TOWARDS MORE ROBUST MODEL SPECIFICATION IN QCA
RESULTS FROM A METHODOLOGICAL EXPERIMENT

COMPASSS – Working Paper

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Abstract

Qualitative Comparative Analysis (QCA) is a research technique which was developed by Charles C. Ragin and has been applied in several studies that appeared in major sociological journals. Recently, QCA has been criticized concerning the validity of the models it generates. Lieberson has hypothesized that QCA is unable to distinguish real from random data. In other words, it is argued that QCA always finds a model even on the basis of random data. The paper addresses this issue through a methodological experiment. It uses randomly created data-matrices to show that QCA can make a distinction between real and random data. However, it only does so under certain conditions namely when the proportion of variables on cases goes below a certain threshold, which differs as a function of the combination of variables on cases. Secondly, it argues that there is an upper-limit to the number of variables which can be used in a QCA-analysis. Both limiting conditions are the result of the problem of uniqueness which is a consequence of the use of Boolean algebra and have not yet been addressed in the literature. Five implications for comparative case research-design and QCA are discussed.

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INTRODUCTION

Qualitative Comparative Analysis (QCA) is a comparative case-oriented research technique, based on Boolean algebra, which was developed by Charles C. Ragin in the 1980's and 1990's. In the 1980's a crisp set approach was developed which uses dichotomous variables. In the 1990's a fuzzy-set approach was (and is) developed which allows for the use of multi-value fuzzy-scores (fsQCA). QCA aims to develop explanatory models on the basis of a systematic comparison of a small number of cases. QCA has been applied in more than a 150 studies in sociology, political science, policy analysis, organizational studies and other fields (for an overview see table 3). As noted by John Gerring (2001) QCA is one of the few genuine methodological innovations of the last few decades. In an era of doubts on macro-quantitative approaches (Kittel, 2004; Ebbinghaus, forthcoming) and increased attention to case studies in many social sciences (Brady & Collier, 2004; George & Bennett, forthcoming, Rodrick, 2003; Bates et. al., 1998) QCA holds the potential to provide a unique set of tools to compare similarities and differences of a limited set of comparable cases and identify structural conditions which proceed an outcome of societal and scientific interest. Due to its emphasis on explaining all the cases it could also generate policy advise since one is able to identify the different paths to an outcome and allows for ex post experimentation/policy manipulation.

Recently, however, QCA – the crisp approach - has been criticized concerning the validity of the models it generates. Stanley Lieberson (2004) has hypothesized that QCA is unable to distinguish real from random data and generates 'valid' models and explanations on the basis of random data. This paper addresses this issue by means of a methodological experiment. It uses randomly created datamatrices to show that QCA can make a distinction between real and random models. However, it only does so under certain conditions namely when the proportion of variables on cases goes below a certain threshold. This threshold differs as a function of the combination of variables on cases. Secondly, it is argued that there is an upper-limit to the number of variables which can be used in a QCA-analysis. Both limiting conditions are the result of the problem of uniqueness which is a consequence of the use of Boolean algebra. The overall conclusion is that a QCA-analysis should be performed with care. However, if the research-design takes the limiting conditions into consideration a QCA-analysis can produce valid models which contribute to model/theory development. The first part focuses on the debate of the validity of models generated via QCA. In a second part, the methodological experiment is introduced and the main results discussed. A third part explains these results. The fourth part discusses the implications for a QCA-research design. Finally, a conclusion is presented.

DEBATE

QCA is an analytic technique which enables researchers to systematically compare differences and similarities of configurations of variables between a set of cases and enables researchers to inductively explore data and develop explanatory models. (Ragin, 1987; 1994; 2000; 2003) The essence of the technique consists of understanding how configurations of variables are linked to a certain outcome. As such, this approach resembles more qualitative-oriented case research than quantitative-oriented variable research and hence can easily complement a qualitative description of cases. In other words, instead of analyzing relationships between two or three variables (standard variable-oriented approach) QCA compares cases by comparing configurations of explanatory variables with the presence or absence of an outcome. Each explanatory variable is typically coded as either being present of absent. It is comparative in the sense that it explores similarities and differences across cases by comparing configurations. The goal is to unravel how different conditions (configurations/causal paths) are connected to different outcomes. In this way it is a comparative exploration and examination of empirical diversity. In addition, QCA allows for *multiple conjunctural causation* (Ragin, 1987; Ragin, 2000; Rihoux, 2004). This means that the technique allows for the possibility that there may be several combinations that generate the same general outcome, can address complex and seemingly contradictory patterns of causation - a condition can be important in both its presence and absence – and that it eliminates irrelevant causes (via logical minimization). An additional feature of QCA is that it is aimed to produce a model which explains all the cases present in a research population.

QCA has recently been criticised for being unable to distinguish real from random data and hence generates explanatory models which are not valid. This impossibility to distinguish real from random data is suggested by Stanley Lieberson (2004) who argues that the QCA-method is unable to distinguish randomly assigned values (a data matrix with no meaning) from a table based on real data. "*If that is the case, how can we evaluate QCA as doing much for us?*". As a result, it is hypothesised that random assignments would result in a QCA-led discovery of 'meaningful' models. The criticism crucially rest on the fact that there is not much difference between a real data-set on which QCA is applied and a randomly created data-set.

Proponents of QCA reject this criticism by arguing that it is one of the key-strengths of the approach to generate a full account of all the cases via a constant dialogue between cases, theories and models. (see Ragin & Rihoux, 2004a; De Meur & Rihoux; 2002; Rihoux, 2003) If for example crucial variables are omitted from an explanatory model – it is assumed – a QCA analysis will not generate a full account of the cases and result in contradictions. Since QCA is deterministic in nature (explaining every case with a given model) it is not straightforward to come up with a model which explains all cases but at the same time omits a key-variable. The presence of the contradictions points to the fact that some cases cannot be explained by the model (contradictory cases – infra). In other words, it is argued that QCA only produces valid models when they exist in the data and in all other circumstances does not produce models. Valid models in this context refer to models which provide an explanation for all the cases in the analysis and which does not generate contradictions. Contradictions occur in QCA when an identical configuration of independent variables accounts for both the presence and absence of an outcome. In QCA-terms[2] a contradiction occurs when:

A.b.C => D

A.b.C => d

In the case of contradictions the model is unable to explain all the cases. The importance of the issue of contradictions in model construction via QCA was recently stressed by Ragin (2005, p. 34) who argued that a QCA-analysis forces "*researchers to deepen their knowledge of cases, as they confront sets of cases that are similar with respect to specified causal conditions but different in their outcomes (such cases are called 'contradictions' in QCA). It is incumbent upon the researcher to resolve as many of such contradictions as possible, through case-oriented analysis, before synthesizing cross-case patterns […] The resolution of contradictions […] deepens knowledge and understanding of cases and also may expand and elaborate theory*."

In other words a QCA-analysis identifies the one model which explains all the cases, other models will result in contradictions. By extension a QCA analysis on random data should result in many contradictions. However, the question of under what conditions it is safe to make this assumption has never been addressed.

The paper addresses this issue via a simulation which uses randomised data. QCA data-matrices are randomly created (random distribution of 0 and 1 over all the cells of a datamatrix) and a QCA analysis is performed (see appendix for more on the procedure). The argument is as follows: if QCA generates valid models (no contradictions) on the basis of random data QCA is not able to distinguish real from random data and hence cannot guarantee the generated model explains the outcome. In other words, there is no way of knowing whether the variables in a model have any explanatory power at all nor can any measurement error or case or variable selection bias be detected. The possibility that with a complete different model QCA again produces a meaningful result is present. Since random data is used it could be objected that a real study with meaningful data and cases is far removed from random data. Surely, a researcher should be able to distinguish a meaningful model from a nonsensical model. This is obviously true. However, for almost any question in the social sciences one can identify several

[2] Uppercases indicate the presence of an explanatory condition or outcome. Lowercase notation the absence of the condition or outcome. (see also Ragin, 1987; 1994)

possibly alternative meaningful variables and the debate cannot be settled if the chances of finding a model randomly are high (see Amenta & Poulsen, 1994; King et. al. 1994, p. 196). Hence, the difference between valid models and nonsensical models is not necessarily a dichotomy, but a continuum. If, on the other hand, an analysis of random data shows that QCA generates contradictory results one has an indication that QCA is able to distinguish real from random data. If many contradictions occur – measured by different indicators (*infra*) – QCA is not able to produce a valid model on random data. Model specifications with high scores on contradictions indicate that the chances of finding a model randomly are non-existing or small. This clearly strengthens the case for QCA.

This paper argues that the validity of models produced by QCA crucially depends on the proportion of variables on cases (design, *infra*) and the maximum number of variables in an analysis. This issue has been overlooked in QCA-applications; and should become a crucial aspect of a comparative case design. QCA applications with more than 8 variables (including the dependent variable) and applications where the proportion of variables on cases is higher than .33 (depending on the combination of variables on cases) are not able to distinguish real from random data due to the problem of uniqueness which will be discussed below. When the proportion of variables on cases decreases significantly, the indicators of contradictions show that the chances of identifying explanatory models on the basis of random data is non-existing. In those cases QCA generates robust results. In a next paragraph the paper presents the randomised trials and summarises the main results.

METHODOLOGICAL EXPERIMENT

In order to explore this issue a methodological experiment was conducted which assesses to what degree QCA is able to distinguish random from real data. In this study only the crisp approach was used which uses dichotomous variables since this approach is most often used.

The random trials were conducted as follows. First, random datamatrices were made in Excell using the Aselect function. Random datamatrices each consisting of a varying number of variables were made for several number of cases ranging from 7 to 50. Fifty cases was taken as an upper-limit for comparative case research. Knowing more than 50 cases more or less in depth becomes difficult. The proportion used to randomly distribute 0 and 1's in a datamatrix was .5. This means that each cell in a datamatrix had an equal chance of getting a 0 or 1. More importantly, this proportion provides for a good distribution on the dependent variable. It should be noted that not each time the dependent variable was split 50-50 due to the randomisation function. Secondly, each datamatrix was imported in QCA and was analysed using the Quine-McCluskey algorithm[1].

An issue in the experiment concerns the number of trials which should be conducted. The paper takes a pragmatic approach on this issue since the aim of the paper is to discover a trend and does not aim to produce exact estimates. In order to generate exact estimates many more trials for each combination of variables on cases should be conducted. Since, conducting one trial is already elaborate the generation of exact estimates will require a significant investment.

How many trials were conducted? For some combinations of variables on cases one does need to do many random experiments to see that no contradictions occur very frequent or contradictions occur rarely. In these extreme cases, a few trials are sufficient and 20 trials were performed. For other combinations more trials were conducted. A comparison of 50 trials to a 100 trials (compare columns 2 and 3; and 4 and 5 respectively in table 1) shows there is little difference between 50 and 100 trials for some of the key-indicators in the study. (The key indicators are explained below) As a result it was decided to conduct 50 trials for most combinations of variables on cases.

Table 1: Comparing 50 trials and 100 trials for 2 combinations of variables on cases

	4 Variables 15 Cases		**5 Variables 20 Cases**	
	50 trials	**100 trials**	**50 trials**	**100 trials**
Lowest Number of Contradictions	2	1	1	1
% Contradictions	100	100	100	100

RESULTS

Table 2 summarizes the results of some of the trials and provides general information on the contradictions issue with regard to some combinations of variables and cases (for a full overview of all the trials see table 3). The table provides the following information. First the lowest number of contradictory configurations gives an indication of the lowest number of contradictory configurations that are found in a given number of trials. In other words, the row presents the lowest number of contradictions that are found on the basis of 20, 50 or 100 trials. If this figure is 0 – no contradictions are found - the table indicates that QCA finds models on the basis of random data and is not able to distinguish random models from real ones and basically supports the argument by Lieberson. The chances of finding such a model is given by the percentage of contradictions in table 2 (row 2). If the percentage is high, between 90 and 100%, the chances are small that one would find a model on random data since there are many contradictions. However, if the number decreases the chances of finding a model on random data are significant. This figure will obviously be 100 if the lowest number of contradictory configurations is higher than 0. Hence, the two rows are crucial in signalling the chances of finding a model which does or does not have contradictions on random data. In other words, once the lowest number of contradictory configurations is 0, the lower the percentage of contradictions the lower the chances of finding a model which explains each case on the basis of random data indicating that the found model is no different from any other random model. In order to be sure to have a valid model the first indicator should be different from 0.

Table 2: Summary of methodological experiment (50 trials for each combination variables/cases)

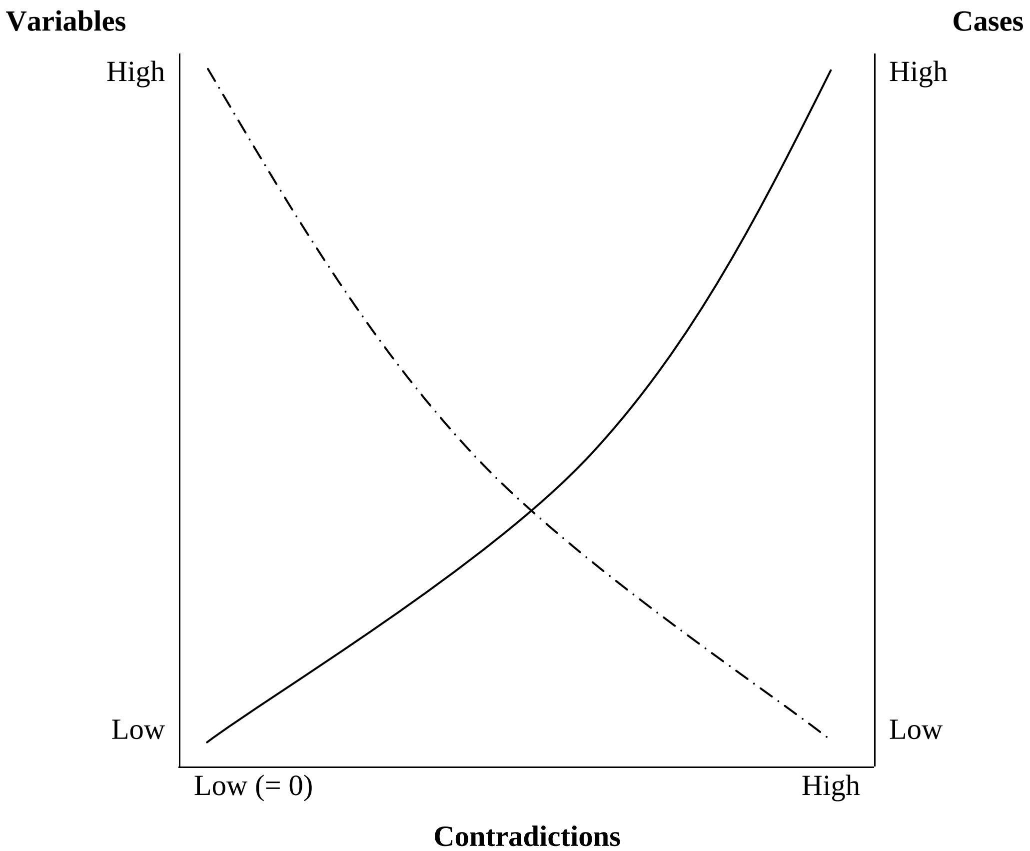
	4 Variables	**5 Variables**	**6 Variables**	**10 Variables**
10 Cases				
Lowest Number of Contradictions	0	0	0	0
% Contradictions	96%	72%	48%	2%
15 Cases				
Lowest Number of Contradictions	2**			
% Contradictions	100%			
20 Cases				
Lowest Number of Contradictions		1**	0	
% Contradictions		100%	94%	
30 Cases				
Lowest Number of Contradictions	5*	4*	2	0*
% Contradictions	100%	100%	100%	45%
40 Cases				
Lowest Number of Contradictions			4*	
% Contradictions			100%	
50 Cases				
Lowest Number of Contradictions				0*
% Contradictions				55%

* = 20 Trials ** = 100 Trials

What does table 2 show? First, moving from left to right within a set of cases (10, 15 – 50) one can observe that the possibilities of finding an explanatory model in random data increases drastically with an increase in number of variables used. For example for 10 cases and 4 variables 96% of the trials generated contradictions. However, for 10 cases and 6 variables this percentage decreased to 48% indicating that there is more than one chance in two that QCA will find a valid model on random data. For 10 variables, there is almost no chance of finding contradictions. This indicates that within a fixed set of cases an increase in variables will lead to a decrease (disappearance) of contradictions and the ability of QCA to make a difference between random and real data. Secondly, moving from top to bottom one can observe that within a set of variables an increase in cases leads to an increase in contradictions. For example, in the case of 4 variables one can observe that with 10 cases there is a 96% chance of getting contradictory results while with 15 cases this has become 0 and with 30 cases the two indicators signal that the random datamatrix does not generate a model and is full of contradictions. This indicates that an increase in cases will result in a more valid model as could be expected on the basis of more traditional approaches.

In sum, the table shows that the relationship of variables on cases is important in the context of distinguishing random from real data. A stylised relationship between these three characteristics - variables, cases and contradictions – for randomised data is presented in figure 1. The full line presents the relationship between cases and contradictions; the dotted line the relationship between variables and contradictions. A randomly produced datamatrix with a high number of cases and a low number of variables produces a high number of contradictions which implies that in this combination of variables and cases QCA can make a distinction between valid models and random models.

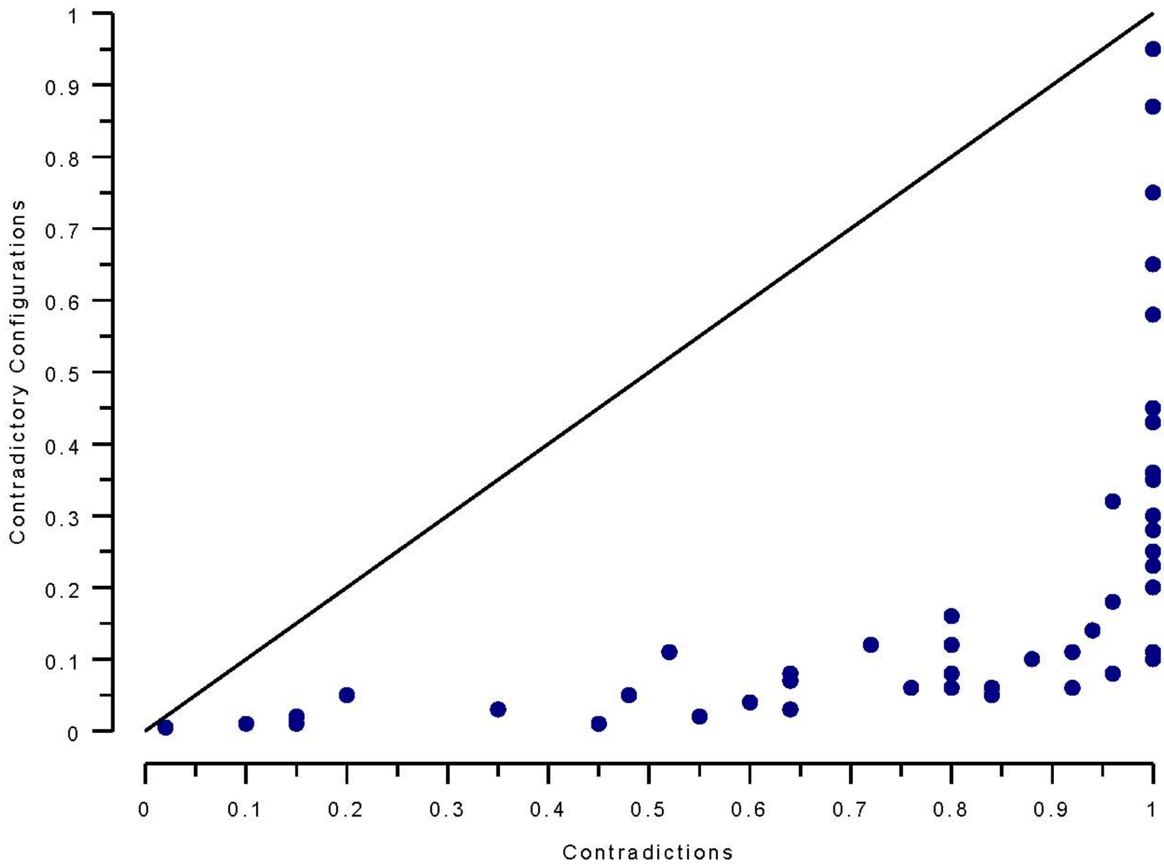
Figure 1: Relationship between cases, variables and contradictions in a QCA-analysed of randomised data



Explanation

How might this be explained? Table 3 further explores this issue. The table summarises all the trials of the methodological experiment and compares the characteristics of the trials with the outcome concerning contradictions. Two measures of contradictions are presented. First, the number of contradictory configurations (contra config) on the total number of configurations is presented. It is computed by dividing the average number of contradictory configurations for a given number of trials by the average number of configurations for the same trials. If the indicator reaches 1 it implies that all configurations are contradictory and QCA can not make sense of the data. If it reaches 0 it means that almost no contradictions are found. This indicator mainly signifies the strength of the contractions issue. The second variable (contradictions) indicates the proportion of trials with at least one contradictory configuration for a given number of trials. If the variable is 1 this means that each trial generated at least one contradictory configuration. If it is 0 this implies that no trial generated a contradiction. In this case QCA cannot make a difference between random and real data. This variable signifies when contradictions start to emerge. The two variables for contradictions are used to explore the implication for QCA research design. It should be noted that the second variable (contradictions) is a subset of the first variable (contradictory configurations)(see Ragin, 2000, pp. 214-218). This relationship is presented in figure 2 (pearson correlation .55 see table 5). [2] [3]

Figure 2: Relationship Contra Configurations and Contradictions



In order to explain the occurrence of contradictions two variables are created, design and complexity. First, the design variable presents the proportion of variables upon cases. If the indicator is 1 there are as many variables as cases. The proportion decreases with an increase of cases given a fixed number of variables. The closer it goes to 0 the bigger the difference is between the number of variables and the number of cases. The second variable, complexity, presents the degree to which QCA reduces complexity for a set of cases, ie pools cases in one or more configurations. It is computed by dividing the average number of configurations by the number of cases. If the indicator reaches 1 it implies that each case is represented by one configuration. In this case there is full complexity and no parsimony. In this sense the complexity indicator is a measure of uniqueness. QCA is not able to pool cases together in a configuration. Moving from 1 to 0 implies moving from full complexity to more parsimony. A low proportion indicates that QCA is able to significantly reduce complexity by pooling cases in a specific configuration.

Table 3: Summary Data on Design, Complexity, Contradictory Configurations and Contradictions

	# Variables	# Cases	Trials	Design	Complexity	Contra Config	Contra
1	4	7	25	0.57	0.79	0.11	0.52
2	4	10	50	0.40	0.57	0.32	0.96
3	4	12	25	0.33	0.51	0.36	1
4	4	15	100	0.26	0.45	0.45	1
5	4	17	125	0.23	0.40	0.36	1
6	4	30	20	0.13	0.26	0.75	1
7	4	40	20	0.1	0.19	0.87	1
8	4	50	20	0.08	0.15	0.95	1
9	5	5	50	1	0.99	0.05	0.2
10	5	10	50	0.50	0.78	0.12	0.72
11	5	12	25	0.41	0.76	0.16	0.8
12	5	15	25	0.33	0.63	0.25	1
13	5	20	100	0.25	0.59	0.28	1
14	5	30	20	0.16	0.44	0.43	1
15	5	40	20	0.12	0.35	0.58	1
16	5	50	20	0.1	0.30	0.65	1
17	6	10	50	0.60	0.89	0.05	0.48
18	6	12	25	0.50	0.83	0.08	0.64
19	6	15	25	0.40	0.76	0.12	0.8
20	6	17	25	0.35	0.74	0.11	0.92
21	6	20	50	0.30	0.77	0.14	0.94
22	6	25	25	0.24	0.72	0.18	0.96
23	6	28	25	0.21	0.67	0.20	1
24	6	30	50	0.20	0.66	0.23	1
25	6	40	50	0.15	0.57	0.30	1
26	6	50	20	0.12	0.52	0.35	1
27	7	9	20	0.77	0.96	0.01	0.1
28	7	12	20	0.58	0.93	0.03	0.35
29	7	15	25	0.46	0.85	0.07	0.64
30	7	17	25	0.41	0.88	0.06	0.8
31	7	20	25	0.35	0.84	0.08	0.8
32	7	25	25	0.28	0.87	0.08	0.8
33	7	28	25	0.25	0.81	0.10	0.88
34	7	30	25	0.23	0.81	0.11	1
35	8	10	20	0.8	0.97	0.02	0.15
36	8	12	20	0.66	0.97	0.01	0.15
37	8	15	20	0.53	0.93	0.03	0.35
38	8	17	20	0.47	0.91	0.04	0.6
39	8	25	25	0.32	0.93	0.03	0.64
40	8	28	25	0.28	0.90	0.05	0.84
41	8	30	25	0.26	0.90	0.06	0.76
42	8	35	25	0.22	0.88	0.06	0.84
43	8	37	25	0.21	0.87	0.06	0.92
44	8	40	25	0.2	0.83	0.08	0.96
45	8	45	25	0.17	0.85	0.1	1
46	9	10	20	0.9	0.98	0.01	0.1
47	9	20	20	0.45	0.98	0.01	0.1
48	10	10	20	1	0.99	0.005	0.02
49	10	30	20	0.33	0.96	0.01	0.45
50	10	50	20	0.2	0.95	0.02	0.55

How might the importance of the proportion of variables be explained? The explanation lies in the nature of Boolean Algebra. Imagine you are looking for an article on Science Direct which also uses Boolean operators to retrieve articles. If you would only type in one keyword the chances are that many articles pop up. The number of articles will decrease if you would put in a key-word AND a word of the title. If you would type in the key-word AND a word of the title AND name of the journal AND name of the author the chances are significant that the one article out of millions you are looking for will show up since the article has the unique configuration of the four aspects mentioned above. The same is basically true for QCA and might in this context be labelled the problem of uniqueness. If the number of variables is close to the number of cases the problem of uniqueness occurs. From a certain number of variables onwards the problem of uniqueness persists.

The problem of uniqueness occurs when each case in the analysis is a unique configuration of variables and is presented by the complexity variable (see table 3). If it comes close to one this means that there are as many configurations as cases; ie each case is unique which makes it impossible for contradictions to occur. The relationship between complexity and contradictions is presented in the figures 3 and 4. Figure 3 shows that if one is able to achieve complexity reduction (complexity indicator <0.7) contradictions will emerge all the time. The close relationship between complexity reduction and the emergence of contradictions is further highlighted in Figure 4 which shows an almost perfect inverse correlation (pearson –0.97 – see note 3) between complexity and contradictions. With a complexity measure of 1 there are no contradictions. In such a context it becomes impossible to distinguish real from random data. With a complexity measure approaching zero a QCA is full of contradictions, ie QCA only finds contradictions.

Figure 3: Relationship Complexity and Contradictions

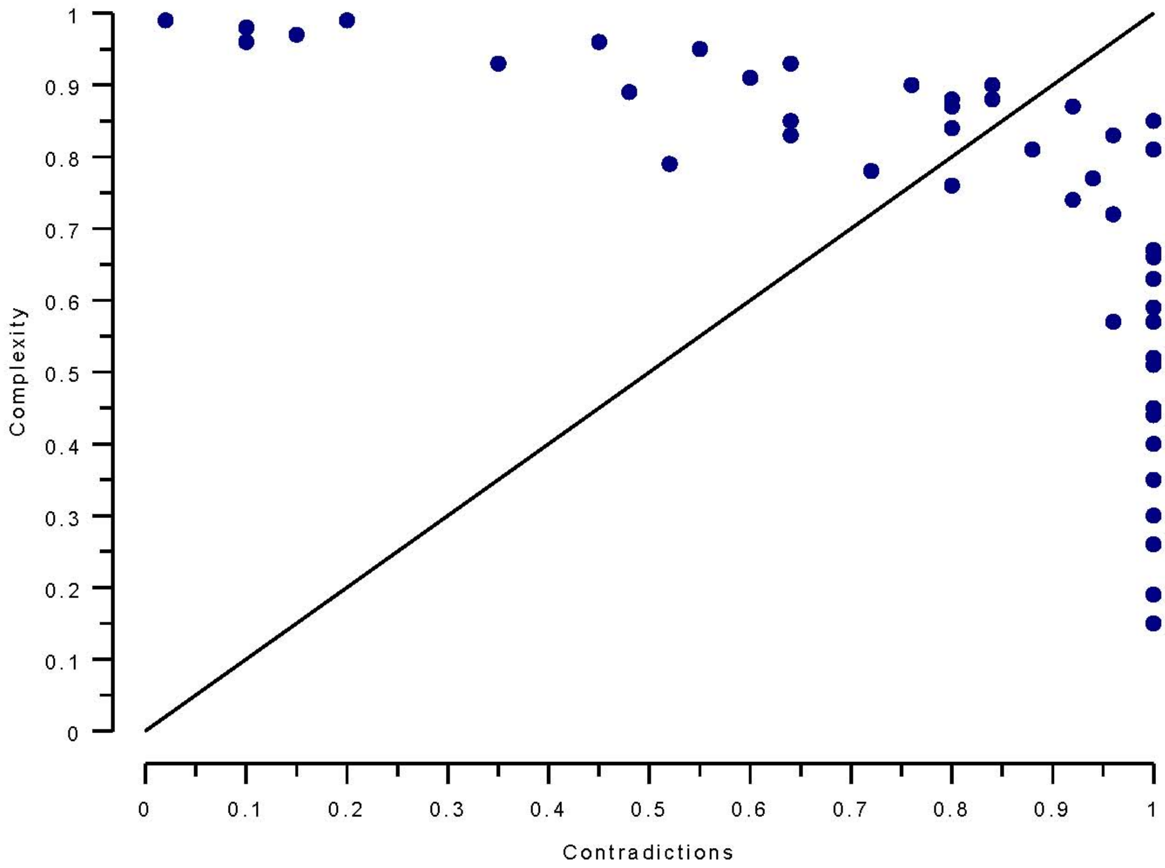
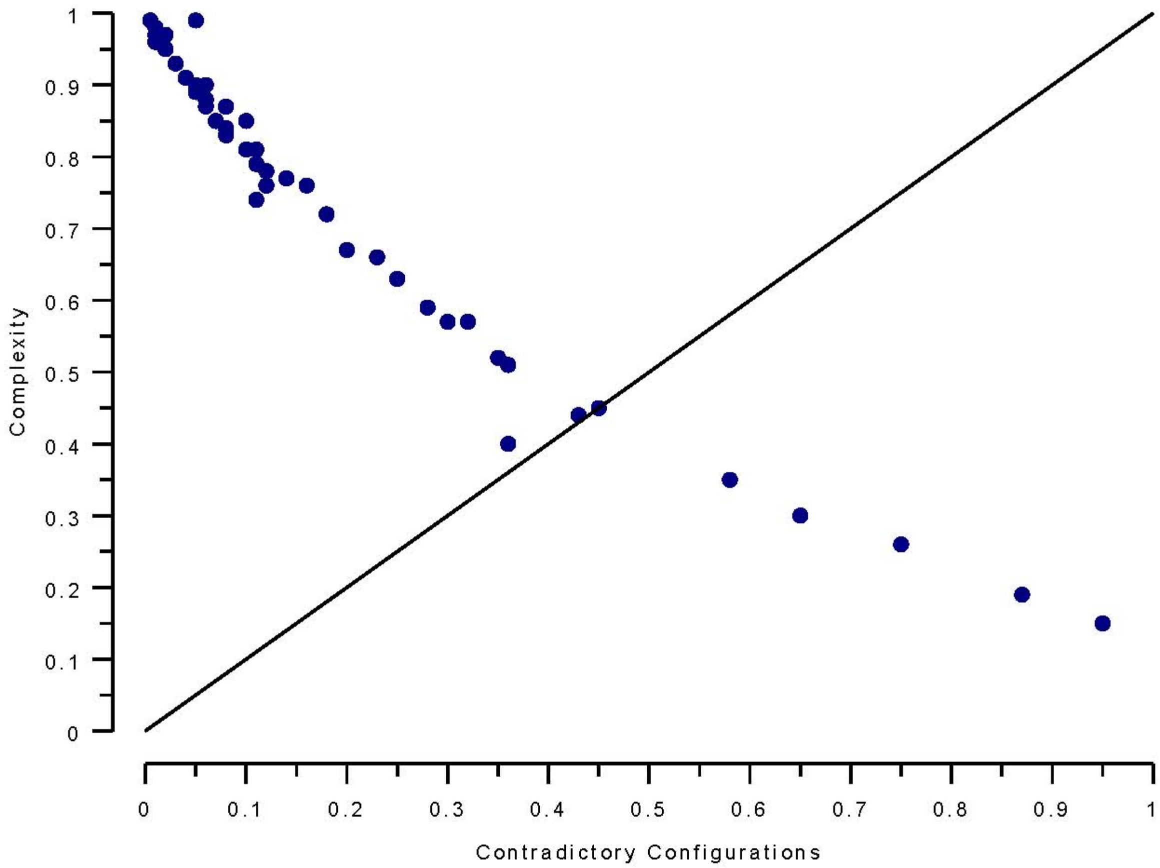


Figure 4: Relationship Complexity and Contra Configurations



When does QCA result in full complexity and when does it achieve parsimony? This issue is analysed in figure 5 which represents the relationship between complexity and design. The figure shows that complexity reduction occurs when the design parameter decreases (pearson correlation of 0.61). In other words, when the proportion of variables on cases decreases (design goes from 1 to zero) parsimony and complexity reduction increases (complexity goes from1 to 0). In fuzzy-set theoretic terms design is a sufficient condition for complexity (reduction) (see Ragin, 2000, pp. 234-238). If the membership in the design-set is 1, the membership complexity set will also be 1. In contrast, low membership in the design set will result in lower membership in the complexity set. In sum, when the proportion of variables on cases decreases complexity reduction occurs and contradictions start to emerge. This is the point from which QCA becomes a valuable tool in model construction. Hence, the issue of contradictions is not only a function of the number of cases as suggested by Ragin (1987, p. 117), but also from the number of variables and the proportion of variables on cases. The latter is a crucial issue for model-specification using QCA. In addition, it should also be noted that the issue of complexity versus parsimony (Ragin & Sonnett, 2004) is not only a theoretical issue (how much parsimony and complexity do we want) but also a methodological issue. The analysis shows that in a quest for more parsimony the problem of uniqueness also limits the degree to which empirical complexity can be reduced.

Figure 5: Relationship Complexity and Design

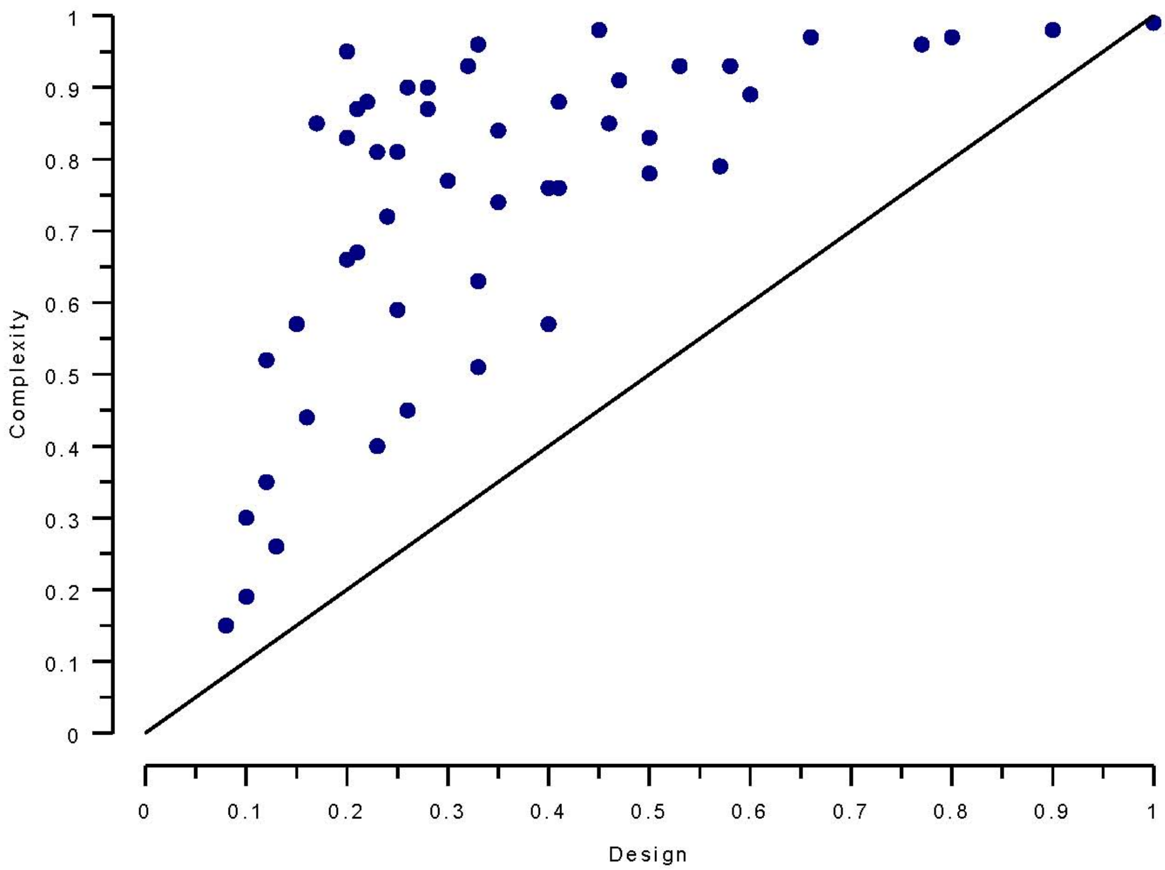


Figure 5 presents two important conclusions. Firstly, complexity increases when design increases. The problem of uniqueness starts to occur when design goes up to one cf. number of variables equals number of cases. Hence, QCA-models should be designed in such a way that they facilitate complexity reduction and allow contradictions to occur. Secondly, the top middle and left of the figure shows that complexity remains high even if the design parameter is low. This is a result of the fact that from a number of variables the problem of uniqueness persists (for a maximum of 50 cases). This implies that there is an upper-limit to the number of variables which can be included in a QCA-analysis.

Implications for Research Design

Little attention is paid to this issue in the literature. It is commonly not mentioned and the use of QCA is advised for small-N analysis (5-50 cases) with 3 to 12 or even more variables (see for example De Meur & Rihoux, 2002; Rihoux, 2003). Table 3 presents an overview of recent QCA applications (with sufficient variation on all the variables) some of which are published in main international journals such as American Journal of Sociology and American Sociological Review. Table 4 clearly shows that the design of variables on cases is not really addressed. Up till now, anything goes. Some studies have more variables than cases, some studies use to many variables (V>7/8) and some studies have a too high proportion of variables on cases. The analysis presented in this paper shows that only limited conclusions can be made on the basis of these studies.

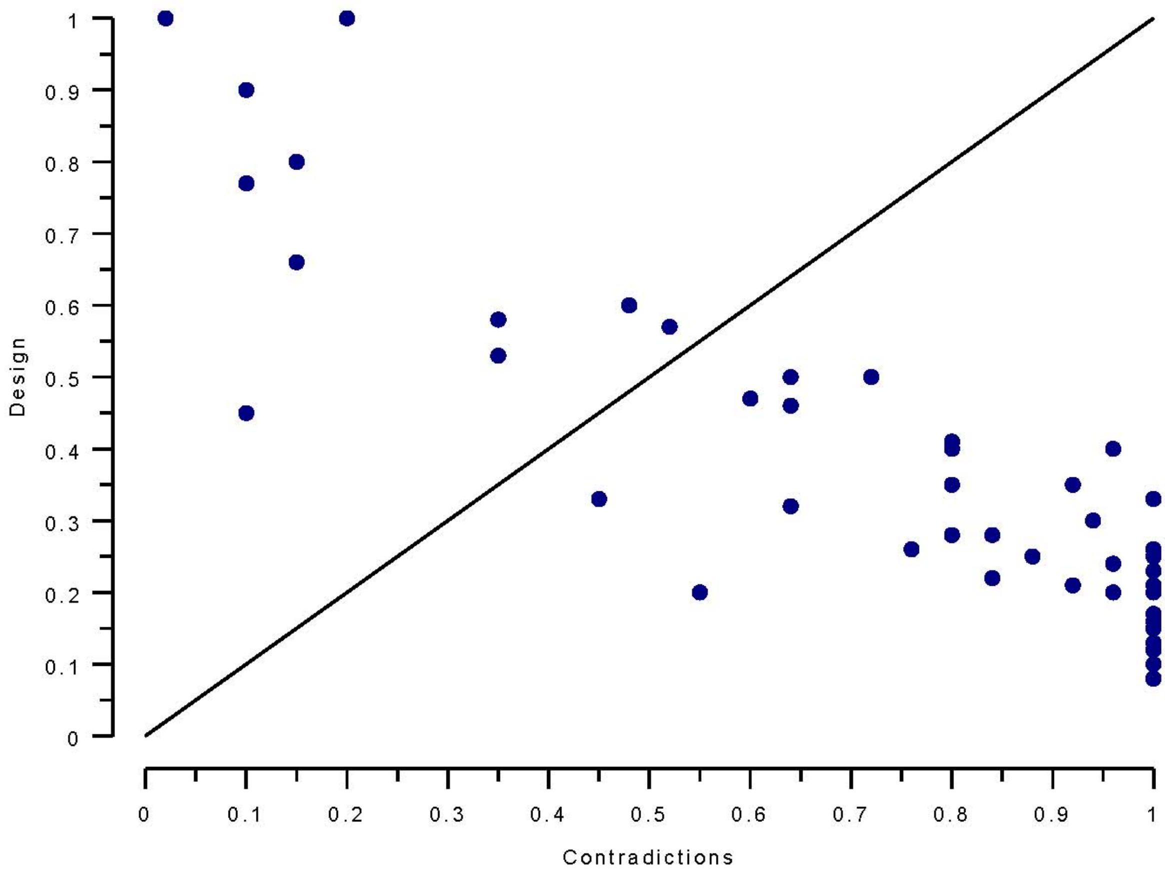
Table 4: Selected Overview of QCA Applications

Reference	# Variables	# Cases	Reference	# Variables	# Cases
Amenta (1994)	10	48	Hollingsworth et. al. (1996)	4	37
Amenta et. al (1992)	6	48	Johnson et. al.	4	9
Amenta/Halfman (2000)	7	86/46	King et. al. (2001)	20	68
Amoroso & Ragin (1992)	7	2964	Kitchener et. al. (2002)	6	5
Berg-Schlosser/Quenter (1996)	9	12	Kittel et. al. (2000)	6	15
Berg-Schlosser (2002)	3 – 4	18	Larose et. al. (1996)	9	100
Berg-Schlosser/De Meur (1997)	4	18	Lesthaeghe (1992)	4	40
Blake/Adolino (2001)	5	20	Melinder/Andersson (2001)	5	12
Boswell/Brown (1999)	3/4/6/7	9	Mengeot (2003)	7	10
Brueggeman/Boswell (1998)	3	7	Miethe/Drass (1999)	23	5755
Clément (2004)	4	9	Musheno et. al. (1991)	5	36
Coverdill/Finlay (1995)	5	22	Nelson (2004)	4	18
Cress/Snow (1996)	15	15	Peillon (1996)	9	25
Curchod et. Al. (2004)	4	16	Queiroz-Athias (2003)	6	26
Drass/Spencer (1987)	11	126	Ragin/Bradshaw (1991)	6	1936
Ebbinghaus/Visser (1998)	4	13/16	Redding/Viterna (1999)	5	18
Egan (2002)	6	22	Rihoux/Yamasaki (2003)	6	26
Goodwin (2001)	6	9	Romain (2003)	13	34
Gordin (2001)	4	12	Romme (1995)	22/18/14	29
Gottcheiner (2003)	7	72	Rudel/Roper (1996)	11	68
Grassi (2004)	7	13	Sager (2004)	4	17
Griffin et. al. (1997)	4	15	Schiffino/Yamasaki (2003)	5	8
Harkreader/Imershein (1999)	7	27	Sicakkan	9	18
Haworth Hoeppner (2000)	4	30	Stevenson/Greenberg (2000)	4	18
Heikkila (2001)	9	70	Stokke (2003)	5	10
Hellström (2001)	10	7	Taras (1993)	4	15
Herala (1995)	8	16	Wickham-Crowley (1991)	5	28
Herala (2004)	12	27/12	Williams/Farrell (1990)	12/5	60
Hicks et. al. (1995)/Hicks 1999	5	15	Yamasaki (2003)	4	18

Bibliographical References see www.compasss.org, which is a resource website for all QCA-applications.

What are the implications of these results for a QCA based research design? Which recommendations should be made? Five implications will be discussed. First of all, when the proportion of variables on cases (Design) goes up to 1 the number of contradictions decrease significantly regardless of the number of variables and cases involved. This means that studies with an equal number of variables and cases have no way of distinguishing random from real data. On the other hand, if one identifies explanatory models via QCA in the context of few variables and significant number of cases one can assume that these models are valid. If the proportion of variables on cases decreases, the number of contradictions increases (see figure 6). Hence, the first implication is to specify the model in such a way that the number of variables is significantly lower than the number of cases (*infra).*

Figure 6: Relationship Design and Contradictions



Secondly, the threshold from which non-contradictions start to emerge is not constant in terms of generating (many) contradictions, but is depending on the number of variables. This study can only provide rough estimates but it seems to be that the threshold from when non-contradictions start to emerge is higher for a small number of variables than for a high number of variables. In the case of 4 variables the proportion seems to be roughly .33 (1/3) since a 100% of contradictions occur when one moves from 10 to 12 cases (compare rows 2 and 3, table 4). It should be noted that in the context of 4 variables/10 cases the percentage of contradictions is still very high. For 5 variables the proportion also seems to be .33 (1/3) since 100% contradictions occur when one reaches 15 cases. For 6, 7 and 8 variables the proportion decreases. For 6 and 7 variables it seems to be 0.25, for 8 variables 0.20. This is a result of the problem of uniqueness.

Thirdly, in the context of small-N (N<50) research there seems to be an upper-limit to the number of variables which can be used in a QCA analysis. On the basis of table 4 it is argued that for 50 cases the upper-limit of variables is 8. More variables can be included in a QCA-analysis if one increases the number of cases. However, a drastic increase in cases will not allow a researcher to get sufficient case knowledge which would allow a dialogue between theory and data.

These three issues are further elaborated in the construction of a benchmark table which enables researchers to assess what the chances are of finding a model on random data for a specific combination of variables and cases (model-specification). Table 5 presents a first draft of such a benchmark table

Four benchmarking standards are used.

0 = Model-specification will always generate contradictions on the basis of random data. None of the trials with this model-specification generated 0 contradictions. Models developed on the basis of this specification are valid.

>1%-<10% = Model-specification will almost always generate contradictions on the basis of random data

>10%-<33% = Model-specification will most of the time generate contradictions on the basis of random data. However, there is a significant possibility of finding non-contradictions.

>33% = Model-specification is not valid. The possibility of finding contradictions on random data are small. The >33% area of the table indicates that models falling in this space could also be generated ad random.

Table 5: Benchmark Table to a Assess the Chances of Finding a Model with a Given Number of Variables and Cases on Random Data

		# Variables				
		4	5	6	7	8
# Cases	5	>33%	>33%	>33%	>33%	>33%
	6	>33%	>33%	>33%	>33%	>33%
	7	>33%	>33%	>33%	>33%	>33%
	8	>33%	>33%	>33%	>33%	>33%
	9	>10%-<33%	>33%	>33%	>33%	>33%
	10	>1%-<10%	>10%-<33%	>33%	>33%	>33%
	11	>1%-<10%	>10%-<33%	>33%	>33%	>33%
	12	0	>10%-<33%	>33%	>33%	>33%
	13	0	>1%-<10%	>10%-<33%	>33%	>33%
	14	0	>1%-<10%	>10%-<33%	>33%	>33%
	15	0	0	>10%-<33%	>33%	>33%
	16	0	0	>1%-<10%	>10%-<33%	>33%
	17	0	0	>1%-<10%	>10%-<33%	>33%
	18	0	0	>1%-<10%	>10%-<33%	>33%
	19	0	0	>1%-<10%	>10%-<33%	>33%
	20	0	0	>1%-<10%	>10%-<33%	>33%
	21	0	0	>1%-<10%	>10%-<33%	>33%
	22	0	0	>1%-<10%	>10%-<33%	>33%
	23	0	0	>1%-<10%	>10%-<33%	>33%
	24	0	0	>1%-<10%	>10%-<33%	>33%
	25	0	0	>1%-<10%	>10%-<33%	>33%
	26	0	0	0	>10%-<33%	>10%-<33%
	27	0	0	0	>1%-<10%	>10%-<33%
	28	0	0	0	>1%-<10%	>10%-<33%
	29	0	0	0	>1%-<10%	>10%-<33%
	30	0	0	0	0	>10%-<33%
	31	0	0	0	0	>10%-<33%
	32	0	0	0	0	>10%-<33%
	33	0	0	0	0	>10%-<33%
	34	0	0	0	0	>10%-<33%
	35	0	0	0	0	>10%-<33%
	36	0	0	0	0	>1%-<10%
	37	0	0	0	0	>1%-<10%
	38	0	0	0	0	>1%-<10%
	39	0	0	0	0	>1%-<10%
	40	0	0	0	0	>1%-<10%
	41	0	0	0	0	>1%-<10%
	42	0	0	0	0	>1%-<10%
	43	0	0	0	0	>1%-<10%
	44	0	0	0	0	>1%-<10%
	45	0	0	0	0	>1%-<10%
	46	0	0	0	0	0
	47	0	0	0	0	0
	48	0	0	0	0	0
	49	0	0	0	0	0
	50	0	0	0	0	0

The benchmark table is based on a 50/50 distribution on the dependent variable. It could be argued that many studies do not have such an equal distribution and that for other distributions another benchmark table should be constructed since a different distribution of the dependent variable might result in different chances of finding contradictions. Hence, the issue of model specification under a skewed dependent variable should also be addressed. For one research design (4 variables – 17 cases) 550 trails were conducted to explore the relationship between contradictions and the distribution of the dependent variable for a proportionate and disproportionate distribution on the dependent variable. Table 6 summarises the results. The table shows that the emergence of contradictions stays almost constant for the different distributions on the dependent variable. The number of contradictory configurations decreases as the distribution on the dependent variable becomes more unequal. In other words, the table shows that the distribution has an effect on how many contradictions will appear in a QCA-analysis however it does not have a strong effect on whether contradictions will appear or not. The later can be explained by looking at the complexity indicator which is more or less the same for all distributions, which in turn is a result of the fact that QCA generates a fixed number of configurations for a given model regardless of the distribution on the dependent variable. Figure 3 (complexity and contradictions) showed that from a certain degree of complexity reduction onwards contradictions appear constantly. As a result the benchmark table can be used for any distribution on the dependent variable with the exception of an extreme unequal distribution such as 90% or more 1's or 0's.

Table 6: Effect of distribution of the dependent variable on contradictions

Dependent Variable	**Distribution Variable**	**Trials**	**Av. # Configurations**	**Complexity**	**Contra**	**Contra Config**
9/8 – 8/9	.52/.48	37	6.8	0.4	1	0.51
10/7	.58/.42	30	6.7	0.4	1	0.53
11/6	.64/.36	55	7.1	0.4	1	0.45
12/5	.70/.30	83	6.8	0.4	1	0.44
13/4	.76/.24	125	6.8	0.4	1	0.35
14/3	.82/.18	114	6.8	0.4	1	0.30
15/2	.88/.12	72	6.8	0.4	0.95	0.23
16/1	.94/.06	34	6.8	0.4	0.88	0.11

N = 550

A fourth implication is that due to the limitations on variables in a QCA-analysis the issue of constructing the research population, and identifying scoping conditions, becomes even more crucial. Ragin (2000) stresses the importance of applying QCA to a set of 'comparable cases' and emphasises the importance of population construction. Gerring (2001) provides a good overview of different types of population construction and case selection strategies in comparative case design. Specifically in relation to QCA it seems to be that a MSDO-design with sufficient variation on all the variables is the most appropriate way to proceed. QCA-applications often use a Most Similar Conditions Different Outcomes design (see Pzewroski & Teune 1970; Ragin et. al., 1994; for an interesting application see Goodwin, 2001, pp. 5-8).

A fifth implication is that the QCA-software should include an additional function for the analysis of data. Given the fact that one often has more variables than the restrictions outlined in the benchmark table QCA should provide summary information on the contradiction issue for all possible models which can be made out of a number of variables. The function should provide information on how many contradictions occur for all possible models given a number of variables. The use of this function should enable researchers to select a model for which contradictions will be solved.

For example, imagine that one wants to compare 15 companies and explain why some companies adopt a system for quality management and other do not. The outcome is having a system (1) or not (0). After a literature review and researching the companies one has 6 possible explanatory variables which might explain adopting a system or not. However, following the benchmark table 7 variables (6 + 1 (outcome)) and 15 cases will almost always generate an explanatory model with no contradictions. Hence, it is not a good idea to use the model for a QCA-analysis since it has little or no discriminating power. Out of the 6 variables a model with at most 4 explanatory variables should be constructed. In order to facilitate the construction of the model one should have information on whether, and how many, contradictions occur for all possible 4 and 3 variables explanatory models which might be made out of the 6 variables. This information might guide researchers in selecting the initial model which can then further be used to compare the cases.

CONCLUSION

The issue of contradictions is of quintessential importance in QCA. Solving contradictions is the way to come to an explanatory model. The rationality of QCA to develop models depends on the interaction of data and theory and the fact that one resolves contradictions via the selection of cases, addressing measurement error or by including new explanatory conditions. However, if there are no contradictions from the outset there are no contradictions to be solved and the model is accepted. However, any other model might proof to be as ‘explanatory’ as another one. So one should specify the model in such a way that contradictions should normally occur if the model has omitted relevant variables, the research population is to heterogeneous (non-comparable cases) and measurement error occurred. If the model is designed carefully the above analysis supports the idea that QCA can distinguish real from random data and seems to do well for what is was designed to do namely ”*determine the number and character of the different causal* [paths] *that exist among comparable cases*” (Ragin 1987, p. 167).

The experiment shows that a QCA-application is restricted by the proportion of variables on cases and by an upper-limit of variables which can be used in an analysis. If both restrictions are not taken into account QCA cannot make a distinction between random and real data. Precise estimates should be produced in order to benchmark a QCA-study in terms of its ability to find a model on the basis of random data. Future research would do well to construct a benchmark-table with exact estimates.

The main consequence of this finding concerns research-design which aims to perform a QCA-analysis. QCA essentially aims to develop models on the basis of empirical data and via dialogue between theory and data. This is often a re-iterative process whereby the researcher test his/her model via a QCA-analysis. Often researchers will encounter contradictory results which will force him/her to redefine the model. One way of dealing with the issue of contradictions is introducing new variables since the previous analysis shows that a crucial one might be omitted. The experiment shows that introducing new variables is not always a legitimate strategy since it also increases the probability of just finding a model ad random.

However, this does not imply that QCA is useless or becomes more limited in its application. To the contrary, it implies that a QCA-analysis will be harder but will force – as it is intended to do – the researcher to really keep on looking to find a model that fits the data. It should be stressed that QCA has some distinctive strengths vis-à-vis standard bivariate techniques as well as single case studies or comparative case analysis of less than 5 cases since it is able to identify configurations of structural conditions which are associated with a certain outcome.

Under the restrictive conditions outlined in the paper this is a hard job which will be both theoretically and empirically demanding. It will require researchers to invest in conceptual innovation and refinement. As a result, a crucial issue in comparative case research will become concept development, refinement and measurement. The use and creation of macro-variables will be one way to deal with the variables restriction. (Berg-Schlosser & De Meur, 1997). Adcock and Collier (2001) provide interesting guidance on concept-development. However, more research should be done in this respect since it is not always straightforward to develop new concepts out of existing ones, aggregate indicators, etc. In addition, good handbooks on concept development are lacking.

Finally, the paper focused only on a dichotomous approach to QCA. Recently multi-value nominal, ordinal and fuzzy-set approaches to QCA were developed. Similar experiments should be conducted to assess the degree to which they generate random models. The multi-value approaches were developed after criticism on the binary approach. The critics basically argued that the binary approach was a to crude measurement instrument. However, as Collier & Adcock (1999) have shown in the case of operationalising democracy dichotomies are not necessarily analytically inferior to more advanced types of measurement. It depends among other things on the aim of the research project and the type of variables. Concerning the latter, there are certainly several variables in all fields of social science which can be coded as being either absent and/or present. As a result, the crisp approach should not be dismissed too quickly.

This point becomes even more valid if one makes a distinction, as Elinor Ostrom (forthcoming) does, between frameworks, theories and models. According to Ostrom models make precise hypotheses about a limited set of variables and are deduced out of theory which in turn focuses on a specific part of a framework which is an overview of all possible relevant variables for a given research topic. This distinction indicates that models consisting of variables which are open to dichotomisation could be explored via QCA. One could even argue that QCA is potentially a powerful tool to develop and test models and generate more precise predictions, because it is deterministic in nature (explaining all the cases) while at the same time allows for multiple causal conjunction within a given model. In other words, QCA can make a significant contribution to model specification because it allows for multiple causal paths which are nested within a model. In this way it can contribute to a challenge posed by Fritz Scharpf (1997, 29) who argued that: "*In a world that is exceedingly complex and in which we will often be studying unique cases, we must have a good idea of what to look for if we wish to discover anything worthwhile. Since a single data point can be 'explained' by any number of regression lines, post hoc explanations are too easy to invent and usually (unless invented with the trained skill of the master historian) totally useless. The implication is that our search for explanations must be disciplined by strong prior expectations and that we must take the disconfirmation of such expectations as a welcome pointer to the development of more valid explanations.*"

A well conducted QCA application has the potential to generate strong expectations. However, this will imply that in the future researchers should give attention to the restrictions outlined in this paper and should design their studies according to some of the design-principles discussed in the paper, namely using MSDO research population construction techniques and finding the right balance between variables and cases. This will make a QCA-application more difficult but will generate more robust results.

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Endnotes

[1] The Software is freely available on the web: http://www.u.arizona.edu/%7Ecragin/fsqca.htm

[2] The paper uses the fuzzy-set software to create scatterplots in order to use its set-theoretic reasoning, where this is not appropriate, the diagonal can be disregarded.

[3] Table 7 presents the correlations of all the variables included in the analysis. The table shows that the design of a model in terms of variables on cases is negatively related to the occurrence of contradictions (two indicators: -0.56 and –0.88).

Table 7: Pearson Correlations for the variables (Table 4)

	V1	V2	V3	V4
Design (V1)	1.000			
Complexity (V2)	0.61	1.000		
Contradictory configurations (V3)	-0.56	-0.97	1.000	
Contradictions (V4)	-0.88	-0.66	0.55	1.000

All significant on the 0.001 level