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Dynamic Capabilities and Performance: Strategy, Structure and Environment

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Dynamic Capabilities and Performance: Strategy, Structure and Environment

Abstract

Dynamic capabilities are widely considered to incorporate those processes that enable organizations to sustain superior performance over time. In this paper, we argue theoretically and demonstrate empirically that these effects are contingent on organizational structure and the competitive intensity in the market. Results from partial least square structural equation modeling (PLS-SEM) analyses indicate that organic organizational structures facilitate the impact of dynamic capabilities on organizational performance. Furthermore, we find that the performance effects of dynamic capabilities are contingent on the competitive intensity faced by firms. Our findings demonstrate the performance effects of internal alignment between organizational structure and dynamic capabilities as well as the external fit of dynamic capabilities with competitive intensity. We outline the advantages of PLS- SEM for modeling latent constructs, such as dynamic capabilities, and conclude with managerial implications.

Keywords: dynamic capability; performance; competition; organizational structure; partial least square modeling; confirmatory tetrad analysis; contingency theory

Introduction

Processes relating to sensing and seizing opportunities and reconfiguring the organizational resource base are often invoked to explain heterogeneity in performance among firms (Teece et al., 1997). Much theoretical effort has been made to understand the micro-foundations of these so-called dynamic capabilities, that is, the organizational and managerial processes and procedures that underlie dynamic capabilities (Teece, 2007). However, our understanding of the conditions under which dynamic capabilities enhance firm performance is limited. Thus, this paper develops and empirically tests a model investigating the contingency effects of competitive intensity and organizational structure on the dynamic capabilities – performance relationship.

Research within the dynamic capabilities field has largely ignored bounding assumptions, such as environmental conditions and organizational structure. As such, there is a need to determine the most relevant contingency hypotheses within the dynamic capabilities approach (Barreto, 2010). Although some may expect that, on average, firms with greater dynamic capabilities represent those firms with stronger performance, there is no assurance that firms actually realize the potential of dynamic capabilities to produce the expected results. This is consistent with Shamsie et al. (2009), who found support for the assertion that the development of dynamic capabilities does not necessarily lead to improved performance; rather, the context within which such capabilities are deployed affects performance. Barreto (2010) concluded that research in this field should focus on the internal and external factors that may enable (or inhibit) firms to realize the potential represented by their dynamic capabilities. Rather than seeking formulas for generalized effectiveness, it is important to recognize that the value of dynamic capabilities is context dependent. In a similar vein, contingency theory suggests that firm performance depends on the alignment of the organization with the environment (external fit), and the congruence of organizational elements with one another (internal fit) (McKee et al., 1989). Thus, we argue that the realization of the potential advantage accruing to dynamic capabilities depends on two factors: organizational structure and competitive intensity in the markets in which the firm is embedded.

Although the relationship between organizational structure and firm performance is well researched, and typically links strategy-structure-performance via external alignment with environmental conditions (Khandwalla, 1973; Lawrence and Lorsch, 1967; Miller and Friesen, 1984), little empirical research has investigated organizational capabilities and processes that are associated with this fit. For example, the value of existing sources of performance, such as a firm's idiosyncratic resource base, may decline due to reduced fit with evolving markets. Therefore, firms must continuously refine or renew their resource base to maintain or enhance their 'external fit' with the environment. Similarly, the 'internal fit' between strategy and structure must also be maintained to achieve superior performance. Maintaining internal and external 'fit' can be achieved through the development and deployment of dynamic capabilities (e.g., Gupta and Govindarajan, 1984; Venkatraman, 1989).

This paper develops and tests a contingency model of how competitive intensity and organizational structure influence the effects of dynamic capabilities on firm performance. As such, our findings advance the work of scholars who have focused on various types of fit between internal organizational structures and external environmental conditions (e.g., Burns and Stalker, 1961). Moreover, we contribute to the ongoing debate on the role and performance consequences of dynamic capabilities (e.g., Protogerou et al., 2011). Specifically, we examine how the dynamic capabilities-performance relationship may be conditioned by organizational structure and competitive intensity. The results obtained from partial least squares structural equation modeling (PLS-SEM) demonstrate how firm performance is determined by internal alignment between organizational structure and dynamic capabilities and external alignment between dynamic capabilities and competitive intensity. Our findings provide new insights into the context-dependent performance impact of dynamic capabilities by investigating both firm financial solvency and sales growth as dependent variables.

Further, this study highlights the value of applying PLS-SEM in empirical strategic management research, which often requires modeling latent constructs (here, dynamic capabilities) and testing complex relationships on small sample sizes (which is common in research involving senior managers). Our study also demonstrates the usefulness of applying PLS-SEM when modeling a second-order latent construct and testing higher-order moderating effects, which we apply to the concept of dynamic capabilities. We also illustrate how to obtain confidence a selected measurement specification through the use of confirmatory tetrad-analysis within a PLS-SEM context.

The paper is structured as follows. First, based on the contingent influence of dynamic capabilities on firm performance, we develop a set of theoretically grounded hypotheses for empirical testing. Subsequently, we discuss our sample data and method before reporting the results of PLS-SEM estimations. We conclude with a discussion of our findings, managerial implications and study limitations.

Dynamic capabilities and firm performance

Dynamic capabilities differ from operational capabilities, which enable the organization to make a living in the present (Winter, 2003). Operational capabilities enable the organization to perform '*an activity on an on-going basis using more or less the same techniques on the same scale to* *support existing products and services for the same customer population*' (Helfat and Winter, 2011: 1244). Dynamic capabilities, on the other hand, are directed towards strategic change and aligning the organization with the environment (Zahra et al., 2006). They can conceptually be disaggregated into a firm's capacities to: 1) sense and shape opportunities, 2) seize opportunities, and 3) redeploy and reconfigure (create, extend and modify) their resource base (Teece, 2007). Sensing and shaping opportunities and threats involves scanning, search and exploration activities across markets and technologies (Teece, 2007). This requires the organization to maintain close relationships with customers, suppliers and R&D partners, and to observe best practices in the industry. Seizing opportunities involves the evaluation of existing and emerging capabilities, and possible investments in relevant designs and technologies that are most likely to achieve marketplace acceptance (O'Reilly III and Tushman, 2008; Teece, 2007). Reconfiguring the resource base is the firm's capacity to recombine resources and operating capabilities '*as the enterprise grows, and as markets and technologies change, as they surely will*' (Teece, 2007: 1335).

Dynamic capabilities positively influence firm performance in multiple ways; they match the resource base with changing environments (Teece et al., 1997), create market change (Eisenhardt and Martin, 2000); support both the resource-picking and capability-building rent-generating mechanisms (Makadok, 2001); and improve inter-firm performance (please also see Gudergan et al., (2012) in this issue). Dynamic capabilities improve the effectiveness, speed, and efficiency of organizational responses to environmental turbulence (Chmielewski and Paladino, 2007; Hitt et al., 2001), which ultimately strengthens performance. They allow '*the firm to take advantage of revenue enhancing opportunities and adjust its operations to reduce costs*' (Drnevich and Kriauciunas, 2011: 258). Through sensing opportunities and reconfiguration, dynamic capabilities provide the organization with a new set of decision options, which have the potential to increase firm performance (Eisenhardt and Martin, 2000; Teece, 2007).

Helfat et al. (2007: 7) suggest that performance effects of dynamic capabilities should be assessed using the concept of 'evolutionary fitness' as '*the extent of evolutionary fitness depends on how well the dynamic capabilities of an organization match the context in which the organization operates*'. Dynamic capabilities that promote high evolutionary fitness enable the organization to survive and grow. Firm survival indicates whether an organization is capable of adapting to its external environment, firm growth incorporates the extent to which the organization has increased in size over time (Helfat et al., 2007; Teece, 2007). We use two evolutionary fitness indicators to capture a firm's capacity to achieve these performance goals: sales growth and financial solvency. While the first is subject to creating opportunities for sales, the latter is associated with a continuing ability to improve or maintain competitive cost levels.

There is some evidence that the influence of dynamic capabilities on a firm's ability to achieve superior performance is contingent on the firm's context (Teece et al., 1997). Following Teece, and drawing on contingency theory, we argue that both the internal and external contexts within which dynamic capabilities are embedded influence the potential of dynamic capabilities to achieve performance consequences. Internal fit is characterized by compatible dynamic capabilities and organizational structure. External fit is reflected in corresponding dynamic capabilities and levels of competitive intensity. Both represent fundamental conditions that facilitate the role of dynamic capabilities in affecting performance. Figure 1 illustrates our dynamic capabilities framework.

Insert Figure 1 here

Dynamic capabilities and organizational structure

The structure of an organization is typically defined as '*the sum total of the ways in which it divides its labor into distinct tasks and then achieves coordination among them*' (Mintzberg, 1979: 2). Structures can be classified using a mechanistic-to-organic structural dimension. Mechanistic structures are characterized by centralized decision-making, adherence to formal rules and procedures, tight control of information flows, and elaborate reporting structures. In contrast, organic structures are typically associated with de-centralized decision-making, open communication, organizational adaptiveness, and de-emphasis on formal rules and procedures (Burns and Stalker, 1961; Lawrence and Lorsch, 1967).

Organizational structures influence firms' responses to change (see for example, Teece, 1996). Although the above mentioned characterization of organizational structures is relatively familiar, simple, and intuitive; the organizational alignment task itself is complex and difficult, requires ongoing environmental sensing and interpretation, and insight into the organization's goals, strategies, and resources (Khandwalla, 1973). This is consistent with contingency theory, which affirms that organizational contexts present constraints to which firms must adjust by modifying their structure. The proper adjustment of endogenous design variables (such as organization structure) with exogenous context variables (such as competitive intensity) helps firms achieve greater performance (Lawrence and Lorsch, 1967).

The effects of organic versus mechanistic structures on performance are multifaceted. For instance, while some studies report a positive relationship between organic structures and firm adaptability and performance (e.g., Zahra and Covin, 1995), others argue that formalized planning and mechanistic structures enhance firm performance (e.g., Adler and Borys, 1996; Schwenk and Schrader, 1993). Rather than attributing such variance to external, environmental contingencies (such as environmental turbulence), we argue that the effects of organizational structure must be investigated in conjunction with the organizational processes associated with opportunity sensing, opportunity seizing and reconfiguring the organization to align with external conditions.

Few studies have explicitly investigated which types of firms (e.g., organic versus mechanistic) are more likely to benefit from dynamic capabilities. Zollo and Winter (2002), in their discussion of learning mechanisms, proposed that larger, multidivisional, and more diversified firms have greater probability of benefiting from deliberate learning mechanisms. Eisenhardt and Martin (2000) postulated that dynamic capabilities may share common features across firms and, thus, cannot be regarded as entirely heterogeneously distributed across firms. They went on to argue that dynamic capabilities are not necessarily themselves sources of firm performance. In a similar vein, Teece (2007) stressed the need of complimentary structures for dynamic capabilities to enhance performance. Consistent with these views, we argue that organizations need to establish internal fit with respect to their organizational structure for dynamic capabilities to work effectively.

In their study on Yahoo and Excite, Rindova and Kotha (2001) find support for the notion that the development and use of dynamic capabilities are contingent on decentralized structures and local autonomy. They suggest that '*organizational form is related to the dynamic capabilities* […] *and can be used as a strategic tool to support the rapid changes in strategy required to compete in dynamic environments*' (Rindova and Kotha, 2001: 1264). The appropriate organizational structure for dynamic capabilities to enhance firm performance is highly organic and responsive, which in turn requires a set of attributes that include '*non-bureaucratic decision-making – decentralised or possibly autocratic, self-managed where possible*; [and] *shallow hierarchies to facilitate both quick decision-making and rapid information flow from the market to the decision makers*' (Teece, 2000: 41). Organizational decentralization in organic structures may lead to more effective, efficient, and adaptive strategy-making, as a result of greater flexibility, creativity, and responsiveness (Andersen and Nielsen, 2009). Further, organic organizational structures inspire employee motivation, loyalty, participation, and creativity, as well as responsiveness to changing market conditions (Schminke et al., 2000). It is these aspects of organic structures that facilitate processes reflecting the sensing and seizing of opportunities and the reconfiguration of a firm's operating capabilities.

Despite a number of advantages of formal and systematic planning (Adler and Borys, 1996; Sine et al., 2006), increased formality, centralization and rigidity associated with mechanistic structure may impede flexible information-processing behaviors (Kenney and Gudergan, 2006) such as sensing and seizing opportunities, which form the basis for dynamic capabilities. Formalized and mechanistic organizational structures may lead to inadequate interaction and undesired conformity in planning and implementation (Bucic and Gudergan, 2004). In contrast , structures low in formalization lead to greater use of new information and, consequently, to more effective seizing of opportunities (Deshpandé and Zaltman, 1982). Hence, decentralization and organic structures are better suited to the long-term strategic development of organizations (Mintzberg, 1979). Within formalized structures, to '*sustain dynamic capabilities, decentralization must be favored because it brings top management closer to new technologies, the customer, and the market*' (Teece, 2007: 1335).

In light of the above, we argue that organizational structure acts as a contextual moderator that conditions the extent to which dynamic capabilities influence firm performance. Specifically, we expect the performance-enhancing effects of dynamic capabilities to be stronger for firms with a more organic organizational structural design, since such organizational structures are likely to facilitate the positive effects attributable to those firms' capacities to: 1) sense and shape opportunities, 2) seize those opportunities, and 3) redeploy and reconfigure their resource base (Teece, 2007):

H1: The effect of dynamic capabilities on firm performance (i.e., sales growth and financial solvency) improves with a more organic organizational structure.

Dynamic capabilities and competitive intensity

Much research emphasizes the importance of considering environmental conditions in the dynamic capability framework (Eisenhardt and Martin, 2000; Protogerou et al., 2011; Teece et al., 1997). There is consensus in the literature that environmental turbulence moderates the relationship between dynamic capabilities and performance (e.g., Eisenhardt and Martin, 2000; Helfat et al., 2007; Zahra et al., 2006). In this context, previous strategy research has stressed the role of competitive intensity in explaining differences in firm performance (e.g., Porter, 1980). We define competitive intensity as a situation where a firm operates in markets that are characterized by a high number of manifestly competing organizations, limiting potential growth opportunities (Auh and Menguc, 2005). Firms struggle for survival in an environment of finite resources: the higher the number of firms in the environment, the higher the competitive intensity among the organizations (Scherer, 1980). Competitive intensity is apparent in conditions such as high price competition and high levels of advertising (Porter, 1980). With increasing competitive intensity the outcomes of an organization's actions will depend on the actions undertaken by competitors.

Despite consensus in the literature, that competitive intensity influences strategic behavior and performance, it is not clear whether and, if so, how it interacts with dynamic capabilities in affecting organizational performance. In the extreme case of a firm having a monopoly in a market, the organization may perform well independent of whether it reconfigures its resource base, and thus deploys dynamic capabilities (Kohli and Jaworski, 1990). Without competition, the organization may not need to use dynamic capabilities; as a result, the development of such capabilities may come at a cost that exceeds their benefits. When faced with low competitive intensity, '*firms can operate with their existing systems to fully capitalize on the transparent predictability of their own behavior*' (Auh and Menguc, 2005: 1654). Thus, they rely less on dynamic capabilities, as they are not required to reconfigure their resource base to achieve external fit.

Aggressive competition puts firms at risk of losing resource advantages (Ferrier et al., 1999; Sirmon et al., 2010), losing customers (Lusch and Laczniak, 1987) and decreasing performance. In response to increased competitive intensity firms may reconfigure their resource base to differentiate via innovation (please also see Berghman et al., 2012 in this issue). By doing so innovative firms may gain first mover advantages and capture new customers. This gives rise to a premium on the firms' ability to sense new market trends and seize opportunities prior to key competitors doing so. Acquiring new resources or recombining existing ones; and developing new capabilities to take advantage of market opportunities, is likely to be most valuable in highly competitive markets, where the benefits of doing so are likely to outweigh the costs (Makadok, 2001; Porter, 1980). This is summarized by Zahra (1993: 324) who suggests that firms deploying dynamic capabilities in highly competitive markets will benefit because '*when rivalry is fierce, companies must innovate in both products and processes, explore new markets, find novel ways to compete, and examine how they will differentiate themselves from competitors.*' In highly competitive environments, responding to competitive challenges through opportunity identification activities should also prepare organizations better for survival.

Summing up, we suggest that the effects of dynamic capabilities are enhanced when the company faces some degree of competitive intensity, as otherwise the organization may not require, or put to use, dynamic capabilities to the same extent and, as a result, the development of such capabilities may come at a cost that exceeds the benefits. Therefore, we hypothesize:

> *H2: The effect of dynamic capabilities on firm performance (i.e., sales growth and financial solvency) improves with greater competitive intensity.*

Methods

Sample and data collection

We selected our sample of organizations from Dun & Bradstreet's database (n=2,747), which is representative of large Australian firms (more than 150 employees) (ABS, 2004) and covers a variety of industries. We avoided organizations that were active in several markets, as business processes relating to dynamic capabilities, such as reconfiguration, as well as the firm's degree of formalization, may differ across different divisions, making company-wide generalizations inappropriate. Further, we focused on large organizations and, thus, only organizations with at least 150 employees and a sales volume of more than US$20 million were included in the study (Henri, 2006; Miller, 1987). This category of organizations encompasses those that are expected to have established procedures and to have allocated specific responsibilities to organizational members, rather than to follow emergent strategies and less formalized roles, as they are commonly apparent in small enterprises.

We used both survey data and reported financial data to test our hypotheses, as the combination of primary and secondary data sources reduces some of the issues frequently associated with common method bias. Subsequent to intensive pretesting of the questionnaire through in-depth interviews with 16 senior managers and four researchers, as well as a pilot study (DeVellis, 2003), the survey data were collected in 2008 from senior managers in large Australian organizations.

Senior managers were chosen as key informants because they are likely to be knowledgeable about the difficult-to-observe relevant processes underlying dynamic capabilities (Chen et al., 1993). We elicited the interest of senior managers in participating in the research through personal phone calls and subsequent emails with details about our survey. Due to the length of the survey and the seniority of the respondents, we achieved a response rate of 8.3%, which was equal to 228 usable responses. Respondents and non-respondents were compared by running Mann-Whitney U tests with respect to several key variables: firm age, firm sales and number of employees. The results of these tests did not show any significant differences; thus, no significant non-response bias seems to underlie our data. On average, responding firms employed 1,155 staff, sales ranged from U$ 20 million to more than U$ 1 billion, and the average firm age was 28 years; 74.6% of respondents were general managers (such as CEO, CFO, or Managing Director), 4.8% had a commercial function such as vice president of marketing, sales, or new business development, and 1.7% had a technical function such as director of R&D or manufacturing/operations. The remaining respondents had titles such as chairman and member of the corporate strategy team. To verify the appropriateness of the key informants, questionnaire items asked about the experience of the respondent. The average respondent had an overall work experience of more than 20 years, of which five to ten years had been spent with the respective organization.

We used several procedures to increase response quality. We sampled senior managers who have relevant roles within their firms and assured full anonymity. Further, we offered to provide a research report upon research completion and a donation to charity on behalf of every respondent (Cycyota and Harrison, 2006). As mentioned earlier, we addressed concerns regarding common method bias by collecting data from multiple sources. Also, we followed guidelines on questionnaire design (Podsakoff et al., 2003) and ran Harman's single-factor test by entering the study variables into a principal-component factor analysis. Results suggest there is no problem with common method bias (Lane et al., 2001; Mattila and Enz, 2002).

Further, financial data regarding sales growth and financial solvency were collected through Dun & Bradstreet's commercial database. To measure financial solvency we selected data on firms' credit ratings that were accessed through Dun & Bradstreet in 2008. Sales data for responding organizations were collected in 2008 and were available for all responding organizations. We then revisited the database three years later to collect sales data for 2010 to assess sales growth between 2008 and 2010. At the point of writing this paper, the data were not (yet) available for all responding organizations and, thus, we were able to include 91 organizations for the purpose of this study.

Analysis

We used PLS-SEM to analyze the data, applying SmartPLS[1] (Ringle et al., 2005). Several features of PLS-SEM have led to its increasing use in management, strategy and marketing research (e.g. Bontis et al., 2007; Drengner et al., 2008; Gruber et al., 2010; Hennig-Thurau et al., 2007; Robins et al., 2002; Sattler et al., 2010).[2] The following features make PLS-SEM especially appropriate to this study. In general, PLS-SEM is a so-called soft-modeling approach (Wold, 1980) and is less suited to testing well-established complex theories due to a lack of a global optimization criterion to assess overall model fit (Hair et al., 2012). PLS-SEM is, however, advantageous compared to covariance-based structural equation modeling when analyzing predictive research models that are in the early stages of theory development (Fornell and Bookstein, 1982). The latter exemplifies the research described in this study: Although organizational structure and the role of environmental turbulence have been discussed in previous research concerning dynamic capabilities, no research has investigated the interaction between competitive intensity as one possible source of environmental turbulence, dynamic capabilities and organizational structure using a contingency theory framework. Further, to the best of our knowledge, no empirical research has addressed these relationships yet. Thus, our framework is not yet well-established in previous research so that PLS-SEM is the appropriate approach for empirically examining it. Second, PLS-SEM allows the researcher to more easily use both reflective and formative measurement scales whereas covariance-based structural equation modeling (SEM) has some limitations when modeling in formative mode (Chin, 1998; Henseler et al., 2009). We used a formative index to measure dynamic capabilities. Third, PLS-

[1] We used the following settings in the SmartPLS software: path-weighting scheme; initial weights set to 1; stop criterion set to 10^{-5}; and maximum number of iterations = 500.
[2] For a review of the increasing use of PLS-SEM in marketing and in management information systems research see Hair et al. (2012) and Ringle et al. (2012) respectively.

SEM is more appropriate when dealing with small sample sizes (Henseler et al., 2009). PLS-SEM exhibits higher statistical power than covariance-based SEM when used on complex models with limited sample size available (Reinartz et al., 2009). This is especially relevant for this study, as our final sample size was 91 observations. To further strengthen confidence in our findings, we conducted a post-hoc power test that revealed that statistical power was above the commonly accepted threshold of 0.8 (Cohen, 1992).[3] Finally, previous research has shown that the PLS-SEM algorithm transforms non-normal data in accordance with the central limit theorem (Hair et al., 2012). This makes PLS-SEM results robust when using skewed data and formative measures (Ringle et al., 2009). We have found that not all data points in the present research follow a normal distribution.

Measurement

Since PLS-SEM is capable of dealing with both reflective and formative measurement, it is important to determine the appropriate mode (Bollen and Lennox, 1991; Coltman et al., 2008), as this decision guides the selection of appropriate data-analysis methods and the relevant criteria for reliability and validity assessment (Diamantopoulos and Winklhofer, 2001). This study used both reflective and formative measurement. The decision regarding the mode of measurement for the newly created dynamic capabilities index was based on intensive review of the literature and the supporting results of confirmatory tetrad analysis in PLS-SEM (CTA-PLS). CTA-PLS

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[3] We used the software G*Power 3.1.3 (Faul et al., 2009) to compute achieved power (F test: Linear multiple regression: Fixed model, R^2 deviation from zero). The input variables were the sample size of 91 cases, a two-tailed test with α=0.05, effect size of f^2=0.43 for financial solvency and f^2=0.43 for sales growth, respectively, and the one predictor dynamic capabilities. The output for financial solvency was λ=39.13, the critical F-value=3.94, df=89 which led to a power (1-β error probability) of 1.00. The output for sales growth was λ=57.33, the critical F-value=3.94, df=89 which led to a power (1-β error probability) of 1.00.

provides insights into whether a reflective indicator specification or formative indicator specification is more appropriate. Following the CTA-PLS process, as suggested by Gudergan et al. (2008), we first formed and computed all vanishing tetrads for the measurement model of each latent variable; we then identified model-implied vanishing tetrads, which was followed by eliminating redundant model-implied vanishing tetrads; and based on examination of the statistical significance test for each vanishing tetrad, we evaluated the results for all model-implied non-redundant vanishing tetrads per measurement model. The results (see Appendix 1) from this process provided support for the reflective mode for the measurement of the dynamic capability index and the underlying first-order constructs.

Dynamic capabilities. We conceptualized dynamic capabilities as a Type II multi-dimensional second-order index (reflective-formative type) (Diamantopoulos and Winklhofer, 2001; Jarvis et al., 2003; Ringle et al., 2012). We followed Jarvis et al.'s (2003) criteria to establish if this newly created index should be modeled in formative or reflective mode (see also Karpen et al., 2012). First, according to the dynamic capability literature, the capacities to sense opportunities, to seize them, and to reconfigure the organizational resource base accordingly are defining components of the overriding dynamic capability construct (Teece, 2007). The dynamic capabilities index is a composite of its components, that is, the components combine to produce the index and changes in the components would lead to a change in the underlying meaning of the construct (Barreto, 2010; Edwards, 2001; Law et al., 1998). Second, the components are not interchangeable; that is, the components do not have the same content and describe significantly different dynamic capability process categories, which cannot substitute each other. Each of the three capacities represents features of dynamic capabilities that could be separate constructs but remain important parts of dynamic capabilities at a more abstract level; dropping one of these capacities would alter the conceptual domain of the overriding index. Third, the components of the dynamic capability index do not necessarily covary with each other. For example, an organization may improve its processes regarding sensing opportunities by intensifying its relationships to suppliers; however, this does not necessarily lead to an improved capacity to reconfigure its resource base. Fourth, the antecedents and consequences of the underlying capacities may share similar antecedents and consequences, but this is not always the case. For example, sensing activities may lead to the creation of new market and technological knowledge and thus improve marketing and technological capabilities. However, seizing activities such as investing in product commercialization does not necessarily lead to an improved technological capability. Thus, the following sections refer to these capacities as first-order dimensions of the second-order dynamic capabilities index.

As no readily available scales for measuring the sub-dimensions dynamic capabilities exist, we employed an a-priori technique that draws on Diamantopoulos and Winklhofer's (2001) approach to index construction and qualitative decision rules for determining whether the construct is of a formative or reflective nature to measure this construct (Jarvis et al., 2003). To define the construct, we started with Teece’s (2007) conceptualization of dynamic capabilities, dividing the relevant processes into three categories: sensing, seizing and reconfiguring. We then determined whether the three first order dimensions of the dynamic capabilities index reflect a measurement mode that is reflective or formative. Constructing a formative index each for the three sub-dimensions of dynamic capabilities would imply that deleting one indicator may lead to the deletion of an unique part of the formative measurement models and, thus, change the meaning of the constructs (Diamantopoulos and Winklhofer, 2001). Consequently, a formative measurement model requires a census of all indicators that determine the construct (Jarvis et al., 2003). Previous literature on firms' diverse sensing, seizing and reconfiguring activities reveals a large number of activities that firms may use to realize these process categories. This makes it practically infeasible to measure exhaustively all relevant activities of the three sub-dimensions, which a formative index specification would require. Thus, in an initial step we created three pools of relevant items that best reflect each of these three underlying dimensions. We found an existing scale to assess 'reconfiguring' (Jantunen et al., 2005), which is based on the renewal activities listed in the Community Innovation Surveys (CIS) of the European Union. For sensing and seizing, we compiled items drawn from relevant existing literature. For 'sensing', we supplemented an existing scanning scale (Danneels, 2008) with items based on Jantunen (2005). For 'seizing' we found items from Jantunen's (2005) knowledge utilization scale. Both 'sensing' and 'seizing' were complemented with items derived from Teece's (2007) theoretical work to more fully capture the theoretical definition of the defined dynamic capability construct. For each of the three dimensions of dynamic capabilities, the selected items all share a common theme, respectively, and are to some degree interchangeable but not across the three dimensions. This interchangeability allows measurement of each of the three constructs by sampling a few relevant indicators underlying the domain of each construct and, hence, requires reflective measurement specification (Churchill, 1979; Nunnally and Bernstein, 1994). Subsequently, we conducted several interviews with target raters and academics to identify those items that were most appropriate for our measurement models. Following this, we tested the derived items using a small-scale survey with 30 respondents. Ultimately, we concluded with a set of questions that allowed us to empirically measure sensing, seizing and reconfiguring activities with measurement scales that are modeled in reflective mode.

This resulted in using a four-item reflective scale to assess the firm's sensing capacity, which included items assessing processes through which the firm and its employees scan the environment, such as reviewing best practices and gathering economic information. We measured the seizing dimension by using a four-item reflective scale that assesses processes such as reacting to defects pointed out by employees or customers and adopting best practice. In order to measure the organization's reconfiguring capability we used a four-item reflective scale (Jantunen et al., 2005). This scale assesses activities such as the adoption of new management methods and renewal of business processes. Respondents were asked to rate these processes that emerge from the three dimensions of dynamic capabilities on a seven-point interval scale, anchored at 1='rarely' to 7='very often'. All relevant items included in this study are shown in Table 1.

Competitive intensity. We used those items from DeSarbo et al.'s (2005) measurement scale on environmental turbulence that specifically relate to competitive intensity. Respondents were asked to assess the competitive situation of the industry, including the existence of promotion wars and price competition, on a seven-point interval scale, anchored at 1='strongly disagree' to 7='strongly agree'.

Organization structure. We measured this construct employing an adapted version of Covin and Slevin's (1988) five-item measurement scale. This scale assesses the extent to which a firm is structured in organic versus mechanistic ways (also called organicity). Measured on a 7-point scale, this semantic differential-type scale asks respondents to evaluate the operating management philosophy of the respective organization. 1 represented statements relating to mechanistic structures whereas 7 was anchored with statements representing organic structures.

Organizational performance. In order to empirically assess the performance construct, we included two different dimensions of evolutionary fitness in our model. First, to measure 'firm survival' in the form of financial solvency, we created a composite measure comprising the Dynamic Delinquency Score (DDS) and the Dynamic Risk Score (DRS) as calculated by Dun & Bradstreet, which both represent credit-worthiness scores. The DDS measure includes financial, credit and demographic factors and assesses the probability of an organization paying its bills in a severely delinquent manner (90+day past terms) over the next year. The DRS evaluates the probability of default within the next 12 months. It thus helps assess the probability that an organization will have to face severe financial distress, including ceasing operations, owing money to creditors and insolvency. D&B defines financial distress as change of control or forced business closure. Both credit-rating measures are benchmarked by individual industry segments. Credit ratings are a good measure of performance, as they can be used to assess the financial conditions of the firm, and also to assess the capital markets' propensity to provide external finance. Second, to measure 'firm growth', we used sales data from Dun & Bradstreet's database from which we calculated the organization's sales growth rate. We obtained sales data for the year of our primary data collection and two years later for each respondent firm to calculate growth between 2008 and 2010. Specifically, we calculated the sales growth rate using the following equation (Morgan et al., 2009):

$$G_{ji} = (S_{ji,(t+2)} - S_{ji,(t)}) / S_{ji,(t)}$$

where S_{ji} refers to sales volume *j* of organization *i* at time *t*.

Control variables. Several control variables were also included in the study: Firm size in terms of employee number and sales volume, firm age, and industry belonging (Danneels, 2008; Garg et al., 2003; Jantunen et al., 2005). We transformed employee number and sales using a natural logarithm to account for non-linear effects. Firm age is measured as the number of years since the firm was incorporated. Finally, based on the business descriptions in Dun & Bradstreet's database and the Standard Industry Classification codes, we inductively derived three broad industry categories: service, manufacturing and mixed firms. Hence, two effect-coded variables were included as controls for the industry of the organization.

Construct validity

In order to assess the validity and reliability of the reflective measures used in this study, initially we carried out exploratory factor analysis, which confirmed the unidimensionality of the constructs (Steenkamp, 1991). To assess convergent validity, we evaluated Cronbach's α, average variance extracted (AVE), factor loadings, and composite reliability. For all constructs, Cronbach's α and the factor loadings show values above the required thresholds of 0.7 and 0.5 for exploratory research, respectively (Fornell and Larcker, 1981; Nunnally, 1978). The composite reliability is above the required threshold of 0.7. For all constructs but the second-order dynamic capabilities construct, the AVE is above the threshold of 0.5 (Hair et al., 2011). To test whether constructs were sufficiently different from each other, discriminant validity was inspected using the Fornell and Larcker (1981) criterion, which calls for a construct's AVE to be larger than the square of its largest correlation with any construct. All constructs used in this study fulfill this requirement. Taken together, these results lend sufficient confidence that the reflective measurement model fits the data well (see Table 1).[4]

[4] Overall, we consider the measurement properties of the dynamic capabilities second-order index acceptable. The study presented in this paper is exploratory in nature as we develop theory as opposed to testing theory. This also applies to the measurement developed to empirically assess dynamic capabilities. First, the three first-order constructs sensing, seizing and reconfiguring all meet the relevant reliability criteria as reported in Table 1. Second, the dynamic capabilities second-order index displays a Cronbach's α of 0.86 which indicates high reliability. Third, the composite reliability is 0.89 and, thus, above the acceptable threshold. Fourth, all factor loadings are significant

Insert Table 1 here

For dynamic capabilities we used a composite model second-order index (Wetzels et al., 2009) (Type II: reflective-formative type). In order to specify the hierarchical latent variable dynamic capabilities in PLS-SEM, we conceptualized the hierarchical components model through repeated use of the manifest variables (i.e., indicators) of the underlying first-order reflective constructs (Tenenhaus et al., 2005; Wold, 1985). Figure 2 shows a graphical representation of the hierarchical components model. Different quality criteria are required to assess the measurement properties of the formative second-order index, as aspects such as internal consistency and convergent validity are not applicable to formative constructs (Bollen and Lennox, 1991). Thus, we tested for multicollinearity (Diamantopoulos and Winklhofer, 2001) using the variance-inflation factors (VIF). Inspection of the VIFs does not raise concern about multicollinearity, as they are well below the cut-off value of 5 (see Table 2) (Hair et al., 2011). Also, the weights of all items are significant as well because negative and positive indicator weights do not co-occur (Cenfetelli and Bassellier, 2009). Finally, the formative

and exceed the required 0.50 level. Fifth, the dynamic capabilities index has discriminant validity, as its AVE is larger than the largest squared correlation with any other main construct within the structural model. The only convergent validity criterion that is not met is the AVE, which is at 0.40 and, by itself, suggests that the second-order index may be problematic. However, Hatcher (2007) suggests that reliabilities can be acceptable even if AVE estimates are less than 0.50. The AVE is calculated as the average of the squared factor loadings; in our case all loadings are above the minimal acceptable level of 0.50, however, some are below the desirable level of 0.70. We decided to not delete any of the items due to their significance to the construct and high reliability which leads to the lower AVE. Researchers often observe weaker outer loadings in social science studies, especially when measurement scales are newly developed (Hulland, 1999). Rather than automatically eliminating indicators when their outer loading is below the 0.70 threshold, careful examination of the effects of removing items on the construct's content validity and composite reliability is required. Generally, indicators with outer loadings between 0.40 and 0.70 should only be removed when deleting the indicator leads to a significant increase in the composite reliability (which is not the case in our analysis). Finally, when deleting additional items to further increase the AVE, the model estimations did not change significantly. Summing up, given the exploratory nature of our study that aims to develop theory and the acceptable Cronbach's alpha, composite reliability and significant factor loadings, we conclude that the properties of the dynamic capabilities index are acceptable.

second-order construct dynamic capability has expert validity, as we discussed this index with managerial experts during the pretesting stage.

Insert Figure 2 here

Insert Table 2 here

Insert Table 3 here

Results

The correlations between the constructs are sufficiently low (Table 3), which suggests that the constructs are independent and suitable for further examination of the relationships between them. Table 4 summarizes the results of the PLS-SEM analysis, which we discuss in the following section. We assessed the path coefficients and their significance values to test the derived hypotheses. To do so we applied the bootstrapping procedure (with a number of 500 bootstrap samples and 91 bootstrap cases; using individual sign changes) to evaluate the significance of the paths (Nevitt and Hancock, 2001). For both financial solvency and sales growth the R^2 values are substantial (0.39 and 0.42, respectively) [5]. Our results, however, suggest that, considered by themselves, dynamic capabilities do not have a significant direct effect on financial solvency (β=-0.08, p>0.10) and even has a negative direct effect on sales growth (β=-0.16, p<0.10) (Model 1).

[5] In this section we report the findings of Model 4, which includes both moderating variables. For step-wise analyses please see Models 1, 2 and 3. The indicators were mean-centred before the interaction terms were created.

Insert Table 4 here

With respect to Hypotheses 1 and 2, we considered the contingency effects of organizational structure and competitive intensity on the dynamic capabilities–performance relationship. Two approaches are available to test moderating effects in PLS-SEM: the product term approach and the group comparison approach. As our moderator variables are continuous, we decided to use the former approach, as both formalization and competitive intensity are non-categorical variables and the product term approach has been found to be superior to the group comparison approach (Henseler and Fassott, 2010; Wilson, 2010).

We ran moderating analyses on the full sample. First, to analyze the moderating effects, we tested whether the path coefficients capturing the moderating effects differed significantly from zero (Henseler and Fassott, 2010). Second, we assessed the strength of the identified moderating effects using the effect size. The results (Table 4, Model 4) show that the impact of dynamic capabilities on both performance measures varies with the organization structure's degree of formalization. The effect of dynamic capabilities on the firm's financial solvency turns positive the more organically an organization is structured (interaction effect $\beta=0.30$, $p<0.01$). Further, the effect of dynamic capabilities on the firm's sales growth also becomes positive when dynamic capabilities are embedded in a more organic structure (interaction effect $\beta=0.42$, $p<0.01$). Hence, Hypothesis 1 is supported. Finally, we investigated whether the effects of dynamic capabilities were contingent on the degree of competitive intensity. We found that dynamic capabilities have a positive effect on both sales growth (interaction effect $\beta=0.23$, $p<0.01$) and financial solvency (interaction effect $\beta=0.26$, $p<0.01$) when the firm is faced with increasing levels of competitive intensity. Thus, Hypothesis 2 is supported.

To determine the strength of the moderating effects, we calculated the effect size (Cohen, 1988). Consequently, we compared the proportion of the variance explained (as expressed by the coefficient of determination R^2) of the main effect model with the R^2 of the full model, which includes both moderating effects. The effect size for financial solvency is 0.41 and for sales growth is 0.60. Thus, the moderating effects have strong effect sizes, as effect sizes of 0.02 may be regarded as weak, effect sizes from 0.15 as moderate and above 0.35 as strong (Cohen, 1988).

Discussion and managerial implications

This research provides several contributions to management research and practice. Although organizational performance has been a core focus in research on dynamic capabilities since the seminal article of Teece et al. (1997), the question of whether and how dynamic capabilities affect performance is still not fully addressed (Drnevich and Kriauciunas, 2011; Helfat et al., 2007). The main contributions of this work to theory are threefold. We provide 1) an operationalization of dynamic capabilities for use in future research; 2) evidence that the possession of dynamic capabilities is a necessary, but insufficient, condition to achieve superior performance; and 3) knowledge of conditions under which dynamic capabilities are likely to enhance firm performance. For management researchers, we also provide insights into the appropriate use of PLS-SEM including a second-order latent construct and confirmatory tetrad analysis, and for managers our work offers guidance concerning the relevance of investing in dynamic capabilities and when and how they can be leveraged. These contributions are discussed in detail below.

First, our research provides important empirical evidence of the impact of dynamic capabilities, for which we developed a new measurement scale, have an impact on firm performance. Consistent with Helfat et al. (2007), we distinguish the role that the resource base plays in delivering day-to-day performance from that of dynamic capabilities in affecting sustainable performance, which is referred to as evolutionary fitness. The latter encompasses firm survival and firm growth and reflects the degree to which the organization operates profitably over time (Helfat et al., 2007; Teece, 2007). Our research captures survival and growth through measures of financial solvency and sales growth respectively. Distinguishing between these two performance outcomes is important as it provides evidence of internal and external performance of the firm. Sales growth is an indication of directly measured organizational output, whereas financial solvency also provides an indication of the capital market evaluation of the firm.

Second, our results suggest that dynamic capabilities, in and of themselves, are not (positively) directly related to firm performance, operationalized as either sales growth or financial solvency. We find that, without accounting for context-dependencies, dynamic capabilities seem to have a negative direct effect on sales growth but a non-significant effect on financial solvency. This supports Eisenhardt and Martin's (2000) contention that the possession of dynamic capabilities *per se* does not necessarily lead to superior organizational performance, and is in line with similar inconsistent findings reported in the literature. This result further supports our core hypothesis that context matters in making use of dynamic capabilities. In addition, this finding points to the importance of employing multiple performance measures in studies of dynamic capabilities. Dynamic capabilities are costly and can therefore lead either to losses, if their benefits are not realized, or gains, if they are. Some affect short-term performance, whereas others are likely to be important in the long run.

Third, having established that it is not the dynamic capabilities *per se* that lead to superior organizational performance, we further develop general arguments presented by authors such as Teece et al. (1997), Eisenhardt and Martin (2000) and Helfat et al. (2007) that the effects of dynamic capabilities on firm performance are context-dependent. We submit that it is the internal and external context within which dynamic capabilities are deployed that determines their performance. To test this assertion, we advance and examine a contingency model that links the performance effects of dynamic capabilities to organizational structure (internal fit) and competitive intensity (external fit). Our empirical findings support the contention that firms must align their internal organizational structure with their capacity to sense and seize external opportunities and reconfigure their resource base accordingly if they are to derive superior performance from dynamic capabilities. Specifically, we find that organic structures positively moderate the relationship between dynamic capabilities and firm performance and so substantiate organizational structure as a critical context in which dynamic capabilities affect organizational performance. We also find that external fit (competitive intensity) is an important determinant of the effectiveness of dynamic capabilities. Our results suggest that when firms compete in environments with finite resources, dynamic capabilities provide a basis for adapting to competitive pressures and for survival. Hence, our insight that competitive intensity affects the extent to which dynamic capabilities influence firm performance implicitly supports Henderson's (1983) biological argument concerning the 'survival of the fittest'. Greater competitive intensity requires greater adaptation to environmental conditions and, hence, necessitates dynamic capabilities. When organizations face less competitive intensity, they can rely on their existing resource base with less reliance on dynamic capabilities, as they do not need to reconfigure their resource base to maneuver in their respective markets. In this sense, our findings confirm Zahra's (1993) view by illustrating that competitive intensity requires the deployment of dynamic capabilities to sustain or improve performance, whereas dynamic capabilities may be redundant and represent overall inefficiencies for organizations facing little or no competition. As such, our results emphasize the importance of establishing the external fit of dynamic capabilities with competitive intensity in enhancing organizational performance.

Overall our results suggest that while dynamic capabilities may influence certain types of organizational performance, ultimately, their potential to achieve superior performance outcomes is contingent upon their fit to the internal organizational structure and the external environment.

For researchers, this paper also illustrates the usefulness of applying PLS-SEM in empirically unpacking the strategic performance differentials as they are examined in the dynamic capabilities research stream. The key illustrations of PLS-SEM applications in this paper include the use of both formative and reflective measurement models (e.g., Coltman et al., 2008); of a second-order measurement model with a demonstration of a Type II multi-dimensional second-order index (reflective-formative type) for the dynamic capabilities construct (Diamantopoulos and Winklhofer, 2001; Jarvis et al., 2003; Ringle et al., 2012); of moderation effects utilizing the product term approach (e.g., Henseler and Fassott, 2010); and of confirmatory tetrad analysis outlining the application of CTA-PLS (Gudergan et al., 2008) to enhance the confidence of measurement mode specifications in empirical strategic management research. Furthermore, this study demonstrates the usefulness of applying PLS-SEM with small samples sizes (which are common when conducting research involving senior managers).

For managers, from a normative perspective, this paper provides guidance concerning the relevance of investing in dynamic capabilities and when and how they can be leveraged. First, senior management operating in highly competitive environments are guided by our findings to invest in putting in place dynamic capabilities so that their firms can adapt and achieve sustainable performance. In environments within which their firms face little or no significant competition, investment in dynamic capabilities may be considered to be lower priority, thus freeing up resources for other purposes. Also, when ample dynamic capabilities are present, top management are encouraged to establish an organic organizational structure in order to better capitalize on these dynamic capabilities. Indeed, a lack of an organic structure may impede any positive effects of dynamic capabilities and may reduce the return on investment in such capabilities.

Also, from a managerial point of view, the sometimes elusive concept of dynamic capabilities may become more operationally meaningful when combined with an organic organizational structure which provides a basis for the utilization of processes for sensing and seizing external opportunities via decentralized decision making. Such insights may translate into organizational policies pertaining to formal reward systems that seek actively to empower middle-management involvement in strategic-management activities. Moreover, to the extent dynamic capabilities are related to the scanning, sensing, and seizing of opportunities, firms may seek to develop organizational structures that enhance access to knowledge repositories and effective information processing, such as process-based knowledge-management systems (Nielsen and Michailova, 2007).

Limitations and future research

Our study has some limitations that offer avenues for further research. The data are cross-sectional in nature, with a focus on large organizations, and thus caution should be exercised when drawing cause-effect inferences. Our findings should not necessarily be interpreted as evidence of underlying causal relationships, but rather as supporting a prior causal scheme. Second, this study was only able to test the effects of dynamic capabilities on sales growth with two-year lagged sales data. Thus, we were limited in empirically assessing the sustainability of dynamic capabilities on organizational performance. An interesting extension of this research would be to design a longitudinal research program to empirically confirm causality and assess firm performance outcomes over time. Third, we were only able to test the model with a small sample of empirical data. Even though PLS-SEM is capable of and suitable for dealing with small sample sizes (Henseler et al., 2009), future studies should aim to replicate the findings with a larger sample and in different settings.

Our results also point to some additional interesting avenues for future research. One opportunity is to investigate potential mediating mechanisms. For instance, it is possible that dynamic capabilities influence performance through specific organizational capabilities (such as absorptive capacity or marketing and technological capabilities) or top management team competencies (such as functional competencies). Future research may benefit from incorporating such mediating mechanisms into a model of the dynamic capabilities-performance relationship. Based on a larger sample, future research may also investigate the three-way interaction between dynamic capabilities, organizational structure, and competitive intensity. Finally, while we elected to focus on organizational structure and competitive intensity, future research may investigate additional aspects of context-dependencies for the performance impact of dynamic capabilities. Such research seems particularly fruitful given our findings that context matters.

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Figure 1: Dynamic capabilities and performance: A contingency framework

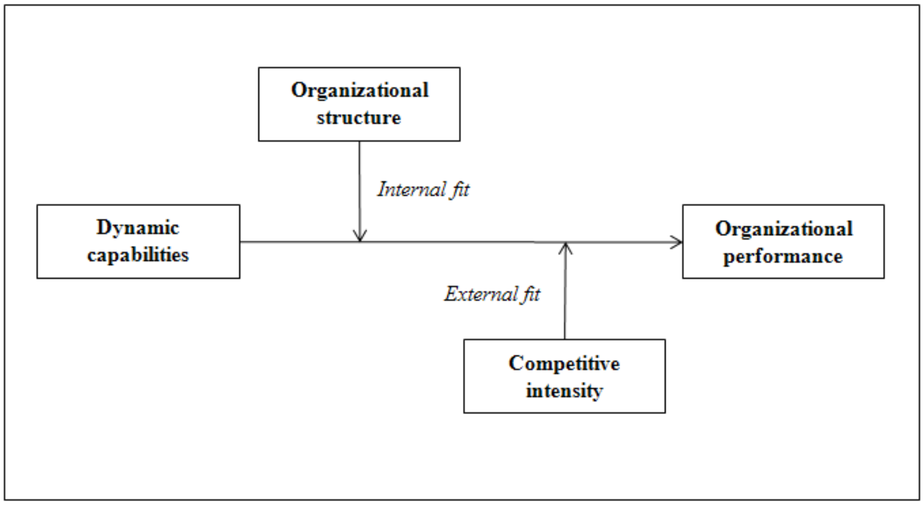
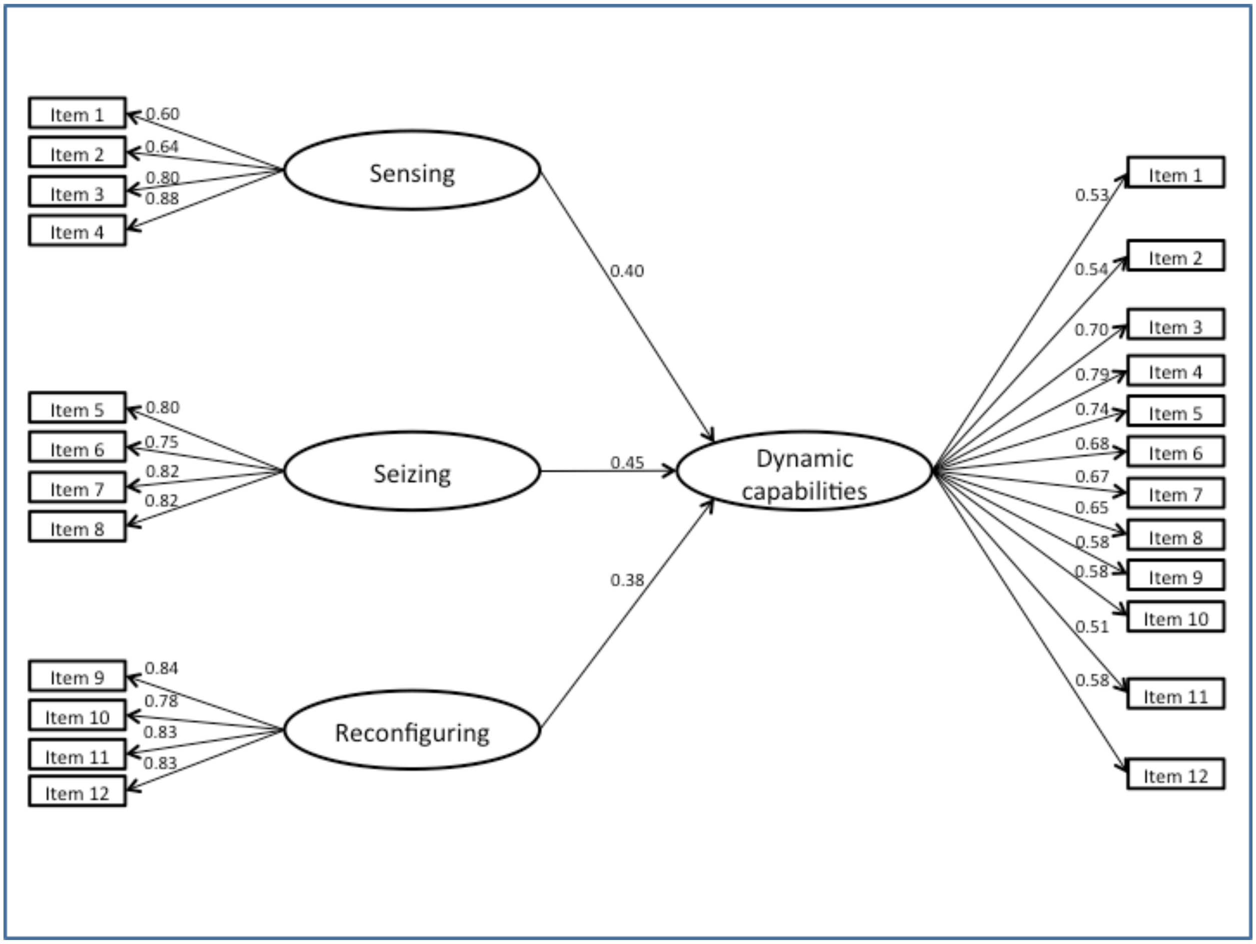


Figure 2: Conceptual representation of hierarchical components model for dynamic capabilities



All loadings and weights are significant at 0.001 (2-tailed)

Table 1: Reflective measurements

Construct	Indicators	Range	Mean	SD	1st order loading	2nd order loading	AVE	CR	α	AVE>$Corr^2$
[a] Dynamic capabilities *(2nd order construct, repeated items see below)*							0.40	0.89	0.86	0.40>0.03
[a] Sensing	In my organization….						0.54	0.82	0.71	0.54>0.52
	people participate in professional association activities.	1-7	4.05	1.39	0.60*	0.53*				
	we use established processes to identify target market segments, changing customer needs and customer innovation.	1-7	4.86	1.45	0.64*	0.54*				
	we observe best practices in our sector.	2-7	4.87	1.45	0.80*	0.70*				
	we gather economic information on our operations and operational environment.	1-7	5.56	1.38	0.88*	0.79*				
[a] Seizing	In my organization….						0.63	0.87	0.81	0.63>0.52
	we invest in finding solutions for our customers.	1-7	5.31	1.23	0.80*	0.74*				
	we adopt the best practices in our sector.	1-7	5.45	1.19	0.75*	0.68*				
	we respond to defects pointed out by employees.	1-7	5.47	1.17	0.82*	0.67*				
	we change our practices when customer feedback gives us a reason to change.	1-7	5.54	1.12	0.82*	0.65*				
[a] Reconfiguring	How often have you carried out the following activities between 2004 and 2008?						0.67	0.89	0.84	0.67>0.16
	Implementation of new kinds of management methods	1-7	4.52	1.25	0.84*	0.58*				
	New or substantially changed marketing method or strategy	1-7	4.46	1.34	0.78*	0.58*				
	Substantial renewal of business processes	1-7	4.63	1.29	0.83*	0.51*				
	New or substantially changed ways of achieving our targets and objectives	1-7	4.56	1.37	0.83*	0.58*				
[c] Organizational structure	The operating management philosophy of the top management of my business unit is.						0.56	0.86	0.81	0.56>0.07
	Tight formal control of most operations by means of sophisticated control and information systems Loose, informal control; heavy dependence on informal relations and norm of co-operation for getting work done	1-7	3.38	1.55	0.71*					
	Strong emphasis on always getting personnel to follow the formally laid down procedures Strong emphasis on getting things done even if this means disregarding formal procedures	1-7	3.18	1.40	0.76*					
	A strong emphasis on holding fast to true and tried management principles despite any changes in business conditions A strong emphasis on adapting freely to changing circumstances without too much concern for past practice	1-7	3.99	1.43	0.60*					
	Strong insistence on a uniform managerial style throughout the business unit Managers' operating styles allowed to range freely from the very formal to the very informal	1-7	4.37	1.48	0.84*					

	Strong emphasis on getting line and staff personnel to adhere closely to formal job descriptions	Strong tendency to let the requirements of the situation and the individual's personality define proper on-job behavior	1-7	3.93	1.51	0.80*				
[b] Competitive intensity	In general, how much do you disagree or agree with each of the following statements characterizing the business environment or conditions in your primary markets?						0.54	0.82	0.73	0.54>0.07
	Competition in our industry is cutthroat.		1-7	4.35	1.86	0.91*				
	There are many 'promotion wars' in our industry.		1-7	3.38	2.13	0.84*				
	Price competition is a hallmark of our industry.		1-7	4.32	1.76	0.54*				
	One hears of a new competitive move almost every day.		1-7	2.92	1.60	0.57*				
Financial solvency							0.70	0.83	0.58	0.70>0.07
	DDS rating		2-7	3.84	1.29	0.84*				
	DRS rating		3-6	4.68	0.71	0.84*				

* significant at 0.001 (2-tailed)

[a] anchored at 1=rarely and 7=very often
[b] anchored at 1=strongly disagree and 7=strongly agree
[c] semantic differential (1-7)
AVE = average variance extracted
$Corr^2$ = highest squared correlation between the model constructs

Table 2: Quality criteria of formative measurements

Construct/item	No. of items	VIF	Weights
Dynamic capabilities			
Scanning	4	2.26	0.40*
Seizing	4	2.07	0.45*
Reconfiguring	4	1.21	0.38*

* significant at 0.001 (2-tailed)

Table 3: Correlations between main constructs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Firm age	1									
(2) Financial solvency	0.10	1								
(3) Dynamic capabilities	-0.03	-0.05	1							
(4) Firm size (employees)	-0.05	-0.18	0.08	1						
(5) Competitive intensity	-0.01	0.27*	0.18	-0.01	1					
(6) Organizational structure	0.01	0.19	-0.16	-0.13	0.19	1				
(7) Industry (manufacturing)	-0.23*	0.14	0.09	0.00	-0.08	-0.05	1			
(8) Industry (service)	-0.01	0.00	0.04	0.11	-0.08	0.07	0.39*	1		
(9) Sales growth	0.15	0.02	-0.14	-0.08	-0.12	-0.23*	-0.13	-0.16	1	
(10) Firm size (sales)	-0.13	-0.31**	0.11	0.66**	0.02	-0.26*	-0.04	0.09	-0.03	1

** significant at 0.01 (2-tailed); * significant at 0.05 (2-tailed)

Table 4: Path coefficients

	Model 1 (base model)	Model 2 (including organizational structure as moderator)	Model 3 (including competitive intensity as moderator)	Model 4 (including both moderators)
Control variables				
Emp -> Financial solvency	0.05	-0.07	0.04	-0.05
Age-> Financial solvency	0.15	0.11	0.04	0.06
Sales -> Financial solvency	-0.31**	-0.13	-0.32**	-0.18
Industry (Service)-> Financial solvency	-0.03	-0.09	-0.04	-0.07
Industry (Manufacturing) -> Financial solvency	0.19**	0.21**	0.13	0.17*
Emp -> Sales growth	-0.10	-0.18*	-0.13	-0.18**
Age-> Sales growth	0.13**	0.09*	0.09***	0.07
Sales -> Sales growth	0.08	0.08	0.06	0.07
Industry (Service) -> Sales growth	-0.14**	-0.15	-0.10	-0.12**
Industry (Manufacturing) -> Sales growth	-0.03	0.01	-0.05	0.01
Main variables				
DC -> Financial solvency	-0.03	-0.05	-0.05	-0.08
DC -> Sales growth	-0.13*	-0.16*	-0.11*	-0.16*
Organizational structure -> Financial solvency		0.16*		0.09
Organizational structure -> Sales growth		-0.26**		-0.23**
DC* Organizational structure -> Financial solvency		0.37***		0.30*
DC* Organizational structure -> Sales growth		0.50***		0.42*
Competitive intensity -> Financial solvency			0.25**	0.24**
Competitive intensity -> Sales growth			-0.17**	-0.05
DC*Competitive intensity -> Financial solvency			0.33**	0.26***
DC*Competitive intensity -> Sales growth			0.40***	0.23**
R^2 (Financial solvency)	0.14	0.27	0.31	0.39
R^2 (Sales growth)	0.07	0.38	0.24	0.42

*** significant at 0.01 (2-tailed), ** significant at 0.05 (2-tailed), * significant at 0.1 (2-tailed)

Appendix 1: Results from confirmatory tetrad analysis (CTA-PLS)

Model implied non-redundant vanishing tetrad	Original sample estimate (Oτ)	Sample mean estimate (Mτ)	Standard deviation (σ)	Bootstrap estimated standard error (se)	t-value (|Oτ/se|)	Bias	Confidence interval low	Confidence interval up	Bonferroni adjustment α	z(1-α)	Adjusted confidence interval low	Adjusted confidence interval up
$\tau_{\text{Sensing. 1234}}$	-0.05	-0.02	0.19	0.19	0.23	-0.02	-0.35	0.30	0.05	1.97	-0.41	0.36
$\tau_{\text{Sensing. 1243}}$	-0.28	-0.25	0.21	0.21	1.33	-0.02	-0.60	0.09	0.05	1.97	-0.66	0.16
$\tau_{\text{Seizing. 1234}}$	-0.03	-0.04	0.12	0.12	0.21	0.01	-0.23	0.16	0.05	1.97	-0.27	0.20
$\tau_{\text{Seizing. 1243}}$	0.14	0.12	0.10	0.10	1.45	0.01	-0.03	0.28	0.05	1.97	-0.06	0.31
$\tau_{\text{Reconfiguring. 1234}}$	-0.07	-0.07	0.21	0.21	0.31	0.00	-0.42	0.28	0.05	1.97	-0.48	0.34
$\tau_{\text{Reconfiguring. 1243}}$	-0.03	-0.03	0.15	0.15	0.23	0.00	-0.28	0.21	0.05	1.97	-0.33	0.26
$\tau_{\text{DC, 9.10.11.12}}$	-0.07	-0.07	0.21	0.21	0.31	0.00	-0.42	0.28	0.00	3.16	-0.73	0.59
$\tau_{\text{DC, 9.10.12.11}}$	-0.03	-0.03	0.15	0.15	0.23	0.00	-0.28	0.21	0.00	3.16	-0.51	0.44
$\tau_{\text{DC, 9.10.11.1}}$	-0.49	-0.51	0.19	0.19	2.56	0.01	-0.83	-0.19	0.00	3.16	-1.12	0.10
$\tau_{\text{DC, 9.11.1.10}}$	0.34	0.34	0.19	0.19	1.78	0.00	0.03	0.66	0.00	3.16	-0.26	0.94
$\tau_{\text{DC, 9.10.11.3}}$	-0.24	-0.24	0.19	0.19	1.24	0.00	-0.56	0.08	0.00	3.16	-0.85	0.37
$\tau_{\text{DC, 9.10.11.4}}$	-0.14	-0.15	0.16	0.16	0.92	0.01	-0.41	0.10	0.00	3.16	-0.65	0.34
$\tau_{\text{DC, 9.10.5.11}}$	-0.01	-0.02	0.14	0.14	0.10	0.01	-0.25	0.20	0.00	3.16	-0.45	0.40
$\tau_{\text{DC, 9.10.6.11}}$	-0.07	-0.06	0.13	0.13	0.53	-0.01	-0.27	0.15	0.00	3.16	-0.47	0.34
$\tau_{\text{DC, 9.11.7.10}}$	-0.09	-0.09	0.17	0.17	0.54	-0.01	-0.37	0.20	0.00	3.16	-0.64	0.46
$\tau_{\text{DC, 9.11.8.10}}$	0.18	0.19	0.14	0.14	1.28	-0.01	-0.04	0.43	0.00	3.16	-0.26	0.64
$\tau_{\text{DC, 9.10.12.2}}$	-0.06	-0.07	0.21	0.21	0.30	0.00	-0.41	0.28	0.00	3.16	-0.73	0.59
$\tau_{\text{DC, 9.12.2.10}}$	0.02	0.02	0.19	0.19	0.13	0.00	-0.30	0.34	0.00	3.16	-0.58	0.63
$\tau_{\text{DC, 9.10.12.5}}$	-0.31	-0.31	0.19	0.19	1.68	0.00	-0.62	-0.01	0.00	3.16	-0.90	0.27
$\tau_{\text{DC, 9.10.12.6}}$	0.05	0.05	0.17	0.17	0.29	0.00	-0.23	0.33	0.00	3.16	-0.48	0.58
$\tau_{\text{DC, 9.10.7.12}}$	0.03	0.03	0.16	0.16	0.17	0.00	-0.23	0.28	0.00	3.16	-0.46	0.52
$\tau_{\text{DC, 9.10.1.3}}$	0.10	0.10	0.16	0.16	0.64	0.00	-0.16	0.36	0.00	3.16	-0.40	0.60
$\tau_{\text{DC, 9.10.4.1}}$	0.30	0.31	0.18	0.18	1.69	0.00	0.01	0.60	0.00	3.16	-0.26	0.87
$\tau_{\text{DC, 9.10.1.5}}$	0.29	0.28	0.15	0.15	1.91	0.01	0.03	0.53	0.00	3.16	-0.19	0.75

Model implied non-redundant vanishing tetrad	Original sample estimate (Oτ)	Sample mean estimate (Mτ)	Standard deviation (σ)	Bootstrap estimated standard error (se)	t-value (|Oτ/se|)	Bias	Confidence interval low	Confidence interval up	Bonferroni adjustment α	z(1-α)	Adjusted confidence interval low	Adjusted confidence interval up
$\tau_{DC,\ 9.2.4.10}$	0.00	0.00	0.07	0.07	0.06	-0.01	-0.12	0.13	0.00	3.16	-0.23	0.24
$\tau_{DC,\ 9.10.2.6}$	0.41	0.39	0.22	0.22	1.87	0.01	0.03	0.75	0.00	3.16	-0.29	1.07
$\tau_{DC,\ 9.10.3.6}$	0.47	0.46	0.22	0.22	2.09	0.01	0.09	0.83	0.00	3.16	-0.24	1.17
$\tau_{DC,\ 9.3.6.10}$	-0.13	-0.12	0.10	0.10	1.25	0.00	-0.29	0.04	0.00	3.16	-0.44	0.19
$\tau_{DC,\ 9.3.8.10}$	0.03	0.04	0.09	0.09	0.37	-0.01	-0.11	0.18	0.00	3.16	-0.24	0.32
$\tau_{DC,\ 9.11.12.4}$	0.21	0.19	0.18	0.18	1.21	0.02	-0.10	0.49	0.00	3.16	-0.36	0.75
$\tau_{DC,\ 9.11.1.7}$	0.32	0.31	0.20	0.20	1.60	0.01	-0.02	0.64	0.00	3.16	-0.33	0.95
$\tau_{DC,\ 9.11.8.1}$	0.18	0.17	0.18	0.18	0.97	0.01	-0.13	0.48	0.00	3.16	-0.41	0.75
$\tau_{DC,\ 9.2.4.11}$	0.06	0.06	0.06	0.06	0.88	0.00	-0.05	0.16	0.00	3.16	-0.14	0.26
$\tau_{DC,\ 9.11.7.2}$	0.61	0.58	0.28	0.28	2.17	0.03	0.11	1.05	0.00	3.16	-0.31	1.47
$\tau_{DC,\ 9.11.2.8}$	0.60	0.57	0.27	0.27	2.23	0.03	0.12	1.01	0.00	3.16	-0.28	1.42
$\tau_{DC,\ 9.11.4.3}$	0.81	0.80	0.25	0.25	3.25	0.01	0.39	1.20	0.00	3.16	0.01	1.58
$\tau_{DC,\ 9.7.8.11}$	0.03	0.02	0.04	0.04	0.67	0.00	-0.04	0.09	0.00	3.16	-0.10	0.15
$\tau_{DC,\ 9.12.2.4}$	0.56	0.56	0.25	0.25	2.21	0.00	0.14	0.98	0.00	3.16	-0.24	1.36
$\tau_{DC,\ 9.3.7.12}$	-0.02	-0.02	0.08	0.08	0.32	0.00	-0.15	0.11	0.00	3.16	-0.26	0.22
$\tau_{DC,\ 9.12.5.7}$	0.71	0.69	0.26	0.26	2.71	0.02	0.26	1.12	0.00	3.16	-0.13	1.51
$\tau_{DC,\ 9.7.8.12}$	-0.03	-0.02	0.04	0.04	0.75	-0.01	-0.09	0.04	0.00	3.16	-0.16	0.11
$\tau_{DC,\ 9.2.7.1}$	0.04	0.03	0.08	0.08	0.48	0.01	-0.10	0.16	0.00	3.16	-0.22	0.28
$\tau_{DC,\ 9.3.6.1}$	-0.06	-0.06	0.10	0.10	0.54	0.00	-0.23	0.11	0.00	3.16	-0.39	0.27
$\tau_{DC,\ 9.1.6.8}$	0.24	0.24	0.19	0.19	1.26	0.00	-0.08	0.56	0.00	3.16	-0.37	0.85
$\tau_{DC,\ 9.1.8.7}$	0.34	0.34	0.24	0.24	1.43	0.01	-0.06	0.73	0.00	3.16	-0.42	1.10
$\tau_{DC,\ 9.4.5.2}$	0.06	0.05	0.10	0.10	0.56	0.00	-0.12	0.22	0.00	3.16	-0.27	0.37
$\tau_{DC,\ 9.2.7.4}$	0.07	0.06	0.11	0.11	0.62	0.01	-0.12	0.23	0.00	3.16	-0.28	0.39
$\tau_{DC,\ 9.3.7.5}$	0.14	0.13	0.18	0.18	0.79	0.02	-0.18	0.43	0.00	3.16	-0.45	0.71
$\tau_{DC,\ 9.3.7.6}$	0.06	0.05	0.12	0.12	0.53	0.01	-0.15	0.25	0.00	3.16	-0.32	0.42

Model implied non-redundant vanishing tetrad	Original sample estimate (Oτ)	Sample mean estimate (Mτ)	Standard deviation (σ)	Bootstrap estimated standard error (se)	t-value (|Oτ/se|)	Bias	Confidence interval low	Confidence interval up	Bonferroni adjustment α	z(1-α)	Adjusted confidence interval low	Adjusted confidence interval up
$\tau_{DC,\ 10.11.3.2}$	0.63	0.61	0.26	0.26	2.37	0.02	0.17	1.05	0.00	3.16	-0.22	1.44
$\tau_{DC,\ 10.11.4.5}$	0.59	0.56	0.20	0.20	2.95	0.03	0.23	0.88	0.00	3.16	-0.07	1.18
$\tau_{DC,\ 10.11.5.6}$	0.33	0.31	0.21	0.21	1.56	0.02	-0.04	0.66	0.00	3.16	-0.36	0.98
$\tau_{DC,\ 10.11.5.7}$	0.65	0.62	0.22	0.22	2.92	0.03	0.25	0.98	0.00	3.16	-0.08	1.32
$\tau_{DC,\ 10.1.5.7}$	0.36	0.35	0.16	0.16	2.29	0.02	0.08	0.61	0.00	3.16	-0.15	0.85
$\tau_{DC,\ 10.2.7.3}$	0.11	0.10	0.15	0.15	0.75	0.01	-0.15	0.35	0.00	3.16	-0.38	0.58
$\tau_{DC,\ 11.3.7.8}$	0.29	0.26	0.16	0.16	1.80	0.03	-0.01	0.52	0.00	3.16	-0.25	0.76
$\tau_{DC,\ 11.6.8.4}$	0.09	0.08	0.13	0.13	0.68	0.01	-0.14	0.30	0.00	3.16	-0.34	0.50
$\tau_{DC,\ 12.1.8.4}$	0.23	0.23	0.18	0.18	1.27	0.00	-0.07	0.53	0.00	3.16	-0.34	0.80
$\tau_{DC,\ 12.1.5.6}$	0.22	0.21	0.14	0.14	1.57	0.01	-0.02	0.44	0.00	3.16	-0.24	0.65

Note: The null hypothesis is H0: τ=0 and a t-value above or below a critical value for the conventional α level supports rejection of the null hypothesis. For all model-implied non-redundant vanishing tetrads in each of the measurement models, the parameter value of H0: τ=0 is in the bias-corrected 90% (one-tailed) Bonferroni-adjusted confidence interval. Hence, CTA-PLS does not reject H0 and, thus, supports the reflective measurement model specification.

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