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ORIGINAL ARTICLE

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

Dawei Lu[1] · Yi Ding[1] · Sobhan Asian[2] · Sanjoy Kumar Paul[3]

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Abstract *This research examines the moderating effect of market uncertainty on the causal effects from supply chain integration to operational performance of a typical supply chain. Based on an extensive and critical literature review, two exploratory conceptual hypotheses have been developed for the nonlinear relationship between the supply chain integration and operational performance of the original equipment manufacturer, and how may that relationship be moderated by a specific construct of market uncertainty. Empirical survey instrument has been designed and applied to gather the data from a wide spectrum of automotive industry in China. Confirmative factor analysis and threshold regression analysis were used as the primary research methodology to test the hypotheses. We find strong support to the hypotheses from the empirical evidence, which leads to the finding that the relationship between the supply chain integration and operational performance is 'nonlinear', and the 'nonlinearity' can be significantly moderated by the market uncertainty as one of the key environmental factors for the supply chain. This study extends the current literature by contributing for the first time the discussion of an analytical model that represents the causal effects from supply chain integration to its operational performance with respect to the market uncertainty as a moderating factor.*

Keywords Automotive industry · Market uncertainty · Operational performance · Supply chain integration · Supply chain management

Introduction

Researchers have long articulated the necessity of a close integration between manufacturers and their suppliers and customers in attempt to deliver the supply chain's optimum performance (Tavakoli et al. 2012; Flynn et al. 2010; Turkulainen and Ketokivi 2012; Zhao et al. 2013; Huang et al. 2014; Prajogo et al. 2015). The degree of interactions between the participating member of the supply chain and the appropriate inter-relationship postures have become the widely acknowledged key enablers for supply chain success (Tyagi et al. 2015). Supply chain integration and its processes that help to develop high level collaboration and partnership with supplier and buyer have been regarded as the undisputable factors for supply chain success (Droge et al. 2012; Wilden et al. 2013). However, with the increased supply chain complexity and sprawling global diversity over the last decade, there has been a call to rethink the universal necessity as well as the theoretical validity of supply chain integration (SCI) under the renewed business environment in respect to its highly acclaimed contribution to the supply chain's competitive performance (Lambert and Cooper 2000; Asian et al. 2009;

✉ Sobhan Asian
sobhan.asian@rmit.edu.au

Dawei Lu
d.lu@warwick.ac.uk

Yi Ding
Yi.Ding@warwick.ac.uk

Sanjoy Kumar Paul
sanjoy.paul@uts.edu.au

[1] WMG, University of Warwick, Coventry CV4 7AL, UK

[2] College of Business, RMIT University, Melbourne, VIC 3000, Australia

[3] UTS Business School, University of Technology Sydney, Sydney, Australia

Liu and Cruz 2012; Huang et al. 2014; Prajogo et al. 2015; Sharifkhani et al. 2016; Somarin et al. 2017a).

We argue that it is far from being certain that the level of the SCI integration will always be positively correlated with the optimum performance (Graham et al. 2005; Wook Kim 2006; Kim 2009). However, evidently, many previous researches appear to have been inconsistent or even conflicting with one another about their findings (Devaraj et al. 2007; Gimenez et al. 2012; Sousa et al. 2012). However, some of the findings on such positive relationship might be assumed to be restricted to certain specific conditions (Cao et al. 2015; Ebrahimi 2015), many others were intended to be general on their findings (Bowersox et al. 1999). No one, however, appear to have attempted any form of *analytical model* to depict the inter-play of supply chain integration (SCI), operational performance (OP) along with exogenous control factors in the business environment. Without an analytical model, the research findings on the relationship between SCI and other constructs often 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 to the problem than a *formative evaluation*.

Extant literature also indicates that the level of SCI and its contribution to the manufacturer's performance are subject to the influence of various exogenous and endogenous factors (Turkulainen 2008; Wong et al. 2011c; Gimenez et al. 2012). In particular, the recent advent of the open-source information system has made SCI and its influence to supply chain performance more susceptible to the exogenous factors (Boehmke and Hazen 2017). These factors may include ones such as competitiveness of the supply chain's product; market uncertainty; national culture, technological environment; and even organisational characteristics. What may be agreeable without being taken into too much controversy is that any attempt to construct a universally applicable relationship/correlation model between SCI and OP is likely to be doomed theoretically. However, what has not been agreed, or still remain inconclusive, is that *how* the relationship between SCI and OP may be influenced and by *which* factors (Van der Vaart and van Donk 2008). This inconclusiveness therefore logically gives rise to the research gap in the SCI related subject areas.

In the light of addressing the research problem raised, the intention of this study is to take a small step forward but in the right direction towards addressing the problem. We define a manageable scope that covers only three key constructs: SCI, OP and *Market Uncertainty* (MU), and attempt to model the relationship in between them analytically. The validity of our choices of the three key constructs for the study will be discussed in the next section.

Thus, the objective of this study is to revisit the causal relationship between the supply chain integration (SCI) and the manufacturer's operational performance (OP) under the full spectrum of market uncertainty (MU) as the exogenous moderating factor, and by using an empirical instrument to create an analytical model that further depicts and explains the inter-play of those three constructs. The *unit of analysis* of this study is defined as the manufacturer that acts as the OEM (original Equipment Manufacturer) in the supply chain. The focus is pitched at the dynamic relationship between SCI and OP.

Our research starts with the identification of the research problems through literature review. Based on some further synthesising of a cluster of more relevant literatures, hypotheses have been developed to attempt a conceptual advancement in terms of the relationship between SCI and OP under the influencing factor of market uncertainty (MU). To rigorously test the hypotheses, the threshold regression methodology has been applied on to the empirically collected data from selected companies in the Chinese automotive industry. Finally, some concluding remarks are drawn from the discussion of the findings.

Despite the acclaimed theoretical contribution, the research is also intended to benefit the front line practitioner by guiding them to anticipate varied levels of performance effects on supply chain integration, which are dependent on the moderating effect of the market uncertainty they are facing. The research finding could also offer some pragmatic guidance on how to achieve performance oriented supply chain integration.

The remainder of the paper is organised as follows. "Theoretical background" section illustrates the theoretical background of the issues in concern and lead to a number of identified research gaps, based on which two hypotheses have been developed. "Research methodology" section is devoted to the choice and description of the methodology applied, including questionnaire design, data collection and data validation, threshold regression process. "Results" section shows the detailed quantitative results from the threshold regress processes. "Discussion" section discussed results in respect to the hypotheses and clarifies the key findings. Finally, in "Conclusions and limitations" section, a number of conclusions are drawn, whereby the novelty and value of the research are further underlined.

Theoretical Background

Supply Chain Integration (SCI)

Supply chain integration (SCI) is one of the widely researched topics in the field of supply chain management. All researchers seem to have agreed that SCI is a critical construct that has profound implication to the manufacturer's performance (Huo 2012; Prajogo and Olhager 2012; Turkulainen and Ketokivi 2012; Zhao et al. 2013; Huang et al. 2014; Ebrahimi 2015). Most researchers seem to have subscribed the concept that SCI promotes positively the supply chain competitive strength and sustainable growth (Rai et al. 2006; Won Lee et al. 2007; Huo 2012). However, literature evidences also show that there are still disputes, including those around its basic definitions. Some define the SCI as the integration between the manufacturer and its suppliers (Huang et al. 2014), others define it as the manufacturer's external integration that includes supplier and customer (Huo 2012), and yet others define it in the three dimensions of supplier integration, internal integration and customer integration (Flynn et al. 2010). Some researches focus on the individual component dimension of the SCI (Graham et al. 2005), and the others focus on the SCI as a single overarching construct (Rai et al. 2006). Notwithstanding the merits of each of those arguments, we choose the definition offered by Flynn et al. (2010), which constitutes supplier, internal, and customer integrations. Subsequently, our empirical data collection on the measurement indicators/variables of SCI will be targeted at those three dimensions accordingly.

Knowing full well that there have been different approaches towards the modelling of SCI, our choice to emphasise on a single latent factor for SCI does not necessarily contravene with the researches that prefer to focus on the individual sub-level components of the SCI. It is the matter of research preferences as far as the literature appears to demonstrate. Both approaches have their merits. We argue that the diverse dimensions of SCI and a multitude of measures of SCI can ultimately be represented by a latent factor (still call it SCI in our model later), which is a relatively convenient way for the investigation. Such a '*dimensional reduction*' approach in conceptual modelling has been proven effective in many past researches (Schreiber et al. 2006; Coleman 2011; Brown 2015).

Operational Performance (OP)

Operational performance (OP) is a key enabler to the overall supply chain performance, which usually is the amalgamated outcome from multiple factors and enablers in the system. Van Hoek (1998) and Beamon (1999) suggested that performance measures for a supply chain should include indicators in the operational dimension, such as customer satisfaction and the operational responsiveness to the changing market demand. Similarly, Neely et al. (1995) enlisted cost, time, quality, delivery and flexibility as the basic measures of operational performance. While addressing the needs for supply chains to balance their attention to the environmental concerns, Jakhar (2014) developed a green supply chain operational performance framework.

We choose *OP* as one of the constructs for this study for two reasons. One is because we see strong evidence that OP is a major enabler of supply chain performance, which draws great deal of attentions from the research community (Devaraj et al. 2007; Wong et al. 2011a); the other is because OP is a measurable construct, which could be influenced by the level of SCI. Furthermore, there is little doubt that OP is a critical and indispensable part of many performance measurement frameworks witnessed in today's literature (Yu et al. 2014; Ebrahimi 2015), albeit their findings are not always consistent with each other.

One may question why not use 'business performance' or 'supply chain performance' instead? Well, 'business performance' involves more environmental influences, including competitors, and infrastructure (Goldman and Nagel 1995), while OP is more internal and can be isolated relatively neatly to the effects from SCI. For 'supply chain performance', it is somewhat beyond our defined 'unit of analysis', which is the manufacturer; also the conceptual scope of 'supply chain performance' can be ambiguous and blurry. However, we admit, for the purpose of this study, that more constructs can be and should be explored in the future.

Market Uncertainty (MU)

Contingency theory (Lawrence and Lorsch 1967; Thompson 1967) suggests that no theoretical models can possibly be universally true at all time. There will be no one-size-fits-all solution to supply chain development (Scott and Cole 2000). Hence, one can deduce that the relationship model of SCI with OP may never exist until or unless we apply one or more contingency conditions. The contingency theory may have also explained why many relationship models between SCI and OP are apparently conflicting with each other (Wong et al. 2011b). Thus, for this study, the causal relationship between SCI and OP is to be researched under the specific moderating effect of an external contingency factor—*market uncertainty* (MU).

For the purpose of this study, MU as one of the environmental factors appears to have high priority among the others. Automotive industry in China, in particular, faces strategic and operational challenges due to the increased market uncertainty in the recent years (Somarin et al. 2016, 2017b; Faghih-Roohi et al. 2016; Asian et al. 2016; Asian and Nie 2014, Ansaripoor et al. 2017; Paul et al. 2017). Shalender and Singh (2015) proposed conceptual framework to address the critical significance of market uncertainty and how company should respond to it flexibly, especially in the automotive industries. Diverse product ranges receive a wide spectrum of domestic market responses. Some can be categorised as the stable markets, others dynamic ones, subject to the stage of product life cycle and/or consumer market segmentation (Lockstroem et al. 2010). Evidently, MU has become one of the key variables that influence the supply chain strategy and operational performances.

To develop a conceptual framework that encapsulates the above-mentioned three key constructs, we resort to a number of well-established theories. Contingency theory stipulates there is no theory that is always correct. Theories tend to be contingent to one or more external factors that moderates or controls the behaviour of the system. Thus, we take the market uncertainty as one of the key exogenous factors that may largely govern the relationship between SCI and OP. MU is an external environmental factor and its behaviour is beyond management control. MU is normally manifested in ‘Fluctuation of demand’, ‘price elasticity’, ‘seasonality changes’ and so on. MU is also one of the widely researched and highly documented factors that appear to draw good level of attentions in the literature (Wong et al. 2011a; He and Zhao 2012; Longinidis and Georgiadis 2013; Huang et al. 2014).

Relationship of SCI to OP

Our literature review shows that many previous researches have already addressed the relationship between SCI and performance (Prajogo et al. 2015; Ebrahimi 2015; Zhao et al. 2015). However, their findings are not always consistent. “Appendix 1” listed a selection of recent articles in regards to their findings on the relationship between SCI and OP.

Configuration theory (Cao et al. 2015) suggests that how successful the patterns of SCI would be related to the operational performance in different configurations. It argues that organizations perform better when they develop better configurations of interconnected elements (Drazin and Van de Ven 1985; Sinha and Van de Ven 2005). It is therefore suggested that a highly integrated supply chain in this sense is likely to perform well in the market place. Configuration theory underlines the necessity for a supply chain to be well integrated in order to deliver high performance. It is thus reasonable to extrapolate that the configuration theory provides a theoretical support for the causality from SCI to OP.

Structural contingency theory (Lawrence and Lorsch 1967; Galbraith 1973; Chandler 1990) suggests that how well a supply chain performs depends on the extent to which the strategy is aligned with its structural design. An even more succinct interpretation of the theory is that the supply chain performance is always contingent upon supply chain structures. However, the theory does not specify how SCI and performance should be aligned with each other. Our literature review shows, unfortunately, there have been some significant inconsistencies. Based on our definition of SCI, we reviewed research findings in areas of *customer integration*, *internal integration* and *supplier integration,* respectively.

Literature findings in the field of *customer integration* have been largely consistent. Since customer integration could and have already generated ample opportunities to enables manufacturers to reduce costs, create greater value and detect demand changes more responsively. Customer integration has long been recognised as a pivotal factor to customer satisfaction (Won Lee et al. 2007) through which product innovation is often achieved (Song and Di Benedetto 2008; Koufteros et al. 2005). On the other hand, some researchers find customer integration does not necessarily contribute to supply chain performance (Devaraj et al. 2007; Jonsson et al. 2011; Turkulainen and Ketokivi 2012).

Browsing through the literatures on *internal integration*, discrepancies are equally apparent. Some authors found there is no direct relationship between internal integration and the operational performance of the manufacturer (Koufteros et al. 2005; Gimenez and Ventura 2005); others found that there is a positive relationship between the *internal integration* and the operational performance, including the performance on process efficiency (Saeed et al. 2005) and logistics service (Stank et al. 2001; Germain and Iyer 2006).

Reviewing the literature findings on the *supplier integration* has also revealed nontrivial inconsistencies. In some literatures, supplier integration has been found to be related to new product introduction processes and product development performance (Koufteros et al. 2005; Petersen et al. 2005) and supplier development and visibility-related measures (Cousins and Menguc 2006). Others, however, have found no significant correlation between supplier integration and operational performance (Stank et al. 2001), or even found a slightly negative relationship (Stank et al. 2001; Koufteros et al. 2005; Swink et al. 2007).

Another area of controversy in the literature is whether SCI should be modelled with the operational performance in general without constraint. For example, Bowersox et al. (1999) discussed the critical factor of SCI without mentioning of any contingency to the finding. Their finding claims that SCI is the centre piece of overall performance, which implies a positive correlation between the two. Our critiques, however, is that there are evidences to suggest the contrary, i.e. sometimes SCI is not positively correlated with supply chain's overall performance (Koufteros et al. 2005; Swink and Song 2007).

Admittedly, many previous researchers were in the same vein as Bowersox's that SCI always positively relates and contributes to the supply chain overall performance. However, equally convincingly, other researchers have demonstrated specifically nonpositive and even slightly negative correlations between the SCI and overall performance. 'Appendix 1' lists the publications that have conflicting opinions on the relationship between the SCI and performance. Such is the status of inconsistency in the concurrent literature, which give rise to the validity of the research problem.

Based on above literature review, we hypothesise the following:

1. The overall pattern of correlation between the supply chain integration and operational performance tends to be 'nonlinear', i.e. not always proportionally correlated.
2. The nature of the 'nonlinearity' between the supply chain integration and operational performance is significantly influenced by the *market uncertainty*.

The first hypothesis is drawn on the basis that SCI, as widely recognised in the literature, has undeniable and often significant contributions to the operational performance of a supply chain. However, the apparent causal relationship from the degree of SCI to the level of OP is not simplistically a 'linear one.' It varies in accordance with the exogenous circumstance. According to the dynamic capability view (Teece et al. 1997), the competitive advantage of a supply chain is believed to be rested on a series of distinctive dynamic ways of coordinating and combining the supply chain's specific asset that also fit to its position in the competitive environment. SCI is such a way that may (or may not) deliver the fit to its competitive environment where heterogeneous factors interact.

The second hypothesis is drawn on the basis that, given the first hypothesis above, the primary influencing factor for the causality between SCI and OP could be the market uncertainty for the specific supply chain market in question. The MU factor here is defined as a demand uncertainty, which often is directly linked to and perhaps measured by the level of market satisfaction within a given standard of OP. Based on the transactional cost economics (TCE) theory (Williamson 1989), one of the ultimate management objective is to minimise the transactional cost throughout the entire supply chain, and managers should do so by first of all identifying the market price (or the changes of it) of the product stream in question (Williamson 1991). This underlines one of the theoretical bases that the supply chain success measured in transaction cost economics has to be contingent to the market dynamics and market uncertainty.

Through a carefully designed empirical study and hypothesis testing process shown in the remainder of the paper, we anticipate contributing to the existing literature with a new conceptual model of the *moderated relationship between SCI and OP subject to MU*.

Research Methodology

To test the proposed hypotheses, we identified the automotive manufacturing companies in China (Xinqiao and Junfeng 2001) as our data gathering field, because China is perhaps one of the biggest automotive markets and also the largest automobile producing country in the world. China has demonstrated a landmark transformation over the last two decades (Flynn et al. 2010; Aláez-Aller and Carlos Longás-García 2010; Mozur 2014). The scope and diversity of China's automotive industry, in terms of product ranges and their market uncertainty (Li et al. 2014) have made it attractive to this research. Furthermore, due to the increasingly inextricable connections to the world economy, China's automotive industry is maturing rapidly (Lockstroem et al. 2010). Its implication in the development of automotive supply chain management could be profound. Our purpose for taking the data sample from just one automotive industrial sector is to avoid unnecessary complications that may arise from the inconsistent market behaviours and managerial patterns of different industries, which may confound the already complicated research problem even further. Notwithstanding that the research of similar problems across different industries could also be perhaps equally beneficial, but it would be an entirely different project altogether.

Questionnaire Design and Measures

We use questionnaire as one of the main empirical instruments for data collection from a carefully selected group of Chinese automotive manufacturers across the country. They are original equipment manufacturers (OEM) to their respective automotive supply chains. The questionnaire was developed in three steps. First, the measures and indicators of the three key constructs, SCI, OP, and MU, were defined based on what has been established in the existing literature. We adopted the SCI measures against Narasimhan and Kim (2002) and Cao et al. (2015); OP measures against Frohlich and Westbrook (2001) and Vickery et al. (2003); and MU measures from Huang et al. (2014) and Jonsson et al. (2011). Second, we managed semi-structured online video interviews with relevant executives and managers to validate the questionnaire design. Third, a pretest process was carried out in 20 selected companies to further assure the validity of the questionnaire. The indicators (measurement variables) were all measured using a seven-point Likert scale (Khazaei Pool et al. 2017a). The complete scales are listed in 'Appendix 2'.

Our questionnaire was originally developed in English and then translated into simplified Chinese (for mainland Chinese use) by two operations management professors in China. Then, they were translated back into English by another two management specialists (to ensure validity), and the translated English version was checked against the original English version for discrepancies (Khazaei Pool et al. 2017b).

Sampling and Data Collection

To ensure a more representative sample group of manufacturing companies were selected, we contacted the China Automotive Association to obtain registered manufacturers. We selected the companies through an impartial sampling process which is carried out more or less randomly. As a result, 65 companies have been selected and follow up contact made via phone calls initially. A profile of those sample companies is presented in Table 1.

We tried a new 'network approach' in order to improve the survey response rate. Firstly, the questionnaire with a cover letter highlighting the study's objectives were created into a Web version (still need to send an email to the respondent to get started) which can be easily accessed and filled by using either a computer or a mobile phone at any time. Second, after all questionnaires were completed and approved by the relevant directors/CEOs of each of the 65 sample companies, we set up several chat groups involving all respondents via Wechat (the 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 477 returns were received from the 700 questionnaires sent out achieving a return rate of 68.1%, within which 120 were invalid, yielding a total of 357 valid responses, which represents a valid response rate of 51%. We estimated the nonresponse bias by using a *t* test, comparing the early and late responses (Gimenez et al. 2012; Sousa et al. 2012). No significant nonresponse bias was found. A profile of the respondents is shown in Table 2. The respondents group was regarded as credible since more than half of them have had at least 3-year of managerial experience.

To further mitigate the potential common method bias (CMB), CFA marker technique (Williams et al. 2010) has been performed on all 15 indicators. The test results indicate no significant presence of single common factor. To further evaluate the CMB, we applied *confirmatory factor analysis* (CFA) (Gimenez et al. 2012; Huo 2012) with the null hypothesis model being that all measurement variables were assigned to a single latent variable. The result comes with: $\chi^2 = 668.552$, $df = 87$, $\chi^2/df = 7.68$, $GFI = 0.75$, $AGFI = 0.68$, $CFI = 0.6$, $RMSEA = 0.21$, $SRMR = 0.18$, showing that the null model is not built on the data set. Thus, CMB should not be an issue.

Reliability and Validity

Then, we test the reliability of each construct (SCI, OP and MU), employing Cronbach's alpha that assesses the scale reliability; and followed by a *corrected item-total correlation* (CITC) reliability test as suggested by Henrysson (1963). The value of estimated Cronbach's alpha is ranging from 0.789 to 0.889, which is greater than the benchmark value of 0.7 (Cronbach 1951; Tan 2009). In addition, the values of CITC test are all over the cut-off value of 0.3 (see Table 3). Thus, the item scales seem to be reliable enough.

The missing data issue in our sampling process appears to be miner, and thus it has been treated by the average imputation method. In order to test the validity of the data we start with Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity. Bartlett's test is to check whether we can reject the null hypothesis that the correlation matrix is not an identity matrix. In our analysis, we have a strong evidence ($p < 0.001$) to reject

Table 1 Profiles of sample companies

Number of Employees	Count	Per cent	Annual income (billion Yuan)	Count	Per cent
<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 2 Respondent features

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

Table 3 Reliability and validity analysis with factor scores

Items	Mean	SD	Factor loading	*t* value	CITC	Cronbach's alpha	KMO and Bartlettis	*Chi-square*	*df*	*Chi-square/df*	AVE	Factor score
Operational performance (OP)						0.840	0.847*	13.91	5	2.8	0.63	
Y1	4.20	1.67	0.773*	Omitted	0.635							0.251
Y2	4.09	1.30	0.829*	12.746	0.707							0.270
Y3	4.18	1.49	0.747*	10.989	0.604							0.243
Y4	4.03	1.45	0.809*	12.316	0.675							0.263
Y5	4.06	1.60	0.758*	11.336	0.613							0.247
Supply chain integration (SCI)						0.921	0.831*	21.82	9	2.42	0.72	
X1	3.29	1.42	0.846*	Omitted	0.777							0.196
X2	3.83	1.44	0.736*	12.313	0.637							0.171
X3	4.23	1.51	0.870*	16.797	0.806							0.202
X4	4.47	1.71	0.909*	19.679	0.855							0.211
X5	4.64	1.58	0.853*	16.696	0.780							0.198
X6	4.53	1.49	0.862*	18.510	0.795							0.200
Market uncertainty (MU)						0.782	0.779*	5.5	2	2.75	0.71	
Z1	3.89	1.55	0.795*	Omitted	0.610							0.328
Z2	3.45	1.61	0.770*	10.296	0.577							0.318
Z3	4.12	1.63	0.772*	10.302	0.582							0.319
Z4	4.23	1.72	0.775*	10.431	0.584							0.320

$n = 357$

* $p < 0.001$

the null hypothesis and therefore prefer the alternative one with KMO values ranging from 0.787 to 0.842, which is greater than 0.5. The convergent validity is tested by using CFA models (Schreiber et al. 2006). In the CFA model, all items are linked to their corresponding latent variables. The resultant loadings and their *t* values of each item are safely greater than 0.5 and 2, respectively, indicating the *convergent validity* (Russell 1978). For *discriminant validity* we apply *average variance extracted* (AVE) for this study. As suggested by Farrell (2010), a value of the AVE that is greater than 0.5 will indicate an adequate discriminant validity. Our AVE ranges from 0.63 to 0.74 (Table 3).

Dimension Reduction

CFA is used to reduce the 15 measurement variables (indicators) to three latent variables: operational performance (OP), supply chain integration (SCI), and market uncertainty (MU). This approach essentially creates the three latent constructs from the 15 measurement indicators by a reflective mode. In a reflective measurement model, it is the construct that lead to a change in the indicators. The CFA provides standardised *factor score* for each measurement. The factor scores are used to determine a measurement's relative standing on the latent dimension (Yusuf et al. 2004; Brown 2015). We use the obtained factor scores (see Table 3) for all the observed variables to generate the data columns of the three latent variables (Flynn et al. 2010; Won Lee et al. 2007; Sezen 2008), on which all the remaining analysis will be based.

As shown in Figs. 1 and 2, the independent variable SCI is scatter-plotted against the dependent variable OP, revealing no or little correlation but a heteroscedastic form of the data (Breusch and Pagan 1979; Koenker and Bassett Jr 1982). However, the visual relationship becomes relatively clearer when the exogenous variable MU is shown on a third axis, which indicates statistically that MU has certain explanatory ability on the relationship between OP and SCI. The observation of MU's explanatory ability is consistent with the findings by Huang et al. (2014) and Wong et al. (2011a, c). On investigating the possible 'nonlinear' OP-SCI relationship, Das et al. (2006) reported a mathematically inversed *V* shaped relationship. Terjesen et al. (2012) directly hypothesised an inversed *U*-shaped relationship, and tested the hypothesis by applying a polynomial multiple regression method. However, one of the obvious weaknesses of their methods is that they were highly subjective in nature. To avoid the subjectivity, we attempted a *threshold regression method* instead (Hansen 1999).

Threshold Regression Analysis

Threshold regression method is chosen here because it is capable of identifying the underlying thresholds that partition the data into clusters and to model their corresponding correlation through regressions. According to Hansen (1999), threshold regressing method is particularly useful in mitigating the errors caused by subjective factors. It can endogenously divide the data clusters based on the data characteristics. It can estimate and eventually form the distinct patterns of correlation.

The threshold model specified here concerns with the regression between the OP as the dependent variable; and SCI as the independent variable. The critical difference here is that the degree of MU is now used as the threshold variable, which is anticipated to have moderating effect on the relationship between OP and SCI. For a single threshold scenario, following Hansen (1999) study, the single threshold should be constructed as:

$$\mathrm{OP}_i = u_i + \beta_1 \mathrm{SCI}_i I(\mathrm{MU}_i \leq \gamma) + \beta_2 \mathrm{SCI}_i I(\mathrm{MU}_i > \gamma) + e_i \tag{1}$$

where β_1 and β_2 are the coefficients of the regressor SCI; *I(.)* is the *indicator* function; represents the unknown threshold to be estimated during the computing process. Based on this model, the observations have now been divided into two 'regimes' (Hansen's choice of word meaning 'regions') depending on whether the threshold variable MU is smaller or greater than the threshold value of 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 means and a finite variance of σ^2 and an alternative and more intuitive way of thinking (1) is:

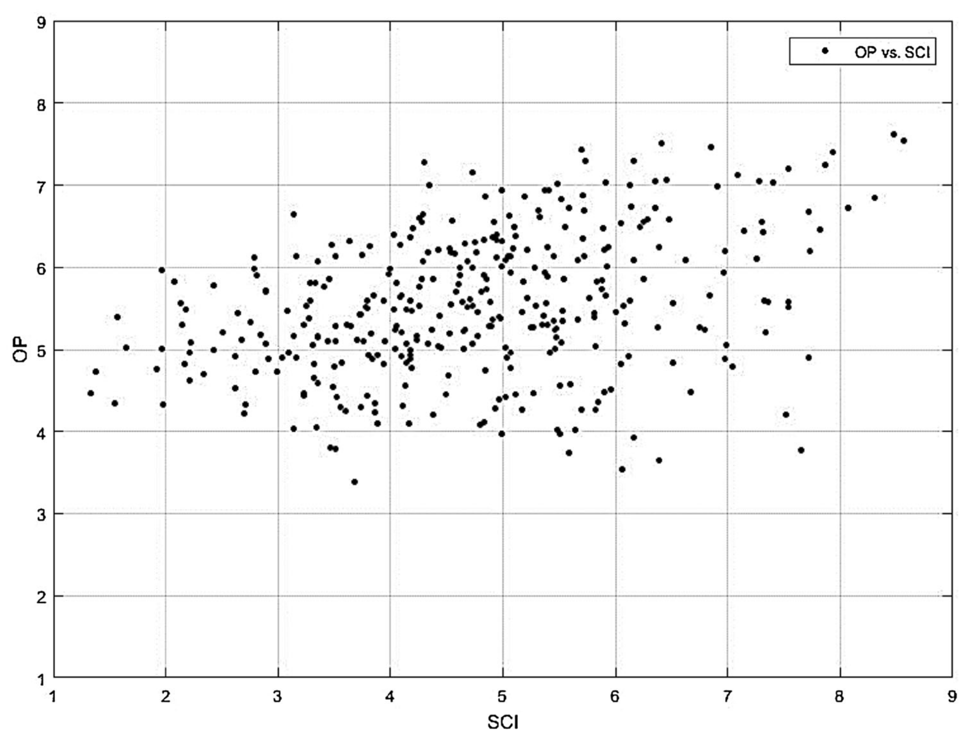

Fig. 1 Scatter plot of OP against SCI

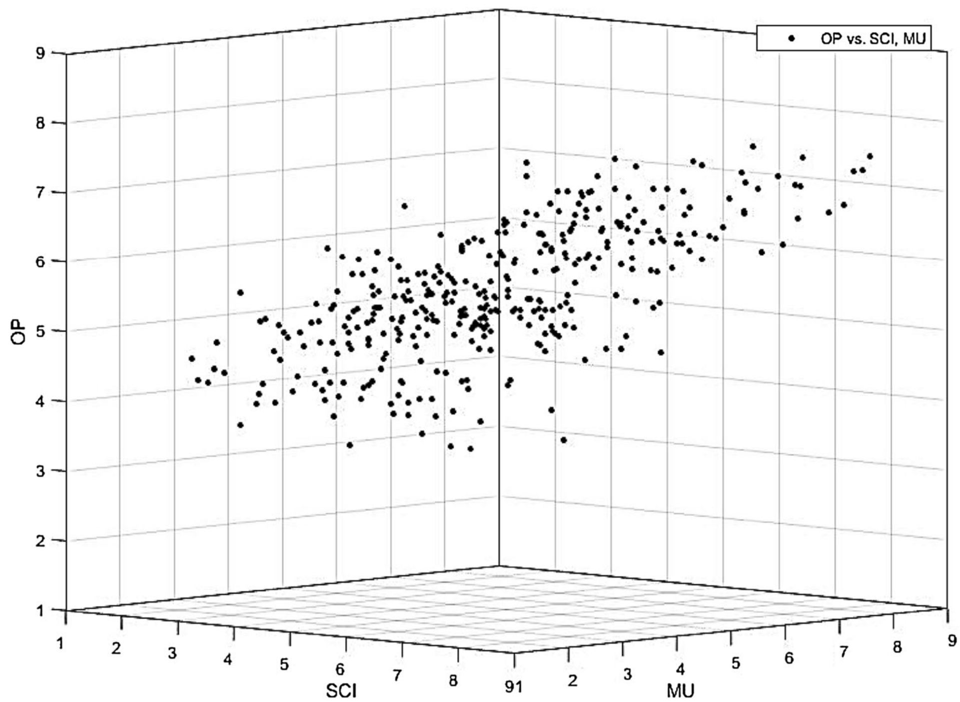

Fig. 2 Scatter plot of OP against SCI and MU

$$\mathrm{OP}_i = \begin{cases} u_i + \beta_1 \mathrm{SCI}_i + e_i, \ \mathrm{MU}_i \leq \gamma \\ u_i + \beta_1 \mathrm{SCI}_i + e_i, \ \mathrm{MU}_i > \gamma \end{cases} \tag{2}$$

To deal with the individual effect of u_i Hansen (2000) suggests to take averages of the Eq. (2):

$$\overline{\mathrm{OP}_i} = \beta' \overline{\mathrm{SCI}_i}(\gamma) + \bar{e}_i \tag{3}$$

And taking the difference between (2) and (3) yields

$$\mathrm{OP}_i^* = \begin{cases} \beta_1' \mathrm{SCI}_i^* + e_i^*, \ \mathrm{MU}_i \leq \gamma \\ \beta_2' \mathrm{SCI}_i^* + e_i^*, \ \mathrm{MU}_i > \gamma \end{cases} \tag{4}$$

The estimation of the slope coefficients $\beta_1{}'$ and $\beta_2{}'$ is by using the *ordinary least square* (OLS) method. However, if the null hypothesis $\beta_1 = \beta_2{}'$ has been rejected, as one or more thresholds may exist, the significance tests cannot be calculated under normal distribution. This is called the 'Davies' problem (Davies 1987) which has been studied by Andrews and Ploberger (1994) and Hansen (2000). As they suggested, one can use *bootstrap* method to simulate the asymptotic distribution of the likelihood ratio tests of the Eq. (4). The significance level of these likelihood ratio tests determines the number of thresholds. And the confidence interval construction method is introduced by Bai (1997).

With the model (4), we hypothesise that there is a threshold effect along the MU dimension, which forms an asymmetric 'nonlinear' relationship between the OP and SCI. It is therefore important to determine whether the threshold effect is statistically significant. To do the test, the null hypothesis and alternative hypothesis for the Eq. (4) are set as:

$$H_0 : \beta_1' = \beta_2'$$
$$H_1 : \beta_1' \neq \beta_2'$$

If the null hypothesis holds, the coefficient $\beta_1{}' = \beta_2{}'$, indicating that the threshold effect between the OP and SCI does not exist. However, if the null hypothesis is rejected and the alternative hypothesis holds, the coefficient $\beta_1{}' \neq \beta_2{}'$ indicating that the threshold effect does exist. If there exist the double thresholds, then the model of Eq. (4) can be modified to:

$$\mathrm{OP}_i^* = \begin{cases} \beta_1' \mathrm{SCI}_i^* + e_i^*, \ \mathrm{MU}_i \leq \gamma_1 \\ \beta_2' \mathrm{SCI}_i^* + e_i^*, \ \gamma_1 < \mathrm{MU}_i \leq \gamma_2 \\ \beta_3' \mathrm{SCI}_i^* + e_i^*, \ \mathrm{MU}_i > \gamma_2 \end{cases} \tag{5}$$

where the threshold value $\gamma_1 < \gamma_2$. This can be expanded to multiple threshold models with $\gamma_1, \gamma_2, \gamma_3, \ldots, \gamma_n$.

Results

Multi-threshold regression analysis described above was used to test both of our hypotheses formulated in "Theoretical background" section. In the first step, the threshold effect of MU on the relationship between OP and SCI was assessed in order to determine whether there was a moderating effect. In the second step, we assessed the relationship between two-way interactions of SCI, SCI square (inverse *U*-shaped relationship hypothesised by Terjesen et al. (2012)) and MU to OP by applying hierarchical regression (Flynn et al. 2010), for the purpose of providing a comparison between the results of threshold regression analysis and hierarchical regression analysis.

Threshold Regression Results

To determine the number of thresholds, Eq. (5) was estimated by OLS, allowing for zero to multiple thresholds. The F test statistics $F1$, $F2$ and $F3$, along with their bootstrap p values, are reported in Table 4. The F tests show that the single threshold effect is highly significant with p value of 0.000, in addition, the test of a double threshold effect is also strongly significant with p value of 0.003. By contrast, the test for a triple threshold effect failed to show a strong significance. Thus, we conclude that there is strong and statistically significant evidence to support the existence of two thresholds in the relationship between OP and SCI.

The two estimated threshold values and their 95% confidence intervals are reported in Table 5. The estimated threshold values are 3.49 and 5.52, which stands on the two sides of the threshold variable mean of 3.98. Thus, the two thresholds divided the MU dimension into three regimes of 'high market uncertainty' ($MU \leqq 3.49$), 'middle market uncertainty' ($3.49 < MU \leqq 5.52$), and 'low market uncertainty' ($MU > 5.52$). Additional information of multi-stage estimation of the threshold values are shown in Figs. 3 and 4a, b below.

Table 6 reports the number of responses which fall into the three regimes. We see that the number of responses in the 'high market uncertainty' regime is 61 (17.1%), the 'middle market uncertainty' regime involves 173 (48.5%) and the 'low market uncertainty' regime covers the rest 123 (34.4%) responses.

The regression slope estimates and the conventional OLS standard errors (SE) are displayed in Table 7. The estimated results suggest that SCI is perhaps negatively correlated with OP in the first regime as shown in Fig. 3a, which could be unexpected to some researchers that such result seems to be counterintuitive and contradictory to the positive relationship established in many integration and performance studies. On the other hand, the estimated slopes become positive in the second and third regimes as shown in Fig. 3b, c, and the magnitude of the slopes rise from 0.061 to 0.237 when it shifts from the second to the third regime. Thus, these results appear to support squarely both of our hypotheses.

Table 4 Tests for threshold effects

Test for single threshold	
$F1$	99.8
P value	0.000
95% critical value	14.8
Test for double threshold	
$F2$	67.2
P value	0.003
95% critical value	14.8
Test for triple threshold	
$F3$	5.6
P value	0.779
95% critical value	14.8

Bootstrap = 2000

Hierarchical Regression Results and Comparison

The results of the hierarchical regression analysis together with the threshold regression results are compared in Table 8. Model 1 represents a significant direct positive relationship between SCI and OP (β_1), and between MU and OP (β_2). Model 2 includes additional regressors of SCI square ($ß_3$), SCI times MU (β_4) and squared SCI times MU (β_5). Adding those additional regressors yielded a significant change in Adjusted-R^2 and contributed significantly to its predictive power, which supports the result of Terjesen et al. (2012). However, in Model 3 the predictive power is even higher as the Adjusted-R^2 reaches 0.612.

As shown in Table 8, Model 1 tests the assumption of a universally positive linear relationship between SCI and OP. Such assumption is supported ($\beta_1 = 0.075$, $p < 0.01$), although the Adjusted-R^2 is only 0.143. Thus, a conclusion of a positive relationship can be drawn based on the results of Model 1. To test the assumption of an inverse U-shaped relationship, following Terjesen et al. (2012), Model 2 tested the joint significance of a squared term of SCI and its interactions with MU by applying the hierarchical regression method. The results of Model 2 support a slightly inverse U-shaped relationship ($\beta_3 = -0.013$, $p < 0.1$), and they also show that the relationship turns linear when considering MU ($\beta_5 = -0.008 > \beta_3$, $p < 0.1$). What is worth mentioning here is that the Adjusted-R^2 of the Model 2 is greater than that of the Model 1 (Δ Adjusted-$R^2 = 0.112$), which means the Model 2 is able to explain additional 11.2% of the data sample. However, it is still hard for the Model 2 to tell how the three variables (OP, SCI and MU) inter-play with each other. To rip away the hazy veil covered on these three variables, as shown in Fig. 3, Model 3 reports the statistically significant regression coefficients of SCI on OP in each of the 3 regimes segmented by MU. In addition, the Model 3 achieved further 35.7% explanatory power with its Adjusted-R^2 reaches 0.612. It is therefore evidently convincing that the Model 3—the threshold method achieves the highest explanatory power of the SCI–OP relationship.

Table 5 Threshold estimates

	Estimates	95% confidence interval
γ_1	3.49	[3.321, 3.556]
γ_2	5.52	[5.501. 5.546]

Discussion

The above results show that Model 1 is just a simple linear function; and both of our hypotheses were supported by Model 2 and Model 3, respectively (Table 8), indicating SCI is 'nonlinearly' related to the OP subject to MU; and the Model 3 (threshold regression analysis) is quite convincingly the most effective approach to show the moderating effect of the exogenous factors. A managerial implication from this finding could be that before implementing any supply chain integration strategies the market condition must be examined and defined according to the model. Thus, the model helps to set a more realistic expectation to the outcome of the SCI strategies.

Looking again closely at the primary data of the three constructs, when the 3D data 'cloud' is segmented by the two thresholds into three regimes along the MU dimension, clear regression patterns emerge. Thus, one may begin to see the benefit of applying the threshold regression analysis.

First, for a given level of SCI, the OP level is always negatively correlated with MU which depicts a negative relation between OP and MU, when the SCI is taken a value of 5 for example. This derived finding from the 3D

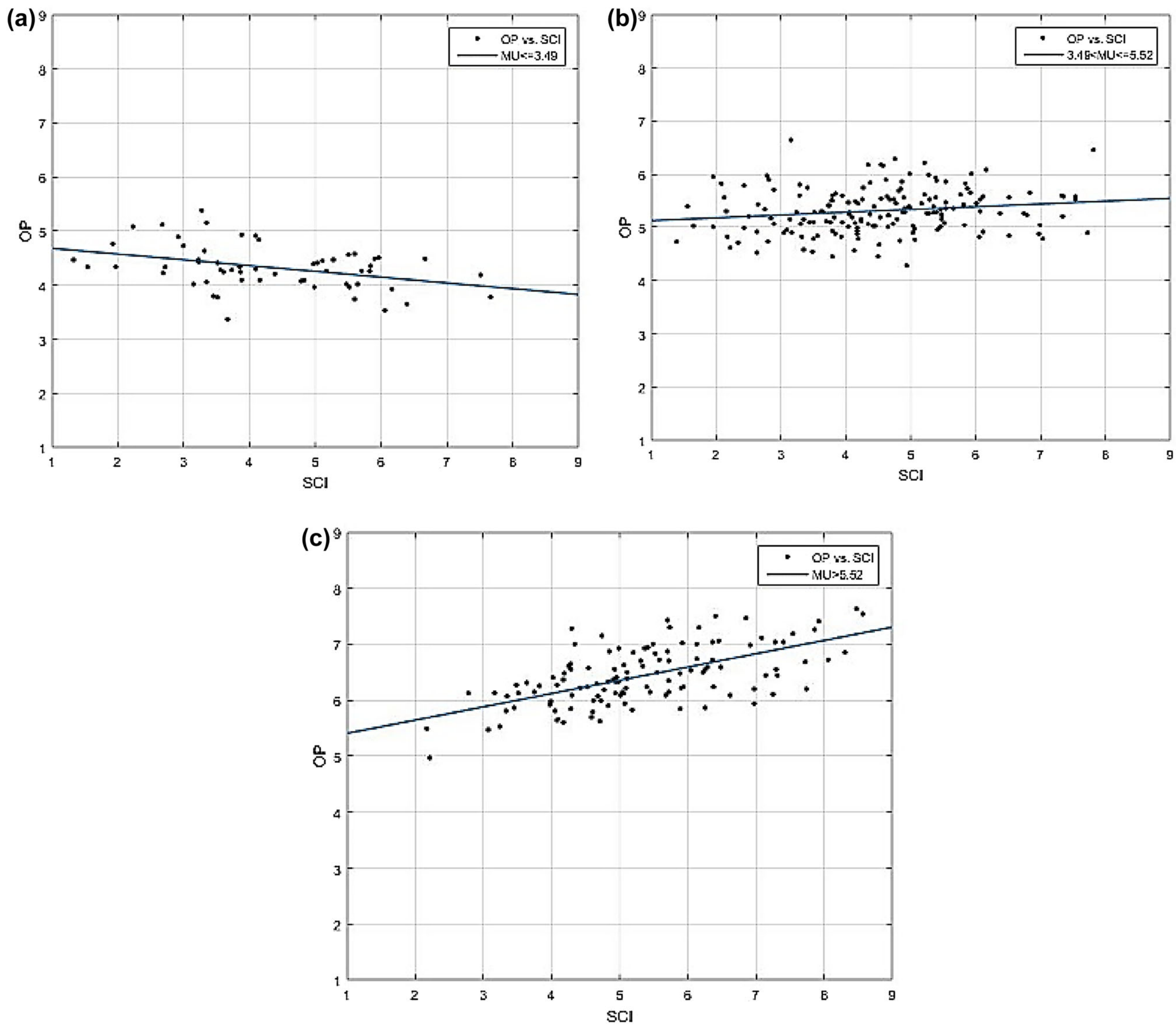

Fig. 3 Scatter plots with regression line in different regimes

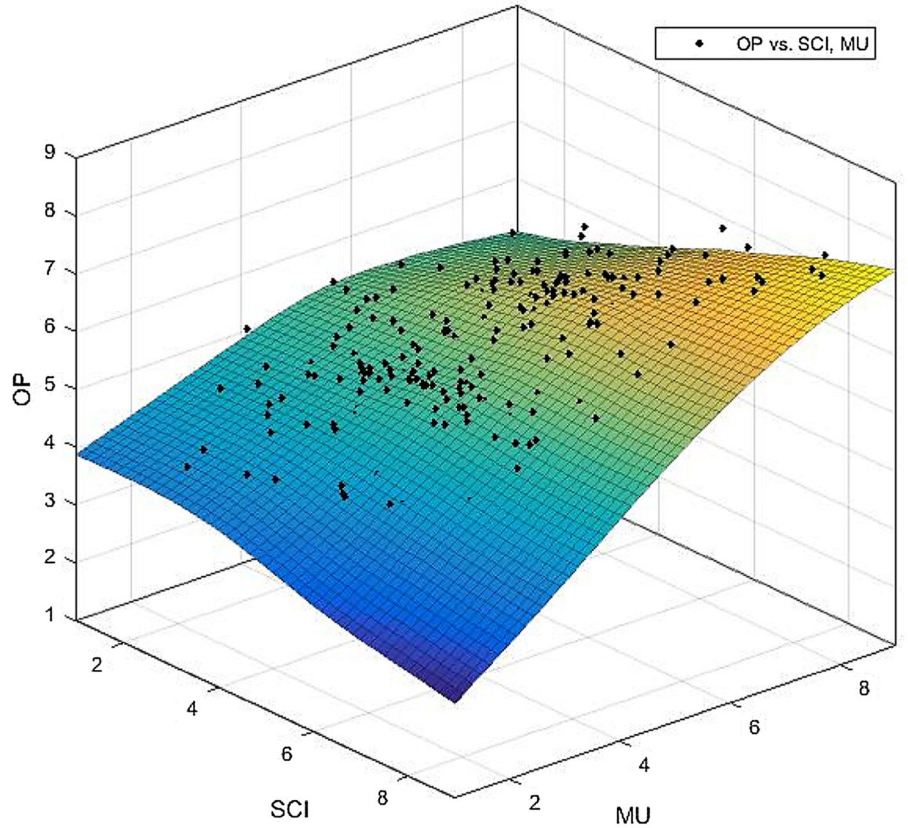

Fig. 4 3D regression plot

Table 6 Number of responses in each regime

Respondents class	Number of responses
MU $\leqq$ 3.49	61
3.49 < MU $\leqq$ 5.52	173
MU > 5.52	123

Table 7 Regression estimates: double threshold model

Regressor	Coefficient estimate	OLS SE
SCI (MU $\leqq$ 3.49)	−0.196***	0.051
SCI (3.49 < MU $\leqq$ 5.52)	0.061***	0.031
SCI (MU > 5.52)	0.237***	0.025

*** $p < 0.01$

model is in fact quite consistent with past research findings that market uncertainty is a negative influencing factor to supply chain operational performance given a constant level of SCI (He and Zhao 2012; Huang et al. 2014). This may be also exemplified by the case when the financial market became uncertain in 2007, the operational performance of banking supply chains across the world declined sharply.

Second, given a fixed value of OP, for example, as a targeted operational performance, the 3D model will reduce to a model that depicts the relationship between SCI and MU, which shows that the level of integration is somewhat negatively correlated with the level of MU. This is also evident in the past literature, when in a highly uncertain market place the supply chain tends to strengthen its competitive performance through flexibility and responsiveness, which often means outsourcing and virtual network with reduced vertical integration (Stratton and Warburton 2003).

Third, given a fixed level of MU, the analytical model shows different patterns of relationship between SCI and OP (Fig. 3):

1. When market uncertainty is low and MU takes high value, indicating the data cloud is in the low market uncertainty regime, then, the correlation between SCI and OP as shown in Fig. 3c is clearly modelled as a *positive relationship*. This is consistent with many main-stream research findings in SCI (Prajogo and Olhager 2012; Jin et al. 2013). A large body of *lean* supply chain management research also represents exactly the point that close partnership and high level of SCI with the first tier suppliers contribute positively to the supply chain's overall performance, while the

Table 8 Direct, polynomial, and threshold regression results

Regressor	Model 1: direct effects	Model 2: nonlinear moderating effects	Model 3: threshold moderating effects
SCI (A) [β_1]	0.075***	0.063*	
MU (B) [β_2]	0.393***	0.331**	
A^2 [β_3]		−0.013*	
A*B [β_4]		0.057**	
A^2*B [β_5]		−0.008*	
A ($B \leqq 3.49$) [β_6]			−0.196***
A ($3.49 < B \leqq 5.52$) [β_7]			0.061***
A ($B > 5.52$) [β_8]			0.237***
Intercept	3.189**	5.22*	4.93***
Adjusted-R^2	0.143	0.255	0.612
Δ Adjusted-R^2		0.112	0.357

* $p < 0.1$;** $p < 0.05$,*** $p < 0.01$

overall market environment is assumed to be relatively stable.

2. When market uncertainty is high and MU takes low value indicating the data cloud is in the high market uncertainty regime. Then, the correlation between SCI and OP in Fig. 3a shows a slightly *negative correlation*. Many extant literatures (Rodrigues et al. 2004; Cousins and Menguc 2006) have also shown findings in a similar vein that SCI does not appear to help much when the supply chain is under a highly volatile market place. Researchers in the area of agile supply chain also echoed their findings in a similar wavelength (Zhang 2011; Vazquez-Bustelo et al. 2007). Essentially, an agile supply chain prefers the management approach through virtual network rather than vertical integration (Agarwal et al. 2006). Transaction cost theory (Williamson 1981; Parkhe 1993) has long concluded that uncertain market and environmental complexity will lead to higher transaction cost and thus lower economic performance.
3. When market uncertainty is medium and MU takes middle value indicating the data cloud is in the medium market uncertainty regime, then the correlation between SCI and OP in Fig. 3b shows that the relationship between SCI and operational performance is somewhat a mixture and may be difficult to define. This is consistent with the findings from 'leagile' supply chain management whereby the market uncertainty is at its transit level between high and low (Agarwal et al. 2006; Goldsby et al. 2006). Research in this transitional regime is very much case sensitive and is largely subject to other contingency factors.

The 3D analytical model (Fig. 4) seems to be useful in explaining the inter-play of the three key constructs. The 'nonlinear' 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 the integration on operational performance. Furthermore, the seemingly inconsistent findings from past literatures, in terms of 'no effect', 'positive', 'negative' and 'it depends' (see 'Appendix 1'), can now be largely reconciled by the findings trough threshold regression, which perceives the SCI–OP relationship through the lens of the exogenous factors' moderating effect. Therefore, perhaps, no one was wrong after all.

Our interpretation of the study results can also be taken from a structural contingency theory (Stonebraker and Afifi 2004; Sousa and Voss 2008) perspective. External fit can be interpreted as a consistency between the supply chain's internal structure and the operational strategies that response to its external environment. Since market uncertainty is an important part of the external environment, a manufacturer should therefore respond to it by developing, selecting and implementing appropriate strategies to maintain the fit with its external environment (Tushman and Nadler 1978; Hambrick 1983; Kotha and Nair 1995). This is how exactly our research results and the analytical model will implicate to the real-world business practices.

Conclusions and Limitations

This study contributes to the existing literature on supply chain integration in two important respects. First, it adds to the literature the moderated effect on supply chain integration by empirically testing the relationship between supply chain integration and operational performance under the influence of market uncertainty—an exogenous factor. Second, it establishes analytically the 'nonlinear' relationship between supply chain integration and operational performance by applying, probably for the first time, the *threshold regression method*. Our research also enriches the growing discussion of SCI by sharing empirical findings from automotive industries in China.

We can conclude that two of our developed hypotheses have been positively supported through a rigorous testing process. We critically reviewed the resent literature in the subject area and identified a number of inconsistencies and research gaps as illustrated in "Theoretical background" section, and our research has substantively filled the research gap by contributing theoretically that the effectiveness of SCI on improving the operational performance is conditioned to, or moderated by the market uncertainty given a specific industrial market.

Based on a properly designed empirical investigation in China's automotive industry, we established the primary data sets through dimensional reduction methods, and the data analysis concludes that the overall pattern of the correlation between the supply chain integration and operational performance tends to be 'nonlinear', and the nature of the 'nonlinearity' is significantly influenced or moderated by the *market uncertainty* as an exogenous environmental factor.

The theoretical implication of the study can be anticipated in the renewed understanding on how supply chain integration may be causally correlated with operational performance under the moderating power of market uncertainty, and as for the practical implication, as mentioned in 'Discussion' section, we can expect a more rational decision-making in regard to the supply chain's integration level and the desired competitive performance, and all is in respect to the changing external business environment.

Despite the above claims, some limitations can also be observed. Since the data source was initially limited to the China's automotive industry, caution needs to be exercised when considering different cultural environment. Regarding the methodology, this study uses cross-sectional design for the threshold regression analysis, thus the time dimension is largely ignored. However, the CMA (common method bias) test has been applied, and it reveals positive outcomes, and other systematic bias factors such as uniformity of respondents, regions and seasons could still have some bias effects lurking in the data. As one of the future research agenda, a longitudinal study that observes the changes of the measures over time would likely shed new lights to the SCI–OP relationship.

Appendix 1

See Table 9.

Table 9 Summary of literature on the relationship between SCI and performance

References	Journals	Relationship
Stank et al. (2001)	TJ	No effect
Vickery et al. (2003)	JOM	No effect
Rodrigues et al. (2004)	JBL	No effect
Gimenez and Ventura (2005)	IJOPM	Positive
Koufteros et al. (2005)	DS	Negative
Rai et al. (2006)	MIS	Positive
Cousins and Menguc (2006)	JOM	No effect
Das et al. (2006)	JOM	Inverse *V* shape
Wook Kim (2006)	SCMAIJ	Positive
Devaraj et al. (2007)	JOM	It depends
Swink and Song (2007)	JOM	Negative
Van der Vaart and van Donk (2008)	IJPE	Positive
Sezen (2008)	SCMAIJ	Positive
Glenn Richey Jr et al. (2009)	IJPDLM	Positive
Kim (2009)	IJPE	Positive
Li et al. (2009)	IJPE	Positive
Flynn et al. (2010)	JOM	Positive
Jonsson et al. (2011)	IJPDLM	Positive
Wong et al. (2011a)	JOM	Positive
Gimenez et al. (2012)	IJOPM	It depends
Huo (2012)	SCMAIJ	Positive
Prajogo and Olhager (2012)	IJPE	Positive
Sousa et al. (2012)	IJOPM	It depends
Turkulainen and Ketokivi (2012)	IJOPM	It depends
Terjesen et al. (2012)	DS	Inverse *U* shape
Jin et al. (2013)	IJPDLM	Positive
Huang et al. (2014)	SCMAIJ	Positive
Yu et al. (2014)	SCMAIJ	Positive

TJ Transportation Journal, *JOM* Journal of Operations Management, *JBL* Journal of Business Logistics, *IJOPM* International Journal of Operations and Production Management, *DS* Decision Sciences, *MIS* MIS Quarterly, *SCMAIJ* Supply Chain Management: An International Journal, *IJPE* International Journal of Production Economics, *IJPDLM* International Journal of Physical and Distribution Logistic Management

Research findings summary of reviewed articles.

Appendix 2: Measurement items (with factor loading)

Supply chain integration (eigenvalue = 4.311). Please indicate the extent of integration or joint activities or information sharing between your organisation and your major 1st-tier supplier in the following areas (1 = not at all; 7 = extensive).

The level of strategic partnership with your key suppliers	0.846
The participating level of your suppliers in the design and planning stage	0.736
Collaboration and coordination level through all your internal functions	0.870
You share your customer demand forecasting with your internal planning and scheduling	0.909
Synchronising your suppliers' capacity with your internal production and customer demand	0.853
The level of information gathering from your customers through information network	0.862

Operational performance (eigenvalue = 3.073). 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).

Your company can quickly modify your products to meet your customer's requirement	0.773
Your company can quickly introduce new products into the market	0.829
The lead time for fulfilling your customers' order is short	0.747
Your company can quickly respond to the changes in the market	0.809
Your company provides a high level of customer service	0.758

Market uncertainty (eigenvalue = 2.423). Please indicate the degree to which you agree to the following statements concerning the market uncertainty with respect to your primary/major products (1 = strongly disagree; 7 = strongly agree).

The market demand for your major products in terms of volume is stable	0.795
Your product sales pattern over different seasons in a year is predictable	0.770
Customer anticipation for the products' features and functions is always known	0.772
Technological innovation arisen from competitors' products will have no impact on the market of your product	0.775

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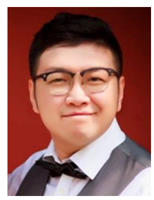
Key Question

1. What is the causal relationship between a supply chain's level of integration and its operational performance; and how might such relationship be influenced by the market uncertainty as an exogenous factor?

Dawei Lu is a Principal Teaching Fellow at WMG, University of Warwick, UK. Dr. Lu is a course leader for Supply Chain and Logistics Management course and a module leader for Supply Chain Management module at the MSc and executive training levels. He delivers the module across six different countries internationally. Dr. Lu has supervised over 14 Ph.D. students, and has written two books, and published over 27 peer-reviewed journal articles. He currently leads a Logistics and Supply Chain Research Team within WMG.



Yi Ding achieved his Ph.D. in Feb 2017 and is now a postdoctoral researcher at WMG. He received his Master degree in Economics from East Anglia University in 2011. Dr Ding has been an outstanding researcher in the Consultant Department of Qilu Bank in China. He currently participates in a Supply Chain Finance project within Qilu Bank. Dr Ding has published five papers.

Sobhan Asian has 10 years of academic and industry experiences in Supply Chains and Operations Management. Sobhan completed his Ph.D. at Nanyang Technological University, Singapore, and at the same time, he was attached to the Singapore Agency for Science, Technology, and Research (A*STAR). Sobhan's research has several applications particularly in complex systems where managing unpredictable accidents and spare parts inventory is critical. Another application of Sobhan's research is developing risk quantification tools and decision support systems for service-based organisations, like healthcare systems, where quantification of operational risks and identification of potential improvement opportunities are essential.

Sanjoy Kumar Paul is lecturer in operations and supply chain management in the University of Technology Sydney (UTS), Australia. He has obtained his PhD from the University of New South Wales, Australia. Prior joining to UTS, he also served RMIT University, Australia, and Bangladesh University of Engineering and Technology, Dhaka, as an academic staff. He has published many articles in top-tier journals including European Journal of Operational Research, International Journal of Production Economics, Computers and Operations Research, International Journal of Production Research, Computers and Industrial Engineering, Journal of Intelligent Manufacturing, Journal of Industrial and Management Optimization. He is also an active reviewer of many reputed journals. His research interest includes supply chain disturbance management, modelling, applied operations research, and intelligent decision-making.