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Net versus combinatory effects of firm and industry antecedents of sales growth☆

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ABSTRACT

This study examines antecedents of sales growth using a two-step mixed-method approach including analyses of net effects and combinatory effects. Based on a sample of 453 respondents from manufacturing and service firms, this article shows how the combination of structural equation modeling (SEM) and fuzzy set Qualitative Comparative Analysis (fsQCA) provides more detailed insights into the causal patterns of factors to explain sales growth. This article contributes to the extant literature by highlighting fsQCA as a useful method to analyze complex causality (specifically combinatory effects of antecedent conditions) and by discussing options regarding how this approach can be used to complement findings from conventional causal data analysis procedures that analyze net effects.

1. Introduction

One of the most dominant and enduring notions emphasized in management research is that of cause and effect mechanisms. This causal logic in research represents a primary focus on analyzing drivers and/or inhibitors of certain outcomes. Prior studies contribute to the understanding of linear causation and the net effects of antecedents on outcomes. However, knowledge about complex causation and corresponding analytical approaches is scarce (Ragin & Fiss, 2008; Woodside, 2014). Complex causation describes a situation "… in which an outcome may follow from several different combinations of causal conditions" (Ragin, 2008a, p. 23). Complex causation implies combinatory effects of multiple antecedent factors on an outcome. Examination of complex causation mirrors managerial practice, which builds upon holistic decisions that include trade-off considerations between several organizational aspects. Managerial decisions typically consider interdependencies among multiple causal factors rather than single causal factors (Meyer, Tsui, & Hinings, 1993). Complex causation

reflects this notion and takes into account all logically possible configurations of causal factors that may influence an outcome in question. Complex causation thus represents a major methodological challenge (Davis, Eisenhardt, & Bingham, 2007; Ragin, 2008a; Wagemann & Schneider, 2010).

The analysis of combinatory effects can play crucial roles in organization theory and management research (Doty & Glick, 1994; Meyer et al., 1993). Considerable parts of extant research understand firms as complex systems that comprise interconnected structures and practices (Clegg, Hardy, & Nord, 1996; Fiss, 2007; 2011). Such configurational research draws on Gestalt theory and involves a holistic approach in which a social entity takes its meaning from the interaction and interdependencies between its elements as a whole and cannot be understood in isolation (Hult, Ketchen, Cavusgil, & Calantone, 2006; Short, Payne, & Ketchen, 2008).

Conventional analytic methods to test configurational theories and combinatory effects are often less proficient at handling multi-faceted interdependencies. Configurations are "nonlinear synergistic effects and high-order interactions" between a broad set of variables (Delery & Doty, 1996, p. 808). Frequently employed data analysis methods such as correlation-based regression analysis or structural equation modeling (SEM) imply symmetric relationships between variables, and aim to improve the understanding of net effects of individual antecedents of an outcome (Woodside, 2013). Correlational methods focus on the extent to which antecedent factors can explain variance in the outcome (analysis of net effects) rather than concentrate on ways in which antecedent factors may combine into configurations to explain an outcome (analysis of combinatory effects).

The overall purpose of this article is to emphasize fuzzy set Qualitative Comparative Analysis (fsQCA; Ragin, 2000; 2008a) as a useful data analysis method of combinatory effects, having the capacity to complement the insights obtainable from the analysis of net effects. This article aims to expand researchers' diagnostic toolkit by illustrating a two-step, mixed-method approach that incorporates analyses of both net effects and combinatory effects to obtain more detailed insights into the patterns of antecedent factors for an outcome. The article therefore advocates methodologically richer approaches that combine analyses of net and of combinatory effects for outcomes of interest.

This article continues as follows. The next section explains basic principles of fsQCA and illustrates potential benefits of this method in comparison to correlational methods. Next, this article presents a study including the analysis of net effects based on variance-based SEM (step 1) and the analysis of combinatory effects based on fsQCA (step 2). The study investigates how three sets of antecedent factors, that is, firm strategic factors, firm demographics, and industry characteristics, relate to sales growth as the outcome of interest.

2. Basic principles and potential benefits of fsQCA

FsQCA is a case-oriented, set-theoretic research approach that describes cases as combinations of attributes as well as the outcome in question (Fiss, 2011; Ragin, 2008a). One of the key differences between fsQCA and correlational methods refers to the *approach of explanation* (Mahoney & Goertz, 2006). For example, firms with superior market performance (as an example outcome of interest) may have excellent market knowledge, a clear management strategy, and an effective strategy implementation (as one example configuration of three causal factors). FsQCA focuses on the extent to which a case has membership in the sets of specific attributes or combinations of these attributes, and the outcome set (Ragin, 2008a). In contrast, the primary focus of correlational methods is to estimate the average effect of one (or more) independent variable(s) in a set of cases to explain a maximum of variance in the dependent variable. For example, one might estimate the net effect of market knowledge on market performance. Correlational methods thus reflect a variable-oriented research approach that focuses on determining the magnitude of the effect of a cause on an outcome.

A further distinction between fsQCA and correlational methods concerns the *concept of causality*. FsQCA builds on multiple conjunctural causality (Ragin, 2008a) and takes into account that an outcome rarely has a single cause, that causes rarely operate in isolation from one another, and that a specific cause may have opposite (i.e., positive or negative) effects depending on context (Greckhamer, Misangyi, Elms, & Lacey, 2008; Rihoux, 2006). Although correlational analyses can involve multiple independent variables and can examine additive and multiplicative functional relationships to explain a dependent variable, they differ from set-theoretic approaches due to the basic assumption of causal symmetry. FsQCA considers causal asymmetry, which implies that solutions (i.e., combinatory effects) for the presence of an outcome can differ substantially from solutions for the absence of the same outcome (Fiss, 2011; Fiss, Sharapov, & Cronqvist, 2013; Ragin, 2008a; Wu, Yeh, Huan, & Woodside, 2014). In correlational analyses, solutions (i.e., models of net effects) of the inverse of a dependent variable remain the same except for sign changes in the coefficients of the independent variables.

Focusing on the *explanations for an outcome*, a major advantage of fsQCA is the incorporation of equifinality (Fiss, 2007; 2011). Equifinality means that "a system can reach the same final state from different initial conditions and by a variety of different paths" (Katz & Kahn, 1978, p. 30). Equifinality implies the coexistence of alternative solutions or causal pathways for an outcome of interest. These solutions reflect different recipes or combinatorial statements and are logically equivalent and thus substitutable (Ragin, 2008a). Identification of equifinality solutions for specific phenomena is an important research area in the marketing and management literature (e.g., Marlin, Ketchen, & Lamont, 2007; Payne, 2006). Consideration of equifinality provides decision makers in firms

with optional design choices to achieve a desired outcome, thus fostering the potential for efficiency gains (Fiss, 2011). In comparison to fsQCA, correlational methods seek to identify one optimal model that best represents the empirical data. For instance, a major goal in covariance-based SEM is to identify a model that fits the observed data. Perfect model fit occurs when the model-implied covariance matrix is equivalent to the empirical covariance matrix. Correlational methods thus typically focus on unifinality, expressed in one optimal model (i.e., one solution).

In order to examine what combinations of attributes lead to the outcome in question, fsQCA relies on Boolean algebra rather than linear arithmetic. FsQCA builds upon the premise that relationships among different variables are understandable in terms of set membership (Fiss, 2007). A fuzzy set is "a continuous variable that has been purposefully calibrated to indicate degree of membership in a well-defined and specified set" (Ragin, 2008a, p. 30). The degree of membership in a fuzzy set can range from 0 to 1 (Ragin, 2008a). To assess set relationships with fsQCA, causal factors and the outcome in question need transformation into fuzzy sets via calibration. FsQCA then explores how the membership of cases in fuzzy sets of causal factors relates to membership in the outcome set (Ragin, 2008a). The analysis of set relationships provides insights into necessity and/or sufficiency of causal conditions for an outcome. A causal condition or a combination of causal conditions is necessary if its occurrence is a prerequisite for an outcome, and a causal condition or a combination of causal conditions is sufficient if its occurrence can produce a certain outcome (Ragin 2000; 2008a).

3. Firm and industry factors as antecedents of sales growth

The number of studies using fsQCA in business research is growing rapidly; these studies provide new insights into a broad range of management (Fiss, 2011; Greckhamer et al., 2008; Leischnig, Geigenmueller, & Lohmann, 2014; Misangyi & Acharya, 2014) and marketing issues (e.g., Leischnig & Kasper-Brauer, 2015; Ordanini, Parasuraman, & Rubera, 2014; Tóth, Thiesbrummel, Henneberg, & Naudé, 2015). Since this article aims to illustrate how analyses of net and combinatory effects help improve the understanding of phenomena and embrace a complementary view by employing a mixed-method approach, the study below addresses a topic that receives continuous interest in research using correlational methods, but which receives only little attention in the QCA literature. Specifically, this research examines how three sets of causal factors relate to sales growth of a focal company (see Fig. 1): firm strategy factors (i.e., customer orientation, competitor orientation, and relationship coordination), firm demographics (i.e., firm size and firm age), and industry characteristics (i.e., industry growth). Organization theory and prior empirical research guides the selection of the constructs that are relevant in the context of this study.

Organization theory suggests that firm-internal strategic orientations interact with characteristics of the firms and the environment (Short et al., 2008). In addition, business relationship and market orientation research suggest that strategic orientations toward different stakeholders in the embedded business network represent important antecedents of sustainable competitive advantage (Achrol & Kotler, 1999). Research into market orientation emphasizes customer orientation and competitor orientation as pivotal concepts in this context (Jaworski & Kohli, 1993; Narver & Slater, 1990). While customer orientation refers to a firm's tendency to continuously create superior value for its customers based on an appropriate understanding of their needs, competitor orientation refers to a firm's tendency to continuously sense competitive actions and respond to them timely and appropriately (Narver & Slater, 1990). Prior studies underline the need to supplement these two strategic orientations through building relationships with key stakeholders (Gulati, Nohria, & Zaheer, 2000; Palmatier, Scheer, Evans, & Arnold, 2008). Firms need to establish routines to coordinate relationships with external partners and to develop appropriate responses to environmental changes (Palmatier et al., 2008). Such relationship coordination refers to a firm's capacity to coordinate and

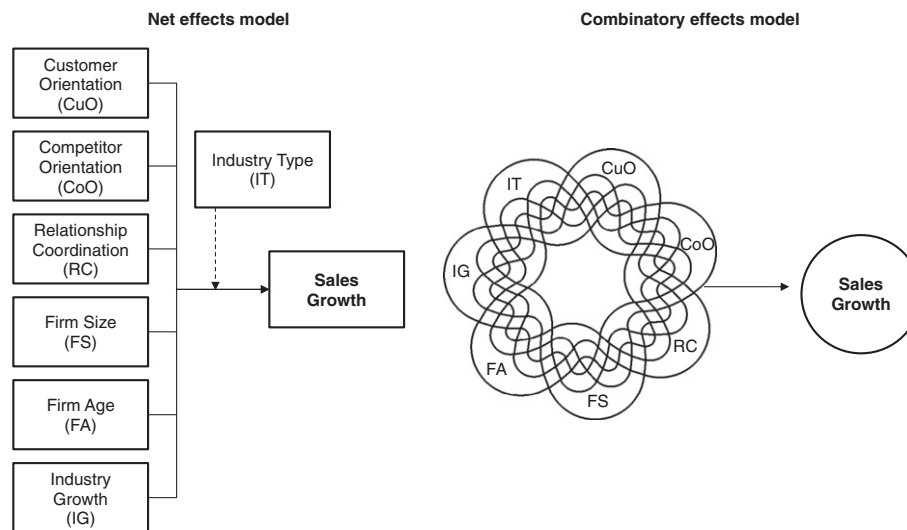**Net effects model**　　　　　　　　　　　　**Combinatory effects model**

Fig. 1. Firm and industry factors as antecedent conditions of sales growth.

collaborate with its counterparts, that is, key stakeholders such as customers and suppliers, based on mutual goals (Walter, Auer, & Ritter, 2006).

In addition to these strategic factors of the firm, this study examines firm demographics and factors of the business environment to explain sales growth. Studies indicate that age and size of the firm relate to sales growth (e.g., Delmar, Davidsson, & Gartner, 2003). As firms mature, learning processes promote the effective planning and implementation of growth strategies. Thus, older firms have experience advantages, which enable them to achieve superior sales growth (Autio, Sapienza, & Almeida, 2000). However, an alternative position views young firms as more innovative and more responsive to environmental changes and market opportunities than older firms, which enables them to capitalize on discovery advantages and grow sales (Steffens, Davidsson, & Fitzsimmons, 2009). In addition, studies indicate that organizational age dependence varies across firm strategies, thus pointing to interaction effects between firm age and firm strategy to explain sales growth (Henderson, 1999). Regarding the impact of firm size on sales growth, prior research is equally inconclusive. Gibrat's (1931) law suggests that sales growth is proportionate to the size of the firm. However, small firms can achieve higher sales growth than large firms due to their ability to make faster decisions (Chen & Hambrick, 1995) and to respond faster to business opportunities in the market place (Darnall, Henriques, & Sadorsky, 2010).

Since the business environment in which a firm operates provides the frame for corporate decisions and actions, this research examines also industry factors (here industry growth) to explain sales growth. In a high-growth industry, a firm is more likely to grow sales since the market potential is higher due to the fact that the competitive strength is likely to be weaker compared to a slow-growth industry (Porter, 1980). Finally, this research considers differences in industry type (i.e., services and manufacturing). Fig. 1 shows how these constructs form two models, one representing the net effects on sales growth, the other representing the combinatory effects on sales growth.

4. Research method: analysis of net and combinatory effects

4.1. Data collection, sample, and nonresponse bias

This study conducted an online survey with executives from multiple firms identified through a proprietary database. Executives' knowledge about the subject at hand was the basis for the selection of the sampling frame. Respondents received an invitation e-mail, including the link to an online questionnaire, followed by three reminders.

Assessments of response patterns based on the procedure as suggested by Fricker, Galesic, Tourangeau, & Ting (2005), respondent knowledgeability, missing values, and industry membership lead to the exclusion of several responses. The final sample includes 453 responses usable for subsequent analysis (response rate: 13%). Of the respondents, 23% have a position in top management, 66% have a position in middle management, and 11% have a position lower than middle management. In addition, 11% of the respondents have less than 2 years, 35% have 2 to 5 years, 36% have 5 to 10 years, and 18% have 10 years or more of experience with the firm. The average firm in the sample employs 750 to 2500 employees and exists for 20 to 30 years. 59% of the firms are service providers, and 41% are manufacturing firms.

This study controls for nonresponse bias through two analyses suggested by Armstrong and Overton (1977). First, this study compares the responses in the key variables and firm characteristics collected in the first (early respondents) and fourth waves (late respondents) of the data collection. A series of χ^2-tests indicates no significant differences between the two groups. Second, this study compares industry sectors in the sample with the population via a χ^2-test. The results indicate that the survey respondents represent the population. Based on these findings, nonresponse bias is not a concern for this study.

4.2. Construct measures

The data collection instrument includes multiple-item and single-item construct measures. This study measures customer orientation and competitor orientation using four items for each construct based on Narver and Slater (1990). To measure relationship coordination, this study uses four items based on Walter et al. (2006). Two items based on Venkatraman (1989) measure sales growth. All multiple-item constructs employ seven-point Likert-type rating scales ranging from 1 = "completely disagree" to 7 = "completely agree." Single-item measures capture firm size, firm age, and industry growth. This study measures firm size based on the number of full-time employees, and firm age based on the number of years a firm has operated in a market. Finally, this study captures industry growth by asking respondents about the overall growth of their industry, using a single-item scale from 1 = "poor" to 7 = "excellent." Table 1 details information on the construct measures.

4.3. Data analysis

Analysis of the data involves two steps. In step 1, this study analyzes the net effects of the firm and industry factors on sales growth using

Table 1
Information on construct measures.

Construct measures	FL (Sig.)
Customer orientation (CA = .90; CR = .93; AVE = .77)	
We closely monitor our level of commitment in serving customers' needs.	.86***
Our business strategies are driven by our goal to create greater value for our customers.	.93***
Our strategy for competitive advantage is based on our understanding of customer needs.	.89***
Our business objectives are driven primarily by customer satisfaction.	.83***
Competitor orientation (CA = .86; CR = .90; AVE = .70)	
Our salespeople regularly share information within our business concerning competitors' strategies.	.82***
We rapidly respond to competitive actions that threaten us.	.87***
Top management regularly discusses competitors' strategies.	.87***
We target customers where we have an opportunity for competitive advantage.	.78***
Relationship coordination (CA = .86; CR = .91; AVE = .71)	
We analyze what we would like to achieve with different business partners.	.87***
We match the use of resources (e.g., know-how, information, people, and assets) to the individual relationship.	.83***
We inform ourselves of our business partners' goals, potentials, and strategies.	.84***
We judge in advance which possible business partners to talk to about building up relationships.	.84***
Sales growth (CA = .89; CR = .95; AVE = .90)	
Sales growth position relative to your major competitor	.95***
Market share gains relative to your major competitor	.95***
Firm size (CA = n.a.; CR = n.a.; AVE = n.a.)	
Number of employees from 1 = "1–10 employees" to 8 = "> 5000 employees"	1***
Firm age (CA = n.a.; CR = n.a.; AVE = n.a.)	
Number of years established from 1 = "less than 5 years" to 7 = "≥ 50 years"	1***
Industry growth (CA = n.a.; CR = n.a.; AVE = n.a.)	
Overall growth of industry	1***

Notes: CA = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted; FL = factor loading; Sig. = significance (based on total sample); *** = p < .01.

Table 2
Means, standard deviations, and correlations.

	M	SD	1	2	3	4	5	6	7
Customer orientation	5.7	1.16	**.77**						
Competitor orientation	5.2	1.23	.43	**.70**					
Relationship coordination	5.2	1.17	.34	.34	**.71**				
Firm size	5.8	2.05	.00	.00	.00	–			
Firm age	4.0	1.93	.00	.00	.00	.20	–		
Industry growth	5.1	1.28	.04	.06	.03	.00	.01	–	
Sales growth	4.6	1.32	.06	.14	.05	.00	.00	.11	**.90**

Notes: AVE in bold on the diagonal; squared correlations between constructs below the diagonal.

between the two factors. Thus, the results indicate satisfactory discriminant validity (see Table 2).

To evaluate the net effects of firm and industry factors on sales growth, this study assesses the variance explained in terms of R^2 and the Stone–Geisser Q^2-criterion of predictive relevance for the dependent variable sales growth. In addition, this study assesses the size and significance of the path coefficients. To evaluate significance, this study performs a nonparametric bootstrapping procedure following Hair et al. (2012) with the analysis settings: 453 cases, 5000 subsamples, and individual sign change. In addition, this study calculates effect sizes (f^2; Cohen, 1988) and predictive relevance scores (q^2; Chin, 1998) for each of the antecedent causal factors. The analysis is run for the total sample as well as for two separate sub-samples consisting of manufacturing and service firms.

4.3.2. Step 2: Analysis of combinatory effects using fsQCA

To complement the insights of the net effect analysis, step 2 of the analysis focuses on combinatory effects analysis based on fsQCA. The fsQCA involves seven causal conditions to predict one outcome. The causal conditions include the six independent variables used in the net effects analysis (i.e., three strategic factors of firms, two firm demographics, and industry growth) plus the industry type (i.e., manufacturing vs. service firms). The outcome of interest is sales growth.

4.3.2.1. Calibration.
To examine the combinatory effects of the causal conditions on sales growth with fsQCA, this study calibrates all construct measures and transforms them into fuzzy set membership scores (Ragin, 2008a). Calibration, in essence, involves rescaling a construct using a cross-over point as an anchor from which deviation scores derive, based on threshold values of full membership and full non-membership in a fuzzy set (Fiss, 2011; Ragin, 2008a). This study defines thresholds for full membership and full non-membership in the fuzzy sets, as well as for the cross-over point to structure the calibration (Ragin, 2000). For all multiple-item construct measures, this study combines the items into average scores. The maximum, the minimum, and the midpoint (i.e., values 7, 1, and 4) of the seven-point Likert-type scales serve as thresholds for full membership, full non-membership, and the cross-over point, respectively. Regarding firm size, firms with 250 and more employees (i.e., value 5 on the scale) are fully in the set of large firms, and firms with 25 or less employees (i.e., value 2 on the scale) are fully out of the set of large firms (or, in other words, are in the set of small firms). The cross-over point is set at value 4, which implies a firm size of between 50 and 250 employees. These thresholds correspond to EU enterprise size classifications (European Commission, 2005). For the calibration of firm age, this study sets the threshold for full membership in the set of old firms at 20 or more years of market presence (i.e., value 4 on the scale) and the threshold for full non-membership in this set at less than 5 years (i.e., value 1 on the scale). The cross-over point is set at value 3, indicating firms with a market presence of 10 to 20 years. In addition, this study calibrates industry type as a so-called crisp set, with service firms being fully in the set and manufacturing firms being out of the set. The fs/QCA software

partial least squares (PLS) SEM and the SmartPLS software program (version 2.0; Ringle, Wende, & Will, 2005). PLS-SEM is a variance-based, iterative estimation procedure that focuses on maximizing the variance of the dependent variables explained by the independent variables (Chin, 1998). Because of its prediction orientation, PLS-SEM is especially useful when the research goal is the prediction of a target outcome or the identification of key drivers of an outcome (Hair, Ringle, & Sarstedt, 2011). In step 2, this study performs an analysis of sufficiency using fsQCA to assess the combinatory effects of firm and industry factors for sales growth. Following the procedure as suggested by Ragin (2008a) and Fiss (2011), the fsQCA proceeds in three stages including the calibration of the construct measures, the construction and refinement of the so-called truth table, and the analysis of the truth table.

4.3.1. Step 1: Analysis of net effects using PLS-SEM

Data analysis begins with the evaluation of the measurement model (Hair et al., 2011; Hair, Sarstedt, Ringle, & Mena, 2012). The results indicate satisfactory levels of composite reliability and average variance extracted for the construct measures since the values obtained exceed the thresholds of .6 and .5, respectively (Bagozzi & Yi, 1988). All factor loadings are high and significant, which indicates satisfactory convergent validity (Hulland, 1999). In addition, the results show that Cronbach's alpha values exceed the cut-off value of .7 for all constructs (Nunnally, 1978). Analysis of discriminant validity as suggested by Fornell and Larcker (1981) indicates that the average variances extracted for any two factors are greater than the squared correlation

program converts the construct measures into fuzzy set membership scores (Ragin, Drass, & Davey, 2006). Because cases with fuzzy set memberships scores of precisely .5 (i.e., the point of most ambiguity) cause difficulties when intersecting fuzzy sets, Ragin (2008a) recommends avoiding the use of a precise .5 fuzzy set membership score for causal conditions. To address this concern, and in line with prior studies (e.g., Fiss, 2011), this study adds a constant of .001 to all causal conditions with fuzzy set membership scores smaller than 1.

4.3.2.2. Construction and refinement of the truth table. After calibration of all causal conditions and the outcome of interest, this study constructs the truth table. The truth table is a data matrix that consists of 2^k rows, where k indicates the number of causal conditions (Ragin, 2008a). The truth table lists all logically possible combinations of causal conditions and displays their degree of empirical representation (Fiss, 2011). To perform a fsQCA, the truth table needs preliminary refinement based on two criteria: frequency and consistency (Ragin, 2008a). Frequency indicates the distribution of empirical cases across the rows (i.e., combinations of causal factors) of the truth table. By defining a frequency cut-off, the analysis of fuzzy subset relationships occurs only for those rows exceeding a specific level of empirical representation. QCA research does not suggest fixed thresholds for frequency. However, researchers should take into account the overall sample size. While in small- (e.g., 10 cases) and medium-sized (e.g., 50 cases) samples frequency thresholds of 1 or 2 are appropriate, for large-scale samples (e.g., >150 cases) frequency cut-offs should be set higher. In addition, QCA literature recommends that the analysis should include at least 80% of the cases of the total sample (Greckhamer, Misangyi, & Fiss, 2013).

The second criterion for truth table refinement is consistency. Consistency captures the degree to which the cases sharing a given causal factor or combinations of causal factors agree in displaying the outcome in question (Ragin, 2006). The definition of a consistency threshold distinguishes (combinations of) causal factors that are consistent subsets of the outcome from those that are not (Ragin, 2008b). QCA literature recommends inspecting dips in consistency scores to identify consistency thresholds and suggests a minimum acceptable consistency level of .8 (Ragin, 2008a). In addition, QCA studies suggest inspecting values of the proportional reduction of inconsistency (PRI) consistency (Misangyi & Acharya, 2014), which is sensitive to causal factors representing subsets of the presence and the negation of an outcome, and that gives small penalties for minor inconsistencies but large penalties for major inconsistencies.

In this study, the truth table contains 128 (i.e., 2^7) rows reflecting all logically possible combinations of the seven causal conditions. Of these, 53 rows show empirical cases, with some rows showing many and some only a few cases. To prepare the truth table for subsequent analysis, this study sets the frequency threshold at 7. This threshold ensures that 84% of the cases in the sample are part of the analysis and that all combinations of causal conditions with less than 7 cases are logical remainders in the analysis. To distinguish configurations that consistently lead to the outcome from those that do not, this study sets the minimum acceptable level of consistency at .85. Next, and for these configurations, this study inspects PRI consistency scores and sets the minimum acceptable level of PRI consistency at .75 (Misangyi & Acharya, 2014). The fsQCA solution table presented below reports the resulting actual raw and PRI consistency values used for the analysis of combinatory effects (see Table 4).

4.3.2.3. Analysis of the refined truth table. FsQCA examines set-subset relationships using the Quine–McCluskey algorithm, which allows logical reduction of complex configurations of causal conditions into a reduced number of configurations that lead to the outcome in question (Fiss, 2011; Ragin, 2008a). The algorithm identifies combinations of causal factors that consistently lead to an outcome by stripping away those factors that are sometimes present and sometimes absent, thus indicating that these factors are not essential parts of a sufficient configuration for

the outcome in question (Fiss, 2011). This study uses the algorithm as implemented in the fs/QCA software program to perform the analysis.

To evaluate the solutions for a particular outcome of interest, fsQCA reports the aforementioned consistency and additional coverage scores. Coverage represents the proportion of cases in a combination of factors sufficient for the outcome in question (Fiss, 2011; Ragin, 2000, 2008a) and helps assess the relative empirical importance of combinatorial statements for an outcome. FsQCA reports an overall solution coverage score for all (equifinal) solutions sufficient for the outcome, as well as raw and unique coverage scores for each of the particular solution terms that form the overall solution. For the particular solutions, raw coverage refers to the extent of overlap between the size of the solution set and the outcome set relative to the size of the outcome set. Since some cases may be present in several solutions, fsQCA controls for these overlaps and partitions the raw coverage to obtain a particular solution's unique coverage with the outcome set (Ragin, 2008a).

5. Results

5.1. Results of the analysis of net effects

Table 3 summarizes the results of the analysis of net effects. For the total sample, the results show R^2- and Q^2-values of .20 and .19, respectively, for sales growth. The net effect analysis indicates a significant positive effect of competitor orientation on sales growth ($\beta = .30$, $p < .01$). In addition, the findings show that firm size has a marginally significant negative effect ($\beta = -.08$, $p < .1$), and that firm age has a marginally significant positive effect on sales growth ($\beta = .09$, $p < .1$). Furthermore, industry growth has a significant positive effect on sales growth ($\beta = .26$, $p < .01$). As an inspection of effect sizes and predictive relevance scores indicates, the independent variables having significant effects on sales growth show low effect sizes and low predictive relevance, which points to weak net effects.

Comparing the results of the net effect analysis for service and manufacturing firms, the results indicate R^2- and Q^2-values for sales growth of .21 and .20, respectively, for service firms and of .23 and .20, respectively, for manufacturing firms. In addition, the results show that competition orientation (service firms: $\beta = .26$, $p < .01$; manufacturing firms: $\beta = .35$, $p < .01$) and industry growth (service firms: $\beta = .31$, $p < .01$; manufacturing firms: $\beta = .19$, $p < .05$) have significant positive effects on sales growth in both industries. While for service firms, firm age relates significantly positive to sales growth ($\beta = .12$, $p < .05$), this effect is insignificant for manufacturing firms. For manufacturing firms, however, firm size has a marginally significant negative effect on sales growth ($\beta = -.12$, $p < .1$).

5.2. Results of the analysis of combinatory effects

Table 4 depicts the results derived from the intermediate and the parsimonious solutions obtained by the fsQCA (see Fiss, 2011; Ragin, 2008a for further details). This study uses an adapted version of the notation suggested by Ragin and Fiss (2008) to illustrate the combinatory effects of the firm and industry factors on sales growth. Full circles indicate the presence of a causal condition, circles with a cross-out indicate its negation, large circles indicate core conditions, small circles indicate peripheral conditions, and blank spaces indicate that a causal condition does not matter in a configuration.

The fsQCA reveals two solutions leading to sales growth (i.e., solutions 1 and 2) which both have two neutral permutations (i.e., 1a and 1b, and 2a and 2b). The overall solution consistency is .89, which indicates that the identified combinations of firm and industry factors represent highly consistent solutions to explain sales growth. In addition, the overall solution coverage is .64, indicating that the solutions explain a substantial proportion of sales growth.

Solution 1a reflects a combination that consists of the presence of customer orientation, competitor orientation, relationship coordination,

Table 3
Results of the analysis of net effects based on PLS-SEM.

Causal factors	Total sample (n = 453)				Service firms (n = 268)				Manufacturing firms (n = 185)			
	β	t-value	f^2	q^2	β	t-value	f^2	q^2	β	t-value	f^2	q^2
Customer orientation	.01	.18	.00	.01	.03	.51	.00	.02	−.02	.41	.00	.03
Competitor orientation	.30	4.27***	.06	.06	.26	2.77***	.04	.05	.35	3.26***	.08	.10
Relationship coordination	.01	.35	.00	.00	−.02	.38	.00	.00	.08	1.24	.01	.00
Firm size	−.08	1.82*	.01	.01	−.04	.88	.00	.01	−.12	1.99*	.02	.01
Firm age	.09	1.90*	.01	.01	.12	2.32**	.01	.01	.02	.52	.00	.00
Industry growth	.26	5.25***	.08	.07	.31	5.43***	.11	.10	.19	2.10**	.03	.03
R^2 sales growth	.20				.21				.23			
Q^2 sales growth	.19				.20				.20			

Omission distance for cross-validated redundancy d = 7; f^2 = effect size;
q^2 = predictive relevance; sales growth as the dependent variable.
*** p < .01.
** p < .05.
* p < .1.

industry growth, and refers to service firms. Competitor orientation, industry growth and the service context are core conditions in this solution, and customer orientation and relationship coordination are peripheral conditions surrounding the core conditions. Firm size and firm age have minor roles in solution 1a as indicated by the blank spaces in Table 4. The consistency score of solution 1a is .89 and its raw and unique coverage scores are .48 and .07, respectively. Thus, service firms operating in a growing market can achieve sales growth if they operate customer- and competitor-oriented and coordinate relationships with key stakeholders.

Solution 1b represents a factor combination including the presence of customer orientation, competitor orientation, firm size, firm age, industry growth, and the services context. Again, competitor orientation, industry growth, and the services context are core conditions. Customer orientation, firm size, and firm age are peripheral conditions, and relationship coordination has a minor role in solution 1b. The consistency score of solution 1b is .91 and its raw and unique coverage scores are .34 and .01, respectively. Thus, established and large service firms

Table 4
Results of the analysis of combinatory effects based on fsQCA.

Causal factors	Solutions for sales growth			
	1a	1b	2a	2b
Firm strategic factors				
Customer orientation	•	•	•	•
Competitor orientation	●	●	•	•
Relationship coordination	•		•	•
Firm demographics				
Firm size		•	⊗	•
Firm age		•	•	⊗
Industry characteristics				
Industry growth	●	●	•	•
Industry type[a]	●	●		
Consistency	.89	.91	.97	.92
Raw coverage	.48	.34	.15	.30
Unique coverage	.07	.01	.03	.09
Overall solution consistency		.89		
Overall solution coverage		.64		

Notes: ● = presence of a causal condition; ⊗ = negation of a causal condition; big circles = core conditions; small circles = peripheral conditions; blank space = absence of a causal condition; analysis thresholds: frequency = 7, consistency = .89, and PRI consistency = .78;
[a] presence indicates service firms.

operating in a growing market achieve sales growth if they show high customer and competitor orientation.

A comparison of solutions 1a and 1b reveals a trade-off (i.e., neutral permutations; Fiss, 2011) between relationship coordination on the one hand, and firm size and firm age on the other. While the presence of relationship coordination is an integral element in solution 1a, its absence characterizes solution 1b. In addition, while the presence of firm size and firm age are integral elements of solution 1b, these causal factors are absent in solution 1a. This finding indicates that in services, strong relationship coordination may compensate for market experience (i.e., high firm age) and manpower (i.e., many employees). In addition, this result implies that large and mature service firms can compensate a lack of relationship coordination with market experience and manpower. However, looking at the coverage score of these two solutions reveals that solution 1a has a greater relative empirical relevance since raw and unique coverages are higher than in solution 1b.

Solution 2a combines the presence of all three strategic factors with the negation of firm size, the presence of firm age, and the presence of industry growth. The negation of firm size is a core condition in solution 2a; all other causal factors are peripheral conditions. The type of industry does not matter in this solution as indicated by the blank space. The consistency score of solution 2a is .97 and its raw and unique coverage scores are .15 and .03, respectively. Thus, established but small firms operating in a growing market can achieve sales growth if they act in a customer-, competitor-, and relationship-oriented manner.

Solution 2b shows a similar combination of firm and industry factors as solution 2a. However, solution 2b differs from solution 2a in that it includes the presence of firm size and the negation of firm age, the latter representing a core condition. This indicates that young, but large firms operating in a growing market can achieve sales growth if they act in a customer-, competitor-, and relationship-oriented manner. The consistency score of solution 2b is .92 and its raw and unique coverage scores are .30 and .09, respectively.

6. Discussion

This research aims to show how the analysis of net effects and combinatory effects of firm and industry factors can improve the understanding of antecedents of an outcome (here sales growth). The net effects analysis based on PLS-SEM (favoring a variable-oriented perspective, building on the assumption of causal symmetry, and promoting the idea of unifinality) provides insights into the average or net effects of firm and industry factors on sales growth across the total sample and the two industry sub-samples. The combinatory effects analysis based on fsQCA (favoring a case-oriented perspective, building on the assumption of causal asymmetry, and considering equifinality)

provides insights into combinations of firm and industry factors sufficient for sales growth.

The results obtained by the analysis of combinatory effects roughly correspond to those obtained by the net effects analysis. For example, all solutions of the fsQCA show that the presence of competitor orientation and industry growth are ingredients of causal recipes that increase sales growth. This finding is in line with the PLS-SEM analysis, which identifies competitor orientation and industry growth as the two constructs with the highest net effect sizes. Thus, with regard to these aspects of the analyses, the mixed-method approach highlights the possibility of validation of results. Besides, the combinatory effects analysis provides additional insights that contribute to a more fine-grained understanding of the causal patterns of firm and industry factors and sales growth, and therefore complements the analysis of net effects.

While the net effect analysis points to a single optimal solution to increase sales growth, the combinatory effect analysis supports the account that several equally successful solutions to achieve sales growth co-exist. The results from the fsQCA indicate two solutions with two neutral permutations for each of these solutions. This finding supports the assumption of equifinality, that is, the existence of multiple realities for an outcome (Woodside, 2014).

A further insight gained from the analysis of combinatory effects relates to trade-off relationships between antecedent conditions. The neutral permutations obtained by the fsQCA indicate such trade-offs. Neutral permutations show that certain conditions are substitutes for each other within solutions (Fiss, 2011). The combinatory analysis therefore discloses micro-level relationships between different antecedent conditions.

In addition, the combinatory effects analysis helps detect asymmetric causal effects of certain antecedent conditions of sales growth. As the results of the fsQCA indicate, both the presence and the negation of firm size and firm age contribute to sales growth. Depending on how these two antecedent conditions combine with the additional conditions, asymmetric effects can occur. Analyses of net effects cannot ascertain such insights.

Besides, the causal essentiality of antecedent conditions vis-à-vis the outcome condition is outlined differently in net and combinatory effects analyses. The analysis of net effects indicates causal essentiality of antecedent conditions by effect sizes and predictive relevance scores. FsQCA provides such information by describing the causal coreness of conditions as part of solutions for an outcome of interest, with core conditions being more essential or central, compared to peripheral conditions (Grandori & Furnari, 2008; Fiss, 2011). For example, the fsQCA shows in solution 1, in line with findings from the net effects analysis, that competitor orientation and industry growth are core conditions. However, in contrast with the net effects analysis, solution 2a indicates that (the negation of) firm size represents a core condition, while in solution 2b (the negation of) firm age is a core condition. Thus, the findings of the analysis of net effects match with characteristics of solution 1, while solution 2 provides additional and previously masked details.

The additional insights obtained by the analysis of combinatory effects find reflection in a high explanatory power. The net effects analysis indicates moderate explanatory power, with an explained variance (R^2) of 20% for sales growth (for the total sample). The analysis of combinatory effects shows an overall solution coverage score of 64%. Thus, the combinatory effects analysis, which indicates complex antecedent conditions sufficient for sales growth, can explain additional proportions of the outcome in question.

The cumulative findings of analyses of net and combinatory effects allow the derivation of important managerial implications. First, competitor orientation and industry growth are critical factors that managers should consider when striving for sales growth. Second, managers should not consider these two factors in isolation since alternative, equally effective factor combinations consisting of additional antecedent factors for sales growth exist. For example, three of the four solutions include also the presence of customer orientation and

relationship coordination. Third, the equifinal solutions represent optional designs for sales growth and enable managers to compare factor configurations as present in their firms with the identified patterns, and thus provide guidance for potential re-configuration approaches.

In summary, this research advocates a mixed-method approach including analyses of net and combinatory effects to obtain more detailed and nuanced insights into the complex causal patterns between antecedent conditions and an outcome of interest. Such an approach is still in its infancy in management research (Woodside, 2014; 2015). The approach that the present article outlines builds on the notion that relationships among constructs not only rely on simple but most commonly complex causality. This article shows how researchers can combine analyses of net and combinatory effects to examine both types of causality, and thus aims to provide impetus for further research on business and management issues.

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