Organizational Research Methods
Volume 11 Number 4
October 2008 695-726

10.1177/1094428107302907
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Using Qualitative Comparative Analysis in Strategic Management Research

An Examination of Combinations of Industry, Corporate, and Business-Unit Effects

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The authors present qualitative comparative analysis (QCA) as a viable method for strategic management research. Specifically, they demonstrate its ability to examine the potential interdependence and complexity among effects through a study of how industry, corporate, and business-unit attributes combine in determining business-unit performance. They present in an accessible manner the consecutive phases of the QCA approach by analyzing a sample of 2,841 cases of business-unit performance, and they examine the insights that the QCA analysis provides for this particular stream of literature. The authors conclude with a discussion of the benefits and limitations QCA poses for strategic management research more generally, including major contingencies under which QCA or linear methods may be more appropriate for strategy research.

Keywords: *qualitative comparative analysis; firm performance; business-unit performance; strategy research*

One of the most prominent and enduring questions addressed by strategic management researchers centers on the determinants of firm performance. This is perhaps most evident in the literature examining the relative importance of industry, corporate, and business-unit effects to business-unit performance. Indeed, since the seminal studies of Schmalensee (1985) and Rumelt (1991), a continuous stream of research has taken up this investigation (e.g., Bowman & Helfat, 2001; Brush & Bromiley, 1997; Hough, 2006; McGahan & Porter, 1997, 2002; Misangyi, Elms, Greckhamer, & LePine, 2006; Roquebert, Phillips, & Westfall, 1996; Short, Ketchen, Bennett, & Du Toit, 2006). At the heart

Authors' note: We thank Joel Baum, Peer Fiss, Bill McKelvey, Hayagreeva Rao, as well as guest editor Dave Ketchen and three anonymous reviewers for their constructive comments on earlier drafts of this article.
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of this line of research is the fundamental debate over whether industry structural conditions (i.e., the IO economic view) or corporate and business-unit attributes and capabilities (i.e., the business strategy view) are the principal sources of profitability differences across firms (Rumelt, 1991). Despite the import of this work to strategic management, the literature offers equivocal conclusions to the relative importance of these effects (Bowman & Helfat, 2001). This is in part due to the limitations of the statistical methodologies employed to investigate this issue—primarily variance components analysis and analysis of variance—which are now well documented (Bowman & Helfat, 2001; Brush & Bromiley, 1997; Brush, Bromiley, & Hendrickx, 1999; McGahan & Porter, 2002).

Perhaps the only enduring point of consensus during the last three decades of research in this literature has been that industry, corporate, and business-unit effects are not independent, and that this condition presents a serious challenge for general linear methodologies given their assumption that effects are independently generated. The most recent contributions to this literature have focused on this nonindependence between effects and have attempted to formally incorporate it into their analyses (Hough, 2006; McGahan & Porter, 2002; Misangyi et al., 2006; Short et al., 2006). These attempts, however, remain limited by a continued reliance on general linear models. For example, one limitation of the cross-nested hierarchical linear modeling approach employed by Misangyi et al. (2006) is that "the non-independence between business-segment and industry effects is not fully incorporated" (p. 580). These limitations of general linear models to fully incorporate the relationships among industry, corporate, and business-unit factors in large part led McGahan and Porter (2002) to suggest that "while there are ways to continue to learn from this research, its limits suggest that the time has come to explore whole new approaches" (p. 850).

The purpose of the current study is to present strategic management researchers with a methodology that specifically focuses on, and is able to address, the interdependence of causal effects. To accomplish this objective, we illustrate how qualitative comparative analysis (QCA; Ragin, 1987, 2000) may be used to study the sufficiency of combinations of industry, corporate, and business-unit attributes for the occurrence of superior or inferior business-unit performance. Rather than trying to understand the relative independent contribution of each of the various industry, corporate, and business-unit level effects to performance, this research approach instead examines what combinations of industry, corporate, and business-unit attributes are necessary and/or sufficient for superior or inferior performance. For example, instead of "How much does corporate strategy matter?" the pertinent question becomes "How do corporate factors combine with industry and business-unit factors to matter?" for business-unit performance. Therefore, QCA allows for the investigation of the complex interdependencies among industry, corporate, and business-unit attributes that potentially underlie business-unit performance. In doing so, it provides a methodological approach that is able to fully incorporate the relationships among these factors, answering McGahan and Porter's (2002) call for "whole new approaches" and contributing directly to this particular stream of strategic management research. More generally, this capability of the QCA approach provides a valuable addition to the strategic management researcher's methodological toolbox.

In the remainder of the article, we present the three phases of the QCA approach in an action-oriented manner. First, we show how to construct a property space out of a set of theoretically relevant causal attributes of interest (in the current study, industry, corporate, and business-unit attributes). Second, we demonstrate how to analyze the diversity and causal complexity underlying the outcome of interest (in this case, superior and inferior business-unit performance). And third, we evaluate and interpret the results of our study. We perform this demonstrative analysis on a sample incorporating 2,841 cases of business-unit performance during a 4-year period, which are embedded within 2,451 corporations and 184 industries. We conclude with a discussion of the benefits and limitations that the QCA approach presents to conducting strategic management research.

Utilizing QCA to Study Business-Unit Performance

QCA was developed primarily by Charles Ragin (1987, 2000) to solve a fundamental problem presented by cross-case analyses: preserving the integrity of cases as complex configurations of causal factors while concurrently allowing for the systematic examination of similarities and differences in causal factors across many cases. To date, the QCA approach has been applied primarily by political science and sociology researchers to study a diverse range of topics such as the differential success of political parties (Redding & Viterna, 1999), the evolution of social spending programs in the United States at the end of the New Deal era (Amenta & Halfmann, 2000; Amenta & Poulson, 1996), the success and viability of the mobilization of social movements (Amenta, Carruthers, & Zylan, 1992; Cress & Snow, 1996), the performance variation of national medical systems (Hollingsworth, Hanneman, Hage, & Ragin, 1996), and the relationship between ruler autonomy and their propensity to start wars (Kiser, Drass, & Brustein, 1995). More recently, management scholars have also taken an interest in this methodology; Kogut, MacDuffie, and Ragin (2004) used a QCA approach to examine the configuration of practices underlying production systems in the automotive industry and Fiss (in press) examines the approach's usefulness for the study of organizational configurations.

QCA starts from the premise that causation is not easily unraveled because (a) outcomes of interest rarely have any single cause, (b) causes rarely operate in isolation from each other, and (c) a specific causal attribute may have different and even opposite effects depending on context.[1] Building on this premise, QCA utilizes Boolean algebra and the logic of Boolean algorithms for performing holistic comparisons (Kogut & Ragin, 2006; Ragin, 1987, 2000; Ragin, Mayer, & Drass, 1984). The basic features of Boolean algebra (see also Fiss, in press; Kogut & Ragin, 2006; Ragin, 1987, 2000) are (a) the use of binary data, (b) combinatorial logic, for example, a logic that does not view causes in isolation but always in the context of the presence or absence of other causally relevant conditions, (c) the application of Boolean algebra operators to express this combinatorial logic, and (d) Boolean minimization to reduce these expressions of causal complexity.

The QCA approach to conceptualizing and analyzing causality decisively differs from statistical analyses based in linear algebra. The latter seek to estimate the separate contribution of each cause (independent variable) in explaining variation in the outcome (dependent variable) in an attempt to understand the causality underlying a particular type of outcome. In contrast, in the QCA approach, cases sharing the same outcome of interest are systematically compared with the intent of identifying the common causal conditions—whether constituted by a single causal factor or combinations of causal factors—across these cases. For example, instead of trying to isolate which industry, corporate, or business-unit factors make the largest relative contribution to explaining the variance in business-unit performance, a QCA approach examines which industry, corporate, and business-unit attributes, and any and all combinations of configurations of these attributes, commonly occur across those cases achieving superior or inferior performance.

The QCA approach involves three distinct phases (Kogut & Ragin, 2006): In the first phase a property space constituted by the cases and the theoretically relevant causal factors under examination is constructed (Ragin, 2000, p. 77); the second phase follows an analysis of this property space, including both the examination of the distribution of cases across this space and a systematic identification of those causal conditions sufficient for the outcome of interest to occur; and in the final phase, the results of these analyses are evaluated and interpreted.

Constructing the Property Space

As described above, the QCA approach seeks to identify the common causal conditions underlying a particular outcome by examining the attributes of cases exhibiting that outcome. To accomplish this analysis, QCA relies on the configurational principles rooted in the property-space approach to typology construction (Barton, 1955; Lazarsfeld, 1937; cf. Ragin, 2000). This approach affords researchers with a means of constituting a population of relevant cases and performing cross-case analyses that preserve and capture the complexity and interdependence of the causal factors underlying outcomes.

A first principle of this configurational approach is that the integrity of cases be maintained in the analysis: "The basic idea behind configurational thinking is that aspects of cases should be examined together, as packages" (Ragin, 2000, p. 72). This perspective is consistent with the notion of organizational configuration in the organization and management literatures (Child, 2002; Doty, Glick, & Huber, 1993; Ketchen, Thomas, & Snow, 1993; Miller, 1986, 1996)—wherein a configuration is defined as "any multidimensional constellation of conceptually distinct characteristics that commonly occur together" (Meyer, Tsui, & Hinings, 1993, p. 1175). A second principle of this configurational thinking holds that a single difference among cases may constitute a difference in kind—the character of any particular case may change qualitatively if a single key attribute is changed:

> For example, a White, suburban, middle class, male professional with three children and a mortgage who votes for the Republican Party differs by only a single trait from a person with these same characteristics but who votes for the Socialist Labor Party. Thus . . . [though] they are very similar. . . . It might be very different to be trapped in an elevator with one versus the other. This qualitative difference captures the essence of viewing cases as configurations: two cases may be similar in most ways but because they differ on one or more key aspects, their difference may be one of kind, not simply one of degree. (Ragin, 2000, p. 71)

A third principle important to understanding this approach is that it is rooted in a "property space approach" to typology (Ragin, 2000, pp. 77-78): Any given set of theoretically relevant attributes constitute a property space such that each combination of attributes represents a specific location within the space and each location potentially constitutes a difference in kind. A configuration is defined as any logically possible combination of these attributes, and the property space is constituted by all logically possible configurations. QCA therefore may be utilized to map the logically possible configurations (i.e., the property space) of a priori selection of theoretically relevant causal attributes underlying an outcome, and the empirically observed and unobserved configurations within this space (Kogut & Ragin, 2006), thereby enabling an analysis of the determinants of an outcome that maintains the integrity of the potential causal complexity underlying each case.

Based on these principles, the first step in the QCA analysis is to select both cases and the attributes that theoretically may cause the outcome of interest, and use these to construct the property space on which the subsequent analyses will take place. For the current study, the outcome of interest is business-unit performance, and thus observations of business-unit performance serve as the basis for constructing cases. In selecting the set of theoretically relevant attributes—in the current inquiry these consist of industry, corporate, and business-unit attributes—theoretical relevance, previous research, and parsimony drove our choices. Because the primary intent of this study is to demonstrate the QCA methodology, we chose attributes that have been suggested by previous theory and/or shown in previous research to substantially affect business-unit performance. This led to the selection of the industry attributes of industry munificence, industry dynamism, industry competitiveness, and industry sector; the corporate attributes of corporate resource availability, corporate diversification, and corporate capital intensity; and the business-unit attribute of size.

To construct our sample, we started by selecting the 200 (4-digit Standard Industrial Classification code [SIC code]) industries that had no missing data for the theoretically relevant attributes just described for the years of 1995 to 1998 from the population of all such industries in the Compustat Annual Industrial file. We then collected data for all business units in each of these industries for each of these years from the Compustat Segments file (based on each business unit's primary SIC designation). Data on the attributes of the parent corporation of each business unit (as identified in the Compustat Segments file) were obtained from the Compustat Annual Industrial file for the years of 1995 to 1998. Finally, we aggregated all observations over time of business-unit performance and of the industry, corporate, and business-unit attributes, thereby using this aggregated data to perform a cross-case comparison.

We aggregated the data for two reasons. The first is parsimony: Though the time dimension has been shown to be an important aspect of understanding the determinants of performance (e.g., Misangyi et al., 2006; Short et al., 2006), our primary interest is in demonstrating QCA's ability to examine the combined causal relationships among industry, corporate, and business-unit effects. Second, as we further discuss below, using average performance over time should increase the reliability of assessing cases' set membership in performance. Thus, in aggregating the data, we included only those cases (business units) that had at least three annual observations of performance during the period of 1995 to 1998, resulting in a final sample consisting of 2,841 cases, comprising 184 industries and 2,451 corporations. An elaboration of the specific measurement of these attributes will follow a brief introduction and explanation of the final principle on which QCA is based: The set-theoretic approach.

A set-theoretic approach (Fiss, in press; Kogut & Ragin, 2006; Ragin, 1987, 2000) preserves the causal complexity underlying each case through the use of set memberships: Each theoretically relevant causal attribute is considered to be a domain in which a case could have membership, and the researcher is required to assess each case's membership in each of these domains or sets. Thus, each case may be a member of multiple sets, and resulting membership combinations are compared and contrasted to identify the decisive patterns of similarity and difference that consequently provide the basis for constructing causal arguments (Kogut & Ragin, 2006). In the present study this means that we examine each business unit's membership in the sets constituted by the causal attributes we included in the analysis (for example, membership in the set of business units faced with munificent industry conditions).

This is accomplished in QCA through the use of "crisp sets." A crisp set is dichotomous and evaluates set membership on the two mutually exclusive states of membership or nonmembership. "In short, crisp sets establish distinctions that are wholly qualitative" (Ragin, 2000, p. 153) and thus QCA focuses on identifying qualitative differences in kind. Because this methodological strategy aims at identifying differences in kind, it becomes important to calibrate breakpoints that properly assign membership of cases as being either in or out of the relevant sets. This calibration relies heavily on theoretical and empirical knowledge of the data at hand to set both theoretically and practically meaningful break points that capture differences in kind (Ragin, 1987, 2000). Therefore, in the present study, the breakpoints established for each of the industry, corporate, and business-unit attributes were based on both extant theory and the distribution of the data in the current sample. In other words, QCA allows for each attribute to be uniquely calibrated in a manner that best captures a difference in kind for the particular set membership, guided by relevant theory and its occurrence in empirical reality.

Industry munificence (i.munificent).[2] A munificent industry environment has the capacity to support growth because of an abundance of resources (Dess & Beard, 1984). Business-unit profitability should be higher in munificent industries, as competition tends to be more relaxed relative to industries in which there is a scarcity of resources (Caves, 1977; Porter, 1980). Following previous research, we calculated munificence for each year by first regressing the annual average sales in each industry during the preceding 5 years (i.e., munificence for 1995 is based on the regression of sales for the years 1990 to 1994), and then divided the regression slope coefficient obtained from this regression by the mean value of the variable (to adjust for absolute industry size; Dess & Beard, 1984; Keats & Hitt, 1988). Given the relatively normal distribution of this variable, we used the average munificence value of the industries included in the present sample as the breakpoint to determine set membership in the set of munificent industries (hence, i.munificent = 1 for industries with above average munificence, 0 for industries with below average munificence).

Industry dynamism (i.dynamic). Dynamism reflects the instability or volatility present in the industry environment (Dess & Beard, 1984) and has been found to be associated with business-unit performance (Keats & Hitt, 1988). Again following previous research (Dess & Beard, 1984; Keats & Hitt, 1988), we measured dynamism as the dispersion about the regression line estimated in the regressions used in arriving at the munificence variable just described, which involves dividing the standard error of the regression slope coefficient by the mean value of sales. Although a main conceptual issue for organization theory and strategy has been the impact of relatively highly dynamic environments on organizations (Dess & Beard, 1984; Emery & Trist, 1965), theory does not offer a clear definition of what constitutes "highly dynamic." The distribution of the data, however, did offer guidance in setting a breakpoint for this set: A qualitative break in the dynamism scores of the sample industries appeared to occur around the 75th percentile, and thus we used this as the breaking point, with industries in the upper quartile being coded as members in the set of highly dynamic industries (i.dynamic = 1), whereas the remaining industries are not members of this set (i.dynamic = 0).

Industry competitiveness (i.competitive). The seller concentration and barriers to entry present in an industry are both theorized to reduce competition, thus increasing profitability (Bain, 1968; Porter, 1980). Theoretically, industries which operate as oligopolies tend to represent a difference in kind from those industries in which competition is more prevalent (Tirole, 1988). We measured seller concentration as the four firm concentration ratio, a commonly used measure of concentration in industrial economic studies (Hay & Morris, 1979). Capital intensity is commonly used in industrial organizational economics as a measure of the barriers to entry existing in an industry (Bain, 1968) and we measured it as the average of the ratio of the net value of property, plant, and equipment to the number of employees (e.g., Hambrick & Abrahamson, 1995) across all business units in each industry for each year. Because theoretically these two constructs should be related, we used the single factor that emerged from a principal components analysis of these two measures (factor loadings of 0.753 and –0.753, respectively). Industries with a high score on the resulting scale represent a condition of increasing concentration and thus less competitive conditions, whereas lower scores represent more competitive conditions. An examination of the nature of the distribution of the data suggested that a breakpoint existed around the 75th percentile, and hence we used this breakpoint to determine the membership in the set of competitive industries. Specifically, given that high values on this measure represent a noncompetitive situation, those industries in the lower three quartiles were coded as members of the set of competitive industries (i.competitive = 1), whereas those industries scoring in the upper quartile were coded as not being members in this set (i.competitive = 0).

Industry sector. Previous studies investigating the relative importance of industry, corporate, and business-unit effects on business-unit performance have sought to examine whether these effects differ across sectors (McGahan & Porter, 1997, 2002; Roquebert et al., 1996). Indeed, McGahan and Porter (2002) suggest that the relative importance of these factors may differ across sectors and argue that this remains one of the key areas needing further research. Thus, consistent with this previous research, we divided our cases into four sets (based on membership in one of the four sectors) of industries, using the SIC classification system to capture the broad industry sectors as follows: mining and construction (SIC codes 1000 to 1999; Sector.Mine); manufacturing (SIC codes 2000 to 3999; Sector.Manuf.); telecommunications, transportation, and utilities (SIC codes 4000 to 4999; Sector.Telecom); and services (SIC codes 6000 to 8999 Sector.Service).

Corporate resource availability (c.slack). Corporate parents with abundant resources, or organizational slack, are better able to absorb a substantial share of the potential variability in the firm's environment (Cyert & March, 1964), thereby affecting performance.

Because there are a host of ways to measure organizational slack (see Bourgeois, 1981), we chose a measure that stands in parallel to the measure of the abundance of resources provided by the industry described above (munificence). A common indicator used in the finance literature for identifying the corporation's ability to invest in its future profitability (see Kallapur & Trombley, 2001) is the market to book value of the corporation ([Common Shares Outstanding × Closing Price] ÷ Total Common Equity). Thus, we measured corporate resource availability as the market to book value of each corporation for each year. Because of the highly skewed nature of the distribution (skewness = 40.1), we used the median of the distribution as the breakpoint to assess set membership: Those corporations above the median were coded as being in the set of corporations with abundant corporate resources (c.slack = 1), whereas those below the median were coded as not being members in this set (c.slack = 0).

Corporate capital intensity (c.cap.intense). Investment in fixed assets by a business unit's corporate parent is also thought to have a negative impact on performance, as capital intensity constitutes potential structural inertia (Hannan & Freeman, 1984). We measured corporate capital intensity in each year as the ratio of the net value of property, plant, and equipment to the number of employees (e.g., Hill & Snell, 1989). In establishing the breakpoint for membership in this set, we again used the median because of the attributes' skewed distribution (skewness = 11). Therefore, those corporations above the median were coded as being members in the set of capital-intensive corporations (c.cap.intense = 1), whereas those below the median were coded as not being members in this set (c.cap.intense = 0).

Corporate diversification (c.diversified). The degree to which the business unit's parent corporation is diversified has also been found to affect business-unit performance (Palich, Cardinal, & Miller, 2000). We operationalized diversification by means of the entropy measure of diversification (Palepu, 1985), which calculates total diversification using a Herfindahl index based on the percentage of sales of each of the *N* business segments (as defined by 4 = digit SIC) in which the corporation is doing business. The distribution of the data guided the establishment of the breaking point at the median of the entropy measure of total diversification: Those business units with an entropy score above the median were coded as being members in the set of highly diversified corporations (c.diversified = 1), whereas those below the median were coded as not being members in this set (c.diversified = 0).

Business-unit size (bu.size). Firm size is an important source of heterogeneity also recognized by industrial organizational economics (Hay & Morris, 1979), and is considered to be a variable on the interface between the organization and its environment in organizational theory (Scott, 1998). Thus, we measured business-unit size in each year as the annual net sales of the business unit (e.g., Hill, 1994). We calibrated the breakpoint for membership in the set of large business units to be the annual net sales of the smallest *Fortune* 1,000 company for 1997 ("The Fortune 1000," 1997). Because this measure distinguishes the largest for-profit organizations in the United States, it presents a key difference in kind for business-unit size.

Business-unit performance (outcome). We measured business-unit performance as the return on assets (calculated as net income divided by total assets; e.g., McGahan & Porter, 1997, 2002; Rumelt, 1991) for each business segment in each year. Following the convention in the strategic management literature of superior (and inferior) profitability as above average (and below average) rates of profit, we used average return on assets as the key breakpoint to decide membership in the sets of superior and inferior performance. Using average performance during the study period was not only consistent with the convention of distinguishing above (or below) average profitability, but also helped to insure reliability in assigning cases' set memberships in performance. For the set of superior performance, business units with a return on assets above the average return on assets in our sample were coded as 1 (*superior*), whereas those cases with a return below the average were coded as 0 (*not superior*). On the contrary, cases with below-average performance were coded as 1 (*inferior*) for the set of business units with inferior performance, whereas those cases with a return on assets above the average were coded as 0 (*not inferior*).

The property space constituted by these attributes can now be constructed. For matters of clarity and depth, and given the focus in previous research on the manufacturing and service sectors (McGahan & Porter, 1997, 2002; Roquebert et al., 1996), our exposition here primarily focuses on these sectors. The left-hand panels of Tables 1 and 2 portray the property spaces for each of these two sectors (manufacturing and service, respectively). These tables are also referred to as *truth tables* in the QCA approach; they report all the logically possible combinations of causal attributes, thus including those that are empirically observed and as those that are not. The Boolean property space is constituted by 2^n configurations, where n is the number of causal attributes included. Thus, for the current data, the property spaces for the manufacturing (see Table 1) and service sectors (see Table 2) are constituted by all 128 logically possible combinations of causal attributes ($2^7 = 128$ configurations), and each of these configurations represents a specific location within this space where cases can occur. For example, Configuration 1 in Table 1 (see the ID column) depicts a location in this property space in which the set memberships combine such that the industry is not highly munificent (i.munificent = 0), not highly dynamic (i.dynamic = 0), and competitive (i.competitive = 1), the corporate parent is not highly diversified (c.diversified = 0), does not have abundant slack resources available (c.slack = 0), and is not capital-intensive (c.cap.intense = 0), and the business unit is not large (bu.size = 0).

Analyzing the Property Space

The second phase of the QCA approach is the investigation of the property space. Two types of analyses are possible. The first is descriptive in nature and involves examining the distribution of cases across the property space: The identification of those locations in the property space that are inhabited by cases and those that are not, and the diversity of this distribution. The second, and most relevant to the current endeavor, involves an investigation of the causal conditions that are sufficient to attain the outcome of interest. We demonstrate each of these analyses in turn.

Analysis 1: Descriptive analysis of the property space. In addition to the property space constituted by the logically possible configurations of set membership, Tables 1 and 2 also

(text continues on p. 714)

Table 1
Truth Table—Manufacturing Sector

Attributes[a]								Frequencies[b]		Case Outcomes[c]			
										Superior Performance		Inferior Performance	
ID	i.munificent	i.dynamic	i.competitive	c.diversified	c.slack	c.cap.intense	bu.size	Number of Cases	%	Cases	%	Cases	%
1	0	0	1	0	0	0	0	96	5.9	30	31.3	66	68.8
2	1	0	1	0	0	0	0	89	5.5	22	24.7	67	75.3
3	0	0	1	0	0	1	0	87	5.3	37	42.5	50	57.5
4	0	0	1	0	1	0	0	84	5.2	47	56.0	37	44.0
5	1	0	1	0	1	0	0	78	4.8	45	57.7	33	42.3
6	0	0	1	0	1	1	0	75	4.6	47	62.7	28	37.3
7	1	0	1	0	1	1	0	72	4.4	39	54.2	33	45.8
8	1	0	1	0	0	1	0	58	3.6	18	31.0	40	69.0
9	0	0	0	0	0	0	0	47	2.9	21	44.7	26	55.3
10	0	0	1	0	1	1	1	40	2.5	31	77.5	9	22.5
11	0	0	1	1	1	1	1	39	2.4	29	74.4	10	25.6
12	1	0	0	0	0	0	0	37	2.3	21	56.8	16	43.2
13	0	0	1	1	0	1	0	36	2.2	23	63.9	13	36.1
14	1	0	0	0	1	0	0	34	2.1	24	70.6	10	29.4
15	0	0	1	0	0	1	1	32	2.0	17	53.1	15	46.9
16	0	0	0	0	0	1	0	30	1.8	14	46.7	16	53.3
17	1	1	1	0	1	1	0	29	1.8	21	72.4	8	27.6
18	0	0	0	0	1	0	0	28	1.7	21	75.0	7	25.0
19	0	0	1	1	0	0	0	26	1.6	14	53.8	12	46.2
20	1	0	1	0	1	1	1	24	1.5	21	87.5	3	12.5
21	0	0	1	1	0	1	1	24	1.5	10	41.7	14	58.3
22	1	0	0	0	1	1	0	23	1.4	20	87.0	3	13.0
23	1	1	1	0	0	1	0	21	1.3	4	19.0	17	81.0
24	1	0	0	0	0	1	0	21	1.3	11	52.4	10	47.6
25	0	0	0	0	1	1	0	19	1.2	16	84.2	3	15.8
26	1	1	0	0	0	0	0	18	1.1	10	55.6	8	44.4
27	0	0	1	1	1	1	0	18	1.1	14	77.8	4	22.2
28	1	0	1	1	1	1	1	15	0.9	11	73.3	4	26.7

(continued)

Table 1 (continued)

Attributes[a] ID	i.munificent	i.dynamic	i.competitive	c.diversified	c.slack	c.cap.intense	bu.size	Frequencies[b] Number of Cases	%	Case Outcomes[c] Superior Performance Cases	%	Inferior Performance Cases	%
29	0	0	0	1	0	1	1	15	0.9	5	33.3	10	66.7
30	1	0	1	1	0	0	0	14	0.9	9	64.3	5	35.7
31	1	0	1	1	1	0	0	14	0.9	10	71.4	4	28.6
32	0	0	0	1	1	0	0	14	0.9	12	85.7	2	14.3
33	0	0	1	1	1	0	0	14	0.9	10	71.4	4	28.6
34	0	1	0	0	0	0	0	13	0.8	5	38.5	8	61.5
35	1	0	0	1	0	0	0	13	0.8	11	84.6	2	15.4
36	0	0	1	0	1	0	1	13	0.8	10	76.9	3	23.1
37	0	0	0	0	0	1	1	12	0.7	4	33.3	8	66.7
38	1	0	0	1	1	0	0	12	0.7	8	66.7	4	33.3
39	0	0	0	1	1	1	1	12	0.7	9	75.0	3	25.0
40	1	1	1	0	1	0	0	11	0.7	7	63.6	4	36.4
41	0	0	0	0	1	1	1	11	0.7	10	90.9	1	9.1
42	1	1	0	0	1	0	0	11	0.7	10	90.9	1	9.1
43	0	0	1	1	1	0	1	10	0.6	7	70.0	3	30.0
44	1	0	1	1	1	1	0	9	0.6	6	66.7	3	33.3
45	0	0	0	1	0	1	0	9	0.6	6	66.7	3	33.3
46	1	0	0	0	1	0	1	9	0.6	7	77.8	2	22.2
47	0	0	0	1	0	0	0	8	0.5	6	75.0	2	25.0
48	1	0	1	1	0	1	0	8	0.5	5	62.5	3	37.5
49	1	0	1	1	0	1	1	8	0.5	5	62.5	3	37.5
50	0	1	0	0	0	1	0	8	0.5	3	37.5	5	62.5
51	0	1	0	0	1	0	0	8	0.5	4	50.0	4	50.0
52	1	1	0	0	0	1	0	7	0.4	2	28.6	5	71.4
53	1	0	0	0	1	1	1	7	0.4	7	100.0	0	0.0
54	1	0	0	1	1	1	1	7	0.4	7	100.0	0	0.0
55	0	0	0	0	1	0	1	7	0.4	7	100.0	0	0.0
56	1	0	0	1	0	1	1	7	0.4	3	42.9	4	57.1
57	0	0	1	0	0	0	1	6	0.4	3	50.0	3	50.0

(continued)

Table 1 (continued)

Attributes[a] ID	i.munificent	i.dynamic	i.competitive	c.diversified	c.slack	c.cap.intense	bu.size	Frequencies[b] Number of Cases	%	Case Outcomes[c] Superior Performance Cases	%	Inferior Performance Cases	%
58	1	0	0	0	0	1	1	6	0.4	4	66.7	2	33.3
59	0	0	0	1	1	1	0	6	0.4	4	66.7	2	33.3
60	1	0	0	1	1	1	0	6	0.4	5	83.3	1	16.7
61	0	0	0	1	1	0	1	6	0.4	5	83.3	1	16.7
62	0	1	0	1	1	1	1	5	0.3	2	40.0	3	60.0
63	1	1	1	0	1	1	1	5	0.3	5	100.0	0	0.0
64	1	1	1	0	0	0	0	5	0.3	2	40.0	3	60.0
65	0	1	0	1	1	0	0	5	0.3	3	60.0	2	40.0
66	0	1	0	1	0	1	0	5	0.3	4	80.0	1	20.0
67	0	0	0	0	0	0	1	4	0.2	3	75.0	1	25.0
68	0	0	1	1	0	0	1	4	0.2	3	75.0	1	25.0
69	1	0	1	0	0	1	1	4	0.2	1	25.0	3	75.0
70	0	1	1	0	0	1	0	4	0.2	2	50.0	2	50.0
71	1	0	0	1	0	1	0	4	0.2	3	75.0	1	25.0
72	1	1	0	0	1	1	0	4	0.2	3	75.0	1	25.0
73	1	0	0	1	0	0	1	3	0.2	2	66.7	1	33.3
74	1	0	1	0	0	0	1	3	0.2	0	0.0	3	100.0
75	1	0	1	0	1	0	1	3	0.2	2	66.7	1	33.3
76	0	1	0	1	0	0	0	3	0.2	1	33.3	2	66.7
77	0	1	1	0	1	0	0	3	0.2	2	66.7	1	33.3
78	0	1	1	0	1	1	0	3	0.2	2	66.7	1	33.3
79	1	0	0	1	1	0	1	3	0.2	3	100.0	0	0.0
80	1	1	1	1	0	0	0	2	0.1	2	100.0	0	0.0
81	0	1	1	1	1	0	0	2	0.1	2	100.0	0	0.0
82	0	1	1	1	0	0	0	2	0.1	2	100.0	0	0.0
83	1	1	1	0	0	1	1	2	0.1	0	0.0	2	100.0
84	1	1	0	1	0	0	0	2	0.1	0	0.0	2	100.0
85	1	1	1	1	1	1	0	2	0.1	0	0.0	2	100.0
86	0	1	0	0	1	1	0	2	0.1	1	50.0	1	50.0

(continued)

Table 1 (continued)

Attributes[a] ID	i.munificent	i.dynamic	i.competitive	c.diversified	c.slack	c.cap.intense	bu.size	Frequencies[b] Number of Cases	%	Case Outcomes[c] Superior Performance Cases	%	Inferior Performance Cases	%
87	1	1	1	1	0	1	1	2	0.1	2	100.0	0	0.0
88	0	1	1	1	0	1	1	2	0.1	0	0.0	2	100.0
89	1	1	0	0	1	0	1	2	0.1	2	100.0	0	0.0
90	1	0	0	0	0	0	1	2	0.1	0	0.0	2	100.0
91	0	1	0	0	0	0	1	1	0.1	1	100.0	0	0.0
92	0	1	1	1	1	1	1	1	0.1	1	100.0	0	0.0
93	1	0	1	1	0	0	1	1	0.1	1	100.0	0	0.0
94	1	0	1	1	1	0	1	1	0.1	1	100.0	0	0.0
95	1	1	0	1	1	1	0	1	0.1	1	100.0	0	0.0
96	0	1	0	1	0	1	1	1	0.1	0	0.0	1	100.0
97	0	1	1	0	0	1	1	1	0.1	0	0.0	1	100.0
98	1	1	0	0	1	1	1	1	0.1	0	0.0	1	100.0
99	1	1	0	1	0	1	1	1	0.1	0	0.0	1	100.0
100	0	1	0	1	1	1	0	1	0.1	1	100.0	0	0.0
101	0	1	1	1	0	1	0	1	0.1	1	100.0	0	0.0
102	0	1	1	1	1	1	0	1	0.1	1	100.0	0	0.0
103	1	1	1	1	0	1	0	1	0.1	0	0.0	1	100.0
104	1	1	1	1	1	1	1	1	0.1	0	0.0	1	100.0
105	1	1	0	1	0	1	0	1	0.1	1	100.0	0	0.0
106	1	1	0	1	1	0	1	1	0.1	1	100.0	0	0.0
107	1	1	0	1	1	1	1	1	0.1	1	100.0	0	0.0
108	0	0	0	1	0	0	1	0	0.0	—[d]	—	—	—
109	0	1	0	0	0	1	1	0	0.0	—	—	—	—
110	0	1	0	0	1	0	1	0	0.0	—	—	—	—
111	0	1	0	0	1	1	1	0	0.0	—	—	—	—
112	0	1	0	1	0	0	1	0	0.0	—	—	—	—
113	0	1	0	1	1	0	1	0	0.0	—	—	—	—
114	0	1	1	0	0	0	0	0	0.0	—	—	—	—

(continued)

Table 1 (continued)

Attributes[a] ID	i.munificent	i.dynamic	i.competitive	c.diversified	c.slack	c.cap.intense	bu.size	Frequencies[b] Number of Cases	%	Case Outcomes[c] Superior Performance Cases	%	Inferior Performance Cases	%
115	0	1	1	0	0	0	1	0	0.0	—	—	—	—
116	0	1	1	0	1	0	1	0	0.0	—	—	—	—
117	0	1	1	0	1	1	1	0	0.0	—	—	—	—
118	0	1	1	1	0	0	1	0	0.0	—	—	—	—
119	0	1	1	1	1	0	1	0	0.0	—	—	—	—
120	1	1	0	0	0	0	1	0	0.0	—	—	—	—
121	1	1	0	0	0	1	1	0	0.0	—	—	—	—
122	1	1	0	1	0	0	1	0	0.0	—	—	—	—
123	1	1	0	1	1	0	0	0	0.0	—	—	—	—
124	1	1	1	0	0	0	1	0	0.0	—	—	—	—
125	1	1	1	0	1	0	1	0	0.0	—	—	—	—
126	1	1	1	1	0	0	1	0	0.0	—	—	—	—
127	1	1	1	1	1	0	0	0	0.0	—	—	—	—
128	1	1	1	1	1	0	1	0	0.0	—	—	—	—

a. Attributes are labeled as follows: 1 = *membership in set*, 0 = *not membership in set*.
b. Percentage of manufacturing sector sample.
c. Percentage of cases within configurations.
d. Not applicable.

Table 2
Truth Table—Service Sector

Attributes[a] ID	i.munificent	i.dynamic	i.competitive	c.diversified	c.slack	c.cap.intense	bu.size	Frequencies[b] Number of Cases	%	Case Outcomes[c] Superior Performance Cases	%	Inferior Performance Cases	%
1	0	0	1	0	1	0	0	141	17.5	77	54.6	45.4	
2	0	0	1	0	0	0	0	106	13.2	28	26.4	78	73.6
3	1	0	1	0	0	0	0	53	6.6	14	26.4	39	73.6
4	1	0	1	0	1	0	0	40	5.0	31	77.5	9	22.5
5	1	1	1	0	1	0	0	29	3.6	17	58.6	12	41.4
6	0	1	1	0	1	0	0	24	3.0	11	45.8	13	54.2
7	0	0	1	0	0	0	1	23	2.9	7	30.4	16	69.6
8	0	0	1	0	1	1	0	23	2.9	15	65.2	8	34.8
9	0	0	1	0	1	0	1	19	2.4	16	84.2	3	15.8
10	1	0	1	0	1	0	1	17	2.1	9	52.9	8	47.1
11	0	0	1	0	0	1	0	16	2.0	6	37.5	10	62.5
12	0	1	1	0	0	0	0	16	2.0	2	12.5	14	87.5
13	1	1	0	0	0	0	0	15	1.9	3	20.0	12	80.0
14	1	0	1	0	0	0	1	14	1.7	4	28.6	10	71.4
15	1	0	1	0	0	1	0	14	1.7	3	21.4	11	78.6
16	1	0	0	0	0	0	0	13	1.6	1	7.7	12	92.3
17	0	0	0	0	0	0	0	12	1.5	3	25.0	9	75.0
18	1	1	0	0	1	1	0	11	1.4	4	36.4	7	63.6
19	0	0	1	0	1	1	1	10	1.2	8	80.0	2	20.0
20	0	0	1	1	0	1	0	10	1.2	3	30.0	7	70.0
21	1	0	1	1	0	1	0	10	1.2	6	60.0	4	40.0
22	1	1	1	0	0	0	0	10	1.2	3	30.0	7	70.0
23	1	1	0	0	0	1	0	10	1.2	1	10.0	9	90.0
24	0	0	0	0	1	0	0	9	1.1	6	66.7	3	33.3
25	1	0	1	0	1	1	0	8	1.0	3	37.5	5	62.5
26	1	1	0	0	1	0	0	7	0.9	3	42.9	4	57.1

(continued)

Table 2 (continued)

Attributes[a] ID	i.munificent	i.dynamic	i.competitive	c.diversified	c.slack	c.cap.intense	bu.size	Frequencies[b] Number of Cases	%	Case Outcomes[c] Superior Performance Cases	%	Inferior Performance Cases	%
27	0	1	1	0	1	1	0	6	0.7	2	33.3	4	66.7
28	1	1	1	0	1	1	0	6	0.7	3	50.0	3	50.0
29	1	0	1	1	0	0	0	6	0.7	2	33.3	4	66.7
30	0	0	1	0	0	1	1	6	0.7	2	33.3	4	66.7
31	1	0	1	1	1	1	0	5	0.6	2	40.0	3	60.0
32	0	0	0	0	1	0	1	5	0.6	2	40.0	3	60.0
33	1	0	1	1	1	0	0	5	0.6	4	80.0	1	20.0
34	1	1	1	1	1	0	0	5	0.6	4	80.0	1	20.0
35	1	1	0	1	0	1	0	4	0.5	3	75.0	1	25.0
36	0	1	0	0	1	0	0	4	0.5	1	25.0	3	75.0
37	1	1	0	0	0	0	1	4	0.5	0	0.0	4	100.0
38	0	1	1	0	0	1	0	4	0.5	0	0.0	4	100.0
39	1	0	0	0	1	0	1	3	0.4	1	33.3	2	66.7
40	0	0	1	1	1	1	1	3	0.4	1	33.3	2	66.7
41	0	1	1	1	0	1	1	3	0.4	0	0.0	3	100.0
42	1	0	0	0	0	1	0	3	0.4	1	33.3	2	66.7
43	0	0	1	1	1	0	0	3	0.4	2	66.7	1	33.3
44	1	0	0	1	0	1	0	3	0.4	1	33.3	2	66.7
45	1	0	1	0	1	1	1	3	0.4	3	100.0	0	0.0
46	1	1	0	0	1	1	1	2	0.2	2	100.0	0	0.0
47	1	0	1	1	1	1	1	2	0.2	2	100.0	0	0.0
48	1	0	0	0	1	0	0	2	0.2	2	100.0	0	0.0
49	1	0	0	0	0	0	1	2	0.2	2	100.0	0	0.0
50	0	1	1	1	0	0	0	2	0.2	2	100.0	0	0.0
51	0	1	1	1	1	0	1	2	0.2	0	0.0	2	100.0
52	0	0	1	1	1	1	0	2	0.2	2	100.0	0	0.0
53	1	0	1	1	0	0	1	2	0.2	1	50.0	1	50.0
54	1	1	0	0	1	0	1	2	0.2	0	0.0	2	100.0

(continued)

Table 2 (continued)

Attributes[a]								Frequencies[b]		Case Outcomes[c]			
ID	i.munificent	i.dynamic	i.competitive	c.diversified	c.slack	c.cap.intense	bu.size	Number of Cases	%	Superior Performance Cases	%	Inferior Performance Cases	%
55	1	1	1	0	0	1	0	2	0.2	0	0.0	2	100.0
56	0	0	0	1	1	0	1	2	0.2	2	100.0	0	0.0
57	0	1	1	1	1	1	1	2	0.2	1	50.0	1	50.0
58	0	0	0	0	0	1	1	2	0.2	1	50.0	1	50.0
59	0	1	1	1	1	0	0	2	0.2	1	50.0	1	50.0
60	0	0	0	1	0	1	0	1	0.1	1	100.0	0	0.0
61	1	1	1	1	1	0	1	1	0.1	1	100.0	0	0.0
62	1	0	0	1	1	1	1	1	0.1	1	100.0	0	0.0
63	1	0	0	0	1	1	1	1	0.1	1	100.0	0	0.0
64	1	0	0	1	1	0	0	1	0.1	1	100.0	0	0.0
65	1	1	0	1	0	0	0	1	0.1	1	100.0	0	0.0
66	1	0	0	1	1	0	1	1	0.1	1	100.0	0	0.0
67	0	1	1	0	1	1	1	1	0.1	1	100.0	0	0.0
68	0	1	0	1	1	0	0	1	0.1	1	100.0	0	0.0
69	0	1	0	1	0	1	0	1	0.1	1	100.0	0	0.0
70	0	1	0	0	1	1	0	1	0.1	1	100.0	0	0.0
71	0	0	1	1	1	0	1	1	0.1	1	100.0	0	0.0
72	0	0	1	1	0	0	0	1	0.1	1	100.0	0	0.0
73	0	0	0	1	1	1	1	1	0.1	1	100.0	0	0.0
74	0	0	0	1	1	0	0	1	0.1	1	100.0	0	0.0
75	1	0	0	0	0	1	1	1	0.1	0	0.0	1	100.0
76	0	0	0	1	0	0	0	1	0.1	1	100.0	0	0.0
77	0	0	0	0	1	1	1	1	0.1	1	100.0	0	0.0
78	1	1	0	1	1	0	0	1	0.1	0	0.0	1	100.0
79	0	1	0	0	0	0	0	1	0.1	0	0.0	1	100.0
80	0	0	1	1	0	0	1	1	0.1	0	0.0	1	100.0
81	0	1	1	1	1	1	0	1	0.1	0	0.0	1	100.0
82	0	1	1	1	0	1	0	1	0.1	0	0.0	1	100.0

(continued)

Table 2 (continued)

Attributes[a]								Frequencies[b]		Case Outcomes[c]			
										Superior Performance		Inferior Performance	
ID	i.munificent	i.dynamic	i.competitive	c.diversified	c.slack	c.cap.intense	bu.size	Number of Cases	%	Cases	%	Cases	%
83	0	0	0	0	0	1	0	1	0.1	1	100.0	0	0.0
84	1	1	1	1	1	1	0	1	0.1	0	0.0	1	100.0
85	1	1	1	1	0	1	0	1	0.1	0	0.0	1	100.0
86	1	1	1	1	0	0	0	1	0.1	0	0.0	1	100.0
87	1	1	1	0	0	0	1	1	0.1	0	0.0	1	100.0
88	1	0	1	0	0	1	1	1	0.1	0	0.0	1	100.0
89	0	1	0	0	1	0	1	1	0.1	0	0.0	1	100.0
90	0	0	1	1	0	1	1	1	0.1	0	0.0	1	100.0
91	0	0	0	1	1	1	0	1	0.1	0	0.0	1	100.0
92	0	0	0	1	0	0	1	1	0.1	0	0.0	1	100.0
93	0	0	0	0	1	1	0	1	0.1	0	0.0	1	100.0
94	0	0	0	0	0	0	1	1	0.1	0	0.0	1	100.0
95	0	0	0	1	0	1	1	0	0.0	—[d]	—	—	—
96	0	1	0	0	0	0	1	0	0.0	—	—	—	—
97	0	1	0	0	0	1	0	0	0.0	—	—	—	—
98	0	1	0	0	0	1	1	0	0.0	—	—	—	—
99	0	1	0	0	1	1	1	0	0.0	—	—	—	—
100	0	1	0	1	0	0	0	0	0.0	—	—	—	—
101	0	1	0	1	0	0	1	0	0.0	—	—	—	—
102	0	1	0	1	0	1	1	0	0.0	—	—	—	—
103	0	1	0	1	1	0	1	0	0.0	—	—	—	—
104	0	1	0	1	1	1	0	0	0.0	—	—	—	—
105	0	1	0	1	1	1	1	0	0.0	—	—	—	—
106	0	1	1	0	0	0	1	0	0.0	—	—	—	—
107	0	1	1	0	0	1	1	0	0.0	—	—	—	—
108	0	1	1	0	1	0	1	0	0.0	—	—	—	—
109	0	1	1	1	0	0	1	0	0.0	—	—	—	—
110	1	0	0	0	1	1	0	0	0.0	—	—	—	—

(continued)

Table 2 (continued)

Attributes[a]								Frequencies[b]		Case Outcomes[c]			
										Superior Performance		Inferior Performance	
ID	i.munificent	i.dynamic	i.competitive	c.diversified	c.slack	c.cap.intense	bu.size	Number of Cases	%	Cases	%	Cases	%
111	1	0	0	1	0	0	0	0	0.0	—	—	—	—
112	1	0	0	1	0	0	1	0	0.0	—	—	—	—
113	1	0	0	1	0	1	1	0	0.0	—	—	—	—
114	1	0	0	1	1	1	0	0	0.0	—	—	—	—
115	1	0	1	1	0	1	1	0	0.0	—	—	—	—
116	1	0	1	1	1	0	1	0	0.0	—	—	—	—
117	1	1	0	0	0	1	1	0	0.0	—	—	—	—
118	1	1	0	1	0	0	1	0	0.0	—	—	—	—
119	1	1	0	1	0	1	1	0	0.0	—	—	—	—
120	1	1	0	1	1	0	1	0	0.0	—	—	—	—
121	1	1	0	1	1	1	0	0	0.0	—	—	—	—
122	1	1	0	1	1	1	1	0	0.0	—	—	—	—
123	1	1	1	0	0	1	1	0	0.0	—	—	—	—
124	1	1	1	0	1	0	1	0	0.0	—	—	—	—
125	1	1	1	0	1	1	1	0	0.0	—	—	—	—
126	1	1	1	1	0	0	1	0	0.0	—	—	—	—
127	1	1	1	1	0	1	1	0	0.0	—	—	—	—
128	1	1	1	1	1	1	1	0	0.0	—	—	—	—

a. Attributes are labeled as follows: 1 = *membership in set*, 0 = *not membership in set*.
b. Percentage of service sector sample.
c. Percentage of cases within configurations.
d. Not applicable.

contain descriptive analyses of the manufacturing and service sectors, respectively (see the right-hand panels in Tables 1 and 2). The "frequencies" column of both tables reports the number of cases inhabiting each of the locations in the property space including the percentage of cases in the respective sector sample this represents reported in parentheses. These distributions show not only the observed configurations in empirical reality but also their diversity and *limited diversity* (Ragin, 1987). Limited diversity refers to a situation where not all theoretically possible configurations exist in empirical reality because "the potential variety is limited by the attributes' tendency to fall into coherent patterns" (Meyer et al., 1993, p. 1176). To more clearly illustrate these patterns, the logically possible configurations in both Tables 1 and 2 are ordered in terms of the frequency of cases: The configuration with the greatest number of cases is presented first and those configurations with no cases are presented at the end. As shown in Table 1, for example, the 1,630 cases in the manufacturing sector fall into 107 configurations, leaving 21 configurations in the property space without observations. The most frequently occurring configuration (ID 1) accounts for 5.9% of the manufacturing sample (96 cases).

The final piece of descriptive information provided in Tables 1 and 2 pertains to the distribution of the outcomes of interest across the property space: the number and percentage of cases displaying above average performance (see the "superior performance cases" columns) and below-average performance (see the "inferior performance cases" columns) within each configuration. For instance, less than one third of the cases (31.3%) of the most frequently occurring configuration in the manufacturing sector (ID 1 in Table 1) achieve superior performance. In the service sector, just more than half of the cases (54.6%) in the most frequently occurring configuration (ID 1 in Table 2) achieve above average profitability.

Table 3 provides a descriptive overview for all four sectors. As can be seen from this table, both the diversity among those cases that empirically exist and the limited diversity differ greatly across sectors. To compare diversity across industry sectors, we calculated a Herfindahl index of diversity (H) and a four-configuration concentration measure. As can be seen from these measures, our sample's diversity is greatest in the manufacturing sector ($H = 0.028$) and smallest in the mining sector ($H = 0.2$).[3] In terms of limited diversity, in the manufacturing sector, 21 configurations are not represented in our sample. In the telecom sector this number is 87, in the service sector 34, and in the mining sector 106.

Analysis 2: Examining the sufficiency of causal conditions. The second analysis that can be conducted once the property space is constructed is the examination of the causal conditions that are sufficient for the outcome of interest. To do so, the QCA approach uses Boolean methods to assess whether attributes of cases are necessary and/or sufficient for the outcome of interest to occur: "A cause is necessary if it must be present for a certain outcome to occur. . . . A cause is defined as sufficient if by itself it can produce a certain outcome" (Ragin, 1987, p. 99). In other words, when a causal condition (a single cause or causal combination) is necessary for an outcome, then all occurrences of the outcome (i.e., cases) will exhibit that same causal condition. On the other hand, when causal conditions are sufficient for an outcome, then all occurrences of the causal conditions are followed by the outcome of interest. Although both necessity and sufficiency should generally be investigated (and indeed, the QCA software enables this), the "main

Table 3
Descriptive Overview of Diversity

	Sector.Mine	Sector.Manuf.	Sector.Telecom	Sector.Service
Number of logically possible configurations	128	128	128	128
Number of configurations existing in our sample	22	107	41	94
Number of configurations not existing in our sample[a]	106	21	87	34
Percentage of configurations not existing in our sample	82.8	16.4	68.0	26.6
Number of cases	165	1,630	242	804
Number of cases of most frequent configuration[b]	55	96	31	141
Percentage of cases of most frequent configuration	33.3	5.89	12.8	17.5
Four = configuration concentration	0.74	0.22	0.41	0.42
Herfindahl index of diversity (H)	0.2	0.028	0.062	0.064

a. Percentage of logically possible configurations.
b. Percentage of cases in sector sample.

recommendation for dealing with causal complexity is to focus on the sufficiency of combinations of causal conditions'' (Ragin, 2000, p. 104). This is because causal complexity inherently means that two or more different combinations of attributes can be sufficient for the same outcome and that a specific attribute may have different and even opposite causal effects depending on the context provided by the configuration with other attributes. Therefore, the QCA approach generally focuses on examining the sufficiency of attributes and their combinations, a focus that we adopt here in the current demonstration.

In assessing causal sufficiency, QCA employs the probabilistic concept of *quasi sufficiency* wherein sufficiency is assessed based on certain benchmarks: A causal condition can be almost always sufficient (significantly passing a benchmark of 0.8), usually sufficient (significantly passing a benchmark of 0.65), or sufficient more often than not (significantly passing a benchmark of 0.50) in causing the outcome (Ragin, 2000). In all following analyses, we uniformly assess quasi sufficiency as usually sufficient (benchmark proportion = .65, (= .05). Statistical significance of quasi sufficiency is assessed by means of z tests for those causal groupings representing more then 30 cases (the z test is a large-N approximation of the binomial probability test and can be applied given 30 or more cases), and binomial probabilities for those configurations representing 7 (given the benchmark set) or more but fewer than 30 cases. However, in situations with very small N values (smaller then 7 cases), probabilistic criteria do not allow us to draw statistically significant conclusions or reject the null hypothesis that the observed proportion of superior (or inferior) performance is the same as or less than the set benchmark, even if all cases uniformly show the same outcome (Ragin, 2000).

The analysis proceeds by utilizing a Boolean algorithm to assess whether any causal combinations are sufficient to cause the outcome of interest. To gain a basic understanding of this algorithm, we introduce fundamental notations of Boolean algebra and three main Boolean operators and their notation: logical *and* (symbolized by the operator •), logical *or* (symbolized by the operator +), and logical *not* (symbolized by the operator ~) (for an in-depth presentation of Boolean operations, see Ragin, 1987, 2000). To exemplify the latter notation, consider the first attribute in the first configuration in Table 1 (ID 1): because i.munificent is equal to 0 (nonmembership in the set of munificent industries), it would be presented in an equation as ~ i.munificent.

The two basic operators in Boolean algebra, logical *and* and logical *or,* facilitate the analysis of combinations of causal factors by representing two primary means by which factors can combine. First, the logical *and* (•) operator represents the intersection of sets. Each location in a property space represents such a combination, representing a logically possible intersection of the causal attributes involved. For example, configuration ID 2 in the service sector (see Table 2) would be written in equation form utilizing Boolean symbols:

$$\sim \text{i.munificent} \bullet \sim \text{i.dynamic} \bullet \text{i.competitive} \bullet \sim \text{c.diversified} \bullet \sim \text{c.slack} \bullet \sim \text{c.cap.intense} \bullet \sim \text{bu.size}.$$

Second, the logical *or* (+) operator represents the union of two sets; it is used when either one causal condition *or* another may lead to the same outcome. Combining this operator with the logical *and* enables the representation of complex causality. For example, suppose that configurations ID 2 and ID 12 from the service sector (see Table 2) were both found to be usually sufficient for yielding inferior performance. Using Boolean algebra, this finding could be represented as follows (where → denotes Boolean implication):

$$\sim \text{i.munificent} \bullet \sim \text{i.dynamic} \bullet \text{i.competitive} \bullet \sim \text{c.diversified} \bullet \sim \text{c.slack} \bullet \sim \text{c.cap.intense} \bullet \sim \text{bu.size} + \sim \text{i.munificent} \bullet \text{i.dynamic} \bullet \text{i.competitive} \bullet \sim \text{c.diversified} \bullet \sim \text{c.slack} \bullet \sim \text{c.cap.intense} \bullet \sim \text{bu.size} \rightarrow \text{inferior performance}.$$

The Boolean algorithm employed by QCA to reduce causal complexity to a minimal Boolean equation of the combinations of attributes that are quasi sufficient for an outcome to occur is putting the Boolean principles briefly discussed here to work. Although an in-depth explanation of this algorithm, and its implementation of the *containment rule*, is beyond the scope of the current presentation, and because a software package is available that performs this algorithm for researchers (Ragin, Drass, & Davey, 2006), we describe it here only briefly (for a more detailed explanation of the containment rule, see Ragin, 2000). In short, this algorithm first establishes the number of logically possible groupings of all Boolean attributes included in the study. This number is arrived at by the formula of $3^k - 1$, where k is the number of attributes (in our case, $3^7 - 1 = 2{,}186$). These groupings incorporate all possible causal conditions: all single causal factors (including their negation; e.g., both bu.size and ~ bu.size are included); all causal combinations including two attributes (e.g., bu.size • c.slack; ~ bu.size • ~ c.slack; bu.size • ~ c.slack; ~ bu.size • c.slack; etc.); and so on (i.e., in the current study through all causal combinations including three, four, five, six, and all seven attributes). The algorithm consequently assesses the probabilistic sufficiency of each combination of attributes; sufficiency tests are conducted for each of the $3^k - 1$ possible combinations, based on the a priori benchmark of sufficiency set by the researcher (i.e., the benchmark for usual sufficiency, benchmark = .65, at (= .05). In the final step, the algorithm uses the containment rule to minimize the Boolean equation of all those combinations of attributes that pass the test of sufficiency. The containment rule applies Boolean logic to simplify the Boolean equation by examining if any of the groupings of attributes that pass the sufficiency test are contained within other groupings and are thus logically redundant and can be joined.

Table 4 reports the final Boolean expressions (minimized through the containment rule) of the causal conditions usually sufficient for superior and inferior performance for both the manufacturing (Panel A) and service (Panel B) sectors. In the next section we turn to the final phase of QCA, an evaluation and interpretation of these results.

Evaluation and Interpretation of Results

The final phase of QCA involves evaluating and interpreting the results of the foregoing analyses. Because the QCA approach presents a paradigmatic shift from conventional linear statistical approaches (Fiss, in press), it is worth reiterating the meaning of sufficiency: A combination of attributes is assessed as being sufficient for the desired outcome when all instances of the combination are followed by the occurrence of the outcome. Again, sufficiency assessments in QCA make use of probabilistic comparisons, therefore a combination is deemed as quasi sufficient if the outcome of interest occurs in a proportion of cases displaying the causal condition that is significantly higher than the set benchmark (here, 0.65 or *usually sufficient*). Thus, the general interpretation of the minimized Boolean equations reported in Table 4 is that these represent the causal conditions that are usually sufficient for superior and inferior performance. Furthermore, recall that in these equations, + denotes Boolean *or*, • denotes Boolean *and*, and the ~ denotes nonmembership in the particular set. Thus, for example, the results in Table 4 suggest that in the service sector (see left side of Panel B), four different combinations of industry, corporate, and business-unit attributes are usually sufficient for superior performance: Each statement joined by the operator • represents a combination of attributes that is usually sufficient for superior performance; these statements are joined by the Boolean operator + signifying that there are four alternative combinations of attributes that are usually sufficient to produce this performance outcome.

These results advance the extant strategic management literature on the industry, corporate, and business-unit determinants of business-unit performance by shedding light on several specific issues: (a) the interdependence among factors, (b) that corporate factors are important to understanding performance, and (c) the complexity underlying the determination of performance. First, the results reported in Table 4 illuminate the interdependence among industry, corporate, and business-unit factors in determining business-unit performance, as the conditions usually sufficient for superior and inferior performance in both sectors encompass a variety of combinations among industry, corporate, and business-unit attributes. In the manufacturing sector, seven conditions were usually sufficient for superior performance (see left side of Panel A, Table 4): One is a single corporate attribute (Condition 1ms); one is a combination of industry and business-unit attributes

Table 4
Industry, Corporate and Business-unit Attributes Usually Sufficient for Superior and Inferior Performance1

Panel A: Manufacturing Sector (Benchmark proportion .65, α = .05)			
Superior Performance		Inferior Performance	
c.slack +	*(1ms)*	i.munificent ● i.competitive ● ~ c.diversified ● ~ c.slack +	*(1mi)*
i.munificent ● c.diversified +	*(2ms)*	i.competitive ● ~ c.diversified ● ~ c.slack ● ~ c.cap.intense	*(2mi)*
i.munificent ● f.size +	*(3ms)*		
i.munificent ● ~ i.dynamic ● ~ i.competitive +	*(4ms)*		
~ i.dynamic ● c.diversified ● ~ c.cap.intense +	*(5ms)*		
~ i.competitive ● ~ c.cap.intense ● f.size +	*(6ms)*		
~ i.dynamic ● ~ i.competitive ● c.diversified ● ~ f.size	*(7ms)*		
→ Superior Performance		→ Inferior Performance	
Panel B: Service Sector (Benchmark proportion .65, α = .05)			
Superior Performance		Inferior Performance	
~ i.dynamic ● c.slack ● f.size +	*(1ss)*	~ c.slack +	*(1si)*
c.slack ● c.cap.intense ● f.size +	*(2ss)*	i.dynamic ● ~ i.competitive ● ~ c.cap.intense ● f.size +	*(2si)*
i.competitive ● ~ c.diversified ● c.slack ● f.size +	*(3ss)*	i.dynamic ● ~ c.diversified ● ~ c.cap.intense ● f.size	*(3si)*
i.munificent ● ~ i.dynamic ● c.slack ● ~ c.cap.intense ● ~ f.size	*(4ss)*		
→ Superior Performance		→ Inferior Performance	

[1]Notation: ● Boolean AND (i.e., intersection);
+ Boolean OR (i.e., union)
~ Boolean Negation (i.e., non-membership)
→ Boolean Implies

(3ms); one is a combination of only industry attributes (4ms); two involve combinations of industry and corporate attributes (2ms, 5ms); and two involve the intersection among industry, corporate, and business-unit attributes (6ms, 7ms). As the right side of Panel A (Table 4) shows, the two conditions usually sufficient for inferior performance in the manufacturing sector are combinations of industry and corporate attributes (Conditions 1mi and 2mi).

Panel B of Table 4 shows the results for the service sector. Three out of the four conditions usually sufficient for superior performance are combinations of industry, corporate, and business-unit attributes (Conditions 1ss, 3ss, and 4ss; left side of Panel B), whereas the remaining one is a combination of corporate and business-unit attributes (2ss). Similarly, two of the three combinations sufficient for inferior performance contain all three types of attributes (Conditions 2si and 3si; see right side of Panel B, Table 4), whereas the other consists of a single corporate attribute (1si).

Second, an examination of the content of these relationships also informs the ongoing debate as to the importance of corporate parents (Bowman & Helfat, 2001; Brush & Bromiley, 1997; Brush et al., 1999). The results suggest that corporate attributes are consequential to performance: With the exception of two of the seven combinations sufficient for superior performance in the manufacturing sector (Conditions 3ms and 4ms; see left side of Panel A, Table 4), the remaining causal conditions involve at least one of the corporate attributes under study. One specific finding is that abundant corporate resources (or lack thereof) are a key for business-unit performance. With regard to superior performance, c.slack is the only single attribute usually sufficient for superior business-unit performance in the manufacturing sector (Condition 1ms, Panel A, Table 4). In the service sector, c.slack is present in all four configurations usually sufficient for superior performance (see left side of Panel B, Table 4). Moreover, corporate parents not having abundant slack resources appear to be an important ingredient for inferior business-unit performance: ∼ c.slack is part of both combinations that are usually sufficient for inferior performance in the manufacturing sector (Conditions 1mi and 2mi; Panel A, Table 4) and it is usually sufficient for the outcome of inferior performance in the service sector (Condition 1si; Panel B, Table 4). A second finding with regard to corporate factors is the role of corporate diversification among the combinations in the manufacturing sector: A highly diversified corporate parent (c.diversified) is part of three of the combinations usually sufficient for superior business-unit performance in this sector (Conditions 2ms, 5ms, 7ms; Panel A, Table 4), whereas the absence of diversification (∼.c.diversified) is part of both combinations that are usually sufficient for inferior performance (see right side of Panel A).

Third, to focus on corporate attributes, however, risks missing the important point that the pattern of results demonstrates the causal complexity of business-unit performance: Performance rarely has a single cause, the causes are interdependent, and the direction of the effect of specific causes may change with causal context. Thus, although the findings show that corporate attributes clearly matter for performance, an overall evaluation of the current analyses suggests that their importance is contingent on the type of industry environment and business-unit conditions with which they combine. The results with respect to corporate diversification (c.diversified) illustrate this conclusion. For example, in the manufacturing sector, c.diversified combines to be usually sufficient for superior performance under three very different conditions, (a) when the business unit is located in a highly munificent industry (Condition 2ms; Panel A, Table 4) or (b) when the business unit is located in an industry that is not highly dynamic and in a corporate parent that is not capital intensive (Condition 5ms) or (c) the business unit is not large and located in an industry that is not highly dynamic and not competitive (Condition 7ms).

Causal complexity can also be examined from the perspective of industry or business-unit attributes. For example, a munificent industry (i.munificent) is part of several very different combinations usually sufficient for superior performance in the manufacturing sector (Conditions 2ms, 3ms, 4ms; Panel A, Table 4). However, unlike with the findings with regard to corporate slack, nonmembership in a munificent industry is not an element in the combinations usually sufficient for inferior performance in the manufacturing sector (or in the service sector for that matter). To the contrary, membership in a munificent industry is part of one of the conditions usually sufficient for inferior performance in the manufacturing sector (Condition 1mi; Panel A). Hence, membership in a munificent industry may contribute to both superior and inferior performance; the type of performance outcome achieved in a munificent industry depends on other industry attributes and as corporate and business-unit attributes.

Discussion and Conclusion

In this study, we have demonstrated that QCA is a valuable addition to the methodological tool kit of strategic management researchers. As a platform for demonstrating QCA, we have shown how QCA can advance our understanding of a fundamental and enduring issue in strategic management research: the industry, corporate, and business-unit determinants of business-unit performance. Thus, the present study not only illustrates the potential of this method for strategic management research, but also sheds light on an issue that has challenged previous linear statistical methodologies in the industry, corporate, and business-unit literature (Hough, 2006; McGahan & Porter, 2002; Misangyi et al., 2006). Specifically, our analysis both finds and investigates the nonindependence of industry, corporate, and business-unit effects by focusing on combinations of these attributes that are sufficient for performance outcomes. Our findings clearly show that there is substantial interdependence among industry, corporate, and business-unit attributes in determining business-unit performance. Moreover, they illustrate the causal complexity that underlies the determination of performance. The results suggest that two or more different combinations of attributes can be sufficient for attaining the same outcome and that any particular attribute may have different and even opposite effects depending on the presence or absence of other attributes.

We have demonstrated the ability of QCA to investigate this kind of interdependence and causal complexity by examining whether and how these causal conditions differ across industry sectors and across performance outcomes, both superior and inferior. Indeed, the results show that the combinations of attributes usually sufficient for superior and inferior performance differ across sectors of the economy, thereby directly addressing an area previously identified as needing future research (McGahan & Porter, 2002). Moreover, the results unequivocally suggest that corporate attributes matter to business-unit performance and help to move the debate in the literature away from "whether corporate strategy matters" (e.g., Bowman & Helfat, 2001) toward "where does corporate strategy matter?"

Although the addition of QCA to the repertoire of methodologies available to strategic management research holds great promise, it is not a panacea for all research venues in the field. Like any methodology, set-theoretic approaches have limitations in their own right. To discuss when QCA may be an appropriate methodology for future strategy research, we first make note of several limitations of the present study and consequently expand the discussion to raise a number of considerations for strategy researchers in deciding whether QCA, in their research projects, may be a desirable alternative to more conventional linear statistical methods.

First, given that the QCA method employs probabilistic criteria in capturing complex combinations of attributes, it is possible that the configurations reported in Table 4 may to some degree capitalize on chance, and thus may not generalize to other property spaces constructed with the same theoretical attributes in different samples. We thus attempted to examine the robustness of our findings by performing a post hoc analysis wherein we split the sector samples randomly into two subsamples and reran the analyses examining the causal conditions sufficient for superior and inferior performance. The findings across the subsamples were qualitatively consistent with those for the full sample as reported in Table 4. In both subsamples, the causal conditions found to be sufficient for the performance outcomes encompassed a variety of combinations of industry, corporate, and business-unit factors; there was a great deal of interdependence among factors; the causal conditions differed across sectors of the economy; corporate attributes played an integral role in the causal conditions; causal complexity was present. This "cross-validation" suggests that the findings in Table 4 and the accompanying interpretations presented above are robust.

Second, in QCA's property space approach, the inclusion of different sets of attributes constructs different property spaces and hence potentially different configurations of causal attributes. Thus, the results of any QCA are bound by the attributes included in the study. An addition of attributes in QCA redefines the property space and the logically possible configurations located within it. Theory, previous research findings, and parsimony guided our choices of the industry, corporate, and business-unit attributes included in our analysis. These particular attributes are by no means exhaustive, however, and clearly the property space they have created for the QCA we performed, and thus its findings, are subject to this limitation. Furthermore, following previous studies in the literature on industry, corporate, and business unit effects on performance (e.g., McGahan & Porter, 1997, 2002; Roquefort et al., 1996), we examined industry sectors at a very broad level, and therefore these industry sectors included a considerable degree of heterogeneity. Future research is needed to further explore the sufficiency of other potential configurations of industry, corporate, and business-unit attributes to business-unit performance, and more refined analyses of industry contexts.

A final caveat with respect to the present study is that in our demonstration we purposefully limited our assessment of set memberships to crisp sets. It is important to recognize, however, that future research can also benefit from a QCA approach that utilizes "fuzzy sets" (for an in-depth discussion, see Ragin, 2000). A fuzzy set, in addition to the two qualitative states of full membership and full nonmembership, also permits partial set membership in the interval between 0 and 1. In other words, the fuzzy set approach allows for the investigation of both differences in kind (as do crisp sets) and differences in degree (which crisp sets do not), and thus offers great potential for more fine-grained assignment of set memberships using information from continuous measurements of data. Although fuzzy sets do allow for a more fine-tuned calibration (an investigation of degree) within any particular set, the approach and methodology (including qualitative break points) are still the same as in QCA: They are both based on Boolean analysis and focused on capturing causal complexity by analyzing patterns in set memberships. Therefore, the current demonstration of the crisp set approach to QCA effectively introduces the set-theoretic methodology in an accessible manner for the new user. Nevertheless, strategic management researchers interested in the QCA approach should also consider the appropriateness of using fuzzy sets when designing set-theoretic studies.

At a more general level, the QCA approach differs from the linear statistical methodologies conventionally utilized by strategic management researchers in both its objectives and means, and is most likely not appropriate for all types of strategic management research. Therefore, we close with a brief examination of some of the contingencies under which a QCA approach may prove especially beneficial to conducting such research and thus be a viable alternative to a linear approach. We focus on two primary considerations in deciding on the use of either QCA or linear modeling, and thus our discussion of contingencies is illustrative rather than exhaustive.

First, a situation for which QCA is especially well suited is that which gave rise to its initial creation: small-*N* analyses in which researchers are faced with a number of cases too small for the application of conventional linear statistical methods but at the same time too large for the in-depth qualitative analysis generally utilized for very small numbers of cases (Ragin, 1987, 2000). For example, future research on strategic groups would benefit from this capability of QCA, as by their very nature strategic groups are theorized to represent differences in kind with regard to the competitors within an industry with a few attributes capturing the essential strategic differences among firms in the industry. Moreover, the number of strategic groups within any particular industry, and the number of firms within them, is generally rather small, and in their respective niches of the industry environment they may face environments that are different in kind (Porter, 1980). QCA's property space approach could thus prove to be beneficial for research on the relations among competitive spaces, strategic behaviors, and organizational performance (Hodgkinson, 1997; Reger & Huff, 1993) by mapping these competitive spaces in situations with small sample sizes. As mentioned above, this is also pertinent within the context of the literature on industry, corporate, and business-unit effects: QCA is well suited to further study cases at more narrowly defined sectoral levels, or even within single industries, wherein the number of competitors may be fairly small. Of course, as the current study illustrates, the usefulness of QCA is not limited to small-*N* samples: Depending on the intent of the research, it can provide an effective alternative to general linear statistical models in large-*N* samples.

Second, a key consideration is whether the researcher is interested in isolating independent effects or in studying combinations of effects. For research interested in the former, linear statistical approaches are clearly more appropriate as they estimate the effect of an independent variable on some dependent variable of interest. For research interested in the latter, QCA is a valuable tool for identifying and investigating interdependencies and causal complexity among causal factors, as was demonstrated in this study. In QCA, causal factors are not expected to independently operate from each other and are expected to vary in their effects on outcomes depending on the presence or absence of other factors. Thus, causal explanations for an outcome become *multiple conjunctural* (Becker, 1998); conjunctural because causes are understood as combinations of factors, and multiple because many different combinations might produce the same outcome of interest. Therefore, QCA is a research strategy and methodology that is highly appropriate for the investigation of configurational theories (see Fiss, in press; Meyer et al., 1993; Miller, 1986, 1996), ideal types or prototypes (Kogut et al., 2004; Mintzberg, 1979, 1980), and theories of embeddedness (e.g., Granovetter, 1985), which all explicitly theorize that causal attributes work in particular combinations rather than in isolation. Moreover, set-theoretic approaches stand to greatly benefit future research on generic strategies; QCA would be an appropriate methodology to investigate Porter's (1980) classic theoretical argument of generic business-level strategies (i.e., cost advantage vs. differentiation advantage). This framework of generic strategies suggests that resources and capabilities (cost and value drivers) combine in specific and different ways to constitute specific strategic positions.

In conclusion, the QCA approach offers strategic management researchers a valuable alternative to conventional statistical linear approaches in investigating some of the most pressing issues in the field. QCA's focus on interdependencies and causal complexity of causal attributes, and its use of a property space approach to assessing the sufficiency of causal conditions to an outcome of interest offers an alternative mode of inquiry which stands to yield new and further insights to the field of strategy. As shown in the current study, for example, rather than treating industry, corporate, and business-unit variables as competing explanations and focusing on their relative importance (as do previous linear approaches), QCA enables the identification and investigation of how industry, corporate, and business-unit attributes combine to be sufficient for different outcomes of business-unit performance across different sectors of the economy. The overarching theme that emerged from the current findings is that the presence of resource abundance—whether such abundance comes through the industry environment (i.munificent), or the corporate environment (c.slack and c.diversified), is part of all causal conditions usually sufficient for superior performance in both the manufacturing and service sectors. At the same time, however, this causality underlying performance is complex: there are a variety of ways that alternative resource conditions combine with other industry, corporate, and business-unit factors to affect performance. Therefore, although previous studies have found the relative importance of all three classes of effects (e.g., Hough, 2006; McGahan & Porter, 2002; Misangyi et al., 2006) and that of corporate resources (Misangyi et al., 2006), the current findings afford a broader level of insight by highlighting their causal complexity. Although the overarching theme of resource abundance is not inconsistent with previous theories regarding the merits of industry munificence (e.g., Aldrich, 1979; Hofer, 1975; Starbuck, 1976), corporate resource availability (e.g., Bourgeois, 1981; Cyert & March, 1964), and corporate diversification strategies (Caves, 1981; Rumelt, 1982; Scherer, 1980) for superior performance, this study points to the need for strategic management researchers to move beyond a focus on examining these factors in isolation of each other and of other attributes. The findings of the present study clearly suggest the need for developing theories regarding how these different sources of resources combine, supplement and even substitute for one another to affect business-unit performance in different contexts. The QCA approach not only illuminates this issue but also provides a methodology for its further study.

Notes

1. Although conceptually the terminology of the qualitative comparative analysis (QCA) approach commonly invokes causation and causality, a terminology we follow here, like other methodologies the QCA approach serves to provide empirical evidence that may or may not support causal inferences based in theory. In other words, similar to investigations conducted with linear statistical methodologies, proving causality with QCA remains elusive; inferences regarding causal relationships are based on theory, and empirically, analyses generally involve probabilistic estimations of these relationships.

2. Abbreviations of these attributes used hereafter in the tables and discussion appear in parentheses.

3. A Herfindahl index of diversity of 1 would signify that all empirically observed cases are of one configuration, whereas a minimum Herfindahl index of .008 (the minimum Herfindahl index is $1/n$, where n is the number of configurations; e.g., Acar & Sankaran, 1999) would indicate that the cases are equally spread across all 128 configurations (approximately 13 cases per configuration in the manufacturing sector and approximately 6 cases in the services sector).

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