193	3.88	2.052	.148	3.59	4.17	1	7
	3	192	4.04	2.061	.149	3.75	4.34	1	7
	Total	430	3.97	2.049	.099	3.78	4.16	1	7
OP1	1	45	3.80	2.128	.317	3.16	4.44	1	7
	2	193	4.11	2.014	.145	3.82	4.39	1	7
	3	192	3.75	2.057	.148	3.46	4.04	1	7
	Total	430	3.92	2.048	.099	3.72	4.11	1	7
OP2	1	45	3.82	2.092	.312	3.19	4.45	1	7
	2	193	4.08	1.928	.139	3.80	4.35	1	7
	3	192	4.22	1.991	.144	3.94	4.50	1	7
	Total	430	4.11	1.973	.095	3.93	4.30	1	7
OP3	1	45	3.98	2.072	.309	3.36	4.60	1	7
	2	193	4.07	2.039	.147	3.78	4.36	1	7
	3	192	4.10	2.026	.146	3.82	4.39	1	7
	Total	430	4.07	2.032	.098	3.88	4.27	1	7
OP4	1	45	3.49	2.107	.314	2.86	4.12	1	7
	2	193	4.21	2.024	.146	3.93	4.50	1	7
	3	192	3.97	1.850	.134	3.71	4.23	1	7
	Total	430	4.03	1.965	.095	3.84	4.21	1	7
OP5	1	45	3.64	2.134	.318	3.00	4.29	1	7
	2	193	4.13	2.075	.149	3.84	4.43	1	7
	3	192	4.11	1.948	.141	3.83	4.39	1	7
	Total	430	4.07	2.026	.098	3.88	4.26	1	7
DU1	1	45	3.71	1.804	.269	3.17	4.25	1	7
	2	193	3.98	2.022	.146	3.70	4.27	1	7
	3	192	4.07	1.992	.144	3.78	4.35	1	7
	Total	430	3.99	1.985	.096	3.80	4.18	1	7
DU2	1	45	4.13	2.018	.301	3.53	4.74	1	7
	2	193	4.23	2.011	.145	3.95	4.52	1	7
	3	192	4.01	2.036	.147	3.72	4.30	1	7
	Total	430	4.12	2.021	.097	3.93	4.31	1	7
DU3	1	45	3.87	1.890	.282	3.30	4.43	1	7
	2	193	3.96	2.109	.152	3.66	4.26	1	7
	3	192	4.23	1.992	.144	3.95	4.51	1	7
	Total	430	4.07	2.036	.098	3.88	4.26	1	7
DU4	1	45	4.04	1.809	.270	3.50	4.59	1	7
	2	193	3.82	1.918	.138	3.55	4.10	1	7
	3	192	3.99	2.071	.149	3.70	4.29	1	7
	Total	430	3.92	1.974	.095	3.74	4.11	1	7

Appendix B

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
SI2	Between Groups	7.321	2	3.661	.933	.394
	Within Groups	1674.530	427	3.922		
	Total	1681.851	429			
SI3	Between Groups	2.282	2	1.141	.279	.756
	Within Groups	1744.193	427	4.085		
	Total	1746.474	429			
SI7	Between Groups	15.014	2	7.507	1.959	.142
	Within Groups	1636.577	427	3.833		
	Total	1651.591	429			
SI8	Between Groups	12.754	2	6.377	1.625	.198
	Within Groups	1675.165	427	3.923		
	Total	1687.919	429			
SI9	Between Groups	3.632	2	1.816	.454	.635
	Within Groups	1707.347	427	3.998		
	Total	1710.979	429			
SI11	Between Groups	5.319	2	2.659	.661	.517
	Within Groups	1718.098	427	4.024		
	Total	1723.416	429			
SI12	Between Groups	9.521	2	4.760	1.160	.314
	Within Groups	1751.930	427	4.103		
	Total	1761.451	429			
SI13	Between Groups	1.380	2	.690	.165	.848
	Within Groups	1784.995	427	4.180		
	Total	1786.374	429			
CI2	Between Groups	1.360	2	.680	.167	.846
	Within Groups	1735.710	427	4.065		
	Total	1737.070	429			
CI4	Between Groups	1.142	2	.571	.130	.878
	Within Groups	1878.765	427	4.400		
	Total	1879.907	429			
CI5	Between Groups	7.429	2	3.714	.876	.417
	Within Groups	1809.818	427	4.238		
	Total	1817.247	429			
CI7	Between Groups	2.120	2	1.060	.283	.753
	Within Groups	1596.924	427	3.740		
	Total	1599.044	429			
CI8	Between Groups	10.676	2	5.338	1.405	.247
	Within Groups	1622.635	427	3.800		
	Total	1633.312	429			
CI9	Between Groups	11.800	2	5.900	1.598	.203
	Within Groups	1576.351	427	3.692		
	Total	1588.151	429			
CI10	Between Groups	2.277	2	1.138	.274	.760
	Within Groups	1772.970	427	4.152		
	Total	1775.247	429			
II1	Between Groups	14.617	2	7.308	1.742	.176
	Within Groups	1791.290	427	4.195		
	Total	1805.907	429			
II2	Between Groups	1.594	2	.797	.194	.824
	Within Groups	1755.823	427	4.112		
	Total	1757.416	429			
II4	Between Groups	11.351	2	5.676	1.426	.241
	Within Groups	1699.867	427	3.981		
	Total	1711.219	429			
II5	Between Groups	11.176	2	5.588	1.431	.240
	Within Groups	1667.869	427	3.906		
	Total	1679.044	429			
II7	Between Groups	7.375	2	3.687	.946	.389
	Within Groups	1664.616	427	3.898		

	Total	1671.991	429			
II8	Between Groups	2.770	2	1.385	.329	.720
	Within Groups	1797.837	427	4.210		
	Total	1800.607	429			
OP1	Between Groups	13.071	2	6.536	1.563	.211
	Within Groups	1785.915	427	4.182		
	Total	1798.986	429			
OP2	Between Groups	6.192	2	3.096	.795	.452
	Within Groups	1663.224	427	3.895		
	Total	1669.416	429			
OP3	Between Groups	.600	2	.300	.072	.930
	Within Groups	1771.019	427	4.148		
	Total	1771.619	429			
OP4	Between Groups	20.318	2	10.159	2.653	.072
	Within Groups	1635.347	427	3.830		
	Total	1655.665	429			
OP5	Between Groups	9.253	2	4.627	1.128	.325
	Within Groups	1751.512	427	4.102		
	Total	1760.765	429			
DU1	Between Groups	4.661	2	2.331	.590	.555
	Within Groups	1686.318	427	3.949		
	Total	1690.979	429			
DU2	Between Groups	4.781	2	2.390	.584	.558
	Within Groups	1747.687	427	4.093		
	Total	1752.467	429			
DU3	Between Groups	9.122	2	4.561	1.101	.333
	Within Groups	1768.785	427	4.142		
	Total	1777.907	429			
DU4	Between Groups	3.551	2	1.776	.454	.635
	Within Groups	1668.916	427	3.908		
	Total	1672.467	429			

Appendix C

Multiple Comparisons

Bonferroni

Dependent Variable	(I) group	(J) group	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
SI2	1	2	.431	.328	.568	-.36	1.22
		3	.421	.328	.600	-.37	1.21
	2	1	-.431	.328	.568	-1.22	.36
		3	-.010	.202	1.000	-.50	.47
	3	1	-.421	.328	.600	-1.21	.37
		2	.010	.202	1.000	-.47	.50
SI3	1	2	.184	.335	1.000	-.62	.99
		3	.049	.335	1.000	-.76	.85
	2	1	-.184	.335	1.000	-.99	.62
		3	-.134	.206	1.000	-.63	.36
	3	1	-.049	.335	1.000	-.85	.76
		2	.134	.206	1.000	-.36	.63
SI7	1	2	.433	.324	.548	-.35	1.21
		3	.073	.324	1.000	-.71	.85
	2	1	-.433	.324	.548	-1.21	.35
		3	-.359	.200	.217	-.84	.12
	3	1	-.073	.324	1.000	-.85	.71
		2	.359	.200	.217	-.12	.84
SI8	1	2	.511	.328	.359	-.28	1.30
		3	.589	.328	.221	-.20	1.38
	2	1	-.511	.328	.359	-1.30	.28
		3	.077	.202	1.000	-.41	.56
	3	1	-.589	.328	.221	-1.38	.20
		2	-.077	.202	1.000	-.56	.41
SI9	1	2	.056	.331	1.000	-.74	.85
		3	.227	.331	1.000	-.57	1.02
	2	1	-.056	.331	1.000	-.85	.74
		3	.171	.204	1.000	-.32	.66
	3	1	-.227	.331	1.000	-1.02	.57
		2	-.171	.204	1.000	-.66	.32
SI11	1	2	.089	.332	1.000	-.71	.89
		3	-.145	.332	1.000	-.94	.65
	2	1	-.089	.332	1.000	-.89	.71
		3	-.234	.204	.757	-.73	.26
	3	1	.145	.332	1.000	-.65	.94
		2	.234	.204	.757	-.26	.73
SI12	1	2	.243	.335	1.000	-.56	1.05
		3	.460	.335	.512	-.35	1.27
	2	1	-.243	.335	1.000	-1.05	.56
		3	.217	.206	.880	-.28	.71
	3	1	-.460	.335	.512	-1.27	.35
		2	-.217	.206	.880	-.71	.28
SI13	1	2	.089	.338	1.000	-.72	.90
		3	-.030	.339	1.000	-.84	.78
	2	1	-.089	.338	1.000	-.90	.72
		3	-.118	.208	1.000	-.62	.38
	3	1	.030	.339	1.000	-.78	.84
		2	.118	.208	1.000	-.38	.62
CI2	1	2	.109	.334	1.000	-.69	.91
		3	-.005	.334	1.000	-.81	.80
	2	1	-.109	.334	1.000	-.91	.69
		3	-.114	.206	1.000	-.61	.38
	3	1	.005	.334	1.000	-.80	.81
		2	.114	.206	1.000	-.38	.61
CI4	1	2	.175	.347	1.000	-.66	1.01
		3	.129	.347	1.000	-.71	.96

	2	1	-.175	.347	1.000	-1.01	.66
		3	-.046	.214	1.000	-.56	.47
	3	1	-.129	.347	1.000	-.96	.71
		2	.046	.214	1.000	-.47	.56
CI5	1	2	.281	.341	1.000	-.54	1.10
		3	.022	.341	1.000	-.80	.84
	2	1	-.281	.341	1.000	-1.10	.54
		3	-.260	.210	.649	-.76	.24
	3	1	-.022	.341	1.000	-.84	.80
		2	.260	.210	.649	-.24	.76
CI7	1	2	.144	.320	1.000	-.63	.91
		3	.003	.320	1.000	-.77	.77
	2	1	-.144	.320	1.000	-.91	.63
		3	-.141	.197	1.000	-.61	.33
	3	1	-.003	.320	1.000	-.77	.77
		2	.141	.197	1.000	-.33	.61
CI8	1	2	.347	.323	.847	-.43	1.12
		3	.525	.323	.315	-.25	1.30
	2	1	-.347	.323	.847	-1.12	.43
		3	.177	.199	1.000	-.30	.65
	3	1	-.525	.323	.315	-1.30	.25
		2	-.177	.199	1.000	-.65	.30
CI9	1	2	.027	.318	1.000	-.74	.79
		3	.355	.318	.798	-.41	1.12
	2	1	-.027	.318	1.000	-.79	.74
		3	.328	.196	.285	-.14	.80
	3	1	-.355	.318	.798	-1.12	.41
		2	-.328	.196	.285	-.80	.14
CI10	1	2	-.192	.337	1.000	-1.00	.62
		3	-.062	.337	1.000	-.87	.75
	2	1	.192	.337	1.000	-.62	1.00
		3	.130	.208	1.000	-.37	.63
	3	1	.062	.337	1.000	-.75	.87
		2	-.130	.208	1.000	-.63	.37
II1	1	2	-.356	.339	.885	-1.17	.46
		3	-.595	.339	.240	-1.41	.22
	2	1	.356	.339	.885	-.46	1.17
		3	-.240	.209	.755	-.74	.26
	3	1	.595	.339	.240	-.22	1.41
		2	.240	.209	.755	-.26	.74
II2	1	2	-.115	.336	1.000	-.92	.69
		3	.009	.336	1.000	-.80	.82
	2	1	.115	.336	1.000	-.69	.92
		3	.124	.207	1.000	-.37	.62
	3	1	-.009	.336	1.000	-.82	.80
		2	-.124	.207	1.000	-.62	.37
II4	1	2	.468	.330	.472	-.33	1.26
		3	.557	.330	.277	-.24	1.35
	2	1	-.468	.330	.472	-1.26	.33
		3	.089	.203	1.000	-.40	.58
	3	1	-.557	.330	.277	-1.35	.24
		2	-.089	.203	1.000	-.58	.40
II5	1	2	-.321	.327	.979	-1.11	.46
		3	-.525	.327	.329	-1.31	.26
	2	1	.321	.327	.979	-.46	1.11
		3	-.203	.201	.941	-.69	.28
	3	1	.525	.327	.329	-.26	1.31
		2	.203	.201	.941	-.28	.69
II7	1	2	-.419	.327	.601	-1.20	.37
		3	-.435	.327	.552	-1.22	.35
	2	1	.419	.327	.601	-.37	1.20
		3	-.016	.201	1.000	-.50	.47
	3	1	.435	.327	.552	-.35	1.22
		2	.016	.201	1.000	-.47	.50
II8	1	2	.164	.340	1.000	-.65	.98
		3	.003	.340	1.000	-.81	.82

	2	1	-.164	.340	1.000	-.98	.65
		3	-.161	.209	1.000	-.66	.34
	3	1	-.003	.340	1.000	-.82	.81
		2	.161	.209	1.000	-.34	.66
OP1	1	2	-.309	.339	1.000	-1.12	.50
		3	.050	.339	1.000	-.76	.86
	2	1	.309	.339	1.000	-.50	1.12
		3	.359	.208	.258	-.14	.86
	3	1	-.050	.339	1.000	-.86	.76
		2	-.359	.208	.258	-.86	.14
OP2	1	2	-.255	.327	1.000	-1.04	.53
		3	-.397	.327	.677	-1.18	.39
	2	1	.255	.327	1.000	-.53	1.04
		3	-.141	.201	1.000	-.62	.34
	3	1	.397	.327	.677	-.39	1.18
		2	.141	.201	1.000	-.34	.62
OP3	1	2	-.090	.337	1.000	-.90	.72
		3	-.126	.337	1.000	-.94	.68
	2	1	.090	.337	1.000	-.72	.90
		3	-.037	.208	1.000	-.54	.46
	3	1	.126	.337	1.000	-.68	.94
		2	.037	.208	1.000	-.46	.54
OP4	1	2	-.724	.324	.078	-1.50	.06
		3	-.480	.324	.418	-1.26	.30
	2	1	.724	.324	.078	-.06	1.50
		3	.244	.199	.668	-.24	.72
	3	1	.480	.324	.418	-.30	1.26
		2	-.244	.199	.668	-.72	.24
OP5	1	2	-.490	.335	.433	-1.30	.32
		3	-.465	.335	.499	-1.27	.34
	2	1	.490	.335	.433	-.32	1.30
		3	.025	.206	1.000	-.47	.52
	3	1	.465	.335	.499	-.34	1.27
		2	-.025	.206	1.000	-.52	.47
DU1	1	2	-.273	.329	1.000	-1.06	.52
		3	-.357	.329	.838	-1.15	.43
	2	1	.273	.329	1.000	-.52	1.06
		3	-.083	.203	1.000	-.57	.40
	3	1	.357	.329	.838	-.43	1.15
		2	.083	.203	1.000	-.40	.57
DU2	1	2	-.100	.335	1.000	-.90	.71
		3	.123	.335	1.000	-.68	.93
	2	1	.100	.335	1.000	-.71	.90
		3	.223	.206	.842	-.27	.72
	3	1	-.123	.335	1.000	-.93	.68
		2	-.223	.206	.842	-.72	.27
DU3	1	2	-.092	.337	1.000	-.90	.72
		3	-.363	.337	.848	-1.17	.45
	2	1	.092	.337	1.000	-.72	.90
		3	-.271	.207	.578	-.77	.23
	3	1	.363	.337	.848	-.45	1.17
		2	.271	.207	.578	-.23	.77
DU4	1	2	.221	.327	1.000	-.57	1.01
		3	.050	.327	1.000	-.74	.84
	2	1	-.221	.327	1.000	-1.01	.57
		3	-.171	.202	1.000	-.66	.31
	3	1	-.050	.327	1.000	-.84	.74
		2	.171	.202	1.000	-.31	.66

Appendix D

Questionnaire BSREC Reference: REGO-2016-1770

Approximately, what is the annual revenue of your firm?

Annual revenue (billion yuan)	Please choose one
10-20	
20-40	
40-60	
60-100	
>100	

Approximately, how many full-time employees work for your company______?

Internal integration. Please indicate the degree of integration in the following areas (1 = not at all; 7 = extensive)

II1	Data integration among internal functions.	
II2	Enterprise application integration among internal functions.	
II4	Real-time searching of logistics-related operating data.	
II5	Real-time searching of the level of inventory.	
II7	The use of cross functional teams in process improvement.	
II8	The use of cross functional teams in new product development.	

Supplier integration. Please indicate the extent of integration or joint activities or information sharing between your organization and your major 1st-tier supplier in the following areas (1 = not at all; 7 = extensive)

SI2	The level of establishment of quick ordering systems with our major supplier	
SI2	The level of strategic partnership with our major supplier	
SI7	Our major supplier shares their production schedule with us.	
SI8	Our major supplier shares available inventory with us.	
SI9	Our major supplier shares their production capacity with us.	
SI11	We share our demand forecasts with our major supplier.	
SI12	We share our inventory levels with our major supplier.	
SI13	We help our major supplier to improve its process to better meet our needs.	

Customer integration. Please indicate the extent of integration or joint activities or information sharing between your organization and your major 1st-tier customer in the following areas (1 = not at all; 7 = extensive)

CI2	The level of computerization for our major customer through information networks.	
CI4	The level of communication with our major customer.	
CI5	The establishment of quick ordering system with our major customer	
CI7	The frequency of period contacts with our major customer.	
CI8	Our major customer share point of sales information with us.	
CI9	Our major supplier shares demand forecast with us.	
CI10	We share our available inventory with our customer.	

Operational performance. Please indicate the degree to which you agree to the following statements concerning your company's performance with respect to your major customer (1 = strongly disagree; 7 = strongly agree)

OP1	Our company can quickly modify your products to meet your customer's requirement	
OP2	Our company can quickly introduce new products into the market	
OP3	Our company can quickly respond to the changes in the market	
OP4	Our company has an outstanding on-time delivery record to our major customer.	
OP5	The lead time for fulfilling customers' orders (the time which elapses between the receipt of customer's order and the delivery of the goods) is short.	

Demand Uncertainty. Please indicate the degree to which you agree to the following statements concerning the demand uncertainty with respect to your primary/major products (1 = strongly disagree; 7 = strongly agree)

DU1	The market order for your major products is stable	
DU2	Your product sales volume over different seasons in a year is predictable	
DU3	Core technologies for the products' features and functions are always known	
DU4	The major product life cycle over different seasons and over years is stable	

Appendix E

Questionnaire Simplified Chinese Version

您所在的公司大约的年收入为多少？

年收入 （亿元)	请选择
10-20	
20-40	
40-60	
60-100	
>100	

您所在的公司大约有多少雇员______?

内部整合： 请指出在以下方面内部整合的程度 (1 = 非常低; 7 = 非常高)

II1	多部门间的数据整合	
II2	多部门间的企业应用程序整合	
II4	与物流相关的运营数据的实时读取	
II5	仓储量的实时读取	
II7	多部门小组成员参与的流程优化	
II8	多部门小组成员参与的新产品开发	

供应商整合： 请指出在以下方面贵公司对一级供应商的整合程度，联合运营程度，或信息共享程度 (1 = 非常低; 7 = 非常高)

SI2	与我们主要供应商之间建立的快速订单系统的程度	
SI2	与我们主要供应商之间的战略合作关系程度	
SI7	我们的主要供应商与我们分享其生产计划	
SI8	我们的主要供应商与我们分享其可用库存	
SI9	我们的主要供应商与我们分享其生产力	
SI11	我们与主要供应商分享需求预测	
SI12	我们与主要供应商分享库存程度.	
SI13	我们帮助我们的主要供应商优化流程来更好的满足我们的需要	

客户整合： 请指出在以下方面贵公司对一级客户的整合程度，联合运营程度，或信息共享程度 (1 = 非常低; 7 = 非常高)

CI2	与我们主要的客户间通过信息网络实现电算化的程度	
CI4	与我们主要的客户沟通的程度	
CI5	与我们主要客户之间建立的快速订单系统的程度	
CI7	与我们主要的客户联系的频率	
CI8	我们的主要客户与我们分享其销售点信息	
CI9	我们的主要客户与我们分享其需求预测	
CI10	我们与主要客户分享可用库存	

经营绩效： 请指出您对于以下关于贵公司与客户相关的经营绩效的阐述的认可程度 (1 = 非常不认可; 7 = 非常认可)

OP1	我们公司可以快速调整产品以适应客户需求	
OP2	我们公司可以快速向市场推出新产品	
OP3	我们公司可以快速响应市场变化	
OP4	我们公司对主要客户有出色的按时交货记录.	
OP5	对于客户订单的交付周期很短（周期指从接到客户订单至产品送达的时间段）	

需求不确定性: 请指出您对于以下关于贵公司主要产品的需求不确定性的阐述的认可程度 (1 = 非常不认可; 7 = 非常认可)

DU1	贵公司主要产品的市场订单量是稳定的	
DU2	贵公司产品销量在不同季节内是可预测的	
DU3	贵公司掌握产品的核心技术	
DU4	主要产品的生命周期在不同季节与不同年份间是稳定的	