CONFIGURATIONS OF STRATEGY, STRUCTURE AND ENVIRONMENT: A FUZZY SET ANALYSIS OF HIGH TECHNOLOGY FIRMS*

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Abstract

Configurations are central to the organizational and strategy literatures and continue to play a crucial role in understanding the determinants of competitive advantage. However, configurational theory also faces a number of challenges, including questions regarding the nature of configurations and the instrumentation used to assess configurational effects. In the current study, I build on prior work by developing a definition of configurational centrality and periphery based on how elements of the configuration are causally connected to a specific outcome, a view that allows for a better assessment of both equifinality and causal asymmetry in configurations. Using a recent dataset of high technology firms, I empirically investigate configurations of strategy, structure, and environment using fuzzy set s and Qualitative Comparative Analysis (QCA). In comparing the results from conventional cluster and deviation score analyses with fuzzy set analyses, I show how the use of set-theoretic methods helps clarify mixed findings in the prior literature and that hybrid configurations can lead to high performance, but very high performance is only achieved by embracing tradeoffs and choosing a "pure" configuration.

The study of organizational configurations—"commonly occurring clusters of attributes of organizational strategies, structures, and processes" (Ketchen, Thomas, and Snow, `1993: 1278)—forms a central pillar of both organizational research and the strategic management literature. Organizational typologies such as those of Burns and Stalker (1961), Etzioni (1961), Blau and Scott (1962), Perrow (1970), Miles and Snow (1978), Mintzberg (1983), Porter (1980), and others have figured prominently in both fields of research and continue to draw considerable attention (e.g. Meyer, Tsui, and Hinings, 1993; Desarbo et al., 2005; Kabanoff and Brown, 2008). Similarly, empirically derived taxonomies that aim to group organizations into clusters sharing certain characteristics have formed an important stream of research on organizational configurations (e.g. Pugh, Hickson, Hinings, 1969; Hambrick 1984; Miller and Friesen, 1984). Although such empirical classifications have recently enjoyed less attention than the theoretically derived typologies that lend themselves more readily to theory testing, taxonomies continue to exert an important influence on empirical research (e.g. Corso et al., 2003; Uhl-Bien and Maslyn, 2003; Lim, Acito, and Rusetski, 2006).

The continuing attention to configurational theories stems to a large extent from the fact that such theories are theoretically attractive to organizational researchers for a number of reasons. Because of their multidimensional nature, they acknowledge the complexity and interdependent nature or organizations where fit and competitive advantage frequently rests not on a single attribute but instead resides in the relationships and complementarities between multiple characteristics (e.g. Miller, 1996; Porter, 1996; Siggelkow, 2001). As such, they are more likely to lead to comprehensive explanations that account for a world where outcomes are more often than not multiply determined, resulting in integrative theories that aim to model systematic interconnections of organizational characteristics and multiple causal directions linking structure, strategy, and environment (Child, 1972; McPhee and Scott Poole, 2001). Configurational approaches are also helpful for both academic researchers and practitioners since they provide handy shortcuts for these systematic interconnections by simplifying them into a few typified and easy to remember profiles or *Gestalten* (McPhee and Scott Poole, 2001). While these ideal types will arguably not always be consistent with the data at hand, they nevertheless provide a useful shorthand for more complex phenomena and thus frequently prove useful as heuristics (Mintzberg, 1979).

Finally, configurational theories are relevant to theory building because they focus our attention towards the concept of equifinality, that is, the notion that "a system can reach the same final state from different initial conditions and by a variety of different paths" (Katz and Kahn, 1978: 30). This idea of equifinal configurations has more recently received increasing attention in the management literature (e.g. Doty, Glick, and Huber 1993; Gresov and Drazin, 1997; Payne, 2006; Fiss, 2007; Marlin et al., 2007). Equifinality in organizations may for instance arise when different structural design alternatives are available to deal with environmental contingencies, resulting in the same functional effect (Gresov and Drazin, 1997). The concept is arguably very promising for organizational and strategy research in explaining the persistence of a variety of design choices that can all lead to the desired outcome, offering considerable promise to organization theory (e.g. Ashmos and Huber, 1987).

However, for all their theoretical attractiveness, configurational theories also face some unique challenges. The same features that make configurational theories so attractive to researchers and practitioners—namely, their ability to marrying complexity with parsimony—also lead to some of their greatest disadvantages. Perhaps most importantly in this regard, configurational theories tend to be based on a logic of consistency—that is, they are usually based on the notion of fit between the different parts that make up the organizational configuration. This fit is commonly the result of one of two mechanisms. First, fit can be based on internal, adaptive learning about how the various elements of the organization are best configured so that engaging in one type of activity will increase returns from another one (Miller, 1990; Milgrom and Roberts, 1995). Second, fit may be based on an external, environmental selection mechanism such as organizational birth and death due to e.g. market competition, which reduces variation in organizational configurations to a smaller number of viable forms (e.g. Hannan and Freeman, 1977, 1984). Regardless of the mechanism, the logic of consistency may in fact frequently be too strong an assumption. Existing configurations are likely to contain inconsistencies, tradeoffs, and irrelevant elements, yet teasing apart the causally relevant characteristics from those that are causally irrelevant is challenging both theoretically and empirically. For instance, not all parts of a configuration are likely to be equally important. The question thus is, what really matters in a configuration, and what are peripheral aspects? In other words, configurations are likely to consist of a core and a periphery, where core elements are essential while peripheral elements are less important and perhaps expendable or exchangeable (Hannan, Burton, and Baron, 1996). Most prior typologies have neglected such consideration by asking us to accept the typology *in toto*. Although a holistic approach is thus a strength of configurational theories, theorizing is more likely to end once a configuration is identified, thus limiting our understanding as to what causal mechanisms are at work and is driving the effect (Reynolds, 1971; McPhee and Scott Poole, 2001).

Furthermore, configurational theories have also faced challenges due to insufficient instrumentation. For instance, Gresov and Drazin (1997) discuss qualitative research, surveys, and factor analysis as several ways to examine the degree of consistency of an organizational configuration, yet each of these methods is quite limited in its ability to accomplish this. As a result, when tradeoffs in configurations due to inconsistencies have been theorized, they have so far rarely been tested (Gresov and Drazin, 1997). Similarly, the concept of equifinality remains underutilized in empirical research since testing for equifinal effects is not easily accommodated within the standard framework of linear modeling (Gresov & Drazin, 1997; Fiss, 2007). These challenges are amplified by data needs that include a considerable number of measures to assess the multidimensional nature of organizational configurations. As a result, most prior research has focused on contingency arguments and has rarely tested theories that concern the simultaneous effects of strategy, structure, and environment, examining for instance partial aspects of a configuration such as fit between structure and strategy or between strategy and environment.

To overcome these challenges, some authors have recently tried to shed a new light on the fundamental question as to how organizational configurations are structured and what is the relationship between their elements. For instance, Siggelkow (2002) has argued it is necessary to develop a better understanding of what the nature of core elements in organizational configurations is. In pointing out that the organizational literature contains no agreement as to what *particular* elements constitute the organization's core, he notes that there is agreement that core elements feature a high interdependency with other organizational elements and exert a large influence on future organizational elements. He accordingly defines "coreness" as connectedness and an organizational core element as "an element that interacts with many other current or future organizational elements" (Siggelkow, 2002: 126-127). Core elements of a configuration are thus surrounded by a series of elaborating elements that reinforce these central features.

In the current paper, I build on this prior work that aims to develop a better understanding of how configurations are structured. Extending Siggelkow's understanding of the core and periphery of a configuration as based on the notion of centrality within a network of configurational elements, I suggest a definition of coreness based on what elements are *causally connected to a specific outcome*. Accordingly, I define core elements as those causal conditions that are necessary or sufficient elements of a configuration exhibiting the outcome of interest. In contrast, peripheral elements are those where the evidence for a causal relationship with the outcome is weaker. While maintaining a concern for what makes elements central, this understanding shifts the focus from the connectedness to other organizational elements to the causal role they play within the configuration relative to the outcome.

Shifting the focus from connectedness with other organizational elements to the causal relation between configurational elements and the outcome in question has several advantages. First, it fits closely with the central concern of organization theory that core elements are those that are important to organizational survival (e.g. Singh, House, and Tucker, 1986; Romanelli and Tushman, 1994). In contrast, connectedness to other organizational elements may frequently be related to outcomes but such connectedness presents only an indirect measure of this relationship.

Second, by basing the a focus on the causal relationship between configurational elements and the outcome in question, the current approach redirects the study of configurations towards the concept of equifinality. Specifically, causal centrality and periphery emphasizes the idea of several causal paths to an outcome. Specifically, the current approach enriches the study of equifinal configurations through the notion of *neutral permutations* of a given configuration, that is, within a given configuration the core causal condition may be surrounded by more than one constellation of different peripheral causes, with the permutations not affecting the overall performance of the configuration. The concept goes beyond the current concept of equifinality as different paths to the outcome by pointing to the fact that while different permutations may be equifinal regarding the outcome, they are not equifinal regarding future states of development (Stadler et al., 2001). As such, an understanding of the causal nature of a configuration is essential for understanding trajectories of organizational change, an issue that has largely been neglected in the study of configurations.

Finally, the notion of centrality based on causal necessity and sufficiency rather than a correlation between the configuration and performance is attractive because it assumes causal asymmetry (Ragin, 2008), that is, the idea that the causes leading to an outcome may be quite different from those leading to the absence of the outcome. In contrast, a correlational understanding of causality assumes causal symmetry since correlations are by their very nature symmetric. For instance, if one were to model the inverse of the outcome the question, then the results of a correlational analysis will be unchanged except for the sign of the coefficients. However, a causal understanding of necessary and sufficient conditions is causally asymmetric, that is, the set of causal conditions leading to the outcome may frequently be different from the set of conditions leading to the absence of the outcome. Shifting to a causal understanding of configurations allows for differing sets of causal conditions leading for instance to average performance, high performance, and very high performance. For the study of organizational configurations, this suggests that "coreness" may change relative to different levels of the outcome, allowing for different configurations as one moves from e.g. average performance to high and very high levels of performance.

The definition proposed here, which views core elements of a configuration as causally defined, draws on prior work that has aimed to place the concepts of causal necessity and sufficiency at the center of theory building and analysis (e.g. Ragin, 1987; 2000). Specifically, it suggests that causal relations in organizations as well as the social world more broadly are usually better understood in terms of set-theoretic relations rather than correlations (Ragin, 1987; 2000; 2008; Fiss, 2007; Ragin and Fiss, 2008). To show its utility and how using a different instrumentation may allow for a much more fine-grained understanding of organizational configurations, I conduct an analysis of configurations of structure, strategy, and environment among a sample of UK high technology firms. In comparing the results from both conventional taxonomic and typological analyses with an analysis focusing on causal necessity and sufficiency, I aim to demonstrate the added value of the approach outlined here for both organizational studies and strategy research.

CONFIGURATIONS AND THE MILES & SNOW TYPOLOGY

In the current study, I draw on the Miles and Snow typology of generic organizational configurations (Miles and Snow, 1978; 2003). As a framework to study configurations and their nature, this typology is particularly attractive for a number of reasons. First, it among the most widely used typologies of organizations, and a number of the classic studies on configurations have tested it and found considerable support for it (e.g. Hambrick, 1983; Doty, Glick, and Huber, 1993; Ketchen, Thomas, and Snow, 1993). In fact, as Hambrick (2003) has noted, is presents one of the most widely tested, validated, and enduring strategy frameworks over the last 25 years, with researchers finding strong and consistent support for the typology across a variety of settings ranging from hospitals to industrial products and life insurance. Moreover, the Miles and Snow typology has recently enjoyed renewed attention, with several studies revisiting it to generate new knowledge (e.g. Slater and Olson, 2000; Desarbo et al., 2005; Kabanoff and Brown, 2008). Finally, the framework is attractive for my current purposes because it explicitly links assumptions that cross several domains, including organizational structures, strategies, and their relationship to the environment. In sum, given its wide usage and continued relevance (Ghoshal, 2003), it is particularly suitable for examining the configurational model presented here.

Miles and Snow's typology is based upon three organizational types which they label the Prospector, Analyzer, and Defender. A fourth type, the Reactor, is largely a residual type since in contrast to the previous three types the Reactor "lacks a consistent strategy-structure relationship"(Miles and Snow, 2003: 29) and thus rather presents an instance of strategy absence rather than a viable strategy (Zajac and Shortell, 1989; Inkpen and Chowdhury, 1995). Table 1 provides an overview of the three ideal type profiles of Prospector, Analyzer, and Defender as they relate to structure and strategy.

----- Insert Table 1 about here -----

The Prospector is typically a small but growing organization continually in search of new product and market opportunities. Change is a prime challenge for this organization, and the administrative challenge is thus how to facilitate rather than control operations. Accordingly, Prospectors tend to score relatively low in regards to formalization and centralization. The need to alter the organizational structure in response to a changing environment means that Prospectors tend to have a less extensive division of labor and flatter organizational structures, resulting in lower degrees of organizational complexity.[1] In terms of their strategy, their focus on innovation and product features makes them highly similar to Porter's differentiators, while the same features mean they score low regarding a cost leadership strategy (e.g. Miller, 1986, Segev, 1989; Parnell, 1997).

In contrast, the Defender is more typically a large and established firm that aims to protect its prominence in a product market. While the Prospector is focused on change, the Defender is focused on stability, which is reflected in its organizational structures. Management usually aims for highly centralized control of the organizational operations and more often use formalized processes and policies to specify the appropriate behaviors for organizational members. Defenders are usually marked by an extensive division of labor and a greater number of hierarchies, indicating a higher degree of administrative complexity. In terms of their strategy, Defenders typically pursue a cost leadership rather than a differentiation strategy (Miller, 1986; Segev, 1989).

As Miles and Snow now, Prospectors and Defenders "reside at opposite ends of a continuum" of strategies, while the Analyzer lies "between these two extremes"(Miles & Snow, 2003: 68). Table 1 reflects this in showing the Analyzer taking an intermediate position between Prospectors and Defenders in terms of its structural attributes and strategy, with the exception of its complexity. The reason for this lies in the hybrid nature of the Analyzer, which has to be able to accommodate both stability and change, indicating that the ideal profile of analyzers will be marked by very complex structures (Miles and Snow, 2003: 79).

[1] The definition of organizational complexity I use here calculates complexity as the product of horizontal and vertical differentiation (Singh, 1986; Wong and Birnbaum-More, 1994). My conceptualization of Prospectors having a low degree of administrative complexity is thus consistent with Miles and Snow's characterization of Prospectors' use of coordinators or integrators to coordinate across "organic" structures using e.g. project groups. As Miles and Snow note, such coordination challenges are arguably also complex, albeit in a different manner.

Regarding the performance of the three types described by Miles and Snow, the literature has offered conflicting results. For instance, Hambrick (1983) found that analyzers tended to outperform both prospectors and defenders on performance measures such as return on investment and market share and suggested that “in general the ‘superior’ strategy was neither of the two extreme strategies” (Hambrick, 1983: 18). Similarly, Kabanoff and Brown (2008) found that analyzers performed relatively well in profitability when compared to the other types, as did Snow and Hrebiniak (1980), although they caution that the sample size for this strategic type was relatively small. These findings would suggest that taking a middle position that “combines the strengths of both the Prospector and the Defender into a single system” (Miles and Snow, 2003: 68) would result in relatively higher levels of organizational performance relative to the extreme types.

In contrast to these findings, other authors have pointed to the importance of tradeoffs in strategy. For instance, Porter (1980; 1995) has argued that differentiation and cost leadership can be combined only on rare occasions. As a result, organizations should pursue either a differentiation or cost leadership strategy but should not try to combine both strategies to avoid getting “stuck in the middle” with relatively lower performance. The rationale for this argument is that both strategies usually involve specific tradeoffs in terms of e.g. production processes, product positioning, and administrative structures, and aiming to take a middle position on these tradeoffs and thus failing to align with either strategy will result in low profitability. As Desarbo et al. (2005) point out, more research is thus needed on the topic of strategic type and performance. In the current study, I revisit the question regarding the relative performance of Prospectors, Defenders, and Analyzers by aiming to show what causal factors and tradeoffs actually result in improved firm performance. Building on the notion of tradeoffs within organizational configurations thus leads to the first research question:

Research Question 1: Do firms fitting the Prospector or Defender type outperform firms fitting the Analyzer type and what accounts for the relationship between configurational types and performance?

Another important aspect of the Miles and Snow typology relates to whether the typology is universally applicable across environments or whether it is context dependent. For instance, Hambrick (1983: 7) notes that the generic character of the typology ignores industry and environmental peculiarities, while Zajac and Shortell (1989: 413) similarly point out that Miles and Snow's notion of generic strategies tends to "assume that the various strategies are equally viable across environmental contexts and, by implication, across time." Building on the notion that strategy selection is usually dependent on the environment (e.g. Hofer and Schendel, 1978), these researchers have instead argued that the performance of Prospectors, Defenders, and Analyzers will depend on the fit of these configurations with the environment they operate in (e.g. Govindarajan, 1986). In this regard, Hambrick (1983) found that Prospectors performed better in innovative environments while Defenders performed worse in such environments. Similarly, Zajac and Shortell report that Defenders were significantly less profitable than other generic strategies in environments calling for proactive strategies. However, as Desarbo et al. (2005) point out, there are very few studies that have empirically examined this relationship between the nature of the environment and strategic type. In fact, apart from the study of Doty, Glick, and Huber (1993), no other research appears to have simultaneously examined configurations of organizational structure, strategy, and environment. This leads to the second research question:

Research Question 2: What is the relationship between Prospector, Defender, and Analyzer types and the nature of the environment and how does it affect firm performance?

Finally, answers to the questions outlined here are to a considerable extent influenced by the analytical approach used. So far, apart from self-typing, two main approaches have been used to study the Miles & Snow typology and its relationship to performance. The first is inductive in nature and primarily uses cluster analysis to derive an empirical solution (e.g. Ketchen, Thomas, and Snow, 1993). The second approach is deductive and uses deviation score analysis to examine the fit with a theoretically defined profile (e.g. Doty, Glick, and Huber, 1993). Which approach and analytical method provides superior results has been contested in the literature. For instance, Ketchen et al. (1993) find that deductively defined configurations were considerably superior to inductively defined configurations in predicting performance differences. In contrast, Hambrick has questioned the ability of deductive typologies to accurately describe reality as "they may serve for descriptive purposes but have limited explanatory or predictive power" (1984: 28). Likewise, Desarbo et al. (2005) have pointed to the advantages of an empirically derived solution based on a clustering procedure and report that their solution also outperformed a classification based on self-typing regarding the Miles and Snow types.

Furthermore, both cluster analysis and deviation score approaches face difficulties regarding their ability to provide insights into the causal nature of the configuration, that is, they are not well suited to shed light on just what aspect of a configuration leads to e.g. high performance (Fiss, 2007; 2008). For instance, cluster analysis assigns cases to clusters based on their similarity along a number of characteristics regardless of the relationship between these characteristics and outcomes of interest. However, in situations where not all characteristics included in the analysis are in fact causally relevant regarding the outcome (which is likely to be the rule rather than the exception), cluster analysis will not be able to distinguish between these characteristics. If cases are similar along causally irrelevant characteristics but differ along a few but causally important characteristics, cluster analysis will nevertheless usually assign these cases to the same cluster, resulting in undesirable causally heterogeneous clusters that are undesirable. Accordingly, while cluster analysis is an excellent exploratory tool for discovering structures in the data without specifying a priori what those structures might be, it is a much less useful tool for understanding what aspects of clusters are causally related to the outcome.

Deviation score analyses likewise face challenges in examining what aspects of the fit between a hypothesized ideal type and empirically observed configuration in fact relate to performance. In this respect, Doty et al. (1993) use canonical analysis to examine what measures of their configurational model had the strongest relationship with model fit, but while such an approach is preferable to cluster analysis it is still quite limited in its ability to determine contextually dependent causal relations within a configuration. In addition, deviation score analyses like cluster analyses exhibit a considerable sample dependence regarding in how profiles are derived (e.g. Drazin and Van de Ven, 1985) and face reliability issues (Gupta & Govindarajan, 1993).

In the current paper, I aim to offer a fresh view of these issues by using set-theoretic methods for studying cases as configurations. The current study builds on the set-theoretic methods first introduced by Ragin (1987) and extended by Ragin (2000, 2008) and Ragin & Fiss (2008). I argue that set-theoretic methods such as fuzzy set Qualitative Comparative Analysis (fs/QCA) are uniquely suitable for configurational theory as such methods explicitly conceptualize cases as combinations of attributes and emphasize that it is these very combinations that give cases their unique nature. Set-theoretic methods thereby differ from conventional, variable-based approaches in that they do not disaggregate cases into independent, analytically separate aspects but instead treat configurations as different types of cases. These features make set-theoretic methods particularly attractive for organizational and strategy researchers, as indicated by several recent studies that have argued for applying QCA and fuzzy sets in organizational settings (e.g. Jackson, 2005; Fiss, 2007, 2008; Greckhamer et al., 2008; Pajunen, 2008). The methodological approach used here thus sheds new light on the causal relationship between the characteristics of a configuration and the outcome of interest. Drawing on these set-theoretic methods, I thus aim to show how instrumentation can affect what we may learn about a configuration, leading to the third research question:

Research Question 3: How do method and instrumentation affect results for Prospector, Defender, and Analyzer types and does a fuzzy set approach offer an improved understanding of causal relationships here?

STUDY DESIGN AND METHODS

For this study, I selected a recent dataset of 205 high-technology manufacturing firms in the UK (Cosh et al., 2002). The data were collected in 1999 via a survey sent to the CEOs and managing directors of these firms as part of a research project that examined strategy in the context of changing environmental conditions. The data are particularly useful for my purposes for several reasons. First, the dataset contains a rich set of measures on the firms' strategy, structure, environment, and performance, thus allowing me to examine the effectiveness of different configurations. Second, the data are restricted to manufacturing firms, assuring comparability regarding operations by excluding for instance service firms that frequently have very different operational requirements. Third, while the data come from the high technology manufacturing sector, they include firms operating in several industries, thus offering variety in terms of the velocity and uncertainty of the competitive environment that is not available in a single industry study. Finally, the data are unusual in that they offer actual financial performance data as opposed to perceived performance data relative to competitors, thereby assuring greater comparability.

While the data are uniquely appropriate for the current study, they also have some limitations. The survey's response rate of 14 percent was somewhat lower than is usually desirable, although it is still slightly above the 10-12 percent response rate that is typical for surveys mailed to U.S. CEOs (e.g. Hambrick et al., 1993; Geletkanycz, 1997). For confidentially reasons, the original investigators were not able to provide response bias analyses or the firm names, and I could therefore not conduct my own analyses. However, response bias is less of a threat to validity than usual in the current study for at least two reasons. First, my interests are not with the UK high technology sector per se, but I instead use the data as the setting to test arguments relating to configurational theory. Accordingly, even if there was some response bias (for instance, if a greater number of smaller or high-performing firms responded), this would not threaten the validity of the findings because the focus of the current study is on configurations and not on the actual population or representativeness of the sample. Nevertheless, the final sample included firms with considerable variation in terms of size, performance, structure, and environment, indicating that the sample is likely representative of the underlying population. Second, the non-parametric nature of fs/QCA as a method of analysis should further alleviate concerns about sample bias. Finally, some of the most influential and path breaking studies such as those of Ketchen et al. (1993) and Doty et al. (1993) have used non-random samples of organizations selected based on geographical proximity and social contacts, indicating that random samples are not an essential feature of the current research context. In sum, the advantages of the data heavily outweigh their limitations, making them a useful setting to test configurational arguments.

Outcome measures

The primary outcome of interest in my study is organizational performance, measured as return on assets (ROA), and calculated as pre-tax profits (losses) before deduction of interest and directors' emoluments divided by total assets. I calibrate this measure by benchmarking it to overall performance of the high technology manufacturing sector rather than using a sample-dependent anchor such as the mean for firms in the sample. Data on average industry performance in the UK high technology manufacturing sector came from *ICC Business Ratio* reports, various years. I averaged ROA across for the main industries in this sector, such as manufacturers of computer equipment, printed circuits, scientific and electronic instruments, electronic component manufacturers, and the aerospace industry. The average ROA for the sector was 7.8%, which is very similar to a median ROA of 7.2% for the US high technology sector in the same time period. While data regarding the variation in performance was very limited in the UK sector, I use upper and lower quartile information for the US sector. These data came from *RMA Annual Statement Studies*.

I create two fuzzy set measures of above average firm performance. The first, membership in the set of *high* performing firms, was coded 0 if a firm showed average or below average performance (ROA $\leq$ 7.8%, i.e. about 50th percentile) and was coded 1 if the firm showed high performance (ROA $\geq$ 16.3%, i.e. 75th percentile or higher). As the crossover point, I chose the halfway mark of about 12%. The second set, membership in the set of *very high* performing firms, was again coded 0 if a firm showed average or below average performance ($ROA \leq 7.8\%$, i.e. about 50^{th} percentile) and but was coded 1 if the firm showed an ROA of 25%—arguably very high performance in the eyes of most analysts. As the crossover point for very high performance, I chose an ROA of 16.3% (i.e. the 75^{th} percentile or full membership in the previous set of high performing firms).

Further, to examine issues of causal symmetry or asymmetry, I also created a measure of membership in the set of firms with *not high* performance. This measure is coded as the negation of the measure of high performance described above. Note that this measure takes a value of 1 if a firm has average or below average performance and a value of 0 if the firm has high performance.

Independent Measures

I assess organizational structure using four different measures usually employed with the Miles and Snow typology as well as other classic studies of organizational structure (e.g. Pugh et al., 1968). The first one, formalization, is measured using a set of nine survey items that assess to what extent a firm e.g. uses formal policies and procedures guide decisions, in how far communications are documented by memos, whether reporting relationships are formally defined, and whether plans are formal and written. The items were measured on a 5-point scale ranging and were combined into a scale that showed very good reliability (Cronbach's $\alpha = 0.83$). Based on the scale, I created a set of membership in the set of firms with a high degree of formalization, with membership coded as fully out for a response of (1) ("almost never") and fully in for a response of (5) ("nearly always"), while the crossover point corresponded to the middle of the scale (3) ("about half the time").

The second measure, centralization, is based on five survey items that assess the last decision maker whose permission must be obtained for organizational decisions such as the addition of a new product or service, unbudgeted expenses, or the selection of the type or brand of new equipment. The items were again measured on a 6-point scale, but actual responses were essentially restricted to four levels (department head, division head, CEO, Board of Directors). The items were combined into a scale that showed acceptable reliability with a Cronbach's α of 0.74, above the frequently recommended value of 0.70 (e.g. Nunnally, 1978). Based on this scale, firms with decision making at the level of the department head was coded as fully out of the set of highly centralized firms, while firms with decision making at the board level were coded as fully in the set, with the scale mid-point (between division head and CEO) serving as the crossover point.

The third measure is administrative complexity, which is created using a combined measure of vertical and horizontal differentiation. Following Pugh et al. (1968), vertical differentiation was measured as the number of levels in the longest line between direct worker and CEO, while horizontal differentiation was measured using the number of functions with at least one full-time employee. Administrative complexity was then calculated as the product of horizontal and vertical differentiation (Singh, 1986; Wong and Birnbaum-More, 1994). The measure was coded into the fuzzy set of firms with high degree of administrative complexity by coding firms in the 1^{st} percentile (1 Level / 1 Function) as fully out of the set and firms in the 99^{th} percentile (6 Levels / 17 Functions) as fully in the set. As a crossover point, I chose the 50th percentile (3 Levels / 9 Functions), which is largely consistent with the mean score of prior studies using a complexity measure (e.g. Wong and Birnbaum-More, 1994).

The last measure of organizational structure is size, which is based on the average number of full time employees, with groupings based on the European Union enterprise size-classes (1-9, 10-49, 50-249, 250+). Specifically, firms with 250 or more employees were coded as fully in the set of large firms, while those with 10 employees or less were coded as fully out of the set, with the midpoint at 50 employees.

Consistent with prior research, I use Porter's (1980) strategy framework, which is consistent with Miles and Snow's typology and prior research (David et al., 2002; Doty et al., 1993). Specifically, I develop measures for Porter's two generic strategies, cost leadership and differentiation. Both items are based on a factor analysis of six items relating to the firms' competitive capabilities. The first four related to low labor cost, low material consumption, low energy consumption, and low inventory cost as elements of the firm's competitive capability over the past 3 years, while the last two related to new product introduction and product features as such elements of competitive capability. A principal component factor analysis with varimax rotation showed a two factor solution, with all items loading highly and cleanly on two factors, as shown in Table 2.

----- Insert Table 2 about here -----

The items were combined into two scales that showed strong reliability ($\alpha = 0.86$ for cost leadership and $\alpha = 0.80$ for differentiation). Based on these scales, I created two fuzzy set measures. Membership in the set of firms with a cost leadership strategy, was coded as fully out for a value of 1 ("not important") and fully in for a value of 5 ("critically important"), with the scale midpoint of 3 as the crossover point. Coding of membership in the set of firms with a differentiation strategy followed the same approach.

I measure environmental context using the two constructs of environmental velocity and uncertainty. The first measure, environmental velocity, measures the speed of technological and competitive change (Bourgeois and Eisenhardt, 1988). In high velocity environments, firms face difficulties earning above average profits for prolonged periods of time based on a single innovation or product (Bogner and Barr, 2000). Velocity here is operationalized as the length of firm's main product's life cycle. A product life cycle of 3 months or less (98th percentile) was coded as full membership in a high velocity environment, a life cycle of 3 years (77th percentile) was set as the crossover point, and a product life cycle of 10 years (25th percentile) was coded as full non-membership in a high velocity environment.

The second measure, environmental uncertainty, was assessed using two items that asked how predictable changes were in the business environment over the past three years. The two items assessed the predictability of technological change for manufacturing products and technology related to product improvement, both measured on a 5-point scale ranging from 1 ("easily predictable") to 5 ("completely unpredictable"). Both items were combined into a scale that showed very good reliability ($\alpha = 0.81$). The fuzzy set measure of high environmental uncertainty was based on this scale and coded as fully out of the set for values of 1 ("easily predictable). Because the maximum observed value was 4, I coded this value as fully in the set of high environmental uncertainty and used the observed scale mid-point of 2.5 as the crossover point. Finally, the measures of velocity and uncertainty tap into different constructs as shown by their low and non-significant correlation of 0.04 ($p = 0.64$).[2]

[2] While environmental uncertainty is arguably a multi-faceted construct that can also relate to e.g. political uncertainty or uncertainty relating to the supply of inputs and factor prices, the current measure relating to

Information on the survey items used to construct the independent measures was missing for on average 14 percent of cases, and listwise deletion would have significantly reduced the overall sample size and likely resulted in biased results (Little and Rubin, 1987). I therefore imputed the missing values using maximum likelihood estimation based on information from all measures (Schafer, 1997). However, I do not impute missing values for my outcome measure, and deleting cases with missing performance information resulted in a valid sample size of 139 cases. All subsequent analyses refer to this final sample.

Calibration

As described above, the process of transforming variables into sets requires the specification of full membership, full non-membership, and the crossover point of maximum ambiguity regarding membership in the set of interest. Given these three qualitative anchors, the transformation of a variable into a set measure is relatively simple. In the current study, I follow the "direct method" described by Ragin (2008). The transformation proceeds in two steps. In the first, variables scores are translated into the metric of log odds. For instance, scores associated with ≥ .99 membership are translated to log odds values of ≥ 5, while scores associated with the crossover point of .5 membership are translated to log odds values of 0. In the second step, set membership scores are calculated using the formula below.

$$\text{Degree of Membership} = \frac{e^{(\log\left(\frac{p}{1-p}\right))}}{1+e^{(\log\left(\frac{p}{1-p}\right))}}$$

technological uncertainty is arguably most closely related to the strategies of cost leadership and differentiation and consistent with prior work (e.g. Desarbo et al. 2005).

Accordingly, the degree of membership in a set is the exponentiated log odds divided by unity plus the exponentiated log odds. The advantage of the log odd transformation is that it converts any interval variable into a set by using a metric that is symmetric around zero and has no floor or ceiling. The rescaled measures range from 0 to 1 and the converted scores are tied to the thresholds of full membership, full non-membership, and the crossover point. In the current version of fs/QCA (2.0), the transformation is automated once the three thresholds are defined. To assure comparability in the coding of the outcome across different analysis methods, I use the fuzzy set outcome for performance in all models. However, I also note any differences in results if the conventional, uncalibrated performance measure is used. The uncalibrated measure is simply the raw ROA score for the firms in the sample.

Plan of Analysis

In order to examine the effect of instrumentation on understanding the nature of configurations, my analysis proceeds in three steps that move from standard statistical approaches for configurational analysis to set-theoretic analyses using fuzzy sets and QCA. In a first step, I generate an empirically derived taxonomy of configurations based on cluster analysis. In a second step, I use a theoretically derived typology based on Miles and Snow and employ deviation score analysis to generate profiles. I combine both the empirically and theoretically derived solutions with regression analysis to examine their ability to explain performance differences across types and environments. After thus establishing a baseline of findings using the standard methodology, the third step employs a set-theoretic approach based on QCA. Using Boolean algebra, I analyze the dataset for the presence of set-theoretic relationships between the different aspects of organizational configurations and again examine the ability of this analysis to explain performance and to examine what causes are central in a configurational analysis of the observed types.

RESULTS

Table 3 presents descriptive statistics and correlations for all measures. The table shows the expected positive correlations between size, formalization, and administrative complexity. In contrast, centralization is negatively correlated with these three measures, which is consistent with the notion of smaller organizations with few levels of hierarchy concentrating decision making at the executive level. As would be expected, there is also a significant and high negative correlation between environmental uncertainty and cost leadership strategy.

----- Insert Table 3 about here -----

Cluster Analysis

To derive an empirical taxonomy of organizational configurations, I use a two-step cluster analysis, which has been the dominant tool of analysis for configurations and strategic groups (Ketchen and Shook, 1996). I use the four structural and two strategy variables and then examine how the derived configurations perform given differing environments. In a first step, hierarchical cluster analyses using Ward's minimum variance method suggested a three-cluster solution based on cutoff values and inspection of dendrograms (Ferguson et al., 2000; Marlin et al., 2007). After determining this three-cluster solution, I used K-means cluster analysis in a second step with the centroid values of the hierarchical analysis as seeds (e.g. Payne 2006; Lim et al., 2006). To assure comparability across variables, all measures were standardized prior to the analysis. Results of the cluster analysis with final cluster centers are presented in Table 4 and are essentially stable across different clustering algorithms.

----- Insert Table 4 about here -----

As the table shows, the solution includes three clusters that map somewhat imperfectly on the Miles and Snow typology. Group 1 (N=93) corresponds roughly to the prospector type, scoring low on size formalization, complexity, and cost leadership, and high on a differentiation strategy. At the other end of the continuum, Group 3 (N=59) approximates the defender type, scoring high on size, formalization, and complexity. However, its score of 0.42 on cost leadership is only slightly higher than that of group 1, while its differentiation score is only slightly lower. Furthermore, again diverging from the ideal typology, centralization scores are high for prospectors and low for defenders. Finally, Group 2 (N=41) does appear to fit the analyzer profile, mostly occupying a middle position except for differentiation, where this group has the lowest score of the three groups.

The empirical results thus bear some resemblance to the Miles and Snow ideal types of prospector, analyzer, and defender, although the fit is less than perfect. To examine the relationship between these ideal types and performance, I regressed dummy variables for cluster membership on the performance measure, with interaction terms for environmental velocity and uncertainty. I use two-limit Tobit regression, which is the appropriate model when the dependent variable is truncated (Long, 1997), as is the case with the fuzzy set measure that calibrates the measure by introducing cutoffs for full membership and non-membership in the set of high performing firms.[3] In the models, the analyzer type is used as the omitted category. Results are presented in Table 5.

----- Insert Table 5 about here -----

Model 1 shows the effect of prospector and defender types on performance, while models 2 to 5 add interaction terms for environmental velocity and uncertainty to examine whether the types perform better or worse in these environments as predicted by the typology. As model 1 shows, only the prospector type exhibits significantly higher performance than the analyzer type. Furthermore, models 2 through 5 offer no evidence that the performance of either the prospector or defender type depends on the environment in which it operates. Alternative models using the defender type as the omitted category also showed no performance differences or dependence of performance on the environment for the analyzer type. Because models using the alternative measure of very high performance resulted in essentially identical results, these models are not reported here but are available from the author on request. In addition, note that model fit is less than desirable, with pseudo R-squared values between 0.04 and 0.05. In sum, the models offer only very limited support for performance differences between these types and they offer no support for performance being contingent on the nature of the environment, as specified by the theory.

Deviation Score Analyses

I follow prior studies in using deviation scores to test the relationship between the fit with a theoretical typology and performance (Doty et al. 1993; Doty and Glick, 1994; Delery and

[3] I also estimated models that used OLS regression in combination with the uncalibrated performance measure. The results were substantively identical with the exception that in these models the coefficient for the prospector type is significant at the .01 instead of the .05 level.

Doty, 1996). The profiles are defined based on the Miles and Snow ideal types of prospector, analyzer, and defender. For each profile, fit is calculated as the deviation of an organization from an ideal type and across all attributes. Based on the fit scores, ideal profile fit is calculated as the minimum deviation across the three profiles according to the formula below.

$$Fit_{IT} = -\left(\begin{matrix} l \\ \min D_{io} \\ i = 1 \end{matrix}\right)$$

Here, D_{io} is the distance between ideal type *i* and organization *o*, and the formula takes the minimum of this distance across all ideal type (Doty et al., 1993). Using the fuzzy set measures constructed above, high ideal profile scores corresponded to full membership while low score corresponded to full non-membership, with medium scores tied to the crossover threshold. Because the prospector and defender ideal types specified by the Miles and Snow typology are the opposite of each other, their deviation scores are inversely correlated with each other. I again use two-limit Tobit regression to then model the relationship between ideal profile deviation and performance. In the models, the analyzer type is used as the omitted category. Results are presented in Table 6.

----- Insert Table 6 about here -----

Model 1 shows the results of an organization's overall ideal profile fit across all profiles. The fit coefficient is positive and significant, indicating that such fit is indeed associated with higher performance. To examine whether this finding was driven by fit with any particular ideal type, models 2 to 4 show the coefficient for deviation from the individual prospector, analyzer, and defender profile. Only the coefficient for the analyzer profile is marginally significant, suggesting that it is not simply one profile that is superior but that likely firms may achieve higher performance by achieving fit with any of the three profile. Note also that the findings using this theoretically derived typology differ from the empirically derived solution based on cluster analysis, where only the prospector type showed increased performance.

Models 5 through 8 show the interaction between deviation from the three ideal types and environmental velocity and uncertainty. As suggested by a model of environmental contingency, model 6 indicates that deviation from the prospector profile decreases performance in high uncertainty environments, although the coefficient is only marginally significant. The models did not indicate any support for the dependence of ideal type fit on the velocity of the environment. Alternative models using the very high performance measure as the dependent variable resulted in essentially identical models and are therefore omitted here. Note also that model fit as measured by the Pseudo R-squared is again rather poor, with values between 0.02 and 0.03 for the overall model. Compared to a baseline model with only environmental controls, the Pseudo R-squared increases only by 0.01 when the ideal type fit measure is included. Accordingly, although the models offer some evidence that ideal type fit is positive for performance and at least for fit with the prospector type does depend on environmental uncertainty, it would not appear that ideal type fit is a crucial ingredient in attaining high performance.[4]

Fuzzy Set Analyses

Most previous fuzzy set analyses have used the inclusion algorithm described in Ragin (2000) to examine the relationship between membership in causal conditions and the outcome of

[4] The results are again identical for OLS regression in combination with the uncalibrated performance measure, the only exception being that the interaction between prospector type deviation and environmental uncertainty is now significant at the 0.05 level instead of the 0.10 level.

interest (e.g. Kogut, MacDuffie, and Ragin, 2004; Kogut and Ragin, 2006). While this algorithm is particularly useful in small-N situations, it circumvents the creation of a truth table and thus forfeits some analytical advantages when e.g. analyzing limited diversity. To overcome this limitation, Ragin (2005; 2008) introduced a truth table algorithm that takes full advantage of the rich information contained in fuzzy sets while also allowing the constructing of a conventional truth table that can be analyzed using standard methods of Boolean algebra. I use this new algorithm in all subsequent analyses.[5]

The truth table algorithm of QCA is based on a counterfactual analysis of causal conditions, which allows for a categorization of causal conditions into core and peripheral causes. Counterfactual analysis is relevant to configurational analysis since even relatively few elements of a configuration quickly lead to an astronomically large number of different possible complex configurations. As Stouffer (1941) has pointed out, for the researcher this means that there are so many configurations that there will frequently be very few or no empirical instances of any particular configuration. This challenge of configurational approaches is known as the problem of limited diversity (e.g. Ragin, 2000), and counterfactual analysis offers a way to overcome the limitations of a lack of empirical instances.

To deal with the problem of limited diversity using counterfactual analysis, the truth table algorithm distinguishes between parsimonious and intermediate solutions based on “easy” and “difficult” counterfactuals (Ragin, 2008). “Easy” counterfactuals refer to situations where a redundant causal condition is added to a set of causal conditions that by themselves already lead to the outcome in question. In contrast, “difficult” counterfactuals refer to situations where a

[5] The truth table algorithm is now the standard algorithm implemented in the fs/QCA software package version 2.0 (Ragin, Drass, and Davies 2006). The current paper does not aim to explain the algorithm in detail and but the interested reader can find an extensive description in the current book by Ragin (2008).

condition is removed from a set of causal conditions leading to the outcome on the assumption that this condition is redundant.

Using both “easy” and “difficult” counterfactuals, the researcher can easily establish two kinds of solutions. The first is a parsimonious solution that includes all simplifying assumptions regardless of whether they are based on “easy” or “difficult” counterfactuals. The second is an intermediate solution that only includes simplifying assumptions based on “easy” counterfactuals.[6] The notion of conditions that are causally central or peripheral in configurations is based on these parsimonious and intermediate solutions. Core conditions are those that are part of both parsimonious and intermediate solutions, while peripheral conditions are those that are eliminated in the parsimonious solution and thus only appear in the intermediate solution. Accordingly, this approach defines causal coreness based on the strength of the evidence relative to the outcome.

The truth table algorithm used here additionally allows the calculation of consistency and coverage scores, thus permitting a finer-grained understanding of the reliability and importance of different causal paths to an outcome. Consistency assesses the degree to which cases sharing a given condition or combination of conditions agree in displaying the outcome in question. A simple way to estimate consistency when using fuzzy sets is the proportion of cases consistent with the outcome. However, this gives undue weight to cases displaying only low membership in the condition of interest. For example, a case with high membership in the set of high performing organizations should have more weight than one with low membership since such a case is arguably of greater interest to the researcher. To address this issue, Ragin (2006) has introduced as an alternative measure of consistency the sum of consistent fuzzy membership scores divided

[6] A third solution, of course, is the most complex one that includes neither easy nor difficult counterfactuals. However, such a solution is usually needlessly complex and provides rather little insight into causal configurations.

by the sum of all membership scores. This measure is further refined by adding to the numerator the part of each inconsistent causal membership score that is consistent with the outcome. As Ragin (2008) notes, this adjustment improves on the previous consistency measure by giving small penalties for minor inconsistencies and large penalties for major inconsistencies. I follow standard practice by setting the minimum acceptable consistency for the solutions at 0.75 (e.g. Ragin, 2006, 2008). Also, the minimum acceptable solution frequency was set at two.

Coverage is a measure of how important a cause or causal combination is to the outcome. It is similar to an R-Square by indicating the number of cases that take this path to the outcome, allowing to evaluate the importance of different causal paths. Coverage is further subdivided into unique coverage of causal conditions, similar to unique R-Squared calculations in regression analysis.

Table 7 shows the results of a fuzzy set analysis of high performance. I use the notation recently introduced by Ragin and Fiss (2008). In this notation, full circles indicate the presence of a condition, while crossed-out circles indicate the absence of a condition. Furthermore, large circles indicate core conditions that are part of the parsimonious and intermediate solutions, while small circles refer to peripheral conditions that only occur in intermediate solutions. Intermediate solutions incorporate only "easy" counterfactuals, while the parsimonious solution incorporates both “easy” and “difficult” counterfactuals based on the actual evidence available (Ragin, 2008).

----- Insert Table 7 about here -----

The table shows that the fuzzy set analysis results in four solutions showing acceptable consistency (i.e. consistency ≥ 0.75). Regarding core conditions, Solutions 1 and 2 indicate that a cost leadership strategy combined with either high centralization or the absence of a high velocity environment are sufficient for achieving high performance, a profile that fits the defender type. These findings suggest that, with a cost leadership strategy, there are tradeoffs between a high degree of centralization and environmental velocity: greater centralization allows for high performance regardless of whether the environment changes at high speeds or not, but in the absence of centralization high velocity becomes a problem for achieving high performance. Regarding peripheral conditions, both solutions 1 and 2 show that these core conditions are usually combined with a high degree of formalization and complexity as well as a differentiation strategy and the absence of high uncertainty in the environment.

Solutions 4a and 4b indicate another path to high performance combining a differentiation strategy with greater decentralization as indicated by low levels of complexity, which is consistent with a prospector strategy. Indeed, in terms of structure and strategy, solution 4a is perfectly consistent with the prospector ideal profile defined by Miles and Snow when peripheral conditions are also taken into account. Solution 4b differs slightly from 4a in that this solution combines centralization with operating in an uncertain environment as peripheral conditions. Note that for both solutions, however, the environment is not a core condition, although high velocity appears to hinder high returns when using a differentiation strategy. In fact, it would appear that, in contrast to the Miles and Snow assumption, a centralized defender configuration (solution 1) is better positioned to operate in a high velocity environment than any prospector (solutions 4a and 4b).

Interestingly, the fuzzy set analysis also indicates the existence of a successful hybrid configuration (solution 3), which combines differentiation and cost leadership strategies with low levels of complexity while avoiding high velocity environments. In terms of overall coverage, the combined models account for about 35% of membership in the outcome. While this value appears high relative to e.g. the R-Squared values of the previous regression models, it also indicates considerable elements of randomness or idiosyncrasy within configurations that lead to high performance.

Table 8 shows the results for the fuzzy set analysis of very high performance. The results indicate the existence of two distinct configurational groupings leading to very high performance. Solutions 1a-1c all rely on a cost leadership strategy in combination with a high degree of formalization and either centralization, not high velocity environments, or both. Solutions 1a and 1b also show clear tradeoffs, with complexity and differentiation associated with 1a being replaced by no differentiation and not high velocity environments in 1b. Note also that for all solutions in Table 8, the minimum number of core conditions has increased from 2 to three, indicating the existence of fewer choices when aiming for very high performance.

----- Insert Table 8 about here -----

The table also shows the existence of a highly successful prospector configuration in solution 4, which largely resembles the prospector configuration of the previous table but includes uncertainty as a core condition. This finding is consistent with the prospector prototype of a small, centralized firm that is highly decentralized, pursuing a differentiation strategy only in a highly uncertain but not too quickly changing environment. It also indicates that very high performance is possible even in usually unfavorable environments given the right configuration. Note also that the results of Table 8 indicate there is no hybrid configuration that achieves very high performance. This is an important finding, as it indicates that tradeoffs may become increasingly pronounced as one moves up the performance scale. Accordingly, it may still be possible to achieve high performance using a hybrid type, but as one approaches very high performance, tradeoffs between e.g. differentiation and cost leadership strategies as well as their associated characteristics of organizational structure appear to make hybrid types such as the analyzer infeasible.

Finally, I conducted fuzzy set analyses modeling the absence of high performance. Note again that in the previous regression analyses, this kind of analysis is always part of the process because of the symmetric nature of relationships in regression. For instance, the results of a regression analysis are unchanged except for the sign if one uses the inverse of the outcome. However, in fuzzy set analyses, causal conditions leading to the outcome may frequently be different from those conditions leading to the absence of the outcome.

As suggested by an asymmetric understanding of causality in configurations, a fuzzy set analysis of the absence of high performance indicated that there was no consistently identifiable solution.[7] The consistency scores for all solutions remained considerably below the acceptable level of 0.75, indicating the absence of a clear set-theoretic relationship. Put differently, there are few configurations that consistently lead to high performance and even fewer that consistency lead to very high performance, but no configuration of strategy, structure, and environment that consistently leads to average or below performance. While such a finding is not part of the

[7] In a regression framework, one might think of this findings as roughly similar to a lack of significance for any of the causal configurations.

regression framework, it is in fact quite common in fs/QCA to find that the specified conditions are linked to either the outcome or its negation but not both.

As a robustness check, I created an additional measure of membership in the set of firms with *low* performance. This measure was coded 1 if the firm had no or a negative return and was coded 0 if the firm had an average ROA (7.8%). Note that this measure of *low* performance is thus different from the measure of *not high* performance. For instance, an average performing firm will have a membership score of 1 for *not high* performance but will have a membership score of 0 for *low* performance. However, this measure likewise failed to result in solutions with an acceptable level of consistency. For the current setting, the finding of asymmetric causality indicates a specific feature of organizational configurations, namely that certain configurational choices reliably achieve high performance, but that average or low performance can be the result of many configurational choices, with none being particular ones that have to be avoided.

DISCUSSION

While configurational theory has figured prominently in organization and strategy research, and while the configurations retains their attraction as evidenced by a number of recent studies, the promise of configurational theory remains still unfulfilled. The current study has aimed to offer a fresh view of the challenges involved in configurational research by shifting the focus towards a definition of configurational centrality that focuses on causal relations with the outcome in question. In doing so, I have argued that such a shift overcomes a number of theoretical and instrumentation issues that have so far plagued configurational research, and that this shift further allows for the analysis of causal asymmetry, an issue that is hard to examine using conventional econometric methods for studying configuration.

In terms of its contribution, I have argued that prior work on organizational configurations has either neglected to specify a clear definition of center and periphery of organizational configurations or this work has employed a definition that is causally only indirectly related to the outcome in question. In contrast, the current understanding of causal centrality relative to the outcome draws on counterfactual analysis in defining central and peripheral elements of a configuration. Building on the notions of limited diversity and counterfactual analysis, I have argued here that fuzzy set analysis allows researchers to gain a clearer understanding just what elements of a configuration are relevant for an outcome and how these elements combine to achieve their effects. Specifically, the solutions found for the sample of high technology firms here demonstrated the existence of several configurations that included several permutations. In this regard, the set-theoretic methods used here hold considerable promise to overcome the current challenges and allow for a detailed analysis of the necessary and sufficient conditions of high performance configurations. The current study thus presents a step towards a stronger capability for building high performance organizations.

Furthermore, the set-theoretic methods used here allow for the analysis of causal asymmetry in configurations, that is, they take into account the fact that the configurations leading to very high performance are frequently different from those leading to merely high or average performance. So far, causal asymmetry has for the most part been neglected both in configurational analysis and in organizational research more broadly. However, causal asymmetry is arguably pervasive in both domains, and failing to take this causal structure into account is likely to lead to incomplete or incorrect recommendations. Specifically, the analysis of causal asymmetry in the current study showed that hybrid analyzer configurations combining elements from both the prospector and defender type were indeed able to achieve high performance, but that such hybrid types were not able to achieve very high performance. Instead, configurations exhibiting very high performance resembled “pure” types rather than hybrids, indicating that to achieve such levels of very high performance, an organizational configuration apparently needed to embrace tradeoffs between different elements.

Finally, I have aimed to examine the role of instrumentation in understanding organizational configurations. By comparing cluster and deviation score analysis with fuzzy set analysis using the same data, the current study provides an opportunity to examine just what each method allows us to see regarding configurational analysis. My goal here was not to discredit either cluster analysis or approaches deviation scores—both arguably have a considerable and successful history in both classifying and evaluating organizational configurations. In fact, the current study found generally support for the utility of both approaches, even though the model fit for both approaches was less than desirably. Instead, my aim has been to demonstrate the added value that a fuzzy set analysis using QCA can bring to the study of configurations, both in terms of providing a greater understanding of how causes combine to create an outcome and a more direct way to model equifinality in organizational configurations. In this regard, fs/QCA would appear to be a particularly useful tool for understanding both complementarities and substitutes in configurations.

Naturally, the current study also has limitations. As Miller (1986) notes, the concepts of strategy, structure, and environment are quite broad and involve multiple dimensions. Accordingly, any given study drawing on these three domains can only select a representative set of categories for characterizing each of them. The current study is no exception in that it has focused on some measures to the exclusion of others that could be used to, for instance, characterize the nature of the environment. Nevertheless, the measures selected for this study are arguably central to the three domains examined here and the current study is quite comprehensive in that it is one of the few to include simultaneously measures of structure, strategy, and environment. As such, while it is no different from other configurational studies in having to select certain measures in favor of others, it goes beyond much previous work in offering a holistic assessment of configurations across a multidimensional property space.

Furthermore, the limited sample size of the current study allowed for statistical significance testing when using conventional econometric analysis such as Tobit regressions but did not permit such testing for the fuzzy set analyses. While fs/QCA can generally employ significance tests to examine for instance consistency of a solution, the specific causal structure of the current sample which included a number of viable solutions resulted in too few cases for each solution to permit statistical tests. This necessarily limits the ability to draw definite conclusions from this dataset and calls for further studies to verify the current results. Similarly, while the current study was able to draw on cross-industry data, the findings are restricted to the high technology sector. While this sector includes a number of important and highly relevant industries such as semiconductors, computer equipment, or scientific instruments, future research would naturally aim to expand the scope beyond the current empirical setting. However, although the findings of the current study are limited in their generalizability, the logic of the configurational approach here is not context specific and thus offers ample opportunity for more research.

The current study, I believe, opens up a number of opportunities to expand configurational analysis. I have argued elsewhere that configurations are arguably pervasive and that a variety of theoretical approaches ranging from complementarities theory (e.g. Milgrom and Roberts, 1995; Siggelkow, 2002) over strategic human resource management (e.g. MacDuffie,

1995) the resource based view (e.g. Barney, 1991), and that the set-theoretic methods employed here can provide different insights that speak well to the assumptions of synergistic, non-linear effects that inform these literatures. As such, there would appear to be ample opportunities to apply the tools of Qualitative Comparative Analysis, and several researchers have already done this in examining for instance the causes informing foreign direct investment decisions (Pajunen, 2008) and the interplay of industry, corporate, and firm level effects in explaining performance (Greckhamer et al., 2008).

Configurational approaches are likely to continue playing a central role in management and strategy research, not the least since configurations arguably present the essence of strategy and are likely to be a far greater source of competitive advantage than any single aspect of the organizational system (Miller, 1986: 510). The current study has argued that our theory of configurations might benefit both conceptually and empirically from a reorientation towards the concepts of causal necessity and sufficiency. I hope that I have made a case for more empirical research to extend this approach and further show its utility in developing a theory of organizational configurations. Given the success that fuzzy set methods are beginning to enjoy in related disciplines such as sociology and political science, the current study will hopefully be but a first step towards the use of QCA in management and strategy research.

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Table 1: Ideal Profiles Based on Miles and Snow (1978)

	Prospector	Analyzer	Defender
Structure			
Size	Low	Medium	High
Formalization	Low	Medium	High
Centralization	Low	Medium	High
Complexity	Low	High	High
Strategy			
Differentiation	High	Medium	Low
Low Cost	Low	Medium	High

Table 2: Principal Component Factor Analysis for Strategy Construct*

Survey Item	Factor 1	Factor 2
1. Low labor cost	**0.81**	-0.08
2. Low materials consumption	**0.84**	0.02
3. Low energy consumption	**0.86**	-0.03
4. Low inventory cost	**0.84**	-0.01
5. New product introduction	-0.07	**0.91**
6. Product features	0.03	**0.91**
Eigenvalue	2.81	1.67
Proportion of variance explained by eigenvector	0.47	0.28

* All items were measured using a 5-point scale ranging from 1 ("not important") to 5 ("critically important")

Table 3: Descriptive Statistics and Correlation Coefficients*

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9
1. Size	0.31	0.29									
2. Formalization	0.62	0.24	0.35								
3. Centralization	0.52	0.24	-0.20	-0.11							
4. Administrative Complexity	0.51	0.25	0.53	0.42	-0.20						
5. Differentiation strategy	0.66	0.30	-0.02	0.18	-0.02	0.14					
6. Cost leadership strategy	0.40	0.25	0.09	0.12	0.05	0.14	-0.02				
7. Environmental velocity	0.35	0.30	0.04	-0.03	-0.01	0.13	0.01	0.17			
8. Environmental uncertainty	0.41	0.29	0.03	-0.19	-0.06	-0.20	-0.17	-0.27	0.05		
9. High performance	0.68	0.44	-0.05	-0.10	0.12	-0.01	0.09	0.03	0.11	-0.07	
10. Very high performance	0.63	0.44	-0.08	-0.08	0.14	-0.02	0.11	0.05	0.13	-0.09	0.97

* Correlations of 0.17 or higher are significant at ≤.05

Table 4: Cluster Analysis Results

	Final Cluster Centers		
	1	2	3
Structure			
Size	0.13	0.22	0.64
Formalization	0.52	0.49	0.76
Centralization	0.62	0.52	0.39
Complexity	0.40	0.42	0.71
Strategy			
Differentiation	0.82	0.19	0.75
Low Cost	0.37	0.42	0.42
N	93	41	59

Table 5: Tobit Regression Models of Cluster Configurations on Performance[a] (n=139)

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Prospector	0.783*	0.739	0.171	0.769*	0.804*
	(0.375)	(0.497)	(0.562)	(0.372)	(0.371)
Defender	0.150	0.151	0.114	0.690	0.769
	(0.377)	(0.377)	(0.373)	(0.520)	(0.586)
Environmental Velocity	0.772	0.715	0.686	1.331*	0.774
	(0.507)	(0.657)	(0.501)	(0.645)	(0.503)
Environmental Uncertainty	-0.590	-0.597	-1.138	-0.580	-0.081
	(0.503)	(0.506)	(0.648)	(0.497)	(0.607)
Prospector × Velocity		0.137			
		(1.013)			
Prospector × Uncertainty			1.388		
			(1.012)		
Defender × Velocity				-1.593	
				(1.050)	
Defender × Uncertainty					-1.451
					(1.045)
Constant	0.844*	0.865*	1.125*	0.663	0.601
	(0.397)	(0.427)	(0.447)	(0.408)	(0.424)
LR Chi-squared	9.97*	9.99	11.88*	12.35*	11.95*
Pseudo R-Squared	0.04	0.04	0.04	0.05	0.04

[a] Standard errors in parentheses.

† $p \leq .10$; * $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

Table 6: Tobit Regression Models of Profile Fit and Deviation on Performance[a] (n=139)

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Ideal Type Fit (min)	1.011*							
	(0.459)							
Prospector Dev.		-0.158			0.030	0.564		
		(0.259)			(0.392)	(0.463)		
Analyzer Dev.			-0.662†				-0.869	-0.724
			(0.400)				(0.588)	(0.719)
Defender Dev.				0.158				
				(0.259)				
Prospector × Velocity					-0.509			
					(0.806)			
Prospector × Uncertainty						-1.556†		
						(0.850)		
Analyzer × Velocity							0.657	
							(1.350)	
Analyzer × Uncertainty								0.139
								(1.347)
Environmental Velocity	0.854	0.842	0.810	0.842	2.077	0.800	-0.192	0.816
	(0.508)	(0.525)	(0.511)	(0.525)	(2.042)	(0.515)	(2.109)	(0.514)
Environmental Uncertainty	-0.752	-0.726	-0.656	-0.726	-0.718	3.063	-0.627	-0.862
	(0.505)	(0.527)	(0.506)	(0.527)	(0.525)	(2.109)	(0.508)	(2.067)
Constant	2.688***	1.655*	2.222***	0.863	1.205	-0.145	2.523**	2.311*
	(0.748)	(0.719)	(0.681)	(0.723)	(0.998)	(1.167)	(0.932)	(1.106)
LR Chi-squared	9.18*	4.35	6.81†	4.35	4.75	7.99†	7.05	6.82
Pseudo R-squared	0.03	0.02	0.03	0.02	0.02	0.03	0.03	0.03
Observations	139	139	139	139	139	139	139	139

[a] Standard errors in parentheses.
† $p \leq .10$; * $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$

Table 7: Configurations for Achieving High Performance

	Solution				
	1	**2**	**3**	**4a**	**4b**
Structure					
Large Size	⊗	•	⊗	⊗	⊗
Formalization	•	•		⊗	
Centralization	●	⊗	•	⊗	•
Complexity	•	•	⨂	⨂	⨂
Strategy					
Differentiation	•	•	●	●	●
Low Cost	●	●	●	⊗	⊗
Environment					
Velocity		⨂	⨂	⊗	⊗
Uncertainty	⊗	⊗	⊗	⊗	•
Consistency	0.76	0.77	0.76	0.76	0.76
Raw Coverage	0.21	0.15	0.21	0.18	0.21
Unique Coverage	0.03	0.02	0.01	0.02	0.04
Overall Solution Consistency		**0.76**			
Overall Solution Coverage		**0.35**			

Table 8: Configurations for Achieving Very High Performance

	Solution			
	1a	**1b**	**1c**	**2**
Structure				
Large Size	⊗	⊗	•	⊗
Formalization	●	●	●	
Centralization	●	●	⊗	•
Complexity	•		•	⨂
Strategy				
Differentiation	•	⊗	•	●
Low Cost	●	●	●	⊗
Environment				
Velocity		⨂	⨂	⊗
Uncertainty	⊗	⊗	⊗	●
Consistency	0.77	0.77	0.76	0.76
Raw Coverage	0.22	0.23	0.16	0.22
Unique Coverage	0.02	0.01	0.02	0.07
Overall Solution Consistency			**0.75**	
Overall Solution Coverage			**0.34**	