Urban Legends in Model Specification for Testing Supply Chain Integration Theories

Christina W.Y. Wong (christina.wy.wong@polyu.edu.hk)
Institute of Textiles and Clothing, The Hong Kong Polytechnic University, Hong Kong.

Sakun-Boon-itt
Thammasat Business School, Thammasat University, Thailand.

Chee Yew Wong
Leeds University Business School, University of Leeds, UK.

Abstract

This paper tests whether the effects of SCI on operations performance vary when different models are specified. Based on data from a survey of 348 Thai manufacturers, four models were tested using multiple regressions, structural question modelling and latent class analysis. Each SCI dimension (supplier, internal and customer integration) and its higher-order SCI construct are significantly and positively associated with all operational performance dimensions. With interaction terms added, the effects of SCI dimensions become insignificant and the signs turned negative. The latent class analysis classes with lower SCI strength had more number of positive performance links.

Keywords: Supply chain integration, Model specification, Theory testing.

Introduction

An urban legend is something being widely accepted without question. For theory testing research, model specification is a crucial but least understood process (MacCallum, 1995; Allen, 1997). Inappropriate model specification could lead to mis-interpretation of findings. A model is over-specified when variables not in the true model are included in the formulated model and under-specified when independent variables in the true model not being included in the formulated model; and regression results will be biased especially when multi-collinearity exists (Deegan Jr. 1976). Moreover, most empirical articles published in Operations Management (OM) journals examine only a single model. If such a model has acceptable p value, fit index and most hypotheses are being accepted, the findings are thought to be valid. We seldomly ask whether there are alternate and yet theoretically plausible models, models that fit the data better, or missing variables that could better explain the phenomenon.

Despite the large volumes of published theory-testing studies on supply chain integration (SCI), little question is asked whether the model specifications that include the three common dimensions of SCI (i.e., internal, supplier and customer integration) would lead to over or under estimation of their effects. Effect estimations could be affected by multi-collinearity between these SCI dimensions (as they share a similar domain i.e., integration), their interaction effects, model specification bias, endogeneity issues, and so on. Using the same dataset, this paper tests whether the use of different models can result in different performance effects three SCI dimensions.

Literature review

Model specification involves the determination of independent variables to be included in or excluded from a regression or structural equation. A model is often specified primarily based on theoretical considerations instead of empirical or methodological ones. Two basic types of specification errors can mislead interpretations. A model is mis-specified when an independent variable that is theoretically irrelevant is being included or when an independent variable that is theoretically relevant is being excluded.

Based on a search in ABI/INFORM database of peer-reviewed journals with a title including "Operations" (February 2018), we found 91 articles that discuss "model specification*". These journals include Annals of Operations Research (22), Manufacturing & Service Operations Management (21), International Journal of Operations & Production Management (17), Production & Operations Management (15), Operations Research (9) and six other journals (7), including Journal of Operations Management (1). Here we summarize some key findings:

- Different model specifications could lead to different interpretations. For example, De Giovanni and Vinzi (2012) shows the use of different measurement model specification (use of formative versus reflective scales) could lead to different conclusions about the effects of independent variables;
- Some studies used theoretical foundation or hypothesis to specify models for testing, especially when independent variables are related to each other. For example, arguing that different operational practices could have either additive or compensatory effects, two models, one based on average value of the practices and another based on a threshold value, are tested (Wu et al., 2012);
- The chosen analytical methods could adequately examine the adequacy of model specification and detect any violation of assumptions (Leachman et al., 2005);
- When samples are divided into sub-groups (typically to test the effect of a moderator), some studies examined whether the separation of the samples has any influence on the discriminative power of the different models and on interpretations of the results from different models (see examples in Gröβler et al., 2006);
- Issues e.g., multi-collinearity, sample selection bias, endogeneity are seldom discussed.

Supply chain integration (SCI) broadly means the strategic collaboration in both intra-organizational and inter-organizational processes (Flynn et al., 2010). SCI is multidimensional variable (Flynn et al., 2010); it involves information sharing, cooperation, partnership, and collaboration across functions, strategic partnership, planning, and joint product development with suppliers and customers (Lai et al., 2010; Ragatz et al., 2002). SCI is further divided into three dimensions: internal integration (II), supplier integration (SI), and customer integration (CI). II involves intra-organizational collaboration across the product design, procurement, production, sales, and distribution functions to meet customer requirements at lower total system cost (Morash et al., 1997).

Figure 1 shows empirical SCI theory-testing studies apply different model specifications (Germain and Iyer, 2006). A common assumption is that operational performance is linearly associated with the strengths of SCI or individual SCI dimensions (i.e., SI, II, CI). Many studies based on regression or structural equation models to examine the effects of individual SCI dimensions separately; these models are labelled Model 1 and called the “individual effect model” (Germain and Iyer, 2006). Instead, Model 2 examines the effects of aggregated SCI dimensions or higher-order SCI. Model 2 is labelled as “unified integration model” (Germain and Iyer, 2006). Model 3 is created when Model 1 is extended by including the interaction effects of SCI dimensions. Model 3 is labelled “interactive model” by Germain Iyer (2006), who stressed the importance of incorporating interaction effects into individual effect model. Model 3 is often used to test models grounded in the contingency theory (e.g., Flynn et al. 2010), which argues the relationship between internal integration and performance can be moderated by supplier and customer integration. Model 4 is labelled as “configuration model” is used by studies that applied quartile or cluster analysis to examine the effects SCI in specific configurations or arcs of integration (Model 4).

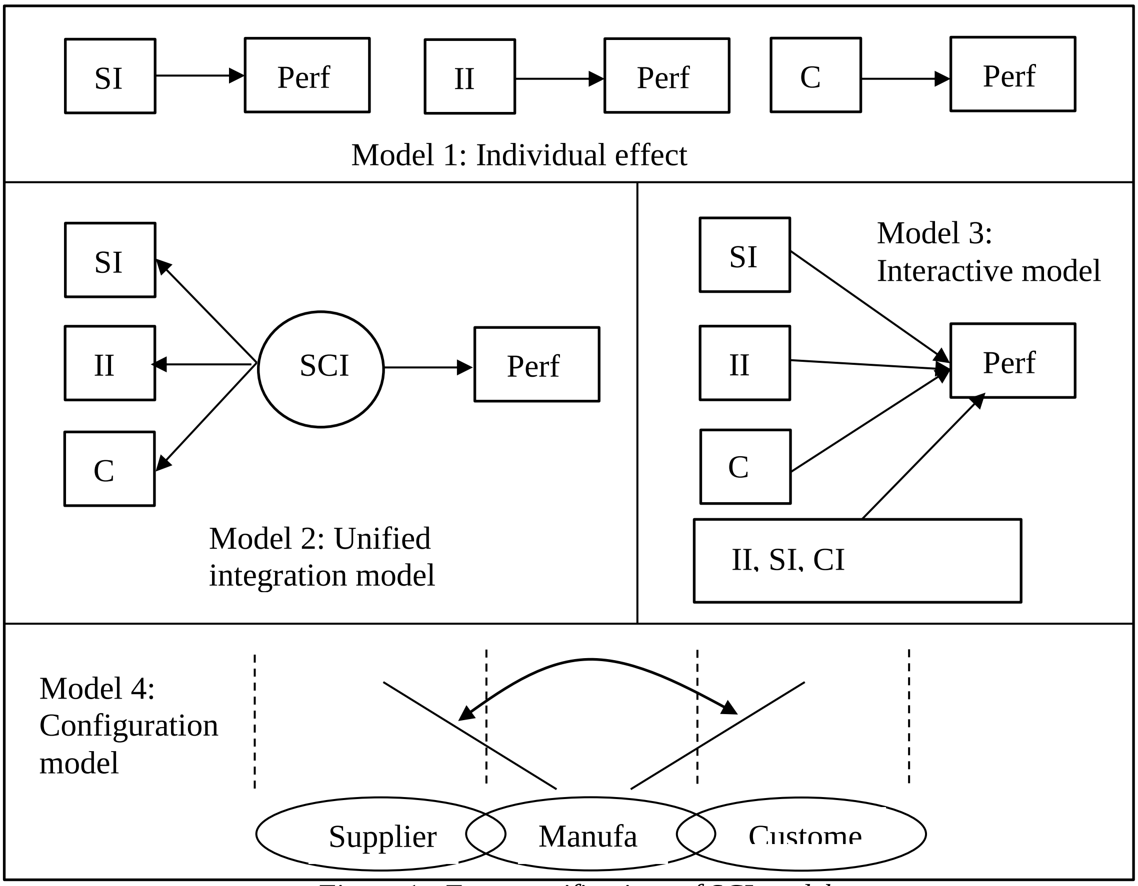

Figure 1 - Four specifications of SCI model

Model 1: models based on individual SCI dimensions. While collectively there are plenty of positive evidence in the literature (see meta-analysis of Leuschner et al., 2013 and Mackelprang et al., 2014), only few studies reported that the strengths of all three SCI dimensions are associated with delivery, cost, quality and flexibility performance (Rosenzweig et al., 2003, Wong et al., 2011). The work of Wong et al. (2011) has particularly reported relatively high R^2 for the relationships between all the three SCI dimensions and four operational performance outcomes. However, the use of separate structural models for each SCI by such studies could possibly lead to errors in effect sizes because the effect of one SCI dimension on another is not being accounted for. A recent meta-analysis of 34 articles reveals “integration *[strength]* is not universally associated with improved performance" and "no type *[dimension]* of integration resulted in notably more or less significant relationships than other forms of integration" (Mackelprang et al., 2014: 82). Perhaps the strength of integration is not a consistent or strong predictor. Fabbe-Costes and Jahre (2008) show that more SCI does not always lead to better performance, and they question if the SCI-performance relationship could be curvilinear.

Model 2: model based on higher-order SCI constructs. Very few studies have examined the aggregated effects of SCI by considering SCI as a higher-order multidimensional constructs. Rosenzweig et al. (2003) shown that SCI intensity (as an aggregated SCI construct measured in terms of internal, supplier, customer and distributor/retailer integration) was significantly associated with delivery reliability, quality, cost and process flexibility.

Model 3: model based on a contingency perspective (interaction effects). Mackelprang et al. (2014) point out that 63% of the integration-performance relationships they evaluated are subjected to unknown moderating factors. The work of Wong et al. (2011) reveals two contingencies by dividing operational performance into time-based versus non-time-based, which help differentiate the moderating effects of environmental uncertainty on the relationships between internal versus external integration. Other moderators such as supply complexity and competitive strategy may explain why SCI performance varies. Another contingency perspective concerns the interactions between SCI dimensions (Flynn et al., 2010). However, there is no agreement which SCI dimension should act as moderators. Some argues II and others suggest SI and CI, as the moderators. Dröge et al. (2004) found that internal integration moderated the effect of external integration on performance. Devaraj et al. (2007) found that CI moderated the relationship between SI and performance. Instead, Flynn et al. (2010) show that the interactions between CI and SI had no effect on the relationships between II and performance (i.e., operational and business). New evidence provided by Schoenherr and Swink (2012) indicates that the relationships between external integration (SI and CI) and performance (i.e., delivery and flexibility) are moderated by II. Apparently, the empirical evidence and such a contingency theory do not add up.

Model 4: Models based on a configuration or arcs of integration perspective. This perspective argues that it is the specific "configurations" of SCI dimensions or "arcs" of integration that explain performance (Frohlich and Westbrook, 2001; Flynn et al., 2010; Schoenherr and Swink, 2012). Such studies often use ANOVA analysis to compare the performance of different clusters of firms identified by quartile or cluster analysis. They conclude that firms with greater SCI strengths and wider arcs of integration outperform others. Particularly, firms with "high-uniform" (high SI, II and CI) and "outward-facing" (high SI and CI) and "forward-facing" or "customer-leaning" (high CI) have achieved better performance (Flynn et al., 2010; Frohlich and Westbrook, 2001; Schoenherr and Swink, 2012). However, owing to the limitation of ANOVA analysis such findings cannot tell us whether it is the SCI configuration, strength, interaction or other factors that have affected performance. The configuration theory of Flynn et al. (2010) argues it is the "fits" among SCI configurations and the environment but such fits have not been empirically examined. We therefore still cannot fully understand how specific SCI configurations or arcs of integration create performance.

Methodology

Sampling and data collection

A survey questionnaire distributed across the automotive, electronics and food industries in Thailand was conducted. These industries are highly diverse and heterogeneous, spanning manufacturers of different structural characteristics and competitive environments in Thailand. They play a major role in terms of Thailand's gross domestic product (GDP). We adopt measurement items from the existing literature to draft a questionnaire to improve the validity and reliability of the scales. The questionnaire was pre-tested by industry representatives and academics specialised in supply chain management (SCM), who suggested minor amendments to the wordings before it was distributed for data collection. This step ensured that the items were clear and providing face validity for the variables examined.

The entire population of 1,859 Thai manufacturing firms from the three industries was identified. A wide range of respondents were included. The respondents comprised of plant managers, CEOs, presidents, vice presidents, and directors. To identify respondents who had intimate knowledge of supply chain management, we retained only the samples of firms that manage their own supply chain. For these selected 1708 firms, the survey was separately sent to 746, 426, and 536 potential respondents from the automotive, electronics, and food industries, respectively. The responding firms consist of manufacturing suppliers and OEMs firms located in Thailand. The final number of completed and usable responses from the automotive industry was 151, indicating a response rate of 20.85%. The electronics industry survey yielded 82 usable responses (19% response rate). The food industry survey received 115 usable responses (21% response rate). This is close to the recommended minimum of 20% for empirical studies in operations management research.

Due to the use of single informants, common method variance was examined in two manners. Harman's one-factor tests show that no single factor was accounted for most of the covariance. Each independent and dependent variable loaded on different factors with the first factor accounting for less than 40% of the total variance. Next, suggestion, we used firm ownership as a marker variable (proxy) because it is theoretically unrelated to at least one of the variables. Ownership was insignificantly related to most variables (6 out of 8 pairs are insignificant), as shown in Table 1.

Table 1 - Mean, standard deviations, and correlations

Variables	Mean	S.D.	II	SI	CI	D	PC	PQ	PF
Internal integration (II)	3.84	.68							
Supplier integration (SI)	3.66	.67	.49**						
Customer integration (CI)	3.79	.73	.57**	.61**					
Delivery (D)	4.12	.65	.45**	.38**	.32**				
Production cost (PC)	3.28	.68	.32**	.34**	.24**	.36**			
Product quality (PQ)	4.13	.62	.44**	.41**	.36**	.54**	.37**		
Production flexibility (PF)	3.74	.67	.28**	.30**	.30**	.30**	.44**	.38**	
Product innovation (PI)	3.70	.71	.26**	.27**	.34**	.20**	.25**	.38**	.43**
Firm ownership[§]	1.76	.86	-.01	.38	.08	.12*	-.08	.16**	-.01

*Note: [§] Marker variable; * P<0.05; ** P<0.01; 2-tailed test*

Non-respondent bias is assessed by identifying any significant differences between early and late respondents for each industry. At the 0.05 significance level, analysis of variance (ANOVA) tests indicate no significant differences in terms of demographic characteristics and variables between the early and late respondents for each industry.

Scale development and validation

We adopted measurement scales from the existing literature. Internal integration measures how much firms integrate internally across functions (Flynn et al., 2010). Scales for supplier and customer integration were adopted from Wong et al. (2011) and Flynn et al. (2010). We also adopted measurement scales for delivery, product quality, and production cost, production flexibility (Wong et al. 2011), and product innovation (Rosenzweig et al., 2003). All these scales are measured at plant level. A five-point Likert scale was used: a higher value indicates a higher level of integration and achievement in performance. (1= very low and 5= very high).

Confirmatory factor analysis (CFA) is used to test construct validity. The CFA results for the measures show that all measurement models have acceptable fit indices. All fit indices are well above the recommended values. Cronbach's Alpha and composite reliability of all the variables are greater than the recommended threshold of 0.70, suggesting reliability of the measurement scales for each variable. Convergent validity was assessed as follows. First, all indicators in their respective variables are statistically significant ($p < 0.05$) with factor loadings from 0.44 to 0.90, which suggests convergent validity of the theoretical variables. Furthermore, the average variance extracted (AVE) of each variable exceeds the recommended minimum value of 0.5. Discriminant validity of the variables is assessed by conducting a series of chi-square difference tests using nested confirmatory factor analysis (CFA) for all pairs of variables. The results show that all chi-square differences between each pair of variables are highly significant (e.g., internal integration vs. supplier integration, $\Delta\chi2 = 73.91$, $p < 0.001$), suggesting discriminant validity of the variables. The square roots of AVE of all variables are greater than the correlation between any of the pairs, indicating discriminant validity.

Lastly, we confirm the data is normally distributed by examining the skewness and kurtosis of each variable. The results suggest that the statistics of skewness and kurtosis of each variable is within the range of -2 and +2, with an average -.39 skewness and .25 kurtosis. The results suggest that the data is normal univariate distribution, indicating that the data is suitable for parametric statistics.

Findings

Model 1 (individual effect model) is assessed by three structural models (SEM) linking each SCI dimensions (i.e., SI, II, and CI) independently with the performance dimensions, without interactions among them. Table 2 shows all three SCI dimensions have significant (p< 0.001) and positive associations with all performance outcomes, with high standardized estimates (from 0.42 to 0.70) and R^2 (0.18 to 0.49).

Table 2 - SEM results for SCI dimensions (Model 1) and SCI (Model 2)

Dependent variable (DV)	Independent variable (IV)			
	II	SI	CI	SCI
Cost (PC)	.55*** (.30)	.57*** (.32)	.46*** (.21)	.56*** (.31)
Flexibility (PF)	.51*** (.26)	.56*** (.31)	.55*** (.30)	.58*** (.34)
Product innovation (PI)	.42*** (.18)	.43*** (.19)	.50*** (.25)	.48*** (.23)
Delivery (D)	.68*** (.46)	.62*** (.38)	.54*** (.29)	.67*** (.4)
Quality (PQ)	.70*** (.49)	.67*** (.44)	.60*** (.35)	.71*** (.41)
Model fits: *SEM 1 for II*: χ^2 = 691.51, df = 290, p < .00; CFI =.92; IFI = .92; TLI =.91; RMR =.06 *SEM 2 for SI: χ2 = 718.20, df = 316, p < .00; CFI =.92; IFI = .92; TLI =.92; RMR =.06* *SEM3 for CI:* χ^2 = 785.34, df = 316, p < .00; CFI =.91; IFI = .91; TLI =.90; RMR =.06 *SEM4 for SCI: χ2 = 1234.63, df = 584, p < .00; CFI =.90; IFI = .90; TLI =.90; RMR =.05*				

*Note: * p<0.05; ** p<0.01; *** p < 0.001*

To test Model 2 (unified integrative model), we established another structural model (SEM) to test associations between a second-order SCI (consider SI, II, and CI as the first-order construct) with performance dimensions. Table 2 shows SCI as the second-order construct is positively associated ($p < 0.001$) with all the performance outcomes, with standardized estimates (from 0.48 to 0.71) and R^2 (0.23 to 0.51).

Model 3 (interactive model) is assessed by hierarchical regression for each performance dimension, including all the three SCI dimensions and their interactions as follows: performance (PQ, PC, PF, D, PI) = constant + SI + II + CI + interaction terms. The results are summarized (see details in the Appendix) here:

- Internal integration (II): Before adding interaction terms, there are significant and positive associations between II and PQ, PC and D; and there are insignificant and positive associations between II on PF and PI. The signs became negative and some significant paths become insignificant after interaction terms are added;
- Supplier integration (SI): When SI is first entered to the regression, there are significant and positive associations between SI and all five performance outcomes. When CI is entered some significant paths turned insignificant. When interaction terms are added, all positive paths become negative, some of which become non-significant;
- Customer integration (CI): Before entering the interaction terms, CI is significantly and positively associated with PQ, PF and PI. When interaction terms are added, all positive paths become negative, some of which become non-significant;
- Interaction terms: While all positive paths between SCI dimensions and performance outcomes turned negative, there are some positive and significant associations between some interaction terms and performance.

Model 4 is assessed by latent class modelling. Unlike cluster analysis, latent class analysis is a model-based approach that uses maximum-likelihood to estimate parameters and it maximizes cluster problems using a log-likelihood function. This method allows us to perform regression on each class (arc of integration) to ascertain the origins of the performance of each integration strategy. Latent class modelling was used to account simultaneously for both the similarity and differences between firms in terms of their levels of internal, supplier, and customer integration. It allows us to address alternative model structure in terms of different parameter estimates, and the extent to which an estimated model applies to a specific firm by the estimation of posterior probabilities that a specific firm falls into a class for which the model is statistically appropriate.

Table 3 - Latent class model selection (Model 3)

Model	AIC	BIC	aBIC	Entropy
2 classes	34221.867	34653.313	34298.013	0.908
3 classes	33639.870	34217.701	33741.852	0.925
4 classes	33094.794	33819.008	33222.612	0.946
5 classes	32811.257	33681.855	32964.910	0.948

Note: AIC = Akaike Information Criterion; BIC = Bayes Information Criterion; aBIC = adjusted Bayesian Information Criterion

Consistent with other clustering approach, latent class modelling to determine the clusters of firms are determined by theory and the meaningfulness and significance differences. The literature suggests no single criterion for choosing the number of classes and the literature suggests the use of several criteria to determine the number of classes. First, the log-likelihood-based model selection criteria (i.e., AIC, BIC and aBIC), which is considered a conservative approach, is used to determine the number of classes. The decreasing numbers of the AIC, BIC, and aBIC indicates a better and more parsimonious model when more classes were added, as shown in Table 3. These criteria and entropy scores suggest a five-class solution as the best classification. Table 4 summarizes the latent class mean values, from lowest to highest SCI dimensions. In addition, we run regression for each latent class, considering all SCI dimensions and their interaction terms. Surprisingly, there are more significant associations between SCI dimensions and performance for clusters with lower SCI strengths.

Table 4 - Latent class mean values and regression results (Model 3)

	Class 1 (n=38)	Class 3 (n=60)	Class 4 (n=53)	Class 2 (n=119)	Class 5 (n=78)
SI	3.04	2.96	3.55	3.86	4.31
II	3.13	3.20	3.98	3.98	4.49
CI	3.20	2.95	3.61	4.08	4.38
Regression results					
Number of significant paths	5	7	2	3	2
With PQ	II*; SIxCI*; SIxII*	II*	*None*	*None*	II*
With PC	*None*	*None*	*None*	*None*	IIxCI*
With PF	II***; SIxII**	*None*	SIxII*	SI*	*None*
With D	*None*	II***; SI*	*None*	-	*None*
With PI	*None*	CI***; SI***; SIxII**; SIxCI***	IIxCI**	SI*; SIxII*	*None*

*Note: * P<0.05; ** P<0.01; < 0.001*

Discussion and conclusion

This paper shows that the significant and positive associations between SCI dimensions (and second-order SCI) and performance reported by Models 1 and 2 could be over-estimated and even lead to false positive. Models 1 and 2 are not the true model because interactions among SCI dimensions are not considered. Models 3 and 4 show that SCI dimensions interact in both trade-off and synergetic manners; but these models cannot fully reveal such behaviours. There may be some multi-collinearity between SCI dimensions. Models 1 and 2 cannot clarify the different roles of SCI dimensions and their interactions. Model 3 shows clusters of firms with high SCI strength do not necessary achieve high operational performance through SCI dimensions and their interactions. Some variables that could affect operations performance are missing in such models (other variables that might affect performance). Model 4 shows there are inconsistent and spurious interactions between SCI dimensions. These findings suggest alternate model specifications and theoretical foundation to truly understand the effects of SCI. It is theory that drives correct model specification but popular theories e.g., RBV and relational-based view are inadequate for explaining distinct and joint effects of SCI dimensions.

References

Allen, M.P. 1997. Model specification in regression analysis. In: Understanding Regression Analysis. Springer, Boston, MA

De Giovanni, P. Vinzi, V.E. 2012. Covariance versus component-based estimations of performance in green supply chain management. International Journal of Production Economics 135, 907-916.

Deegan Jr., J. 1976. The consequences of model misspecification in regression analysis. Multivariate Behavioral Research 11(2), 237-248.
Devaraj, S., Krajewski, L., Wei, J.C. 2007. Impact of e-business technologies on operational performance: the role of production information in the supply chain. Journal of Operations Management 25(6), 1199–1216.
Dröge, C., Jayaram, J., Vickery, S.K. 2004. The effects of internal versus external integration practices on time-based performance and overall firm performance. Journal of Operations Management 22, 557-573.
Fabbe-Costes, N., Jahre, M., 2008. Supply chain integration and performance: a review of the evidence. The International Journal of Logistics Management 19(2), 130-154.
Flynn, B.B., Huo, B., Zhao, X., 2010. The impact of supply chain integration on performance: A contingency and configuration approach. Journal of Operations Management 28(1), 58–71.
Frohlich, M.T., Westbrook, R., 2001. Arcs of integration: An international study of supply chain strategies. Journal of Operations Management 19, 185–200.
Germain, R., Iyer, K.N.S. 2006. The interaction of internal and downstream integration and its association with performance. Journal of Business Logistics 27(2), 29-52.
Größler, A., Grübner, A., Milling, P.M. 2006. Organisational adaptation processes to external complexity. International Journal of Operations & Production Management 26(3), 254-281.
Lai, K.H., Wong, C.W.Y., Cheng, T.C.E., 2010. Bundling digitized logistics activities and its performance implications. Industrial Marketing Management 39(2), 273-286.
Leachman, C., Pegels, C. C., Shin, S. K. 2005. Manufacturing performance: Evaluation and determinants. International Journal of Operations & Production Management 25(9), 851-874.
Leuschner, R., Rogers, D., Charvet, F.F. 2013. A meta-analysis of supply chain integration and firm performance. Journal of Supply Chain Management 49(2), 35-47.
MacCallum, R. C. 1995. Model specification: Procedures, strategies, and related issues. In R. H. Hoyle (Ed.), Structural equation modeling: Concepts, issues, and applications (pp. 16-36). Thousand Oaks, CA, US: Sage Publications, Inc.
Mackelprang, A.W., Robinson, J.L., Bernardes, E., Webb, G.S. 2014. The relationship between strategic supply chain integration and performance: a meta-analytic evaluation and implications for supply chain management research. Journal of Business Logistics 35(1), 71-96.
Morash, E.A., Dröge, C., Vickery, S., 1997. Boundary-spanning interfaces between logistics, production, marketing and new product development. International Journal of Physical Distribution and Logistics Management 27(5/6), 350-369.
Ragatz, G.L., Handfield, R.B., Peterson, K.J., 2002. Benefits associated with supplier integration into new product development under conditions of technology uncertainty. Journal of Business Research 55(5), 389-400.
Rosenzweig, E.D., Roth, A.V., Dean Jr., J.W. 2003. The influence of an integration strategy on competitive capabilities and business performance: an exploratory study of consumer products manufacturers. Journal of Operations Management 21, 437-456.
Schoenherr, T., Swink, M. 2012. Revisiting the arcs of integration: Cross-validations and extensions. Journal of Operations Management 30(1-2), 99–115.
Wong, C.Y., Boon-itt, S., Wong, C.W.Y. 2011. The contingency effects of environmental uncertainty on the relationship between supply chain integration and operational performance. Journal of Operations Management 26(9), 604–615.
Wu. S.J., Melnyk, S.A., Morgan, S. 2012. An empirical investigation of the combinatorial nature of operational practices and operational capabilities. International Journal of Operations & Production Management 32(2), 121-155.

Appendix - Multiple regression results (Model 3)

M	Variables	PQ						PC						PF				D				PI			
		β	t	Tolerance	VIF	R^2	ΔR^2	β	t	Tolerance	VIF	R^2	ΔR^2	β	t	R^2	ΔR^2	β	t	R^2	ΔR^2	β	t	R^2	ΔR^2
1	Constant	2.494	9.653***	1.00	1.00	.200	-	2.001	7.138***	1.00	1.00	.116	-	2.850	9.503***	0.055	-	2.361	8.627***	.197	-	2.648	8.451***	.072	-
	II	.413	60.97***					.325	4.421***					.231	2.944**			.434	6.053***			.279	3.396***		
2	Constant	1.923	6.818***			.282	.082	1.468	4.725***			.183	.067	2.445	7.213***	0.091	.036	1.865	6.128***	.253	.056	2.107	6.025***	.130	.058
	II	.269	3.681***	.76	1.32			.191	2.365*	.76	1.32			.129	1.473			.309	3.919***			.143	1.574		
	SI	.302	4.107***	.76	1.32			.283	3.491***	.76	1.32			.214	2.428*			.263	3.309***			.287	3.145**		
3	Constant	1.791	6.212***			.298	.016	1.398	4.361***			.188	.005	2.259	6.549***	0.121	.003	1.856	5.895***	.253	.000	1.837	5.249***	.186	.056
	II	**.208**	**2.620****	.638	1.57			**.158**	**1.790***	.638	1.57			.043	.455			**.305**	**3.516*****			.018	.184		
	SI	**.228**	**2.760****	.603	1.66			**.244**	**2.649****	.603	1.66			.111	1.117			**.257**	**2.848****			.136	1.356		
	CI	**.166**	**1.882***	.534	1.87			.088	.900	.534	1.87			**.234**	**2.221***			.012	.122			**.340**	**3.172****		
4	Constant	3.638	2.394*			.338	.040	3.372	1.949*			.196	.008	5.129	2.781**	0.146	.025	3.077	1.815*	.264	.011	5.980	2.357***	.239	.053
	II	-.899	-2.052*	.019	51.68			-.302	-.606					-.488	-.917			-.005	-.009			1.157	-2.184*		
	SI	.398	.814	.020	48.92			-.199	-.358					-.114	-.192			-.452	-.829			-.049	-.083		
	CI	.073	.167	.020	49.81			-.106	-.213					-.628	-1.181			.372	.761			-.630	-1.190		
	II x SI	.113	.927*	.006	156.14			.089	.646					-.028	-.189			.185	1.637			.037	.254*		
	II x CI	.189	2.046*	.010	99.54			.034	.322					.174	1.552			-.107	-1.035			.284	2.544		
	SI x CI	-.160	-1.679	.010	97.93			.026	.242					.076	.657			.009	.087			-.002	-.013		
5	Constant	14.95	2.644**			.338	.000	5.414	.809			.196	.000	18.962	2.763*	0.171	.025	14.915	2.360*	.283	.019	22.877	3.375***	.273	.034
	II	3	-2.554*	.002	468.22			-.889	-.474					-4.462	-2.263*			-3.405	-1.875*			-6.011	-3.086*		
	SI	-4.150	-1.750*	.002	480.67			-.800	-.413					-4.185	-2.058*			-3.936	-2.101*			-5.022	-2.500**		
	CI	-2.933	-1.947*	.002	492.28			-669	-.370					-4.436	-2.340*			-2.886	-1.653*			-5.281	-2.820*		
	II x SI	-3.041	2.246*	.001	1608.7			.260	.478					1.127	1.973*			1.173	1.680*			1.448	2.566**		
	II x CI	1.057	2.463*	.001	1528.68			.193	.384					1.254	2.237*			.807	2.230*			1.603	3.072*		
	SI x CI	1.072	1.667*	.001	1578.43			.189	.368					1.178	2.184*			.952	1.917*			1.344	2.524*		
	II x SI x	.741	-2.075*	.000	3258.70			-.046	-.324					-.309	-2.091*			-.264	-1.943*			-.377	-2.585*		
	CI	-.252																							

**** p<0.001; ** P<0.01; * p<0.1*