BUILDING BETTER CAUSAL THEORIES:
A FUZZY SET APPROACH TO TYPOLOGIES IN ORGANIZATION RESEARCH

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Abstract

Typologies are an important way of organizing the complex cause-effect relationships that are key building blocks of the strategy and organization literatures. Here, I develop a novel theoretical perspective of causal core and periphery based on how elements of a configuration are connected to outcomes. Using data on high-technology firms, I empirically investigate configurations based on the Miles & Snow typology using *fuzzy-set Qualitative Comparative Analysis* (fsQCA). My findings show how the theoretical perspective developed here allows for a detailed analysis of causal core, periphery, and asymmetry, shifting the focus to mid-range theories of causal processes in typologies.

… types and typologies are ubiquitous, both in everyday social life and in the language of the social sciences. Everybody uses them, but almost no one pays any attention to the nature of their construction (McKinney, 1969: 4)

INTRODUCTION

The notion of causality plays a key role in both the strategy and organization literatures. For instance, cause-effect relationships are the central way in which strategic decisions and organizational structures are understood and communicated within organizations (Ford, 1985; Huff, 1990, Huff & Jenkins, 2001). Building on this insight, the cognitive strategy literature has aimed to map and explain the causal reasoning of managers regarding both organizational performance and the competitive environment (e.g., Barr, Stimpert, & Huff, 1992; Nadkarni & Narayanan, 2007a, 2007b; Reger & Huff, 1993). Similarly, cause-effect relationships are the main building blocks for the organizational design literature and have recently received increasing attention (e.g., Burton & Obel, 2004; Grandori & Furnari, 2008; Romme, 2003; Van Aken, 2005).

A key way of organizing the complex webs of cause-effect relationships into coherent accounts is by means of typologies. As Doty and Glick (1994) argue, typologies are a unique form of theory building in that they are complex theories that describe the causal relationships of contextual, structural, and strategic factors, thus offering configurations that can be used to predict variance in an outcome of interest. As such, typologies have been very popular and form a central pillar of both the strategic management and organizational literatures. For instance, typologies such as those of Blau and Scott (1962), Burns and Stalker (1961), Etzioni (1961), 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., DeSarbo et al., 2005; Kabanoff & Brown, 2008; Meyer, Tsui, & Hinings, 1993).

Typologies are theoretically attractive for a number of reasons. Because of their multidimensional nature, the configurational arguments embedded in typologies acknowledge the complexity and interdependent nature of organizations, in which fit and competitive advantage frequently rest not on a single attribute but instead on the relationships and complementarities between multiple characteristics (e.g., Burton & Obel, 2004; Miller, 1996; Siggelkow, 2002). As such, typologies at their best result in integrative theories that account for multiple causal relationships linking structure, strategy, and environment (Child, 1972; McPhee & Scott Poole, 2001). Typologies are furthermore helpful because they provide "a form of social scientific shorthand" (Ragin, 1987: 149) for these multiple causal relationships by simplifying them into a few typified and easy-to-remember profiles or *Gestalten* (McPhee & Scott Poole, 2001), inviting their use as heuristic tools for researchers and practitioners alike (Mintzberg, 1979).

However, for all of their theoretical attractiveness and considerable success in portraying cause-effect relationships, typologies also face some considerable challenges. The same features that make typologies so appealing to researchers and practitioners—namely, their holistic approach and their ability to combine complexity with parsimony—are at the same time some of the greatest disadvantages of configurational arguments. Perhaps most importantly in this regard, typologies 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 overall ideal type or configuration. While a few researchers have pointed to the varying theoretical importance of constructs in typologies (e.g., Doty & Glick, 1994; Mintzberg, 1979), most prior typologies have neglected such considerations by asking us to accept the typology *in toto*. However, this is a problematic proposition; although a holistic approach can be useful at times, theorizing is more likely to end once a typology is identified, thus limiting our understanding as to what causal mechanisms are at work and what is driving the effect (McPhee & Scott Poole, 2001; Reynolds, 1971).

In this study, I argue that the logic of consistency that flows from the holistic nature of typologies presents a fundamentally problematic assumption that is likely to lead both researchers and practitioners astray. For example, existing typologies are likely to contain inconsistencies, trade-offs, and—perhaps most importantly—irrelevant elements. However, if not all parts of a configuration are equally important, the issue becomes: which are the critical aspects in a typology, and which are nonessential elements? The challenge of typologies thus is determining what really matters—and to what degree—in understanding the causal structure of a type.

How, then, can we reconceptualize the causal relationships in typologies to move away from a fully holistic view to a more fine-grained understanding of what is causally relevant? To address this problem, I develop a different theoretical perspective on causal relationships in typologies. Drawing on arguments from the strategy and organizational design literatures (e.g., Grandori & Furnari, 2008; Siggelkow, 2002), I argue that typologies will frequently consist of a *core* and a *periphery*, with the core elements being essential and the peripheral elements being less important and perhaps even expendable or exchangeable (e.g., Hannan, Burton, & Baron, 1996). Specifically, I develop a definition of coreness based on the elements that are causally connected to the outcome of interest. Accordingly, I define core elements as those causal conditions under which the evidence indicates a strong causal relationship with the outcome of interest, while peripheral elements are those for which the evidence for a causal relationship with the outcome is weaker.

Adopting the theoretical perspective that I propose here contributes to the literature in several ways. First, the distinction between causal core and periphery allows me to extend prior theory by introducing the notion of *neutral permutations*. This notion suggests that, within a given typology, the core causal condition may be surrounded by more than one constellation of different peripheral causes, with these permutations of peripheral elements being equally effective regarding performance. As I will show, this notion extends current theories of equifinality, or the idea that "a system can reach the same final state from different initial conditions and by a variety of different paths" (Katz & Kahn, 1978: 30). Equifinality has recently received increasing attention in the management literature (e.g., Doty, Glick, & Huber 1993; Fiss, 2007; Gresov & Drazin, 1997; Marlin, Ketchen, & Lamont, 2007; Payne, 2006) because it provides a theoretical underpinning for the persistence of a variety of design choices that can all lead to the desired outcome, thus offering considerable promise for organization theory (e.g., Ashmos & Huber, 1987; Short, Payne, & Ketchen, 2008).

Second, the notion of causal core and periphery extends prior thinking on cause-effect relationships by assuming *causal asymmetry* (Ragin, 2008)—that is, the idea that the causes leading to the presence of an outcome of interest may be quite different from those leading to the absence of the outcome. This view stands in contrast to the common correlational understanding of causality, which assumes causal symmetry because correlations are by their very nature symmetric; for example, if we model the inverse of high performance, 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 presence of the outcome may frequently be different from the set of conditions leading to the absence of the outcome. Shifting to a causal, core-periphery view of typologies allows for such differing sets of causal conditions across the range of an outcome, with one set leading, for instance, to average performance, while a different set may lead to high performance, and yet another set may lead to very-high performance. As I argue, making this theoretical shift has important implications for understanding the relationships among strategy, organizational design, and environmental context, and thus it carries significant implications for organizational design and strategy more broadly.

I empirically test the arguments developed here on a sample of high-technology firms using a novel methodology for modeling causal relations: fuzzy-set Qualitative Comparative Analysis (fsQCA). This approach is based on the idea that causal relations are frequently better understood in terms of set-theoretic relations rather than correlations (Fiss, 2007; Ragin, 1987, 2000, 2008; Ragin & Fiss, 2008). Using the well-known Miles and Snow typology as an example, my results indicate that the core-periphery model of typologies proposed here offers both a different and a more fine-grained understanding of the causal relationships among the elements of typologies—a key issue for both strategy and organizational design (e.g., Grandori & Furnari, 2008). Likewise, the concepts of neutral permutations and causal asymmetry enrich our understanding of the relationship between configurational ideal types and performance, again providing a much closer look at the causal processes involved. Finally, the theoretical perspective proposed here speaks to a number of substantive issues in both the management and strategy literatures, such as ambidexterity and planned organizational change, and I conclude by discussing these implications as well as outlining a way forward for empirical research.

RETHINKING CAUSALITY IN TYPOLOGICAL THEORIES

Having an accurate understanding of causal relationships is essential for both strategic management and organization theory (Durand & Vaara, 2009). Viable competitive strategies rest on the decision makers' understanding of the appropriate causal relationships between those variables that management controls, such as strategy and organizational structure, and those that are mostly outside the direct control of management, such as the nature of the industry (e.g., Galbraith & Schendel, 1983; Porter, 1980). Furthermore, these causal understandings have to relate to the strategies of rivals and the dimensions on which they compete, as well as to those of the decision maker's own firm and its internal processes (Porac & Thomas, 1990; Porac et al., 1989). Because of the importance of causal processes, research from a variety of literatures has focused on cause-effect relationships as well as their understanding by strategic decision makers (e.g., Barr, Stimpert, & Huff, 1992; Durand & Vaara, 2009; Grandori & Furnari, 2008; Huff, 1990; King & Zeithaml, 2001; Reger & Huff, 1993).

Perhaps the most widely applied tool for mapping the competitive landscape and guiding strategic analysis is the use of typologies and strategy archetypes (e.g., Burns & Stalker 1961; Hofer & Schendel, 1978; Miles & Snow 1978; Mintzberg, 1983; Porter, 1980). Furthermore, typologies are also very popular among researchers and educators and have inspired a considerable amount of both conceptual development and empirical research (e.g., Ketchen, Thomas, & Snow, 1993). Here, I follow the definition of typologies proposed by Doty and Glick (1994: 232), which holds that typologies are "conceptually derived interrelated sets of ideal types" that "identify multiple ideal types, each of which represents a unique combination of the organizational attributes that are believed to determine the relevant outcome(s)." This definition is helpful for several reasons. First, it identifies typologies as complex theoretical statements that emerge from a unique form of theory building—or, as McKinney notes, "types function as theory" (1969: 8), a view that also informs my understanding of typologies as ways to organize complex cause-effect statements. Second, as Doty and Glick note, "the organizational types identified in typologies are developed with respect to a specified organizational outcome" (1994: 232). This insight likewise resonates with the conceptual and empirical approach developed here that focuses on configurations of causes in relation to an outcome of interest. Finally, the definition clearly distinguishes theoretically derived typologies from empirically derived taxonomies or classification systems, thus avoiding the confusion between these different concepts (McKelvey, 1975).[1]

The process of constructing a typology usually involves the definition of an n-dimensional property space from which the typology may be empirically reproduced. Since the purpose of the typology is to reduce the complexity of the empirical world, typification usually involves the pragmatic reduction of an extensive set of attributes to a limited set relevant to the purpose at hand (Bailey, 1973; McKinney, 1969). This process of reduction creates two kinds of typologies: monothetic typologies, in which each feature is necessary for membership and the set of features is sufficient, and polythetic typologies, which can be formed from different combinations of values on the features of interest. Because they allow the grouping of cases that are similar though perhaps not identical in terms of their features, polythetic typologies tend to ensure greater parsimony and are considered superior for research that actually aims to identify specimens as part of a type (Bailey, 1973). In the following, I will focus on such polythetic typologies.

Typologies are theoretically attractive because they move us beyond traditional linear or interaction models of causality such as contingency theories (Doty & Glick, 1994). They can accommodate multiple relationships between their constructs that may be marked by complementary, additive, substitution, or suppression effects, thus accommodating considerable levels of causal complexity. As shorthand devices, they furthermore allow managers and researchers to cognitively simplify a complex environment by highlighting commonalities between firms and allowing comparisons (e.g., Hambrick, 1983).

[1] A full review of the literature on types and typology is beyond the scope of this manuscript. However, a few relevant sources include Bailey (1973), Bendix (1963), Capecchi (1966), Doty and Glick, 1994, Lazarsfeld (1937), McKelvey (1982), McKinney (1966, 1969), Rich (1992), Rose (1950), Weber (1949), and Winch (1947).

Because they are based on complex, synergistic patterns of relationships, typologies orient us toward a holistic understanding and ideal profiles (Doty & Glick, 1994; McKelvey, 1982). Yet, this holistic nature is not without problems. For instance, in describing the difficulties of developing typological theory, Doty and Glick note that "as the number of descriptive dimensions is increased, it becomes more difficult to ensure that only those dimensions that are causally related to the dependent variable are included in the typology" (1994: 245). Similarly, Scott (1981) has argued that including dimensions that are only spuriously correlated with the outcome in question may lead to a misunderstanding of the true causal processes involved. Summarizing the key challenge of typological theories, Doty and Glick (1994) argue that "the intuitive simplicity of typologies masks some important complexities." Typologies can be deceptive.

There are several reasons why—as tools for understanding and summarizing complex causal effects—typologies may lead us astray. To further examine these reasons, I draw on the literature on causal attribution (e.g. Gopnik & Schulz 2007; Kim, Dirks, Cooper, & Ferrin, 2006; Sloman, 2005; Waldman, Hagmayer, & Blasdell, 2006) and the cognitive strategy literature (e.g., Abrahamson & Fombrun, 1994; Barr, Stimpert & Huff, 1992; Huff, 1990; Reger & Huff, 1993), which provides insight into the processes of constructing mental models of causal relationships. While this cognitive literature has been largely taxonomic in nature (e.g., Porac & Thomas, 1990) and is conceptually different from typologies in that it has focused on eliciting causal understandings and "theories in use" from respondents, I suggest that its insights regarding biases and tendencies to perceive causal relationships are not restricted to classification but frequently also pervade the construction of typologies. Accordingly, I draw upon this perspective to better understand why the construction of typologies may at times be problematic.

For instance, cognitive research suggests that causal inferences may lead to illusory causation when the true nature of the causal relationships is poorly understood or inappropriately defined (e.g., Nadkarni & Narayanan, 2007). Two mechanisms in particular are relevant in this regard. First, when faced with complex relationships, typologies may fulfill the cognitive need for simplification when we are faced with "information overload" (e.g., Schwenk, 1984). Second, when faced with incomplete information, decision makers will frequently engage in elaboration by filling in—often unconsciously—gaps in the data when interpreting stimuli (Reger & Huff, 1993; Rosch, 1981). In combination, the two cognitive mechanisms of simplification and elaboration are likely to be present in typologies and may result in causal understandings that are frequently inaccurate and potentially misleading. Furthermore, because established notions of causal processes are difficult to discard (Carley & Palmquist, 1992; Hodgkinson, 1997), typologies are likely to promote cognitive inertia, a process that has been shown by cognitive researchers to prevent decision makers from acquiring new knowledge and exploring alternatives (e.g., Reger & Palmer, 1996).

Although a holistic approach is thus a strength of configurational theories, it can also inhibit the development of accurate understandings of the processes involved because theorizing is more likely to end once a configuration is identified, thereby limiting our understanding as to what causal mechanisms are at work and are driving the effect (McPhee & Scott Poole, 2001; Reynolds, 1971). Specifically, "most configurational theories are what Althusser (1972) called "expressive totalities"—they are supposed to be consistent because each part reflects the underlying logic of the whole" (McPhee & Scott Poole, 2001: 515). However, a good theory should question the assumption of consistency—that is, the assumption that all parts of the configuration are equally necessary or important.

These concerns regarding typological theories are magnified by the limited empirical support for the causal processes involved. For instance, the conceptual dimensions of many typologies are derived “without much empirical support beyond perhaps some grounding in case studies and anecdotal accounts of competitive activity” (Galbraith & Schendel, 1983: 155). At the same time, there is a lack of theory allowing prediction and explanation of which organizational practices are complementary (Grandori & Furnari, 2008). Typologies are thus a double-edged sword. At their best, they are memorable, neat, and evocative (Miller, 1996). At their worst, typologies are little more than simplistic overviews that offer only a cursory look at organizations (Rich, 1992).

The Core-Periphery Distinction

To develop a framework for understanding the causal processes involved in typological theory, I draw on the dual concepts of core and periphery. The distinction between core and periphery appears particularly useful for understanding typologies for a number of reasons. At a most basic level, cognitive researchers have argued that the human mind’s ability to classify is better understood in terms of a conceptual structure consisting of core and periphery categories (Hahn & Chater, 1997; Hunn, 1982; Rosch, 1978, 1981). As such, the distinction is grounded in a considerable body of research on the cognitive foundations of classification.

Furthermore, the notion of a core-periphery distinction has been successfully used in a number of domains of the organization and strategy literature. For instance, classic arguments in organization theory and design have used the notion of a core and periphery in relation to an organization’s primary technology and decision making (e.g., Pfeffer, 1976; Thompson, 1967), and current theorizing has likewise emphasized the core-periphery distinction (e.g. Grandori & Furnari, 2008).

Perhaps the most influential view of core versus periphery in organizations is that of Hannan and Freeman (1984), who define the organization's core as the organization's mission, authority structure, technology, and marketing strategy. In their definition, "coreness means connectedness" (Hannan, Burton, & Baron, 1996: 506), with change in core elements requiring adjustments in most other features of an organization. This definition of core versus peripheral elements has been adopted in a considerable number of subsequent studies (e.g., Kelly & Amburgey, 1991; Sing, House, & Tucker, 1986).

Likewise, strategy researchers have argued for the distinction between core and peripheral concepts in understanding strategic schemas—the knowledge structures that top management uses in making strategic decisions (e.g., Eden et al., 1992; Gustafson & Reger, 1995; Lyles & Schwenk, 1992; Porac & Rosa, 1996). These researchers have argued that depth and significance are higher for core than for peripheral concepts (Nadkarni & Narayanan, 2007a). Furthermore, prior studies have suggested that the notion of core versus peripheral concepts is important with regard to causal inferences (Carley & Palmquist, 1992) and may draw the decision maker's attention to non-existent relationships because managers tend to automatically infer new events by the use of core concepts (Barr et al., 1992; Nadkarni & Narayanan, 2007a).

At a more aggregate level, strategy researchers have pointed to the presence of core and peripheral groupings in understanding the structure of strategic groups (Dranove, Peteraf, & Shanley, 1998; McNamara, Deephouse, & Luce, 2003; Reger & Huff, 1993) and have applied the core-periphery distinction to understanding a firm's diversification strategy in terms of overlapping product and industry segments (e.g., Siggelkow, 2003; Wiersema & Liebeskind, 1995).

The concepts of core and periphery have also figured prominently in the literature on social networks (e.g., Borgatti & Everett, 1999; García Muñiz & Ramos Carvajal, 2006) and have featured prominently in organizational network analysis. For instance, Stuart and Podolny (1996) employed the distinction to classify the technology position of Japanese semiconductor firms in terms of their knowledge domains, while Gulati and Gargiulo (1999) identify core and periphery patterns based on inter-organizational alliances. Similarly, the literature on the diffusion of innovations has used a core-periphery model to explain adoption patterns of organizational practices (e.g., Abrahamson & Rosenkopf, 1997; Galaskiewicz & Wasserman, 1989).

A Causal Core-Periphery Perspective

The core-periphery distinctions have thus been crucial to understanding a variety of substantive issues in both organization theory and strategy, and this distinction may also be useful in informing typological theories. For instance, several studies have suggested that firms vary in the degree to which they identify or are associated with a strategic group—some firms follow the strategy closely and may be considered "core" firms, while others follow the strategy less closely and may be categorized as secondary or "peripheral" (McNamara, Deephouse, & Luce, 2003; Peteraf & Shanley, 1997). In particular, Reger and Huff (1993) have argued that group membership is a matter of degree and that strategic groups are akin to "fuzzy sets"—an argument that I will likewise pursue here and actually implement in the measurement of type membership.

Similarly, Siggelkow (2002) has argued that it is necessary to develop a better understanding of the nature of core elements in organizational configurations. Drawing upon network measures and the notion that "coreness means connectedness" (Hannan et al., 1996), Siggelkow defines 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 or peripheral elements that reinforce the central features of the core (Grandori & Furnari, 2008).

Applying these insights to the literature on typologies, I argue that the notions of core and periphery are useful for enhancing our understanding of causality in typologies. This argument extends prior theorizing on typologies, which has suggested that the contribution of a specific attribute to an ideal type needs to be weighed by its theoretical importance (Doty & Glick, 1994), thus pointing us toward a view of typologies as being made of elements with differing significance. Furthermore, this literature suggests that ideal types are "pure" forms of a configuration (Miles & Snow, 2003: 30) and that deviation from the ideal type will usually result in lower performance (Doty et al., 1993; Van de Ven & Drazin, 1985).

Building on these insights regarding the differing importance of configurational elements can also extend our understanding of causal relationships within typologies. Specifically, I suggest here a definition of coreness based on which elements are causally connected to a specific outcome. In accordance with this understanding, I define core elements as those causal conditions under which the evidence indicates a strong causal relationship with the outcome of interest. In contrast, peripheral elements are those for which the evidence for a causal relationship with the outcome is weaker. While maintaining a concern for what makes elements causally relevant, this understanding importantly shifts the focus from the connectedness with other organizational elements to the causal role they play within the configuration relative to the outcome. It moreover fits closely with the central concern of organization theory that core elements are those that are most important to organizational performance and survival (Romanelli & Tushman, 1994) and that types are understood in relation to an outcome (Doty & Glick, 1994). In sum, this suggests the following proposition:

Proposition 1: Typological configurations will be characterized by a core and a periphery.

Furthermore, by basing the focus on the causal relationships among configurational elements and the outcome in question, the theoretical perspective introduced here carries implications for our understanding of equifinality in typologies and configurations. A model of causal core and periphery emphasizes the idea of several causal paths to an outcome—that is, the existence of equifinal configurations (e.g., Doty et al., 1993; Gresov & Drazin, 1997; Payne, 2006). However, the current perspective enriches the study of equifinal configurations through the notion of *neutral permutations* of a given configuration. Specifically, I suggest that, within any 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. This argument builds on prior work that has shown how trade-offs between, for example, strategies and functions may frequently lead to several equifinal configurations that each result in effective performance (e.g., Delery & Doty, 1996; Marlin et al., 2007). As these researchers have argued, typological configurations may be marked by hybrid types, all of which may result in the specified level of the dependent variable (Doty & Glick, 1994), suggesting that there is a need to further explore viable strategic alternatives, and particularly with a focus on understanding intra-type similarities and dissimilarities (Reger & Huff, 1993). The notion of neutral permutations introduced here builds on these arguments by enhancing the current concept of equifinality in several ways. First, the concept of neutral permutations provides a more fine-grained understanding of the different cause-effect relationships related to an outcome by distinguishing between first- and second-order equifinality. By first-order equifinality, I mean equifinal types that exhibit different core characteristics (e.g., type *A* vs. type *B*). By second-order equifinality, I mean neutral permutations within a given first-order equifinal type (e.g., type A_1 vs. $A_2 \ldots A_n$).

Second, the concept of neutral permutations contributes to the theory of equifinality by implying 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 important issue that has largely been neglected in the study of configurations (Grandori & Furnari, 2008). In sum, my arguments suggest the following regarding the nature of typological configurations:

> *Proposition 2: Core and periphery in typological configurations will frequently exhibit neutral permutations.*

The theoretical perspective on typologies introduced here also carries implications for how cause-effect relationships combine to achieve the outcome of interest. Specifically, it builds upon a recent and growing interest in understanding the causal necessity and sufficiency of, rather than the correlations between, configurations and performance (e.g., Fiss, 2007; Kogut, MacDuffie, & Ragin, 2004). Such an argument is both attractive and important because it assumes *causal asymmetry* (Ragin, 2008)—that is, it implies that causes leading to the presence of an outcome of interest may be quite different from those leading to the absence of the outcome. In contrast, a correlational understanding of causality assumes causal symmetry because correlations tend to be symmetric. For instance, if one were to model the inverse of high performance, 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 presence of the outcome may frequently be different from the set of conditions leading to the absence of the outcome. For instance, even though the presence of a particular combination of causes may lead to high performance, it may not be merely the absence of this particular combination of causes, but an entirely different set of causes that may lead to low performance. Introducing this notion of causal asymmetry builds on prior work arguing that typological theories allow us to move beyond traditional linear or interaction theories because they shift our understanding toward configurational thinking and non-linear relationships among constructs (Doty et al., 1993; Meyer et al., 1993). Such complex relationships and patterns can frequently not be represented with traditional bivariate contingency theories, and two organizational characteristics may be positively related in one ideal type, negatively related in another, and unrelated in a third type (e.g., Delery & Doty, 1996; Doty & Glick, 1994). Thus, a configurational approach conceives of causal relationships not so much in terms of correlations as in terms of *sets* of equally effective patterns (Doty et al., 1993; Van de Ven & Drazin, 1985). The concept of causal asymmetry builds on this understanding by indicating that equifinality may change depending on outcome levels—as one moves across outcome *levels*, there may be different *sets* of equally effective configurations.

Shifting to a causal core-periphery view of organizational typological configurations thus allows for such differing sets of causal conditions, with one set leading, for instance, to average performance, while a different set may lead to high performance, and yet another set may lead to very-high performance. These arguments suggest the following:

Proposition 3: Typological configurations will be marked by causal asymmetry.

THE MILES AND SNOW TYPOLOGY OF ORGANIZATIONAL CONFIGURATIONS

To empirically test the theoretical perspective I have developed here, I draw on the Miles and Snow typology of generic organizational configurations (Miles & Snow, 1978, 2003). This is perhaps the most widely used typology of organizations, and classic studies on configurations have tested it and found considerable support for it (e.g., Doty, Glick, & Huber, 1993; Hambrick, 1983; Ketchen, Thomas, & Snow, 1993). In fact, as Hambrick (2003) has noted, it presents one of the most widely tested, validated, and enduring strategy frameworks of 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., DeSarbo et al., 2005; Hult et al., 2006; Kabanoff & Brown, 2008; Olson, Slater, & Hult, 2005; Slater & Olson, 2000). In sum, given its wide usage and continued relevance, the Miles and Snow typology is particularly suitable for applying the theoretical perspective presented here.

Miles and Snow's typology is based on three organizational types: Prospector, Analyzer, and Defender. A fourth type, the Reactor, is largely a residual type because in contrast to the previous three types the Reactor "lacks a consistent strategy-structure relationship" (Miles & Snow, 2003: 29) and thus rather presents an instance of strategy absence rather than a viable strategy (Inkpen & Chowdhury, 1995; Zajac & Shortell, 1989). 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 with regard 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. 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; Parnell, 1997; Segev, 1989).

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 uses 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 (e.g., Miller, 1986; Segev, 1989; Shortell & Zajac, 1990).

As Miles and Snow note, 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 structural attributes and strategy, with the exception of 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 rather complex structures (Miles and Snow, 2003: 79).

Open Questions Regarding the Miles and Snow Typology

Although the overall Miles and Snow typology has found widespread usage, the evidence on its specific propositions is in fact less than clear (e.g., Hambrick, 1983; Zahra & Pearce, 1990). In reviewing the literature and empirical studies on the Miles and Snow typology, Zahra and Pearce (1990) note that there has been essentially no research on how firms of different strategic types utilize different organizational structures and coordination mechanisms. As such, the important question of which elements of the typology are relevant and which elements are either peripheral or even irrelevant has received essentially no attention. This problem is further magnified by the widespread use of a self-typing instrument where survey respondents identify themselves with strategic archetypes (Zahra & Pearce, 1990), which largely rules out gaining a better understanding of the causal processes involved in the different types.

Furthermore, while the typology posited equal effectiveness for the three strategy types, 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 with the other types, as did Snow and Hrebiniak (1980), although the sample size for this strategic type was relatively small. These studies suggest that taking a middle position that "combines the strengths of both the Prospector and the Defender into a single system" (Miles & Snow, 2003: 68) would result in relatively higher levels of organizational performance relative to the extreme types, thus supporting the arguments of the ambidexterity literature, which points to the possibility of achieving superior performance by simultaneously achieving efficiency and adaptiveness (e.g., Raisch & Birkinshaw, 2008; Tushman & O'Reilly, 1996;).

In contrast, other authors have pointed to the importance of trade-offs in strategy. For instance, Porter (1980, 1996) 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 so as to avoid getting “stuck in the middle” with relatively lower performance. Similarly, March (1991) has argued for a fundamental trade-off between the exploration and exploitation strategies. As DeSarbo et al. (2005) point out, more research is thus needed on the topic of strategic type and performance and how different elements of the three strategic types relate to one another.

Yet another important but unresolved aspect of the Miles and Snow typology relates to whether the typology is universally applicable across environments or is context dependent. 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.” 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 by Doty, Glick, and Huber (1993), no other research appears to have simultaneously examined configurations of organizational structure, strategy, and environment. Yet, a configurational approach as posited by the typology demands a detailed understanding of the causal relationships among internal organizational features, such as structural characteristics and strategy type, on the one hand, and external, environmental characteristics on the other. In sum, these open questions indicate that, despite its wide use and continued influence, the Miles and Snow typology faces a number of challenges characteristic of typological theories, thus making it a suitable choice for the current study.

Modeling Causal Configurations

Answers to the questions outlined here are to a considerable extent influenced by the analytical approach employed. 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, & 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, & Huber, 1993). While both approaches have considerably enhanced our understanding of typological and configurational theory, they nevertheless also face difficulties regarding their ability to provide insights into the causal nature of the configuration—i.e., they are not well suited to shed light on just which aspect of a configuration leads to high performance (Fiss, 2007, 2009).

In the current paper, I complement the theoretical perspective I introduce by using set-theoretic methods for studying cases as configurations. The current study thus builds on the set-theoretic methods first introduced by Ragin (1987) and extended by Ragin (2000, 2008), Ragin and Fiss (2008), and Rihoux and Ragin (2009). Set-theoretic methods such as fuzzy-set QCA are uniquely suitable for testing typological and configurational theory because 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 attractive for organizational and strategy researchers, as indicated by several recent studies that have demonstrated the value of applying QCA and fuzzy sets in organizational settings (e.g., Fiss, 2007, 2009; Grandori & Furnari, 2008; Greckhamer et al., 2008; Jackson, 2005; Kogut, MacDuffie, & Ragin, 2004; Pajunen, 2008; Schneider, Schulze-

Bentrop, & Paunescu, 2009). The methodological approach used here thus sheds new light on the causal relationship between the characteristics of a configuration and the outcome of interest.

DATA AND METHODS

I use data on a sample of 205 high-technology manufacturing firms located in the United Kingdom. The data were collected in 1999 using a survey sent to the CEOs and managing directors of these firms (Cosh et al., 2002) and are especially useful for my purposes for several reasons. First, the data contain 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 example, service firms that frequently have very different operational requirements. Finally, while the data come from the high-technology manufacturing sector, they include firms operating in several industries, thus offering variation in terms of the rate of change and uncertainty of the competitive environment that would not be available in a single-industry study.

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 CEOs in the United States (e.g., Hambrick et al., 1993; Geletkanycz, 1997). For reasons of confidentiality, 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, the representativeness of the sample is less of a threat to validity than usual in the current study for at least three reasons.

First, my interests are not with the U.K. high-technology sector per se, but instead I use the data as the setting to test arguments relating to configurational theory. Accordingly, even if there was some response bias (e.g., if a greater number of smaller or high-performing firms responded), this would not threaten the validity of the findings because the primary focus of my study is generating theory about causal thinking and typologies, not the high-tech sector. Nevertheless, the final sample included firms with considerable variation in terms of size, structure, and environment, and comparisons with available aggregate statistics indicate that the sample is representative of the underlying population in terms of organization size. Second, some of the most influential and path-breaking studies such as those of Ketchen et al. (1993) and Doty et al. (1993) have in fact 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. Third, and perhaps most importantly, in contrast to the standard econometric methods such as regression analysis commonly used, the non-parametric, fuzzy-set methods I employ here make representativeness of the sample less of an issue. This is the case because—unlike, for example, regression analysis—fsQCA makes no assumption that the data are drawn from a given probability distribution. Furthermore, as I explain below, I employ calibrated sets to measure my constructs of interest. This calibration reduces sample dependence as set membership is defined relative to substantive knowledge rather than the sample mean, thus further reducing the importance of sample representativeness. In sum, this suggests that the advantages of the data heavily outweigh their limitations.

Analysis

The current study employs a set-theoretic approach based on fuzzy-set QCA, an analytic technique grounded in set theory that allows for a detailed analysis of how causal conditions contribute to an outcome in question. This approach is uniquely suited for analyzing causal processes in typologies because it is based on a configurational understanding of how causes combine to bring about outcomes and because it can handle significant levels of causal complexity (e.g., Fiss, 2007; Ragin, 2000, 2008). The basic intuition underlying QCA is that cases are best understood as configurations of attributes resembling overall types and that a comparison across cases can allow the researcher to strip away attributes that are unrelated to the outcome in question. In its logic, this approach is based on the "method of difference" and the "method of agreement" outlined by John Stuart Mill, in which the researcher is concerned with instances of the cause and outcome to understand patterns of causation.[2] However, set-theoretic analysis performs this analysis of causal patterns by focusing on the set-subset relationship. For instance, in order to understand what configurations lead to high performance, it examines cases with membership in the set of high-performing organizations and then identifies the varying combinations of attributes that are associated with this outcome of interest using Boolean algebra and a set of algorithms that allow for the logical reduction of numerous, complex causal conditions into a reduced set of configurations that lead to the outcome.

To empirically accomplish this identification of causal processes, QCA proceeds in three steps. After the independent and dependent measures have been transformed into sets as described above, the first step involves using these set measures to construct a data matrix known as a truth table with 2^k rows, where k is the number of causal conditions used in the analysis. Each row of this table is associated with a specific combination of attributes, and the full table thus lists all possible combinations. The empirical cases are sorted into the rows of this truth table based on their scores on various attributes, with some rows containing many cases, some rows just a few, and some rows containing no cases if there is no empirical instance of the particular combination of attributes associated with a given row.

[2] For further background on QCA, the reader is referred to the works by Ragin (2000, 2008). For a shorter introduction as well as tutorials and empirical examples, the reader is referred to Fiss (2007), Greckhamer et al. (2008), Herrmann and Cronqvist (2009), Jackson (2005), Rihoux and Ragin (2009), and Schneider and Wagemann (2007). While QCA was initially conceived as a small-N approach (e.g. between 15 and 40 cases), the current study follows more recent works that have extended QCA to large-N settings (e.g. Ragin & Fiss, 2008)

In a second step, the researcher then reduces the number of truth table rows based on two conditions: (1) the minimum number of cases required for a solution to be considered, and (2) the minimum consistency level of a solution. Consistency here refers to the degree to which cases correspond to the set-theoretic relationships expressed in a solution. A simple way to estimate consistency when using fuzzy sets is the proportion of cases consistent with the outcome—e.g., the number of cases that exhibit a given configuration of attributes as well as the outcome divided by the number of cases that exhibit the same configuration of attributes but do not exhibit the outcome. The current study uses a refined measure of consistency introduced by Ragin (2006) that gives small penalties for minor inconsistencies and large penalties for major inconsistencies. I set the lowest acceptable consistency for solutions at >0.80, which is again above the minimum recommended threshold of 0.75 (e.g., Ragin, 2006, 2008). Also, the minimum acceptable solution frequency was set at three. Overall, 56 cases fell into configurations exceeding the minimum solution frequency. Of these cases, 40 also exceeded the minimum consistency threshold of 0.80 for higher performance, and 33 cases exceeded this threshold for very-high performance. No case exceeded the consistency threshold for the absence of high or very-high performance, a finding I further discuss in the results section.

In a third step, an algorithm based on Boolean algebra is used to logically reduce the truth table rows to simplified combinations. The current study uses the truth table algorithm described by Ragin (2005; 2008). This algorithm is based on a counterfactual analysis of causal conditions, which has the advantage of allowing for a categorization of causal conditions into core and peripheral causes. Counterfactual analysis is relevant to configurational analysis because even relatively few elements of a configuration quickly lead to an astronomically large number of truth table rows. For the researcher, this means 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 in which a redundant causal condition is *added* to a set of causal conditions that by themselves already lead to the outcome in question. As an example, assume we have evidence that the combination of conditions *A•B•~C* (read: A and B but not C) leads to the presence of the outcome. We do not have evidence as to whether the combination *A•B•C (*read: A and B and C) would also lead to the outcome, but theoretical or substantive knowledge links the presence (not the absence) of C to the outcome. In such a situation, an “easy” counterfactual analysis indicates that both *A•B•~C* and *A•B•C* will lead to the outcome, and the expression can be reduced to *A•B* because whether C is absent or present has no effect on the outcome. In “easy” counterfactual analysis, the researcher thus asks: would *adding* another causal condition make a difference? If the answer is “no”, we can proceed with the simplified expression.

In contrast, “difficult” counterfactuals refer to situations in which a condition is *removed* from a set of causal conditions leading to the outcome on the assumption that this condition is redundant. For instance, we might have evidence that the combination *A•B•C* leads to the outcome, but we do not have evidence as to whether the combination *A•B•~C* would also lead to the outcome in question. This case is of course the inverse of the situation above. In a “difficult” counterfactual analysis, the researcher asks: would removing a causal condition make a difference? This question is more difficult to answer. Theoretical or substantive knowledge links the *presence*, not the absence, of *C* to the outcome, and since we have no empirical instance of

A•*B*•~*C*, it is much harder to determine whether *C* is in fact a redundant condition that may be dropped, thus simplifying the solution to merely *A*•*B*.

Distinguishing between "easy" and "difficult" counterfactuals allows us to 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.[3] The notion of causal conditions belonging to core 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, not on connectedness to other configurational elements.

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. [4] 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

[3] 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.

[4] Because the firm performance data were self-reported by the CEOs and managing directors, there is the possibility of common-method bias. In order to assess this possibility, I used Harman's single-factor test, a common way to examine common-method bias (e.g., Konrad & Linnehan, 1995; Hult et al., 2006). If common-method bias is a serious problem, a single latent factor should account for a large proportion of the variance in the sample. However, the unrotated principal component factor solution suggested that common-method bias is not an issue. The analysis of the full sample and all measures resulted in four factors with eigenvalues larger than one, rather than a single factor. Furthermore, the largest factor accounted for 22.4% of the variance, and the largest three factors together accounted for 51% of the variance, indicating again that there is not one general factor. While the results do not perfectly rule out the existence of common-method bias, they do suggest that it is unlikely to affect the results in any substantive way.

performance in the U.K. high-technology manufacturing sector came from *ICC Business Ratio* reports. I averaged ROA across the main industries in this sector, such as manufacturers of computer equipment, printed circuits, scientific and electronic instruments, electronic components, and manufacturers in the aerospace industry. The average ROA for the sector was 7.8 percent, which is very similar to a median ROA of 7.2 percent for the U.S. high-technology sector in the same time period. Because data regarding the variation in performance were not available for the U.K. sector, I used upper- and lower-quartile information for the U.S. sector, obtained from *RMA Annual Statement Studies*.

The analysis with fsQCA requires the transforming of variables into sets that are calibrated regarding three substantively meaningful thresholds: full membership, full non-membership, and the crossover point—that is, “the point of maximum ambiguity (i.e., fuzziness) in the assessment of whether a case is more in or out of a set” (Ragin 2008: 30). The crossover point thus qualitatively anchors a fuzzy set’s midpoint between full membership and full non-membership (see also Ragin, 2000: 158). Following this approach, I created 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 ≤ 7.8%; i.e., about the 50th percentile) and was coded 1 if the firm showed high performance (ROA ≥ 16.3%; i.e., the 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 ≤ 7.8%; i.e., about the 50th percentile) but was coded 1 if the firm showed an ROA of 25%—arguably very-high performance in the eyes of most analysts, even though I was not able to obtain data regarding the corresponding sector percentile. As the crossover point for very-high performance, I chose an

ROA of 16.3% (i.e., the 75th percentile or full membership in the previous set of high-performing firms).

To additionally examine what causes led to the absence of high performance, I also created measures of membership in the set of firms with *not-high* performance and *low* performance. The measure of *not-high* performance is simply 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. I therefore also created a measure of *low* performance (ROA of 0.0% = full membership, ROA of 7.8 % = full non-membership, crossover set at 3.9%). In sum, the four outcome measures cover the full spectrum of performance outcomes, including *very-high*, *high*, *not-high*, and *low* 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 questions that assess the extent to which a firm uses, for example, formal policies and procedures to guide decisions and to determine how far communications are documented by memos, and whether reporting relationships are formally defined and plans are formal and written. The answer to each question was scored on a scale ranging from 1 to 5, where a value of 1 indicated that the practice about which the question asked (e.g., formal and written plans) was used “almost never,” 3 indicated that the practice was used “about half the time,” and 5 indicated that the practice was used “nearly always.” I combined the nine survey questions into a scale that showed very good reliability (Cronbach’s $\alpha = 0.83$). Based on the scale, I created a measure of membership in the set of firms with a high degree of formalization, with membership coded as fully out for a response of “almost never” and fully in for a response of “nearly always,” while the crossover point corresponded to the middle of the scale—i.e., the practice was used “about half the time.”

The second measure, *centralization*, is based on five survey questions 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. Answers to these questions were again measured on a 5-point scale, but actual responses were essentially restricted to four levels (department head, division head, CEO, board of directors). The items were again combined into a scale that showed acceptable reliability with a Cronbach’s α of 0.74, which is 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 were 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 the product 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 & Birnbaum-More, 1994). The measure was coded into the fuzzy set of firms with a 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 product of the 50^{th} percentile values of each of the individual measures (3 Levels times 9 Functions—i.e., a score of 27 on the complexity measure), which is largely consistent with the mean score of prior studies using this complexity measure (e.g., Wong & Birnbaum-More, 1994). However, this score based on the medians of the two individual measures is also very close to the median of the combined complexity measure (which was 33), and robustness checks indicated that results do not depend on the choice of coding.

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 less than 10 employees were coded as fully out of the set, with the midpoint at 50 employees.

Regarding my measures of firm strategy, I used Porter's (1980) strategy framework, which is consistent with Miles and Snow's typology and prior research (David et al., 2002; Miller, 1988). For instance, Doty et al. (1993) state that "Defenders compete by producing low-cost goods or services and obtain efficiencies by relying on routine technology and economies of scale gained from largeness" (1226). Likewise, Shortell & Zajac (1990) note that the Defender's strategy "emphasizes tight controls and continually looks for operating efficiencies to lower costs," in contrast to a Prospector strategy that "frequently adds to and changes its products and services, consistently attempting to be first in the market" (818). Furthermore, based on a systematic comparison of the Porter and Miles & Snow typologies, Segev (1989) suggests a typology that equates Defenders with cost leader/cost-focus and Prospectors with differentiation/differentiation-focus.[5]

[5] A slightly different view of the relationship between the Miles & Snow typology and Porter's strategies has been proposed by Walker & Ruekert (1987), who develop a hybrid model that subdivides the defender type into low-cost defenders and differentiated defenders. While prior empirical support of this distinction has been limited (e.g., Olson, Slater, & Hult, 2005; Slater & Olson, 2000), I examine the implications of this view in my discussion of the results below.

The measures for Porter's two generic strategies, *cost leadership* and *differentiation*, are based on a factor analysis of six items relating to the firms' competitive capabilities. The first four are 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 are related to new-product introduction and product features as 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 the two factors, as shown in Table 2.

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

The items were combined into two scales that showed strong reliability (α = 0.86 for cost leadership and α = 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 measured environmental context using the two constructs of environmental *rate of change* and *uncertainty*, which in combination assess the dynamism of the competitive environment (Baum & Wally, 2003; Dess & Beard, 1984). By making choices regarding both aspects of their product-market domains, the firms in my sample largely commit to either a stable or continuously changing domain, a key aspect of the entrepreneurial challenge faced by all firms (Miles & Snow, 2003). As prior studies have shown, the high-technology sector shows considerable variation with regard to both constructs (e.g., Fine, 1998; Mendelson & Pillai, 1999). The first measure, rate of change, measures the speed of product and competitive change

(Bourgeois & Eisenhardt, 1988; Jurkovich, 1974).[6] In environments with a high rate of change, firms face difficulties earning above-average profits for prolonged periods of time based on a single innovation or product (Bogner & Barr, 2000). I operationalize the rate of change as the length of a firm's main product life cycle. A product life cycle of 3 months or less (98th percentile) was coded as full membership in an environment with a high rate of change, a product life cycle of 10 years (25th percentile) was coded as full non-membership in environments with a high rate of change, and a life cycle of 3 years (77th percentile) was set as the crossover point.[7]

While an environment may be changing rapidly, these changes may nevertheless be fairly predictable, and uncertainty is thus a second key dimension of the organization's environment (Miles & Snow, 1978). Environmental uncertainty was assessed using two items that asked how predictable changes were in the business environment over the past 3 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

[6] I use the term rate of change to distinguish this construct from the related but more extensive and multidimensional construct of environmental velocity (McCarthy, Lawrence, Wixted, & Gordon, 2010).
[7] A lack of information on each firm's industry rather than overall sector does not allow me to measure environmental and rate of change using archival measures at the industry level. However, recent studies indicate that the survey-based measures of environmental characteristics used here are highly correlated with alternative archival measures (Baum & Wally, 2003; Mendelson & Pillai, 1999), suggesting that they are a satisfactory choice for the current purposes.

point. Finally, as suggested by theory, the measures of rate of change and uncertainty tap into different constructs, as shown by their low and non-significant correlation of 0.05 ($p = 0.56$).[8]

Information on the survey items used to construct the independent measures was missing for an average of 14 percent of cases, and listwise deletion would have significantly reduced the overall sample size and likely resulted in biased results (Little & 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, variable raw scores can be transformed into set measures using the "direct method" of calibration described by Ragin (2008). The basic intuition underlying this calibration is that it rescales an interval variable using the crossover point as an anchor from which deviation scores are calculated, with the values of full membership and full non-membership as the upper and lower bounds.[9] The rescaled measures range from 0 to 1 and the converted scores are tied to the

[8] Environmental uncertainty is arguably a multi-faceted construct that can also relate to, for example, political uncertainty or uncertainty relating to the supply of inputs and factor prices, and my measure may thus not capture the full spectrum of the entrepreneurial problem or the broadness versus narrowness of the firm's product market domain (Miles & Snow, 2003). However, the current measure relating to technological uncertainty is arguably most closely related to the strategies of cost leadership and differentiation and consistent with prior work on the typology (e.g., Desarbo et al. 2005).

[9] An intermediate step of the direct method of calibration involves the transformation of these deviation scores into the metric of log odds, which is advantageous since log odds provide a metric that is centered around zero and has no upper or lower bound. For a detailed description of the calibration procedure, see Ragin (2008: 86-94). Because the laws governing the intersection of fuzzy sets make cases with scores of exactly 0.5 difficult to analyze, Ragin (2008) recommends avoiding the use of a precise 0.5 membership score for causal conditions. To achieve this, I add

thresholds of full membership, full non-membership, and the crossover point. In the current version of fs/QCA (2.5), the transformation is automated in the *compute* command and can be easily executed once the three thresholds are defined.

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 negative correlation between environmental uncertainty and cost leadership strategy.

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

High-Performance Configurations

Table 4 shows the results of a fuzzy-set analysis of high performance. I use the notation for solution tables recently introduced by Ragin & Fiss (2008), according to which full circles indicate the presence of a condition, while crossed-out circles indicate the absence of a condition. Furthermore, large circles indicate core conditions, while small circles refer to peripheral conditions. Blank spaces in a solution indicate a "don't care" situation in which the causal condition may be either present or absent.[10] Solutions are grouped by their core conditions.

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a constant of 0.001 to the causal conditions below full membership scores of 1. Adding this constant across all conditions does not affect the results of the regression analyses reported in the appendix but it does assure that no cases are dropped from the fuzzy-set analyses.

[10] The solution tables only list configurations that consistently led to the outcome of interest—configurations that do not lead to high performance, that did not pass the frequency threshold, or that showed no consistent pattern and thus did not pass the consistency threshold are not included in the tables.

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

The solution table shows that the fuzzy-set analysis results in four solutions exhibiting acceptable consistency (i.e., consistency ≥ 0.80) and furthermore indicates the presence of both core and peripheral conditions as well as neutral permutations of two configurations. The presence of several overall solutions thus points to a situation of first-order or across-type equifinality of solutions, while the neutral permutations within solutions 1 and 3 furthermore point to the existence of second-order or within-type equifinality.

Regarding core conditions, Solutions 1a and 1b indicate that a cost leadership strategy combining formalization and centralization as well as the absence of uncertainty as peripheral conditions is sufficient for achieving high performance, a profile that fits the Defender type. These solutions furthermore suggest that, with a cost-leadership strategy, there are trade-offs between a high degree of complexity and a high rate of environmental change. Specifically, solution 1b of Table 4 indicates that greater complexity allows for high performance regardless of whether the environment changes at high speeds or not, as indicated by the blank space for environmental change that signals a “don’t care” situation for that causal condition. In contrast, solution 1a shows the opposite pattern: in the absence of a high rate of change, complexity may be either high or low. Comparing solutions 1a and 1b thus indicates that high complexity and the absence of a high rate of change may be treated as substitutes. Furthermore, both solutions 1a and 1b show that not being large and using at least to some extent a differentiation strategy are also parts of this causal configuration. Interestingly, this finding lends some support to the suggestion of Walker & Ruekert (1987), who have argued for considering the notion of a differentiated Defender firm that aims to protect a niche while also pursuing some differentiation. Finally, note how the current findings highlight the ability of QCA to understand the relationships internal to configurations, and particularly substitution and complementarity effects that usually have to remain black-boxed in the other, more standard statistical approaches.

Solution 2 indicates the existence of a successful hybrid configuration that combines differentiation and cost leadership strategies as core conditions with a low degree of formalization. This solution resembles the Analyzer type of Miles and Snow, but in contrast to their theory it appears that this type does not operate well in either quickly changing or uncertain environments.

Solutions 3a and 3b indicate a third important path to high performance, combining a differentiation strategy with informal organization, which is consistent with a Prospector strategy. Indeed, in terms of structure and strategy, solution 3a is perfectly consistent with the Prospector ideal profile defined by Miles and Snow when peripheral conditions are taken into account. Solution 3b differs slightly from 3a in that this solution combines complexity with operating in a rapidly changing environment as peripheral conditions. Note that for all solutions except solution 4, the environment is not a core condition, although higher levels of uncertainty appear to hinder high returns for all configurations at this performance level. Still, in line with the Miles and Snow assumption, an informally organized Prospector configuration (solution 3a) is better positioned to operate in a quickly changing environment than any other configuration.

Finally, solution 4 indicates that size in fairly predictable environments also allows firms to achieve high returns, which indicates the existence of economies of scale. However, these economies appear to be highly dependent upon a stable industry environment, as indicated by the core condition requiring that environmental uncertainty be “not high.”

The table also provides scores for coverage that indicate the percentage of cases that take this path to the outcome, allowing me to evaluate the importance of different causal paths. In terms of overall coverage, the combined models account for about 36% of membership in the outcome. While this value is substantive, it also indicates considerable elements of randomness or idiosyncrasy within configurations that lead to high performance. Finally, the models in Table 4 indicate the existence of two possible necessary conditions that are shared across all solutions, namely a lack of uncertainty and a differentiation strategy. However, since the solutions do not cover all possible paths to achieving high performance and since there are in fact other configurations that do not pass the consistency and frequency thresholds imposed here but lead to high performance, the results indicate that there are several sufficient solutions but likely no necessary condition for achieving high performance in this sector. These findings demonstrate the ability of a set-theoretic approach to examine necessity and sufficiency of configurations and their elements, which are not easily examined using standard, non-Boolean approaches.

Very-High Performance Configurations

Table 5 shows the results for a fuzzy-set analysis of very-high performance. The results indicate the existence of two distinct configurational groupings, which again suggests the presence of first-order equifinality. Solutions 1a and 1b again rely on a cost-leadership strategy in combination with a high degree of complexity and avoidance of rapidly changing environments. The solutions also show clear trade-offs, with size and centralization substituting for each other and allowing for neutral permutations around the core conditions, thus also indicating the presence of second-order equifinality. Note also that the overall number of solutions has dropped from five to three and that for all solutions in Table 5 the minimum number of core conditions has increased from one to three, indicating the existence of fewer choices with greater constraints when aiming for very-high performance, which provides evidence of asymmetric causality.

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

The table also shows the existence of a highly successful Prospector configuration in solution 2, which largely resembles the Prospector configuration of the previous table but now includes uncertainty as a core condition. This finding is consistent with the Prospector prototype of a small firm with informal relations and centralized decision making 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 normally unfavorable environments given the right configuration.

Note further that the results of Table 5 indicate there is no hybrid Analyzer configuration that achieves very-high performance. This is an important finding, as it indicates that trade-offs may become increasingly pronounced as one moves up the performance scale. The results thus indicate that it may be possible to achieve high performance using a hybrid type, but as one approaches very-high performance, trade-offs between differentiation and cost leadership strategies as well as their associated characteristics of organizational structure appear to make hybrid types such as the Analyzer infeasible—the very-high performers appear to rely on "pure" types.

In terms of coverage, the solutions account for about 27% of membership in those achieving very-high performance, which is slightly less than for the analysis of high performance above. While there are thus three sufficient configurations, the analyses again indicate the same potential necessary conditions with the addition of a low-cost strategy, but the less-than-perfect coverage and examination of conditions not passing the minimum threshold test again suggests that there are other paths to the outcome in question that do not rely on these conditions.

Configurations Leading to Not-High or Low Performance

These differences between configurations leading to high vs. very-high performance already demonstrate the need to shift toward an asymmetric understanding of causality.

However, to further explore this issue, I also conducted fuzzy-set analyses modeling the *absence* of high performance well as *low* performance. Note again that with standard regression analyses, this kind of analysis (i.e., predicting the absence of high performance) is always part of the process because of the symmetric nature of relationships in regression models. However, in the theoretical perspective suggested here, causal conditions leading to the presence of the outcome may frequently be different from those conditions leading to the absence of the outcome.

Consistent with 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, and consistency scores for all solutions remained considerably below the acceptable level of 0.75. These findings indicate the absence of a clear set-theoretic relationship when using either the absence of high performance or the presence of low performance as the outcome. In other words, there are many ways to be non-performing here, but no consistent pattern.

In combination with the results above, modeling the absence of the outcome complements the current findings to suggest a clear picture of asymmetric causality. Specifically, the current analyses describe the results for four different outcomes: very-high performance (ROA of 25 %), high performance (ROA of 16.3%), not-high performance (ROA of 7.8%) and low performance (ROA of 0.0%). The results indicate that there are few configurations that consistently lead to high performance, and even fewer that consistently lead to very-high performance, but there is no configuration of strategy, structure, and environment that consistently leads to average or below-average performance.

Sensitivity Analyses

I conducted several robustness checks and sensitivity analyses. First, I compare the results of the fsQCA analyses conducted here with more traditional methods for the analyses of typologies, such as cluster analysis (e.g., Ketchen, Thomas, & Snow, 1993) and deviation score approaches (e.g., Doty, Glick, & Huber, 1993). Details on estimation and the results are provided in Appendix A. The results provide broad support for the existence of the Miles and Snow types and their relationship with performance, yet also show the methodological differences of these approaches that allow for a limited insight into the causal processes inside of typologies. Specifically, while the results of the cluster and deviation score analyses find support for the overall typology, in contrast to the fuzzy-set QCA conducted here they offer only limited insight into the internal causal structure of the different types, the neutral permutations inherent to the types, or the asymmetric causal relationships present across the performance spectrum.

I furthermore conducted sensitivity analyses to examine whether my findings are robust to the use of alternative specifications of my causal conditions, using a different coding for complexity, size, and the rate of change, where alternative crossover points would appear to be most plausible. Specifically, I conducted alternative sets of analyses where I varied the crossover point between +/- 25 percent for all three measures. While there are minor changes regarding the kind of neutral permutations that occur as well as what the specific number of solutions and sub-solutions is, the interpretation of the results remains substantively unchanged.

DISCUSSION

While typologies have figured prominently in organization and strategy research and retain their attraction as evidenced by a number of recent studies, their promise as well as that of configurational theory remains still unfulfilled (cf. Short, Payne, & Ketchen, 2008). In this study, I have argued that a key challenge of typological theory relates to understanding cause-effect relationships inherent to configurations. To overcome this challenge and allow us to build better causal theories, I have proposed a theoretical perspective that shifts the focus toward a definition of configurational core and periphery based on causal relations with the outcome in question.

Such a shift allows a more fine-grained understanding of typological theories by additionally introducing the concepts of neutral permutations and causal asymmetry.

In addition to introducing a fresh theoretical perspective and a vocabulary for understanding cause-effect relationships in typologies, I further introduced fuzzy-set analysis as a corresponding method for gaining a clearer understanding of 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 examined here demonstrated the existence of several equifinal configurations that included core and peripheral elements as well as neutral permutations of these elements. 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. In combining a theoretical approach and a novel methodology, the current study thus presents a step toward building a better understanding of the crucial role of cause-effect relationships in organizations—a theme that is central to both the strategy and organization literatures.

As I have noted, the set-theoretic methods used here allow for the analysis of causal asymmetry—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 typological theory 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 trade-offs between different elements. This finding carries direct implications for the growing literature on organizational ambidexterity (e.g., Tushman & O’Reilly, 1996). Specifically, shifting toward an asymmetric understanding of how ambidexterity relates to performance may resolve some of the mixed findings on the relationship between ambidexterity and performance (cf. Raisch & Birkinshaw, 2008).

The notion of causal asymmetry also carries implications for strategy and organization research more broadly. Specifically, most current research would appear to assume a linear (or curvilinear) relationship between its theoretical constructs of interest, leading to a potential mismatch between an essentially symmetrical theoretical relationship and an actual underlying asymmetric causal relationship. If so, this mismatch may be to blame for inconsistent empirical findings that have plagued several literatures, such as that on the relationship between strategic change and firm performance (e.g. Rajagopalan & Spreitzer, 1997) or research on the relationship between corporate governance practices and performance (e.g. Daily, Dalton, & Cannella, 2003). For instance, consider the possibility that good governance is a necessary, though not sufficient condition for high performance. If this is the case, then firms will on average need good governance arrangements to maintain high performance, but by themselves such governance arrangements will not guarantee high performance. While perfectly consistent with a set-theoretic, asymmetric relationship, such a pattern of data would in fact lead to weak or no correlations between good governance and performance. If this is correct, then applying the theoretic approach and methods used here may hold considerable promise for resolving the inconsistent findings in these literatures.

Furthermore, the perspective and methods employed here allow for a close analysis of the equifinal configurations leading to both high and very-high performance. By incorporating the notion of neutral permutations into our understanding of causal configurations, I have argued that the causal “core” of a configuration may be surrounded by different constellations of peripheral elements that are equifinal regarding the outcome in question. To allow for a finer-grained understanding of equifinality, I have introduced the notions of first-order equifinality (i.e., equifinality across types) and second-order equifinality (i.e., equifinality of permutations within types). The distinction between these forms of equifinality is important for at least two reasons. First, while the different types and permutations may be equifinal relative to one outcome, this is not likely to be the case for other relevant outcomes. Different types or permutations may, for instance, result in different interactions with other organizational or environmental characteristics. Second, different types and permutations are likely to affect future organizational states in affecting the trajectories of subsequent organizational development by establishing path dependencies, thus making certain trajectories more likely while reducing the likelihood of others. The current study thus carries important implications for the organizational design literature by providing not only insight into the workings of design elements but also a way to conceptualize how such elements will affect future organizational change efforts (Grandori & Furnari, 2008; Rivkin & Siggelkow, 2007). In addition, while I have not focused here change in configurations, future research will hopefully expand towards understanding dynamic mechanisms in configurations or on the notion that configurations themselves may be dynamic.

A further aim of this study has been to demonstrate the added value that a fuzzy-set analysis using QCA can bring to the study of typologies, 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, fsQCA presents a particularly useful tool for understanding both complementarities and substitutes in configurations. Accordingly, fuzzy-set analyses would appear to complement other standard approaches to testing typological theories—such as cluster analysis and deviation-score approaches—by offering a tool for understanding “mid-range” theories of the causal processes involved in configurations rather than “grand” theories of overall types. It is this fine-grained examination of causal processes as well as causal asymmetry in which fuzzy-set approaches can contribute in particular.

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 study aiming to examine typologies crossing these three domains can only select a representative set of categories for characterizing each of the domains. The current study is no exception in that it has focused on some measures to the exclusion of others that could be used to characterize variables such as 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 only a handful to include simultaneously measures of the structure, strategy, and environment relating to a typology. As such, it goes beyond much previous work in offering a holistic assessment of typological configurations across a multidimensional property space.

The limited sample size of the current study did not permit further statistical testing for the fuzzy-set analyses. While fsQCA can generally employ significance tests to examine, for instance, the 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 data set 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, and airplane manufacturing, future research would naturally aim to expand the scope beyond the current empirical setting. Likewise, it would be preferable to have further information regarding the representativeness of the sample relative to the overall population of U.K. high-tech firms, and to expand the analysis to the industry level rather than the aggregate high-tech sector. However, although the findings of the current study are thus limited in their generalizability, the logic of conclusions is not context specific and thus offers ample opportunity for more research.

While QCA appears particularly appropriate for the study of complex causal relationships and multiple interactions, this ability also has limitations that may make the method more appropriate for some contexts than others. In particular, because QCA is based on fully interactive models that consider all possible configurations, its data matrices increase exponentially with the number of causal conditions considered. Accordingly, the number of causal conditions analyzed simultaneously is restricted by the number of cases available, and the researcher will need to be careful to assure there are sufficient degrees of freedom to avoid the results being overdetermined.[11]

Typologies are likely to continue playing a central role in management and strategy research, not the least because the configurations embedded in them 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 typologies might benefit both conceptually and empirically from a reorientation toward the concepts of causal core and periphery, neutral permutations, and causal asymmetry. I hope

[11] Some guidance regarding the appropriate ratio of causal conditions to cases is provided by Marx (2006).

that I have made a case for more research to extend this approach and further show its utility in developing the theory of causal mechanisms in organizations.

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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	10	11	12	13
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 rate of change	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. Ideal type fit (min)	-1.67	0.35	-0.10	-0.34	0.31	-0.26	-0.07	-0.07	-0.04	0.10					
10. Prospector deviation	2.38	0.59	0.66	0.55	0.17	0.61	-0.32	0.49	0.10	-0.16	-0.13				
11. Analyzer deviation	1.79	0.44	-0.45	-0.22	0.15	-0.67	0.08	-0.22	-0.05	0.12	-0.24	-0.54			
12. Defender deviation	2.62	0.59	-0.66	-0.55	-0.17	-0.61	0.32	-0.49	-0.10	0.16	0.13	-1.00	0.54		
13. High performance	0.69	0.43	-0.06	-0.10	0.11	-0.01	0.09	0.03	0.11	-0.07	0.12	-0.05	-0.05	0.05	
14. Very high performance	0.64	0.43	-0.08	-0.08	0.13	-0.03	0.12	0.04	0.13	-0.09	0.12	-0.06	-0.03	0.06	0.97

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

Table 4: Configurations for Achieving High Performance

	Solution					
	1a	1b	2	3a	3b	4
Structure						
Large Size	⊗	⊗	⊗	⊗	⊗	●
Formalization	•	•	⨂	⨂	⨂	•
Centralization	•	•	•	⊗	⊗	⊗
Complexity		•	⊗	•	⊗	•
Strategy						
Differentiation	•	•	●	●	●	•
Low Cost	●	●	●	⊗	⊗	
Environment						
Rate of Change	⊗		⊗	•	⊗	⊗
Uncertainty	⊗	⊗	⊗	⊗	⊗	⨂
Consistency	0.82	0.82	0.86	0.83	0.83	0.82
Raw Coverage	0.22	0.22	0.17	0.14	0.19	0.19
Unique Coverage	0.01	0.01	0.02	0.01	0.02	0.04
Overall Solution Consistency		**0.80**				
Overall Solution Coverage		**0.36**				

Table 5: Configurations for Achieving Very High Performance

	Solution		
	1a	1b	2
Structure			
Large Size	•	⊗	⊗
Formalization	•	•	⨂
Centralization	⊗	•	•
Complexity	●	●	⊗
Strategy			
Differentiation	•	•	●
Low Cost	●	●	•
Environment			
Rate of Change	⨂	⨂	⊗
Uncertainty	⊗	⊗	●
Consistency	0.83	0.83	0.84
Raw Coverage	0.17	0.22	0.17
Unique Coverage	0.03	0.04	0.03
Overall Solution Consistency		**0.81**	
Overall Solution Coverage		**0.27**	

APPENDIX A

Cluster Analysis

To derive an empirical taxonomy, I use a two-step cluster analysis, which has been the dominant tool of analysis for configurations and strategic groups (DeSarbo, Grewal, & Wang, 2009; 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 6 and are essentially stable across different clustering algorithms.

----- Insert Tables 6 and 7 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 and mostly occupies a middle position except for differentiation, in which 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 indicator variables for cluster membership on the performance measure, with interaction terms for environmental rate of change 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.[12] In the models, the Analyzer type is used as the omitted category. Results are presented in Table 7.

Model 1 shows the effect of Prospector and Defender types on performance, while Models 2 to 5 add interaction terms for environmental rate of change 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 upon 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

[12] 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 0.01 instead of the 0.05 level.

models offer only very limited support for performance differences between these types, and they offer no support for performance being contingent upon 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 & Glick, 1994; Delery & 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 following formula:

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

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 types (Doty et al., 1993). However, while Doty et al. used uncalibrated measures to create their ideal profiles, I use the fuzzy-set measures to assure comparability across all three types of analysis. Accordingly, high ideal-profile scores corresponded to full membership, while low scores 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 model the relationship between ideal-profile deviation and performance. In the models, the Analyzer type is used as the omitted category. The results are presented in Table 8.

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

Model 1 shows the results of an organization's overall ideal-profile fit across all profiles, thus testing whether a firm performs better if its structural features resemble any of the ideal types identified by the theory (Doty, Glick, & Huber, 1993). The fit coefficient is positive and marginally significant, which indicates that such a fit is likely 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. However, these models indicate that it is not simply one profile that is superior. Note also that the findings using this theoretically derived typology differ from the empirically derived solution based on cluster analysis, in which only the Prospector type showed increased performance.

Models 5 through 8 show the interaction between deviation from the three ideal types and environmental rate of change 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. The models did not indicate any support for the dependence of ideal-type fit on the environmental rate of change. 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 0.04 for the overall model. Compared with a baseline model with only environmental controls, the Pseudo R-squared increases by only 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 that fit with the Prospector type is beneficial in uncertain environments, it would not appear that ideal-type fit is a crucial ingredient in attaining high performance.[13]

[13] The results are identical for OLS regression in combination with the uncalibrated performance measure, including significance levels.

Table 6: 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 7: Tobit Regression Models of Cluster Configurations on Performance[a] (n = 139)

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Prospector	1.137*	1.159†	0.264	1.123*	1.154*
	(0.532)	(0.700)	(0.771)	(0.528)	(0.527)
Defender	0.130	0.129	0.081	0.796	0.933
	(0.521)	(0.522)	(0.515)	(0.721)	(0.807)
Environmental Pace	1.146	1.175	1.029	1.817*	1.158
	(0.710)	(0.918)	(0.697)	(0.903)	(0.705)
Environmental Uncertainty	-0.853	-0.850	-1.649	-0.830	-0.206
	(0.700)	(0.704)	(0.920)	(0.692)	(0.829)
Prospector × Rate of Change		-0.068			
		(1.383)			
Prospector × Uncertainty			1.977		
			(1.406)		
Defender × Rate of Change				-1.937	
				(1.448)	
Defender × Uncertainty					-1.910
					(1.466)
Constant	0.793	0.783	1.196	0.568	0.488
	(0.542)	(0.583)	(0.612)	(0.560)	(0.579)
LR Chi-squared	11.66*	11.66*	13.72*	13.53*	13.43*
Pseudo R-squared	0.04	0.04	0.05	0.05	0.04

[a] Standard errors in parentheses.

† p ≤ .10; * p ≤ .05; ** p ≤ .01; *** p ≤ .001.

Table 8: 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)	0.801†							
	(0.598)							
Prospector Dev.		-0.212			0.082	0.814		
		(0.280)			(0.422)	(0.529)		
Analyzer Dev.			-0.023				-0.509	-0.485
			(0.456)				(0.677)	(0.791)
Defender Dev.				0.212				
				(0.280)				
Prospector Dev.× Rate of Change					-0.800			
					(0.886)			
Prospector Dev. × Uncertainty						-2.077*		
						(0.951)		
Analyzer Dev. × Rate of Change							1.584	
							(1.649)	
Analyzer Dev. × Uncertainty								1.049
								(1.470)
Environmental Rate of Change	1.186	1.227†	1.161	1.227†	3.444	1.140	-1.638	1.162
	(0.718)	(0.731)	(0.725)	(0.731)	(2.608)	(0.713)	(2.954)	(0.722)
Environmental Uncertainty	-0.989	-1.012	-0.925	-1.012	-1.001	4.708†	-0.919	-2.814
	(0.714)	(0.728)	(0.724)	(0.728)	(0.723)	(2.638)	(0.718)	(2.767)
Constant	2.725*	1.959*	1.415	0.686	1.159	-0.911	2.275†	2.228
	(1.130)	(0.901)	(0.901)	(0.989)	(1.227)	(1.488)	(1.281)	(1.467)
LR Chi-squared	6.21*	4.91	4.33	4.91	5.75	10.61*	5.27	4.85
Pseudo R-squared	0.02	0.02	0.03	0.02	0.02	0.04	0.02	0.02

[a] Standard errors in parentheses. T-tests are one-tailed where predicted, otherwise two-tailed.
† p ≤ .10; * p ≤ .05; ** p ≤ .01; *** p ≤ .001.