CHAPTER 3

THE TWO QCAs: FROM A SMALL-N TO A LARGE-N SET THEORETIC APPROACH

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ABSTRACT

Although QCA was originally developed specifically for small-N settings, recent studies have shown its potential for large-N organization studies. In this chapter, we provide guidance to prospective researchers with the goal of opening up QCA's potential for widespread use in organization studies involving large-N settings, both as an alternative and as a complement to conventional regression analyses. We compare small-N and large-N QCA with respect to theoretical assumptions and objectives, processes and decisions involved in building the causal model, selecting the sample, as well as analyzing the data and interpreting the results. Finally, we discuss the prospects for large-N configurational analysis in organization studies and related fields going forward.

Keywords: QCA; fuzzy sets; set theoretic methods; case-oriented research; comparative analysis; configurational methods

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INTRODUCTION

Configurational thinking has a long tradition in organization studies. Yet, the promise of configurational research has remained largely unfulfilled, not least because of a lack of adequate methodological tools to match the theoretical assumptions of the configurational approach (Fiss, 2007). Recently, however, a methodological framework has emerged that is particularly well suited for viewing organizations as configurations and examining the interdependence of the causal effects underlying organizational outcomes: Qualitative Comparative Analysis (QCA) (Ragin, 1987, 2000, 2008). As a research strategy, The Comparative Method generally and QCA[1] specifically were originally developed to extend the systematic, in-depth, qualitative approach exemplified by the comparative case study design to research settings entailing more than a few cases. Although most prior studies using QCA have involved relatively small-N settings (10–50 cases), recent studies (e.g., Fiss, 2011; Greckhamer, Misangyi, Elms, & Lacey, 2008) have shown the promise of QCA as a useful tool for analyzing large-N situations (i.e., more than 50 cases).

While remaining configurational in its theoretical and methodological approach, the application of QCA to large-N research situations inevitably involves a departure from some of the underlying ideas of the original small-N QCA approach. The primary purpose of this chapter is to provide a theoretical framework and practical guidance for the use of QCA in large-N applications and thereby to open up QCA for wider usage in organizational studies. To accomplish this objective, in this chapter we use the small-N approach to QCA as a springboard for discussing the respective considerations, strengths, and trade-offs involved in extending applications of QCA to large-N settings.

Specifically, we compare small-N and large-N QCA with respect to their theoretical assumptions and objectives, processes and decisions involved in building the causal model, selecting the sample, as well as analyzing the data and interpreting the analyses. We particularly aim to outline QCA's potential for widespread use involving large-N settings, both as an alternative and as a complement to conventional regression-oriented statistical approaches. In addition to facilitating the use of large-N applications, our comparison of the small-N and large-N QCA approaches provides guidance for researchers choosing between these two approaches in a manner that capitalizes on their advantages while avoiding their pitfalls. Furthermore, although we pay particular attention to applying QCA to the study of organizations, our general arguments readily apply to QCA independent of its field of application.

THE COMMON PROPERTIES AND ASSUMPTIONS OF SMALL-N AND LARGE-N QCA APPROACHES

Starting from the general observation that most empirical social science research involves a comparison among cases, Ragin (1987) developed the QCA approach to account for two fundamental insights that are frequently neglected by empirical cross-case analyses: (1) that cases are best viewed as configurations of attributes or causal conditions (hereafter we use these terms interchangeably) and (2) that causality tends to be complex and conjunctive as outcomes typically occur as a result of several different combinations of causal conditions. QCA affords researchers with the formal analytical tools and procedures to capture the diversity of causal combinations that constitute cases, to both map this diversity of cases and to systematically analyze combinations of causal conditions that are linked to an outcome of interest under study. In short, the two fundamental assumptions – that cases are configurations of causal attributes and thus there is a need to study the diversity of cases and its attendant causal complexity – apply to all research settings, regardless of whether they involve a small or large sample size. We thus begin by briefly highlighting these commonalities between small-N and large-N QCA that enable them to account for the configurational nature of causal complexity: their set theoretic perspective, using Boolean algebra to map and systematically analyze the diversity of cases and causal relations, and their multiple conjunctive conception of causality informed by the set theoretic perspective.

An essential property of QCA, for both its small-N and large-N approaches, is that it is set theoretic in nature; it conceptualizes the connection between causal conditions and outcomes in terms of set membership and subset relations (Fiss, 2007; Ragin, 2000, 2008). This means that both the outcomes of interest and the conditions expected to be causally linked to these outcomes[2] are viewed as sets and that each case is assessed for its membership in each of these sets, making the process of determining set memberships (i.e., calibration) the key to capturing the meaningful diversity of cases. In crisp set QCA (csQCA), set memberships are evaluated in a dichotomous ("crisp") manner, which captures differences in kind. Based on theoretical or empirical knowledge, cases are thus classified as either "fully in" (1) or "fully out" (0) of the sets. For example, a specific organization may belong or not belong to the set of large organizations. The fuzzy set approach (fsQCA), on the other hand, allows the researcher to capture both differences in kind as well as degree; in addition to the two qualitative states of full membership and full nonmembership, a case may have partial membership in a set and thereby be assigned scores in the range from 0 to 1. To continue with the example of large organizations, rather than simply being classified as fully in or out of the set of large organizations, a specific organization may be assessed as having partial membership in the set (e.g., it may be "more in than out" of the set of large organizations). Thus, all approaches to QCA – csQCA and fsQCA, small-N and large-N QCA – involve the calibration of set memberships and the specification of these critical qualitative anchors (Ragin, 2000, 2008).

Set memberships form the basis of the truth table approach to typology utilized in QCA (Ragin, 2000, 2008), which captures the (limited) diversity of cases. The truth table is a chart with 2^k rows (k = number of included sets) which displays all logically possible combinations of the included theoretical attributes under study. Thus, it is the key tool of set theoretic analysis as it enables the researcher to map both the empirically occurring configurations of attributes as well as those logically possible configurations that do not occur. As Ragin (1987, 2000) points out, truth tables usually contain hypothetical combinations that lack empirical instances, which underscores the limited diversity of many social phenomena – the attributes of cases tend to occur in coherent patterns, including in organizations (e.g., Meyer, Tsui, & Hinings, 1993).

As noted above, QCA conceptualizes causal relations among social phenomena as set relations. This perspective allows for the analysis of causal complexity through the construction and examination of arguments regarding the necessity and/or sufficiency of causal conditions – combinations of the theoretically relevant causal attributes under study – for a particular outcome. Examination of whether any combinations may be necessary and/or sufficient for the occurrence of an outcome involves examining the subset relations: when set memberships in the outcome are a subset of the attribute set memberships (i.e., all occurrences of the outcome exhibit the same causal attribute(s)), a causal condition can be argued to be necessary for an outcome to occur. On the other hand, when the causal condition is a subset of the outcome (i.e., all cases with the particular attribute(s) will display the outcome), a causal condition can be argued to be sufficient for the occurrence of an outcome. This mapping of set memberships and analysis of their subset relations is enabled through the combinatorial logic of Boolean algebra,[3] and can be applied to both small-and large-N research contexts. See Greckhamer et al. (2008) for a comprehensive demonstration of these properties to a large-N organizational setting.

In sum, the basic premise of QCA is that aspects of cases should be examined as combinations of set memberships and that a single difference between cases may constitute a difference in kind. This approach – both its small-N and large-N approaches – thus permits researchers to capture and explore the diversity of organizations through configurations. Furthermore, this also means that both small-N and large-N QCA are premised on the notion of a *multiple conjunctural* understanding of causality; causality is conjunctural in that causes are seen as operating in combination rather than independently, and multiple (i.e., equifinal) because more than one combination may produce the same outcome (Becker, 1992; Ragin, 2000). This implies that outcomes of interest rarely have a single cause, causes rarely operate in isolation, and specific causes may have opposite (i.e., asymmetrical) effects depending upon context.

CONTRASTING SMALL-N AND LARGE-N QCA

To strengthen the theoretical and practical basis of large-N applications of QCA and provide guidance to interested researchers, we utilize the small-N approach as a point of departure. Our goals are to clarify the differences between small-N and large-N QCA approaches with respect to their theoretical assumptions and objectives, the processes, and decisions involved in building the causal model, selecting the sample, as well as analyzing the data and interpreting the analytical results. In addition to elucidating the large-N approach, our hope is that this comparison may serve as a guide for future researchers in deciding which of the two approaches to implement. An overview and summary of the main points of comparison is contained in Table 1.

Objectives: Reasoning and Primary Goals

As discussed in the previous section, both small-N and large-N applications of QCA lend themselves to empirical analyses of the configurational nature of causal relationships. However, the potential objectives – and thus

Table 1. Small- and Large-N QCA Approaches.

	Small-N QCA	Large-N QCA
Objectives		
Reasoning	Mostly inductive	Inductive or deductive
Primary Goal	Theory building	Theory building and testing
Sample and causal model		
Number of cases	12–50	50+
Relationship to cases	Relatively close, based on knowledge of each case	Relatively distant, based on knowledge of conceptual relationships
Sample/case selection	Theoretical sampling based on theoretical relevance or significance of the case	Theoretical or random sampling; random sample may be inappropriate for large-N research primarily interested in diversity
Number of causal conditions	Typically 4–8	Typically 6–12
Analyses processes		
Consistency	Consistency $=1$ (i.e., "Always sufficient") is plausible (though minimum threshold consistency of .80 can be used).	Consistency $\geq .80$ (i.e., "Almost always sufficient") is convention.
Resolving contradicting observations	Various strategies; intimacy with cases may benefit some while small-N may limit others	Various strategies; large-N may benefit some while distance from cases may limit others
Coverage	Typically high – all cases accounted for after iterations of building the model based on in-depth case knowledge	Relatively lower – large coverage desirable but not necessary
Frequency threshold	Minimum typically one or two cases	Minimum typically higher (3+); tradeoff between potential for deductive analysis and inclusion of rare configurations
Interpretation of findings	Results of necessity and sufficiency are interpreted by returning back to cases; case knowledge is used to build theory	Results of sufficiency and necessity are interpreted primarily as patterns across many cases without returning back to cases; statistical inferences are possible

analytical reasoning – will tend to differ across small-N and large-N approaches. To begin with, although QCA is capable of incorporating probabilistic criteria to account for randomness and error (see Ragin, 2000, pp. 109–115), it has typically not been viewed as a hypothetico-deductive technique (Ragin, 2006, 2008). In short, the QCA approach has been described as a tool that contributes "to theory building by providing a rigorous way to combine verbal statements with logical relationships" (Fiss, 2007, p. 1181). As a result, small-N studies utilizing QCA have tended to aim at theory building, and have primarily employed inductive reasoning. Nevertheless, small-N QCA applications could be used to test theories deductively by constructing (non-probabilistic) evidence to either support or refute theories, as is true for case study research designs more generally (e.g. Bitektine, 2008; Ridder, Hoon, & McCandless, 2009; Yin, 1994). Large-N inquiries utilizing QCA in organization studies have also been designed with the primary goal of theory elaboration. For example, Greckhamer et al. (2008) explored how configurations of industry, corporate and business-unit factors affect business performance on a sample of 2,841 business-units spanning 2,451 corporations and 184 industries.[4] While this study demonstrates the utility of large-N QCA for inductive, theory building inquiry, no methodological reasons hold back large-N QCA approaches from being used deductively (e.g., see Fiss, 2011). Hypothetico-deductive large-N QCA applications are not only possible but in our view present one of the most promising areas to extend the set theoretic approach.

In this regard, as opposed to theorizing and trying to isolate the independent effects of single causes, QCA's configurational nature both enables and guides the researcher to theorize about combinations of causal attributes that are necessary or sufficient for the occurrence of an outcome and enables the testing of hypotheses of these causal relations of necessity and sufficiency. For this purpose, as mentioned above, QCA enables the use of probabilistic criteria. Hence, a researcher may specify a set of hypotheses (e.g., "configuration X will be sufficient for outcome Y"), set parameters surrounding the acceptable threshold for the consistency (i.e., $\geq .80$; Ragin, 2000, 2008) of the hypothesized set relation(s) required to constitute evidence of support of the hypotheses, as well as probabilistic criteria (i.e., $p < .05$) used to assess whether this consistency, that is, the proportion of cases displaying the hypothesized configuration (e.g., "X") and manifesting the outcome (e.g., "Y"), is significantly greater than the designated threshold (for a detailed explanation, see Ragin, 2000, pp. 115–119).

The challenges for conducting hypothetico-deductive large-N QCA studies are primarily theoretical, as opposed to methodological, in nature. The reason for this is that due to the dominant position of (net effects-oriented) general linear regression approaches in organizational research, unsurprisingly extant theorizing has primarily focused upon identifying the (strengths and direction of) relationships of single causes with outcomes of interests (see Abbott, 1988). The challenge, then, lies in the fact that QCA's set theoretic approach requires researchers to shift away from ''net effects'' thinking and instead focus their attention on how causes combine to bring about outcomes. Thus, as opposed to theorizing about and trying to isolate the independent effects of single causes (i.e., their ''net effects''), QCA's configurational approach both enables and guides researchers toward theorizing about causality in terms of the necessity and/or sufficiency of combinations of attributes (Fiss, 2007; Ragin, 2000, 2008). For example, Fiss's (2011) study of 139 high-tech UK firms takes a deductive orientation to theorize and empirically examine the core and periphery aspects of organizational configurations (i.e., Miles and Snow's typology of strategic organizations). This study illustrates that the long tradition of configurational theorizing by organizational and strategy scholars (e.g., Fiss, 2007; Meyer et al., 1993; Miller, 1986, 1996; Miller & Friesen, 1978, 1984; Mintzberg, 1979) can serve as rich foundation for future deductive large-N QCA research. Furthermore, considering the difficulty in interpreting multi-way interactions (e.g., 3-way, 4-way, etc.) in regression-based analyses (e.g., Aiken & West, 1991), another avenue forward for large-N QCA studies could be to build on more micro-oriented theories that have theorized such interactions (e.g., Oldham & Cummings, 1996; Skarlicki & Folger, 1997; Wood, Michela, & Giordano, 2000). For instance, QCA is well suited to examine the hypothesis that creative performance is highest when individuals with creative personalities work in complex jobs and have supportive and un-controlling supervisors (i.e., a four-way interaction; Oldham & Cummings, 1996).

In summary, both small-N and large-N QCA studies can be used for either theory testing or theory building. Large-N QCA studies, however, are relatively better positioned for theory testing as they can conform to the widely held expectations in organization studies that hypothetico-deductive theory testing be tightly coupled with statistical testing of probabilistic criteria. Indeed, we envision that deductive theory testing could become the typical mode of inquiry for large-N QCA studies and suggest that such research can build upon extant theorizing on organizational configurations, typologies, and multi-way interactions to chart its course.

Building the Sample and Causal Model

The Number of Cases

Not surprisingly, the number of cases under study is a point of difference across small-N and large-N QCA studies. Nevertheless, a few points are worth highlighting here. First, small-N studies typically involve between 12 and 50 cases. QCA has occasionally been applied to analyze samples of 12 or even fewer cases (see Marx, 2010). However, in such cases a systematic comparison of the necessity or sufficiency of attribute combinations depends on substantial in-depth cross-case and within-case analyses. QCA may be utilized to formalize cross-case comparisons; however if not combined with these in-depth cross-case and within case analyses, QCA analyses with 10 or fewer cases do not provide sufficient evidence to construct robust causal models (Marx, 2010). Systematic comparison of causal connections across more than 10–12 cases becomes quite unwieldy without a tool for systematic comparison such as QCA; a deep, rich investigation which is the signature of qualitative and case oriented research is still possible when examining 12–50 cases via QCA. Thus, QCA offers researchers a tool that supports both a deep qualitative analysis of cases and a systematic comparison. Large-N QCA studies typically will involve more than 50 and, as for example Greckhamer et al. (2008) demonstrate, QCA may handle even thousands of cases. Indeed, theoretically the sample size would be limited only by hardware and software limitations rather than methodological impediments.

The Researcher's Relationship to Cases

The relationship that the researcher has to the cases under study differs somewhat between small-N and large-N QCA studies. As just described, researchers involved in small-N QCA settings will typically have a relatively deep knowledge of each case. Inevitably, such a close relationship is decreasingly feasible as the analysis involves 50, a few hundred, or even thousands of cases. In this way, large-N QCA somewhat resembles regression analysis approaches commonly used to study large samples. Yet, this is where the resemblance to statistical analysis ends. Unlike in correlational analysis, in which ''measures vary around an inductively derived, sample-specific mean'' (Ragin, 2008, p. 8), the set memberships of each theoretical attribute in the QCA approach must be calibrated. As described above, this means that the researcher must establish, a priori to testing, qualitative anchors to capture differences in kind (i.e., full membership and full nonmembership) as well as differences in degree (partial membership in the continuum between 0 and 1) based upon both theoretical and substantive knowledge (Ragin, 2000, 2008).[5] Thus, while the researcher's relationship to the cases in large-N QCA research is somewhat less intimate than in small-N research, the designation of anchors still requires greater familiarity with the data – both theoretically and empirically – than is commonly expected in standard correlational analyses. Accordingly, QCA pushes researchers to fully understand how to calibrate the particular attributes under study, even though prior theory is unlikely to always be a reliable guide here, as we discuss further below. Overall, the researchers' relationship to the studied cases differs across small-N and large-N QCA studies, from relatively close to relatively distant. Nonetheless, the QCA method to large-N studies both requires and affords researchers a closer and more intimate relationship with the data than is required in large-N correlational studies.

Case Selection

In general, QCA uses a purposive sampling method; because QCA examines commonalities across the same outcome in cases (i.e., subset relations), researchers begin with the outcome of interest they wish to study in order to identify the population of cases of theoretical interest. For example, if one is interested in understanding the causes of success of mergers of manufacturing firms one would accordingly identify manufacturing firms that experienced mergers. In small-N studies, the sample is typically selected by purposefully selecting cases where either (1) all of the cases fall into the identified domain (i.e. the entire population) and thus within the established theoretical boundaries (e.g. all manufacturing firms that experienced mergers), or (2) a few relatively representative cases are selected from the larger population of cases for purposeful in-depth study (e.g., select a number of representative cases of mergers of manufacturing firms). Furthermore, this purposeful sampling may be an iterative procedure that is guided by the original research question and the relevant theory, justifying the inclusion of each case on theoretical grounds (e.g., Rihoux & Ragin, 2009).

Purposive sampling should also be used in large-N QCA studies. The large-N QCA researcher may again choose to study the whole population of theoretically relevant firms (i.e., the set of cases relevant to a question) or select some sub-sample. For example, a researcher interested in understanding the causality of performance in a certain industry with many competitors may study all the competitors in the industry. Alternatively, the researcher might construct a stratified sample of the theoretically relevant population (i.e., all firms competing in the industry) of cases representative of the population's diversity of cases. Note that drawing a random sample of a population may not always be the best choice for large-N QCA researchers for two reasons. First, the logic of generalizing from random samples to populations in regression analyses presupposes a substantial degree of homogeneity of cases in the population (Ragin, 2000), and is consequently basing generalizations on properties of central tendency, variability, and the shape of sampling distributions (e.g., Schwab, 1999). Thus, when using a random sample in large-N QCA studies, researchers may only generalize beyond the sample if it is reasonable to believe that the sample is a representative one. Second, random sampling is not appropriate for large-N researchers primarily interested in exploring the diversity of cases. This is due to the fact that a random sample may not represent the full diversity of cases – some configurations that occur only very rarely in a larger population (say, configurations represented by only one or two organizations in a population of 1,000 or more cases) may not be represented in the sample, thus requiring oversampling. For example, a random sample may not represent relatively uniquely differentiated organizations that represent very successful but rare configurations, which may not be desirable for organizational scholars.

The Number of Causal Conditions

An important consideration in QCA is the number of causal conditions included in the causal model under study. In small-N settings, researchers need to pay careful attention to the number of causal conditions in relation to the number of cases when designing a QCA study (Lieberson, 2001, 2004; Marx, 2010; Marx & Dusa, 2011; Rihoux & Ragin, 2009). This is because as the number of conditions and thereby the number of logically possible configurations of conditions increases, each case will tend to become its own unique configuration. Such situations make it difficult for QCA to find any commonality across cases in explaining the outcome as well as to rule out ill-specified or even nonsensical theoretical models. Simulations of csQCA models by Marx and colleagues (Marx, 2010; Marx & Dusa, 2011) demonstrate that the possibilities of finding an explanatory model in random data increases as the proportion of conditions to cases exceeds certain thresholds. Their findings suggest that a consequence of exceeding this threshold is the violation of QCA's core assumption that ill-specified or atheoretical models will have low consistency, thereby violating the assumption that high consistency implies validity of the set theoretic relation and thus the analyzed model (Marx & Dusa, 2011). This implies that in cases where these thresholds of proportions of conditions to cases are exceeded, the use of

QCA should be accompanied by in-depth cross-case and within cases analyses; even in such situations QCA provides a systematic mapping of causal conjunctions as well as introducing simplifying assumptions in a manner that are closely connected to the cases (e.g., Stokke, 2007). Overall, researchers need to be mindful of Marx and colleague's (Marx, 2010, Marx & Dusa, 2011) tentative guidelines when conducting and specifying csQCA models in small-N QCA studies.[6]

Large-N applications, on the other hand, do not as readily face this same problem. Nevertheless, a limit to the number of conditions still exists within large-N settings, mainly due to reasons of complexity. This is because each additional condition (k) doubles the number of logically possible configurations (i.e., logically possible configurations $= 2^k$). For example, increasing the number of conditions from 10 to 12 quadruples the number of logically possible configurations from 1,024 to 4,096 ($2^{10} = 1{,}024$; $2^{12} = 4{,}096$), and adding one more condition doubles this number yet again ($2^{13} = 8{,}192$). One implication of this exponentially increasing complexity is that as the number of conditions examined increases, so too does the difficulty of interpreting the findings, because of an increase of both the number of configurations that may be sufficient (and/or necessary) for the occurrence of an outcome and of the complexity of the configurations themselves. Indeed, given this complexity, the results of an analysis involving more than 8–10 conditions are likely to be intractable (Ragin, 2008).

We foresee another implication that will directly impact researchers conducting large-N QCA studies: following the prevailing logic in research applying general linear regression approaches (e.g., Davis, 2010; Edwards, 2008; Williams, Vandenberg, & Edwards, 2009), it is likely that reviewers (and peers) will request the inclusion of more "control variables" in their QCA models. This extant expectation for the use of control variables constitutes a potential (and perhaps formidable) barrier for the acceptance of large-N QCA research in highly regarded journals. While this will require researchers to make compelling conceptual arguments for their specification of included conditions – which as argued above constitutes a vast opportunity given the relative dearth of configurational theorizing – this will also involve methodological arguments that go beyond the already well-articulated "case-oriented" versus "variable-oriented" arguments (e.g., Fiss, 2007; Ragin, 2000, 2008). Researchers conducting large-N QCA studies here can draw on criticism recently leveled against practices surrounding the use of control variables in regression analyses.

Specifically, researchers have recently critiqued the "rampant and relatively unthinking use of control variables" (Davis, 2010, p. 701). This critique draws on the observation that control variables may frequently affect the interpretation of effects primarily ascribed to substantive variables of interest (Edwards, 2008, pp. 481–482). Additionally, as measurement errors in control variables increase, so too does the interpretation of the focal variables under study (Williams et al., 2009). Thus, rather than simply accounting for alternative explanations (and using up degrees of freedom) as conventionally believed, this recent literature suggests that control variables bias the results regarding the substantive variables under study. Furthermore, although statistical control is very different in nature from experimental control (Ragin, 1987), Davis (2010) argues that another reason for the overuse of control variables is that researchers (and reviewers) fail to recognize that their studies are quasi-experiments and thus rather than taking the appropriate steps to remediate the resulting design weaknesses (e.g., Cook & Campbell, 1979), they add control variables to their models, which often is an inexpensive and convenient remedy considering the increasingly abundant data in many areas of organizational research.

In sum, decisions regarding the number of causal conditions to include in QCA studies are vital. Small-N researchers including too many conditions may inadvertently render their results meaningless. Large-N QCA researchers have the option of including a greater number of conditions (from 6 to up to 12 conditions) but are likely to face additional hurdles in explaining why they did not include more conditions in their modeling. To navigate these hurdles, large-N applications of QCA may (at least initially) need to clearly articulate why their specifications of perhaps 7–8 (or fewer) conditions is not only adequate but appropriate. Methodologically, this will require a shift away from conventional "net effects" notions to configurational thinking in the evaluation of large-N QCA research. At the same time, large-N QCA researchers who are prepared to provide theoretical arguments for the conditions included (and excluded) from their specifications and are able to enhance a study's validity by ruling out alternative explanations via remedies other than control variables (e.g., Cook & Campbell, 1979) or through alternative tests (e.g. Fiss, Sharapov, & Cronqvist, 2013) will be better positioned to overcome expectations and requests to include more control variables in their QCA specifications, in addition to developing more soundly specified causal models.

Analyses Processes

Consistency

Consistency "indicates how closely a perfect subset relation is approximated" (Ragin, 2008, p. 44). The basic notion of consistency is perhaps most easily conveyed in connection with csQCA as it describes the proportion of cases belonging to any particular configuration (for in-depth discussions of consistency see Ragin 2000, 2008). For example, assume that for a certain configuration of causal attributes 26 of the 30 firms sharing the configuration also display the outcome (and thus 4 do not), the consistency of this configuration would equal 0.867 (i.e., about 87% of cases in the configuration share the outcome). While it is desirable to have consistency as close to 1 as possible, (near) perfect consistency is more likely to be obtained in small-N studies (Ragin, 2006). Regardless of the sample size, Ragin (2008) has suggested a minimum consistency of .80 for inferring a subset relationship, and extant organizational research has been at or above this recommendation (e.g., Crilly, 2011; Fiss, 2011; Greckhamer, 2011). Applying this consistency threshold, the example configuration can be said to be consistently linked to the outcome, and given appropriate theoretical justification can be said to be a sufficient causal combination for the occurrence of the outcome.

There are two main considerations that somewhat differ across small-N and large-N studies with respect to consistency. To begin with, while the use of probabilistic criteria and benchmarks is limited in small-N studies, they are a viable option in large-N settings. Even a finding of perfect consistency in small-N settings may not support an argument that a causal combination is sufficient at a statistically significant level, because depending upon how small the sample is, the evidence may not be adequate to rule out that the finding has occurred by chance (Ragin, 2000). Large-N settings afford the possibility to determine whether relationships of necessity or sufficiency occur at a statistically significant level. Second, and as discussed in more detail below, consistency may be shaped by possibilities to resolve contradictory configurations. The presence of contradictory configurations by definition lowers consistency scores. Hence, strategies for the resolution of contradictory configurations become vital to potentially enhance the consistency of QCA results, and these strategies differ between small-N and large-N QCA studies. In any case, researchers should observe the recommended minimum consistency thresholds (i.e., $\geq$.80; Ragin, 2008) to confidently draw inferences from their findings.

Resolving Contradictory Configurations

Contradictory configurations occur when cases in the same configuration show different outcomes. For QCA, contradictions weaken set theoretic consistency, making it more difficult to draw inferences about causal relationships. Ragin (2008) and Rihoux and Ragin (2009) offer several strategies for resolving these logical contradictions, which entail a mix of theoretically and empirically driven recommendations. Those authors' recommendations were tailored to small-N studies, and below we highlight how the various strategies they proposed may be extended to large-N studies.

The first potential strategy is to review case selection rules. Here, researchers would question whether all of the selected cases are actually part of the relevant population. For instance, a researcher interested in studying the causes of performance in large firms could reassess whether all firms in the sample are indeed "large." Indeed, if contradictions are attributed to "borderline" cases (i.e., cases near the specified threshold of what constitutes large firms), then dropping these cases may well be warranted. As is true for all modes of inquiry, and particularly for QCA, the research process is very much an iterative one: theory and empirics should come together to refine the research design and thus strengthen the inquiry (Ragin, 2000, 2008). In the current running example, the theoretical threshold for what constitutes a "large" firm is ambiguous at best, and thus this type of iteration very much would help to inform theory (as well as potentially resolve occurring contradictions).

A second strategy to deal with contradictory configurations involves the addition, removal, or replacement of one or more of the theoretically important causal conditions in the model. While this strategy is perhaps more accessible in large-N as compared to small-N studies – due to a reduced danger of surpassing the threshold of maximum proportion of causal conditions to cases – it is vital that large-N researchers rely on extant theory to identify attributes that have the potential to differentiate contradictory cases and thereby resolve contradictory configurations. While exploratory data analysis can be a useful tool and be part of the iterative nature of developing the causal model, data mining and fishing expeditions are no more valid in QCA than they are in regression-oriented analyses.

A third recommendation to resolve contradictory configurations involves the re-examination of the ways in which sets – including the outcome set – are operationalized and calibrated. Inappropriate calibration of sets (i.e., the qualitative thresholds of full membership, full nonmembership, and degrees of membership are not well specified) will place cases that should be differentiated into the same configuration (i.e., differences in kind are not captured). This strategy appears to be a potentially very fruitful strategy for large-N samples. Because large-N researchers lack intimate knowledge of each individual case, and moreover because extant theory will often prove to be ambiguous in guiding the specification of the anchors used in calibration (e.g., what constitutes a "large" firm), researchers might have to rely on empirical knowledge such as central tendencies in the data when initially calibrating sets (e.g., mean, median, quartiles). However, as discussed above, contradictory configurations may provide an opportunity to advance theory; an examination of the cases falling into contradictory configurations, combined with extant theory, may improve specifications of the anchors in calibration (i.e., rather than simply central tendencies) and thus help to refine theory in this regard. Relatedly, large-N QCA researchers should be mindful of the quality of the data underlying the sets and how any potential problems with the quality of the data (e.g., random or systematic errors in archival sources) may be contributing to the occurrence of contradictory configurations. These recommendations also apply to the outcome, and contradictions may be resolved by reevaluating whether the outcome has been defined and calibrated properly.

A fourth strategy involves developing deeper knowledge of each of the cases involved in a study so as to identify aspects of the cases that would help to resolve the occurring contradictions. While at first consideration this strategy does not appear to be practicable for large-N studies, it may nevertheless be possible considering that only the cases falling into the contradictory configuration(s) need to be so explored. For example, if the number of cases displaying the contradiction is limited (e.g. 15 or 20 cases), then it might be possible for the researcher to gain more detailed knowledge on these particular cases that helps to both resolve the contradictions and to develop a more in-depth knowledge of the cases under study. Additionally, even if the number of cases is quite large, an alternative possibility could be to take an in-depth qualitative look at a randomly selected sample of contradictory cases (e.g., Eisenhardt, 1989; Yin, 1994).

A final strategy is to rely on a frequency criterion. For example, if only one in twenty cases is contradictory (e.g., 19 cases have the outcome of high performance and one has the outcome of not-high performance), one could make the judgment that this does not constitute a theoretically significant contradiction, but may more reasonably be assumed to involve factors such as coding error or randomness. As Rihoux and Ragin (2009) point out, this is the most controversial strategy as it is purely probabilistic in nature and does not lend itself to combining theoretical and substantive knowledge. Approaching contradictory configurations in this manner nevertheless constitutes a viable strategy assuming that the implications of applying this probabilistic logic are discussed as potential limitations. However, it also leaves the task of more deeply investigating the contradictory cases to subsequent studies. Overall, as is the case with this and all the other strategies described, transparency is of the utmost importance when performing QCA research (Ragin, 2008), thus small-N and large-N researchers alike should report both the contradictory configurations and any steps taken to resolve it.

Coverage

Coverage is a measure of the proportion of cases that display the causal configuration; note that determining adequate consistency is a precondition for calculating a configuration's coverage, because without it one cannot infer that a set relation between a configuration and an outcome exists in the first place (Ragin, 2008). Again, the concept of coverage is most easily conveyed in connection to csQCA, as this proportion is calculated by dividing the number of cases showing a specific configuration by the total number of instances of the outcome. Continuing with the example above, this configuration's raw coverage would be calculated based upon the 26 out of 30 cases displaying the outcome; assuming that in this study there were 104 cases displaying the outcome, the raw coverage score for this particular configuration would be 0.25.[7] In short, because QCA allows for equifinality, coverage provides an assessment of the relative empirical importance of each configuration that was found to be consistently linked to the outcome. It therefore is an important indicator for both small-N and large-N QCA studies.

Small-N and large-N studies differ with respect to coverage in at least one important way. The first issue concerns the combined coverage of all configurations consistently linked to the outcome, or the solution coverage. Given the primary objective of small-N QCA studies to build or elaborate theory as well as the more intimate relationship the researcher has to cases in these settings, it is desirable and usually possible to attain near perfect solution coverage (i.e., after iterations of building the causal model, including application of the strategies to resolve contradictions as discussed above). Put differently, a causal model that accounts for all occurrences of an outcome can usually be developed if the number of cases under study is relatively small and allows for the building of in-depth knowledge to continuously revise and refine the model based upon qualitative exploration of the cases. To the extent that large-N QCA studies are more deductive in their focus, researchers likely have to settle for lower levels of solution coverage. Imperfect solution coverage indicates incomplete causal evidence that leaves some paths to the outcome unaccounted for. However, considering solution coverage roughly as analogous to an overall R^2 in a regression analysis, it is worthwhile to remember that the explained variation is frequently quite low in regression-based organizational research – for the overall model specifications and particularly so for the substantive variables under study.

Frequency Threshold
An additional consideration pertains to decision-making surrounding the appropriate specification of the frequency threshold for configurations' inclusion in causal analyses. That is, QCA maps all logically possible configurations as well as the full range of diversity of empirically existing configurations, and thus the researcher has to specify the minimum number of cases that must be observed for each configuration in order for it to be considered relevant for purposes of causal analysis of necessity and sufficiency. The appropriate minimum level of cases will depend upon the objectives of the study, which as discussed above, tend to differ between small-N and large-N QCA studies. In the context of small-N studies, it is common to specify a minimum frequency of one or two cases, given the small number of cases and the exploratory nature of such research as well as the researcher's intimate knowledge with the cases.

The minimum frequency for large-N studies, however, would potentially be much higher, particularly if the objective is a hypothetico-deductive model. In such studies, it may not be desirable to include configurations that occur among only very few cases in the analyses, because the presence of these low-frequency configurations might represent random forces or measurement errors (Ragin & Fiss, 2008). On the other hand, setting the minimum frequency too high may result in a reduction of the number of cases included in the analysis. In order to establish the proper level of this threshold, the researcher will typically have to use empirics as a guide. For example, Ragin and Fiss (2008) selected a frequency threshold that captured more than 80% of the cases for the analyses. If strictly adhering to an a priori set threshold (say for instance, a minimum frequency of 14 cases per configuration) results in a low inclusion of the overall cases in the analysis (60% for instance), then this implies that there is a relatively large degree of diversity present (implications could range from a small number of relatively well-represented configurations being excluded to a relatively large number of configurations containing relatively few cases being excluded) and thus excluding this diversity would be undesirable and should be avoided by selecting a proper frequency threshold that takes this tradeoff into account.

It is also important to note that while researchers may exclude configurations not represented by some minimum number of cases from causal analyses, any such rare configurations nonetheless may highlight cases of interest to explore in more depth to fully understand the diversity of cases under study. For example, some of these rarely occurring configurations may represent vital niches or populations of relatively newly created organizations to be explored further in a subsequent study (i.e., a follow-up small-N or case study analysis). Alternatively, the inclusion of rare configurations may be warranted theoretically: if, for example, an inquiry is about firm performance, and to the extent that competitive advantage is necessarily held by very few firms in an industry (e.g., Peteraf, 1993), excluding such rare configurations may be detrimental to the study's research design. In such projects, researchers may be able to reduce the likelihood that rare configurations are the result of measurement errors; for example, in their study of firm performance, Greckhamer et al. (2008) aggregated performance and causal attributes over three time periods to increase the reliability of cases' set membership. In short, unless the researcher has theoretical reasons for doing so, we suggest that in setting their minimum frequency thresholds, large-N researchers strike a balance between the inclusion of at least 80% (see also Ragin & Fiss, 2008) of the overall cases and a relatively high number of cases per configuration. Moreover, researchers conducting large-N studies may consider experimenting with both relatively high and relatively low frequency thresholds, which would yield more coarse-grained analyses focusing on the dominant configurations linked to the outcome of interest and more fine-grained analyses influenced by relatively rare configurations, respectively.

Interpretation of Findings

In the interpretation of findings, differences between small-N and large-N QCA come back full circle to the goals of the research: whereas small-N QCA studies are typically aimed at theory building and tend to follow an inductive logic, large-N QCA studies may be utilized to build or test theories, thus following an inductive or deductive logic. Because existing literature provides guidance with respect to interpreting small-N QCA findings (e.g., Ragin, 2000, 2008) as well as inductive large-N QCA findings (e.g., Greckhamer et al., 2008; Ragin & Fiss, 2008), here we focus on highlighting a few issues involved in the interpretation of deductive large-N QCA inquiries. First, considering the potential challenges involved in deducing hypotheses regarding multiple conjunctive causality, we emphasize that large-N studies following a hypothetico-deductive logic *must* clearly specify hypotheses about predicted relationships of causal necessity and/or sufficiency. For example, hypotheses such as "equifinal causal configurations will lead to outcome Y" or "configurations of firm practices will lead to high firm performance'' are not readily testable and falsifiable; they simply reiterate configurational assumptions rendering them to be tautology. Building on the latter example (and the hindsight provided by the findings of Greckhamer et al., 2008), hypotheses such as ''a high level of corporate slack resources is a sufficient condition by itself for achieving high performance among manufacturing firms'' or ''a combination of abundant corporate slack resources, large firm size, and industry stability leads to high performance among service firms'' provide enough specificity to be testable (i.e., falsified).

Second, as discussed above, large-N QCA applications including those of a hypothetico-deductive nature share the basic properties and assumptions of QCA and set theoretic methods; these assumptions shape (and limit) the extent to which the findings of large-N QCA studies lend themselves to empirical generalizations. In short, the extent to which researchers can generalize findings of relations supporting claims of necessity and sufficiency beyond their sample will depend upon the initial construction of the study sample and the incorporation of any simplifying assumptions. With respect to the former, researchers need to be mindful that in large-N QCA applications the emphasis remains on complexity, even in hypothetico-deductive studies. That is, in the inevitable tradeoff between complexity and generalizability of findings – ''an appreciation of complexity sacrifices generality; an emphasis on generality encourages a neglect of complexity'' (Ragin, 1987, p. 54) – QCA's focus on complex causal combinations and the integrity of cases trades off generalizability for contextual realism and complexity. Thus, for example, a finding of support for the hypothesis that a combination of abundant corporate slack resources, large firm size and industry stability is sufficient for high organizational performance among a representative sample of S&P 500 service firms has limited generalizability in that it has no implications for cases beyond this population of organizations (i.e., S&P 1500 service firms; smaller service firms, etc.) nor does it have implications for S&P 500 service firms not displaying all elements of this configuration of attributes. In sum, to the extent that generalizability is desirable and given these properties of QCA, the study sample should be constructed at the outset with due consideration for representativeness – as discussed above, a representative random sample or a stratified sample that captures the diversity of cases – or alternatively include the population of cases.

Simplifying assumptions about configurations not found in the dataset (i.e., easy and difficult counterfactuals taken into account in deriving the solutions; see Ragin, 2008) also affect interpretation. While a discussion of the interpretation of the alternative solutions available in QCA (i.e., complex, parsimonious, intermediate) is beyond the purview of the current chapter, suffice it to say that any conclusions drawn from hypotheses tests and consequently any generalizations drawn from empirical results hinge on the plausibility of any included simplifying assumptions and the extent to which researchers can defend their inclusion on theoretical grounds (Ragin, 2000, 2008). Thus, not only should interpretations of results be made with these simplifying assumptions in mind, but also should researchers transparently explicate those simplifying assumptions that may affect their interpretations in their discussion of the results.

Third, interpretations of large-N QCA studies, not unlike those of their small-N counterparts, are shaped by the fact that set theoretic relationships allow for asymmetric causal relationships, that is, the causal conditions leading to an outcome's presence may be quite different from simply being the opposite of the causes leading to the outcome's absence (Fiss, 2011; Ragin, 2008). Moreover, frequently researchers studying an outcome (e.g., firms with high performance) may not be interested in what leads to the absence of the outcome (e.g., firm with not high performance), but rather in an outcome that is best captured by means of a separate set (e.g., membership in the set of firms with low performance – in which membership would be calibrated according to theoretical and substantive knowledge as to what constitutes low performance). Therefore, any findings for hypothesized configurations of firm attributes leading to high firm performance, for example, cannot be generalized as also having implications for configurations leading to low performance. Instead, researchers would need to calibrate the set of firms with low performance. Indeed, as previous research has shown, the causal combinations that lead to not high or low performance may be quite different (and sometimes asymmetrical) to those leading to high firm performance (see Fiss, 2011; Greckhamer et al., 2008).

In addition to these considerations for the interpretation of deductive large-N studies, interpretations of large-N QCA studies more generally will be affected by the difference in relationship that the researcher has with the cases themselves. As discussed above, the researcher's relationship to the cases in small-N applications is much more intimate and thus interpretation of the results of causal analysis of necessity and sufficiency can greatly benefit from linking the observed cross-case patterns with in-depth knowledge of individual cases (Rihoux & Ragin, 2009). Conversely, in large-N studies a return to the cases may not be (immediately) possible or feasible, due to the greater distance of the researcher from the cases and the lack of case-specific knowledge needed to return to the cases. Thus, results of causal analysis of sufficiency and necessity are interpreted primarily as patterns across many cases and as we outlined above, researchers should take care not to interpret their findings beyond the boundaries inherent to their study's research design.

THE PROSPECTS FOR LARGE-N CONFIGURATIONAL ANALYSIS

QCA can lay claim to being one of the few genuine methodological innovations to have occurred in the social sciences over the last few decades (Gerring, 2001). While QCA's initial development and proliferation was driven in small-N situations, this chapter suggests that there is both a need for a large-N QCA approach and potential to enhance QCA's applicability to large-N situations. Our preceding discussion of contrasting small-N and large-N QCA shows that they share vital basic foci on configurations and complex causality and that they both employ a set theoretic perspective and a Boolean algebraic approach. At the same time, a large-N QCA approach differs from its small-N counterpart with respect to goals, assumptions, and research processes. In particular, in addition to its potential to support theory building shared with small-N approaches, large-N QCA can be utilized for hypothesis testing and deductive reasoning and by its very nature maintains a distance between the researcher and the cases. In these respects large-N QCA applications are analogous to conventional general linear approaches that currently dominate large-N organization studies; despite these analogies, however, the QCA approach differs from the general linear approach in vital fundamental assumptions constituting its configurational nature. Because these foundational differences are in detail discussed by Ragin (2000, 2008), our focus in this last section of the chapter is to highlight the value QCA contributes to large-N organization studies. In short, the large-N QCA approach can complement existing general linear approaches to the study of organizations in at least two fruitful ways: as a standalone configurational alternative to standard regression analyses or as a complementary component in mixed-methods approaches integrated with standard regression analyses.

The first issue relates to the ability to generate novel theories and insights that are fundamentally configurational, making QCA a vibrant alternative with substantive application potential for large-N organizational research. In this regard, QCA provides an alternative understanding of causality for organizational researchers by making the leap from net-effects thinking to configurational thinking, also emphasizing the diversity of organizations (e.g., Fiss, 2007, 2011; Greckhamer & Mossholder, 2011; Greckhamer et al., 2008; Kogut, Macduffie, & Ragin, 2004; Ragin, 2000, 2008). This is very important to the study of organizations as a mismatch between theories and methods currently pervades much of organization studies: while theoretical discussions about organizations frequently stress nonlinear relationships and equifinality, empirical research has typically drawn on general linear model methodologies that by their very nature tend to imply singular causation and linear relationships (Fiss, 2007). While these methodologies are powerful tools for empirical research in their own right, QCA offers an approach that allows researchers to (re)discover important phenomena and research questions that do not comply with a general linear understanding of reality they construe (see Abbott, 1988). Because they start from the assumption that theory building and testing as well as formulating predictions and generalizations regarding causal processes need to take into account the diversity of cases (here organizations) (Ragin, 2000), large-N QCA applications have the potential to make unique contributions to organizational research.

The second way forward for large-N QCA relates to utilizing the method as a direct complement to conventional regression analyses and a suitable component of mixed-methods approaches. Such mixed-method studies could be utilized in a host of fruitful ways. For one, they could be used to answer (a) particular research question(s) by examining the same data from these alternative perspectives in a manner that employs the strength of each. For example, studies that hypothesize independent main effects (best tested by linear regression) as well as complex interaction effects (best examined via QCA) may be best served in this way, particularly when the hypothesized interaction effects involve multiple attributes (and thus may go untested in general linear approaches). Another potential use is that of triangulation: these alternative methods may serve as robustness checks for each other. For instance, one might utilize QCA to identify a particular configuration leading to the outcome in question by and then use solution membership as a predictor in a more standard regression analysis, allowing further for the addition of control variables that might make a QCA analysis too unwieldy. While considerable work remains to be done to explore the intersection and the potential complementarities between QCA and standard regression analysis, current efforts to explore these complementarities are under way (Fiss et al., 2013); we believe doing so presents a promising way forward.

Additionally, large-N QCA can also be complemented by either small-N QCA or qualitative exploration of cases. That is, the results of large-N QCA studies could be used to identify cases of certain configurations as vital for understanding causal relations and to guide selection of cases for more in-depth study of the causal mechanisms underlying patterns of relationships. For example, researchers studying the determinants of organizational performance could choose (a sample of) cases representing a configuration that is linked to the outcome of interest with high consistency, and conduct in-depth qualitative case studies to explore why combinations of attributes representing the configuration may lead to the outcome of interest.

In closing, QCA holds great promise for both small-N and large-N social research in general and organization studies in particular, and both of these variants of QCA should become standard tools in the organizational researcher's toolbox. The purpose of this chapter was to establish that due to its alternative perspective and complementary properties as compared to conventional general linear approaches, large-N QCA holds significant potential for organization studies. To help future researchers harness this potential, we provided guidance for large-N QCA applications by discussing the ways in which it departs from small-N QCA applications. In order for large-N QCA analysis to flourish, best practices and conventions still need to be developed. To do so, we hope that organizational scholars using QCA continue the dialogue on large-N applications of QCA in organization studies we aimed to begin with this chapter.

NOTES

1. In this chapter, we use Qualitative Comparative Analysis (QCA) to encompass both crisp-set (csQCA) and fuzzy-set (fsQCA) QCA and only use the more specific terms when warranted by the discussion.

2. Although "causal conditions" and "causality" is the terminology commonly used in the QCA approach, we fully recognize that QCA has the same limitations as other methodologies (i.e., regression-oriented approaches) when it comes to making causal inferences. See Greckhamer et al., (2008, footnote 1) and Ragin (2008, pp. 13–20) for more on this issue.

3. The primary means of designating and examining set relations are the two basic Boolean operators – logical *and* and logical *or*. The operator *and* represents the intersection of sets, and is used when conditions A *and* B combined may lead to an outcome. The operator *or* represents the union of sets, and is used when either one condition *or* another may lead to the same outcome. For more detailed explanations, see for example, Fiss (2007), Greckhamer et al. (2008) and Ragin (1987, 2000, 2008).

4. Examples of large-N QCA studies in other disciplines taking an inductive approach include Amoroso and Ragin (1999), Miethe and Drass (1999), Ragin and Bradshaw (1991), and Ragin and Fiss (2008).

5. As discussed above, csQCA requires the researcher to specify full membership, while fsQCA requires thresholds for full, non, and partial memberships; partial membership can be calibrated through setting of a cross-over point in continuous fuzzy sets or the setting of multiple anchors to calibrate multi-value fuzzy sets, for example four-value (e.g., Crilly, 2011), five-value or seven-value fuzzy sets (Ragin, 2000, 2008).

6. While their guidelines are tentative, Marx and Dusa (2011) suggest that csQCA models that exceed the proportion of conditions to cases recommended based on their simulation study should not be analyzed because the probability of generating results with random data increases beyond a 10% chance. The implications of their work for fuzzy set analysis have not yet been determined.

7. In addition to calculating a configuration's raw coverage as demonstrated here, researchers can calculate each configuration's unique coverage (i.e., the amount of coverage that does not overlap with other configurations) as well as the overall solution coverage (i.e., the proportion of cases showing the outcome falling into any of the configurations consistently linked to the outcome) (see Ragin, 2006, 2008).

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