Heterogeneity in dynamic capability configurations: Equifinality and strategic performance

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Abstract

The present article outlines an approach that combines finite mixture partial least squares analysis with fuzzy-set qualitative comparative analysis to assess the performance impact of dynamic capability configurations, conditional on certain levels of environmental dynamism. In consideration of business model sensing, strategic learning, and strategic reconfiguring, the findings imply that these three dynamic capability processes do not necessarily co-occur; different configurations of these processes can yield superior strategic performance, conditional on the levels of environmental dynamism.

Keywords: dynamic capabilities, strategic performance, environmental dynamism, FIMIX-PLS, fuzzy set qualitative comparative analysis

1. Introduction

A configurational approach assumes that *gestalts*, rather than independent factors relate to strategic performance (Fiss, 2007). Configuration typologies, such as those by Miles and Snow (1978) or Porter (1980), remain central to strategy research, but recent discussion on the role of equifinality within the dynamic capabilities view likewise alludes to the importance of distinct capability configurations in the pursuit of superior performance (Eisenhardt & Martin, 2000). A few studies assess configurations of the processes that make up dynamic capabilities (e.g., Löwik, 2013; Vergne & Depeyre, 2015) but tend to assume heterogeneous performance impacts, without empirically testing for such heterogeneity or theoretically explaining its possibility in dynamic capability configurations.

To close this gap, the current article draws upon the dynamic capabilities view (Eisenhardt & Martin, 2000; Teece, 2007) and examines how a set of interrelated dynamic capability processes leads to superior strategic performance (Bingham, Heimeriks, Schijven, & Gates, 2015; Lin & Wu, 2014, Schilke, 2014). In doing so, this article offers a contribution that concerns the dynamic capabilities view and one that is methodological in nature: First, this study refines current assumptions about the sequencing of three dynamic capability processes (business model sensing, strategic learning, and strategic reconfiguring) that, according to conventional understanding, would yield superior strategic performance when occurring consecutively. In support of Eisenhardt and Martin (2000), the findings suggest that these three strategic processes do not always co-occur; rather, their different configurations yield certain strategic performance outcomes, conditional on the levels of environmental dynamism. Accordingly, this study identifies heterogeneous dynamic capability configurations that produce the same performance outcome; supporting the equifinality assumption within the dynamic capabilities view.

Second, since standard applications of partial least squares structural equation modeling (PLS-SEM), that would commonly serve to examine the performance impact of certain dynamic capability processes (e.g., Wilden, Gudergan, Nielsen, & Lings, 2013), face limitations in identifying heterogeneous equifinal dynamic capability configurations, this study proposes and implements an approach that combines finite mixture partial least squares (FIMIX-PLS) analysis (Sarstedt, Ringle, & Gudergan, 2015) with fuzzy-set qualitative comparative analysis (fsQCA) (Fiss, 2011) to assess potentially unobserved heterogeneity and identify ensuing equifinal dynamic capability configurations.

Using survey data from top-executives in the German chemical industry, the empirical analysis with PLS-SEM suggests that strategic learning and strategic reconfiguring fully mediate the relationship between business model sensing and strategic performance. In line with the findings of the FIMIX-PLS analysis, the fsQCA further demonstrates the existence of four idiosyncratic dynamic capabilities configurations when considering environmental dynamism as an additional causal condition. Consequently, this study affirms that different *gestalts* of dynamic capability processes open different paths to superior strategic performance, conditional on environmental dynamism.

2. Theory and hypotheses

2.1. Dynamic capabilities view

Firms require idiosyncratic and difficult-to-imitate dynamic capabilities to achieve sustainable competitive advantages in fast-moving environments (e.g., Helfat, Finkelstein, Mitchell, Peteraf, Singh, Teece, & Winter, 2007; Teece, 2007). Dynamic capabilities represent the capacity of firms to integrate, build, and reconfigure resources (Teece, Pisano, & Shuen, 1997). A firm's dynamic capabilities, which allow it to adapt to changing environments (Zahra, Sapienza, & Davidsson, 2006) or develop new business models (Teece, 2010), affect performance by strategically transforming the business (Helfat et al., 2007).

Teece (2007) conceptualizes dynamic capabilities as encompassing three processes: sensing and shaping opportunities and threats, seizing opportunities, and reconfiguring the business enterprise's resource base. Yet dynamic capabilities function in firm-specific, idiosyncratic ways (Drnevich & Kriauciunas, 2011; Eisenhardt & Martin, 2000). As Pettus, Kor, and Mahoney (2009, p. 189) suggest, even if the processes underlying dynamic capabilities overlap, "…they serve unique and complementary roles to boost the likelihood of operating successfully in environments of significant change." The processes that constitute dynamic capabilities thus "neither exist uniformly in all firms, nor matter equally in all industries" (Pettus et al., 2009, p. 191; see also Delmas, Russo, & Montes-Sancho, 2007; Winter, 2003).

Therefore, effective dynamic capabilities share some commonalities, but the ways firms practice them differ since they are path dependent and subject to organizational inertia and commitment (Eisenhardt & Martin, 2000). In consideration of such firm idiosyncrasies (Winter, 2000), dynamic capabilities reflect firm-specific positions, paths, and processes (Schreyögg & Kliesch-Eberl, 2007) and their performance impacts are not necessarily homogeneous but differ across firms, subject to how they form in those firms. Also, the impacts of dynamic capabilities vary with external conditions (Eisenhardt & Martin, 2000) and are contingent on environmental dynamism (Li & Liu, 2014; Schilke, 2014; Wilden & Gudergan, 2015; Wilden et al., 2013). Any assessment of heterogeneity needs to account for both the ways that dynamic capabilities shape within firms and the environmental dynamism they face.

2.2 Hypotheses

2.2.1 Homogeneous impacts of dynamic capabilities

A firm's capacity to sense and filter strategic opportunities concerning its business model is an important means to address changing business environments (Teece, 2012). This process of business model sensing, or the firm's capacity to validate its business model, involves monitoring competitors' business models, scanning for external and internal discontinuities that potentially threaten an existing business model, and assessing this business model (Teece, 2010).

Because business model sensing generates new information (e.g., new revenue models) and can monitor market opportunities, it supports a firm's ability to create strategically relevant knowledge. This knowledge-generating proficiency is an important basis for strategic learning (Zollo & Winter, 2002), denoting "a firm's proficiency at deriving knowledge from past strategic actions and subsequently leveraging that knowledge to adjust firm strategy" (Anderson, Covin, & Slevin, 2009, p. 218). That is, business model sensing fosters not only knowledge generation but also strategic change, through leveraging the strategic knowledge. In turn, business model sensing promotes strategic change, because "a plethora of business models … can be designed and employed, but some will be better adapted to the ecosystem then others" (Teece, 2007, p. 1330). Firms with high awareness of their own and competitors' business models are in a better position to identify new business models that fit the ecosystem, such that these firms can better seize new opportunities and strategically reconfigure their business than companies with low awareness (Pavlou & El Sawy, 2011).

Hypothesis 1: Business model sensing relates positively to (a) strategic learning and (b) strategic reconfiguring.

Strategic learning enables firms to innovate and adapt to changes in technology and markets (Helfat & Raubitschek, 2000; Anderson et al., 2009) and also facilitates the modification and transformation of firms' business (Nooteboom, 2009). Firms that engage in learning should experience less organizational inertia (Levinthal, 1991), such that strategic reconfigurations are more likely. Thus, strategic learning facilitates both the effective selection and the actual development of business models that yield competitive advantages (Teece, 2007).

Hypothesis 2: Strategic learning relates positively to (a) strategic reconfiguring and (b) strategic performance.

Strategic reconfiguring processes influence firm performance (Helfat & Peteraf, 2009) and enable firms to adapt more quickly and effectively, creating a stream of temporary competitive advantages (Teece et al., 1997; Helfat et al., 2007). By reconfiguring their business in novel ways, firms can leverage new opportunities and new sources of economic value (Galunic & Rodan, 1998).

Hypothesis 3: Strategic reconfiguring positively relates to strategic performance.

2.2.2 Heterogeneous impact of dynamic capabilities

In the implicit, evolutionary novelty creation sequence (i.e., H1–H3; see also Teece, 2007; Zollo & Winter, 2002), strategic reconfiguring depends on prior strategic learning, which in turn rests on business model sensing. This sequencing concurs with prior conceptualizations (e.g., Dess & Lumpkin, 2005; Eisenhardt & Martin, 2000), but the processes likely develop and function differently across firms, due to firm idiosyncrasies such as path dependencies. The impact of dynamic capabilities also varies with environmental conditions (Eisenhardt & Martin, 2000; Schilke, 2014). Thus, and in drawing on Löwik (2013) and Vergne and Depeyre (2015), there likely is heterogeneity in how certain dynamic capability processes affect firms' strategic performance, and environmental dynamism likely affects their impact.

Hypothesis 4: Equifinality characterizes certain dynamic capability configurations, conditional on environmental dynamism.

3. Research design, data, and methodology

3.1 Sample

The empirical data of this study is cross-sectional and part of a larger study investigating organizational capabilities within the German chemical industry in 2014. The chemical industry is particularly suitable to study dynamic capabilities as it is facing shifting market dynamics. By making use of an online questionnaire, this study solicits data from top-managers as key informants. To ensure that these key informants are knowledgeable to adequately respond to the questions under examination, the study applies the following key-informant criteria: (1) involvement in strategic, operational, and innovation decision making; (2) job experience; (3) job title; and (4) organizational tenure (see Appendix A). From an initial sample of 286 respondents, this study discards 187 entries, due to missing data or mismatches with the key informant criteria. The final sample of 99 respondents represents a response rate of 34.61% (accounting for all participants who started the online survey; Joshi, Kathuria, & Porth, 2003).

Two post-hoc analyses (employing Mann-Whitney U tests) of the differences between early and late respondents, and between participants completing and those abandoning the survey indicate that non-response bias is not a concern. Harman's single-factor test and the inclusion of a common factor, containing all items of the principal constructs in the structural model, also suggest that common method bias is not an issue.

3.2 Measures

This study introduces a four-item scale to measure business model sensing (BMS) (Appendix B). Strategic learning (SL) draws on a six-item scale from Anderson et al. (2009); strategic reconfiguring (SR) uses a three-item scale based on Ling, Simsek, Lubatkin and Veiga (2008) and Zhou and Wu (2010); and strategic performance (SP) adapts three items from Schilke (2014). Firm age (number of years since the firm's inception) and firm size (full-time employees) serve as control variables. This study also controls for company type (manufacturing vs. service) and the price and quality of products (Tracey, Vonderembse, & Lim, 1999).

3.3 Methodology

To assess H1–H3, this study applies PLS-SEM (with SmartPLS 2.0 M3; Ringle, Wende, & Will, 2005). To assess H4, FIMIX-PLS analysis serves to examine empirically whether the performance impact of certain dynamic capability processes is heterogeneous. Establishing the presence of heterogeneity is a prerequisite for examining whether equifinality characterizes certain dynamic capability configurations, possibly conditional on environmental dynamism. Despite the necessity of this step, common assessments of configurations that draw on fsQCA do not establish heterogeneity in advance. Subsequently, fsQCA provides a further assessment of the presence and nature of dynamic capability configurations and their equifinality.

4. Analysis and results

4.1 Measurement scales

Table 1 details the measurement characteristics. All indicators' (standardized) outer loadings exceed .70 (Hulland, 1999; Hair, Ringle, & Sarstedt, 2011), indicating adequate individual item reliability. The constructs all exceed the .70 threshold for Cronbach's alpha and composite reliability (CR) (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014). The average variance extracted (AVE) values all exceed .50, in support of convergent validity (Henseler, Ringle, & Sinkovics, 2009). Since the square root of each construct's AVE also exceeds the correlation with any other measurement construct, the measures of this study also fulfill the Fornell-Larcker criterion. In Appendix B, each indicator loading with the associated construct exceeds any loading with any other construct, which suggests adequate discriminant validity also at the indicator level.

Table 1 here

4.2 Structural model

This study estimates the path coefficients using PLS-SEM; the corresponding standard errors derive from a bootstrapping procedure with replacement, using 500 resamples. Figure 1 and Table 2 contain the PLS-SEM analysis results. This study assesses the structural model by means of its R^2 values. All endogenous constructs exceed the threshold for moderate explanatory power: SL (.44), SR (.46), and SP (.56) (Chin, 1998).

Figure 1 and Table 2 here

To evaluate the mediating effects of SL and SR, the present study applies Subramani's (2004) approach and compares a full and a partially mediated (nested) model. The results suggest that SR fully mediates the relationships between BMS and SP (f^2 = .00, *p* = .64) and between SL and SP (f^2 = .01, *p* = .36), whereas SL partially mediates the relationship between BMS and SR (f^2 = .09, *p* = .00).

4.3 Prediction analysis

While R^2 values indicate how well the proposed structural model explains the outcome of interest, this study also assesses the prediction ability of the structural model (e.g., Armstrong, 2012; Chin, 2010; Woodside, 2013). Since all Stone-Geisser Q^2 values are greater than zero, all endogenous constructs show adequate prediction validity (Henseler et al., 2009). This study further evaluates predictive validity with a prediction analysis, using a holdout sample (Woodside, 2013). A PLS-SEM estimation using the estimation sample (n = 66) produces the weights and path coefficients to predict the dependent variables in the holdout sample (n = 33). The comparison of predicted and calculated values of the construct scores reveals the following values of the correlation (r) and the root-mean-square error (RMSE): SL (r = 0.57; RMSE = 0.83), SR (r = 0.71; RMSE = 0.70), and SP (r = 0.25; RMSE = 0.99).

4.4 FIMIX-PLS and unobserved heterogeneity

To account for unobserved heterogeneity, the FIMIX-PLS analysis (Sarstedt et al., 2015) identifies whether firms' dynamic capability processes affect strategic performance differently. The FIMIX-PLS algorithm proceeds 10 times each for different segment solutions (g = 2 – 5) (Sarstedt et al., 2015). The Akaike information criterion (AIC), Bayesian information criterion, heuristic consistent AIC, and normed entropy statistic (Table 3) serve to identify the appropriate segmentation solution (Sarstedt et al., 2015); these criteria specify the four-segment solution as the most adequate. Thus, the FIMIX-PLS analysis establishes that heterogeneity exists here and that equifinality characterizes certain dynamic capability configurations.

Table 3 here

The smallest segment of the four-segment solution offers a size of only 14%, so further segment-specific PLS-SEM analyses are not appropriate. However, fsQCA can evaluate the existence of various segments by forming a set of different configurations that might explain variance in the outcome of interest (Fiss, 2011). As a configurational approach, fsQCA assumes "variables found to be causally related in one configuration may be unrelated or even inversely related in others" (Meyer, Tsui, & Hinings, 1993, p. 1178) and thus can examine effects caused by unobserved heterogeneity.

4.5 fsQCA

While PLS-SEM accounts for pre-determined relationships that explain the dependent variable of interest, fsQCA allows testing several alternative causal recipes (e.g., Ragin, 2008; Woodside, Hsu, & Marshall, 2011; Woodside, Ko, & Huan, 2012; Woodside, 2013). Hence, instead of considering the isolated net influence of each variable on the outcome, fsQCA examines how variables combine into configurations to explain the outcome and, therefore, represents an important complementary analysis procedure to methods such as PLS-SEM (e.g., Tóth, Thiesbrummel, Henneberg, & Naudé, 2015; Woodside et al., 2012; Woodside, 2013). FsQCA accounts for three premises: (1) the interplay of different attributes causes an outcome (conjunction), (2) alternative attribute configurations can cause the same outcome (equifinality), and (3) causes of the presence of an outcome might differ from causes of its absence (asymmetry) (Fiss, 2011; Greckhamer, 2015). Also, fsQCA embraces the idea of set memberships. Each case belongs to a configuration to some degree and exhibits varying degrees of membership across various configurations (Fiss, 2011).

Consistent with the idea of set memberships, the first analysis step transforms the measurement variables into fuzzy sets, ranging from 0 (full non-membership) to 1 (full membership), with a cross-over point of .50 (maximal ambiguity) (Fiss, 2011; Woodside, 2013). For the analysis in fs/QCA 2.5, this study uses unstandardized latent variables scores. On a seven-point Likert scale, the calibration of the core variables (BMS, SL, SR, and SP) uses the following thresholds scores: 6 for full membership, 2 for full non-membership, and 4 as the indifference point (Ordanini, Parasuraman, & Rubera, 2014).

Because FIMIX-PLS and the subsequent fsQCA seek to detect unobserved heterogeneity and identify factors that might explain differences across various groups of firms, this study includes an environmental dynamism variable, following the preceding argument. The five-item environmental dynamism scale reflects “the rate of change and the degree of instability of the environment” (Jansen, van den Bosch, & Volberda, 2006, p. 1664). To derive unstandardized latent variables scores as input for fs/QCA 2.5 and evaluate the adequacy of the measurement scale, environmental dynamism enters the model estimation as an additional variable. To ensure adequate reliability, only items with loadings that exceed .70 remain (Appendix B).

First, this study examines whether any of the four conditions (ED, BMS, SL, SR) is necessary for causing the outcome of interest (SP). The analysis of necessary conditions reveals consistency scores that range from .31 to .85. Since none of the conditions (presence and absence) exceed the threshold of .90, the four conditions are not necessary for causing strategic performance (Tóth et al., 2015). The subsequent analysis of sufficient conditions involves the construction, redefinition, and analysis of the truth table. The redefinition of the truth table and its reduction to meaningful conditions reflects the minimum number of cases that is necessary to consider a solution as well as the minimum consistency level. In light of the small sample size in this study, the minimum number of cases is two. The threshold for the minimum consistency level of a solution is .93, which reflects the point at which a clear drop in consistency occurs in the ordered consistency values from the truth table (Leischnig & Kasper-Brauer, 2015). Table 4 summarizes the results of the analysis of the complex, parsimonious, and standard solution terms. Consistent with FIMIX-PLS, the fsQCA indicates four solutions with an overall consistency level of .92 and an overall solution coverage of 0.77. That is, the four identified configurations account for 77% of the membership in the outcome (presence of SP). While solutions 1 and 2 reveal the presence of environmental dynamism as a peripheral condition, solutions 3 and 4 suggest its absence. As Table 4 indicates, the consistency level of each individual solution exceeds the recommended threshold of .75 (Ragin, 2008). While all solutions indicate adequate raw coverage (ranging from .19 to .64), the unique coverage of solution 4 does not exceed the value of 0 and, thus, does not substantially contribute to the explanation of the outcome of interest (Tóth et al., 2015).

Table 4 here

5. Discussion and conclusion

This study examines the common view that concerns the sequencing and co-occurrence of dynamic capability processes; namely, that business model sensing precedes strategic learning which, in turn, directs strategic reconfiguring. The guiding argument in this study draws on the notion that firms are heterogeneous in their dynamic capabilities, so "there is no such thing as a dynamic capability that is exactly alike across firms because such capabilities, while showing common features, are still idiosyncratic in their details" (Barreto, 2010, p. 263). Prior literature, however, often rests on the assumption of co-occurring dynamic capability processes (e.g., Dess & Lumpkin, 2005; Eisenhardt & Martin, 2000). In contrast to this assumption, the present findings show that the three dynamic capability processes, that this study considers, do not always co-occur and different configurations can yield superior strategic performance. Therefore, the findings from this study question the commonly assumed sequencing of dynamic capability processes and imply that firm-specific paths, unique resource positions, and distinctive processes produce heterogeneity in dynamic capabilities across firms; different *gestalts* of dynamic capability processes also open different routes to superior performance.

In addition, this study affirms that equifinality characterizes certain configurations of dynamic capabilities. In dynamic environments, two distinct configurations yield high strategic performance (see Table 4). In Solution 2, firms rely predominantly on their ability to generate and act on strategic knowledge in the pursuit of superior strategic performance. Dynamic environments feature substantial and unpredictable change, so identifying the right business model or proper strategy is difficult, and failures are likely (Anderson et al., 2009). The firm's ability to accumulate strategic knowledge and modify its business model design and competitive choices accordingly can lead to superior strategic performance. Meanwhile, Solution 1 reveals that firms that do not learn strategically can still achieve superior strategic performance. These firms rely on their capacity to validate their business model; for example, business model sensing might be sufficient to achieve superior strategic performance if the company's analytical systems for sensing, filtering, and calibrating opportunities and threats enable the firm to adapt its established business model gradually to the dynamic environment. Instead of conducting strategic experiments to select and design new business models, these companies leverage the strengths of their existing models to shape opportunities and achieve superior strategic performance.

The results also describe configurations that lead to high strategic performance in non-dynamic environments. Following prior literature (Gunawan & Huarng, 2015; Tóth et al., 2015), this discussion focuses solely on solutions with substantial, unique coverage, thereby excluding Solution 4. The remaining solution (Solution 3) indicates that firms rely on both business model sensing and strategic learning to achieve superior strategic performance in non-dynamic environments, which may prevent firms from escaping established industry paradigms or trajectories easily. For example, firms that aim to compete by introducing new ways of doing business in established markets cannot rely solely on their pronounced understanding of existing business models but also need to test and evaluate new mechanisms to create and capture value that break with current market rules. Selecting, designing, and adjusting a business model that enables a firm to outperform competitors in a stable, predictable ecosystem may thus require both business model sensing and strategic learning.

Accordingly, researchers should consider the effects of different dynamic capability configurations on performance outcomes. A combination of FIMIX-PLS analysis and fsQCA supports tests of whether unobserved heterogeneity exists and empirical assessments of the performance impacts of different dynamic capability configurations in an equifinality context. Verifying heterogeneity is a prerequisite for analyzing equifinality, so researchers who seek to assess the impact of certain configurations in an equifinality context should consider a priori using methods that can reveal whether unobserved heterogeneity characterizes the study context.

Likewise, managers should be cognizant of the role that different dynamic capability configurations possibly play across different firms and environments. That is, strategic decision makers may not always need to follow a complete sequence of dynamic capability processes, as the following case of the chemical company Lanxess allows to highlight: Since its foundation, Lanxess transformed from a collection of unprofitable businesses spin-off from Bayer to the world's biggest producer of synthetic rubber. Erstwhile a success story, Lanxess is today in a process of reconfiguration to regain fit with its business environment. At the core of the firm's realignment program is the role-out of a new business model supported by the adaptation of enterprise structures and decision-making procedures. In this process, Lanxess rather relies on its ability to derive strategic knowledge and act on that knowledge than its capacity to validate its present business model in regaining competitive advantage. Thus, once an established business model is no longer competitive, companies like Lanxess may not rely on high levels of business model sensing but rather on high levels of strategic learning to achieve strategic performance in dynamic environments.

In building on this study's insights, future research should explore the generalizability of these findings in other contexts, such as in emerging markets. Additional research should also consider longitudinal studies, to explore how different configurations of dynamic capabilities evolve over time. Then, further research should explore *how* specific firm-specific paths and unique resource positions produce heterogeneity in dynamic capability configurations and affect equifinality in their strategic performance.

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Appendix A: Descriptive statistics

Key informant descriptive statistics

Job title		
CEO	15	15.15 %
CTO	1	1.01 %
Executive director	1	1.01 %
Director	4	4.04 %
Chairman	2	2.02 %
Vice president	1	1.01 %
Business unit manager	5	5.05 %
Head of department	21	21.21 %
Senior manager	2	2.02 %
Partner	1	1.01 %
General manager	40	40.40 %
Operations manager	6	6.06 %
Involvement in…	**ME**	**SD**
…strategic decision making	5.14	1.72
…innovation decision making	5.39	1.52
…operational decision making	4.91	1.77
Organizational tenure (in years)	12.64	9.87
Overall work experience (in years)	19.87	10.23

Firm descriptive statistics

Firm size (number of full time employees)		
1-10	3	3.03 %
11-50	8	8.08 %
51-250	6	6.06 %
251-1000	14	14.14 %
1,001-50,000	53	53.54 %
> 50,000	15	15.15 %
	ME	**SD**
Firm age (in years)	86.10	53.68

Appendix B: Measures

Measurement Construct	Measurement Item	Source	ME	SD	BMS	SL	SR	SP	CL	QL	ED
Business Model Sensing (BMS)	BMS 1 We are aware of discontinuities (social. technical. or political) that could significantly reduce the economic power of our current business model	n/a	5.10	1.10	**.75**	.42	.46	.31	.11	.32	.27
	BMS 2 All units that make our firm (departments. sections. groups. individuals) know how they contribute to our business model.		4.48	1.30	**.79**	.55	.49	.42	.18	.31	.31
	BMS 3 We are aware of our competitors' business models.		4.66	1.25	**.76**	.40	.37	.35	.10	.37	.28
	BMS 4 We constantly test and evaluate our current business model.		4.68	1.38	**.82**	.60	.48	.41	.18	.47	.21
Strategic Learning (SL)	SLC 1 My business is good at identifying strategies that haven't worked.	Anderson, Covin, & Slevin (2009)	4.44	1.36	.49	**.75**	.43	.33	.13	.26	.12
	SLC 2 My business unit is good at pinpointing why failed strategies haven't worked.		4.19	1.31	.47	**.82**	.45	.31	.13	.14	.19
	SLC 3 My business unit is good at learning from its strategic/competitive mistakes.		4.19	1.48	.59	**.86**	.55	.38	-.04	.13	.19
	SLC 4 My business unit regularly modifies its choice of business practices and competitive tactics as we see what works and what doesn't		4.46	1.43	.47	**.84**	.57	.40	.11	.24	.20
	SLC 5 My business unit is good at changing its business strategy midstream as we get a sense of the likely effectiveness of our actions.		4.63	1.33	.55	**.88**	.57	.37	-.01	.33	.26
	SLC 6 We are good at recognizing alternative approaches to achieving our business unit's objectives when it becomes clear that the initial approach won't work.		4.35	1.27	.66	**.87**	.51	.36	.03	.34	.23

Appendix B: Measures (continued)

Strategic Reconfiguring (SR)	SR 1 The reallocation of organizational resources to support the firm's intended product strategies.	Zhou & Wu (2010)	4.34	1.42	.31	.42	**.72**	.35	-.06	.14	.27
	SR 2 Over the past three years, this company has reorganized operations to ensure increased coordination and communication among business units.	Ling, Simsek, Lubatkin, & Veiga (2008)	5.06	1.42	.40	.44	**.73**	.41	.20	.14	.37
	SR 3 Over the past three years, this company has introduced a large number of new products/services to the market.		4.55	1.62	.57	.53	**.83**	.50	.08	.29	.46
Strategic Performance (SP)	SP 1 We have gained strategic advantages over our competitors.	Schilke (2014)	5.23	1.24	.49	.45	.59	**.78**	.14	.35	.23
	SP 2 We have a large market share.		5.17	1.57	.36	.21	.39	**.86**	.28	.28	.30
	SP 3 Overall, we are more successful than our major competitors.		4.74	1.52	.39	.43	.45	**.90**	.30	.36	.35
Price Offered (CL)	CL 1 We offer competitive prices.	Tracey, Vonderembse, & Lim (1999)	5.09	1.44	.08	-.04	.03	.23	**.85**	.17	.03
	CL 2 We are able to compete based on our prices.		5.03	1.48	.26	.17	.16	.26	**.90**	.26	.07
	CL 3 We are able to offer prices as low or lower than our competitors.		3.98	1.62	.08	-.03	.03	.24	**.81**	.13	.07

Appendix B: Measures (continued)

Quality of Products (QL)	QL 1 We are able to compete based on quality.	Tracey, Vonderembse, & Lim (1999)	5.93	1.13	.44	.25	.29	.30	.19	**.82**	.19
	QL 2 We offer products that are highly reliable.		5.97	1.06	.35	.17	.14	.35	.19	**.85**	.01
	QL 3 We offer products that are very durable.		5.38	1.58	.33	.30	.20	.31	.20	**.72**	.22
	QL 4 We offer high quality products to our customers.		6.09	1.08	.41	.21	.19	.32	.16	**.86**	.05
Environmental Dynamism (ED)	ED 1 Environmental changes in our local market are intense.*	Jansen, van den Bosch, & Volberda (2006)	5.07	1.36	-	-	-	-	-	-	-
	ED 2 Our clients regularly ask for new products and services.		5.04	1.38	.33	.25	.52	.42	.06	.16	**.97**
	ED 3 In our local market, changes are taking place continuously.		5.04	1.18	.23	.12	.26	.05	.07	.06	**.75**
	ED 4 In a year, nothing has changed in our market. (RV)*		5.27	1.62	-	-	-	-	-	-	-
	ED 5 In our market, the volumes of products and services to be delivered change fast and often.*		3.94	1.54	-	-	-	-	-	-	-

SD = Standard deviation, * Items dropped due to measurement concerns, RV = Reverse coded, n/a = not available

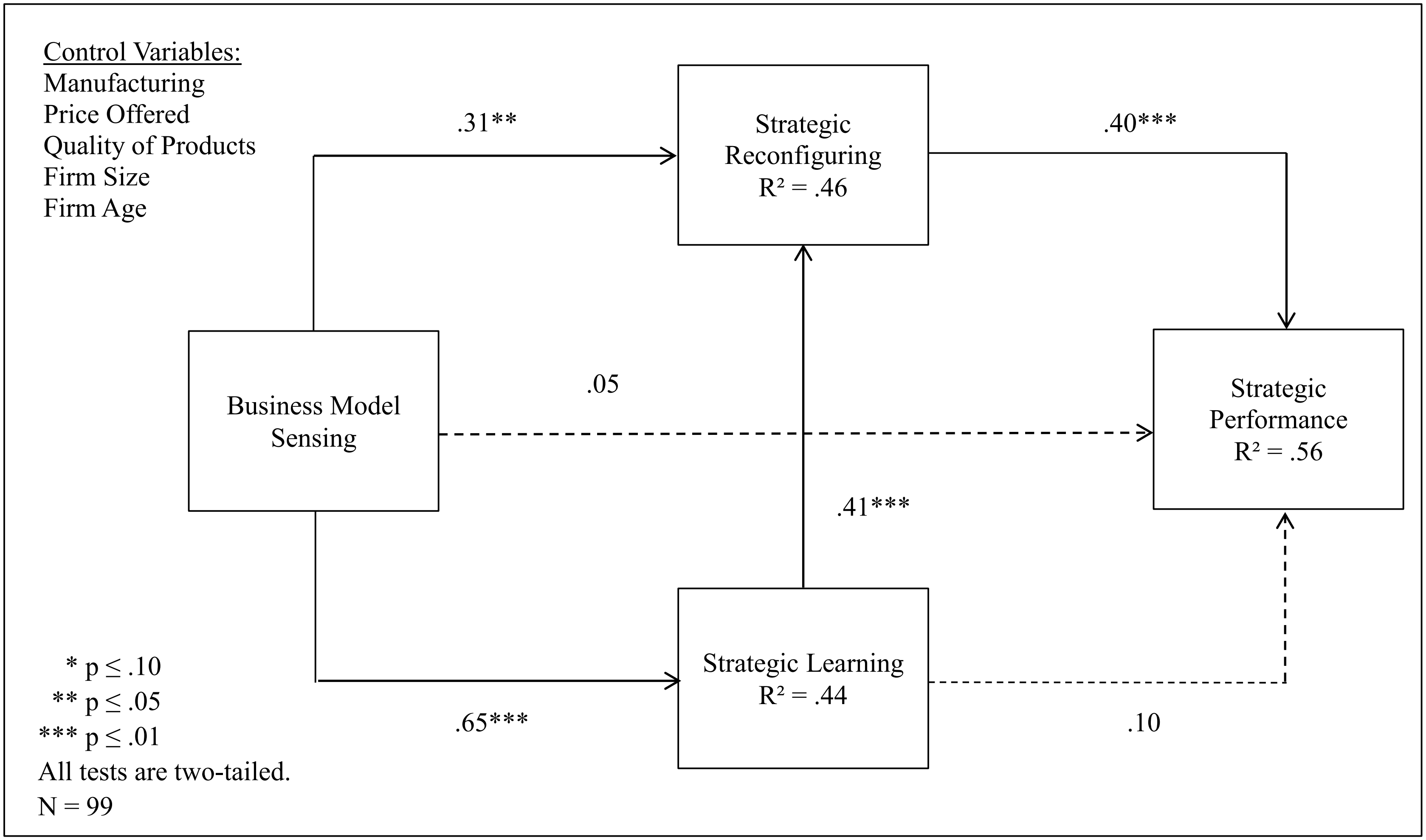

Figure 1. Results of structural equation modeling with PLS

Table 1. Properties of measurement scales and correlations

	ME	**SD**	**CR**	**CA**	**AVE**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1. Business Model Sensing	4.74	.98	.86	.78	.61	**.78***								
2. Strategic Learning	4.38	1.14	.93	.92	.70	.65	**.84***							
3. Strategic Reconfiguring	4.65	1.13	.80	.64	.58	.58	.61	**.76***						
4. Strategic Performance	5.05	1.22	.88	.80	.72	.48	.43	.56	**.85***					
5. Firm Age	86.10	53.68	-	-	-	.22	.16	.22	.46	**1.00***				
6. Firm Size	4.53	1.24	-	-	-	.07	-.06	.07	.34	.63	**1.00***			
7. Manufacturing	.56	.50	-	-	-	-.06	-.09	-.16	.14	.00	.15	**1.00***		
8. Price Offered	4.74	1.29	.89	.82	.73	.19	.06	.10	.29	.12	.00	-.04	**.85***	
9. Quality of Products	5.90	.96	.89	.83	.66	.47	.29	.26	.39	.25	.13	-.07	.23	**.81***

ME = Mean, SD = Standard Deviation, CR = Composite Reliability, AVE = Average Valence Extracted, * Value on the diagonal is the square root of AVE.

Table 2. Results of structural equation modeling with PLS

	β-value	**p-value**
H1a: Business Model Sensing – Strategic Learning	.65	<.01
H1b: Business Model Sensing – Strategic Reconfiguring	.31	<.01
H2a: Strategic Learning – Strategic Performance	.10	.33
H2b: Strategic Learning – Strategic Reconfiguring	.41	<.01
H3: Strategic Reconfiguring – Strategic Performance	.40	<.01
Controls:		
Business Model Sensing – Strategic Performance	.05	.65
Firm Age – Strategic Learning	.14	.15
Firm Age – Strategic Reconfiguring	.06	.57
Firm Age – Strategic Performance	.20	.07
Firm Size – Strategic Learning	-.18	.04
Firm Size – Strategic Reconfiguring	.06	.57
Firm Size – Strategic Performance	.14	.13
Manufacturing – Strategic Learning	-.03	.67
Manufacturing – Strategic Reconfiguring	-.12	.13
Manufacturing – Strategic Performance	.21	<.01
Price Offered – Strategic Learning	-.07	.48
Price Offered – Strategic Reconfiguring	.01	.90
Price Offered – Strategic Performance	.19	.01
Quality of Products – Strategic Learning	-.02	.88
Quality of Products – Strategic Reconfiguring	-.04	.73
Quality of Products – Strategic Performance	.14	.23

Table 3. FIMIX-PLS

S	Akaike Information Criterion (AIC)	Bayesian Information Criterion (BIC)	Consitent AIC (CAIC)	Entropy Statistic (EN)	Relative Segment Sizes π_G				
					g = 1	g = 2	g = 3	g = 4	g = 5
s = 2	691.59	818.75	819.25	.85	.20	.80			
s = 3	665.45	857.49	858.23	.86	.59	.14	.26		
s = 4	614.74	871.66	872.65	.93	.47	.21	.18	.14	
s = 5	205.85	527.65	528.89	.89	.22	.25	.26	.19	.08

Table 4. fsQCA configuration analysis

Configurations for Achieving High Strategic Performance				
		Solution		
	1	**2**	**3**	**4**
Context				
Environmental Dynamism	●	●	⊗	⊗
Dynamic Capabilities				
Business Model Sensing	⬤		⬤	⬤
Strategic Learning	⊗	⬤	⬤	
Strategic Reconfiguring		●		⊗
Consistency	.95	.93	.95	.95
Raw Coverage	.35	.64	.22	.19
Unique Coverage	.05	.33	.03	.00
Overall Solution Consistency		**.92**		
Overall Solution Coverage		**.77**		

⬤ = core condition present, ⨂ = core condition absent,
● = peripheral condition present, ⊗ = peripheral condition absent,
blank spaces = „don‘t care“